申报	系列：教师系列教学型 A 类
	专业：计算机科学与技术
	职称：副教授

业绩成果材料

（申报人的业绩成果材料包括论文、科研项目、获奖以及其他成果等）

单　位（二级单位）：数学与信息学院

姓　名　　**杨磊**

材料核对人:　　单位盖章:

核对时间:

华南农业大学制

目　　录

一、教学研究业绩

1.教学研究项目（主持）

1.1 关于广东省教育教学改革项目：基于 SPOC 的《计算机组成原理》翻转课堂教学模式研究的立项通知（合同）及有关佐证材料.....1

1.2 关于广东高校公共计算机课程教学改革项目：公共计算机课程《C 语言程序设计》SPOC 翻转课堂混合教学模式研究的立项通知（合同）及有关佐证材料.....10

1.3 关于华南农业大学教育教学改革项目：基于知识图谱的《计算机组成原理》课程智慧化教学研究与实践的立项通知（合同）及有关佐证材料.....14

1.4 关于华南农业大学教育教学改革重点项目：基于 SPOC 的《计算机组成原理》翻转课堂教学模式研究的立项通知(合同）及有关佐证材料.....21

1.5 关于华南农业大学教育教学改革重点项目:基于 MOOC 的《数据库技术应用基础》翻转课堂教学模式研究的立项通知（合同）及有关佐证材料.....30

1.6 关于华南农业大学教育教学改革项目：基于 Moodle 的《大学计算机基础》课程在线学习平台的设计与应用研究的立项通知（合同）及有关佐证材料.....35

1.7 关于华南农业大学课程思政示范项目：典型案例 C 语言程序设计-循环结构的立项通知（合同）及有关佐证材料...37

2.教改论文

2.1 教学改革论文（核心 C 类）检索证明.....45

2.2 基于认知负荷理论的《计算机组成原理》实验教学设计与成效研究.....46
2.3 基于 CIPP 的《计算机组成原理》翻转课堂教学模式的应用效果评价.....57
2.4 基于 SPOC 的《计算机组成原理》翻转课堂教学模式研究.....65
2.5 基于Moodle的大学计算机基础实验课程教学设计与实现.....76
2.6 虚拟校园的研究与实践-以华南农业大学红满堂为例.....83
3.教学比赛证书
3.1 全国高校教学创新大赛广东省赛二等奖.....96
4.教学评价佐证
4.1 近 5 年 5 学期评教前 20%佐证.....97
5.教学成果奖证书
5.1 省级一流课程《计算机组成原理》（排名 3）.....98
5.2 广东省计算机教育软件比赛优秀奖（排名 2）.....99
5.3 广东省计算机教育软件比赛优秀奖（排名 3）.....100
5.4 校级教学成果一等奖（排名 5）.....101
5.5 校级教学成果二等奖（排名 5）.....102
6.编写教材
6.1 人工智能理论及应用 主编（第四）.....103
二、科研项目
1.主持
1.1 关于广东省自然科学基金面上项目（2020）的立项通知（合同）及有关佐证材料.....108
1.2 关于广东省科技计划项目（2014）的立项通知（合同）

及有关佐证材料.....118
1.3 关于广东省科技计划项目（2015）的立项通知（合同）及有关佐证材料.....132
1.4 关于广东省科技计划项目（2016）的立项通知（合同）及有关佐证材料.....147
1.5 关于广东省农业科技特派员项目(2018)的立项通知(合同）及有关佐证材料.....160
1.6 关于广州市农村科技特派员项目(2021)的立项通知(合同）及有关佐证材料.....172
1.7 关于国家星火计划项目（2015）的立项通知（合同）及有关佐证材料.....187
1.8 关于国家星火计划项目（2013）的立项通知（合同）及有关佐证材料.....188
1.9 关于广东省大任务专项项目（2023）的立项通知（合同）及有关佐证材料.....189
2.主参
2.1 全国教育科学规划项目（2019，排名 2）..... 203
2.2 国家自然科学基金（2017，排名 3）..... 204
2.3 国家重点研发计划（2023，排名 3）..... 206
2.4 国家重点研发计划（2023，排名 3）..... 208
2.5 省百千万工程项目（2024，排名 2）..... 210
三、论文、著作等
1.检索证明.....214
2.以第一作者发表本专业论文情况
2.1 A Many-Objective Evolutionary Algorithm Based on Interaction Forces and Hybrid Evolutionary Mechanism 218

2.2 A many-objective evolutionary algorithm based on reference vector guided selection and two diversity and convergence enhancement strategies.....238
2.3 Many-Objective Evolutionary Algorithm Based on Spatial Distance and Decision Vector Self-Learning256
2.4 A vector angles-based many-objective particle swarm optimization algorithm using archive.....272
2.5 Ant colony classification mining algorithm based on pheromone attraction and exclusion.....288

3.以通讯作者发表本专业论文情况

3.1An Enhanced Diversity Indicator-Based Many-Objective Evolutionary Algorithm With Shape-Conforming Convergence Metric 301
3.2 面向高维多目标优化的双阶段双种群进化算法 320
3.3 较短的长序列时间序列预测模型 333
3.4 面向复杂约束多目标优化问题的双种群双阶段进化算法 341

4.理论文章、学术专著等

4.1 信息技术背景下科技情报研究与科技信息云服务探索（副主编）.....351

四、科研成果

1.知识产权

1.1 专利授权证书：基于约束多目标进化算法的区域农业种植结构优化方法、装置、设备及介质.....354
1.2 专利授权证书：基于向量角粒子群的多目标控制排水模型的求解方法..... 355
1.3 软件著作权..... 357

五、其他业绩

1.指导学生学科竞赛

1.1 第十六届蓝桥杯 Java 软件开发国赛二等奖（T2）.....384
1.2 第十六届蓝桥杯 Java 软件开发国赛二等奖（T2）.....385
1.3 第十六届蓝桥杯 Python 程序设计国赛三等奖（T2）..386
1.4 第十六届蓝桥杯 Python 程序设计国赛三等奖（T2）..387
1.5 第十六届蓝桥杯 C/C++程序设计国赛三等奖（T2）.....388
1.6 第十五届蓝桥杯 C/C++程序设计国赛二等奖（T2）.....389
1.7 第十五届蓝桥杯 C/C++程序设计国赛三等奖（T2）.....390
1.8 第十四届蓝桥杯 C/C++程序设计国赛三等奖（T2）.....391
1.9 第十四届蓝桥杯 C/C++程序设计国赛优秀奖（T2）.....392
1.10 第十三届蓝桥杯 C/C++程序设计国赛三等奖（T2）...393
1.11 第十三届蓝桥杯 C/C++程序设计国赛三等奖（T2）...394
1.12 第十三届蓝桥杯 C/C++程序设计国赛 A 组优秀奖（T2）
.....395
1.13 美国数学建模大赛二等奖（T2）.....396
1.14 中国研究生创新实践大赛三等奖（A）.....397
1.15 中国大学生程序设计大赛银奖（A）.....398
1.16 第十六届蓝桥杯 Java 软件开发省赛一等奖（B）.....399
1.17 第十六届蓝桥杯 Java 软件开发省赛一等奖（B）.....400
1.18 第十六届蓝桥杯 Python 程序设计省赛一等奖（B）..401
1.19 第十六届蓝桥杯 Python 程序设计省赛一等奖（B）..402
1.20 第十六届蓝桥杯 C/C++程序设计省赛一等奖（B）.....403
1.21 第十六届蓝桥杯 Python 程序设计省赛二等奖（B）..404
1.22 第十六届蓝桥杯 C/C++程序设计省赛三等奖（B）.....405
1.23 第十六届蓝桥杯 C/C++程序设计省赛三等奖（B）.....406
1.24 第十五届蓝桥杯 C/C++程序设计省赛一等奖（B）.....407

1.25 第十五届蓝桥杯 C/C++程序设计省赛一等奖（B）.....408
1.26 第十五届蓝桥杯 C/C++程序设计省赛二等奖（B）.....409
1.27 第十五届蓝桥杯 C/C++程序设计省赛二等奖（B）.....410
1.28 第十五届蓝桥杯 Java 软件开发省赛二等奖（B）.....411
1.29 第十五届蓝桥杯 Java 软件开发省赛二等奖（B）.....412
1.30 第十五届蓝桥杯 C/C++程序设计省赛三等奖（B）.....413
1.31 第十五届蓝桥杯 C/C++程序设计省赛三等奖（B）.....414
1.32 第十五届蓝桥杯 C/C++程序设计省赛三等奖（B）.....415
1.33 第十五届蓝桥杯 Java 软件开发省赛三等奖（B）.....416
1.34 第十四届蓝桥杯 C/C++程序设计省赛一等奖（B）.....417
1.35 第十四届蓝桥杯 C/C++程序设计省赛一等奖（B）.....418
1.36 第十四届蓝桥杯 C/C++程序设计省赛一等奖（B）.....419
1.37 第十四届蓝桥杯 C/C++程序设计省赛二等奖（B）.....420
1.38 第十四届蓝桥杯 C/C++程序设计省赛二等奖（B）.....421
1.39 第十四届蓝桥杯 C/C++程序设计省赛三等奖（B）.....422
1.40 中国高校计算机大赛华南赛区二等奖（B）.....423
1.41 泛珠三角大学生计算机作品大赛三等奖（C）.....424
1.42 广东省大学生计算机作品赛三等奖（C）.....425
1.43 广东省大学生计算机作品赛三等奖（C）.....426
1.44 广东省大学生计算机作品赛三等奖（C）.....427
2.个人荣誉
2.1 校级“教书育人先进个人”证书.....428
2.2 院级“十佳教学工作者”证书.....429
2.3 院级“十佳教学工作者”证书.....430
2.4 院级“十佳科研工作者”证书.....431
2.5 院级“十佳教学工作者”证书.....432
2.6 院级“十佳教学工作者”证书.....433

2.7 院级“十佳管理工作者”证书.....434
2.8 院级“就业工作积极分子”证书..... 435
2.9 五次考核优秀材料..... 436

【佐证材料切记与目录页所列页码对应，不要用图片格式的材料进行打印。】

广 东 省 教 育 厅

广东省教育厅关于公布2019年广东省高等教育教学改革项目立项名单的通知

各本科高校:

按照《广东省教育厅关于开展2019年度省高等教育教学改革项目推荐工作的通知》安排，省教育厅组织各本科高校开展了2019年度省高等教育教学改革项目（以下简称“教改项目”）遴选推荐工作。现将本年度省教改项目立项名单予以公布，并就有关事项通知如下:

一、立项情况

根据文件要求，省教育厅对学校推荐的材料进行了形式审查，确定2019年度省高等教育教学改革项目共立项779项（详细名单见附件）。

二、项目经费

项目由各校统筹省“创新强校工程”专项资金及自有资金等，根据立项项目研究内容、性质和特点，综合确定资助额度，保障项目顺利开展研究和实践。

省教改项目的立项建设是申报省高等教育教学成果奖的重要基础，项目建设成效同时列入学校“创新强校工程”绩效考核因素，

并直接影响下一年度学校教改项目立项限额。

三、项目管理

（一）日常管理

省高等教育教学改革项目要求立足学校教学改革实际，突出问题导向、实践导向和应用导向，项目最终要为推动学校教学改革服务。项目所在高校要加强对项目的日常管理、指导和检查，为项目研究并切实应用于教学实践提供必要条件。

（二）中期检查和结题验收

项目建设周期一般不超过3年，请学校管理部门按期做好项目中期检查和校内结题验收等工作。校内结题时，邀请校外评审专家人数不得少于专家总人数的三分之二。

满足以下条件的项目，经学校正式申请，可以参与省教育厅统一组织的项目验收：

1.项目已完成立项时设定的主要建设目标，且项目建设成果已在教学实践中有效应用；

2.已按照要求完成项目校内结题；

3.符合当年度省统一验收规定的其他条件。

（三）项目变更和调整

为保证项目建设的延续性和成果的一致性，原则上，项目研究过程中不得更换项目负责人；不得大幅变更研究内容或研究方向；不得拖延项目建设进程。

如遇特殊情况需要进行项目变更或延期的，须由项目负责人

在项目结题前至少6个月向学校提出书面申请，学校审核同意后，以正式函件形式（并附相关材料）报省教育厅。

对擅自做出变更决定或临时延长建设期限的项目，将视情予以撤销或终止项目研究，取消相应负责人3年内省教改项目的申报资格，并核减项目所在学校下一轮次教改项目推荐数额。

四、其他事项

（一）2019年度各校向省教育厅推荐并获得立项的项目，学校须将相关项目校内评审推荐及立项材料妥善保存，留底备查。

（二）项目立项后，学校应组织专家对项目进行开题论证，进一步优化项目建设目标和实施计划。

（三）省高等教育教学改革项目优秀成果将以适当方式在省级平台上向广大高校推介。

联系人：王欢、李成军，联系电话：020-37627703、37629463；传真：020-37627963。

附件：2019年度广东省高等教育教学改革项目立项名单

广东省教育厅

2019年12月6日

公开方式：主动公开

校对人：王欢

附件

2019年度广东省高等教育教学改革项目立项名单

序号	单位名称	项目名称	项目负责人
1	中山大学	海洋科学人才培养“十大育人体系”构建	陈省平
2	中山大学	模拟教学在培养医学生临床胜任力中的作用探讨	陈海天
3	中山大学	实习医生胆道镜技能培训课程	蔡建鹏
4	中山大学	大数据环境下信息管理与信息系统专业人才创新能力培养研究	陈明红
5	中山大学	“双一流”背景下城乡规划专业设计类课程的优化及教学创新路径	产斯友
6	中山大学	国外高校俄语专业本科人才培养模式探究及借鉴	郭丽君
7	中山大学	精神科标准化病程首记模版的编制	甘照宇
8	中山大学	以学生为主体的情景模拟教学联合Mini-CEX/DOPS在急诊医学教学中的应用探讨	黄勇
9	中山大学	TBL结合模拟教学在本科生急诊临床思维能力培养中的应用研究	黄应雄
10	中山大学	TBL联合翻转课堂教学方法在口腔修复学临床实践教学中的应用	浩志超
11	中山大学	基于CBL的实践教学改进营养通识课程教学成效的研究初探	韩宗萍
12	中山大学	科教融合，将一流的化学科研成果转化为优质有机化学实验的教学改革与实践	李厚金
13	中山大学	医学伦理学视角下叙事医学的平行病历在临床教学中的应用研究	李平甘
14	中山大学	新媒体环境下技术驱动会展专业拔尖人才培养模式及“课程思政”建设研究	罗秋菊
15	中山大学	CBL教学法联合SEGUE Frame-work评价在儿科实习中提高医学生医患沟通能力的探索	黎雅婷
16	中山大学	“一带一路”沿线语种国别区域研究人才培养：模式与路径	马妍哲
17	中山大学	虚拟现实技术在骨科疾病诊治及临床解剖学融合教学中的应用	祁方昉
18	中山大学	培养卓越医学人才综合素质——多种教学模式结合的混合式教学探讨	谭红梅
19	中山大学	动态能力导向的物流管理专业人才培养能力评价体系构建研究	田宇
20	中山大学	以初级卫生保健创新能力与人才培养为导向的社区多重慢病防治教学改革与实践研究	王皓翔
21	中山大学	“四位一体”学校体育目标下大学体育第二课堂的构建研究	王守力
22	中山大学	病例导入式教学法联合网络互动模式在口腔黏膜病本科教学中的应用	夏娟
23	中山大学	基于设计思维和团队项目的学生创新能力培养模式研究	于洪彦
24	中山大学	基于尸体解剖的病理实习数字化教学在MBBS留学生临床病理教学中的改革及应用	杨诗聪
25	中山大学	中国史遗迹考察类实践课程的教学资料体系与效果评估体系建设	于薇

26	中山大学	基于SEGUE的沟通教育在《儿科护理学》混合教学中的应用与效果评价	张利峰
27	中山大学	双一流”建设背景下《外科护理学》课程改革与探索研究	张美芬
28	中山大学	高校“教、训、赛”一体化体育课程体系改革与实践	张新萍
29	中山大学	医学本科生SAS软件的自主学习系统的建立与完善	张晋昕
30	中山大学	医学生物化学教学模式与评价体系双效改革创新的实践研究	周倜
31	华南理工大学	强化《城乡社会综合调查研究》在规划专 业培养体系中课程媒介作用的教学研究与实践	李昕
32	华南理工大学	基于移动端互动反馈技术的分析化学多切入点启发式教学改革研究与实践	陶佳
33	华南理工大学	高校网络辅助教学平台优化-基于大数据理念及Learning Analytics技术	李弘扬
34	华南理工大学	基于数字化平台的土木工程专业内涵建设和发展	潘建荣
35	华南理工大学	新媒体传播创新人才培养实践 —— 以广府文化虚拟呈现与聚合传播为例	韩镁
36	华南理工大学	新工科发展潜在的数学化与创新能力培养	黄平
37	华南理工大学	新工科背景下工程实训教育探索与实践	胡青春
38	华南理工大学	以创新能力和工程能力提升为目标的区块链实践教学模式探索与实践	许可
39	华南理工大学	基于创新能力培养的新能源汽车本科实验教学方法研究与实践	李广龙
40	华南理工大学	“新工科”理念下城市设计创新人才培养模式探索	李敏稚
41	华南理工大学	在线课程中深层学习的机制及促进策略研究	刘广
42	华南理工大学	面向工程教育的自动化专业课程内涵建设与探索	罗家祥
43	华南理工大学	以科研实践驱动创新能力培养的计算机本科专业课教学改革研究	毛爱华
44	华南理工大学	工程教育专业认证背景下《高分子物理综合实验》的教学改革与实践	赵颖
45	华南理工大学	中国武术“长兵”项目高校创新发展研究	黄帝全
46	华南理工大学	基于虚拟仿真软件平台的化工自动化类课程教学改革研究	沈文浩
47	华南理工大学	基于“导师制-创新基金-自主科研训练课”的生物类本科创新人才培养	王菊芳
48	华南理工大学	“设备平台+虚拟仿真”的全景式电气实验教学探索与实践	王智东
49	华南理工大学	深度学习理论下“SPOC+PBL+FCM”混合式教学改革在《配送中心设计与管理》的探索与实践	万艳春
50	华南理工大学	面向“新工科建设F计划”的大学物理“一流课程”建设	钟小丽
51	华南理工大学	金融科技人才培养的校企合作模式探索	徐枫
52	华南理工大学	基于翻转课堂的商务英语混合教学模式	徐鹰
53	华南理工大学	面向“新工科”土木工程创新人才培养的虚拟仿真教学模式实践研究	熊焱
54	华南理工大学	基于系统与“结构稳定-分岔-分形”的数学教学体系构建与实践	杨启贵

55	华南理工大学	环境工程微生物学混合式教学的探索与实践	银玉容
56	华南理工大学	遗传咨询案例分析在医学本科生教学中的实践与应用	张春玉
57	华南理工大学	新工科背景下基于创新能力培养的课程教学改革	赵俊红
58	华南理工大学	车辆工程一流专业建设实践研究	赵克刚
59	暨南大学	问题驱动、线上线下多元聚力，“导+学” 教学模式在医学《生理学》教学中的研究与实践	柏志全
60	暨南大学	数据驱动耦联认知的基础医学课程考核体系探索与实践	程欣
61	暨南大学	OBE教学理念下基础日语智慧课堂的构建与实施	董芳良
62	暨南大学	基于粤港澳大湾区跨境法律人才培养的四方复合教学模式研究与实践	方赛迎
63	暨南大学	多方共建、多维实践、多元成果————网络与新媒体专业深化产教融合校企合作的创新路径研究与实践	谷虹
64	暨南大学	“基础写作”课程创新与教学优化研究与实践	花宏艳
65	暨南大学	“新工科”背景下工程科技人才创新能力培养模式的探索与实践	黄世清
66	暨南大学	服务粤港澳大湾区及社会主义先行示范区的创新型IT&T人才定制化培养模式的研究与应用	景秀丽
67	暨南大学	演训赛一体化模式下高校运动体操课程考核方式的研究与实践	刘超
68	暨南大学	基于移动互联网的混合式教学设计与实践—以“市场研究”为例	刘静岩
69	暨南大学	基于“赋能式教育”理念的境外生智慧课堂实践探索—以“资讯科技”雨课堂建设为例	刘小丽
70	暨南大学	基于中华优秀传统文化传承弘扬的中医精英人才培养模式的改革与实践	马民
71	暨南大学	基于“中药炮制学”虚拟仿真实验教学平台的教学创新实践	马志国
72	暨南大学	“新工科”背景下专业课程群的“产学合作”构建与实践-以城市水工程课程为例	任刚
73	暨南大学	科教双驱型本科人才培养创新与评价的研究与实践	史进程
74	暨南大学	面向港澳学生的专业课程思政教学改革——以《中国旅游地理》课程为例	王华
75	暨南大学	基于知识产权保护的大学生创新创业项目管理优化的改革与实践——以暨南大学为例	王璐
76	暨南大学	基于行动学习法的电子商务教学方式改革与实践	王玮
77	暨南大学	雨课堂辅助的英美文学课程翻转课堂教学体系构建与研究 ——以“英国文学史”为例	肖淳端
78	暨南大学	“双一流”大学创新型人才培养的探索与实践——以暨南大学生态学专业本科生导师制改革为例	许德麟
79	暨南大学	基于CBI理念的“医学汉语”课程融合式教学模式创新与实践	徐富平
80	暨南大学	基于课语整合式学习理论的华文教育专业“教育类课程”教学改革与实践	许文果
81	暨南大学	创新型化学人才培养模式研究与实践 ——以无机化学课程为平台	杨芳

82	暨南大学	基于护士核心能力培养的创新高仿真模拟教学在护理综合实训课程中的应用及评价	杨巧红
83	暨南大学	本科荣誉辅修学位项目制度设计的应用研究	颜海波
84	暨南大学	基于产教融合的工科应用型课程教学模式的改革与实践	晏日安
85	暨南大学	激进社会思潮背景下在粤求学香港青年国民教育补偿机制的探索与实践——以中国历史科为例	张龙平
86	暨南大学	暨南大学在线开放课程共享与应用机制的探索与实践	张小欣
87	暨南大学	粤港澳大湾区学生临床医学专业课程与素养教育相结合培养模式的创新与实践	赵长鹰
88	暨南大学	培养港澳籍学生国家认同的教学内容设计与应用	赵子乐
89	暨南大学	面向粤港澳大湾区的分段递进港澳医师执业准入培养体系构建与医学教育模式创新实践	钟敬祥
90	华南农业大学	农业高校推进校企协同科研育人的模式探讨	严会超
91	华南农业大学	A系列课程质量及其影响因素调查研究	黎华寿
92	华南农业大学	基于蚕病学课程的全英教学和管理模式研究	孙京臣
93	华南农业大学	海洋生物调查虚拟仿真实验设计及多层次教学模式的构建	孙际佳
94	华南农业大学	大湾区背景下海洋科学专业实践教学体系的改革与探索	杨慧荣
95	华南农业大学	OBE理念下城乡规划专业创新人才培养的进阶式教学模式研究	王凌
96	华南农业大学	“新工科”背景下以创新人才为培养导向的农用无人机通识教育教学改革	文晟
97	华南农业大学	基于农林院校创新型英语人才培养的英语教学模式研究	邓飞
98	华南农业大学	《舞蹈鉴赏》课程中“艺术+思政”的改革探索与实践研究	殷舒
99	华南农业大学	多学科实验平台开展安全教育的分科类教学资源体系构建与实践	劳媚媚
100	华南农业大学	基于课程思政的高校职业生涯教育研究与实践	朱钧陶
101	华南农业大学	新工科背景下多维度提升“高等数学”教学质量的研究与实践	李娇娇
102	华南农业大学	培养云计算环境下应用数学能力的实践教学改革研究	岑冠军
103	华南农业大学	大学物理“课程思政”的探索与实践——融入优秀传统文化	徐初东
104	华南农业大学	《无机化学》课程思政的建设与实践	刘晓璐
105	华南农业大学	基于SPOC的《计算机组成原理》翻转课堂教学模式研究	杨磊
106	华南农业大学	马克思主义情景剧与“原理”课实践教学改革研究	王竹波
107	华南农业大学	环境设计专业学生创新实践应用能力培养模式的研究与探索	郑欣
108	华南农业大学	“新农科”的时代内涵及华南农业大学建设方案初探	杨玉浩
109	华南农业大学	基于能力结构的卓越农林教师教学发展模式研究	朱蕾
110	华南农业大学	基于微信公众号平台和雨课堂的“八度”混合式教学模式探索与实践	廖杨

111	华南农业大学	以科研成果促进遗传学实验教学创新改革的研究与实践	刘自强
112	华南农业大学	《植物学》“课程思政”的探索与实践	白玫
113	华南农业大学	丁颖班组织胚胎学实验课程教学素材改革及云平台搭建	梁晓欢
114	华南农业大学	基于国际标准培养木材科学与工程新工科专业特色人才的研究与实践	古今
115	华南农业大学	新工科背景下化工原理虚拟仿真实验教学改革与实践	袁腾
116	华南农业大学	基于一流人才培养的“金课”标准与评价研究	欧阳娟
117	华南农业大学	基于创新能力培养的多层级探究式教学改革研究及实践——以《土木工程材料》为例	李庚英
118	南方医科大学	“书院制”背景下“互联网+医学”创新教育课程体系建设与实践	陈士良
119	南方医科大学	双师制教学模糊化评价体系构建	陈瑶
120	南方医科大学	基于“互联网+”移动学习《中医外科学》 混合教学模式构建与形成性考核评价	邓燕
121	南方医科大学	医学院校生物技术专业《酶工程》课程教学资源建设与混合式教学实践	杜红延
122	南方医科大学	高校思政课混合教学模式与效果研究	傅义强
123	南方医科大学	基于 “德术兼授，以文化人”的中医学专业课程思政体系的构建与探索	贺松其
124	南方医科大学	实时病理远程诊断系统与PBL和CBL结合在病理学实验教学中的应用	梁莉
125	南方医科大学	医科院校“书院制+课程思政” 双驱同向模式研究	刘昂
126	南方医科大学	医学生“双维度四环节”死亡教育课程体系的构建及效果评估	李晓丹
127	南方医科大学	基于早期新药研发的校企合作药学本科生个性化培养模式	庞建新
128	南方医科大学	基于MOOC的《医学寄生虫学》 混合式教学模式研究	彭鸿娟
129	南方医科大学	《临床技能学》混合式教学课程体系的建立	田京
130	南方医科大学	机能实验学混合式教学移动教学平台建设与实践	田映红
131	南方医科大学	新高考改革背景下高等院校招生改革应对策略研究与实践	王飞
132	南方医科大学	临床医学专业课程思政教育教学改革路径探索	谢小燕
133	南方医科大学	《蛋白质工程》课程思政的探索与实践	徐伟文
134	南方医科大学	高校理工专业课程思政教学育人模式构建与实践	杨谊
135	南方医科大学	《护理学导论》课程思政教育的建设与实施	曾凯
136	南方医科大学	助产学情景模拟教学改革实践与效果评价	翟巾帼
137	南方医科大学	中医药类专业中基文史类课程课程思政的构建与实践	张国华
138	南方医科大学	基于混合式教学的《高等数学》课程思政建设	张明慧
139	南方医科大学	基于叙事理念的“4+X”结构化大学生心理健康教育模式探索	赵静波
140	南方医科大学	《康复医学》课程思政改革建设	赵一瑾

关于公布2021年度广东高校公共计算机课程教学改革项目立项项目的通知

各高等学校：

根据《广东高校公共计算机课程教学改革项目实施方案》及《关于2021年度广东高校公共计算机课程教学改革项目申报的通知》的要求，广东省高等学校公共计算机课程教学指导委员会（以下简称“教指委”）组织专家对申报项目进行评审，确定拟立项项目29项并进行公示。经公示无异议，现对立项项目进行公布（具体名单见附件）。

请各项目承担单位和项目组根据项目管理办法与项目申报书的研究计划，积极开展研究与教学改革，确保按质按量完成研究任务。项目的具体实施要求如下：

1. 建设周期：本次立项项目研究周期为2年，建设期从2021年5月开始。

2. 中期检查。根据项目申报书的建设内容、目标和要求，教指委将于2022年6月对项目进行中期检查。

3. 验收结题。根据项目申报书的成果要求，教指委将于2022年6月对项目进行结题验收。

联系人：郭泽颖；电子邮箱：guozeying@m.scnu.edu.cn；电话：（020）85212456-8005。

附件：2021 年度广东高校公共计算机课程教学改革项目立项项目名单

广东省高等学校公共计算机课程教学指导委员会

（主任单位华南师范大学代章）

二〇二一年五月二十五日

附件：

2021 年度广东高校公共计算机课程教学改革项目立项项目名单

序号	项目名称	负责人	所在单位	起止时间
2021-GGJSJ-001	基于计算思维培养的 C++程序设计课程混合式教学研究	李家春	华南理工大学	2021.05-2023.05
2021-GGJSJ-002	面向创新应用型人才培养的“案例式 Python 程序设计教程”的构建与实施	梁云	华南农业大学	2021.05-2023.05
2021-GGJSJ-003	程序设计类公共课实践教学公共平台的构建和应用	陈湘骥	华南农业大学	2021.05-2023.05
2021-GGJSJ-004	公共计算机课程《C 语言程序设计》SPOC 翻转课堂混合教学模式研究	杨磊	华南农业大学	2021.05-2023.05
2021-GGJSJ-005	《数据库原理与应用》课程资源库的建设	刘冬杰	华南师范大学	2021.05-2023.05
2021-GGJSJ-006	基于程序赋能思维的《Python 程序设计及应用》线下线上混合教学模式探究	潘明	华南师范大学	2021.05-2023.05
2021-GGJSJ-007	课程思政背景下《Python 程序设计与应用》课程改革研究与实践	郭泽颖	华南师范大学	2021.05-2023.05
2021-GGJSJ-008	融入课程思政元素的《电子商务概论》课程立体教材研究	蔡韶华	华南师范大学	2021.05-2023.05
2021-GGJSJ-009	结合专业需求的 Python 课程教学改革——以语言类专业为例	李宇耀	广东外语外贸大学	2021.05-2023.05
2021-GGJSJ-010	课程思政背景下大学计算公共课程主题式教学研究与实践	吴杰	广州大学	2021.05-2023.05
2021-GGJSJ-011	面向新医科提高信息素养与数据分析能力的计算机基础课程改革	叶辉	广州中医药大学	2021.05-2023.05
2021-GGJSJ-012	学习特征感知的知识推荐与实训优化方法研究	朱嘉贤	肇庆学院	2021.05-2023.05
2021-GGJSJ-013	“Python 程序设计”课程问题导向研讨式教学模式研究与实践	赖锦辉	广东石油化工学院	2021.05-2023.05

2021-GGJSJ-014	面向立德树人、铸魂育人的计算机应用基础课程思政案例研究	龚玉清	吉林大学珠海学院	2021.05-2023.05
2021-GGJSJ-015	“四新”背景下应用型本科 Python 课程体系探索与工程应用实践	李昱	吉林大学珠海学院	2021.05-2023.05
2021-GGJSJ-016	新文科视角下基于项目任务式的《Python 语言程序设计》教学改革研究	陈颂丽	广州商学院	2021.05-2023.05
2021-GGJSJ-017	计算机通识课程线上线下混合模式教学改革	马汝祯	广州商学院	2021.05-2023.05
2021-GGJSJ-018	应用型高校公共计算机课程教学与创新创业教育融合的改革探究	郑燕姣	广州商学院	2021.05-2023.05
2021-GGJSJ-019	智能时代高效计算机公共课混合教学改革与实践	谢新就	广州商学院	2021.05-2023.05
2021-GGJSJ-020	基于“课程思政”的《Python 语言程序设计》教学改革探索	王轻纱	广州商学院	2021.05-2023.05
2021-GGJSJ-021	课程思政元素融入《Python 语言程序设计》教学体系建设研究	邹锋	广州商学院	2021.05-2023.05
2021-GGJSJ-022	基于医药专业岗位的计算机应用基础课程教学改革与实践研究	吴柏雄	广东江门中医药职业学院	2021.05-2023.05
2021-GGJSJ-023	新工科背景下高职“新一代信息技术+”复合型技能人才培养研究与实践	赖晶亮	广东轻工职业技术学院	2021.05-2023.05
2021-GGJSJ-024	《Python 数据分析基础》课程综合改革研究	钟广玲	广州华商学院	2021.05-2023.05
2021-GGJSJ-025	高职“计算机组装与维护”实践课程的螺旋式教学改革	钟少波	广州铁路职业技术学院	2021.05-2023.05
2021-GGJSJ-026	基于人工智能技术的公共计算机课程教学内容及模式改革研究	王倩	广州铁路职业技术学院	2021.05-2023.05
2021-GGJSJ-027	面向新医科专业群的计算机基础课程建设	孙玮	广州卫生职业技术学院	2021.05-2023.05
2021-GGJSJ-028	高职扩招背景下基层医疗人才计算机基础课程教学改革与实践	周挺	肇庆医学高等专科学校	2021.05-2023.05
2021-GGJSJ-029	面向新医科的专科医学院校计算机基础课程建设	陈剑	肇庆医学高等专科学校	2021.05-2023.05



关于公示2023年拟推荐省级教学质量与教学改革工程项目和拟立项校级教学质量与教学改革工程项目名单的通知

来源单位及审核人： 编辑： 审核发布：本科生院（招生办公室） 发布时间：2023-12-11 浏览次数： 1818

各学院（部）、各单位:

根据《广东省教育厅关于开展2023年度广东省本科高校教学质量与教学改革工程项目申报推荐工作的通知》和学校《关于开展2023年度本科教学质量与教学改革工程项目申报工作的通知》精神，学校组织开展了本年度教学质量与教学改革工程项目的遴选工作。

经项目负责人申请、所在单位遴选推荐和学校组织专家评审等环节，本年度拟计划立项校级教学改革项目122项，并拟推荐“高阶思维视域下《种子生物学》‘四维融合’混合式教学模式改革与实践”等28项申报省级教学改革项目，具体名单见附件1；本年度拟计划立项校级质量工程项目47项，并拟推荐“绿色与智能精准纳米农 药实验室”等18项申报省级质量工程项目，具体名单见附件2。

现予以公示。公示期自2023年12月11日至12月15日。公示期间，如有异议请以书面方式提交（附必要的证据材料），并署真实姓名，否则不予受理。

联系人：孙齐胜，电 话：85288020

孙 航，电 话：85280052

地 址：行政楼329

邮 箱：gjyj@scau.edu.cn

附件1.2023年拟推荐省级教学改革项目和校级教学改革拟立项项目名单.pdf

2.2023年拟推荐省级质量工程项目和校级质量工程拟立项目名单.pdf

本科生院（招生办公室）

2023年12月11日

校长信箱 国家科研平台
招标采购 阳光体育
质量工程 校园地图
开放教育资源 精品课程资源

SCAU Copyright © 2018
华南农业大学 All rights reserved
地址：广州市天河区五山华南农业大学 邮编：510642
备案编号：粤ICP备05008874号 4401060500010
管理登录

附件1

2023年拟推荐省级教学改革项目和校级教学改革拟立项项名单

序号	项目名称	项目负责人	拟立项级别	备注
1	高阶思维视域下《种子生物学》“四维融合”混合式教学模式改革与实践	周玉亮	校重点项目	拟推荐省级
2	新林科视域下森林培育学知识图谱课程建设与教学模式创新	邱权	校重点项目	拟推荐省级
3	一流专业建设背景下风景园林规划设计课程教学改革研究	陈崇贤	校重点项目	拟推荐省级
4	一流农科高校基础实验课程思政教学一体化改革与实践——以大学物理实验课程为例	劳媚媚	校重点项目	拟推荐省级
5	双一流高校“科-教-思”融合培养学生高阶思维的实验教学改革研究——以遗传学实验为例	李楠	校重点项目	拟推荐省级
6	工程结构设计软件课程的"融合+分层"教学	李文雄	校重点项目	拟推荐省级
7	基于竞赛和创新方法提升大学生创新能力的实证研究	易欣	校重点项目	拟推荐省级
8	基于创新创业能力培养的“赛教融合”《养羊学》课程改革与实践	柳广斌	校重点项目	拟推荐省级
9	人工智能赋能生态化大学英语混合教学改革研究	苏君	校重点项目	拟推荐省级
10	基于创新能力培养的《电路实验》教学改革研究与实践	王建华	校重点项目	拟推荐省级
11	新时代高校思政课“问题链”教学模式研究——聚焦《习近平新时代中国特色社会主义思想概论》课程	何艳玲	校重点项目	拟推荐省级
12	三产融合理论在《茶叶生物化学》中的应用	张钰乾	校重点项目	拟推荐省级
13	工程认证背景下基于知识图谱的新工科一流专业建设和提升的研究与实践	王金凤	校重点项目	拟推荐省级
14	融合数据分析思维和学科交叉的《线性代数》课程教学创新与实践	张伟峰	校重点项目	拟推荐省级
15	基于创新能力培养的统计学专业数据分析类实验课程改革探索与实践	周燕	校重点项目	拟推荐省级
16	基于知识图谱的农业院校课程思政建设探索—以公共数学基础课为例	张娜	校招标项目	拟推荐省级
17	基于新兽医人才培养的《分子生物学》课程改革与实践探索	沈永义	校重点项目	拟推荐省级
18	思政视角下《国际金融》课程教学改革与实践	周超	校重点项目	拟推荐省级
19	新农科背景下基于“数字标本”的智慧植保实验体系研究与实践	李云锋	校重点项目	拟推荐省级
20	低碳农业背景下基于一特两驱教学模式的环境土壤学课程体系构建	林庆祺	校重点项目	拟推荐省级
21	“双一流”建设视野下安全教育模式嵌入环境化学实验室课程体系的实践与优化	高婷	校重点项目	拟推荐省级
22	“三台协同，以美育人”——以课程教学为基础的高校舞蹈美育建设研究与实践	郑琳喆	校重点项目	拟推荐省级
23	劳动教育融入设计类专业课程路径探索——以《纤维艺术造型设计》课程为例	林汉聪	校重点项目	拟推荐省级
24	人工智能背景下的新文科艺术专业人才培养研究与创新：以动画专业为例	王柯	校招标项目	拟推荐省级

25	“新农科”背景下《植物学》课程教学创新改革研究与实践	白玫	校重点项目	拟推荐省级
26	基于真人图书馆的“就业创业+思政”融合课程体系改革研究——以法学专业为例	李玮舜	校重点项目	拟推荐省级
27	生成式人工智能背景下公共管理类课程教学模式创新研究与实践	张小娟	校重点项目	拟推荐省级
28	基于课程思政融合及项目驱动教学创新方法的研究与实践	孔莲芳	校重点项目	拟推荐省级
29	工程教育认证背景下的教学过程评价体系研究——以《区块链原理与技术》课程为例	肖媚燕	校招标项目	
30	面向乡村振兴的农业高校传媒类新文科人才培养研究	胡辉	校招标项目	
31	以教育数字化转型为契机的《林木遗传育种 学》混合式教学创新研究	李培	校重点项目	
32	国际合作办学背景下建成环境历史课的中外融合与创新	李晓雪	校重点项目	
33	“双碳”背景下《包装材料学》课程教学改革与实践	刘涛	校重点项目	
34	构建《遗传学》课程思政教学体系的探索与实践	刘自强	校重点项目	
35	基于数据挖掘的土木工程专业人才培养方案优化研究	张巍	校重点项目	
36	以培养创新人才为导向的《分析化学实验》教学改革与实践	熊亚红	校重点项目	
37	课程思政引领的《药剂学实验》 线上线下混合式教学探究与实践	胡洋	校重点项目	
38	课程链模式下农林院校学生用外语讲中国农耕文化故事能力的培养	秦建华	校重点项目	
39	基于人工智能技术的大学物理课程思政教学研究与实践	徐初东	校重点项目	
40	“大思政课”视域下高校思政课实践教学 协同育人创新模式研究与实践	林晓燕	校重点项目	
41	基于文本挖掘的课程思政元素挖掘研究--以应用统计学为例	张建桃	校重点项目	
42	新农科背景下《动物解剖与组织胚胎学》课程思政改革创新	马勇江	校重点项目	
43	学科交叉融合的植物检疫学线上线下一体化教学实践	何晓芳	校重点项目	
44	测绘地理信息类专业“学赛研”三位一体实践教学改革研究	刘惠明	校重点项目	
45	新农科建设背景下高校图书馆开展中华优秀传统文化教育的探索与实践	黎小妮	校重点项目	
46	大学生创新创业训练计划培育机制改革及育人实效提升研究——以华南农业大学为例	萧润正	校重点项目	
47	以赋能乡村振兴为导向的一流动画专业优化提升建设的探索和实践	涂先智	校重点项目	
48	面向工程教育认证的农业院校车辆工程人才培养探索	郭嘉明	校重点项目	
49	面向社会服务的风景园林规划设计类课程教学改革与实践	汤辉	校一般项目	
50	基于创新能力培养的《林木细胞生物学》课程教学方法改革与实践	刘林川	校一般项目	
51	乡村振兴背景下规划专业人才软技能培养体系研究	王凌	校一般项目	

52	“食品仪器分析”线上线下混合式一流课程的建设与实践	陈运娇	校一般项目	
53	课程思政与“五育并举”融合发展的高校足球课程改革与实践研究	陈存志	校一般项目	
54	思政引导的体育课程内容体系改革与实践--以瑜伽课为例	何灵捷	校一般项目	
55	新农科背景下的《遗传学》教学改革与实践	汪文毅	校一般项目	
56	“双一流”背景下基于信息技术的实验室安全教育优化建设	陈志民	校一般项目	
57	理论力学多平台混合教学线上线下一体化设计与实践	刘新红	校一般项目	
58	《饲料学》线上线下一体化混合教学设计探究	朱勇文	校一般项目	
59	新农科背景下融合“课程思政+国际化”的《蚕桑概论》课程改革与实践	杨婉莹	校一般项目	
60	多模态话语分析理论下《跨文化交际》课程中中国文化对外传播路径研究	杜龙鼎	校一般项目	
61	人工智能赋能英语语言技能课程教学创新实践研究	李飞武	校一般项目	
62	基于研究性教学的大学物理实验课程思政实践教学探索	杨小红	校一般项目	
63	高校思政课问题式教学的探索研究 ——以“思想道德与法治”课程为例	刘智娴	校一般项目	
64	《果蔬栽培学》课程思政设计与实践	苏钻贤	校一般项目	
65	《园艺种质资源与分类》实验教学内容体系优化的研究与实践	张志珂	校一般项目	
66	“真人+数字人”的智能教学模式探索与实践--以《数据结构》课程为例	梁云	校一般项目	
67	数字化背景下《大学生心理健康教育》课程思政建设与实践	严颖	校一般项目	
68	基于创新型人才培养目标对《海洋环境化学》的教学改革研究	公晗	校一般项目	
69	“四微一体”课堂教学实践与应用-以“水产品质量安全控制”课程为例	周爱国	校一般项目	
70	数智时代《财务管理》课程教学改革研究	周小春	校一般项目	
71	虚-实二维教学模式在环境监测实践课程中的应用	郑芊	校一般项目	
72	能源动力类专业课程产教研协同育人模式探索与实践	魏国强	校一般项目	
73	心理资本视域下心理健康课程改革探索	林媛	校一般项目	
74	“轻咨询”融入高校心理健康教育课程的实践路径研究	刘桂娥	校一般项目	
75	基于可持续创新人才培养的《首饰镶嵌工艺》教学改革与实践	潘子广	校一般项目	
76	“声动岭南”——音乐与表演专业中的新媒体技术创新教学项目研究与实践	冯逸章	校一般项目	
77	人工智能技术背景下影像艺术课程的内容改革：以乡村影像为例	程蔚新	校一般项目	
78	《植物学实验》“课程思政”的探索与实践	梁祥修	校一般项目	

79	聚焦SCAU特色的遗传学课程思政建设的维度研究与实践	郑少燕	校一般项目	
80	教育数字化转型背景下微课赋能古代文学教学应用研究	李桂芹	校一般项目	
81	领军人才培养目标下的《人类行为与社会环境》教学改革与实践	林诚彦	校一般项目	
82	行政管理专业法学类课程思政教学改革研究与实践——以《行政法》为例	宋丽娟	校一般项目	
83	融合“新工科”视野的工业设计专业--交互设计课程跨学科融合与实践创新	李莎莎	校一般项目	
84	以知识图谱的构建赋能信号类课程的OBE理念教学模式探索	徐梅宣	校一般项目	
85	基于工程教育认证的食品科学与工程“流专业人才生产实践教学体系重构	黎攀	校青年项目	
86	基于“新工科”背景的《畜产食品工艺学》多模式教学探索与实践	艾民珉	校青年项目	
87	传感检测类课程的混合式教学创新与实践	冯婉媚	校青年项目	
88	优秀传统文化融入“马克思主义基本原理”课程的路径研究	刘海成	校青年项目	
89	案例教学法在《习近平新时代中国特色社会主义思想概论》课程的创新与运用	朱露	校青年项目	
90	“大历史观”引领《中国近现代史纲要》研究与实践	李征	校青年项目	
91	基于“SPOC+Seminar”的《形势与政策》教学模式改革与实践	聂锐	校青年项目	
92	数字化兽医病例库的构建及其在OBE教学模式下《兽医临床诊断学》教学中的探索与实践	廖建昭	校青年项目	
93	新文科背景下本科生《产业经济学》课程体系建设与教学改革路径优化	赵纯凯	校青年项目	
94	教育数字化背景下高校管理会计课程改革探析	张京心	校青年项目	
95	高校史学理论教学的多元化模式研究——以《史学概论》为例	赖泽冰	校青年项目	
96	树立文化自信的城市建设史与规划史课程思政探索与实践	王婷	校自筹项目	
97	深化产教融合校企合作的育人模式探索与实践--以华南农业大学为例	解加米	校自筹项目	
98	以学生为中心的城乡规划专业基础类课程混合式教学模式探索与实践	吴宝娜	校自筹项目	
99	高校体育课程思政教学质量评价指标体系构建研究	姚业戴	校自筹项目	
100	基于翻转课堂的管理通识训练课程混合式教学模式的探索与实践	谢佳佳	校自筹项目	
101	探究式教学模式在绿色建筑设计与节能技术课程中的实践	崔艳琦	校自筹项目	
102	新农科背景下《基因工程原理》线上线下教学一体化教学设计与实践	孙媛	校自筹项目	
103	语言智能时代非英语专业学生翻译能力提升路径创新研究	李志英	校自筹项目	
104	大学英语四级词汇教学改革与实践：比较文化的视角	黄海翔	校自筹项目	
105	农业院校统计学专业的新创业教育的研究与实践	徐小红	校自筹项目	

106	基于知识图谱的《计算机组成原理》课程智慧化教学研究与实践	杨磊	校自筹项目	
107	管理类本科创新创业实践教学生态圈构建	毛小娟	校自筹项目	
108	基于新农人创新能力培养的“四位一体”教学方法研究与实践	郭永龙	校自筹项目	
109	以价值引领、学科融合、全面育人为目标的公选课混合式教学模式探究——以《奇妙的动物	曾芳	校自筹项目	
110	“百千万工程”背景下高校“三大课堂”融合培育爱农兴农人才的教学体系研究与实践	陈洋	校自筹项目	
111	双一流建设背景下丁颖班本科人才培养机制深化研究	陈建平	校自筹项目	
112	工程测量学实践、实验教学内容体系改革和整体优化	林观土	校自筹项目	
113	基于虚拟仿真平台的《测量学》虚实融合的混合式实验教学改革	于红波	校自筹项目	
114	多元信息素养教育中线上线下教学一体化研究	刘汉忠	校自筹项目	
115	学科交叉在生物学中的教学实践—以课程《细胞的语言》建设为研究案例	胡宇飞	校自筹项目	
116	历史建筑档案在文化遗产研学中的教育教学功能开发策略研究	谢君	校自筹项目	
117	教与评：新文科背景下思政教育融入“中国史学史”课堂教学的探索与实践	翟麦玲	校自筹项目	
118	课程思政背景下国际法专业教学模式创新与实践研究	官隆清	校自筹项目	
119	后疫情时代《大学生心理健康教育》课程教学质量提升研究	石如彬	校自筹项目	
120	新文科背景下本科生就业能力评价及提升策略研究——以土地资源管理专业为例	朱庆莹	校自筹项目	
121	基于工程实践的工程热力学与传热学课程混合教学设计研究与实践	张烨	校自筹项目	
122	融合AIGC建设工业设计创新性实验课程的研究与实践	曾志雄	校自筹项目	

华南农业大学文件

华南农教〔2019〕61号

关于华南农业大学2019年度教育教学改革与研究项目立项的通知

各学院、部处、各单位:

为进一步推进我校教育教学改革与研究，提高人才培养质量，根据《教育部关于加快建设高水平本科教育全面提高人才培养能力的意见》（教高〔2018〕2号）精神，学校组织开展了2019年度教育教学改革与研究项目申报工作。经组织申报、资格审查、专家评审、公示等环节，确定“马克思主义情景剧与原理课实践教学改革研究”等154项校级教育教学改革与研究项目予以立项。其中，针对学校本科人才培养改革重点领域，本年度特设思想政治理论课专项10项，课程思政专项11项，青年专项41项，金课改革专项33项。具体立项和资助情况详见附件。

请各项目负责人务必按项目计划要求及时开展研究工作，确

保研究工作如期完成，并力争取得高水平的研究成果。

附件：华南农业大学2019年度教育教学改革与研究项目一览表

华南农业大学

2019年9月27日

（联系人：曹广祥、伍鹏，电话：85280052）

公开方式：主动公开

华南农业大学校长办公室　　2019年9月29日印发

附件

华南农业大学2019年度教育教学改革与研究项目一览表

编号	项目名称	申报人	专项类别	资助方式
JG19001	马克思主义情景剧与原理课实践教学改革研究	王竹波	思政课程	重点资助
JG19002	基于 SPOC 的混合式《形势与政策》教学模式构建研究	项赠	思政课程	一般资助
JG19003	习近平新时代中国特色社会主义思想进“思政课“教材研究	潘利红	思政课程	一般资助
JG19004	立德树人视域下推动习近平新时代中国特色社会主义思想“三进”研究	王超	思政课程	一般资助
JG19005	基于教育生态学的高校思想政治理论课堂教师组控能力研究	李虎	思政课程	一般资助
JG19006	思政课中红色电影的应用探究	袁炎林	思政课程	一般资助
JG19007	社会主义核心价值观引领大学生思想政治教育实践机制研究	韩淑梅	思政课程	一般资助
JG19008	提升高校思政课教师教学积极性的机制研究	汤丽莉	思政课程	一般资助
JG19009	《测量学》课程思政教学改革研究	姚朝龙	青年/课程思政	重点资助
JG19010	基于云课堂的混合式教学在《药剂学实验》中的应用研究与实践	胡洋	青年/金课改革	重点资助
JG19011	“翻转课堂”在《公共管理学》全英教学中的创新与实践研究	吴彦	青年/金课改革	重点资助
JG19012	公众健康导向下的《城市交通与道路系统规划》多形式教学改革研究	杨文越	青年	重点资助
JG19013	《兽医寄生虫学》研究性教学模式的探索和实践	郭亚琼	青年	重点资助
JG19014	人工智能技术背景下的《C 语言程序设计》课程教学探究	王国华	青年	重点资助
JG19015	新时代高校思想政治理论课的话语转换机制研究——立足提升“毛中特”课程教学质量	何艳玲	青年/思政课程	一般资助
JG19016	思政课时事教育实践模式研究	李俊宏	青年/思政课程	一般资助
JG19017	基于库伯经验学习圈的宏观经济学翻转课堂模式设计与应用	段伟	青年/金课改革	一般资助
JG19018	“线上”+“线下”混合式教学模式研究与实践-以《R 语言及应用》课程为例	周磊	青年/金课改革	一般资助
JG19019	《信息系统安全与保密》课程的翻转课堂教学模式研究与实践	宋歌	青年/金课改革	一般资助
JG19020	基于雨课堂的《城市林业》课程智慧课堂建设与实践	邱权	青年	一般资助

JG19021	思维导图在《微观经济学》教学中的应用研究	申津羽	青年	一般资助
JG19022	基于 OBE 理论的全英教学模式创新研究—以农林产品国际贸易课程为例	张奕婧	青年	一般资助
JG19023	乡村振兴背景下风景园林设计课程体系与教学改革研究	陈崇贤	青年	一般资助
JG19024	国际认证背景下新工科专业的品牌化建设与实践——以家具专业为例	易欣	青年	一般资助
JG19025	新工科视域下以农业机械设计为导向的人机工程学教学研究	付函	青年	一般资助
JG19026	基于案例的情景模拟教学在公共事业管理类课程中的应用	张小娟	青年	一般资助
JG19027	新农科背景下植物生理学实验教学模式的探索与实践	李淮源	青年	一般资助
JG19028	文学影视作品融入《城市广场景观设计》课程的教学研究与实践	戚芳妮	青年	一般资助
JG19029	“互联网+”背景下创新创业教育与农业生态学专业教学、实训教育的融合研究	向慧敏	青年	一般资助
JG19030	珍贵植物真菌病害标本的整合与开放	孔广辉	青年	一般资助
JG19031	“线上-线下-实践”三位一体的《生态工程学》课程建设研究	田纪辉	青年	一般资助
JG19032	基于视频微课的《遗传学》教学改革与实践	金晶	青年	一般资助
JG19033	新型开放性实验在植物学实验课程教学中的探索与实践	何韩军	青年	一般资助
JG19034	工程教育认证下食品科学与工程专业多维实践教学体系及模式的探索与实践	黎攀	青年	一般资助
JG19035	案例教学在环境化学课程中的应用	郑晓波	青年	一般资助
JG19036	“新国标”背景下基于 CBI 教学理念的高级日语教学模式改革研究	张秀娟	青年	一般资助
JG19037	协同教学在服装专业课程中的研究与应用——以服装结构设计课程为例	马宏林	青年	一般资助
JG19038	基于人工智能背景下的教学教务管理信息化探索与研究	王宣琳	青年	一般资助
JG19039	《物理化学》教学中落实“课程思政”理念的改革与探索	秦为为	青年/课程思政	自筹
JG19040	中华传统优秀文化融入高等农林院校思政课的教学模式改革研究	李玮舜	青年/课程思政	自筹
JG19041	基于微课的翻转课堂模式在《茶叶审评与检验》实验教学中的创新与实践	孟慧	青年/金课改革	自筹
JG19042	园林专业双语教学体系研究与改革 ——以《园林植物概论》双语课为例	施诗	青年	自筹
JG19043	基于校企联合培养基地的实践教学改革与创新	孙理超	青年	自筹
JG19044	车辆工程专业实践教学产教融合校企合作育人	周锡恩	青年	自筹

	模式的探索与实践			
JG19045	新媒体平台在《有机化学》课程教学改革中的应用	李兆栋	青年	自筹
JG19046	教育国际化背景下日本园艺科学教材中跨学科内容与非文字符号要素的探析与在《设施园艺学》课程中的应用研究	张轶婷	青年	自筹
JG19047	结合从业上岗证培训的“实验动物学”课程的改革与实践	余文兰	青年	自筹
JG19048	研究性学习在生物防治教学中的探索与实践	桑文	青年	自筹
JG19049	《形势与政策课》在线课程建设与应用实践研究	陈巍	青年	自筹
JG19050	知识传授、文化传承、价值引领三位一体的课程思政教学改革与创新----以大学物理基础课程为例	徐初东	课程思政	重点资助
JG19051	《舞蹈鉴赏》课程中“艺术+思政”的改革探索与实践研究	殷舒	课程思政	重点资助
JG19052	职业生涯教育课程思政功能的探索与实践	朱钧陶	课程思政	重点资助
JG19053	基于课程思政新理念下的《植物学》课程教学改革与初探	白玫	课程思政	重点资助
JG19054	《无机化学》课程思政的建设与实践	刘晓瑭	课程思政	重点资助
JG19055	《数字电子技术》课程思政建设研究	赵文锋	课程思政	重点资助
JG19056	在农林类专业课程中融入“课程思政”的探索与实践研究--以《农业生态学》为例	舒迎花	课程思政	重点资助
JG19057	高校“三全育人”模式下我校就业创业课程的“课程思政”实现路径研究	戴育滨	课程思政	一般资助
JG19058	基于一流人才培养的“金课”标准与评价研究	欧阳娟	金课改革	重点资助
JG19059	基于 SPOC 的《计算机组成原理》翻转课堂教学模式研究	杨磊	金课改革	重点资助
JG19060	基于微信公众号平台和雨课堂的“八度”混合式教学模式探索与实践	廖杨	金课改革	重点资助
JG19061	基于"MOOC+翻转课堂"的《食品营养学》混合式教学模式创新与实践	杨瑞丽	金课改革	重点资助
JG19062	混合式教学环境下大学生古典文学素养教与学模式实践研究	李桂芹	金课改革	重点资助
JG19063	基于深度学习理念的精准农业航空线上线下混合式“金课”探索与实践	张波	金课改革	重点资助
JG19064	采用混合式教学模式打造“金课”的探索——以专业核心课程《基础写作》为例	王青	金课改革	一般资助
JG19065	基于雨课堂及精品网课资源的农业院校公共有机化学混合式教学改革	丁唯嘉	金课改革	一般资助
JG19066	基于雨课堂平台的混合式教学模式改革研究—	骆泽顺	金课改革	一般资助

	—以《旅游市场营销》课程为例			
JG19067	“线上+线下”的遗传学实验混合教学模式探索研究	郭海滨	金课改革	一般资助
JG19068	基于慕课的《林木育种学》混合式教学方法探索	骈瑞琪	金课改革	一般资助
JG19069	《养羊学》课程内容优化及微课、翻转课堂在教学实践中的应用研究	柳广斌	金课改革	一般资助
JG19070	基于“线上”+“线下”的《生物信息学》课程混合式教学模式研究与实践	王波	金课改革	一般资助
JG19071	“金课”视域下城乡规划专业中外建筑史混合式教学模式探索与实践	吴宝娜	金课改革	一般资助
JG19072	基于交互式在线教育平台应用的混合教学模式探究--以文献检索课为例	刘洋	金课改革	一般资助
JG19073	“互联网+”翻转课堂的智慧微学习空间建设研究与实践——以华南农业大学为例	江晓庆	金课改革	一般资助
JG19074	新工科背景下高等数学混合式金课的研究与实践	刘丹	金课改革	一般资助
JG19075	“翻转+对分”混合教学模式研究--以《跨文化交际》课程为例	钟建玲	金课改革	一般资助
JG19076	《动物解剖学-感觉器官》章节基于雨课堂翻转教学模式设计与实践	许丹	金课改革	一般资助
JG19077	以打造“金课”为导向促进教师教学能力提升的探索和实践	钟建英	金课改革	自筹
JG19078	项目驱动下统计学专业实践混合式教学的创新研究	周燕	金课改革	自筹
JG19079	翻译技术辅助大学英语翻译混合式教学模式有效性研究	李志英	金课改革	自筹
JG19080	基于 SPOC“农业植物病理学实习”线上线下混合式教学的创新实践	纪春艳	金课改革	自筹
JG19081	基于翻转课堂的高校图书馆信息素养教育模式研究	关磊	金课改革	自筹
JG19082	线上线下混合式教学模式在法学专业课程中的应用研究	李福芹	金课改革	自筹
JG19083	基于翻转课堂的细胞生物学综合性实验教学改革	彭海峰	金课改革	自筹
JG19084	“雨课堂”混合式教学工具在兽医外科手术学教学中的应用研究	周沛	金课改革	自筹
JG19085	基于能力培养的多层级探究式教学改革研究及实践--以《土木工程材料》为例	李庚英		重点资助
JG19086	新工科背景下多维度提升工科高数课程教学质量的研究与实践	李娇娇		重点资助
JG19087	以科研成果促进遗传学实验教学创新改革的研究与实践	刘自强		重点资助

JG19088	基于蚕病学课程的全英教学和管理模式研究	孙京臣		重点资助
JG19089	新农科的时代内涵及我校建设方案初探	杨玉浩		重点资助
JG19090	海洋生物调查虚拟仿真实验设计及多层次教学模式的构建	孙际佳		重点资助
JG19091	A 系列课程质量及其影响因素调查研究	黎华寿		重点资助
JG19092	基于农林院校创新型英语人才培养的英语教学模式研究	邓飞		重点资助
JG19093	基于能力结构的卓越农林教师教学发展模式研究	朱蕾		重点资助
JG19094	基于国际标准培养木材科学与工程新工科专业特色人才的研究与实践	古今		重点资助
JG19095	丁颖班组织胚胎学实验课程教学素材改革及“云”尝试	梁晓欢		重点资助
JG19096	环境设计专业学生创新实践应用能力培养模式的研究与探索	郑欣		重点资助
JG19097	新工科背景下化工原理虚拟仿真实验教学改革与实践	袁腾		重点资助
JG19098	大湾区建设背景下海洋科学专业实践教学体系的改革与探索	杨慧荣		重点资助
JG19099	OBE 理念下城乡规划专业创新人才培养的进阶式教学模式研究	王凌		重点资助
JG19100	培养云计算环境下应用数学能力的实践教学改革研究	岑冠军		重点资助
JG19101	“新工科”背景下以创新人才为培养导向的农用无人机通识教育教学改革	文晟		重点资助
JG19102	推进校企合作，构建科研育人新模式	严会超		重点资助
JG19103	多学科实验平台开展安全教育的分科类教学资源体系构建与实践	劳媚媚		重点资助
JG19104	新农科背景下草业科学人才培养的专业定位及课程设置探索	张向前		重点资助
JG19105	基于移动互联网的在线考试系统的搭建与应用	刘极龙		重点资助
JG19106	课程育人与科研育人相结合——《药物分析》研究性教学探索	林雅铃		重点资助
JG19107	医务社会工作“四位一体”实习模式构建	韩丽		重点资助
JG19108	基于 OBE 理念的乡村规划课程体系优化研究	陈思颖		重点资助
JG19109	基于工程教育专业认证的工程基础教学模式研究与实践	郑丁科		重点资助
JG19110	图书馆服务“立德树人”根本任务的探索与创新研究——基于习近平新时代中国特色社会主义思想资源库建设的实践	吕剑红		重点资助
JG19111	可编程器件原理与应用实验在线课程建设与应用	徐海涛		一般资助

JG19112	社会学专业社会调查类课程群的协调联动架构研究	王宇丰		一般资助
JG19113	微课环境下遗传学开放实验体系的构建与实践	李亚娟		一般资助
JG19114	参与式规划设计教学——基于广州、澳门城市更新的实践	叶昌东		一般资助
JG19115	基于信息化建设的本科教学类档案管理模式研究	谢正生		一般资助
JG19116	液压与气动课程创新性实验实践教学的研究与实践	曾文		一般资助
JG19117	以拔尖创新性人才培养为目的的《农业植物病理学》课程教学探索	许美容		一般资助
JG19118	3+1 模式中外合作办学生物学人才培养模式的实践与创新	肖豫涵		一般资助
JG19119	新工科理念下《通信与计算机网络》实验教学创新研究	韩方珍		一般资助
JG19120	弹性云服务器（ECS）在工程类实验教学改革中的实践研究—以《物联网技术与应用》为例	张凯		一般资助
JG19121	依托广东非物质文化遗产构建设计类实践创新课程	陈金怡		一般资助
JG19122	基于 OBE 教育理念的《食品安全与质量控制》教学模式研究与实践	王光		一般资助
JG19123	信息化环境下案例教学法在生态统计学中的应用	秦钟		一般资助
JG19124	服装设计及作品展示虚拟仿真实验教学	赵英姿		一般资助
JG19125	基于项目驱动的《资源环境分析》教学模式探索	白翠华		一般资助
JG19126	基于素质与专业能力培养的农业大学博物馆展纲构建与教学实践	崔大方		一般资助
JG19127	《禽病学实验》教学模式改革	瞿孝云		一般资助
JG19128	新工科背景下线性代数教学改革的探索与实践	陈银辉		一般资助
JG19129	基于可持续发展观培育的环境设计专业实践教学模式创新与研究	吴宗建		一般资助
JG19130	动物医学专业核心课程双语教学新模式的探索—以国家级双语示范课程《兽医寄生虫学》为例	李娜		一般资助
JG19131	在生物化学课程中构建低年级大学生研究性学习引导机制研究	孙加节		自筹
JG19132	面向人工智能背景的会计学专业核心课程教学改革	董丽		自筹
JG19133	“线上线下”相结合的《社会保障学》课程“四位一体”教学模式探讨	徐强		自筹

JG19134	基于“互联网+”技术在基础化学实验教学的改革与实践	肖勇		自筹
JG19135	学分制模式下动物科学专业人才培养方案的修订	吴银宝		自筹
JG19136	基于速课微课堂教学平台的物理化学教学难点突破研究	陈明洁		自筹
JG19137	校企合作背景下材料化学专业人才培养模式探讨	张超群		自筹
JG19138	校内动物医院早期临床实训对于兽医麻醉学教学的改革与实践	吴志文		自筹
JG19139	联合教学背景下建筑学三年级快题设计教学改革研究	屈寒飞		自筹
JG19140	“技能传授+价值引领”的高校军事体育课程体系构建的研究	单宇		自筹
JG19141	新时代背景下产业学院本科生实践能力提升机制研究——以华南农大—温氏集团产业学院为例	何小敏		自筹
JG19142	农业昆虫学微课应用研究与实践	潘慧鹏		自筹
JG19143	通过丝绸文化课程提升大学生对中华文化自信	陈芳艳		自筹
JG19144	多媒体网络技术在基础化学实验教学中的应用探索	唐小兰		自筹
JG19145	面向新能源汽车产业需求的车辆工程本科生专业知识渗透与提升研究	郭嘉明		自筹
JG19146	基于大数据背景的高校教学改革的创新实践研究--以金融工程教学为例	李倩		自筹
JG19147	基于微信公众平台的辅助课程教学实践研究	彭利民		自筹
JG19148	将“研究性学习”理念引入《食品微生物检验》课程的建设与创新	邹苑		自筹
JG19149	线上线下双导式影视动画创作实践教学模式研究	王柯		自筹
JG19150	传统工艺传承与创新教学中的新型学徒关系研究——以香云纱实验教学为例	陆珊		自筹
JG19151	微生物学研究技术开放性实验课程建设	王海洪		自筹
JG19152	基于创新能力培养的小动物寄生虫病学课程教学方法改革研究与实践	元冬娟		自筹
JG19153	《人工智能》	陈琰	继续教育	400/学时（继续教育学院资助）
JG19154	《城市绿地规划》	邱巧玲	继续教育	400/学时（继续教育学院资助）

华南农业大学文件

华南农教〔2016〕47号

关于华南农业大学2016年度教育教学改革与研究项目立项的通知

各学院、部处，各单位:

为进一步推进我校教育教学改革与研究，提高人才培养质量，根据教育部、财政部《关于实施高等学校本科教学质量与教学改革工程的意见》（教高〔2007〕1号）精神，结合我国高等教育教学发展形势和学校实际，学校组织开展了2016年度教育教学改革与研究项目申报工作。经各单位推荐申报、学校教学指导委员会专家评审，主管校领导同意，决定对“通识管理能力训练课程教学体系的设计与研究”等45个校级教改重点项目予以立项资助，对“基于案例教学法的风景园林专业人才培养模式研究”等49个校级教改一般项目予以立项资助，对“大学生创新创业能力影响因素探索与培养模式构建——基于华南农业大学工

科类学院的实证研究”等 41 个校级教改自筹项目予以立项，对“管理学基础”等 20 个校级教改继续教育类项目予以立项资助（详见附件）。

请各项目负责人务必按项目计划要求及时开展研究工作，确保研究工作如期完成，并力争取得高水平的研究成果。

附件：华南农业大学 2016 年度教育教学改革与研究项目一览表

华南农业大学

2016 年 8 月 30 日

公开方式：主动公开

华南农业大学校长办公室　　2016 年 8 月 30 日印发

附件

华南农业大学2016年度教育教学改革与研究立项项目一览表

编号	项目名称	项目类别	主持人	经费（单位:元）
JG16001	通识管理能力训练课程教学体系的设计与研究	重点项目	库夭梅	10000
JG16002	基于学分制背景的高校教学管理信息化建设——以华南农业大学为例	重点项目	黄亚月	10000
JG16003	应用化学专业人才培养质量标准的研制	重点项目	汤日元	10000
JG16004	动物医学专业《兽医临床诊断学》PBL 教学模式的探讨与实践	重点项目	郭剑英	10000
JG16005	经济管理类大学生创新创业实践教学体系重构研究——就业竞争力提升视角	重点项目	罗军	10000
JG16006	高等农林院校本科应用型人才培养的政校企合作模式研究——以城乡规划专业为例	重点项目	卢丹梅	10000
JG16007	“云平台+服务”的计算机实践教学模式探索	重点项目	田绪红	10000
JG16008	翻转课堂教学模式在《家畜环境卫生学》的应用研究与实践	重点项目	王燕	10000
JG16009	大类招生培养制度下基于职业资格标准的房地产开发与管理专业人才培养模式研究	重点项目	袁中友	10000
JG16010	本科毕业论文（设计）质量保障与监测体系建设研究	重点项目	孙振刚	10000
JG16011	基于深度学习理念的SPOC教学模式研究与实践	重点项目	黄继青	10000
JG16012	创新人才培养模式——本科生导师制的探索与实践	重点项目	苗建银	10000
JG16013	环境工程典型污水处理工艺的3D建模、3D打印及其在教学中的应用研究	重点项目	余光伟	10000
JG16014	MOOC环境下大学生信息素养自主学习的实践研究	重点项目	伍玲	10000
JG16015	“互联网+”背景下高校教师信息化教学能力培养机制研究	重点项目	房三虎	10000
JG16016	大学生翻译与二语写作能力协同发展研究：生态语言学视角	重点项目	周美珍	10000

编号	项目名称	项目类别	主持人	经费（单位:元）
JG16017	基于专业导向的《高等数学》教学模式创新与资源优化配置研究与实践	重点项目	张伟峰	10000
JG16018	以就业为导向的土木工程毕业设计的职业标准化探索	重点项目	唐贵和	10000
JG16019	音乐学专业教育课程群的多模态教学实践研究	重点项目	李美群	10000
JG16020	以就业为导向的木材科学与工程专业人才培养模式创新与实践	重点项目	鲁群霞	10000
JG16021	新形势下广东省高校体能训练课程建设探究——以华南农业大学为例	重点项目	吕立	10000
JG16022	基于慕课（MOOC）的《遗传学》教学改革与实践	重点项目	王少奎	10000
JG16023	学分制视野下的汉语言文学专业本科人才培养机制研究	重点项目	王瑛	10000
JG16024	高校思想政治理论课教师课堂教学问题行为及对策研究	重点项目	周师	10000
JG16025	《茶树栽培学》课程规划与教学改革	重点项目	曹藩荣	10000
JG16026	基于导学案的学生自主学习机制建设研究与实践	重点项目	王石安	10000
JG16027	微课在《食品生物技术》等课程中的作用	重点项目	林晓蓉	10000
JG16028	农村社工培养链：实践教育模式创新和实践教学基地建设改革与实践	重点项目	李锦顺	10000
JG16029	《动物生物化学》微课开发与应用	重点项目	孙加节	10000
JG16030	基于慕课（MOOC）技术的《生态工程》课程建设研究	重点项目	黄飞	10000
JG16031	高等学校二级学院教学质量评估体系的构建与实践	重点项目	罗小珍	10000
JG16032	基于创新方法的《环境工程设备》课程教学改革实践	重点项目	王春铭	10000
JG16033	基于 MOOC 的《数据库技术应用基础》翻转课堂教学模式研究	重点项目	杨磊	10000
JG16034	生态语言学视阈下的大学英语翻转课堂教学模式研究	重点项目	苏君	10000
JG16035	从“水平评估”到“审核评估”的督导工作创新方式研究	重点项目	钟建英	10000

编号	项目名称	项目类别	主持人	经费（单位:元）
JG16036	《水生生物学》标本库的建设和实验教材的编写	重点项目	唐汇娟	10000
JG16037	以合唱艺术为载体的大学生艺术素质教育创新实践研究	重点项目	刘敏	10000
JG16038	农科学生通过校企协同育人机制促进创业的创新模式	重点项目	张展基	10000
JG16039	《食品工艺原理》双语教学应用探索	重点项目	王凯	10000
JG16040	新形势下包装工程学生机械知识的拓展与应用研究	重点项目	蒋卓	10000
JG16041	优质教学资源共享建设：基于知识关联的网络课程群构建研究	重点项目	吴茵茵	10000
JG16042	基于SPOCs的在线教学平台和视频资源建设实用策略研究	重点项目	余杏芬	10000
JG16043	英语课堂教学模式的优化研究与学生思辨能力的培养——以华南农业大学分层教学为例	重点项目	邓琳超	10000
JG16044	《种子健康检测》实践性教学探讨	重点项目	舒灿伟	10000
JG16045	校企协同培养工业工程创新型人才的实践与研究——基于佛山中格威电子有限公司	重点项目	张凯	10000
JG16046	基于案例教学法的风景园林专业人才培养模式研究	一般项目	翁殊斐	4000
JG16047	农业航空应用技术专业设置与培育	一般项目	李继宇	4000
JG16048	“三明治”教学法在公选课《环境与人类》中的应用	一般项目	赵本良	4000
JG16049	《水工钢筋混凝土结构学》教学改革研究与实践	一般项目	陈方竹	4000
JG16050	基于微课和翻转课堂的大学物理实验教学改革	一般项目	吕红英	4000
JG16051	基于产学研的校外实践教学基地改革创新研究与实践	一般项目	赵力超	4000
JG16052	农业院校特色的材料类专业实验材料与课程教学的改革研究	一般项目	胡航	4000
JG16053	基于岭南乡村建设需求的建筑学专业实践教学模式创新研究	一般项目	郭焕宇	4000
JG16054	电子类专业基础课——电路课程标准研究	一般项目	殷惠莉	4000

华南农业大学2013年度教育教学改革与研究一般、自筹项目一览表

序号	项目名称	项目负责人	项目类别
1	单片机课程网络教学资源建设与考核方式改革	邓小玲	一般项目
2	《企业网组网实验》课程的优化研究	韩方珍	一般项目
3	国际班双语教学PBL教学模式研究与实践	张霞	一般项目
4	《包装印刷工艺实验》课程的整合设计与教学实践	范小平	一般项目
5	基于研究型实验的《化学生物学》实验教学的探索与实践	熊亚红	一般项目
6	园林专业《园林工程学》课程实践教学改革与创新研究	汤辉	一般项目
7	《汽车构造》精品课程建设的研究与实践	武涛	一般项目
8	专业大类教学模式下《概率论与数理统计》课程教学改革与实践	徐小红	一般项目
9	教师角色理论在《植物学》实验课程教学组织中的应用研究	白玫	一般项目
10	《植物制片与形态结构》课程内容体系改革和优化的研究与实践	梁社坚	一般项目
11	《大学物理》实验教学模式改革的研究	刘勇	一般项目
12	院级实验教学示范中心公共创新平台运行模式的探讨	黄九九	一般项目
13	高校移动网络教学模式的探索与研究	曾鸣	一般项目
14	基于Moodle的《大学计算机基础》课程在线学习平台的设计与应用研究	杨磊	一般项目
15	基于移动计算技术的高等教育信息化服务体系的研究与探索	梁茹冰	一般项目
16	《汽车试验学》课程改革与实践研究	吴伟斌	一般项目
17	《森林生态学》双语课程教学资源整合与实践	贾小容	一般项目
18	《生物质能源工程》课程教学改革与探索	王明峰	一般项目
19	《环境保护与可持续发展》课程教学改革与实践	赵本良	一般项目
20	《食品生物技术》“快捷式”教学过程探索与实践	陈忠正	一般项目
21	本科生推荐免试研究生后期质量跟踪调查与信息反馈——基于地方重点院校的实证研究	孟成民	一般项目
22	基于网络平台的高等农业院校参与公益性农技推广人员培训的模式研究	宋欢	一般项目
23	师生互动环节在《毛泽东思想和中国特色社会主义理论体系概论》课程中的方法设计与应用研究	崔慧霞	一般项目
24	我校大类招生人才培养模式下本科生专业分流机制优化研究	刘春桃	一般项目
25	工商管理本科应用型人才培养的问题与对策研究——以华南农业大学为例	郭萍	一般项目
26	阳光体育运动下的普通高校耐力跑课程的教学设计改革与实践	周华锋	一般项目
27	《创业管理》课程教学内容体系改革和整体优化研究与实践	杨学儒	一般项目
28	文化素质教育课程建设与教学改革——基于大学生心理素质教育课程建设与教学改革研究	宋迎秋	一般项目
29	基于文化创意产业特点的《基础写作》课程教学研究	王青	一般项目
30	社会化背景下学校社区工作的育人功能研究	李敏	一般项目
31	高校人才培养与企业需求有效对接的研究——以法学专业为例	郑大睿	一般项目
32	基于珠三角会展经济发展的《展示设计》课程教学改革研究	李女仙	一般项目
33	构建“华农文库”，推动华南农业大学学科建设	何建新	一般项目
34	汉语言文学专业百篇作文训练培养模式研究	韦盛年	一般项目
35	高校《思想道德修养与法律基础》课师生互动教学模式的效果评估指标体系研究	张机	一般项目
36	电子沙盘模拟在管理类专业课程实验教学中的应用研究	张程	一般项目
37	中外合作办学项目教学质量监控体系的构建与实践——基于华南农业大学的实证研究	魏旭娇	一般项目
38	基于WebQuest的大学英语研究性教学模式的建构与实践	仇如慧	一般项目
39	视觉化下的英语口语教学研究	魏清华	一般项目
40	基于校企联合培养模式的财会专业学生创业教育研究	刘卫民	一般项目
41	基于自建专门用途英语（ESP）教学语料库的词块研究——探索大学英语教师向ESP教师转型的途径	秦建华	一般项目
42	以校园文化讲坛为载体的大学生文化素质教育模式的创新与实践	汪路勇	一般项目
43	新人才培养方案指导下的法学专业课程整合与优化	李文丽	一般项目
44	高校思政课对话教学模式的建构与研究	蔡小婷	一般项目
45	创意思维训练模式在动画剧作教学中的实践	王柯	一般项目
46	以创新型人才培养为目标的艺术素质教育改革的研究与实践	石娟娟	一般项目
47	优化整合校内媒体资源建设广播电视编导专业教育实训基地	王敏	一般项目
48	基于企业合作的动画专业实践教学研究与实施	吴祝元	一般项目
49	开放•交叉•融合——普通高校体育课双语教学模式的研究与实践	单宇	一般项目
50	基于协同创新的高校校企合作人才培养模式研究	欧阳倩兰	一般项目
51	高校校园文化品牌培育模式的研究与实践	张春苑	一般项目
52	教学团队建设的研究与实践——以A系列课程《创业学》为例	陈建	一般项目
53	少学时条件下的课程教学改革研究——以《工程光学》课程教学为例	刘建斌	自筹项目
54	《食品工程原理课程设计》课程的教学改革	李雁	自筹项目
55	基于聚合算子决策的学科交叉课程设计培养方案	刘鹏飞	自筹项目
56	茶艺美学资源开发及《茶艺学》教学内容体系改革研究与实践	张凌云	自筹项目

57	适于高等农业院校的入侵生物学教学课程体系的构建与探索	陆永跃	自筹项目
58	高等教育大众化视域下大学生学习动力系统分析与构建研究	房三虎	自筹项目
59	基于DUS三性判定的农事训练模式的探索与实践	徐振江	自筹项目
60	《摄影测量学》课程实践教育模式创新和实践教学基地建设改革与实践	王长委	自筹项目
61	农林院校化学类专业开放性实验室的管理与改革实践	温青	自筹项目
62	在制药工程专业设立“创新学分”的探索研究	林雅铃	自筹项目
63	《植物检疫学》课程教学改革探索	胡琼波	自筹项目
64	《生物统计附试验设计》课程教学改革与实践	张哲	自筹项目
65	以问题求解能力为核心的渐进式程序设计实验教学改革研究与实践	林毅申	自筹项目
66	工科类工业设计专业产品设计表现技法课程实践教学改革	郭晓燕	自筹项目
67	高等农业院校统计学专业实践教学的研究和探讨	肖莉	自筹项目
68	动物科学学院《微生物学》课程教学团队的改革与建设	刘丽	自筹项目
69	工程训练模式下教学管理的创新与实践	任春涛	自筹项目
70	面向卓越工程师教育培养的电子科学与技术专业实践教学体系研究	罗霞	自筹项目
71	以培养应用能力为导向的《生物防治》课程教学改革与实践	许小霞	自筹项目
72	《食品工艺原理》课程教学改革的实践与探索	赵雷	自筹项目
73	基于学生综合能力培养的机械实验课程改革探索与实践	甄文斌	自筹项目
74	以实践教学改革为核心的道路与桥梁工程应用型人才培养模式研究	黄俐	自筹项目
75	《环境化学》课程教学内容与教学过程的优化建设	蒋成爱	自筹项目
76	《土壤农化分析》实验课实验方法的改进与探索	赵兰凤	自筹项目
77	精品课程《森林经理学》信息技术服务体系的构建与实践	王本洋	自筹项目
78	《生物化学实验》课程教学改革与实践	蒋珺	自筹项目
79	大学生课外学术创新能力培养模式的探索与实践	许益镌	自筹项目
80	学研结合的《动物营养与饲料学》实践教学改革探索与实践	叶慧	自筹项目
81	基于创新能力培养的实验教学改革与实践——以《动物遗传学》课程为例	刘满清	自筹项目
82	以兴趣培养为核心的《植物学》课程教学的改革	龚维	自筹项目
83	非英语专业大学生英语学习“动机缺失”研究	彭英	自筹项目
84	我校专门用途英语（ESP）课程建设研究	李飞武	自筹项目
85	基于高校学生社区的社会工作专业校本实践平台建设研究	周志荣	自筹项目
86	《制度经济学》课程设计创新与教学体系改革实践	何一鸣	自筹项目
87	大学英语分层教学模式下《跨文化交际》作为拓展课程的教学实践与探索	赵勇	自筹项目
88	综合性高校音乐学科改造与特色建设的研究与实践	胡远慧	自筹项目
89	历史学专业课程中教学方法的创新研究	殷小平	自筹项目
90	英语分层教学模式下学生需求、认知风格与自我效能的分析与应对策略研究	吕丽珊	自筹项目
91	《马克思主义基本原理概论》课教学设计研究	黄浩	自筹项目
92	高校校外实践模式、创业教育对大学生就业影响研究	李尚蒲	自筹项目

附件

华南农业大学2023年度课程思政示范项目建设名单

序号	类别	项目名称	单位	项目负责人	团队成员（不含负责人）
kcsz2023001	试点学院	课程思政试点学院	工程学院	李　君	
kcsz2023002	试点学院	课程思政试点学院	植物保护学院	闫笑久	
kcsz2023003	试点学院	课程思政试点学院	食品学院	魏剑波	
kcsz2023004	示范团队	农学专业课程思政教学示范团队	农学院	刘自强	马启彬、王少奎、周玉亮、王小龙、王兰、冯发强、吴锦文、汪文毅
kcsz2023005	示范团队	集成电路课程群课程思政示范团队	电子工程学院（人工智能学院）	刘洪山	谢家兴、梁亨茂、代秋芳、薛秀云、殷惠莉、罗霞、王建、张宇、赵懿琨
kcsz2023006	示范团队	以农史教育为特色的中国史课程思政教学团队	人文与法学学院	刘玲娣	杨品优、赵艳萍、衷海燕、王福昌、翟麦玲、周晴、余格格、陈志国
kcsz2023007	示范团队	《大学数学》课程思政示范团队	数学与信息学院、软件学院	杨德贵	肖莉、何婧、付银莲、李凤、周燕、杨志程、丁仕虹、夏英俊、李朗

kcsz2023008	示范团队	茶学专业核心课程思政教学团队	园艺学院	张凌云	黄亚辉、陈文品、张灵枝、孙彬妹、郑鹏、马红彦、李丹、晏婵妤、谭新东
kcsz2023009	示范团队	机械设计制造及自动化专业课程思政教学团队	工程学院	王红军	王慰祖、刘天湖、段洁利、夏红梅、金莫辉、甄文斌
kcsz2023010	示范团队	《理论力学》课程思政教学示范团队	水利与土木工程学院	胡圣荣	卢玉华、许静静、刘新红、张秀丽
kcsz2023011	示范课程	电机学	工程学院	孙振刚	闫国琦、陆永超、孔莲芳、梅慧兰、莫嘉嗣、周锡恩
kcsz2023012	示范课程	电子工艺实习（电类）	电子工程学院（人工智能学院）	薛秀云	殷惠莉、李震、宋淑然、孙道宗、吕石磊
kcsz2023013	示范课程	遗传学实验	基础实验与实践训练中心	郭海滨	刘向东、库夭梅、刘自强、李亚娟、李楠、吴锦文
kcsz2023014	示范课程	应用统计学	数学与信息学院、软件学院	张建桃	宋世领、黄丽清、刘伟章、朱梅阶
kcsz2023015	示范课程	耕作学	农学院	王小龙	祁剑英、潘圣刚、陈健文、王媛媛
kcsz2023016	示范课程	民族服饰传承与传播	艺术学院	陈金怡	金惠、赵英姿 杨翠钰、马宏林
kcsz2023017	示范课程	旅游生态学	资源环境学院	叶延琼	章家恩、陈丽丽、赵飞、秦钟
kcsz2023018	示范课程	线性代数	数学与信息学院、软件学院	张伟峰	魏福义、朱艳丽、赵峰、李凤、陆琪、刘文琰、尤雪莲

kcsz2023019	示范课程	园艺植物生物技术	园艺学院	刘朝阳	张志珂，彭泽，傅嘉欣，秦永华，杨向晖，颜爽爽，程蛟文，徐婧
kcsz2023020	示范课程	安全通识教育	基础实验与实践训练中心	陈志民	库夭梅、李玉峰、刘小波、叶志婵、戴勇谦、谢虎、张伟东
kcsz2023021	示范课程	民间文学与民间文化	人文与法学学院	关溪莹	王青、梁颖稚、李飞、张吕坤、陈保菊、陈刚
kcsz2023022	示范课程	投资学	经济管理学院	董　莹	柳松、周丽云、莫易娴、蔡键、陈霄
kcsz2023023	示范课程	包装色彩学及色彩管理技术	食品学院	范小平	岳淑丽，刘涛，曹黎明，冯洪炬(企业导师)
kcsz2023024	示范课程	实用情景英语口语	外国语学院	吕丽珊	苏君、荣莉、李姝惠、张汉娇
kcsz2023025	示范课程	机械设计基础	工程学院	夏红梅	王慰祖、甄文斌、曾文
kcsz2023026	示范课程	产品设计方法学	工程学院	高锐涛	杨慧珠、胡炼、汪隽、郭涵
kcsz2023027	示范课程	公共政策学	公共管理学院	高青莲	巩玉涛、林纯颖、吴法、游艳玲
kcsz2023028	示范课程	海洋生物学基础	海洋学院	严慕婷	苏婉、唐汇娟
kcsz2023029	示范课程	民 间 文 献 学	人文与法学学院	衷海燕	刘玲娣、赵艳萍、杨品优、苏蓉
kcsz2023030	示范课程	社会学概论	公共管理学院	程启军	王建平、王宇丰、曲霞

kcsz2023031	示范课程	程序设计与算法语言	数学与信息学院、软件学院	蔡贤资	黄小虎、廖彬、张连宽、罗志坚
kcsz2023032	示范课程	摄影测量	资源环境学院	王长委	姚朝龙、林观土、薛卫星、丁华祥、王建芳、万欢
kcsz2023033	示范课程	旅游法规	林学与风景园林学院	孟　威	唐松、林敏慧、李艳丽、丛艳国
kcsz2023034	示范课程	混凝土结构基本原理	水利与土木工程学院	吕艳梅	陈凯、谢攀、杨雨冰
kcsz2023035	示范课堂	“数值分析”第四章第一节拉格朗日插值法	数学与信息学院、软件学院	李娇娇	
kcsz2023036	示范课堂	《舞蹈鉴赏》第二章第一节	艺术学院	郑琳喆	
kcsz2023037	示范课堂	概率论-第一章第四节条件概率与乘法公式	数学与信息学院、软件学院	周　燕	
kcsz2023038	示范课堂	广州本土原创音乐剧赏析（二）（课程归属：中国音乐剧鉴赏）	艺术学院	栾志弘	胡远慧
kcsz2023039	示范课堂	大学语文《小城三月》	人文与法学学院	吴　琪	
kcsz2023040	示范课堂	《网络安全技术与实践》第五章:探索网络安全与创新解决方案	数学与信息学院、软件学院	张　凯	
kcsz2023041	示范课堂	《世界古代史1》第六章第一节	人文与法学学院	邵兆颖	
kcsz2023042	示范课堂	《中国历史文选》第二单元 编年体史书《左传》	人文与法学学院	赵艳萍	

kcsz2023043	示范课堂	“政治学”课程思政示范课堂	公共管理学院	吴　法	
kcsz2023044	示范课堂	数学建模（第四章第二节）	数学与信息学院、软件学院	王　霞	
kcsz2023045	示范课堂	大学英语 III 第四册第四单元（Text A）	外国语学院	林桂珊	
kcsz2023046	示范课堂	《普通植物病理学》-植物病原原核生物难培养菌	植物保护学院	郑　正	邓晓玲、李云锋、许美容、丘麒
kcsz2023047	示范课堂	药用植物遗传育种-组织培养育种	林学与风景园林学院	李　培	
kcsz2023048	示范课堂	管理通识训练课程—新媒体应用管理	基础实验与实践训练中心	谢佳佳	李玉峰
kcsz2023049	示范课堂	机械工程材料 第十一章 机械制造中零件材料的选择	工程学院	刘天湖	
kcsz2023050	示范课堂	《茶艺与茶文化学》课程思政示范课堂	园艺学院	李　丹	黄亚辉、晏媚妤、郑鹏
kcsz2023051	示范课堂	园艺植物生物技术《原生质体融合》	园艺学院	张志珂	秦永华，刘朝阳
kcsz2023052	示范课堂	植物检疫学-红火蚁的监测与防控	植物保护学院	王　磊	
kcsz2023053	示范课堂	农业植物病理学	植物保护学院	孔广辉	姜子德、习平根
kcsz2023054	示范课堂	汽车拖拉机学，第十四章第 5 节，汽车制动系统	工程学院	李　庆	
kcsz2023055	示范课堂	跨文化交际第四章第 2 节 Relationships between Humans	外国语学院	叶茂连	

kcsz2023056	示范课堂	《毛泽东思想和中国特色社会主义理论体系概论》课程思政示范课堂	马克思主义学院	李俊宏	
kcsz2023057	示范课堂	农业生产机械化（A 系列）	工程学院	贾瑞昌	
kcsz2023058	示范课堂	金工实习钳工	基础实验与实践训练中心	李　捷	温威
kcsz2023059	示范课堂	大学英语 III Unit 6	外国语学院	李　莉	
kcsz2023060	示范课堂	社会保障导论	公共管理学院	李　倩	
kcsz2023061	示范课堂	模拟电子技术	电子工程学院（人工智能学院）	殷惠莉	
kcsz2023062	示范课堂	土壤生态学 第二章土壤食物网的结构与功能	资源环境学院	余玲玲	
kcsz2023063	示范课堂	国际私法：国际民事诉讼管辖权与国家利益	人文与法学学院	王　慧	陈莉、官隆清
kcsz2023064	示范课堂	材料力学第五章第 6 节提高弯曲强度措施	水利与土木工程学院	刘新红	
kcsz2023065	示范课堂	健美操	体育教学研究部	赵　燕	
kcsz2023066	典型案例	现实主义电影：从意大利“新现实主义”到当下华语电影中的“温暖现实主义”	艺术学院	苏珊珊	
kcsz2023067	典型案例	材料力学“课程思政”教学案例-压杆稳定的概念	水利与土木工程学院	许静静	

kcsz2023068	典型案例	《工程热力学与传热学》第四章第二节：热能利用率和㶲效率	工程学院	张　烨	
kcsz2023069	典型案例	《半导体照明技术》“课程思政”教学案例	电子工程学院（人工智能学院）	胡旭波	
kcsz2023070	典型案例	大学英语口语 I《中国饮食文化：为何能走向世界》	国际教育学院（广州都柏林国际生命科学与技术学院）	邱　倩	
kcsz2023071	典型案例	《林业经济管理学》“课程思政”教学案例	经济管理学院	周　伟	
kcsz2023072	典型案例	《林木育种学》课程思政教学典型案例	林学与风景园林学院	周　玮	
kcsz2023073	典型案例	国际民事诉讼：海外流失文物的“回家”之路	人文与法学学院	官隆清	
kcsz2023074	典型案例	《机械制造工艺学》第一章第四节:定位原理（定位的分类及应用）	工程学院	曹亚超	
kcsz2023075	典型案例	水工建筑物——4.1 拱坝概述	水利与土木工程学院	刘　远	周浩澜
kcsz2023076	典型案例	《高等数学》课程思政教学案例—第一章第二节数列极限	数学与信息学院、软件学院	王雪琴	
kcsz2023077	典型案例	《机电一体化与过程控制》第五章第 4 节：串行数据通信	工程学院	马锐军	

kcsz2023078	典型案例	基于“三位一体”目标导向的食品分析及实验课程思政教学实践研究——以“酸度的测定”为例	食品学院	温　棚	徐振林、 沈玉栋、徐小燕、杨金易、肖治理、 罗林
kcsz2023079	典型案例	感悟生命 追寻价值—大学生生命教育	海洋学院	苏　婉	
kcsz2023080	典型案例	《植物分类与标本制作技术》实验课程 ——“腊叶标本的制作”思政教学案例	基础实验与实践训练中心	郑明轩	
kcsz2023081	典型案例	免疫检测技术“课程思政”教学案例	食品学院	李向梅	雷红涛、徐振林、沈兴
kcsz2023082	典型案例	《跨文化交际》Chapter 12 Barriers and Bridges 12. 1 Barriers in Intercultural Communication	外国语学院	李　雅	
kcsz2023083	典型案例	“小”药片蕴含“大”民生——湿法制粒压片制备阿司匹林片	材料与能源学院	胡　洋	倪春林、周武艺、霍理坚、高永峰
kcsz2023084	典型案例	《机械制造工艺学》第一章第一节：机械制造工程学科的发展	工程学院	黄光文	
kcsz2023085	典型案例	生涯思政双融双促，培养德法兼修法治人才 （ 有“划”好好说——生涯意识唤醒）	人文与法学学院	陈　琦	
kcsz2023086	典型案例	C 语言程序设计-循环结构	数学与信息学院、软件学院	杨　磊	
kcsz2023087	典型案例	叶绿体色素的提取、分离、理化性质及含量测定	基础实验与实践训练中心	李淮源	

SCAULIB202625822

检索证明

根据委托人提供的论文材料，委托人华南农业大学数学与信息学院 杨磊(学科类型:自然科学) 1 篇论文收录情况如下表。

序号	论文名称	发表刊物及发表的年月卷期/页码等	作者排名	论文等级	作者文中单位	收录情况	影响因子	中科院大类分区
1	基于认知负荷理论的计算机组成原理实验教学设计与应用	实验室研究与探索 出版年：2025 出版日期：2025-01-20 13:14 卷期：44 01 页码：- 文献号： 文献类型：期刊论文	第一作者	C 类	华南农业大学数学与信息学院	北大核心	无	无

说明：论文等级和中科院大类分区按《华南农业大学学术论文评价方案（试行）》划分。

报告免责声明:如未盖章,报告无效

检索员：田成

华南农业大学图书馆

2026-03-11

华南农业大学图书馆 信息检索专用章

华南农业大学图书馆SCAULIB202625822

中华人民共和国教育部 主管
上海交通大学 主办

CN 31-1707/T
ISSN 1006-7167
CODEN: SYYTAZ

实验室研究与探索

Shiyanshi Yanjiu yu Tansuo
Research and Exploration in Laboratory

中国高等教育学会实验室管理工作分会会刊
中文核心期刊
中国科技核心期刊
RCCSE中国权威学术期刊

2025/01
第44卷 第01期
Vol. 44 No.01
总第347期（月刊）
Serial No. 347(Monthly)

ISSN 1006-7167
01>

实验室研究与探索（月刊）
SHIYANSHI YANJIU YU TANSUO
第 44 卷第 1 期总第 347 期 1982 年创刊 2025 年 1 月出版
期刊基本参数：CN31－1707/T＊1982＊m＊A4＊268＊zh＊P＊26.00＊6300＊49＊2025－01

目　次

·实验技术·
LCR 测试柱体水果电学特性实验平台设计与应用 …… 付　函，刘桂成，刘　烽，等 1
基于 Sobol 参数敏感性分析法的馈能减振座椅优化设计 …… 关　栋，李梦祥，吴倩雯，等 5
多单元混合倍压直流变换器及其损耗分析 …… 程若发，康智文 11
改进 YOLOv7 算法的钢板表面缺陷检测方法 …… 孙　超，刘均学，陈正超，等 19
用于电类实验测量数据异常检测的 MVAE 神经网络 …… 申赞伟，刘彦博，杨　柳，等 24
基于极化脏星座的无线隐蔽通信教学实验设计 …… 吉小鹏，张秀再 30
利用液体温变介电特性的微流体温度传感器 …… 刘　琦，陈子琛，王颖超 35
拉曼光谱成像在牙本质粘接界面研究中的应用 …… 毕　超，刘双双，洪晓黎，等 39
X70 钢在模拟北部湾海水环境中腐蚀行为教学实验设计 …… 李　岩，刘芯月，何家明，等 44
纺织品中稀土含量测试标准的验证方法 …… 周　威，马玉新，杨任游，等 50
透射电镜表征磁性样品的前处理技术路线探索 …… 郭新秋，韩贵华，李晓惠，等 56
土石坝隐蔽病害跨孔雷达探测实验系统设计 …… 唐　玉，康　飞，宿晓辉，等 60
管线钢动态应力下的原位氢渗透测试实验方法 …… 邢云颖，赵　茜，杨芝乐 64
风电场群自动电压控制硬件在环试验平台设计 …… 晏　波，陈　卓，郝正航，等 69
·仪器设备研制与开发·
基于正交切削理论的切削性能测试实验平台开发 …… 郭森现，罗世金，卫守恒，等 74
通信机柜用空调热管一体化设备运行参数优化 …… 崔四齐，李慧鑫，白　静，等 79
·专题研讨——虚拟仿真技术(135)·
面向 I^3 型卓越人才培养的嵌入式人工智能实验教学探索 …… 陆玲霞，于　森，彭勇刚 85
基于 DDPM 的盲解调实验系统设计 …… 臧　淼，邢志强，李　响 91
医学虚拟仿真实验教学课程的建设与思考 …… 施菊花，顾鸣敏，蒋　益，等 96
基于数字孪生的电力设备实验教学及在人才培养的应用 …… 江友华，宋文敏，陈江伟，等 100
新质生产力视域下机器人虚实结合轨迹优化实验教学设计 …… 杨　勇，胡家康 106
心理学教学中的神经解剖虚拟仿真实验教学改革 …… 刘　帅，于克欣，武　琨，等 112
·计算机技术应用·
计及复杂流－热耦合场的发电机冷却结构鲁棒设计与优化实践 …… 李龙女，李运浩，朱高嘉 117
基于无线局域网的羽毛球球拍数据采集实验系统研究 …… 陈　力，陈景源，冯　辉，等 121
·国家重点实验室·
德国国家级科研机构管理的经验及借鉴 …… 刘瀛弢，王方宏，金楷承 126
·实验教学示范中心建设·
融入 BOPPPS 的混合式形态学实验教学探索与实践 …… 邱燕燕，范嘉盈，夏　青，等 136
基于 5G 技术的实验实践教学应用平台探索 …… 胡国强，张　森，王西军 141
·实验教学与创新·
基于深度 Q 网络的平衡杆优化控制实验教学案例设计 …… 钟　珊，杜　鑫，司亚利，等 146
基于机器视觉的平凸透镜曲率半径检测方法 …… 许灿华，薛孔松，王雅婷，等 153
深部高应力下花岗岩力学损伤的孔隙水压影响 …… 云　丽，张志龙，刘　洋，等 158

融入科研能力训练的生理学实验教学设计——以骨骼肌收缩实验为例 …… 蔡维维,赵晨阳,朱雪雪,等 164
认知工作分析在智能交互设计教学中的应用 …… 王建民,许忆芊,付倩文,等 171
基于认知负荷理论的计算机组成原理实验教学设计与应用 …… 杨 磊,司国东,王春桃,等 177
能源转型下石油工程专业实践教学体系创新实践 …… 刘永旺,管志川,齐 宁,等 182
应用问题导向的项目式化学实验教学设计与实践——以黄连素改性及染色项目为例 …… 刘玉霞,曹机良,吕名秀,等 186
数字电路综合性实验项目的设计与教学实践 …… 张 熠,朱震华 191

·实习与实训·

OBE-CDIO 理念下可逆固体氧化物电池智能管控实训项目教学设计 …… 吴肖龙,胡建功,曹 晔,等 196
设计思维导向的工程训练课程教学探索与实践 …… 张金海,马 聪,高 琴,等 202
含能材料性能测试 3D 虚拟仿真实验系统开发 …… 蔡兴旺,杨继华,李宸欣,等 209
磷石膏固体废弃物利用的综合化学实验教学探索 …… 张 娟,张文鹏,孙 琦 215

·实验室建设与科学管理·

高校化学类实验室“双防一全”机制的探索与实践 …… 王继锋,卢立珏,张若妤,等 219

·文经管类实验室·

麻省理工学院媒体实验室建设对国内高校的启示 …… 王洋洋,张 媛 223
“温州指数”为基础的互联网理财仿真实验系统设计 …… 白延虎,罗建利,俞中坚 228

·仪器设备供应与管理·

高校大型仪器设备开放共享协同治理模式探索 …… 樊 冰,郭春伟,姜 斌,等 235
行业研究型高校大型仪器设备共享改革与探索 …… 钱晓辉,宗思雨,吴丝雨 241
深圳高校大型仪器开放共享赋能企业科技创新 …… 阳洪波,谢宇聪,吴文政,等 245

·实验室环境与安全·

基于物联网和神经网络的实验室安全智慧化管理系统 …… 汤志伟,黄 亮,施书彬 249
深度学习的高校实验室安全感知系统设计 …… 李琳琳,杨镇铭,王纪奎 257
基于能力提升的研究生涉化实验安全培训课程建设 …… 刘浴辉,陈少才,周 森,等 263

《实验室研究与探索》第十一届编辑委员会名单

高级顾问

中国科学院院士 陈 竺 陈洪渊 邓子新 严纯华 赵进东 朱清时

中国工程院院士 杜善义 林忠钦 刘经南 翁史烈 谢和平 朱 静 左铁镛

主 任 丁奎岭

副主任 毕卫民 陈江平 胡国庆 蒋兴浩 李淑云 刘克新 毛继泽 彭华松 邵 岚 孙延鹏 唐睿康 唐毅谦 王玉军 吴 兵 席海涛 熊宏齐 薛照明 占金华 张徐祥 钟代笛 朱 臻

编 委 蔡 丹 蔡以兵 曹 蓓 常 乐 常 亮 陈 越 陈晓猛 陈心浩 董华青 杜华云 方建慧 盖宏伟 韩英霞 何邦进 贺 剑 侯 珏 胡朝斌 黄富贵 计宏伟 江培翊 蒋文春 金永东 康传红 康智勇 赖延清 李 进 李 崧 李东云 李海川 李剑利 李立光 李明伦 李鹏健 李天书 李向阳 李彦鸿 李长利 梁 勇 刘 一 刘 锋 刘 刚 刘 哲 刘国锋 刘红军 刘兼唐 刘鹏展 刘琦晖 刘延安 刘志军 卢 坤 陆 玮 马 宁 马国杰 毛昌杰 孟庆繁 孟兆磊 朴虎森 任志波 邵光辉 沈 勇 沈清明 孙琦龙 孙胜春 孙淑强 唐俊峰 唐立新 田志刚 汪力君 王 建 王 强 王 巍 王海洁 王耀峰 王玉龙 王哲强 王子南 魏永前 吴 凡 吴金栋 吴 卫 吴文华 吴祝武 夏海兰 熊 兵 许 广 许燕滨 杨 冰 杨 华 杨宏云 杨立成 杨立功 杨旭静 姚丽华 姚作芳 于江华 余自中 袁洪学 张 臣 张 东 张 巍 张 文 张道兵 张德君 张冠鹏 张明生 张若妤 张新生 张雅林 张燕勤 章明卓 赵 明 赵冬梅 赵咏芳 钟华勇 周 涛 周 晔 朱正茂 庄志洪

特邀编委 敖天其 楚丹琪 方东红 冯建跃 符宁平 高 欣 管图华 胡今鸿 姜文凤 金仁东 雷敬炎 李 霆 李震彪 史天贵 王 健 王 杰 王 勤 伍 杨 张 林 张海峰 赵建新

编辑部

主 编 蒋兴浩 副主编 彭华松 周伯明 编 辑 陶世弟 秦杏荣 吴 炎 张小凡 方能虎

编 务 周雨卫 冯 霞 本期责任编辑 吴 炎 终 审 蒋兴浩

RESEARCH AND EXPLORATION IN LABORATORY
(Monthly)
Vol. 44 No. 1 Serial No. 347 Jan. 2025
Serial paraments: CN31 - 1707/T * 1982 * m * A4 * 268 * zh * P * 26.00 * 6300 * 49 * 2025 - 01

CONTENTS

· Experimental Technology ·
Design and Application of Experimental Platform for Electrical Properties Testing of Cylindrical Fruits Based on LCR Meter ..... FU Han, LIU Guicheng, LIU Feng, et al 1
Optimized Design of Energy Harvesting Vibration Damping Seat Based on Sobol Parameter Sensitivity Analysis ..... GUAN Dong, LI Mengxiang, WU Qianwen, et al 5
Multi-unit Hybrid Voltage Doubling DC Converter and Its Loss Analysis ..... CHENG Ruofa, KANG Zhiwen 11
Surface Defect Detection Method of Steel Plate Based on Improved YOLOv7 Algorithm ... SUN Chao, LIU Junxue, CHEN Zhengchao, et al 19
MVAE Neural Network for Anomaly Detection of Electrical Experimental Measurement Data ... SHEN Zanwei, LIU Yanbo, YANG Liu, et al 24
Experiment Design of Wireless Covert Communication Based on Polarization Dirty Constellation ..... JI Xiaopeng, ZHANG Xiuzai 30
Microfluidic Temperature Sensor Exploiting Temperature-dependent Dielectric Properties of Liquid ..... LIU Qi, CHEN Zichen, WANG Yingchao 35
Application of Raman Spectroscopy Mapping in the Study of Dentin Bonding Interface ... BI Chao, LIU Shuangshuang, HONG Xiaoli, et al 39
Teaching Experimental Design for Corrosion Behavior of X70 Steel in Simulated Beibu Gulf Seawater Environment ..... LI Yan, LIU Xinyue, HE Jiaming, et al 44
Studies on Verification Method of Testing Standard for Rare Earth Content in Textiles ..... ZHOU Wei, MA Yuxin, YANG Renyou, et al 50
Exploration of Pre-processing Methods for TEM Characterization of Magnetic Samples ..... GUO Xinqiu, HAN Guihua, LI Xiaohui, et al 56
An Experimental System for Hidden Defects Detection of Earth-rock Dam Based on Crosshole Ground Penetrating Radar ..... TANG Yu, KANG Fei, SU Xiaohui, et al 60
Experimental Method for In-situ Hydrogen Permeation of Pipeline Steel under Dynamic Stress Conditions ..... XING Yunying, ZHAO Qian, YANG Zhile 64
Design of Wind Farm Cluster AVC Hardware-in-loop Testing Platform ..... YAN Bo, CHEN Zhuo, HAO Zhenghang, et al 69
· R & D of Instruments and Apparatus ·
Development of Cutting Performance Testing Experiment Platform Based on Orthogonal Cutting Theory ..... GUO Miaoxian, LUO Shijin, WEI Shouheng, et al 74
Optimization of Operating Parameters of Air Conditioning and Heat Pipe Integrated Equipment for Communication Cabinet ..... CUI Siqi, LI Huixin, BAI Jing, et al 79
· Special Topic Discussion——Virtual Simulation Technology(135) ·
Exploration of Embedded Artificial Intelligence Experimental Teaching for Cultivating I^3-type Outstanding Talents ..... LU Lingxia, YU Miao, PENG Yonggang 85
Design of a Blind Demodulation Experimental System Based on DDPM ..... ZANG Miao, XING Zhiqiang, LI Xiang 91
Construction and Reflection of Medical Virtual Simulation Experimental Teaching Courses ..... SHI Juhua, GU Mingmin, JIANG Yi, et al 96
Experiment Teaching of Electric Power Equipment by Using the Digital Twin and Its Application in Talent Training ..... JIANG Youhua, SONG Wenmin, CHEN Jiangwei, et al 100
Design of Experimental Teaching for Robot Trajectory Optimization in the New Quality Productivity Perspective with Virtual and Real Experiments ..... YANG Yong, HU Jiakang 106
Reform of Neuroanatomy Virtual Simulation Labratory Teaching in Psychology Education ..... LIU Shuai, YU Kexin, WU Kun, et al 112
· Application of Computer Technology ·
Robust Design and Optimization Practice of Motor Cooling Structure Considering Complex Flow-Temperature Coupled Fields ..... LI Longnü, LI Yunhao, ZHU Gaojia 117
Research on a Badminton Racket Data Acquisition Experimental System Based on Wireless Local Area Network ..... CHEN Li, CHEN Jingyuan, FENG Hui, et al 121
· State Key Laboratory ·
Experiences and Enlightenment Learned from the Management of National Research Institutions in Germany ..... LIU Yingtao, WANG Fanghong, JIN Kaicheng 126
· Demonstration Center Construction of Experimental Teaching ·
Exploration and Practice of Blended Medical Morphology Experiment Teaching Integrated with BOPPPS ..... QIU Yanyan, FAN Jiaying, XIA Qing, et al 136

Exploration of Experimental Practice Teaching Application Platform Based on 5G Technology…… *HU Guoqiang, ZHANG Sen, WANG Xijun* **141**

· Experimental Teaching and Innovation ·

Design of an Experimental Teaching Case for Balance Pole Optimization Control Based on Deep Q-Network …… *ZHONG Shan, DU Xin, SI Yali, et al* **146**

Machine Vision-based Method for Detecting the Radius of Curvature of Plano-Convex Lenses …… *XU Canhua, XUE Kongsong, WANG Yating, et al* **153**

Effect of Pore Water Pressure on Mechanical Damage of Granite under Deep High Stress …… *YUN Li, ZHANG Zhilong, LIU Yang, et al* **158**

Design of Physiology Experiment Teaching by Integrating Scientific Ability Training——An Example of Skeletal Muscle Contraction Experiment …… *CAI Weiwei, ZHAO Chenyang, ZHU Xuexue, et al* **164**

Application of Cognitive Work Analysis in Intelligent Interaction Design Education …… *WANG Jianmin, XU Yiqian, FU Qianwen, et al* **171**

Research on Instructional Design and Effectiveness of "Computer Composition Principle Experiments" Based on Cognitive Load Theory …… *YANG Lei, SI Guodong, WANG Chuntao, et al* **177**

Innovation and Practice of Practical Teaching System in Petroleum Engineering under the Background of Energy Transition …… *LIU Yongwang, GUAN Zhichuan, QI Ning, et al* **182**

Design and Practice of Project Based Chemistry Experiment Teaching Guided by Application Problems——Taking the Modification and Dyeing Project of Berberine as an Example …… *LIU Yuxia, CAO Jiliang, LÜ Mingxiu, et al* **186**

Design and Teaching Practice of Comprehensive Experimental Project in Digital Circuits …… *ZHANG Yi, ZHU Zhenhua* **191**

· Training and Practice ·

Teaching Design of Reversible Solid Oxide Fuel Cell Intelligent Control Training Project Based on OBE-CDIO Concepts …… *WU Xiaolong, HU Jiangong, CAO Ye, et al* **196**

Exploration and Practice of Engineering Training Course Teaching Based on Design Thinking Cultivation …… *ZHANG Jinhai, MA Cong, GAO Qin, et al* **202**

Development of a 3D Virtual Experimental System for Testing the Performance of Energetic Materials …… *CAI Xingwang, YANG Jihua, LI Chenxin, et al* **209**

Teaching Exploration of Comprehensive Chemistry Experiment Based on the Utilization of Phosphogypsum Solid Waste …… *ZHANG Juan, ZHANG Wenpeng, SUN Qi* **215**

· Laboratory Construction and Scientific Management ·

Exploration and Practice of the "Double Prevention and Full Coverage" Mechanism in Chemistry Laboratories in Higher Education Institutions …… *WANG Jifeng, LU Lijue, ZHANG Ruoyu, et al* **219**

· Laboratory of Arts-Economics-Management ·

The Enlightenment of the Construction of the Media Laboratory at the Massachusetts Institute of Technology on Domestic Colleges and Universities …… *WANG Yangyang, ZHANG Yuan* **223**

Design and Development of an Internet Financial Simulation System Based on the "Wenzhou Index" …… *BAI Yanhu, LUO Jianli, YU Zhongjian* **228**

· Supply and Management of Apparatus and Equipment ·

Exploration of the Collaborative Governance Model for the Opening and Sharing Management of Large-scale Instruments and Equipment in Universities …… *FAN Bing, GUO Chunwei, JIANG Bin, et al* **235**

Dilemma and Exploration of Large Scale Instrument and Equipment Sharing in Industry Research Universities …… *QIAN Xiaohui, ZONG Siyu, WU Siyu* **241**

Opening and Sharing of Large Instruments in Shenzhen Universities Empowers Enterprises with Technological Innovation …… *YANG Hongbo, XIE Yucong, WU Wenzheng, et al* **245**

· Environment and Safety of Laboratory ·

Smart Management System of Laboratory Safety based on Internet of Things and Neural Network …… *TANG Zhiwei, HUANG Liang, SHI Shubin* **249**

Design of University Laboratory Safety Perception System Based on Deep Learning …… *LI Linlin, YANG Zhenming, WANG Jikui* **257**

Graduate Course Construction of Safety Training in Chemistry Experiments Based on Ability Enhancement …… *LIU Yuhui, CHEN Shaocai, ZHOU Sen, et al* **263**

Research and Exploration in Laboratory (Monthly, Started in 1982)

In charge: Education Ministry, P. R. China
Published by: Shanghai Jiao Tong University
Editor-in-Chief: JIANG Xinghao
Editied by: Editorial Department of Research and Exploration in Laboratory
Address: 1954 Huashan Rd., Shanghai, P. R. China
Zip Code: 200030
Tel/Fax: 86-21-62933165
Submission: http://sysy.cbpt.cnki.net
E-mail: sysy@mail.sjtu.edu.cn
Issue number: ISSN 1006-7167 / CN 31-1707/T
CODEN: SYYTAZ

获奖：

中国高校特色科技期刊
中国高校优秀科技期刊
《CAJ-CD规范》执行优秀期刊
全国高校优秀编辑质量科技期刊
华东地区优秀期刊
上海市高校优秀科技期刊

入选下列网站、数据库及检索系统：

- 《中国学术期刊 (光盘版)》
- 《中国期刊网》
- 《万方数据——数字化期刊群》
- 科技期刊世界影响力指数 (WJCI) 报告 (2023) 收录
- 《中国核心期刊(遴选)数据库》
- 《中国学术期刊综合评价数据库》
- 《中文科技期刊数据库》
- 《中文电子期刊服务》
- 《中国学术期刊文摘 》(中文版)
- 俄罗斯《文摘杂志》(AJ，VINITI)
- 美国《化学文摘》(CA)
- 美国《剑桥科学文摘》(CSA)
- 美国《乌利希国际期刊指南》(UIPD)
- 英国《INSPEC》数据库
- 美国《史蒂芬斯数据库》(EBSCOhost)
- 日本科学技术振兴机构数据库 (JST)

实 验 室 研 究 与 探 索
Shiyanshi Yanjiu yu Tansuo
（月刊，1982 年创刊）
第 44 卷　第 01 期　总第 347 期
2025 年 1 月 25 日出版

Research and Exploration in Laboratory
(Monthly, Started in 1982)
Vol. 44 No. 01 (Serial No. 347)
January. 25, 2025

主办：上海交通大学
主编：蒋兴浩
编辑出版：《实验室研究与探索》编辑部
地址：上海市华山路 1954 号
上海交通大学（徐汇校区）交大慧谷楼415室
邮编：200030
电话：(021) 62932952　62932875
广告热线：(021) 62933165
在线投稿网址：http://sysy.cbpt.cnki.net
电子邮箱：sysy@sjtu.edu.cn（办公）
sysydk@163.com（订刊）
sysyggy@163.com（广告）
网址：http://sysy.cbpt.cnki.net
印刷：上海麒麟士企业发展有限公司衡船印刷分公司

广告经营登记证：3101045000324
国内统一连续出版物号：CN 31-1707/T
国际标准连续出版物号：ISSN 1006-7167
国际期刊编码：CODEN: SYYTAZ
国内发行：上海市报刊发行局
发行范围：国内外公开发行
邮发代号：4-834
定价：26元 / 册

ISSN 1006－7167
CN 31－1707/T

实验室研究与探索
RESEARCH AND EXPLORATION IN LABORATORY

第44卷第1期　2025年1月
Vol. 44 No. 1　Jan. 2025

DOI:10.19927/j.cnki.syyt.2025.01.033

基于认知负荷理论的计算机组成原理实验教学设计与应用

杨　磊[a]，　司国东[a]，　王春桃[a]，　黄沛杰[a]，　肖克辉[a]，　杜治国[b]

（华南农业大学 a. 数学与信息学院；b. 信息网络中心，广州 510642）



摘　要：计算机组成原理实验教学能提高学生系统设计及应用创新能力，但因其实验原理抽象、知识点多，实验平台复杂等特点也让学生在实验过程中产生较高的认知负荷。为解决高认知负荷对实验教学造成的负面影响，基于认知负荷理论对实验进行教学设计，分析学生学习需要因材施教控制学生内部认知负荷，优化实验教材设计及呈现方式降低学生外部认知负荷，激发学生学习兴趣以提高学生相关认知负荷，提升实验教学效果。教学实践表明，新型教学设计有效降低学生实验过程中的认知负荷总量，计算机系统设计及创新能力得到较高的提升。此方法也可为其他实验课程教学改革提供参考。

关键词：计算机组成原理；认知负荷理论；实验教学；成效研究

中图分类号：G 642.0　　**文献标志码**：A　　**文章编号**：1006－7167(2025)01－0177－05

Research on Instructional Design and Effectiveness of "Computer Composition Principle Experiments" Based on Cognitive Load Theory

YANG Lei[a]，　*SI Guodong*[a]，　*WANG Chuntao*[a]，　*HUANG Peijie*[a]，　*XIAO Kehui*[a]，　*DU Zhiguo*[b]

(a. College of Mathematics and Informatics; b. Information Network Center, South China Agricultural University, Guangzhou 510642, China)

Abstract: Experiment teaching of computer composition principles can improve students' system design and application innovation abilities, but due to its abstract experimental principles, multiple knowledge points, and complex experimental platform, students have high cognitive load during the experimental process. In order to solve the negative impact of high cognitive load on experimental teaching effectiveness, a teaching design for "computer composition principle experiments" based on cognitive load theory is proposed. We analyze the need of students and implement individualized teaching to control their internal cognitive load, optimize the design and presentation of experimental teaching materials to reduce their external cognitive load, stimulate their learning interest to improve their related cognitive load, which improves the teaching effectiveness of "computer composition principle experiments". Practice teaching shows that the new instruction design effectively reduces the total cognitive load of students in the experimental process, and students achieve high improvement in computer system design and innovation ability. The method can also provide reference for the reform of experimental teaching in other courses.

Key words: principles of computer composition; cognitive load theory; experimental teaching; effectiveness research

收稿日期：2024-06-04

基金项目：2023年度华南农业大学教育教学改革项目(JG23106)；2024年度全国高等院校计算机基础教育研究会计算机基础教育教学研究项目(2024-AFCEC-387)；2023年度华南农业大学课程思政示范项目(kcsz2023086)

作者简介：杨　磊(1978－)，男，河南南阳人，博士，讲师，主要研究方向为教育信息化、智慧教学、计算机系统结构。

Tel.：15918597385；E-mail：yanglei_s@scau.edu.cn

中国知网　https://www.cnki.net

0 引 言

计算机组成原理是计算机专业的核心课程，主要讲授单处理器系统的组成和工作原理。计算机组成原理实验能将抽象的理论具体化，引导学生深入认识计算机硬件系统、理解各个功能部件的组织结构和工作原理、掌握其设计研发的方法，培养学生的系统分析和设计能力。计算机组成原理实验教学普遍存在如下问题：

（1）“重理论，轻实验”，理论与实验教学脱节。

（2）实验教学前序知识较多，缺乏顶层设计。

（3）实验教学手段单一，评价方式不够科学合理。

（4）实验教学没有区分不同基础的学生。

目前国内高校正在对计算机组成原理实验教学进行改革，如基于工程教育认证指导的计算机组成原理实践教学改革[1]、面向系统能力培养的计算机硬件教学设计[2]、虚实结合的计算机组成原理实验教学体系构建[3]、学科竞赛驱动的计算机组成原理实践教学探索[4]和人工智能背景下面向计算思维能力培养的计算机组成原理教学改革与实践[5]等，均在不同角度取得了一定的成效。计算机组成原理实验因其自身特点，让学生产生较高的认知负荷，是对学生实验造成不利影响和实验教学效果难以提升的主要原因。要想降低这些不利的影响，保证实验效果，需认真分析学生在实验过程中的认知负荷，优化实验教学及学习资源的设计。本文基于认知负荷理论，深度分析计算机组成原理实验教学中认知负荷的来源，并以控制学生内部认知负荷、降低外部认知负荷和提高相关认知负荷为目的，进行新型教学设计及实践，分析实验教学效果，验证基于认知负荷理论的计算机组成原理实验教学设计的有效性。

1 计算机组成原理实验教学的认知负荷分析

1.1 认知负荷理论

认知负荷理论（Cognitive Load Theory，CLT）目前已经发展成为一个对教学设计起重要指导作用的心理学理论[6-7]。认知负荷理论基于资源有限和图式理论从资源分配角度来考察学习[8]。学生学习过程中的认知负荷按其来源可分为内部、外部和相关的认知负荷[9]。内部认知负荷来源于学习材料本身，当学习材料具有高元素交互性而学生又未充分掌握适宜的图式时会出现高内部认知负荷；外部认知负荷来源于教学材料的组织和教学设计与方法，拙劣的教学材料和不当教学设计会减少学生用于学习的工作记忆总量，增加其外部认知负荷；相关认知负荷是指学生在图式建构和自动化过程中意欲投入的认知资源数量，提高学生的主观能动性，增加其认知努力，可引导学生将工作记忆投入更深层的图式建构和存储，促进学生的学习和知识的应用。

1.2 计算机组成原理实验教学的认知负荷来源

（1）计算机组成原理实验教学要用到汇编语言、数字逻辑、操作系统、硬件描述语言及现场可编程逻辑门阵列（Field Programmable Gate Array，FPGA）等内容，前序知识点较多，同时选课人数较多，教学中很难兼顾学生学习基础的差异，难以做到因材施教，学生在实验时内部认知负荷较高。

（2）计算机组成原理实验教学内容存在各自为政，缺乏系统的顶层教学设计，学生为做好实验，需要通过工作记忆去整合教学材料中没有提供的信息，进一步增加了学生的外部认知负荷。

（3）计算机组成原理课程实验原理抽象、实验平台复杂，学生在实验过程中动力不足，积极性不高，造成学生在图式建构过程中投入的认知资源较少，相关认知负荷不足。

学生总的认知负荷等于内部认知负荷、外部认知负荷及相关认知负荷之和，如果总的认知负荷超过有限资源的工作记忆，就会降低学习效果，有效的教学设计应该避免产生超额的认知负荷[10]。内部认知负荷是学习任务固有的，无法改变但可以控制；外部认知负荷依赖于信息的设计、材料的组织及呈现方式，是可以改变的[11]；相关认知负荷有助于学生图式建构和自动化，能够促进学习效果的提升。

2 基于认知负荷理论的计算机组成原理实验教学设计

计算机组成原理实验需要制定合理的教学方案。

（1）设计良好的学习对象，分析学生的学习需要及认知水平，控制内部认知负荷。

（2）研发教学资源，优化教材的组织及呈现方式，降低外部认知负荷。

（3）采取措施激发学生学习兴趣，引导其加大认知努力，提高相关认知负荷。

基于认知负荷理论的计算机组成原理实验教学设计如图1所示。

2.1 控制内部认知负荷

根据计算机组成原理实验课特点设计3种方法控制内部认知负荷。

（1）基于先行组织者引导并促进学生有意义的学习。在展示学习对象之前，基于先行组织者策略给予学生引导性材料，以概念图或思维导图的形式呈现实验前序知识基础、知识结构等充实学生的先存知识，以便学生在后续实验过程中主动、有目的地分配认知资源进行图式建构，控制内部认知负荷。

（2）设计小粒度学习对象降低实验难度。学习对

中国知网 https://www.cnki.net

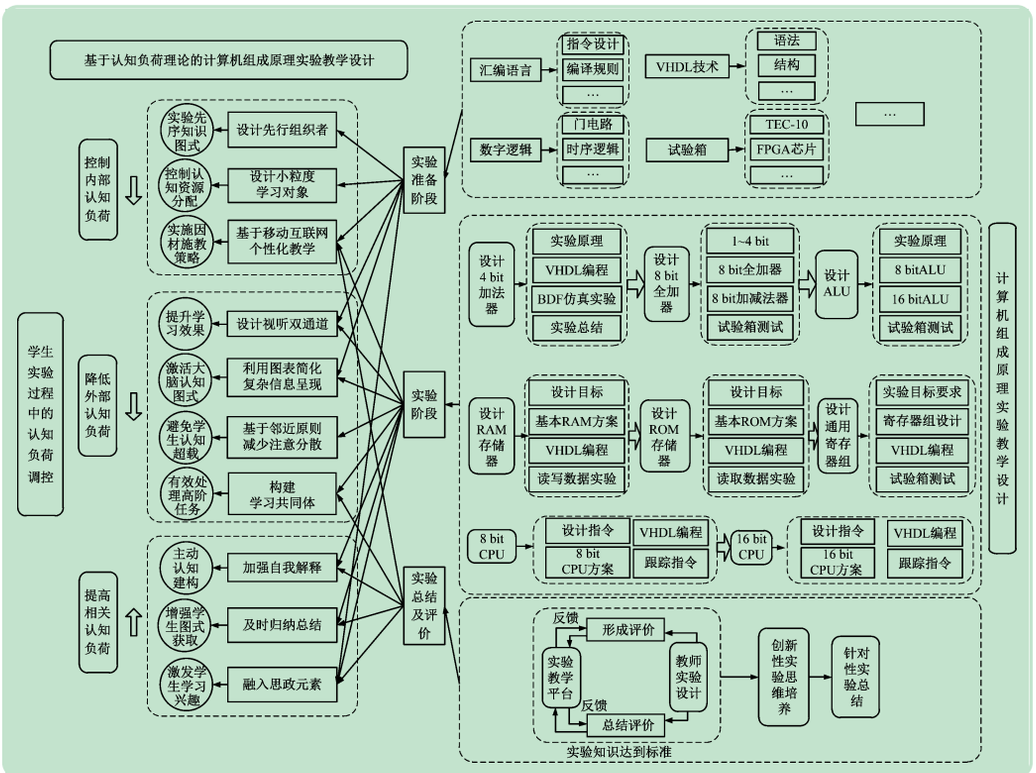


图 1　基于认知负荷理论的计算机组成原理实验教学设计

象是一个独立封装的可重用学习资源,实验学习对象采用小型化设计策略,使得学习对象知识的组成成分和相互作用关系减少,内部认知负荷较低;由于单次学习的时间较短,学生无论能力高低,都能比较容易地控制学习进度和分配认知资源,也能减少外界环境对学习的干扰。

(3) 基于移动互联网实施个性化教学。学生学习需要不同,认知水平不同,实验难度也会有所不同。实验设计时须充分考虑学生不同的基础,借助移动互联网实施因材施教,提供个性化教学;学生可根据自己的基础安排实验进度,降低实验难度,控制学生内部认知负荷。

2.2　优化教学资源降低外部认知负荷

降低外部认知负荷主要是减少学生所需加工的与实验教学目标无关的信息,最大限度呈现直达实验教学目的的学习内容。

(1) 设计视听双通道优化实验教学内容。设计组成原理实验视听双通道信息呈现方式,除实验讲解采用传统的图文同步课件外,用动画加解说的方式呈现内容,知识可同时通过视觉和听觉进行工作记忆,有助于学生对知识理解,降低外部认知负荷。

(2) 善用图表简化复杂信息。组成原理实验涉及较多的抽象概念、逻辑框图、结构示意及电路图等。精心设计图表可让高阶知识直观清晰,使抽象内容形象化,特别是实验重点及难点,图表能提升学生视觉搜索速度,有效激活大脑认知图式进行学习,降低外部认知负荷。

(3) 基于邻近原则减少注意分散。组成原理实验知识点在空间完整呈现相关的文字和图像,文字邻近或嵌入图像中,空间邻近更有利学生专注学习;时间上的图文同步可避免注意力分散导致的认知超载。

(4) 构建学习共同体分化复杂任务。构建组成原理实验学习共同体,学生自由组队,通过教师讲解,学生协作,小组汇报,教师点评,使每位学生获得启发和提升,共同体中个体认知负荷的压力就会减少。通过学习共同体复杂实验任务被分化为简单的子任务,学生实验探究更加主动,个体认知负荷得到了处理,认知水平得到提升。

2.3　提高相关认知负荷

计算机组成原理实验教学主要采用以下 3 种策略,促进学生图式建构和激发学生学习兴趣。

(1) 加强自我解释提升实验能力。学生在进行组成原理实验的关键步骤需标记并做出自我解释,帮助理解实验原理及解决复杂实验问题。自我解释能让学生在新图式和已有图式之间建立有效连接,积极主动地进行认知建构活动,提高相关认知负荷水平。

(2) 及时归纳小结促进图式构建。实验知识的及时归纳小结,能将零散的知识点有机关联起来,增强学生图式获取能力,提高相关认知负荷。如 16 bit CPU 的设计性实验,归纳课堂讲授的指令、CPU 理论知识、ALU 及存储器实验等帮助学生建立该实验的关联图式,并给出电路模块和实验情境,引导学生主动探究。学生通过师生、生生讨论认真思考实验中用到的知识点,即可高效完成实验任务。

中国知网　https://www.cnki.net

（3）挖掘思政元素端正学习动机。在实验教学中融入思政元素，如存储器实验融入我国长江存储发展历程，CPU 实验融入华为被禁用 ARM 指令集 V9 和华为突破 Mate60Pro 麒麟 9000 处理器的故事，思政元素的融入可增强学生的时代责任担当和投身国产 IT 事业的使命感，同时还能增强学生的民族自豪感和爱国情怀，端正学生学习动机，激发学生学习热情，认真完成实验任务。

3 基于认知负荷理论的计算机组成原理实验教学效果分析

3.1 实验教学效果评价方法

从学院计算机科学与技术专业 2021 级随机选择 2 个教学班，共 123 人参加实验，其中实验班 62 人，普通班 61 人。测试材料主要包括认知负荷测量量表，计算机组成原理实验学习成绩前测与后测。认知负荷测量采用 PAAS 量表（Paas & Van Merrienboer）[12]，该量表主要包括任务难度和心理努力两个维度，其中任务难度是指被试者对完成的实验任务难度的评价[13-14]，心理努力是指被试者对完成实验任务过程中所付出的心理努力程度的评价[15-16]；学习成绩前测的主要内容是计算机组成原理实验前序知识，采用试卷方式；后测主要内容是计算机组成原理实验，后测成绩由实验报告 + 现场检查（生讲和生评）+ 实验汇报（组讲加师评）综合评定，成绩采用百分制。

计算机组成原理实验共 8 周，授课教师相同，均在硬件实验室进行，授课内容及实验环境完全一致。第 1 次实验课进行前测，检验 2 个班的认知负荷情况及实验前序知识掌握情况，对实验班根据本文提出基于认知负荷理论的计算机组成原理实验教学设计进行实验教学，普通班则采用传统方式进行实验教学。

3.2 实验教学效果分析

本文采用 SPSS Statistics 22.2 统计软件采集数据并进行统计分析、独立样本 t 检验等。

实验教学 2 个班 PAAS 认知负荷主观量表的回收率及有效率均为 100%，利用 SPSS 对总体认知负荷进行数据分析，结果见表 1。

表 1 实验班与普通班总体认知负荷前后测数据分析

变量	总体认知负荷前测	总体认知负荷后测	Sig
实验班(62 人)	7.951 6 ±0.876 4	6.435 5 ±0.822 3	0.001
普通班(61 人)	8.163 9 ±0.799 5	8.049 2 ±0.693 4	0.399
Sig	0.163	0.027	

2 个班总体认知负荷前测维度双尾检验的 Sig 值为 0.163，大于 0.05，说明实验前 2 个班的总体认知负荷相近，不存在显著差异；后测维度双尾检验的 Sig 值为 0.027，小于 0.05，存在着明显的差异；普通班前后测双尾检验的 Sig 值为 0.399，大于 0.05，说明普通班前后总体认知负荷相近，不存在显著差异；实验班总体认知负荷前后测双尾检验的 Sig 值为 0.001，小于 0.05，存在明显差异，总体认知负荷降低了很多，如图 2 所示。原因是实验班进行了基于认知负荷理论的计算机组成原理实验教学。

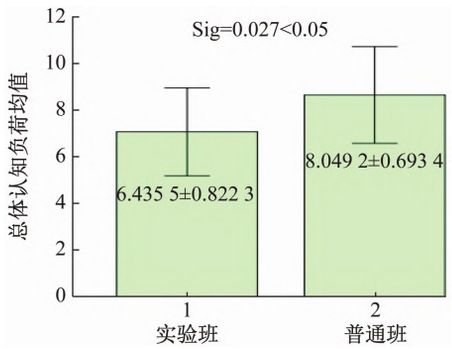


图 2 实验班与普通班总体认知负荷后测 t 检验（误差条：±2 SD）

对 2 个班的任务难度自评分数进行独立样本 t 检验，结果见表 2。2 个班任务难度后测维度双尾检验的 Sig 值为 0.004，小于 0.05，有显著差异，如图 3 所示。

表 2 实验班与普通班任务难度前后测数据分析

变量	任务难度前测	任务难度后测	Sig
实验班(62 人)	4.080 6 ±0.684 6	3.371 0 ±0.834 3	0.005
普通班(61 人)	4.098 4 ±0.568 7	4.147 5 ±0.749 2	0.684
Sig	0.876	0.004	

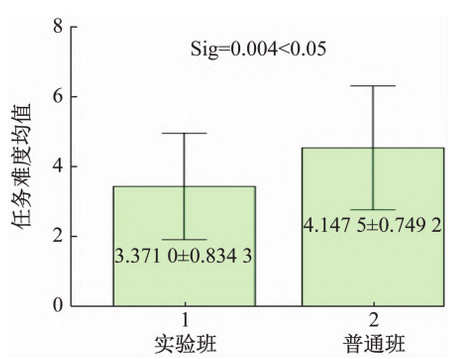


图 3 实验班与普通班任务难度后测 t 检验（误差条：±2 SD）

实验班的任务难度显著低于普通班，因为实验班的实验教学基于小粒度设计了学习对象，进行视听双通道优化了实验教学内容，使用图表简化复杂信息呈现，构建学习共同体分化了复杂任务等，有效地降低了实验任务的难度。

对 2 个班同学的心理努力自评分数进行独立样本 t 检验，结果见表 3。2 个班同学心理努力后测双尾检验的 Sig 值为 0.003，小于 0.05，有显著差异，如图 4 所示。

表 3 实验班与普通班同学心理努力前后测数据分析

变量	心理努力前测	心理努力后测	Sig
实验班(62 人)	3.871 0 ±0.664 9	3.048 4 ±0.777 3	0.000 4
普通班(61 人)	4.065 6 ±0.573 5	3.967 2 ±0.515 3	0.321
Sig	0.085	0.003	

中国知网 https://www.cnki.net

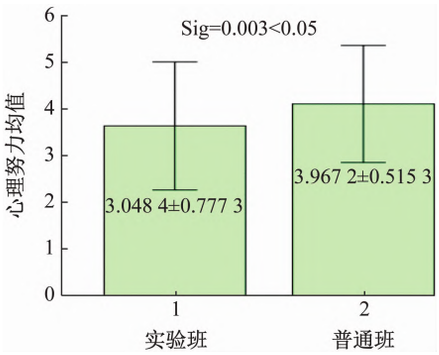


图 4　实验班与普通班心理努力后测 t 检验
(误差条:±2 SD)

实验班同学的心理努力付出程度明显低于普通班,因为实验班的实验教学中,教师基于邻近原则减少了学生注意力分散,通过加强自我解释提升了学生的实验能力,及时归纳小结有效促进了学生的图式建构,挖掘思政元素端正了学生的学习动机等,使学生在实验过程中绕开工作记忆认知资源有限阻碍,将实验过程发生在长时记忆,学生可付较低的心理努力得到最优的学习效果。

对 2 个班同学的成绩独立样本 t 检验,2 个班学习成绩前测双尾检验的 Sig 值为 0.838,大于 0.05,说明 2 个班在实验前的成绩差异不大,结果见表 4。

表 4　实验班与普通班学生学习成绩前后测数据

	学习成绩前测	学习成绩后测	Sig
实验班(62 人)	92.161 3 ±3.572 1	94.000 0 ±3.400 2	0.002
普通班(61 人)	92.311 5 ±4.514 9	92.491 8 ±4.295 8	0.822
Sig	0.838	0.026	

2 个班学习成绩后测双尾检验的 Sig 值为 0.026,小于 0.05,表明 2 个班在成绩后测上差异较大,实验班的后测成绩明显高于普通班如图 5 所示。说明将认知负荷理论用于实验教学有助于提升学生的学业成绩。

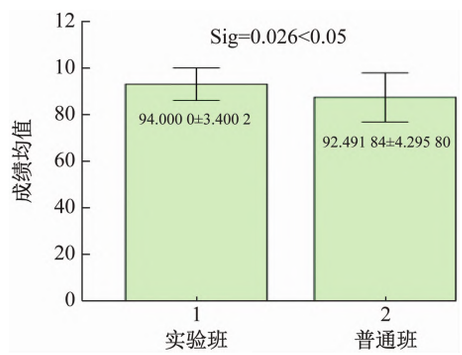


图 5　实验班与普通班学习成绩后测 t 检验
(误差条:±2 SD)

在实验教学中还向学生推荐了计算机组成原理的相关竞赛,如“龙芯杯”全国大学生计算机系统能力培养大赛、全国大学生集成电路创新创业大赛等计算机系统能力方面的大赛,并鼓励他们参赛。实验班已经有 4 位同学报名参加,普通班尚未有同学报名。说明将认知负荷理论融入实验教学能有效提高学生的学习热情,激发其学习兴趣。

4　结　语

计算机组成原理实验课具有系统性强、专业性强,学生学习难度大等特点。本文基于认知负荷理论,分析了计算机组成原理实验教学中认知负荷的来源,并以控制内部认知负荷、降低外部认知负荷和提高相关认知负荷为目的,对计算机组成原理实验教学进行新型教学设计,选择 2 个班实验对比。实践表明,基于认知负荷理论的计算机组成原理实验教学有效降低学生实验过程中认知负荷总量,提升学生对实验的兴趣,加深学生对理论知识的理解,增强学生开发复杂计算机系统的实践技能,深度优化该课程的实验教学效果。

参考文献(References):

[1] 张　强,刘三荣,李学辉,等. 面向工程教育专业认证的计算机组成原理实验教学设计[J]. 计算机教育 2020(9):141-144.
[2] 尚　俊,余良俊. 面向系统能力培养的计算机硬件实验教学设计[J]. 湖北第二师范学院学报,2024,41(2):54-60.
[3] 李　黎,杨　爽,苏玉萍. 虚实结合的计算机组成原理实验教学体系构建[J]. 计算机教育, 2023(6):184-188.
[4] 樊彦恩,张俊霞. 学科竞赛与课程设计有机融合的计算机组成原理实验教学探索[J]. 软件导刊, 2023, 22(6):182-186.
[5] 郭　萍,庄　伟,许小龙. 人工智能背景下面向计算思维能力培养的《计算机组成原理》教学改革与实践[J]. 实验室研究与探索,2023,42(12):129-135.
[6] Sweller J, Ayres P, Kalyuga S. Cognitive load theory[M]. New York: Springer,2011.
[7] Sweller J. Human cognitive architecture[J]. Instructional Science, 2008,32(1):9-31.
[8] 吕立霞. 基于认知负荷和机器学习算法的计算机教学平台设计与应用[J]. 电脑知识与技术,2024,20(8):46-48.
[9] 薛耀锋,王　坤,邱奕盛,等. 基于多模态数据的在线学习认知负荷评估[J]. 现代教育技术,2024,34(3):79-88.
[10] 宋　雨,刘　杨,高　强,等. 基于脑电多域特征融合的跨任务认知负荷研究[J]. 实验技术与管理,2024,41(2):73-80.
[11] 郑　富,李宛濛. 降低认知负荷的费曼学习法自学模式设计[J]. 科学咨询(科技·管理),2024(1):183-186.
[12] Paas F, Renkl A, Sweller J. Cognitive load theory: Instructional implications of the interaction between information structures and cognitive architecture[J]. Learning Science, 2004,32(1/2):1-8.
[13] 李　晶,郁舒兰,金　冬. 均衡认知负荷的教学设计及知识呈现[J]. 电化教育研究, 2018, 39(3):23-28.
[14] 王　珍,王海智. 基于均衡认知负荷理论的 VR 数字博物馆界面设计方法研究[J]. 中国科技论文在线精品论文, 2023,16(3):321-327.
[15] 郝晓鑫,李　艳,耿凤基. 计算思维的层级加工理论假说及教育启示[J]. 电化教育研究,2024,45(8):71-79.
[16] 周子琳. 竞技运动中的认知负荷评估[J]. 体育研究与教育, 2024,39(2):82-87.

中国知网　https://www.cnki.net

COMPUTER EDUCATION

计算机教育

《计算领域高质量科技期刊分级目录》T2类期刊
CCF推荐中文科技期刊
中国最具国际影响力学术期刊
《中国学术期刊影响因子年报》统计源期刊

CN 11-5006/TP

06
2023
总第342期

www.jsjjy.com



“科教+思政”融合的人工智能拔尖人才培养模式探索

信息技术赋能教学能力内涵式发展的演进路径及实践

基于ROC教学法的开源操作系统教材建设

行业划转院校软件工程学科建设发展现状分析与路径探索

ISSN 1672-5913

06 >

中华人民共和国教育部主管　清华大学主办

计算机教育
Jisuanji Jiaoyu

2023年6月10日 第6期 总第342期

2003 年创刊

主管 中华人民共和国教育部
主办 清华大学

顾问委员会

主 任 周远清
副主任 张尧学
委 员 陈 冲 孙家广 谭浩强 杨芙清

编辑委员会

主 任 李 未
副主任 周立柱 王志英
委 员 (按姓名拼音排序)
陈道蓄 陈 明 陈 钟 戴建耘
丁刚毅 冯博琴 傅育熙 甘 勇
高 林 古天龙 管会生 过敏意
韩 臻 何炎祥 洪 玫 黄国兴
黄心渊 蒋宗礼 赖剑煌 李 颉
李晓明 李轩涯 廖明宏 刘乃琦
卢 苇 罗钟铉 马殿富 孟祥旭
潘 毅 孙建国 孙茂松 孙 伟
唐 群 吐尔根·依布拉音 王金龙
魏晓辉 温 涛 吴文虎 徐晓飞
杨士强 臧斌宇 郑 莉 周激流
周兴社 庄越挺 邹北骥

主 编 奚春雁
编辑部主任 宋文婷
编 辑 孙怡铭 史志伟 赵 原
责任编辑 孙怡铭
编 务 陈 昕
发 行 综合业务室

编辑出版发行：《计算机教育》杂志社有限公司
社址：北京市海淀区双清路学研大厦B座908室
邮编：100084
编辑部电话：(010) 83470487 83470489 83470503
广告营销：(010) 83470506
杂志社邮箱：jsjjy@vip.163.com
网址/投稿平台：http://www.jsjjy.com
刊号：ISSN 1672-5913 CN 11-5006/TP
邮发代号：80-171
印 制：北京地大彩印有限公司
定 价：45.00元

《计算机教育》杂志社有限公司版权声明
本刊所登作品，一律文责自负。
本刊鼓励原创作品，杜绝刊登盗用、拼凑等类文章，凡检举以上现象者，本刊赠阅全年杂志一套。本刊及网站所载内容版权归本杂志社所有，凡引用时必须注明稿件源于《计算机教育》杂志。

目 次

人才培养

1 “科教+思政”融合的人工智能拔尖人才培养模式探索
王淑营，杨 燕，李天瑞，刘晓棠

7 新工科背景下计算机类实践教学创新培养与成绩溯源
边小勇，李 晨，吴志祥，张 凯，张晓龙

课程思政

12 数据结构与算法课程思政三维结构内容体系构建 崔 青

17 混合教育背景下的数据库类课程思政教学探索 闫 蓉

23 信息类通识课课程思政建设 周淑一，方炜炜，徐英慧，潘淑文

29 价值塑造与专业能力培养共蕴互促的课程思政体系建设
于元隆，张友坤，朱丹红

35 以“走向深蓝战场”为牵引的计算机基础课程思政资源优化
王博伦，史 珂，陈慧女

41 程序设计类一流课程“专业+思政”教育协同效应探索与实践
赵榆琴，李晓伟，陈建华，赵秦怡

46 Linux编程技术课程思政教学探索 黄 茹，王春梅，王小银，张丽丽

2023第十四届全国密码学与信息安全教学研讨会

52 信息安全数学基础课程思政教学实践 贾春福，哈冠雄，李瑞琪，高敏芬

56 “一体两翼四驱”实战化模拟仿真教学环境建设与运用 李秀广

60 信息安全专业虚拟教研室建设实践与思考
刘文超，刘轶群，周潭平，柯 彦，苏婷婷

64 人工智能与算法课程思政设计与实践 张瑞杰，魏福山，郭渊博，程庆丰

67 基于迁移教学法的密码学教学研究——从中国剩余定理到拉格朗日插值法到正则嵌入 周潭平，丁玉洁，刘文超，杨晓元

72 密码学选修课程的教学改革探索与实践 李曼曼，陈少真，罗 东，任炯炯

76 网络与信息安全方向系列课程贯通式教学探索与实践
苏 婷，蒋 琳，房 敏

81 基于OBE教育理念与KSA能力体系融合的密码科学与技术专业实践教学模式改革探索 王永娟，韩 宇，袁 博，王向宇，葛爱军

实验与实训

87 专业认证视域下的软件工程专业创新型实践教学体系探索
张 强，吴秀芹，薛继伟，王 颖，吕升义

92 软件测试课程三向驱动及PTCF实践教学模式
马媛媛，胡星宇，张 恩，王晓东，刘金金

98 Web服务渗透虚拟仿真实验教学设计与实践
梁琳琳，张妮娜，黄海燕，张跃宇，尹 钰，李 晖

核心课程建设

103 操作系统课程混合式教学与课程思政融合途径探索
叶晓霞，彭小红，余应淮

教改纵横

109 工程教育专业认证下的程序设计课程群教学改革
龚 俊，吴福英，柯胜男，李 萍

116 基于CBE的地方本科院校数据结构教学改革 王 霞，徐永华，胡彩平

121 基于师生赋能的计算机公共课程体系四维协同教学探索
王 杨，杨 梅，王 玥，胡 杨
126 基于超星平台的JavaScript程序设计课程教学改革
王 渊，柯胜男，汪万根，李弟平，熊小勇

教育与教学研究

130 面向openGauss的数据库课程教学探索 张国富，苏兆品
136 以成果为导向的课外实践教学体系构建与实践
柳丽召，蔡 彪，吴媛媛，吴 静，林 杰
141 新工科背景下基于OBE理念的信息类课程群建设
唐 丹，尹宏鹏，方 觅，黄云峰
145 基于“闭环式”结构的创新创业教育体系构建
王 芳，潘理虎，武鸿泽，田 涛，李翔宇
150 多媒体信息处理的主动学习教学框架 刘 江，章晓庆
156 以人工智能为主线的计算机通识课程体系设计与实践
张晨静，袁红春，梅海彬
162 大数据处理技术“三心两重一体”混合式教学模式探索 翟 娜，李雷孝
169 信息技术赋能教学能力内涵式发展的演进路径及实践 王若宾
174 基于CIPP的计算机组成原理翻转课堂教学评价指标体系构建与应用
杨 磊，黄沛杰，吴理华，肖克辉，江晓庆，徐东风
179 基于形成性评价的软件工程课程导学探索
姜 瑛，王红斌，丁家满，贾连印，游进国
184 虚实结合的计算机组成原理实验教学体系构建 李 黎，杨 爽，苏玉萍
189 OJ系统和在线课程混合驱动的程序设计课程教学新模式
秦汉林，卢成浪，邹会来
194 个性化项目驱动的混合式教学模式设计与实践 张 莉，邵 兵，葛 宁
199 混合式教学课前导图笔记法教学环节设计与实践 刘 辉，王妮娅
203 基于问题导向的人工智能应用案例式教学 刘瑞芳，孙 勇

教材建设

209 基于ROC教学法的开源操作系统教材建设 王俊超，姚金阳，单 征

中小学教育

213 培养计算思维的高中人工智能校本课程设计 刘江岳，马 静

一线调查

220 行业划转院校软件工程学科建设发展现状分析与路径探索
陈万志，浦胜良，赵 帅

扫一扫
或搜索jsjjyzz
微信也精彩

* * * * *
本刊为
中国知网数据库(CNKI)全文收录期刊
中国期刊全文数据库(GJFD)全文收录期刊
中国学术期刊综合评价数据库(CAJCED)统计源期刊
中国重要会议论文全文数据库(CPCD)收录期刊
万方数据—数字化期刊群全文收录期刊
* * * * *

计算机教育

2023 年度协办单位

清华大学计算机科学与技术系
北京航空航天大学软件学院
北京航空航天大学计算机学院
国防科技大学计算机学院
北京林业大学信息学院
哈尔滨工业大学计算学部
复旦大学软件学院
北京信息科技大学信息管理学院
西安邮电大学计算机学院
吉林大学软件学院
北京邮电大学软件学院
北京交通大学软件学院
上海交通大学软件学院
武汉科技大学计算机科学与技术学院
深圳大学计算机与软件学院
山东工商学院计算机科学与技术学院
湖北工业大学计算机学院
温州商学院信息工程学院
嘉兴技师学院
清华大学出版社计算机与信息分社
百度在线网络技术（北京）有限公司

文章编号：1672-5913(2023)06-0174-05　　中图分类号：G642

基于 CIPP 的计算机组成原理翻转课堂教学评价指标体系构建与应用

杨　磊[1]，黄沛杰[1]，吴理华[1]，肖克辉[1]，江晓庆[2]，徐东风[1]
（1. 华南农业大学 数学与信息学院，广东 广州 510642；
2. 华南农业大学 信息网络中心，广东 广州 510642）

摘　要：针对基于 SPOC 的计算机组成原理翻转课堂传统教学评价中存在的问题，提出基于 CIPP 的计算机组成原理课程多元评价指标体系，介绍评价指标体系的构建模型与结构，通过评价应用结果分析，给出翻转课堂教学模式的改进策略。

关键词：CIPP；计算机组成原理；翻转课堂；教学效果评价
DOI:10.16512/j.cnki.jsjjy.2023.06.019

0　引　言

计算机组成原理课程主要讲授单处理器系统的组成和工作原理，并在此基础上扩展到并行体系结构，课程具有知识面广、内容多、难度大、更新快等特点。基于 SPOC 的计算机组成原理翻转课堂教学模式，利用 SPOC 学习资源和移动学习工具，创设了泛在学习环境，优化了教学流程，不仅对学生学习的主动性提出了更高要求，对传统的教学评价方式也产生了重要影响。传统的教学评价主要围绕着教师课堂教学进行，对课前的规划、准备和导学，课后的多元反馈及创新性思维培养等环节不够重视，评价的结果往往不客观、不全面。

基于建构主义“双主型”翻转课堂教学模式，特别强调课前、课中及课后环节，而建立学习过程与学习结果融合的评价模式至关重要，因此以多元评价理论为指导、以发展性评价为主体，构建基于 CIPP 模型的计算机组成原理翻转课堂教学评价指标体系。指标体系从目标设置、过程评价与教学反馈等对翻转课堂教学进行多维度、全过程评价的研究，以期进一步提升计算机组成原理翻转课堂教学质量，推动计算机组成原理翻转课堂教学模式深入发展。

1　基于CIPP的计算机组成原理翻转课堂教学评价指标体系

1.1　计算机组成原理翻转课堂教学评价现状

国内高校于 2015 年起开始使用基于 MOOC、微课、翻转课堂、在线教学平台、APP 和小程序等方式进行多样化的混合教学，在 2017—2018 年得到了快速发展。文献 [1] 对基于翻转课堂理念的计算机组成原理教学进行了研究，并进行了课堂教学评价，取得了较好的教学效果。文献 [2] 基于微课与翻转课堂改进了计算机组成原理课程教学，在课后指导学生通过学习总结、小组评议等方式对翻转课堂教学进行总结评价。文献 [3] 对计算机组成原理翻转课堂进行了线上线下混合式教学模式的应用实践，改善了教学效果。文献 [4] 对计算

基金项目：2019 年度广东省教育教学改革项目“基于 SPOC 的计算机组成原理翻转课堂教学模式研究”；2019 年度华南农业大学教育教学改革重点项目“基于 SPOC 的计算机组成原理翻转课堂教学模式研究”（JG19059）；2020 年度华南农业大学质量工程项目（线上线下结合精品课程）“计算机组成原理”（zlgc19028）；2021 年度广东高校公共计算机课程教学改革项目“公共计算机课程 C 语言程序设计 SPOC 翻转课堂混合教学模式研究”（2021-GGJSJ-004）。
第一作者简介：杨磊，男，讲师，研究方向为教育信息化、智慧教学、计算机系统结构，yanglei_s@scau.edu.cn。

(C)1994-2023 China Academic Journal Electronic Publishing House. All rights reserved.　http://www.cnki.net

机组成原理云环境下的翻转课堂应用进行了研究，设计了课堂考核机制表，进行了师生、生生互评，进一步发挥了翻转课堂的优势。文献 [5] 对计算机组成原理实验教学进行了过程性教学评价，提升了学生学习的兴趣。文献 [6] 设计了基于 SPOC 的翻转课堂教学模式，以计算机组成原理为案例，从学习过程、结果、学生满意度等方面进行教学评价。文献 [7] 设计了留学生计算机组成原理课程教学评价新方式，体现出对平时学习的督促，对创新协作的鼓励。文献 [8] 提出了一种计算机组成原理多元教学模式，进行多元评价提升了教学质量。

目前，国内很多高校也在进行计算机组成原理翻转课堂的教学实践，在各大学习平台上也在进行着 SPOC 课程教学，但在知网数据库中检索到的相关文献还较少，利用“计算机组成原理 + 教学评价”为主题关键词进行检索的相关文献几乎没有，因此基于计算机组成原理翻转课堂教学和教学评价的经验总结，以及系统的、完整的理论研究还有待进一步完善。

1.2 CIPP 课程评价模型及翻转课堂教学评价

CIPP（决策导向评价模型）是美国学者斯塔弗尔比姆（Stufflebeam D.L.）提出的 [9]，该模型将评价过程分为背景评价（Context Evaluation）、输入评价（Input Evaluation）、过程评价（Process Evaluation）和成果评价（Product Evaluation）4 个部分，背景评价是对教学的目标进行合理性分析，输入评价是对教学的可行性进行鉴定，过程评价是对教学的有效性进行评判，成果评价是对教学的效果进行评估。CIPP 评价模型的目的是动态改进，重视过程评价和反馈作用，具有规划、实施、循环改进的动态评价特点，能够把教学过程中实施教学活动的具体表现纳入评价，从而避免教学评价只重结果不重过程的片面性 [10]。

基于 SPOC 的翻转课堂强调“以学生为主体，以教师为主导”的“双主型”教学，目的在于提高学生的综合能力。CIPP 是一种综合性评价模型，整个评价都围绕学生的学习展开，对课程资源设计开发、教学活动实施和教学效果进行动态评价，其理念与翻转课堂完全吻合。利用 CIPP 模型对翻转课堂进行评价有利于基于 SPOC 的翻转课堂以评促教，动态改进教学，提高教学质量。基于 CIPP 的计算机组成原理翻转课堂教学评价模型如图 1 所示，该评价模型的优点在于能够及时准确地反馈课程教学的优缺点，并动态解决课程教学中的失误与偏差，促进教学质量螺旋式的提升。

1.3 基于 CIPP 的计算机组成原理翻转课堂评价指标体系构建

基于 CIPP 的评价标准能够对计算机组成原理课堂教学要素进一步反馈优化，在构建的计算机组成原理翻转课堂教学评价指标体系中，一级指标 4 个、二级指标 12 个、三级指标 50 个，CIPP 评价模型与计算机组成原理翻转课堂评价指标体系对应关系如图 2 所示。

在背景评价中使用教学需要分析作为一级指标，二级指标中的学生学习需要分析主要包括是否具备学习本门课程的基础，是否能够利用移动设备进行自主学习，课前能否安排好时间主动完成 SPOC 的学习；教师课程知识准备主要包括是否了解学生的学习基础，是否愿意进行线上线下混合教学，是否能够利用基于 SPOC 的翻转课堂教学模式进行教学设计；教学基础环境准备主要包括是否具备线上线下教学场地和网络，是否配备了运转良好的教学媒体设备，教学内容是否适用于翻转课堂教学。

在输入评价中使用教学条件评估作为一级指标，二级指标中的学生学习条件分析主要包括能否在课前安排时间自主学习，能否保证学习 SPOC 视频资源的时间及效率，能否主动应对学习困难，能否进行师生学习交互；教师教学条件分析主要包括是否设计开发了基于 SPOC 的泛在学习资源，是否进行了系统的教学设计，课前是否进行导学，是否在泛在环境中与学生进行有效的交互；学校教学服务保障主要包括是否为教师提供了线上线下教学能力提升的培训机会，是否为困难学生提供线上教学的设备及网络，是否为教学计划的有效实施提供制度保障，是否为教师进行翻转课堂教学提供支持与鼓励。

在过程评价中使用教学过程实施作为一级指标，二级指标中的学生学习过程表现主要包括课堂听讲情况（认真、深入思考、创新）、学习展示（积极主动、一般、没有）、交流合作（生生

(C)1994-2023 China Academic Journal Electronic Publishing House. All rights reserved. http://www.cnki.net

交流、师生交流、讨论与反思）、完成作业及测验情况（独立完成、协作完成、未完成）、学习总结（认真负责、一般）、评价情况（好、一般、差）；教师课堂教学情况主要包括集体授课、个性化指导，是否记录了学生的课堂学习表现，是否进行了详细的教学活动的组织与管理，是否根据学生个体和群体的表现给出了实时教学反馈，是否进行了课堂总结（知识回顾、课堂小结、布置作业）；教学活动整体表现情况主要包括教学内容（优秀、一般、缺乏趣味性）、教学方法（讲授、演示、讨论、观摩）、教学时间安排（准时、迟到、早退、拖堂）、课堂教学效果（学生接受程度高、课堂氛围好），以及教学目标是否达到、师生互动是否活跃。

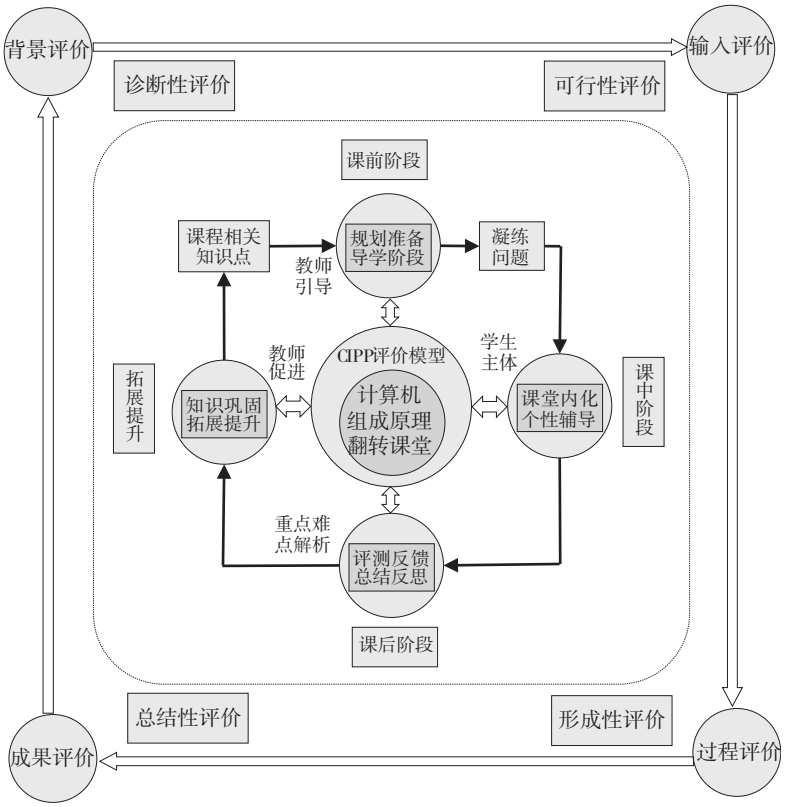


图 1　基于 CIPP 的计算机组成原理翻转课堂教学评价模型

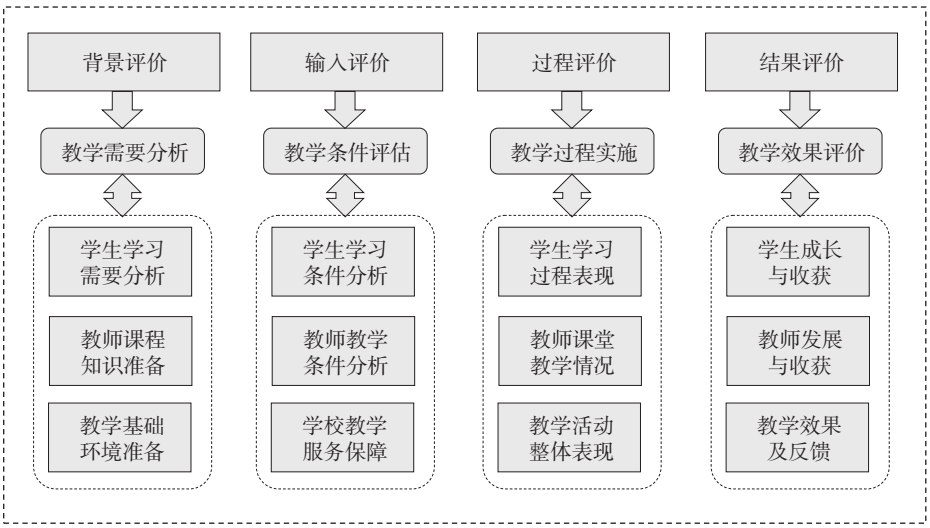


图 2　CIPP 评价模型与翻转课堂评价指标体系对比关系

(C)1994-2023 China Academic Journal Electronic Publishing House. All rights reserved. http://www.cnki.net

在成果评价中使用教学效果评价作为一级指标，二级指标中的学生成长与收获主要包括学习成绩，是否学习态度与学习成绩密切相关，是否学习准备及积极性与学习成绩密切相关，是否学习过程中的交流互动与学习成绩密切相关；教师的发展与收获主要包括教学成绩（主要是评教分数），是否教师的教学态度与教学成绩密切相关，是否教师的教学设计及课程资源开发与教学成绩密切相关，是否教师的课堂教学组织管理与教学成绩密切相关；教学效果及反馈主要包括整体教学效果（很好、好、一般、差）、教学改进建议，以及是否可以推广。

基于 CIPP 的计算机组成原理翻转课堂教学模式的应用效果评价指标体系，在课堂教学开始前进行背景评价和输入评价，完成教学需要及教学条件的诊断性评价和可行性分析；课堂教学中通过向教师和学生发放学生学习过程和教师教学过程的问卷调查表，进行教学过程的形成性评价；在学期结束时通过发放教学效果评价表，完成计算机组成原理的翻转课堂教学总结性评价。

2 教学模式分析与改进

为了客观评价基于 SPOC 的计算机组成原理翻转课堂教学模在泛在学习平台及微课、微实验的试点应用效果，对大二计算机科学与技术专业的 4 个班级、4 位担任计算机组成原理任课教师及负责课程教务及实验等相关教师进行了问卷调查，针对学生发放了问卷 123 份、回收有效问卷 118 份，任课教师发放问卷 4 份、回收有效问卷 4 份，负责教务督导及实验等教师发放了问卷 6 份、回收有效问卷 6 份。

在针对学生的问卷调查中，调研内容主要分为基于 SPOC 的翻转课堂的和翻转课堂实施后利用 CIPP 模型进行评价两部分。在基于 SPOC 的翻转课堂部分，有 94.92% 的学生听过 SPOC、翻转课堂等概念，96.61% 的学生认为教师在课堂教学中应该是主导角色，94.92% 的学生认为学生应该是学习的主体，71.19% 的学生在传统课堂上会遇到跟不上教师讲课节奏、听不太明白的情况，86.44% 的学生希望课前预习时教师多提供一些通俗易懂的学习资源，76.27% 的学生希望课后作业需要交流，83.05% 的学生认为课堂上要增加交流互动，84.75% 的学生对新型教学模式满意，87.29% 的学生使用泛在学习工具觉得方便好用，86.44% 的学生偏向选择翻转课堂，89.83% 的学生觉得翻转课堂提升了他们的兴趣和积极性，93.22% 的学生喜欢基于 SPOC 的计算机组成原理翻转课堂教学。在利用 CIPP 模型对翻转课堂进行评价部分，88.14% 的学生具备了学习计算机组成原理的先续基础，96.61% 的学生能利用移动设备进行自主学习，74.58% 的学生可以安排好时间课前完成 SPOC 的学习，76.27% 的学生课前可以安排时间自主学习，83.05% 的学生能够保证 SPOC 学习的时间及效率，89.49% 的学生能够主动应对学习困难，84.75% 的学生课前可以通过泛在平台进行交互，86.44% 的学生课堂听讲认真，67.80% 的学生课堂上进行汇报展示，27.97% 的学生课堂上进行了讨论与反思，86.44% 的学生完成了课堂作业及测验，87.29% 的学生认真负责完成了学习总结，93.22% 的学生课堂听讲很好，学生学习成绩基本呈正态分布，58.47% 的学生成绩在 80~90 分，96.61% 的学生认为学习态度与学习成绩密切相关，84.75% 的学生认为学习准备及积极性与学习成绩密切相关，81.36% 的学生认为学习过程中的交流互动与学习成绩密切相关。

针对任课教师的问卷中全部教师都了解学生学习计算机组成原理的基础，50% 的教师十分愿意进行线上线下混合教学，75% 的教师能够利用基于 SPOC 的翻转课堂进行教学设计，25% 的教师设计并研发了泛在学习平台，75% 的教师课堂上进行了知识回顾、课堂小结和布置作业，50% 的教师进行了导学，75% 的教师在泛在环境进行了交互，100% 的教师进行了集体授课，75% 的教师进行了个性化的指导，25% 的教师记录了学生课堂表现，50% 的教师进行了详细的教学活动组织与管理，75% 的教师及进行了实时教学反馈，75% 的教师学生评教在 90~95 分之间，全部教师都认为教学态度与学生评教成绩密切相关，50% 的教师认为教学设计及课程资源开发与学生评教成绩密切相关，75% 的教师认为课堂教学组织管理与学生评教成绩密切相关。

(C)1994-2023 China Academic Journal Electronic Publishing House. All rights reserved. http://www.cnki.net

针对教务、督导等教师的问卷调查中全部具备了线上线下的教学场地和网络，全部配备了运转良好的教学媒体设备，83.33% 的教师认为教学内容适用于翻转课堂，83.33% 的教师认为单位为教师提供了线上线下教学能力提高的培训，66.67% 的教师认为单位为困难学生提供线上教学的设备及网络，50% 的教师认为任课教师课堂教学内容优秀，所有教师都认为任课教师以讲授为主，附以演示、讨论与观摩，83.33% 的教师认为任课教师课堂教学时间安排准时，66.67% 的教师认为任课教师的课堂教学学生接受程度高、课堂氛围好，66.67% 的教师认为课后反馈的整体效果好，100% 的教师认为单位为教学计划的有效实施提供了制度保障，33.33% 的教师认为单位为教师进行翻转课堂教学提供了支持与鼓励，83.33% 的教师认为任课教师课堂教学目标已经达到，50% 的教师认为任课教师课堂教学互动活跃，66.67% 的教师认为基于 SPOC 的翻转课堂教学模式可以推广应用。

经过对计算机组成原理课程的背景评价、输入评价、过程评价和结果评价等问卷调查的反馈情况，综合上文的调查结果，初步得到基于 SPOC 的计算机组成原理翻转课堂教学的分析结果：教学开设状态良好，课程的教学资源配置较为合理，课程目标及教学目标设置明确，各项教学工作设置符合课程的标准和教学设计，学生在课程学习中的主动探究学习能力得到了提升，师生交流协作进一步增强，利用计算机组成原理泛在小程序激发了学生学习兴趣。然而，也存在不足之处，有约 20% 的学生成绩不理想，还有约 5% 的学生成绩不及格，可能与课程采用翻转课堂后学生学习监控不足有关，可能还与学生的学习习惯、学习态度等有关。另外，任课教师对基于 SPOC 的翻转课堂的实践能力还有待进一步提升。基于本次调查结果，对学院、教师和学生分别提出相关建议，以期提高计算机组成原理教学质量，深度优化课程的教学效果。

3 结 语

构建基于 CIPP 的计算机组成原理翻转课堂多元评价指标体系，对基于 SPOC 的计算机组成原理翻转课堂教学进行背景、输入、过程及结果等 4 个方面的评价，不仅可以更加全面地评估课程的教学效果，而且能够对课程教学过程进行动态调整，促使教学质量螺旋式提升。未来，笔者将思考进一步完善基于 CIPP 的多元评价指标体系，持续对计算机组成原理课堂教学进行 CIPP 多元评价，并推广应用到其他课程的教学评价中。

参考文献：

[1] 林克正, 刘彦君, 金恩海, 等. 基于翻转课堂理念的计算机组成原理教学研究[J]. 计算机教育, 2016(4): 117-120.
[2] 农健, 龚平. 基于微课与翻转课堂的“计算机组成原理”课程教学模式研究[J]. 梧州学院学报, 2017, 27(3): 113-116.
[3] 杨欣宇, 李诚, 张浩鹏. 混合式教学在计算机组成原理课程中的应用研究[J]. 高师理科学刊, 2019, 39(10): 77-79, 83.
[4] 王红梅, 赵学良, 田娟, 等. 云计算环境下翻转课堂的应用研究: 以“计算机组成原理”为例[J]. 科技创新导报, 2018, 15(1): 246-247.
[5] 马莉, 秦彩云. 计算机组成原理及课程设计实验教学改革初探[J]. 计算机教育, 2018(3): 147-150.
[6] 宋峰. 基于SPOC的翻转课堂教学模式在“计算机组成原理”教学中的应用研究[D]. 呼和浩特: 内蒙古师范大学, 2019: 11-34.
[7] 赵明波, 林浩, 韩慧. 来华留学生“计算机组成原理”课程建设探索[J]. 电脑知识与技术, 2021, 17(4): 168-169, 172.
[8] 贾惠珍, 王同罕, 王强, 等. 新工科背景下的“计算机组成原理”多元化教学模式研究[J]. 东华理工大学学报(社会科学版), 2020, 39(2): 197-200.
[9] 谢娟, 张婷, 程凤农. 基于CIPP的翻转课堂教学评价体系构建[J]. 现代远程教育研究, 2017(5): 95-103.
[10] 黄琼.综合实践活动课程的核心立意与实施策略[J]. 中国教育学刊, 2018(2): 68-72.

（编辑：史志伟）

更正：2023 年第 5 期 179 页作者简介应为周红旭，女，研究生在读。特此更正。

(C)1994-2023 China Academic Journal Electronic Publishing House. All rights reserved. http://www.cnki.net

《科技创新导报》编辑部

学术论文征集启事

《科技创新导报》是经国家科技部、原国家新闻出版总署批准，由中国宇航出版社和北京合作创新国际科技服务中心共同主办的国家级综合科技期刊。国内统一连续出版物号:CN 11-5640/N；国际标准连续出版物号：ISSN 1674-098X;邮发代号80-542。已进入国家新闻出版广电总局第一批认定学术期刊目录。

《科技创新导报》期刊坚持以传播科技理念，报道科技前沿、倡导科技创新、促进科技进步为办刊宗旨。本刊现面向各单位科研管理人员、科技企业科研开发人员、高等院校师生、科研院所工作人员和关心高科技转化的社会各界人士征集学术论文。

◇主要栏目：

信息化工业、航空航天科学技术、工程技术、工业技术、环境科学、信息科学、建筑科学、创新管理、创新教育、创新论坛等。

◇稿件要求：

1.稿件应具有科学性、先进性和实用性，论点明确、论据可靠、数据准确、逻辑严谨、文字通顺。

2.计量单位以国家法定计量单位为准；统计学符号须按国家标准《统计学名词及符号》的规定书写。

3.所有文章标题字符数在20字以内。

4.参考文献按引用的先后顺序列于文末。

5.正确使用标点符号，表格设计要合理，推荐使用三线表。

6.图片要清晰，注明图号。

◇投稿说明：

1.来稿一律使用word排版且具有一定的学术水平，不少于3000字符，并保证文章版权的独立性，严禁抄袭，文责自负，请勿一稿多投，欢迎投稿。

2.本刊已加入《中国学术期刊（光盘版）》《中文科技期刊数据库》《万方数据数字化期刊群》等网络媒体，本刊发表的文章将在网络媒体上全文发布，若不同意在以上媒体发布，请勿投稿。

3.本刊编辑部对来稿有修改权，不愿改动者请事先说明。自收稿之日起1个月内未收到刊用通知，作者可自行处理。

4.来稿请注明作者姓名、单位、通讯地址、邮编、联系电话及电子信箱。

5.本刊发表周期为10天，出刊后5天内邮寄样刊。

如有一稿多投、剽窃或抄袭行为者，一切后果由作者本人负责。

欢迎各院校师生、科研教育机构等单位的相关部门或个人帮助组织推荐稿件。

本刊并面向社会各界招聘特约编委，详情请登录：www.chinakjcxdb.com

本刊长期与《科技资讯》和《当代体育科技》期刊开展学术交流，优秀稿件我刊可推荐至以上刊物优先发表。

地址：北京市100025信箱72分箱　　邮编：100025　　网址：www.chinakjcxdb.com

电话：010—87382766　　传真：010—67343626　　投稿信箱：bjb@chinakjcxdb.com

《科技创新导报》杂志社
官方微信

我社已开通在线投稿系统（www.chinakjcxdb.com）为方便广大作者第一时间了解稿件进度，建议采用在线投稿系统投递稿件，望广大作者支持我社工作。

科技创新导报　Science and Technology Innovation Herald　2021年　第9期　总第549期　2021-3-21

中国核心期刊（遴选）数据库收录期刊
中国学术期刊（光盘版）收录期刊
万方数据数字化期刊群收录期刊

ISSN 1674-098X
CN 11-5640/N

CHINA
www.chinakjcxdb.com

Science and Technology Innovation Herald
科技创新导报

编辑：《科技创新导报》编辑部　　邮发代号：80-542　　2021年 第9期 总第549期　　2021-3-21

J通用航空有限公司信息化发展方略

航空搜索救援任务下城市应急救援装备配备分析

网址：www.chinakjcxdb.com　　投稿邮箱bjb@chinakjcxdb.com

ISSN 1674-098X

9 771674 098198

邮发代号：80-542
中国大陆地区定价：20元（RMB）

微信公众平台

中国宇航出版有限责任公司
China Astronautic Publishing Co.,Ltd
北京合作创新国际科技服务中心
Beijing Cooperation Innovation International Science and Technology Service Center



科技创新导报

KEJICHUANGXINDAOBAO

公开发行（2004年创刊）

第18卷 第09期

出版日期:2021-03-21

编辑出版 中国宇航出版有限责任公司

网络出版 中文集团数字出版传媒股份有限公司
（http://www.cnknowledge.com）

数据服务 中文百科数据有限公司
中文百科智库有限公司

经营代理 中文集团

社长
总编 戴敦文

编辑部 刘亚静 张卉竹 刘桂芳

电话 010-59679360

学术部 尹艳艳 王 艳 丛高贞

电话 010-87382766

传真 010-67343626

融合出版部 杨国凯

联系电话 010-65017459

E-mail marketing@medibigdatabase.com

网址 www.chinakjcxdb.com

E-mail kjcxdb2021@136.com

通讯地址 北京市100025信箱72分箱

邮政编码 100025

监督电话 010-59679690

发行总代理 北京报刊发行局

发行范围 公开发行

邮发代号 80-542

广告经营许可证 京东工商广字第8023号

印刷 廊坊市瀚源印刷有限公司

国内统一连续出版物号 CN 11-5640/N

国际标准连续出版物号 ISSN 1674-098X

网络版刊号 CN 11-6023/N

零售价 30.00元（RMB）每期

特别提示

为共同维护新闻纪律与尊严,请被采访对象及作者勿向本刊编辑及其他工作人员支付任何费用。否则,出现纠纷,本刊不承担任何责任,并保留依法追究责任人法律责任的权利。

科技创新导报

Science and Technology Innovation Herald

主管单位 中国航天科技集团公司

主办单位 中国宇航出版有限责任公司
北京合作创新国际科技服务中心

联系电话 010-68768540

详细地址 北京市阜成路14号

邮政编码 100048

专家指导委员会

主任： 邓宁丰

委员： 倪光南 中国工程院院士
第八届全国人大代表
第八届、第九届全国政协委员

简水生 中国科学院院士
北京交通大学光波技术研究所所长
国家新闻出版广电总局特邀高级顾问
江西省政府科技顾问
南昌大学首席科学家

朱英国 中国工程院院士
武汉大学教授、博士生导师

梁维燕 中国工程院院士
国务院三峡工程建设委员会三峡枢纽工程质量检查专家组成员

办刊宗旨 本刊坚持以传播科技理念、报道科技前沿、倡导科技创新、促进科技进步为办刊宗旨。

刊登内容 本刊主要刊登我国当前科技及与科技发展有关的航天技术、创新管理、创新方法、两化融合等方面具有一定学术和应用价值的学术文献和反映各学科各领域的新成果、新技术、新工艺、新产品等方面的文章。

主要栏目 航空航天科学技术、工程技术、工业技术、环境与建筑科学、信息科学、创新管理、创新教育、探索与创新、专家论坛

读者对象 各单位科研管理人员、科技企业科研开发人员、高等院校师生、科研院所工作人员、各大企业的广大科技工作者和关心高科技转化的社会各界人士。



Science and Technology Innovation Herald

KEJICHUANGXINDAOBAO

Public Issue (first issue in 2004)

Vol. 18 No. 09

Publication Date:2021-03-21

Unit in Charge	China Aerospace Science and Technology Corporation
Organizer	China Aerospace Publishing Co., Ltd. Beijing International Science and Technology Service Center for Cooperation and Innovation
Editor and Publisher	China Aerospace Publishing Co., Ltd.
Web Publisher	Chinese Group Digital Publishing Media Co., Ltd.(http://www.cnknowledge.com)
Data Service	Chinese Encyclopedia Data Co., Ltd. Chinese Encyclopedia Think Tank Co., Ltd.
Management Agent	Chinese Group
President **Chief Editor**	DAI Dunwen
Editorial Department	LIU Yajing ZHANG Huizhu LIU Guifang
Telephone	010-59679360
Academic Department	YIN Yanyan WANG Yan CONG Gaozhen
Telephone	010-87382766
Fax	010-67343626
Fusion Publisher Department	YANG Guokai
Contact Number	010-65017459
E-mail	marketing@medibigdatabase.com
Website	www.chinakjcxdb.com
E-mail	kjcxdb2021@136.com
Postal Address	Branch Mail Box 72, Mail Box 100025, Beijing, China
Postcode	100025
Supervisory Telephone	010-59679690
General Publishing Agency	Beijing Publications Distribution Bureau
Issuance Range	Public Issue
Post Issue Number	80-542
Advertising Business License	Jingdong Industry and Commerce GuangZi No. 8023
Printer	Langfang Hanyuan Printing Co., Ltd.
National Unified Serial Publication Number	CN 11-5640/N
International Standard Serial Publication Number	ISSN 1674-098X
Web edition CN	CN 11-6023/N
Retail price	30.00 RMB per issue

Science and Technology Innovation Herald

Expert Steering Committee

Director: DENG Ningfeng

Member: NI Guangnan
Academician of Chinese Academy of Engineering
Representative of the 8th National People's Congress
Member of the 8th and 9th CPPCC National Committee

JIAN Shuisheng
Academician of Chinese Academy of Sciences
Director, Institute of Lightwave Technology, Beijing Jiaotong University
Invited Senior Advisor of the State Administration of Press, Publication, Radio, Film and Television of the People's Republic of China
Science and Technology Consultant of the Government of Jiangxi Province
Chief Scientist of Nanchang University

ZHU Yingguo
Academician of Chinese Academy of Engineering
Professor and Doctoral Supervisor of Wuhan University

LIANG Weiyan
Academician of Chinese Academy of Engineering
Member of the Three Gorges Project Quality Inspection Expert Group of the State Council Three Gorges Project Construction Committee

Purpose of the publication This publication adheres to the purpose of disseminating scientific and technological concepts, reporting the frontiers of science and technology, advocating scientific and technological innovation, and promoting scientific and technological progress.

Publication content This publication mainly publishes academic literature with certain academic and application value and articles reflecting new achievements, new technologies, new processes and new products in various disciplines and fields in China's current science and technology as well as in aerospace technology, innovation management, innovative methods and integration of informatization and industrialization related to science and technology development.

Main columns Aerospace science and technology, Engineering technology, Industrial technology, Environmental and building science, Information science, Innovation management, Innovation education, Exploration and innovation, Expert forum

目次

航空航天科学技术

点阵结构技术在航天飞行器的应用分析……钟杰华　赵文利　蔡昱（1）
一种天基监视SAR系统参数设计方法 ……郭子涵　李飞　张岩岩　韩硕（5）
SVG矢量图模拟渲染效果绘制飞机开关图解 ……张丛远（12）
地效飞行器发展综述……罗战虎（17）

工程技术

农村地区低压燃气管线水堵成因及抢修方法探索……汪建平　张淇（23）
管桩群桩水平承载特性数值计算分析……郭志成　于瀚（27）
基于均值漂移理论的机动单目标跟踪方法研究……张乐　赵心宇（32）
公路工程全生命周期造价风险识别及预防研究……王玉娥（36）
自升式平台桩腿各构件对桩腿强度影响规律探讨……贾森　刘安琴　刘鹏飞（39）
多平台机载激光扫描输电线路勘测对比应用研究……程海涛　杜伟　费敏　朱晓康　孙鸿博（43）
风电项目建设过程中的电气工程施工质量把控措施……刘国辉（47）
沥青混合料拌和楼生产过程中质量控制对策探究……陈夏娟（50）
建设工程质量检测见证取样分析探讨……韩光辉（53）
全面平价时代风电运维成本控制初探……岳辉（56）

工业技术

有关激光加工的综述……赵思博　李成栋（60）
端屏蔽冷却系统堆腔最大补水速率估算……秦川　张晓晖　曾博文　章鹏华（63）
基于卡尔曼滤波算法的自平衡机器人检测分析……易强　宋子瑜（67）
基于HLK-V20模块的LED智能语音灯设计 ……杨银住　郭春凤　王凤超　邓雪莲　李威　李永冲　李科（71）
一种无接触共享餐柜……刘仁实　董春芳　薛源　马雪君　吴国元　宋嘉慧（74）
机械自动化设计与制造存在问题及应对措施……王晓英（77）
一种采集蛤蜊及育苗一体机的设计……迟铭凯　尹玉亮　李之培　郝义涛　杨传升　王一钦（80）
基于智能控制的煤矿机电一体化系统……张衍军（83）
一种基于CNPO-IMS平台的核电站在役检查无损检测报告文件生成系统研制 ……马奔宇　张文哲　夏清友（86）
探析电路系统中电力电子技术的应用……曾健洪　段金成　赵志晓　蔺兰翔（89）
开关磁阻电机高效运行的控制模式研究……李岳峰　蔡燕（92）
障碍物对容器出口处颗粒物堵塞概率影响分析……周益娴　廖凯　关艺璞（95）

区块链技术在轨道交通装备制造业应用方案研究…… 刘泰　吴士林　崔玉龙　樊玉明（99）

环境与建筑科学

雨洪滞留措施在梅雨期面临的挑战……李楠　王旻忆　李星竹　张帅康（104）
建筑防火设计中有关防火分区问题的几点看法…… 冯伟彪（107）
城市生活垃圾焚烧底灰在建筑材料中的资源化利用…… 綦懿　王万里　范程程（110）
无人机在环境污染物监测中应用价值研究……葛佳琦　陈宇航　杨忠　胡文竞　王炜栋（113）

信息科学

基于光学雷达系统的计算机软件设计…… 孙婉婷　荆涛　陈沭（116）
人工智能在高校智慧图书馆建设研究……崔元超（120）
中国实验快堆传感器数据挖掘有效性研究……蒋煜卿　陈树明（123）
计算机网络运维与发展趋势探讨……李佳珣子　朱佳丽（129）
基于BIM的智慧消防应急服务平台设计研究 …… 白海江（132）
大数据背景下图书馆情报工作创新模式研究…… 鲁鹏（135）

创新管理

创新视角下从科研项目管理出发提高制造型企业的科研能力……康毅　高山　刘建国　丁菲（138）
基于大数据的电力工程造价信息化管理研究…… 朱春智（141）
基于NSGA-II 的多机场终端区进场航班排序研究 …… 张艺峰（144）
基于卓越绩效模式下的企业品牌影响力提升研究…… 江朝虎（148）
变电运维验收管理中的关键点及预防措施创新举措……刘志鹏　陈思哲　张曼　郑丹　俞飞（151）
智能菜品分析管理系统在企业食堂中的应用…… 冯晓亮（154）
浅谈元器件质量信息管理…… 王国义（157）
浅述如何加强基层质量分析工作……余跃　王蕊　李文（160）
对消防控制室规范化建设的几点探究……符永祯（163）
基于兴趣点数据的疫情背景下旅客出行目的分析……周康胜　彭睿哲　李卓（166）
通过仓库整合和物流改善提高效率降低成本…… 张永桢（171）
高校科研信息化管理建设现状及策略研究…… 史敬伟（174）
网络经济下工商管理的发展策略…… 张登锐（177）
制药企业关于数据完整性的探讨……裘燕　吕婷婷（180）

加强建筑消防设施维护管理信息化建设的策略…… 龙翔（183）
浅谈药品质量标准的建立和有效期的评估……石水萍　梁芳芳（186）
视频监控在一起物流仓库火灾调查中的运用……张海峰　田欢（189）
基于C#技术的机务维修管理系统设计与实现 ……关世超（192）
试论“互联网+”时代高职院校图书馆管理模式创新 ……蔡舟洲（196）
合理利用小时补贴政策对风电项目经济效益影响分析……侯彬（199）

创新教育

地方高校科技成果转化效率研究……王盛（204）
基于SPOC的《计算机组成原理》翻转课堂教学模式研究 …… 杨磊　黄沛杰　吴理华　肖克辉　江晓庆（208）
世界慕课大会推动下的《数据库原理》线上线下混合教学模式的探索与展望……
…… 刘超　徐正芳　郑晓霞　陆上　邹钰　吴长伟　刘宇阳（213）
信息技术环境下高校大学生在线学习力提升研究…… 张海丽　张伟新　张英艳　唐美玲　李强（217）
基于SPOC+MOOC的线上教学体系的探索与实践…… 顾硕鑫　张婷　黄小燕　付克昌（220）
模糊同余与模糊群……赵云平（223）
信息化教学技术在“1+X”失智老年人照护职业技能等级证书培训教学中的应用与探讨 …… 向岚（226）
FluidSIM软件在《液压与气动技术》教学中的应用探讨…… 王维英　陆新（229）
智能化课堂应用于高职内科护理教学必要性探讨……刘博（233）
高职院校教育扶贫“精准滴灌”的策略探索……孙霞（236）
科技馆教育活动策划设计创新研究……许雯（239）
可摘局部义齿工艺技术实践教学的改进策略……张秀景（242）

探索与创新

移动终端高速发展背景下高校图书馆服务模式新探讨……王琦博（245）
大屏幕显示无缝拼接专利技术综述……梁燕　田卓（248）
融媒体环境下短视频的发展研究……穆钰（251）
大数据在高校图书馆管理与服务中的应用……刘筑闵（254）

期刊基本参数：CN11-5640/N*2004*t*A4*256*ZH*P*￥30.00*1000*073*2021-09

DOI: 10.16660/j.cnki.1674-098X.2012-5640-1448

基于SPOC的《计算机组成原理》翻转课堂教学模式研究①

杨磊[1] 黄沛杰[1] 吴理华[1] 肖克辉[1] 江晓庆[2]
（1.华南农业大学 数学与信息学院 广东广州 510642；2.华南农业大学现代教育技术中心 广东广州 510642）

摘 要: 为了提高《计算机组成原理》的教学效果，实现人才培养的目标，针对该课程传统教学中存在的问题，以建构主义学习理论为指导，通过设计基于SPOC的《计算机组成原理》翻转课堂新型教学模式，研发并集成多元化学习平台，精心制作教学资源，将线上和线下教学紧密结合。实践教学表明，该新型教学模式激发了学生的学习兴趣，提高了学生学习的积极性，并取得了很好的教学效果。

关键词: SPOC 翻转课堂 计算机组成原理 教学模式
中图分类号: TP301-1;G434 **文献标识码:** A **文章编号:** 1674-098X(2021)03(c)-0208-05

Research on the Flipped Classroom Teaching Mode of "Principles of Computer System"Based on SPOC

YANG Lei[1] HUANG Peijie[1] WU Lihua[1] XIAO Kehui[1] JIANG Xiaoqing[2]
(1.Mathematics and Informatics College, South China Agricultural University,Guangzhou, Guangdong Province,510642 China; 2. Modern Educational Technology Center, South China Agricultural University, Guangzhou, Guangdong Province, 510642 China)

Abstract: In order to improve the teaching effect of "Principles of Computer System" and achieve the goal of talent training, In view of the main problems existing in the traditional teaching of this course, guided by constructivism learning theory, through the design of a new flipped classroom teaching mode of "Principles of Computer System" based on SPOC, the diversified learning platform is developed and integrated, and the teaching resources are elaborately produced, Online and offline teaching is closely combined.Practical teaching shows that this new teaching model not only improves students' learning enthusiasm and interest, but also achieves better teaching effect.

Key Words: SPOC; Flipped classroom; Principles of computer system; Teaching mode

①基金项目：2019年度广东省教育教学改革项目：基于SPOC的《计算机组成原理》翻转课堂教学模式研究；2019年度华南农业大学教育教学改革重点项目：基于SPOC的《计算机组成原理》翻转课堂教学模式研究（项目编号：JG19059）；2020年度华南农业大学教育教学改革项目：基于腾讯课堂+SPOC的《汇编语言程序设计》翻转课堂教学模式研究；2020年度华南农业大学质量工程项目(线上线下结合精品课程)：《计算机组成原理》（项目编号：zlgc19028）。

作者简介：杨磊（1978—），男，博士，讲师，研究方向为教育信息化、计算机系统结构。
黄沛杰（1981—），男，博士，副教授，研究方向为计算机系统结构。
吴理华（1976—），男，博士，讲师，研究方向为计算系统结构。
肖克辉（1981—），男，博士，高级实验师，研究方向为计算机硬件。
江晓庆（1981—），男，硕士，实验师，研究方向为系统集成。

1 引言

教育部《教育信息化2.0行动计划》提出："以习近平新时代中国特色社会主义思想为指导，坚持信息技术与教育教学深度融合的核心理念，以信息化引领构建以学习者为中心的全新教育生态。"[1]。随着我国教育信息化的不断纵深，课堂教学模式和学生学习方式出现了新的特点，基于信息技术的教学模式改革在教学质量提升、优秀人才培养及教育强国建设等方面发挥着重要的作用。

本文设计了基于SPOC的《计算机组成原理》翻转课堂教学模式并进行教学实践，通过微课和微实验等SPOC学习资源的制作以及移动学习工具的研发，创设泛在学习环境激发学生学习兴趣和主动性，实现学生对所学知识的意义建构，解决了《计算机组成原理》传统教学模式存在的主要问题。

2 基于SPOC的翻转课堂教学模式

2013年加州大学福克斯教授提出了SPOC（Small Private Online Course），认为SPOC用于课堂教学能够增强教师的指导作用、学生掌握知识程度以及参与度，SPOC将授课、视频等要素融合，赋予学生深入学习体验提升自主学习的效果。翻转课堂（Flipping Classroom）起源于2007年美国的乔纳森·伯尔曼和亚伦·萨姆斯，翻转课堂中教师由知识拥有者演变为教学活动的指导者和促进者，学生知识的获取也由被动接受转变为主动参与。基于SPOC的翻转课堂得到许多学者的关注，卢锋等[2]对基于SPOC的翻转课堂实验教学进行了行动研究，实验效果表明，学生对实验教学的翻转课堂持肯定态度，对"教师"维度最满意；柳春艳等[3]对贫困地区的基础教育SPOC翻转课堂应用路径进行了研究；钟华美[4]从资源、平台、学校、教师和学生五个方面提出基于SPOC的翻转课堂教学模式的优化应用对策，以便更好地完善教学；丁永刚等[5]对基于SPOC的翻转课堂2.0教学模式进行了研究；郭牧[6]对基于蓝墨云班课的SPOC翻转教学效果进行了验证与评价。

借助于SPOC实现《计算机组成原理》课程的"翻转课堂"，构建基于"双主"型教学新模式并进行探索性教学实践，既保证学生作为学习对象的主体性，又发挥教师的主导作用，从而提高课程的教学质量，进一步优化教学效果。

3 基于SPOC的《计算机组成原理》翻转课堂教学模式设计

3.1 《计算机组成原理》教学存在的问题

笔者以华南农业大学《计算机组成原理》课程为例，通过问卷调查、访谈等方式了解目前该门课程的授课现状，发现该门课程的教学并没有达到预期的教学效果，当前主要存在以下几个方面的问题。

3.1.1 传统教学无法满足学生个性化学习的需要

该课程采用大班授课制，教师讲授为主，由于课程概念性、原理性知识较多，学生缺乏学习兴趣，很难满足其个性化学习的需求，使预期教学目标难以实现。

3.1.2 教学方法单一，师生间缺乏协作互动

该课程理论教学在课堂上使用多媒体PPT课件结合板书的方式进行教学，由于课程内容抽象，计算机部件原理复杂，学生很难将所学知识完全理解透彻，教师忙于教授学习内容，师生之间难以建立有效的协作互动。

3.1.3 理论课与实验课没有无缝融合

该课程理论课为48学时，实验课为16学时，理论与实验分开进行，实验课上学生根据实验教材按部就班完成实验操作，并没有完全理解计算机的工作原理。分析原因，一方面是因为学生对理论课学习的相关部件基本原理没有理解透彻；另一方面理论和实验脱节，没有好的教学策略激发学生探究实验的兴趣。

3.1.4 师生期望改变传统教学模式

课程组希望能够利用SPOC、微课、微实验及翻转课堂来提高教学效果；同时在华南农业大学计算机专业中选取了6个班级做问卷调查，发放问卷180份，收回有效问卷179份，其中针对"你是否愿意接受基于SPOC的翻转课堂新型教学模式"，有158位学生选择愿意，大概有88%的学生希望改变传统教学，赞成基于SPOC的翻转课堂作为新型教学模式。

3.2 基于SPOC的《计算机组成原理》翻转课堂教学模式设计

SPOC注重知识的建构与生成，制作丰富的教学资源并随时随地提供给学生，SPOC资源为翻转课堂提供了知识获取的强力保障；翻转课堂则可以让学生在课前利用教师精心制作的微视频学习新的概念和知识，课堂上通过自主探究、小组协作等方式完成知识的深度内化和应用。笔者以《计算机组成原理》这门

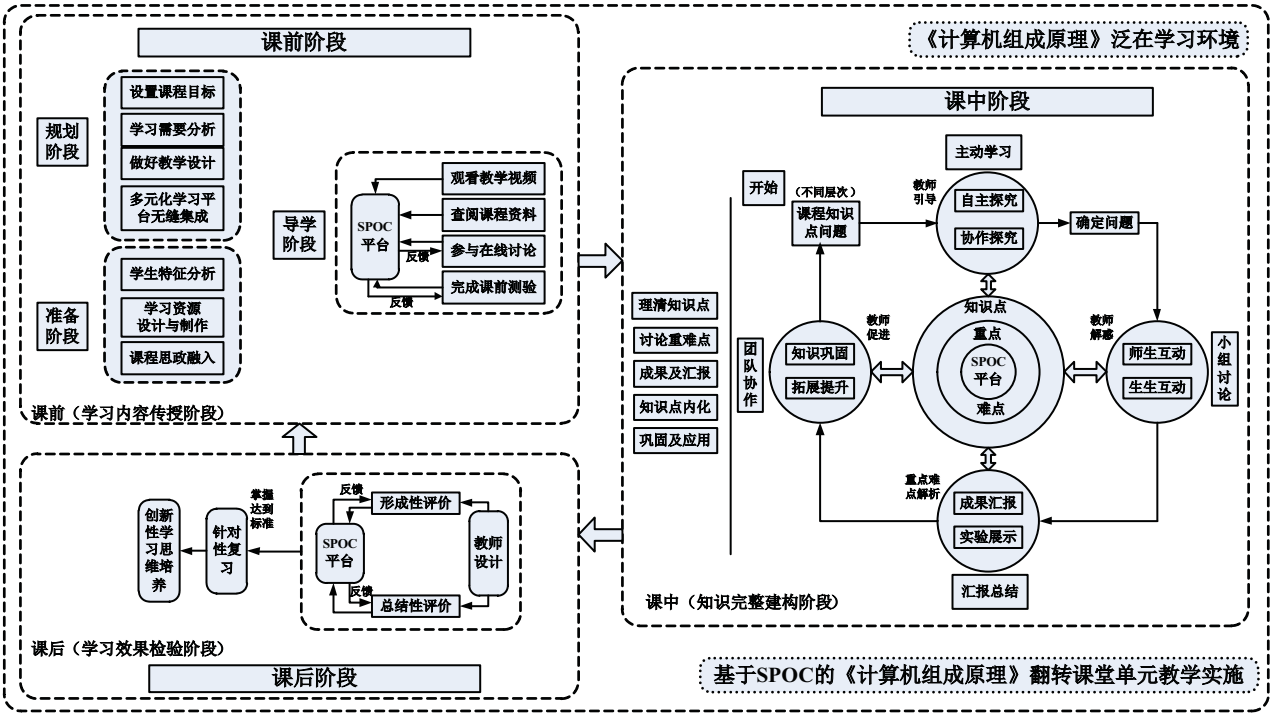


图1 基于SPOC的《计算机组成原理》翻转课堂教学模式

课程为例，设计了基于SPOC的《计算机组成原理》翻转课堂教学模式，该教学模式分为课前、课中和课后阶段，其结构如图1所示。

3.2.1 课前

分为规划阶段、准备阶段和导学阶段。规划阶段包括：学习需要分析，多元化学习平台无缝集成；准备阶段包括：学习资源设计与制作，课程思政融入；课前导学阶段教师创设泛在学习环境指导帮助学生课前学习。

(1)学生学习需要分析：分析学生学习需要可以了解其当前的学习状况与期望达到的学习状况之间的差距，为教师制作学习内容、设计教学活动及进行教学评价等提供真实的依据。

(2)多元化学习平台无缝集成：《计算机组成原理》SPOC学习资源部署在在线教育综合平台上，平台能够及时收集学生学习过程遇到的问题，跟踪学生的学习轨迹，根据学习反馈分析学生对知识的掌握情况，以便有针对性进行课堂教学活动；设计开发了《计算机组成原理》的移动学习工具，具有知识点呈现、视频观看、移动答疑、作业考试及测试等功能模块，同时设计了弹幕功能，便于课前导学的生生互动，移动学习工具和管理后台无缝集成，能够最大限度地满足学生“泛在学习”的需要。

(3)学习资源设计与制作：根据《计算机组成原理》的教学大纲和课程标准要求，将课程知识点录制为微课，便于学生课前预习、课中学习、课后复习，考虑到学生的学习需要，知识点由简入难，循序渐进，以此强化学生的学习动机，并激发他们的学习兴趣。课程重点难点主要包括：运算方法和运算器、存储器容量的扩展、CACHE存储器的基本原理、指令及数据的寻址方式、CPU的工作原理、微程序控制器的工作原理、总线仲裁、磁盘存储设备的工作原理、程序中断等。笔者将SPOC微视频长度控制在10min左右，通过采用Screenbits、SnagIt、Premiere、Goldwave等软件制作而成，同时将抽象知识点设计为动画，微视频讲解主要的理论及概念，动画展示部件的工作原理。根据教学大纲的要求，《计算机组成原理》的实验内容主要包括：VHDL语言及TEC-CA平台、加法器实现、运算器ALU的VHDL的实现、存储器ROM和RAM的VHDL的实现、通用寄存器组的VHDL的实现、设计8位及16位CPU等，笔者制作了微实验视频及虚拟实验视频，便于同学们随时学习实验知识，分析实验原理，了解实验步骤，认真完成实验。

(4)课程思政的融入：坚持把立德树人作为中心环节，把思想政治工作贯穿教育教学全过程，实现全程育人、全方位育人，努力开创我国高等教育事业发展新

局面[7]。《计算机组成原理》课程中蕴含着丰富的思政育人资源，如在计算机系统的发展史知识点，融入思政内容，我国超级计算机发展迅速，2019年神威太湖之光排名世界第二；在CPU发展知识点，引入华为公司的发展案例，华为的麒麟5G技术已经领先世界，激发同学们的爱国热情。通过课程思政的融入，可以把同学们的“专业梦”和“中国梦”的理想信念有效结合，产生课程思政的协同育人效应。

(5)课前导学：设计导学大纲，课前提供给同学们，导学大纲以知识点为基础，标注知识点的先后关系以满足不同学生的学习需求，通过课前导学学生可以在已有知识的基础上，进一步学习新知识，同时在导学的过程中，学生也可以通过弹幕、留言、评论和点赞等方式与教师和其他学生进行交流互动，导学过程中遇见问题记录下来，以待课中与教师、同学交流互动解决。

3.2.2 课中

基于SPOC的《计算机组成原理》翻转课堂在课中主要体现在教学活动上，涵盖学生自主探索、协作探究，师生、生生之间互动交流，学习成果展示汇报、知识巩固与拓展提升等多个环节。

(1)学生自主探究、协作探究：教师可以根据学生的学习需要及教学内容特点，用心设计问题情境，为学生的独立探究和协作探究搭建情境舞台；学生可以根据自己的认知特点、能力、水平选择适合自己的学习路径，通过自主探究，学生更加专注于自身知识点的内化，通过协作探究，小组成员的智慧和思维就可被共享，共同完成对所学知识的意义建构。

(2)师生、生生互动交流：《计算机组成原理》课程教学“以学生为主体，以教师为主导”，除了传统的线下课堂中师生、生生交流互动外，还设计了基于SPOC平台的线上虚拟学习社区和移动学习工具，加入了“在线弹幕”“在线留言”“在线测试”等功能，同时还可以利用QQ、微信等移动教学终端，重构课堂教学互动新布局，教学互动的时空得以无限扩充。

(3)学习成果展示汇报：针对《计算机组成原理》理论课程中的案例和问题以及实验课程中的每个实验，采用小组协作的方式来完成，分组讨论相关问题，完成报告，并进行讨论成果的展示与汇报，该方法不仅可以提高学生独立思考的能力，还可以提升学生团队协作的能力，也能够进一步提升学生对有效信息获取的能力以及语言逻辑组织能力，增加学生成就感，进一步激发学习动机，完成知识的进一步内化过程。

(4)知识巩固与拓展提升：知识巩固是对所学知识的进一步加深，为后续学习做好知识准备，《计算机组成原理》理论课程每章最后都有一个知识巩固的模块，完成一个与本章难点重点相关的一个巩固案例；拓展提升则是一个更高级的内化学习，为学生提供深化学习的途径，如实验最后要求学生完成一个“16位CPU的设计，编码与调试运行”。通过该阶段学生可以将所学知识点融会贯通，并知道如何去应用所学知识去解决一个具体问题。

3.2.3 课后

主要完成学习效果的评价和创新性学习思维的培养。

(1)学习效果评价：设计形成性评价+总结性评价相配合的方式对学生学习进行考查，考核方式采取“30%+40%+30%”结构，泛在学习平台学习占比30%，包括《计算机组成原理》在线学习平台和移动学习工具的知识点学习档案记录等；课中学习情况占比40%，主要是线下课堂出勤、课上重点难点解析及小组汇报等综合表现；课后期终考试和拓展提升占比30%。形成性评价主要是对学生学习活动的考查，通过教师评价+学生自评+生生互评来完成；期终考试作为总结性评价的参考依据，可以给学生适当压力，有助于学生知识的准确深度内化。

(2)创新型学习思维培养：关注学生学习思维，培养学生的创新素养和创造性思维能力，可以培养符合“大众创业，万众创业”的社会背景的智慧型人才[8]。基于《计算机组成原理》课程的学习活动，进一步培养与课程相关的创客小组，使课程的学习由内化到创意到创造，进一步培养学生的创新型学习思维。

3.3 基于SPOC的《计算机组成原理》翻转课堂教学模式的效果

基于SPOC的《计算机组成原理》翻转课堂教学模式是线上线下混合教学的有效策略和方式，以学生为中心，学生是知识的主动建构者，是认知的主体，教师帮助和促进学生对知识的意义建构和内化。该新型教学模式较传统教学模式在教学效果上有进一步的优化和提升。

(1)学生主动探究的学习能力得到了提升。教师精心设计并制作符合不同学生个性化学习需要的各种教学资源，能够满足学生的自主学习和探索的需要，促

进学生自主探究学习能力的形成与提升。

（2）交流协作进一步加强，综合能力得到了全面锻炼。师生、生生之间多维互动的课堂形式，不仅增进了小组团队合作精神，而且培养了学生语言表达、沟通交流、组织协调及问题解决的综合能力。

（3）提供“泛在学习”环境，激发了学生学习兴趣。不少同学反馈说，新型教学模式提供了“泛在”情境，让他们能够更灵活地学习知识，在任何时间、任何地点使用智能终端设备来进行学习，尤其是利用碎片化时间，而且基于知识点的微课、微视频、微实验及动画，将抽象变具体，从一定程度上激发了学生的学习兴趣，能够在不知不觉中学到了很多知识。

（4）学生成绩稳步提升，针对学生《计算机组成原理》课程的课前、课中和课后的多元评价方法，同学们的平均成绩和优秀率有大幅度上升，不及格率有明显的下降。与课程相关的创新创业项目的申报率和命中率也得到了提升。

4 结语

本文以SPOC和翻转课堂为教学工具，以《计算机组成原理》这门课程为研究对象，通过微课和微实验等SPOC学习资源的制作以及移动学习工具的研发，设计了基于SPOC的《计算机组成原理》翻转课堂新型教学模式并进行探索性教学实践，较好地解决了传统教学存在的问题，接下来通过持续的教学实践和反馈评价，不断完善基于SPOC的《计算机组成原理》翻转课堂教学模式，以期进一步优化教学效果，实现新时代创新性人才培养的目标，以此促进我国高校创新教学模式的改革与教育教学质量的提升。

参考文献

[1] 教育部(2018).教育信息化2.0行动计划[EB/OL]. http://www.moe.gov.cn/srcsite/A16/ s3342/ 201804/ t20180425_334188.html.

[2] 卢锋，马荣炜.基于SPOC的“电视作品编导与制作”翻转课堂实验教学行动研究[J].中国电化教育，2018(4):111–118.

[3] 柳春艳，傅钢善.基础教育SPOC式翻转课堂应用路径在贫困地区的实践研究[J].电化教育研究，2018(6):107–113.

[4] 钟华美.基于SPOC的翻转课堂教学模侯及在旅游管理专业的应用研究[D].大连:辽宁师范大学,2020.

[5] 丁永刚，金梦甜，张馨，等.基于SPOC的翻转课堂2.0教学模式设计与实施路径[J].中国电化教育，2017(6)：95–101.

[6] 郭牧.基于蓝墨云班课的SPOC翻转课堂教学设计与实践[D].保定:河北师范大学,2019.

[7] 吴晶，胡浩.习近平在全国高校思想政治工作会议上强调把思想政治工作贯穿教育教学全过程开创我国高等教育事业发展新局面[J].中国高等教育，2016(20):5–7.

[8] 祝智庭，雷云鹤.翻转课堂2.0:走向创造驱动的智慧学习[J].电化教育研究，2016,37(3):5–12.

(上接207页)

能完成职称晋升的“刚性指标”，有效释放高校教师创新活力。

参考文献

[1] 卢伟，张海军.地方高校科技成果转化绩效影响因素研究——以辽宁省30所高校为例[J].中国高教研究，2019（11）:48–54.

[2] 梁树广.高校科技成果转化效率的区域差异及其影响因素分析[J].统计与决策，2018,34(12):86–89.

[3] 罗建，史敏，彭清辉，等.核心利益相关者认知差异视角下高校科技成果转化问题及对策研究[J].科技进步与对策，2019,36(13):112–117.

[4] 林青宁，毛世平.高校科技成果转化效率研究[J].中国科技论坛，2019(5):144–151,162.

[5] 罗林波，张刚刚，李剑，等.高校科技成果转化管理改革的问题及对策[J].中国高校科技，2019(5):83–86.

[6] 王金龙，沈丽娜，王明秀.国外科技成果转化的成功经验及启示分析[J].生产力研究，2017(12):103–106,112.

[7] 逄红梅，邱爱莲.基于DEA的普通高等院校科技成果转化效率研究——以沈阳市部分普通高校为例[J].现代教育科学，2019(1):47–55.

[8] 中国科技成果管理研究会，国家科技评估中心，中国科技技术信息研究所.中国科技成果转化年度报告2018（高等院校与科研院所篇）[M].北京:科学技术文献出版社，2019.

ISSN 2096-000X
CN 23-1593/G4

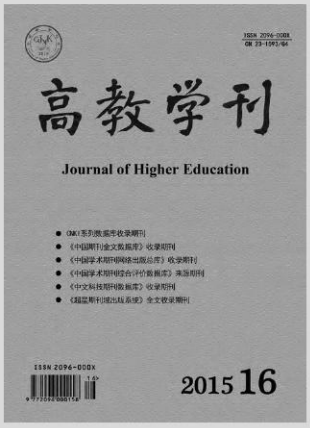
高教学刊

Journal of Higher Education

- CNKI系列数据库收录期刊
- 《中国期刊全文数据库》收录期刊
- 《中国学术期刊网络出版总库》收录期刊
- 《中国学术期刊综合评价数据库》来源期刊
- 《中文科技期刊数据库》收录期刊
- 《超星期刊域出版系统》全文收录期刊

ISSN 2096-000X
9 772096 000158 16>

2015 16



刊名题字　胡志平

主管　黑龙江省科学技术协会
主办　黑龙江省创联文化传媒有限公司
　　黑龙江省高等教育教学评估中心

社长/总编辑　杨大伟
编辑部主任　温雪梅
责任编辑　尹艳凌　刘敏惠　尹思雯
编　辑　鲁　艳　于会兰　曲庆莲
　　杨丽荣　赵　双
办公室　温洪雨
美术编辑　孙大鹏

总 编 辑　0451-82613427
编 辑 部　0451-82614854
投稿信箱　gjxkzzs@163.com
网　　址　www.gjxkzzs.com
　　www.gjxk.cbpt.cnki.net

国内统一刊号　CN 23-1593/G4
国际标准刊号　ISSN 2096-000X

刊　期：半月刊(每月 10 日、25 日出版)
编　辑：《高教学刊》编辑部
出　版：黑龙江省创联出版有限公司
地　址：哈尔滨市香坊区和平路 66-3 号
　　创展国际 B 座 1405 室
邮　编：150040

contents 目录

前沿视界

1　北京高校党组织和党员维护校园安全稳定途径和方法的研究 …… 张国柱
6　“互动参与式”教学法在设计课堂中的应用解析
　　——以广西艺术学院建筑艺术学院《设计方法论》课堂教学为例
　　…… 黄文宪　曾晓泉
8　新时期下大学生创业教育的实践探索 …… 向　瑛
10　多元社会需求和多元目标取向下的大学英语教育 …… 刘立勇
11　论怎样看待马克思主义在当代世界的总体发展状况及趋势 …… 马　越
14　中日文化差异对大学日语教学的影响 …… 高媛媛
16　耶鲁大学政治系和哲学系通识德育课的比较以及对中国高等教育的启示
　　…… 杨月琦
18　澳门博彩旅游产业教育研究 …… 陈坤仪
21　动词态中中文“了”和日语“タ」的对照分析 …… 董毅敏
23　研究生创新教育发展思路刍议 …… 龚德全

课题研究

25　师范生教育实习中教研活动开展情况的调查研究 …… 押辉远　苗梦林
27　高职院校科研团队创新能力研究 …… 郑小燕
29　大学生团队合作能力的培养与践行 … 石　茶　王胜迎　宋建卫　张　蕾
31　昆明理工大学学生党员法律素养调查报告 …… 周国兴　李生米
34　浅谈新时代下高校对大学生文明礼仪缺失的改善途径 … 陈薇薇　魏凤阳
36　当前大学军事理论课教学中存在的问题与对策
　　——以唐山师范学院军事理论教学为例 … 边宏广　韩振国　沈　芝
38　应用型创新人才培养模式的探索与实践 …… 陈贞丰
39　经济欠发达农村地区儿童阅读推广策略研究 …… 刘　珊
42　新形势下高校大学生党建品牌建设的探索与实践
　　——以天津科技大学机械工程学院为例 …… 莫继承

教海探新

44　“数学模型”课程中实行“翻转式课堂”的探索 … 王诗云　王　莉　王利岩

46 基于翻转课堂理念的高校商务日语课程教学模式的研究 …… 潘仰旻
48 浅谈新疆汉语教学部汉语教学与德育、能力培养的结合——以乌鲁木齐职业大学汉语教学部快、中班为例 …… 钱 昆
50 基于 Moodle 的大学计算机基础实验课程教学设计与实现 …… 杨 磊 江晓庆
52 浅谈如何加强高校外语教学建设——以浙江越秀外国语学院为例 …… 潘 亮
54 促进语言学课程知识体系由"单向型"向"复合型"转变 …… 高 莉
56 提高涉海专业综合实践环节教学质量的几点思考 …… 张 硕 钱卫国 李云凯
58 积分在概率论中的应用 …… 俞 霜
59 葫芦丝作品《竹林深处》教学重点解析 …… 魏 波
61 基于产品设计思维模式下绘本创作的教学探究 …… 苏沙·托依拉
63 任务型教学法在大学英语阅读教学中的应用研究 …… 王 蓓 陆晓华
65 教师在"发现教学法"中的作用研究——以日语专业低年级《基础日语》教学为对象 …… 邓 佳
67 文化形式在中国学生英语写作中间接表达方式的体现 …… 杨学远
69 启发讨论式教学法在"信号与系统"课程教学中的应用 …… 李敏通 吴婷婷 赵继政 迟 茜
71 药学专业技能抽查标准融入课堂教学的探讨 …… 欧阳卉
73 体育教学实施赏识教育的思考 …… 王长宏
74 基于本体的 C 语言网络教学模式研究 …… 赵晓萌 贾丙静
76 关于对外汉语教学中师生话语误解的分析路径探讨 …… 邹小利 刘 杨
79 多媒体课件的制作和应用——以《车工工艺学》为例 …… 林绿凤
81 轴系主要零件的综合智能 CAI 设计系统研究 …… 韩泽光 郝瑞琴 韩 煜
83 网络环境下高校思政课教师话语策略 …… 陈 雨
85 基于研究专题的《电子商务》课程教学设计与实施 …… 毛小娟 凌立文 黄文玲 曹 咏 陈炜颖

教改新论

87 融合清洁生产理念的认识实习教学改革与实践 …… 刘春涛
89 误差理论与数据处理教学改革与实践 …… 任 菡 李 颖 张辉斌
91 基于应用型人才培养的行政管理专业教学改革 …… 张 磊
93 数控专业英语教学改革的探索与研究 …… 孙 静
95 原子发射光谱法——本科生教学培训课程的探索与实践 …… 张 伟
97 基于课程协作模式的英美文学前置介入教学改革研究 …… 徐 飞

高教管理

99 对民办高校教学管理队伍结构优化的几点思考 …… 章含知
101 新常态下高校学生党员培育和管理机制的建设 …… 卢金明 曾少英
103 独立学院学生班主任制度的探索 …… 鲍向梅
105 高校科研项目管理存在问题及对策研究 …… 杨 洪

职教论坛

107　高职院校应用参考咨询的探索——以天津商务职业学院图文信息中心为例 …… 任巨凤
109　高职基础英语教学与专业知识有机结合的探索——以汽车营销专业为例 …… 曾　峥
111　基于提高五年制高职护理专业职业素养的语文阅读教学研究 …… 马　励
113　高职数据库应用技术课程教学方法探索 …… 龚　健
115　HPM 视角下高职数学中二重积分的教学探讨 …… 缪烨红
117　浅谈高职基础会计教学应把握的几个关键环节 …… 黄波兰
119　浅析高职物联网专业建设及发展的思考 …… 张　梅　孟　霞

高校建设

121　高校贫困生资助的人文关怀构建模式探赜 …… 王　莹
123　浅谈学生干部在高校学风建设中的作用 …… 林恒进　屈婉婷
125　机械制造与自动化专业人才培养模式及课程改革探索与实践 …… 杨海峰　陈　强　张玉兰　高　波
127　普通高校生涯辅导体系建设研究 …… 刘贤峰
129　浅谈大学生就业困难群体的特征及指导对策 …… 武金璇
131　女大学生就业难问题探讨 …… 李永洪　周丽莉
133　地方高校多媒体教室建设与管理的实践思考 …… 李群英　刘　佳
135“ 恒大冰泉杯”大五联赛运作模式及其对校园足球的影响 …… 张孝禄　李蜀伟
137　读者决策采购与高校图书馆文献资源建设 …… 王小宁
139“ 一体化开放式”市场营销专业综合改革研究 …… 刘金花　刘　洁　李云贤
141　新建地方本科院校校企合作育人机制探讨 …… 杨红梅　陈畅子　姜海翔
143　理工科院校媒介素养教育的方式与意义——以河南理工大学为例 …… 吴鋆萍
145　高校体育教师能力体系的建构研究 …… 文海林

师资建设

148　基于 CRP 背景下的高职教师培训模式构建 …… 王露芳
150　民办高校青年教师培训体系构建的研究——以浙江越秀外国语学院为例 …… 王　芳
152　大学教师教学智慧培养策略探析——以音乐教学为例 …… 朱银华

教育实践

154　课堂上机编程仿真实践教学方法和效果 …… 姬金祖
156　情境体验式教育模式的探索和尝试
　　——以河北医科大学临床学院为例 …… 李　苗
158　基于疾病治疗知识重构的《生物医用材料学》课程教学实践
　　…… 王富平　陈忠敏

160 Pro/E 在理论与实践一体化教学中的作用 …… 曹 田 任 琳
161 旅游管理本科生酒店顶岗实习改善策略研究
——基于利益相关者不满意状况的探讨 … 张明川 李勤梅 李 利
165 ADAMS 软件实践教学方法研究 …… 刘晓敏 赵云伟
166 信息技术条件下《纳米的神奇与魅力》课程教学研究与实践
…… 邢 琳 曲良辉 李 红 冯军兰

实验平台

168 刍议如何通过实验课来培养学生的安全素质 …… 秦海燕
170 集约化校企共建实验平台体系的构建 …… 张丽杰

思政探索

172 论思想政治教育中社会主义社会人的本质 …… 陈百君
174 基于网络新媒体人际互动的高校大学生网络思想政治教育体系的建构思考
…… 穆庆夏 许 涛 于 海
176 以科学发展观统领大学生思想政治教育的现实意义 …… 林 政
179 实践教学:高职 立德明法"育人路径摭析 …… 林国强
181 佛山市大学生自杀意念及影响因素分析 …… 吕 欢
183 基于文化教育的大学生第二课堂思想政治教育模式研究 … 赵 阳 崔友洋
185 新形势下大学生思想政治教育逆反心理与优化措施分析 …… 吴玉刚
187 高校隐性思想政治教育的魅力与创新 …… 宋增伟 任凤梅

理论研究

189 曲靖市中学教师职业倦怠现状研究 …… 吴 予 雷 芸
191 近十年大学生理想信念教育研究综述 …… 陈 红
193 西安高校在读研究生体育锻炼干预策略研究 …… 齐 锋

高教科研

195 浅析肩部训练在蒙古族舞蹈中的重要性 …… 侯 骁
197 毕业设计分组答辩成绩统计算法改进研究 …… 闫亚坤 丛颖波 麻文焱
199 数列极限求解方法研究 …… 王淑芳 杜继明
201 " 高"、低"在词汇层面的对称性研究 …… 申 雪
203 农村中小学体育对社区特色体育项目的支撑与影响
——以珠江三角洲为例 …… 王 静 曹 泉 招乐辉

印 刷:哈尔滨翰翔印务有限公司
发 行:黑龙江省邮政报刊发行局
发行范围:公开发行
邮发代号:14-357
定 价:40 元/册

本刊常年法律顾问
黑龙江宜友律师事务所 石江锋 律师
电话:18686862678

本刊声明

我刊为《中国学术期刊网络出版总库》收录期刊、CNKI 系列数据库收录期刊、《中国学术期刊综合评价数据库》来源期刊,凡在我刊投稿并被录用的稿件,由编辑部统一纳入以上期刊网和数据库,有不同意者,请另投他刊或特别声明,本刊不承担文章来源的合法性责任,不再另付上网服务报酬。

DOI:10.19980/j.cn23-1593/g4.2015.16.023

基于Moodle的大学计算机基础实验课程教学设计与实现*

杨 磊[1] 江晓庆[2]

(1、华南农业大学 数学与信息学院,广东 广州 510642 2、华南农业大学 现代教育技术中心,广东 广州 510642)

摘 要:本文主要根据大学计算机基础实验课程的特点,借助Moodle平台的优势,在充分分析教学目标、教学内容、学习者特征的基础上,利用Camtasia Studio等软件为该课程的每一个实验制作了视频教程等教学资源;设计了讨论区方便学生异步交流,并开发了聊天室供学习者实时沟通。最后,通过反馈获取学习者对平台的评价,吸纳合理的建议来达到改善平台,优化教学效果的目的。

关键词:Moodle平台;大学计算机基础实验;教学设计;评价

中图分类号:G642 文献标志码:A 文章编号:2096-000X(2015)16-0050-02

Abstract: This paper uses Camtasia Studio software to produce video tutorials for every experiment of "Introduction to Computer Experimental Course", with the advantages of Moodle platform, on the basis of full analysis of the instructional objectives, content of courses, learner characteristics and so on. And designs forum activity module to provide asynchronous communication platform and chat room for learners to communicate in real time. Finally, through the evaluation for learners to the feedback module, absorb the reasonable suggestion to achieve the purpose of improving platform and optimization teaching effect.

Keywords: Moodle; computer basics experiments; instructional design; evaluation

引言

随着现代教育技术与网络技术的不断发展,网络教学已经成为当前教育领域中的一种主要的教学方式。如何帮助学习者学会学习的方法使之具有自我获取知识与更新知识的能力并确保有较高的教学质量和教学效率以便与"信息爆炸"和知识迅速更新换代的发展趋势相适应,成为教育不得不考虑的问题[1]。《大学计算机基础》是一门实践性、技能性很强的课程,是高校本、专科生必修的重要基础课程[2]。学生的计算机知识水平与应用能力的提高在很大程度上取决于学生上机实验效果[3]。因此,实验教学是该课程教学的一个重要环节,实验教学相对于理论教学更具有直观性、实践性和创新性,在加强学生的素质教育与创新能力培养等方面有着重要的、不可替代的作用,有利于学生就业素质培养和专业能力的提高[4]。Moodle平台是基于建构主义教学理论的课程管理系统,它把教师和学生当作平等的主体,在教学活动中,师生相互协作,在原有知识和经验的基础上通过探究去构建新的知识体系[5]。

本文选取了华南农业大学约120名新生作为研究对象,通过访谈、文献调研和问卷调查等方法分析了研究他们的计算机起始能力、学习动机等,完成了基于Moodle平台的大学计算机基础实验课程的教学设计与实现,并引导学生参与到Moodle平台的网络学习中来,从而实现学生自主学习,教师辅助指导,以期最终通过促进该实验课程的内容及形式的改革,达到优化教学效果的目的。

一、基于Moodle平台的实验课程教学设计与实现

(一)基于Moodle平台的实验课程的教学设计

Moodle的设计是以社会建构主义理论为指导的,Moodle自带"所见即所得"的编辑器,可以对媒体资源进行编辑,提高课程资源编辑的工作效率[5]。Moodle网络课程的设计在教学系统设计理论、自主学习理论、和社会建构主义学习理论的指导下,才可以充分发挥其开放性、多样性、和社会性等优势[6]。

基于Moodle平台设计的《大学计算机基础实验课程》的设计要符合新生们的学习需求,为了更客观地了解学习者的先前知识和经验、学习动机、一般特征等,文章采用了问卷调查的方法,发放问卷120份,回收114份,有效问卷107份,并对问卷进行简单的数据分析。根据分析结果要求设计平台教学内容分类明确,知识结构清晰,导航清楚;界面设计要美观,提供不同的学习资源,真正体现个别化学习、自主学习的现实要求,该教学平台采用自主、交互、评价和反馈等教学策略。

(二)基于Moodle平台的实验课程的实现

《大学计算机基础实验课程》内容比较丰富,选择主题方式,设计了如下功能模块:1. Moodle平台使用说明,可以帮助学习者快速了解平台使用方法及平台上的内容;2. 资源模块,支持显示任何电子文档、Word文档、视音频等多种学习资源;3. 讨论区模块,为学习者提供在实验过程中遇到的问题并提出相应的解决方法,可以进行文字或视频的异步沟通,以巩固学习者的操作知识;4. 聊天模块,主要用于学习者与学习者之间、教师与学习者之间的同步交流,聊天记录能够保存下来,方便学习者日后查看;5. 作业模块,主要是为了督促学习者完成实验任务,规定了上交实验成品的时间;6. 反馈模块等。

(三)基于Moodle平台的实验课程反馈与评价

为了综合评价该在线学习平台的实验效果,作者设计了

*华南农业大学校级教改项目《基于Moodle的大学计算机基础课程在线学习平台的设计与应用研究》(项目编号:JG13047);华南农业大学校级重点教改项目《基于"翻转课堂"自主学习的新型教学模式设计与应用研究》(项目编号:JG15014)

作者简介:杨磊,男,讲师,研究方向为计算机技术教育应用。

江晓庆,男,工程师,研究方向为网络平台开发。

中国知网 https://www.cnki.net

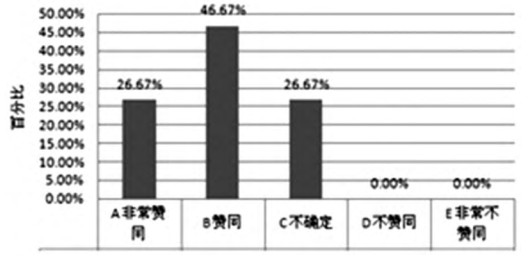


图1 Moodle平台上的资源模块设置合理图

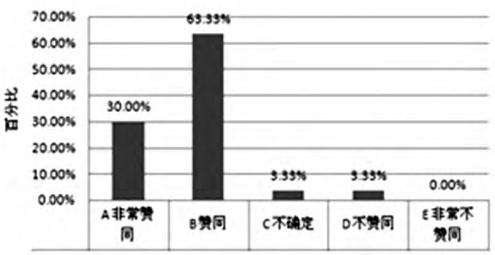


图2 借助Moodle平台来完成实验更易于对知识的理解与掌握

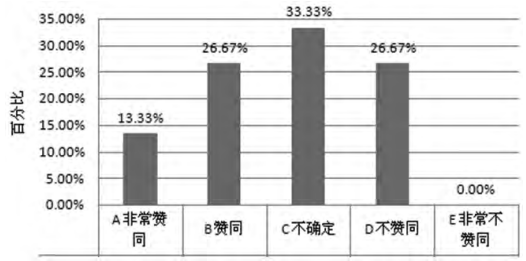


图3 更愿意通过Moodle平台向老师请教

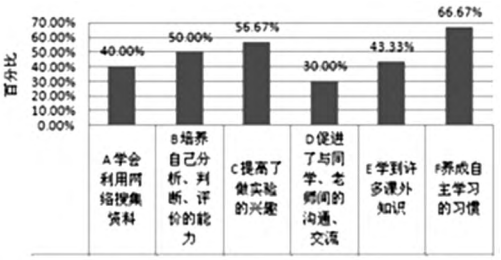


图4 通过Moodle在线学习平台学习的收获

一份“使用Moodle平台学习效果反馈”问卷，被试者共35人，回收有效问卷30份，所得数据信息具体如下：1. 平台设计方面 如图1所示，70%以上的学习者认为Moodle上资源模块设计合理，方便他们快速地查找所需资源。但有将近30%的学习者不确定模块设计是否合理，分析其原因是这部分学习者对Moodle平台的不熟悉以及较少使用。2. 学习资源方面 将近95%的学习者认为借助Moodle平台来完成实验册上的实验更易于对知识的理解与掌握，如图2所示。3. 交互设计方面 从图3我们可以看出，大部分学习者不愿意通过讨论区或者聊天室获取对操作难点的解决方法，他们更习惯于当面向老师、同学请教，原因是这些资源的使用更加方便快捷。但如果不能实时交流，他们中的部分人则会通过异步交流（讨论区）向其他人请教。4. 学习效果方面 从图4得知通过在线平台的学习，学习者不但学到了书本上的操作知识，更学到了很多额外知识，部分学习者养成了自主学习的习惯。

二、结束语

本文通过分析《大学计算机基础实验课程》的内容、教学现状，在研究Moodle平台的特点、功能以及优势等的基础上，设计并开发了基于Moodle平台的大学计算机基础实验网络课程。通过问卷和访谈发现大部分新生表示喜欢可视化教学优于印刷教材教学，而这部分新生大多能够很好地完成实验，并得到更多的实验操作。该平台提升了学生学习的积极性，促进了教学改革，优化了教学效果。

参考文献

[1]王丁.基于Moodle平台的网络课程的研究[D].成都：四川师范大学，2008.
[2]王华东.《大学计算机基础》网络课程的设计与实现[J].计算机时代，2007(11)：75-77.
[3]周栩.关于大学计算机基础实验课程的思考[J].时代教育(教育教学)，2011(9)：187.
[4]胡绪英，何明瑞.大学计算机基础实验课程的设计[J].电脑知识与技术，2010(15)：4066-4067.
[5]王大庆.Moodle平台的建设及扩展[J].软件，2011(6)：32-34.
[6]Willian H. Rice IV. Moodle E-Learning Course Development. Packt Publishing Ltd., 2006.

（上接49页）

一段课文内容，让他进行讲解，对于讲的好的学生给予平时成绩的奖励，这样可以促进学生的学习积极性，让学生体会当老师的感觉，也能够让学生充分感受到作为教师的责任。

这样在学习过程中，学生就可以慢慢找到一种适合自己的学习方法，在学生完成教学任务的过程中教师是以指导为主，而非否定其教学过程，学生有自己的想法，他可以去践行，要以鼓励为主，这样能够提高学生积极性。

汉教部的学生学习汉语，同时在学习汉语的过程中通过任务导向型教学树立个人目标，能够帮助其进行大学生活规划，通过德育与教学相结合，能够帮助学生建立正确的三观，通过掌握一种适合自己的学习方法，能够帮助学生适应专业的学习。汉教部的学习对于学生来说并非简单的汉语学习，而是全面的学习，是一个学生从中学到大学的适应过程，能够在汉教部学好，则能够更好地学习专业知识，如果在汉教部仅仅是进行汉语学习，而忽视了其他方面，那将对专业学习造成不利的影响。

四、结束语

本人在近些年的实践中，针对快班的实践较为成功，大部分学生在进入专业后能够利用在汉教部学习的内容很好地学好专业知识，并能正确树立自己得人生目标，同时在能力上也有了提高。但中班的一些学生在进入专业后仍然不能很好地适应专业学习，存在迷茫的状态。在今后的教学中，本人将继续探索，以求找到更好地方式，帮助学生上好大学，找到自己的人生方向。

参考文献

[1]王虹.大学生全程德育教育体系探析[J].高等农业教育，2011(6).
[2]李本宽，王俊梅.强化德育教育 培养合格的高职人才[J].工会论坛(山东省工会管理干部学院学报)，2001(1).
[3]王道发.论高校教师素质与学生关键能力的培养[J].铜陵职业技术学院学报，2011(3).
[4]马乔林.论高职院校学生关键能力的培养[J].南通航运职业技术学院学报，2007(1).

中国知网 https://www.cnki.net
51436

★中国学术期刊综合评价数据库统计源期刊
★中国期刊全文数据库全文收录期刊
★中国核心期刊（遴选）数据库收录期刊
★中国学术期刊（光盘版）收录期刊

■国际标准刊号：ISSN 1009-3044
■国内统一刊号：CN 34-1205/TP

电脑知识与技术

DIANNAO ZHISHI YU JISHU

第7卷 第31期 2011年11月
Volume 7 Number 31 November 2011

ISSN 1009-3044

安徽省科技情报学会
中国计算机函授学院 主办

安徽省优秀科技期刊

Computer Knowledge And Technology

Vol. 7 No. 31 November 2011 CONTENTS

Database & Information Management

7569 The Scientific Research Information Management Platform of Design and Implementation ····· LI Xin-zhan, ZHAO Wei, LI Da-wei

7576 Realization of Permission Management in URP Management System ····· SU Dong

7579 Research on the Information Management System of Freeway based on the Internet of Things ····· SHI Rong-gang, LI Jiu-ying ,ZHANG Lin, WANG Zhe

7581 Step-by-step Establishment of Data Marts Integrated Enterprise-level Data Warehouse ····· WANG Jing-ting

7587 Application Research of Data Mining in Travel Agency's Customer Relationship Management ····· XIE Hai-ying

7594 The Applied Research of Web Usage Mining to Electronic Commerce Website ····· ZOU li-xin

7600 Discussion on GIS Technology in the Electric Power Enterprise Information System Application ····· ZHENG Ya-nan

Network Communication & Security

7606 Network Device IP Address Management Based on SNMP ····· CHEN Ming, HU Meng-fei, MA Liang

7608 Analysis and Research to the Compatible Problem of Experiment Rack between RuiJie and Cisco ····· CHEN Rong-jun, LIN Cheng-kuang

7610 Discussion on Network Security Management in Hospitals and Sanatoriums ····· CHEN Yan-qun, ZHANG Hua-gui

7613 The Wireless Gateway Desiging Based on the Embedded Linux System ····· DU Ting-long, LI Guo-peng, XIE Qing-song

7618 An Design Proposal of Campus Network Based on Global Security ····· HUANG Xin, ZHAO Zhi-gang

7620 Weak Random Numbers Vulnerabilities and Defensive Methods ····· HUANG Yao-feng

7623 A Secure Network Coding Scheme Based on LFSR ····· LIU Qiong, PAN Jin, LIU Xiao-qiong

7626 Stuey on the P2P Content Inspection ····· LIAO Xiao-feng, WU Hua, YANG Lu

7630 An Online Software Licensing System Security Model ····· QIN Hao ,ZHANG Hao

7632 Research on the Security Mechanism of Internet of Things Based on 3G Networks ····· SUN Chang-ming, LI Ya-ping, ZHOU Jian

7635 The Design and Implementation of the Wireless Voice Communication System Based on ZigBee ····· WANG Fang

The Editorial Board

Director:
ZHANG Fu-yan ZHOU Jian-qiang

Assistant Director:
CHEN Da-zhang CHEN Guo-liang CHENG Hui-xia

Members

WANG Shi-min	SHI Ji-min	FENG Bo-qin	ZHU Yi-fen	LIU Da-xin
QU Yu-zhong	ZHANG Shao-lin	CHEN Qing-zhang	CHEN Xing-ye	ZHOU Pei-de
ZHEN Guo-liang	ZHAO Zhen-xi	YANG Shou-bao	TU Xu-yan	DONG Ji-run
LAI Xiang-fei	CAI Qing-sheng	PAN Jin-gui		

7643 Design and Implementation of Alarm Access Gateway Based on Soft-switch ..... WU Qi-yan, MIAO Chang-yun, WU Zhi-gang
7646 The Research on the Security Audit Framework for Campus Network System ..... XIE Zhi-peng, YANG Xuan-dan, LIANG Zhi-quan, ZENG Song-xin, SONG Si-yu
7648 Research and Implementation of Digital Signature Technology in the Network Identity Authentication ..... YAN Xin-zhang
7653 Research of Application Layer Multicast Model Based on Wheel-Tree Architecture ..... YAN Ying
7657 SOA-based Unified Collection Platform of the Communication Support System ..... ZHU Dong-mei, ZHAO Wan-ting
7659 Design and Implementation a Short Message Filtering System Based on Self-renewal Special Symbols Library ..... CHEN Li-ping, ZHAO Li-ping, CHEN Xin-min
7661 Application of WinPcap in the Network Traffic Monitoring ..... ZHANG Xue-jun, XU Yuan
7664 SAP System Implementation of Sales Discount ..... ZHANG Zhen

Design & Development of Software

7670 The CRM System of TengFei Designand Implementation ..... FAN Guang-hui
7672 Software Configuration Management Based on Harvest CM ..... GAN Qing-yun
7674 Design and Implementationof the Enterprise Employee Management System Based on J2EE Technology ..... HAN Xue
7676 Design and Realization of a General GraphicReport Based on .NET4.0 Chart Control ..... LIU Hui, HAO Wei
7677 Image Encrypt TransmissionBased on javascript ..... LIU Hua-yu, HUANG Shao-long
7679 The Score Report Based on Facade ..... LAN Ying
7681 Investigation of C Program Languagefor Beginners to Get Started ..... NIU Ji-lai, LIU Yong
7683 Evaluation System for Nuclear Accident Based on J2EE and Arcgris ..... SHEN Jun
7685 Demonstrate System Based on VC++ for Data Structure Algorithm ..... SHEN Li-min
7688 Considerations of Object-oriented Language in the Compiler ..... WU Yan-qiu
7690 Automatic MonitorIng Alarm Software of Automatic Weather Station Data in Real-time ..... PAN Xu-guang, CHI Shu-qin, ZANG Ke-min, HA Yan-li, WANG Kai-ying, GAO Yong-zhen, HUANG Ben-feng
7692 The Research on Backup System for Data Storage Disaster Recovery of Earthquake Emergency Command System ..... HE Lin, PAN Dan, DING Juan, LIU Shi-jing
7698 Brief Discussion of Implementation of Winsock to be Parameterized in Load Runner ..... ZHANG Hai-mei, XUE Ya-min
7703 Research of the Scene Optimization and Navigating Technology of Virtual Architecture Based on VRML ..... ZHANG Lei

7706 Nuclear Accident Emergency Response and Decision Support System Development
…… ZHANG Sheng-tao, ZUO Gui-qi
7709 Analysis and Examination of the Investigative Reactor Emergency Data Base System
…… ZHANG Xue-peng, ZUO Gui-qi
7711 FIXatdl Technology Introduction …… ZHANG Yong-li

Artificial Intelligence & Recognition Technology

7715 Research on Vehicle Monitoring System for Emergency Logistics Based on the Google Maps API
…… FU Kai, XU Wei-sheng
7720 Seal Design for Special Characters and Layout System Design and Implementation
…… HOU Rong-xu, LIU Yong
7723 An Algorithm of Digital Image Blind Watermarking Based on JADE
…… LI Sheng, ZHU Su-yang, ZHAO Yu, MA Xiao-hu
7726 The Analysis of Improvement of Ant Colony Algorithm …… LI Yun, ZHANG Yong-ping
7731 The Research of The Selection of Knowledge Reasoning Method Based on Genetic Algorithm
…… TAN Hui-lin, LIU Xian-feng
7734 An Algorithm Based on the Satellite for Image Enhancement …… TIAN Xin-li, LIAO Wei
7737 The Study of Binocular Vision 3D Surface Based on The Structural Characteristic Points
…… XIE Li-hui, YU Hui, CAI Bo, LIU Mai-lu
7739 The Study and Practice of Virtual Campus-Hongmantang as the Example
…… YANG Lei, ZENG Ling, CHEN Shao-hong
7742 Survey of Watermarking Performance Evaluation Indices on Digital Image …… YU Xiao-qing
7744 Game Theoretical Application in the Network Congestion Control …… ZHONG Bo-cheng
7747 Implement of Simple Signal Transmission Performance Analyzer …… ZHAO Lin-jun
7749 Image Digital Watermarking Technology in the Application of Information Hiding …… ZHANG Mao
7756 Face Recognition of the Robot Design and Implementation
…… LEI Hong-le, WEI Zhong-heng, PENG Yan-jun

Multimedia Technology & its Application

7759 Project Teaching Method in Teaching of Photoshop Graphic Design Application …… KAI Hao
7767 Discussion on the Function of Multimedia Teaching in Higher Vocational Education …… WANG Jia-luo

Application of Computer Engineering

7771 Video Compression in the Network about Management of Server …… FENG Zhan, WU Xin-jun

7773 The Research of Signal Generator ····· LIU Feng
7778 Computer Simulation Methods in the Field of Polymer
····· LIU Ying-tao, WANG Xin, CAO Yang, CHEN You-xin
7780 Model-Based Systems Engineering And Systems Modeling Language ····· SUN Yu, MA Li
7784 Step Angle Subdivision Design of Stepper Motor Based on FPGA
····· WANG Jian, YANG Rui, CHEN Jia-lin
7787 Angle Measurement of Absolute Optical Encoder Based on Virtual Instruments
····· ZHANG Hui, LIU Jing, QIU Chang-li
7789 Application of PLC in Automatic Control System of Walking Beam Furnace ····· ZHANG Yu-jun

Integration of Courses & Informational Technology

7792 Discussion on Extensive Teaching Method of Computer Language Course ····· CHEN Guo-chao
7794 Network Engineering Application-oriented Training Model to Explore
····· CHENG Kun-shan, HUANG Da-jun
7796 The Exploration of Teaching Java ····· FENG Ying-ling
7801 Design and Practice of Experiment Teaching for Computer Network Management Course
····· JING Peng-sen, YAN Dan-dan, WU Jun
7805 The Building of Softswitch Network Platform Based on Engineering Practice Training
····· LUO Hui, WANG Chuan-yun
7808 The Analysis About the Construction for the Information Platform of the Matic Networks in the
Colleges and Universities Quality Education ····· LIN Han-hui, LIN-Cong
7810 The Application of Virtualization Technology in Universities Information ····· LIU Jian-feng
7814 Instructional Design Model Based on Performance Technology LI Yong-shan, LI Yong-jiang, LI Hai-qing
7816 Gathering the Result Table Using VBA ····· MAO Zhan-jun
7819 The Teaching of Optimization Principle for Dynamic Programming ····· QIN Dan
7821 The Solution of Virtual Computer Lab based on Cloud Computing ····· WANG Jie
7823 Discussion on C Language Teaching Methods for Non-specialized Computer in Electrical Information
····· WU Jia-zhou, HUANG Hua, LAI Wei
7827 Improving Experimental Teaching in the Electronic Information Profession by Simulation
····· WANG Yan, WU Bo, WANG Fang
7829 The Innovation to Think about Construction and Management of Foreign Language Experimental Teaching Center ····· YU Zheng

期刊基本参数: CN34-1205/TP * 1999 * *16 * 264 * zh * p * ￥35 * 9000 * 105 * 2011-11

电脑知识与技术 COMPUTER KNOWLEDGE AND TECHNOLOGY

目 次（第7卷第31期 2011年11月）

数据库与信息管理

7569 科研信息管理平台的设计与实现 …… 李新战 赵 伟 李大为
7572 中尺度加密站气象资料数据库的设计与应用 …… 陈 斌 陈 凯
7574 企业信息门户搜索引擎技术的研究 …… 冯姝雯 战 莹 李一为
7576 高校信息管理系统中权限管理的实现 …… 苏 冬
7579 基于物联技术的高速公路信息管理系统研究 …… 石荣刚 李九英 张 琳 王 喆
7581 分步骤建立数据集市集成企业级数据仓库 …… 王静婷
7583 基于Web日志挖掘的策略研究 …… 王彦丽 王洪伟
7585 服装专卖店的数据库设计 …… 夏海静
7587 数据挖掘在旅行社客户关系管理中的应用研究 …… 谢海英
7589 基于B/S模式的安徽省创业投资引导基金管理系统的研究与设计 …… 姚宇广
7592 收费站收费管理系统的组成与管理 …… 周彬彬
7594 Web使用挖掘在电子商务网站的应用研究 …… 邹丽新
7597 JavaEE开发环境下Sql Serve数据库优化 …… 杨浮群 邹利艳 徐 丽
7600 浅谈GIS技术在电力企业信息系统中的应用 …… 郑亚楠

网络通讯及安全

7603 计算机网络安全防护技术探究 …… 边云生
7605 浅议基于MPLS的VPN技术 …… 陈华华
7606 基于SNMP网络设备IP地址管理系统的设计 …… 陈 明 胡梦飞 马 亮
7608 锐捷与思科实验RACK的兼容问题分析与研究 …… 陈荣军 林丞匡
7610 医院和疗养院网络安全管理探析 …… 陈燕群 张华贵
7613 基于嵌入式linux的无线网关设计 …… 杜廷龙 李国朋 谢青松
7615 基于多Agent的智能网络答疑系统的研究与设计 …… 顾煜新 于雪晶 于雪莲
7618 基于全局安全的高校校园网络设计方案 …… 黄 欣 赵志刚
7620 弱随机数漏洞及防治方法 …… 黄耀锋
7623 一种基于LFSR的安全网络编码 …… 刘 琼 潘 进 刘小琼
7626 P2P安全内容监管系统技术研究 …… 廖晓锋 吴 华 杨 璐
7630 嵌入式Linux的IPSec VPN实现 …… 秦 浩 张 皓
7632 基于3G的物联网安全机制研究 …… 孙长鸣 李亚平 周 健

7635 基于ZigBee技术的无线语音通信系统设计与实现 …… 王 芳
7638 面向客户需求的信息安全服务机制描述框架研究 …… 王金云
7643 基于软交换技术的报警接入网关设计与实现 …… 伍启炎 苗长云 武志刚
7646 校园网安全审计模式初探 …… 谢志鹏 杨选丹 梁志权 曾嵩訚 宋思宇
7648 数字签名技术在网络身份认证中的研究与实现 …… 颜新章
7651 网站项目管理需求分析 …… 姚玉勃
7653 基于树–轮结构的应用层组播模型研究 …… 严 英
7657 基于SOA架构的通信支撑统一采集平台的设计 …… 朱冬梅 赵婉婷
7659 基于自学习规避库的短消息过滤系统的设计与实现 …… 陈丽萍 赵利平 陈新敏
7661 WinPcap技术在网络流量监测中的应用 …… 张雪军 徐 圆
7664 SAP系统实现销售折扣探讨 …… 张 震

软件设计开发

7667 SSH框架技术在文件系统中的应用研究 …… 多结仁欠
7670 腾飞公司CRM系统设计与实现 …… 范广慧
7672 基于Harvest CM的软件配置管理 …… 甘清云
7674 基于J2EE技术的企业员工管理系统的设计与实现 …… 韩 雪
7676 一种基于.NET4.0 Chart的通用图形化统计模块的设计与实现 …… 刘 辉 郝 伟
7677 基于javascript的图像加密传输 …… 刘华煜 黄绍龙
7679 基于Facade模式的成绩报表设计 …… 蓝 鹰
7681 C语言程序设计初学者的入门方法探讨 …… 牛继来 刘 勇
7683 基于J2EE和ArcGis的核事故评价系统 …… 申 君
7685 基于VC++的数据结构算法演示系统 …… 沈丽民
7688 面向对象语言在编译器中的考虑 …… 吴艳秋
7690 自动气象站实时数据自动监控报警软件
…… 潘旭光 迟淑芹 臧克民 哈艳丽 王开英 高永臻 黄本峰
7692 地震应急系统数据存储容灾备份机制的研究 …… 何 琳 潘 丹 丁 娟 刘世靖
7695 软件和服务外包产业竞争力影响因素分析 …… 赵 枫
7698 浅谈LoadRunner中Winsock参数化的实现 …… 张海梅 薛亚敏
7703 基于VRML的虚拟建筑中场景优化与漫游技术的研究 …… 张 磊
7706 基于ArcGis的核事故应急响应与决策支持系统的设计与实现 …… 张升涛 左贵启
7709 基于操作干预水平的核应急决策支持系统 …… 张学鹏 左贵启
7711 FIXatdl技术简述 …… 张永利

人工智能及识别技术

7715 基于Google maps API的应急物流车辆监控系统的研究 …… 付 凯 许维胜

7718 多agent在网络智能答疑系统上的应用 …… 顾煜新 于雪晶 于雪莲
7720 面向特殊字符的印章设计与排版系统的设计与实现 …… 侯荣旭 刘 勇
7723 一种基于JADE的数字图像盲水印算法 …… 李 生 朱苏阳 赵 煜 马小虎
7726 浅谈改进的蚁群算法 …… 李 云 张永平
7729 基于多特征融合的古汉字特征提取方法 …… 孙 华 满龙林
7731 基于遗传算法的知识推理研究 …… 谭慧琳 刘先锋
7734 一种基于卫星图像的特征信息检测的实现 …… 田新利 廖 薇
7737 基于结构特征点的双目三维表面研究 …… 谢丽慧 余 慧 蔡 波 刘满禄
7739 虚拟校园的研究与实践——以华南农业大学红满堂为例 …… 杨 磊 曾 玲 陈少红
7742 数字图像水印性能评估方法研究 …… 虞晓庆
7744 博弈论在网络拥塞控制中的应用 …… 钟伯成
7747 简易数字信号传输性能分析仪实现 …… 赵林军
7749 图像数字水印在信息隐藏中的应用 …… 张 茂
7751 基于STC89C52单片机的智能循迹小车设计 …… 朱 涛
7754 基于ARM-Linux的视频监控系统 …… 高 会 王彦超 刘延军 向明尚
7756 人脸识别机器人的设计与实现 …… 类红乐 魏忠恒 彭延军

多媒体技术及其应用

7759 项目教学法在Photoshop平面设计教学中的应用初探 …… 开 浩
7761 几种常用课件开发工具的比较 …… 吕光金
7763 职教《网络动画设计》课程改革的探索 …… 刘彦武
7765 浅谈屏幕广播技术在计算机实验室管理平台的应用——以海南大学三亚学院计算机应用基础实验中心为例 …… 梁志勇 臧辉如 伍添秀
7767 浅谈高职教育中多媒体教学的作用 …… 王珈珞

计算机工程应用技术

7769 基于模型计算机的单总线、多总线结构存储器的比较与设计 …… 安 锋 富 坤 耿恒山
7771 服务器网络管理中的视频压缩 …… 冯 瞻 吴新军
7773 虚拟信号发生器的研究与设计 …… 刘 凤
7776 提升炼化行业APC应用水平的研究与实践 …… 李亚洁 许广辉 王长明
7778 高分子领域中的计算机模拟方法 …… 刘英涛 王 鑫 曹 洋 陈有鑫
7780 基于模型的系统工程和系统建模语言SysML 浅析 …… 孙 煜 马 力
7784 基于FPGA的步进电机步距角的细分设计 …… 王 剑 杨 睿 陈家林
7787 基于虚拟仪器的绝对式光电编码器的角度测量 …… 张 晖 刘 晶 裘昌利
7789 PLC在步进梁式加热炉自动控制系统中的应用 …… 张玉军

信息技术与课程整合

7792 计算机语言课程拓展式教学方法探讨 …… 陈国超

7794 网络工程应用型本科人才培养模式的探索
…… 程昆山 黄大君

7796 Java教学之探索 …… 冯颖凌

7799 高等学校计算机类课程教学与考试方法改革的
实践与探讨 …… 胡明霞 汪海涛

7801 计算机网络管理课程实验教学设计与实践
…… 景朋森 颜丹丹 吴 军

7805 基于工程实践能力培养的软交换网实训平台建设
…… 罗 晖 王传云

7808 高校素质教育专题网络信息平台的建设分析
…… 林韩辉 林 聪

7810 虚拟化技术在高校信息化建设中的应用
…… 刘剑锋

7812 在计算机教学中关于“帮助”的学习 …… 李文召

7814 基于绩效技术的教学设计模型研究
…… 李永珊 李永江 李海清

7816 利用VBA汇总成绩表 …… 毛战军

7819 动态规划法之最优性原理教学 …… 秦 丹

7821 基于云计算的实验机房解决方案 …… 王 杰

7823 电气信息类非计算机专业C语言教学探讨
…… 吴家洲 黄 华 赖 薇

7825 信息技术背景下推行研究性教学的现状与策略分析
…… 韦新丹

7827 采用仿真技术推进电子信息类专业实验教学
…… 王 燕 伍 博 王 芳

7829 外语语言实验教学中心建设与管理创新思考
…… 余 征

COMPUTER KNOWLEDGE AND TECHNOLOGY

电脑知识与技术

(旬刊,1999年创刊)

第7卷第31期

2011年11月

主管单位:安徽省科技厅
主办单位:安徽省科技情报学会
中国计算机函授学院

编辑出版:《电脑知识与技术》杂志社
地 址:安徽省合肥市濉溪路333号
邮 编:230041
电 话:0551-5690964(编辑部)
0551-5690966(发行部)
传 真:0551-5690975
网 址:www.dnzs.net.cn
投稿信箱:xsjl@cccc.net.cn
jslt@cccc.net.cn
wltx@cccc.net.cn
eduf@cccc.net.cn
info@cccc.net.cn
kfyj@cccc.net.cn
wyl@cccc.net.cn

社 长:钱洲胜
总 编:杨辉军
编 辑:代 影(责编) 唐一东 王 力
谢媛媛 冯 蕾 梁 书
张 薇 施 游 光文玲
朱宝贵 杨菲菲 闻翔军
傅勤奎 束孟卿
美术编辑:夏美娅
内文版式:王 军
发 行:李 周 光文玲

内文印刷:合肥学林印刷厂
封面印刷:合肥学林印刷厂
订 阅:各地邮局
邮政发行代号: 26-188
国际标准刊号: ISSN1009-3044
国内统一刊号: CN34-1205/TP
定 价:35元

如果杂志出现装订错误或缺页、漏页等情况,
请寄回杂志社,我们负责给予调换。

《电脑知识与技术》编审委员会

The Editorial Board of Computer Knowledge and Technology

主任(Director)：张福炎　ZHANG Fu-yan
　　周建强　ZHOU Jian-qiang

副主任(Assistant Director)：陈大章　CHEN Da-zhang
　　陈国良　CHEN Guo-liang
　　程慧霞　CHENG Hui-xia

委员(Members)：

王世民	WANG Shi-min	史济民	SHI Ji-min	冯博琴	FENG Bo-qin
朱逸芬	ZHU Yi-fen	刘大昕	LIU Da-xin	瞿裕忠	QU Yu-zhong
张绍林	ZHANG Shao-lin	陈庆章	CHEN Qing-zhang	陈兴业	CHEN Xing-ye
周佩德	ZHOU Pei-de	郑国梁	ZHEN Gůo-liang	赵振西	ZHAO Zhen-xi
杨寿保	YANG Shou-bao	涂序彦	TU Xu-yan	董继润	DONG Ji-run
赖翔飞	LAI Xiang-fei	蔡庆生	CAI Qing-sheng	潘金贵	PAN Jin-gui

电脑知识与技术

Diannao Zhishi yu Jishu

（旬刊，1999年创刊）

第7卷 第31期　2011年11月

Computer Knowledge and Technology

(A Publication Issued Once Every Ten Days)
(Started in 1999)

Volume 7 Number 31 November 2011

主办单位：安徽省科技情报学会、中国计算机函授学院
主管单位：安徽省科技厅
社　　长：钱洲胜
总　　编：杨辉军
编辑出版：《电脑知识与技术》编辑部
（合肥市濉溪路333号 邮编 230041）
电话：0551-5690963 / 5690964
E-mail：xsjl@cccc.net.cn
网址：http://www.dnzs.net.cn
印　　刷：合肥学林印刷厂
订 购 处：全国各地邮局

Sponsor by Society for Information Science and Technology in Anhui and China Computer Correspondence College
Agency: QIAN Zhou-sheng
Editor-in-Chief: YANG Hui-jun
Editored and Published by Editorial Board of Computer Knowledge and Technology
(No. 333, Suixi Road, Hefei 230041, P.R.China)
Tel: 0551-5690963 5690964
E-mail: xsjl@cccc.net.cn
http://www.dnzs.net.cn
Printed by Hefei Xue Lin Printing House
Domestically Distributed by All Local Post Offices in China

■国内统一刊号：CN 34-1205/TP
■国际标准刊号：ISSN 1009-3044
■邮发代号：26-188
■定价：35元

ISSN 1009-3044



ISSN 1009-3044
Computer Knowledge and Technology 电脑知识与技术
Vol.7, No.31, November 2011.

E-mail: eduf@cccc.net.cn
http://www.dnzs.net.cn
Tel:+86-551-5690963 5690964

虚拟校园的研究与实践——以华南农业大学红满堂为例

杨磊,曾玲,陈少红

(华南农业大学,广东广州 510642)

摘要:虚拟校园是利用虚拟现实技术,在计算机中模拟再现真实校园景观,让那些不能在实地参观的人拥有身临其境的感受。该文初步探究了X3D技术,并基于该标准,运用记事本进行X3D程序编码,在运用3DS Max创建的虚拟空间的基础上实现了虚拟红满堂漫游系统。

关键词:虚拟现实;虚拟校园;X3D漫游

中图分类号:TP393 **文献标识码**:A **文章编号**:1009-3044(2011)31-7739-03

The Study and Practice of Virtual Campus-Hongmantang as the Example

YANG Lei, ZENG Ling, CHEN Shao-hong

(College of Informatics, South China Agricultural University, Guangzhou 510642, China)

Abstract: Virtual Campus is based on the virtual reality technology and the realistic campus can be simulated by computer. People can roam in the virtual scene though the computer and let those who cannot visit the campus on-the-spot have the immersive feel. This paper studies the X3D technology initially, programs X3D code with Notepad based on the standard, realize the roaming system of the virtual Hongmantang which is constructed by the 3DS Max software.

Key words: virtual reality; virtual campus; X3D roaming

虚拟校园漫游系统是数字校园建设的基础,它的研究和应用对数字校园的建设有重要的现实意义。本文以华南农业大学的红满堂为虚拟空间,创建出红满堂主体及周围场景如道路、草坪、树木等虚拟模型,实现了基于X3D的逼真虚拟校园漫游系统,用户既可以自由地选择不同视点游览漫游,也可以进行实时地交互性漫游。

1 虚拟校园开发的基础

虚拟现实即"Virtual Reality",是一项综合集成技术,它用计算机生成逼真的三维视,听,嗅觉等感觉,使人自然地对虚拟世界进行体验和交互。本虚拟校园实现的硬件环境:英特尔Core i3 M 350,2.27GHz,2GB内存, Nikon D80。软件环境:Windows 7 家庭普通版操作系统,3DS Max 2009软件,记事本,BS_Contact 7.0, Photoshop软件。系统实现的关键技术有:X3D技术,使用记事本来编写X3D源程序,源程序的文件扩展名为*.X3D或*.x3dv。3D Studio max,用3ds max软件创建所有虚拟场景,将文件导出为.wrl文件,再通过BS Contact浏览器转换为.x3d文件。BS_Contact 浏览器,BS_Contact良好的图形渲染效果为x3d虚拟现实系统的开发提供了编程的接口,大大提高了构建x3d虚拟现实系统的效率。

2 虚拟校园的开发

2.1 系统的需求分析及设计目标

本系统旨在开发华南农业大学的标志性建筑红满堂的校园虚拟漫游。首要工作是根据实际的自然场景对红满堂及周围场景进行建模,通过建模得到红满堂的虚拟场景。系统拟实现红满堂外部场景的漫游,实现的目标如下:运用3DS Max创建真实地反映红满堂风貌的虚拟场景;在虚拟场景中设置不同的视点形成漫游路径;用户可以通过鼠标或键盘在红满堂场景中漫游。根据系统目标,实现流程分为两大步骤:

虚拟红满堂场景的创建:在实地考察红满堂的布局,测量各实体对象,并基于所得红满堂照片的基础上,建立模型,得到zhuti.max的虚拟红满堂场景。

视点浏览与漫游的实现:通过预先设定的路径实现的自动漫游;实时控制漫游方向,速度,视点高度等的交互式漫游。其中,自动漫游是通过Viewpoint视点节点创建多个观测点,形成漫游路径;实时漫游是通过NavigationInfo导航节点实现的。

2.2 虚拟校园场景的建立

2.2.1 信息的收集与处理

原始数据主要来自数码相机所拍摄的照片和实地考察,根据各实体对象实际的占地位置,进行目测及实际测量,计算出主体的大概面积,高度;材质贴图主要通过数码相机拍摄得来,并作亮度,色调,角度等处理。

收稿日期:2011-08-15
基金项目:广东省教育科研"十一·五"规划研究项目:基于本体的《计算机导论》课程适应性学习系统相关研究(2009tjk068)
作者简介:杨磊,男,硕士,讲师,研究方向为计算机辅助教育,人机交互;曾玲,女,博士,讲师,研究方向为远程教育,教育信息化。

(C)1994-2023 China Academic Journal Electronic Publishing House. All rights reserved. http://www.cnki.net

2.2.2 虚拟场景的建模

为建模方便,对主体中的各实体进行命名,见图1。主体的建模所做的工作主要分三步:(1)测量整理主体的数据。方柱正面的宽度,方窗的宽度、高度,方窗下沿突出的宽度、高度,圆墙体的高度,圆墙体距底柱的宽度等相关数据。(2)分析主体各实体对象,确定建模方案。从下至上观察主体:底座是圆柱体,圆环形墙体及方形窗上下沿,分别有20根方柱,16个方形窗和4扇门(门与方形窗的宽度相同),20个半管状窗顶,20根圆柱,20个小方窗,10个大扇形组成的大顶,而最顶为1圆墙体、20个小扇形及一个避雷针。(3)主体各实体对象的建模。

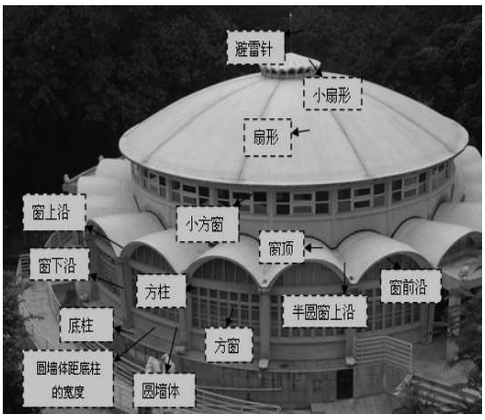


图1　实体命名图

2.2.3 模型的优化与贴图

红满堂虚拟场景中的实体对象相对比较多,必须精简优化模型:用圆柱体或长方体建模时,减少各自的分段数,以减少多余的面数;去除冗余实体外部观察模型时不可见的部分;同类型的对象成组,复制时选择关联复制选项等也可减少一些面数,边数。精简优化模型之后即可对模型进行纹理贴图。本文采用Bitmap位图贴图方式,将之前用Photoshop处理好的照片导入到材质球中,根据需要可创建反射、凹凸等效果,并为模型添加UVW贴图命令,可设置参数,修改贴图坐标,当贴在模型上的图不规则时,选择UVW贴图命令的Gizmo对贴图使用移动,旋转,缩放等工具进行调整,以完成贴图。红满堂虚拟场景贴好图渲染输出后的效果如图2,图3,图4,图5所示:

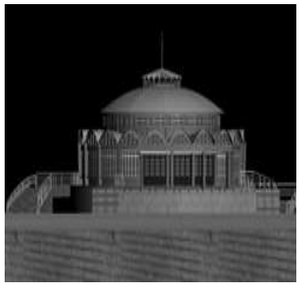

图2　前视图


图3　左视图

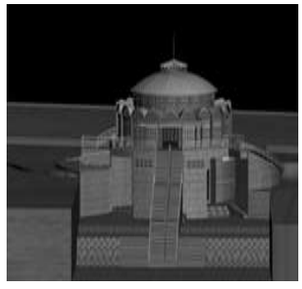

图4　后视图


图5　右视图

2.3 虚拟校园漫游的设计与实现

2.3.1 虚拟场景的背景和灯光设置

用3DS Max建立好的红满堂虚拟场景保存为zhuti.max文件,为使虚拟场景更加逼真且实现漫游和交互功能,首先在3DS Max软件中导出zhuti.wrl文件,用BS Contact浏览器打开并保存为zhuti.x3d文件,接着用记事本打开zhuti.x3d文件,进行X3D程序编辑,并将文件保存为main.x3d,然后添加了Background节点,设置了虚拟校园的背景;添加了DirectionLight节点,为虚拟场景提供光源;同时利用Viewpoint节点和NavigationInfo视点导航信息节点,实现了在红满堂虚拟场景中进行自动漫游和交互式漫游功能。

为逼真地表现虚拟显示所描述的环境,可以通过Background节点设置背景。通过颜色插值模拟大地和天空,实现的代码如下:

<Background DEF="_Background" skyAngle="1.309, 1.571,1.571" skyColor="1 1 1,0.2 0.2 1,1 1 1,0.6 0.6 0.6"/>

上述代码描述的是这样的背景:浅灰色的大地,蓝色天空,大地和天空相接处颜色渐白。

DirectionLight是定向光源节点,即生成的光线是平行向前发射的,可模拟成太阳光为虚拟场景提供光源。利用DirectionLight节点在红满堂虚拟场景中实现了理想的光照效果,代码如下所示:

<DirectionalLight DEF="_DirectionlLight" ambientIntensity='0.25' color='1 1 1' direction='0 -1 0' intensity='0' on='true' global='true'></DirectionalLight>

2.3.2 自动漫游的设计与实现

采用设定坐标的方式来实现自动漫游。在X3D文件中,视点是在虚拟场景中预先定义观察位置和空间朝向,浏览者可以观察到在虚拟世界中相应的场景。Viewpoint视点节点确定在X3D空间坐标系中的观察位置,指定了这个观察位置在X3D立体空间中的三维坐标、立体空间朝向及视野范围等参数。将zhuti.wrl文件用BS_Contact7.0浏览器打开,在File菜单栏下选择“Save State As”,在弹出的对话框中,将文件名命名为main,选择保存类型为.x3d。用记事本打开main.x3d文件,并在其中编辑X3D程序为使浏览者可以全方位地浏览红满堂概貌,利用视点坐标预设了浏览路径。该路径为分别从正面,左面,后面,右面及顶部总览红满堂,并在各个面近距离地浏览红满堂的风貌格局。该路径中共预设了12个不同的观测点,分别命名为view,Front,Left,Left 1,Back,Back1,Back2,Right,Right1,Top,Top1,及Top2,这12个视点展示了红满堂的最佳场景,浏览者可以在浏览器中按右键,在弹出的菜单栏中呈现这12个视点,可自由地选择所感兴趣的观察点,也可选择视点漫游选项,浏览器会自动地从当前视点切换到新的视点。

2.3.3 交互式漫游的实现

红满堂虚拟场景采用了交互式漫游方式,即利用NavigationInfo提供的替身在虚拟现实世界空间中以移动,行走等多种浏览方式实现漫游功能。浏览器创建一个浏览者的替身,该替身是不可见的,浏览器所展现的景物便是以替身的视角来观察的。为了控制浏览的状态,可通过NavigationInfo节点进行控制,NavigationInfo称为导航节点,描述了场景观看方式和替身的物理特征。它利用该替身来进行碰撞检查,可设置浏览的速度、浏览方式、头顶灯以及浏览器替身的大小。系统添加的NavigationInfo视点导航节点与

94/436
(C)1994-2023 China Academic Journal Electronic Publishing House. All rights reserved. http://www.cnki.net

Background背景节点平行使用。浏览者可以通过鼠标或键盘任意地控制漫游位置,方向,速度,以多种方式在虚拟场景中漫游。实现该交互式漫游的部分代码如下所示:

<NavigationInfo avatarSize="25 1020 875" headlight="true" speed="950" type="WALK ; ANY;"/>

上述代码实现的效果是,浏览者可以通过鼠标、键盘的上下左右键随意改变漫游的方向,位置,速度,在虚拟红满堂中进行交互式的漫游。

3 总结

本文对用3DS Max进行虚拟场景建模和模型的优化进行了一些研究,对基于X3D实现虚拟漫游作了初步的探索。但目前实现的虚拟校园只强调了几何建模,因此创建的红满堂虚拟场景不够逼真;另外在虚拟校园所提供的功能相对简单,只提供单用户在三维空间中的漫游。

参考文献:

[1] 张金钊,张金锐,张金镝.X3D虚拟现实设计[M].北京:电子工业出版社,2009:1-285.
[2] 胡小强.虚拟现实技术基础与应用[M].北京:邮电大学出版社,2007:18.
[3] 张金钊,张金锐,张金镝,等.X3D动画游戏设计[M].北京:中国水利水电出版社,2010:338-349.
[4] 王秀丽,朱正平,岳秋菊.构建虚拟校园漫游系统[J].自动化与仪器仪表,2010(5):1-3.
[5] 周希望.基于X3D的虚拟校园交互式漫游系统[D].北京:北京服装学院,2009:8-13
[6] 程娟,钱晋,钱钶.虚拟数字校园漫游系统中的模型构建技术研究,2010(25):1-2
[7] 丁勇.虚拟校园景观的构造及漫游系统的实现[J].电脑知识与技术,2007(14):525-526.
[8] 吴迪.虚拟校园漫游系统的研究与开发[D].天津:天津大学,2007:1-25
[9] 冯莉莉,武卫玲.基于3ds max的虚拟校园三维模型的创建[J].林业科技情报,2009(1):10-11.
[10] 马萍,孟祥增.虚拟校园漫游系统的构建[J].中国教育技术装备,2010(36):102-103.

(上接第7736页)

```
    CH1=NULL;
    if (CH2) delete[] CH2;
    CH2=NULL;
    if (CH3) delete[] CH4;
    CH4=NULL;}
```

2.2 实现效果

图3为检测前原始卫星图像,图4中白色区域即为云图,经过卫星图像定位系统分析,该区域云区显示符合图像截取时实际状况。



图3 原图

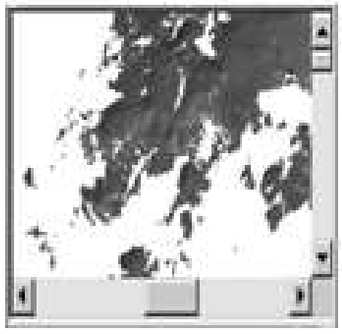


图4 云检测图

3 结束语

卫星遥感在生态环境监测中发挥着重要的作用,其影像图的质量直接影响监测的效果以及产品的质量,利用图像处理技术,更好的处理卫星图像,解译图像中携带的特征信息,云检测技术的发展和实现将更加推广卫星图像的应用领域。

参考文献

[1] 章毓晋.图像处理和分析[M].北京:清华大学出版社,1999.
[2] 何斌,马天予,王运坚,等.Visual C++数字图像处理[M].北京:人民邮电出版社,2001.
[3] 肖温格.遥感中的图像处理和分类技术[M].北京:科学出版社,1991.
[4] Gao B C,Yang P,Li R R.Detection of High Clouds in Polar Regions during The daytime Using the MODIS 1.375um Channel[J].IEEE Trans. On Geo science and Remote Sensing,2003(41):474-481.
[5] Gao B C.Cirrus Cloud Detection from Airborne Imaging Spectrometer Data Using the 1.38mm Water Vapor Band[J].Geophysical Research Letters,1993,20(4):301-304.

(C)1994-2023 China Academic Journal Electronic Publishing House. All rights reserved. http://www.cnki.net

NATIONAL TEACHING INNOVATION CONTEST FOR COLLEGE TEACHERS
全国高校教师教学创新大赛

第五届全国高校教师教学创新大赛广东分赛
暨广东省高校教师教学创新大赛

获奖证书

主讲教师：杨磊

团队成员：/

主讲课程：计算机组成原理

获奖等级：新工科 二等奖

证书编号：GDTIC2025013

广东省教育厅

广东省高等教育学会

二〇二五年六月

学年学期	分数	参评人数	单位排名	开课单位	排名占比
2021-2022学年第一学期	94.28	126	175-24	数学与信息学院、软件学院	13.72%
2021-2022学年第二学期	92.47	63	173-64	数学与信息学院、软件学院	36.99%
2020-2021学年第二学期	94.19	118	160-18	数学与信息学院、软件学院	11.25%
2022-2023学年第一学期	96.65	176	176-33	数学与信息学院（软件学...	18.75%
2023-2024学年第一学期	95.39	162	174-87	数学与信息学院（软件学...	50.00%
2022-2023学年第二学期	96.425	131	173-44	数学与信息学院（软件学...	25.43%
2023-2024学年第二学期	98.74	98	175-6	数学与信息学院（软件学...	3.43%
2024-2025学年第一学期	97.26	205	181-63	数学与信息学院（软件学...	34.81%
2024-2025学年第二学期	96.89	97	175-84	数学与信息学院（软件学...	0.48
2025-2026学年第一学期	98.92	224	183-9	数学与信息学院（软件学...	0.04918032786885246

类型	学年学期	附件	审核单位/角色	数据来源	业绩审核意见
近五年，本科评教结果在本单位排名前10%的学期	2025-2026-1，2023-2024-2		本科生院（招生办公室）/教学质...	个人填写	通过
近五年，本科评教结果在本单位排名前20%的学期	2025-2026-1，2023-2024-2，2022-2023-1，2020-2021-2，2021-2022-1		本科生院（招生办公室）/教学质...	个人填写	通过

广东省一流本科课程

证

书

★ ★ ★ ★ ★

课　程　名　称：计算机组成原理

课　程　类　别：线上线下混合式一流课程

课 程 负 责 人：黄沛杰

课程团队其他主要成员：王春桃、杨磊、万军洲、刘财兴、林丕源、肖磊、田绪红、肖克辉、肖媚燕

主要建设单位：华南农业大学

广东省教育厅

2022年10月

证　书　编　号：202210149

98/436

证　书

《基于本体的<计算机导论>个性化教学系统》在2012年广东省计算机教育软件评审活动中获高等教育组网络课程优秀奖。特发此证，以资鼓励。

制作者：华南农业大学　曾　玲、杨　磊、陈孟娴、徐东风、梁燕琴

广东省教育

二〇一二年十二月

99／436

证 书

《基于交互理论的“算法基础”可视化学习系统》在2012年广东省计算机教育软件评审活动中获高等教育组多媒体课件优秀奖。特发此证，以资鼓励。

制作者：华南农业大学 王楚璇、曾 玲、杨 磊

广东省教育

二〇一二年十二月

華南農業大學

教学成果奖

获奖证书

获奖成果： 大学计算机基础教学改革与实践

获 奖 者： 徐东风　林丕源
肖　磊　高月芳
杨　磊

获奖等级： 二等奖

证书编号： 2012206

二〇一三年一月

華南農業大學

本科教学成果奖

获奖证书

获奖成果： 国产筑基，数智赋能：卓越软件工程师人才培养模式的探索与实践

获 奖 者： 王金凤、黄　琼、孙微微、张丽霞、杨　磊、张　猜、黄立峰

获奖等级： 一等奖

证书编号： JXCG24020

华南农业大学

2025年9月9日



人工智能理论及应用

主编 梁云林琛 涂淑琴 杨磊

厦门大学出版社 国家一级出版社
XIAMEN UNIVERSITY PRESS 全国百佳图书出版单位

图书在版编目（CIP）数据

人工智能理论及应用 / 梁云等主编. -- 厦门 : 厦门大学出版社，2024. 8. -- ISBN 978-7-5615-9475-9

Ⅰ. TP18

中国国家版本馆 CIP 数据核字第 2024B6J949 号

责任编辑　郑　丹
美术编辑　李嘉彬
技术编辑　许克华

出版发行　厦门大学出版社
社　　址　厦门市软件园二期望海路 39 号
邮政编码　361008
总　　机　0592-2181111　0592-2181406(传真)
营销中心　0592-2184458　0592-2181365
网　　址　http://www.xmupress.com
邮　　箱　xmup@xmupress.com
印　　刷　厦门市竞成印刷有限公司

开本　787 mm×1 092 mm　1/16
印张　18.5
字数　440 千字
版次　2024 年 8 月第 1 版
印次　2024 年 8 月第 1 次印刷
定价　45.00 元

本书如有印装质量问题请直接寄承印厂调换

厦门大学出版社
微信二维码

厦门大学出版社
微博二维码

近年来，全球人
科技和产业加速发
类社会发展新的增

我国也高度重
长引擎。我国正积
业，加快发展新质生

面对这一时代
同编写本书，旨在为
会贯通，并助力培养

本书共分九章
念、发展历程，为读
搜索求解策略及推
经网络、计算机视觉
介绍了近年来迅猛

总的来说，本书
习资源。

本书具有以下

(1) 课程思政
发展的先进案例，在
的 ERNIE(THU)
民族自豪感；讲解人
生的国家安全意识

(2)与时俱进，
能在文本生成领域
人工智能课程教材
科发展前沿。

(3)夯实基础，
适时拓展。总体脉
术方法，方便读者

(4)生动丰富，
图表等多种方式进
更加深入直观地理

之可以作为社会各

书的主编为华南农
晶老师；副主编为南
学周子涵副教授和
智能药学和智慧医
编写分工如下：第1
和钟灿珉编写，第6
、7.5节和8.3节由
他们的辛勤工作使

主任、中山大学深圳
更好地渐入人工智

主所难免，欢迎广大

编者
2024年7月

目 录

第1章 绪论 …… 1
1.1 人工智能的基本概念 …… 3
1.2 人工智能的发展简史 …… 9
1.3 人工智能的研究内容及应用 …… 17
1.4 小结 …… 29
1.5 思考题 …… 30

第2章 知识表示 …… 31
2.1 知识表示的概念 …… 33
2.2 一阶谓词逻辑 …… 34
2.3 产生式表示法 …… 41
2.4 数据标注的概念 …… 45
2.5 公开数据标注方法 …… 47
2.6 知识表示的应用案例：知识图谱 …… 53
2.7 小结 …… 61
2.8 思考题 …… 62

第3章 搜索求解策略及推理 …… 63
3.1 搜索的概念 …… 65
3.2 状态空间知识表示法 …… 67
3.3 盲目的图搜索策略 …… 70
3.4 启发式搜索策略 …… 75
3.5 小结 …… 83
3.6 思考题 …… 85

第4章 进化计算与群体智能 …… 87
4.1 进化计算 …… 89
4.2 群体智能算法 …… 97
4.3 遗传算法的应用 …… 103

4.4 群体智能算法的应用 …… 113
4.5 小结 …… 116
4.6 思考题 …… 118

第 5 章 机器学习 …… 119
5.1 机器学习的基本概念 …… 121
5.2 回归与优化算法 …… 125
5.3 分类与聚类 …… 132
5.4 K-Means 算法实现鸢尾花聚类 …… 138
5.5 深度学习理论及应用 …… 144
5.6 小结 …… 148
5.7 思考题 …… 149

第 6 章 神经网络及其应用 …… 151
6.1 BP 神经网络 …… 153
6.2 卷积神经网络 …… 159
6.3 Transformer 神经网络 …… 169
6.4 卷积神经网络实现图像分类 …… 172
6.5 基于 Transformer 神经网络的多目标跟踪技术 …… 176
6.6 小结 …… 180
6.7 思考题 …… 181

第 7 章 计算机视觉 …… 183
7.1 计算机视觉概述 …… 185
7.2 计算机视觉的研究内容 …… 189
7.3 计算机视觉的数据集及应用 …… 204
7.4 猪只多目标跟踪实际应用 …… 214
7.5 尿液细胞的图像实例分割应用 …… 224
7.6 小结 …… 236
7.7 思考题 …… 236

第 8 章 大数据挖掘及应用 …… 237
8.1 大数据概述 …… 239
8.2 数据获取与处理 …… 248
8.3 大数据在生物医学中的应用 …… 262
8.4 大数据在电子商务中的应用 …… 265
8.5 小结 …… 269
8.6 思考题 …… 270

第 9 章 生成式人
9.1 生成式人
9.2 生成式人
9.3 生成式人
9.4 生成式人
9.5 小结 ……
9.6 思考题 …

参考文献 ……

第 9 章　生成式人工智能 …… 271
9.1　生成式人工智能概述 …… 273
9.2　生成式人工智能模型的构建流程 …… 276
9.3　生成式人工智能在自然科学中的应用 …… 279
9.4　生成式人工智能的局限与未来 …… 282
9.5　小结 …… 284
9.6　思考题 …… 284

参考文献 …… 285

受理编号：c20140500000842

项目编号：2020A1515010690

文件编号：粤基金字〔2020〕4号

广东省基础与应用基础研究基金项目

合同书

项目名称：基于概率分布及学习技术的高维多目标进化算法研究及其在精准农业中的应用

项目类别：广东省自然科学基金-面上项目

项目起止时间：2019-10-01 至 2022-09-30

管理单位（甲方）：广东省基础与应用基础研究基金委员会

依托单位（乙方）：华南农业大学

通讯地址：广东省广州市天河区五山路483号

邮政编码：510642 单位电话：020-85283435

项目负责人：杨磊 联系电话：020-85280320-612

2020A1515010690

广东省基础与应用基础研究
基金委员会
二〇一九年制

（广东科技微信公众号）

（受理纸质材料二维码）

一、主要研究内容和要达到的目标

针对高维多目标优化问题的难点，综合考虑高维多目标优化算法收敛性、分布性及多样性三方面评测指标，本项目的研究内容包括四个部分： 1）研究并设计提高进化种群选择压力的新型占优关系；设计一种新型Pareto支配关系，通过对支配关系进行改进来提高算法收敛性，拟设计新型支配关系可以扩大个体的支配区域，从而使得进化过程中产生的非支配解在种群中所占比重下降，进而增加选择压力，提高算法的收敛性，最终达到提高算法在高维多目标优化问题中的性能的目的。2）研究并设计基于概率分布的混合型选择策略；本项目将着重研究进化算法不同的进化操作。拟混合使用Gaussian、Cauchy、Levy和单点变异等操作可以提高进化算法的效率。根据高维多目标问题的特点将EA建模为多个互相关联的单个个体搜索，并将每个个体搜索生成新解的行为建模为概率分布，计算对概率分布之间的距离，使多个单个体搜索能够明确地搜索解空间的不同区域，从而更精细地控制个体的选择生成机制。 3）研究并设计新型Baldwin及Lamarckian学习技术引导种群进化；设计一种新型的Baldwin学习策略，根据当前种群的概率分布模型，将当前种群看成一个整体而不是一系列独立的解集，利用学习策略学习当前种群中的概率分布模型，通过不断进化该概率分布模型来获得进化历史，通过概率分布模型和进化历史的学习来获得个体潜在的进化方向，最终引导进化搜索到好的解集同时加速种群收敛到Pareto最优集；同时设计一种新型Lamarckian学习算子，作为一种局部搜索机制引入到高维多目标优化中，通过加强的局部搜索操作，个体在生命周期内获得的适应度的提高以表现型的形式传递给下一代，使算法获得的种群具有更好的多样性和收敛性。4）建立基于概率分布及学习技术的高维多目标进化算法仿真实验平台并应用于精准农业中，分析影响土壤采样分布的多种农田环境因素，设计土壤养分采样高维多目标优化决策模型；设计水田灌溉模型并进行优化，建立水分利用效率—肥料使用量—产量—环境效益等优化模型；分析农产品价格影响因素并对预测模型进行多目标优化建模。本项目研究最终要达到的目标为：定义一种新型的Pareto占优关系；设计一种基于概率分布的混合型选择策略；设计一种基于种群特征的学习模型；完成基于概率分布及学习技术的高维多目标进化算法的实验与测试；构建一套精准农业高维多目标优化建模及价格预测仿真平台。

2020A1515010690

二、研究成果及形式

<table>
<tr><td rowspan="2">论文及专著情况</td><td colspan="2">国家统计源刊物以上刊物发表论文（篇）</td><td colspan="2">5</td><td colspan="2" rowspan="2">科技报告（篇）</td><td colspan="2" rowspan="2">1</td></tr>
<tr><td colspan="2">专著（册）</td><td colspan="2">0</td></tr>
<tr><td rowspan="3">专利情况(项)</td><td colspan="2">发明专利</td><td colspan="2">实用新型专利</td><td colspan="2">外观设计专利</td><td colspan="2">国外专利</td></tr>
<tr><td>申请</td><td>授权</td><td>申请</td><td>授权</td><td>申请</td><td>授权</td><td>申请</td><td>授权</td></tr>
<tr><td>1</td><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td></tr>
</table>

2020A1515010690

三、项目进度和阶段目标

1.项目起止时间： 2019-10-01 至 2022-09-30		
2.项目实施进度及阶段主要目标：		
开始日期	结束日期	主要工作内容
2019-10-01	2020-09-30	分析研究制约高维多目标进化算法多样性、收敛性及分布性的主要原因及目前主要解决策略；设计新型占优方法；研究高维多目标种群进化特征及概率分布的建模方法；设计基于种群特征的进化学习机制；参加国内智能算法学术会议2次，每次2人，与国内同行专家交流；撰写相关论文1至2篇。
2020-10-01	2021-09-30	分析进化算法中种群变化的特点，设置动态调整概率分布及学习技术在算法中的影响参数；完成基于概率分布及学习技术的的高维多目标进化算法整体编码；将算法应用于标准测试数据集进行算法有效性验证，并对算法的收敛性、分布性、稳定性以及有效性进行分析；1-2人参加国际智能算法学术会议1次，邀请1位国外专家交流项目研究工作；撰写相关论文1至2篇；申请专利1项。
2021-10-01	2022-09-30	基于模块化构建思想，将本项目研究的高维多目标进化优化算法应用于精准农业，研发一套基于高维多目标算法的精准农业优化控制及农产品价格预测仿真平台；对项目整体进行分析、总结；参加国内智能算法学术会议1次，每次2人，与国内同行专家交流；申报软件著作权1项；撰写相关论文1至2篇；项目结题。

2020A1515010699

四、项目总经费及省基金委经费预算

1.省基金委经费下达总额： （大写）壹拾万圆整；（小写 ）10万元；

2.省基金委经费年度下达计划：

年度	2020 年	年	年	年	年
经费(万元)	10.00				

3.总经费及省基金委经费开支预算计划：

经费筹集情况： （单位：万元）

省基金委经费	自筹资金				合计
	自有资金	贷款	地方政府投入	其它	
10.00	0	0	0	0	10.00

政府部门、境外资金及其他资金投入情况说明：	无

2020A1515010690

五、人员信息

项目负责人

姓名	证件号码	年龄	性别	职称	学历	在项目中承担的任务	所在单位	签名
杨磊	410711197809240099	42	男	讲师	博士研究生	项目负责人	华南农业大学	

项目组主要成员

姓名	证件号码	年龄	性别	职称	学历	在项目中承担的任务	所在单位	签名
李珂	E05459777	35	男	副教授	博士研究生	基于种群特征的概率模型构造	University of Exeter	
李康顺	362101196203110035	58	男	教授	博士研究生	新型占优关系的设计与测试	华南农业大学	
陈琰	642101197704260025	43	女	副教授	博士研究生	多样性选择策略及学习机制的设计	华南农业大学	
吴理华	362222197609243032	44	男	讲师	博士研究生	高维多目标进化优化算法设计与代码实现	华南农业大学	
潘春华	362525197401150932	46	男	未取得	博士研究生	精准农业土壤采样及水田灌溉精准建模	华南农业大学	
胡鑫	500382199510174837	25	男	未取得	本科	农产品价格多因素分析及预测问题建模	华南农业大学	
黄康	430405199304281011	27	男	未取得	本科	算法研发与基准数据集实验	华南农业大学	
张子同	341224199203260518	28	男	未取得	本科	算法测试与仿真实验	华南农业大学	

2020A1515010690

六、依托单位与合作单位的合作协议

承担/参与单位名称（盖章）	工作分工	总经费分摊（万元）	省基金委经费分配（万元）
华南农业大学			
University of Exeter			
	合计		

七、合同条款

第一条 甲方与乙方根据《中华人民共和国合同法》及国家有关法规和规定，为顺利完成（2020）年基于概率分布及学习技术的高维多目标进化算法研究及其在精准农业中的应用 专项项目（文件编号： 粤基金字〔2020〕4号）经协商一致，特订立本合同，作为甲乙双方在项目实施管理过程中共同遵守的依据。

第二条 甲方的权利义务：

1.按合同书规定进行经费核拨的有关工作协调。

2.根据甲方需要，在不影响乙方工作的前提下，定期或不定期对乙方项目的实施情况和经费使用情况进行检查或抽查。

3.根据《广东省科技计划项目信用管理办法(试行)》对乙方进行科技计划信用管理。

第三条 乙方的权利义务：

1.确保落实自筹经费及有关保障条件。

2.乙方是项目资金管理的责任主体，应当建立健全科研项目资金管理制度，严格按照省科技经费使用范围和有关规定管好用好财政资金；应当按合同书规定，对甲方核拨的经费实行专款专用，单独列账，并随时配合甲方进行监督检查。

3.实施“包干制”的面上项目及青年基金项目，依托单位应参照国家杰出青年科学基金试点项目经费使用“包干制”要求，制定经费使用“包干制”内部管理规定。项目经费支出应实际用于研发活动相关支出，使用范围限于设备费、材料费、测试化验加工费、燃料动力费、差旅/会议/国际合作与交流费、出版/文献/信息传播/知识产权事务费、劳务费、专家咨询费、依托单位管理费用、绩效支出以及其他合理支出。依托单位管理费用由依托单位根据实际管理支出情况与项目负责人协商确定。绩效支出由项目负责人根据实际科研需要和相关薪酬标准自主确定，依托单位按照现行工资制度进行管理。其余用途经费无额度限制，由项目负责人根据实际需要自主决定使用。项目验收时应提交经费决算表。

4.项目负责人是项目资金使用的直接责任人，对资金使用的合规性、合理性、真实性和相关性承担法律责任。

5.使用财政资金采购设备、原材料等，按照《广东省实施〈中华人民共和国招标投标法〉办法》有关规定，符合招标条件的须进行招标。

6.项目合同任务完成后，或合同书规定的任务、指标及经费投入等提前完成的，乙方可按照《广东省省级科技计划项目结题管理实施细则（试行）》提出验收结题申请，并按甲方要求做好项目验收结题工作。

7.若项目发生需要终止结题的情况，乙方须按照《广东省省级科技计划项目结题管理的实施细则（试行）》提出终止结题申请，并按甲方要求做好项目终止结题工作。

8.在每年规定时间内向甲方如实提交上年度工作情况报告，报告内容包含上年度项目进展情况、经费决算和取得的成果等。

9.按照国家和省有关规定，提交科技报告及其他材料。

10.利用甲方的经费获得的研究成果，项目负责人和参与者应当注明获得“广东省基础与应用基础研究基金（英文：Guangdong Basic and Applied Basic Research Foundation）（项目编号）”资助或作有关说明。

11.乙方要恪守科学道德准则，遵守科研活动规范，践行科研诚信要求，不得抄袭、剽窃他人科研成果或者伪造、篡改研究数据、研究结论；不得购买、代写、代投论文，虚构同行评议专家及评议意见；不得违反论文署名规范，擅自标注或虚假标注获得科技计划（专项、基金等）等资助；不得弄虚作假，骗取科技计划（专项、基金等）项目、科研经费以及奖励、荣誉等；不得有其他违背科研诚信要求的行为。

12.确保本项目开展的研究工作符合我国科研伦理管理相关规定。

第四条 在履行本合同的过程中，如出现广东省相关政策法规重大改变等不可抗力情况，甲方有权对所核拨经费的数量和时间进行相应调整。

第五条 在履行本合同的过程中，当事人一方发现可能导致项目整体或部分失败的情形时，应及时通知另一方，并采取适当措施减少损失，没有及时通知并采取适当措施，致使损失扩大的，应当就扩大的损失承担责任。

第六条 本项目技术成果的归属、转让和实施技术成果所产生的经济利益的分享，除双方另有约定外，按国家和广东省有关法规执行。

第七条 根据项目具体情况，经双方另行协商订立的附加条款，作为本合同正式内容的一部分，与本合同具有同等效力。

第八条 本合同一式三份，各份具有同等效力。甲、乙方及项目负责人各执一份，三方签字、盖章后即生效，有效期至项目结题后一年内。各方均应负合同的法律责任，不应受机构、人事变动的影响。

第九条 乙方必须接受甲方聘请的本项目合同监理单位的监督和管理。监理单位按照甲方赋予的权利对本项目合同的履行进行审核、进度调查，对项目合同变更、经费使用情况进行监督管理及组织项目验收。

说明：1.本合同书中，凡是当事人约定无需填写的内容，应在空白处划（/）。

2.委托代理人签订本合同书的，应出具合法、有效的委托书。

2020A1515010690

八、本合同签约各方

管理单位（甲方）：　广东省基础与应用基础研究基金委员会　（盖章）

法定代表人（或法人代理）：_____（签章）

年　月　日

依托单位（乙方）：华南农业大学　（盖章）

法定代表人（或法人代理）：刘雅红　（签章）

联系人（项目主管）姓名：郑鹏　（签章）

Email：kjcgxk@scau.edu.cn

电话：020-85283435 / 13560344902

开户单位名称：华南农业大学

开户银行名称：广东广州工行五山支行

开户银行帐号：3602002609000310520

2020年3月20日

联系人（项目负责人）姓名：杨磊　（签名）

Email：yanglei_s@scau.edu.cn

电话：020-85280320-612

2020年3月20日

2020A1515010690

受理编号：c1430550100152

项目编号：2014A020208087

文件编号：粤科规财字[2015]72号



广东省省级科技计划项目

合同书

项目名称：基于数据挖掘的畜禽疫病智能诊疗系统研发与应用

计划类别：农村科技领域

项目起止时间：2015-01-01　至　2016-12-31

管理单位(甲方)：广东省科学技术厅

承担单位(乙方)：华南农业大学

乙方主管部门(丙方)：华南农业大学

通讯地址：广东省广州市天河区广州市天河区五山路483号

邮政编码：510642　　单位电话：020-38632819

项目负责人：杨磊　　联系电话：020-85280320-612

项目联系人：杨磊　　联系电话：020-85280320

2014A020208087

广东省科学技术厅
二〇一四年制

一、项目实施内容

项目研究的主要内容有：

1、畜禽疫病知识的获取与表示：利用畜禽养殖大户和畜禽疫病专家在线输入的畜禽疫病症状及病理特征数据，采用群体智能算法进行分类规则挖掘，让计算机系统进行机器学习并自主形成畜禽疫病规则库；在借鉴畜禽疫病专家思维的基础上，对畜禽疫病规则库进行分析、表示、组织并建立畜禽疫病知识数据仓库。

2、设计一个畜禽疫病智能诊断算法，结合相关的畜禽疫病知识规则库，针对畜禽病症证据在获取时存在的不确定性，建立加权诊断算法和综合诊断算法，运用混合推理机制，设计出畜禽疫病诊断的推理模型。

3、完成基于数据挖掘的畜禽疫病智能诊疗系统研发与应用，该系统可以为畜禽养殖大户提供畜禽疫病远程诊断和防治的服务，同时也可以对知识库和规则库进行维护和动态更新；设计并实现简洁、友好的人机交互界面，为畜禽养殖大户提供畜禽疫病知识资讯并完成留言反馈等功能。

拟解决的关键问题和技术路线：

本项目拟解决的关键问题：1、畜禽疫病数据采集规范的制定及疫病数据采集；2、基于群体智能算法的畜禽疫病分类规则挖掘；3、畜禽疫病诊断算法的设计及基于数据挖掘的畜禽疫病智能诊疗系统研发。

项目技术路线：该项目根据畜禽疫病智能诊疗系统的需求，按照软件系统设计的原则和开放性设计思想来设计和实现，主要分为：系统需求分析、畜禽疫病知识获取、数据处理与知识库建立、系统开发、智能诊断等几个阶段。系统的开发拟采用JAVA技术、ORACLE数据库技术及Web Service技术，JAVA技术实现该系统功能模块的设计与实现，ORACLE用来存储畜禽疫病规则及诊断知识和治疗措施，并利用Web Services技术完成从简单的请求到复杂诊断推理等各种功能。

2014A020209087

二、项目考核指标

1.项目完成后提供的研究开发成果及形式（须明确产品、专利、版权、标准等成果的类型及数量）

成果形式		成果数量	成果形式		成果数量
发明专利	申请		引进人才(人)		
	授权		培养人才(人)		
实用新型专利	申请		科技人才奖励(人)		
	授权		技术标准制定	牵头(个)	
外观设计专利	申请			参与(个)	
	授权		科技报告(篇)		
国外专利	PCT受理		软件著作权(项)		1
	授权		论文论著(篇)		1
获得国家级奖项(项)			其中：被收录论文数(篇)	SCI	
获得省级奖项(项)				EI	1
新服务(项)				ISTP	
新产品（或新材料、新装备、新品种（系））			新工艺（或新方法、新模式、新技术）		
创新载体项目必填	技术服务数量（项）				
	服务企业数量（家）				5
科技金融项目必填	开展培训宣讲活动场次(次)				
	服务企业数量(家)				
	帮助企业融资(万元)				
	引进专业机构(家)				
院士工作站项目必填	引进院士及其团队科技成果转化数量				
	院士开展的战略咨询和技术指导次数				
	院士年进站次数				
	院士及院士团队年进站时间				
软科学项目必填	决策咨询报告(篇)(至少1篇)				
	研究总报告(篇)(至少1篇)				
	研究中期报告(篇)				
	研究分报告(篇)				
	调研报告(篇)				
	专著(篇)[须注明“广东省软科学研究计划项目(项目编号：)资助”]				
	核心期刊论文(篇)[以第一作者发表，须注明“广东省软科学研究计划项目(项目编号：)资助”]				
	培养人才(人)				

20140020087

	获国家级奖项(项)	
	获省级奖项(项)	
	其他（具体形式：用户填）	
其他成果及形式说明：		
2.主要技术经济指标及社会效益		
累计新增销售收入（万元）		
累计新增利税（万元）	40.00	
其他主要技术经济指标及社会效益说明：		
项目负责人（签章）：杨磊　　2015年 4 月 5 日		

2014A020208003

三、项目进度和阶段目标

开始日期	结束日期	主要工作内容
2015-01-01	2015-01-31	成立项目领导小组，召开项目启动会议，明确项目工作内容和目标，项目前期调研。
2015-02-01	2015-06-30	畜禽疫病数据处理规范研究、系统架构总体设计，项目关键技术的研究和攻关，智能算法的改进、畜禽疫病分类算法设计。
2015-07-01	2016-06-30	基于数据挖掘的畜禽疫病智能诊疗系统研究与开发应用，进行该系统的功能和性能测试，以及联调，完善系统的各项功能指标。
2016-07-01	2016-10-31	建立畜禽智能诊疗示范基地，部署该系统的基地运营环境，搭建运营平台进行系统试运行。
2016-11-01	2016-12-31	进行项目的推广和组织示范应用，准备总结验收相关材料，组织项目验收。

2014A020208087

四、承担、参与单位工作分工及经费分配情况

承担/参与单位名称（盖章）	工作分工	总经费分摊（万元）	省科技厅经费分配（万元）
华南农业大学	项目申报单位华南农业大学负责分类规则挖掘技术研究、智能诊疗系统原型开发、用户测试、知识产权申请、负责项目的结题与验收等工作。	12.00	12.00
广东省农业科学院动物卫生研究所	畜禽疫病数据规范制定、畜禽疫病数据采集、协助用户测试、系统应用推广。	8.00	8.00
	合计	20.00	20.00

2014A020208087

五、项目总经费及省科技厅经费预算

1.省科技厅经费下达总额： （大写）贰拾万圆整；（小写 ）20.00万元;						
2.省科技厅经费年度下达计划：（第一期）20.00万元; （余额）0.00万元						
3.总经费开支预算计划：						
经费筹集情况：						（单位：万元）
总投入经费：20.00						
	省科技厅经费	自筹资金				合计
		自有资金	贷款	地方政府投入	其它	
已投入经费：						
新增经费：	20.00					20.00
政府部门、境外资金及其他资金投入情况说明：						

新增经费预算：				（单位：万元）
	新增经费总额		省科技厅经费	
支出经费	经费额	用途说明	经费额	用途说明
基建费：				
1、直接费用：	19.00		19.00	
(1)设备费：	5.00	用于购置畜禽疫病诊疗实验用高性能计算机、打印机一体机、数据挖掘仿真软件等	5.00	用于购置畜禽疫病诊疗实验用高性能计算机、打印机一体机、数据挖掘仿真软件等
(2)材料费：	3.00	用于购买墨盒、硒鼓、打印纸、存储设备等消耗材料等	3.00	用于购买墨盒、硒鼓、打印纸、存储设备等消耗材料等

2014A020208087

(3)测试化验加工外协费：				
(4)燃料动力费：	0.80	用于项目实验示范及推广应用的电力、汽油等费用	0.80	用于项目实验示范及推广应用的电力、汽油等费用
(5)差旅费：	1.20	用于项目应用推广的交通费、住宿费、伙食补助费、长途电话费以及其他各种杂费等	1.20	用于项目应用推广的交通费、住宿费、伙食补助费、长途电话费以及其他各种杂费等
(6)会议费：	2.00	用于项目日常会议、中期会议和结题会务费、租用会议场所费用、会议资料费、交通费、茶水费、餐费、住宿费等	2.00	用于项目日常会议、中期会议和结题会务费、租用会议场所费用、会议资料费、交通费、茶水费、餐费、住宿费等
(7)国际合作与交流费：	2.00	用于项目组成员出国参加畜禽疫病和数据挖掘国际会议和邀请项目组以外的相关领域外国专家短期来访的费用	2.00	用于项目组成员出国参加畜禽疫病和数据挖掘国际会议和邀请项目组以外的相关领域外国专家短期来访的费用
(8)出版/文献/信息传播/知识产权事务费：	2.00	用于资料费、论文出版费、文献检索费、专业通信费、软件著作权申请及其他知识产权事务等费用	2.00	用于资料费、论文出版费、文献检索费、专业通信费、软件著作权申请及其他知识产权事务等费用
(9)租赁费：				
(10)人员费：	2.00	用于研究生及临聘人员开发应用推广的补贴	2.00	用于研究生及临聘人员开发应用推广的补贴
(11)专家咨询费：	1.00	项目临时聘请的相关领域咨询专家的费用	1.00	项目临时聘请的相关领域咨询专家的费用
(12)直接费用其他支出：				
(13)科技金融服务体系其他费用：	0.00		0.00	
①信用评级补贴：				
②大赛场租：				
③特派员奖励与补贴：				
2、间接费用：	1.00		1.00	
科研管理费：	1.00	5%的科研管理费	1.00	5%的科研管理费
合计：	20.00		20.00	

2014A020208007

六、人员信息

项目负责人情况

姓名	年龄	性别	职称	职务	学历	在项目中承担的任务	所在单位	签名
杨磊	37	男	讲师	教师	硕士研究生	项目总负责、方案设计、项目日常管理和协调	华南农业大学	杨磊

主要研究开发人员

姓名	年龄	性别	职称	职务	学历	在项目中承担的任务	所在单位	签名
李康顺	52	男	教授	院长	博士	分类算法及群体智能算法设计指导	华南农业大学	李康顺
马勇江	40	男	副教授	系副主任	博士	数据采集关键技术研究	华南农业大学	马勇江
陈琰	37	女	讲师	教师	硕士	数据挖掘算法及系统平台研发	华南农业大学	陈琰
左磊	24	男	未取得	研究生	本科	项目软件开发与测试	华南农业大学	左磊
魏文康	43	男	研究员	主任	博士	畜禽疫病防治技术、数据采集规范研究	广东省农业科学院动物卫生研究所	魏文康
翟少伦	31	男	助理研究员	研究人员	硕士	畜禽疫病防治知识处理、数据采集	广东省农业科学院动物卫生研究所	翟少伦
温肖会	32	女	助理研究员	研究人员	硕士	畜禽疫病防治技术、协助项目的应用推广	广东省农业科学院动物卫生研究所	温肖会
陈永波	36	男	工程师	工程师	本科	系统管理与项目的应用推广	广东省农业科学院动物卫生研究所	陈永波

2014A020208087

七、承担、参与单位合作协议（须与申报书中合作协议或意向书相一致）

2014年广东省公益研究与能力建设专项资金项目

“基于数据挖掘的畜禽疫病智能诊疗系统研发与应用”

合 作 协 议 书

甲方：华南农业大学

乙方：广东省农业科学院动物卫生研究所

经甲乙双方共同协商，决定联合申报2014年广东省科技计划项目，项目名称“基于数据挖掘的畜禽疫病智能诊疗系统研发与应用”，并达成如下合作协议，双方共同恪守。

第一条 项目研究工作分工

甲方(主持方)：分类规则挖掘技术研究、智能诊疗系统原型开发、用户测试、知识产权申请、负责项目的结题与验收；

乙方(参与方)：畜禽疫病数据采集、协助用户测试、系统应用推广。

第二条 经费管理与分配

华南农业大学负责科研项目管理工作，严格按照国家的有关规定进行，并建立行之有效的项目管理、财务管理制度。由专门的财务、审计部门负责对项目经费的管理，审核各项开支，以保证资金的合理使用，专款专用和课题顺利完成。如果本申报项目获批立项，按政府下达的资助经费，甲方、乙方同意此经费分别按政府资助经费的甲方：60% 乙方：40％ 进行分配。

第三条 知识产权

各方独立完成的成果，其知识产权归各方单独享有，双方共同完成的成果，其知识产权归参与各方共同所有。

第四条 各方责任、权利、义务

在项目申报成功后经双方协商后另行签定协议。各方对各自提供的与项目申报相关资料的真实性和合法性承担全部责任。

第五条 项目合作时间

本项目合作期限为：2015年1月1日至2016年12月31日。

第六条 合作研究内容

双方合作的项目名称：基于数据挖掘的畜禽疫病智能诊疗系统研发与应用。

第七条 其它

1. 此协议在实施过程中如有其它需补充完善的内容，双方可协商另订补充协议。
2. 此协议一式五份，甲、乙双方各执一份。
3. 此协议自双方签字之日起生效。

2014A020209087

八、合同条款

第一条 甲方与乙方根据《中华人民共和国合同法》及国家有关法规和规定，为顺利完成（2014）年**基于数据挖掘的畜禽疫病智能诊疗系统研发与应用** 专项项目（项目编号： 2014A020208087 ）经协商一致，特订立本合同，作为甲乙双方在项目实施管理过程中共同遵守的依据。

第二条 甲方的权利义务：

1.按合同书规定进行经费核拨的有关工作协调。

2.根据甲方需要，在不影响乙方工作的前提下，定期或不定期对乙方项目的实施情况和经费使用情况进行检查或抽查。

3.根据《广东省科技计划项目信用管理办法(试行)》对乙方进行科技计划信用管理。

第三条 乙方的权利义务：

1.确保落实自筹经费及有关保障条件。

2.按合同书规定，对甲方核拨的经费实行专款专用，单独列账，并随时配合甲方进行监督检查。

3.使用财政资金采购设备、原材料等，按照《广东省实施〈中华人民共和国招标投标法〉办法》有关规定，符合招标条件的须进行招标。

4.项目实施完成或实施到一定程度，须按照《广东省省级科技计划项目结题管理的实施细则（试行）》提出验收或终止结题的申请，并按甲方要求做好项目结题工作。

5.在每年1月向甲方如实提交上年度工作情况报告，报告内容包含上年度项目进展情况、经费决算和取得的效果等。

6.按照国家和省有关规定，每年须提交年度科技报告；项目验收时，须提交验收科技报告。

第四条 在履行本合同的过程中，如出现广东省相关政策法规重大改变等不可抗力情况，甲方有权对所核拨经费的数量和时间进行相应调整。

第五条 在履行本合同过程中，需要对项目起止时间、项目经费使用（包括自筹经费、经费分配及经费支出预算等）、项目内容（包括研发内容、技术指标、经济指标及成果指标等）、项目名称、项目承担单位（包括承担单位更名、承担单位替换）、参与单位、项目负责人和成员等进行变更的，甲乙双方按照《广东省省级科技计划项目合同书管理的
实施细则（试行）》有关规定执行。

第六条 在履行本合同的过程中，当事人一方发现可能导致项目整体或部分失败的情形时，应及时通知另一方，并采取适当措施减少损失，没有及时通知并采取适当措施，致使损失扩大的，应当就扩大的损失承担责任。

第七条 本项目技术成果的归属、转让和实施技术成果所产生的经济利益的分享，除双方另有约定外，按国家和广东省有关法规执行。

2014A020208087

第八条 属技术保密的项目，甲乙双方应另行订立技术保密条款，作为本合同正式内容的一部分，与本合同具有同等效力。

第九条 根据项目具体情况，经双方另行协商订立的附加条款，作为本合同正式内容的一部分，与本合同具有同等效力。

第十条 本合同的争议应由双方本着协商一致的原则解决，如双方协商不成的，则应向甲方所在地法院提起诉讼。

第十一条 保密条款：

1.本合同保密内容范围为：

/

2.本合同保密期限为：

/

3.乙方应与可能知悉保密内容的人员签订技术秘密保护协议。

4.各方应建立技术秘密保护制度。

5.属技术保密的项目必须经省负责技术保密部门审查后，确定可否发表或用于国际合作和交流。

第十二条 甲方可根据具体情况决定乙方是否需要单位担保，若需要保证单位，应订立担保条款，作为本合同正式内容一部分。当乙方不履行或不完全履行本合同，以及没有或没有完全承担违约责任时，乙方的保证单位承担连带保证责任。

第十三条 本合同一式六份，各份具有同等效力。甲方存三份，乙方存二份，丙方存一份，本合同自签字之日起生效，有效期至项目结题后一年内。各方均应负合同的法律责任，不应受机构、人事变动的影响。

说明：本合同书中，凡是当事人约定无需填写的内容，应在空白处划（/）。

2014A020208087

九、本合同签约各方

管理单位（甲方）：　广东省科学技术厅　（盖章）

单位地址：　广州市连新路171号大院信息大楼

法定代表人（或授权代表）：　黄宁生　（签章）

联系人（经办人）姓名：　林振亮　（签章）

Email：　linzl@gdstc.gov.cn

电话：　020-83163905

年　月　日

承担单位（乙方）：　华南农业大学　（盖章）

二级部门：　华南农业大学数学与信息（软件）学院

单位地址：　广东省广州市天河区广州市天河区五山路483号

法定代表人（或法人代理）：　陈晓阳　（签章）

联系人（项目主管）姓名：　夏斌　（签章）

Email：　kjcgxk@scau.edu.cn

电话：　020-85283435

开户单位名称：　华南农业大学

开户银行及帐号：　广东广州工行五山支行　3602002609000310520

年　月　日

乙方主管部门（丙方）：　华南农业大学　（盖章）

单位地址：　广东省广州市天河区广州市天河区五山路483号

法定代表人（或法人代理）：　陈晓阳　（签章）

联系人（项目主管）姓名：　夏斌　（签章）

Email：　kjcgxk@scau.edu.cn

电话：　020-85283435

开户单位名称：　华南农业大学

开户银行及帐号：　广东广州工行五山支行　3602002609000310520

年　月　日

受理编号：c1530550100085

项目编号：2015A020209119

文件编号：粤科规财字[2015]150号



广东省省级科技计划项目

合同书

项目名称：基于大数据的动物疫病免疫检测信息智能分析系统研发与应用示范

计划类别：农村科技领域

项目起止时间：2015-09-01　至　2017-09-01

管理单位(甲方)：广东省科学技术厅

承担单位(乙方)：华南农业大学

乙方主管部门(丙方)：华南农业大学

通讯地址：广东省广州市天河区五山路483号

邮政编码：510642　　单位电话：020-38632819

项目负责人：杨磊　　联系电话：020-85280320-612

项目联系人：杨磊　　联系电话：020-85280320-612

2015A020209119

广东省科学技术厅
二〇一四年制

一、项目实施内容

项目研究的主要内容：

1、构建动物养殖档案信息化管理系统。该系统具有如下功能：按地域管理辖区内养殖场；分类、分批录入养殖场动物信息。动物养殖档案内容主要包括：动物的品种、数量、引进地和进出场日期；检疫、免疫、消毒情况；动物疫病诊疗情况；动物死淘和无害化处理情况等。

2、制定动物免疫程序信息化编码标准，完成动物免疫程序算法设计。主要针对猪瘟、蓝耳、口蹄疫、禽流感等动物疫病，制定动物免疫程序信息化编码标准；设计一套合理的免疫程序,规定对动物免疫接种的日期和顺序。结合动物养殖数字档案,研制出免疫程序的计算机算法,并开发后台计算机程序，生成对应的免疫任务。

3、免疫检测信息智能分析系统的设计与实现。完成动物疫病免疫检测信息的数据仓库的构建，并对其进行智能处理及分析，确认动物疫病疫苗接种效果，并结合区域动物疫病分布情况和疫病发展趋势，生成预警信息。

4、研制基于移动互联网的动物免疫任务提醒系统及动物免疫情况反馈系统。动物免疫任务提醒系统可以把生成的免疫任务及时提供给兽医站及养殖场，免疫情况反馈系统可以将免疫检测信息智能分析结果通过APP或微信的方式反馈给规模养殖场、兽医站及相关行政部门作为决策的数据依据。

5、完成基于大数据的动物疫病免疫检测信息智能分析系统的应用示范。

2015A020209019

二、项目考核指标

<table>
<tr><td colspan="6">1.项目完成后提供的研究开发成果及形式（须明确产品、专利、版权、标准等成果的类型及数量）</td></tr>
<tr><td colspan="2">成果形式</td><td>成果数量</td><td colspan="2">成果形式</td><td>成果数量</td></tr>
<tr><td rowspan="2">发明专利</td><td>申请</td><td></td><td colspan="2">引进人才(人)</td><td></td></tr>
<tr><td>授权</td><td></td><td colspan="2">培养人才(人)</td><td></td></tr>
<tr><td rowspan="2">实用新型专利</td><td>申请</td><td></td><td colspan="2">科技人才奖励(人)</td><td></td></tr>
<tr><td>授权</td><td></td><td rowspan="2">技术标准制定</td><td>牵头(个)</td><td></td></tr>
<tr><td rowspan="2">外观设计专利</td><td>申请</td><td></td><td>参与(个)</td><td></td></tr>
<tr><td>授权</td><td></td><td colspan="2">科技报告(篇)</td><td></td></tr>
<tr><td rowspan="2">国外专利</td><td>PCT受理</td><td></td><td colspan="2">软件著作权(项)</td><td>1</td></tr>
<tr><td>授权</td><td></td><td colspan="2">论文论著(篇)</td><td>1</td></tr>
<tr><td colspan="2">获得国家级奖项(项)</td><td></td><td rowspan="3">其中：被收录论文数(篇)</td><td>SCI</td><td></td></tr>
<tr><td colspan="2">获得省级奖项(项)</td><td></td><td>EI</td><td>1</td></tr>
<tr><td colspan="2">新服务(项)</td><td></td><td>ISTP</td><td></td></tr>
<tr><td colspan="2">新产品（或新材料、新装备、新品种（系））</td><td></td><td colspan="2">新工艺（或新方法、新模式、新技术）</td><td></td></tr>
<tr><td rowspan="2">创新载体项目必填</td><td colspan="4">技术服务数量（项）</td><td></td></tr>
<tr><td colspan="4">服务企业数量（家）</td><td>1</td></tr>
<tr><td rowspan="4">科技金融项目必填</td><td colspan="4">开展培训宣讲活动场次(次)</td><td></td></tr>
<tr><td colspan="4">服务企业数量(家)</td><td></td></tr>
<tr><td colspan="4">帮助企业融资(万元)</td><td></td></tr>
<tr><td colspan="4">引进专业机构(家)</td><td></td></tr>
<tr><td rowspan="4">院士工作站项目必填</td><td colspan="4">引进院士及其团队科技成果转化数量</td><td></td></tr>
<tr><td colspan="4">院士开展的战略咨询和技术指导次数</td><td></td></tr>
<tr><td colspan="4">院士年进站次数</td><td></td></tr>
<tr><td colspan="4">院士及院士团队年进站时间</td><td></td></tr>
<tr><td rowspan="9">软科学项目必填</td><td colspan="4">决策咨询报告(篇)(至少1篇)</td><td></td></tr>
<tr><td colspan="4">研究总报告(篇)(至少1篇)</td><td></td></tr>
<tr><td colspan="4">研究中期报告(篇)</td><td></td></tr>
<tr><td colspan="4">研究分报告(篇)</td><td></td></tr>
<tr><td colspan="4">调研报告(篇)</td><td></td></tr>
<tr><td colspan="4">专著(篇)[须注明“广东省软科学研究计划项目(项目编号：)资助”]</td><td></td></tr>
<tr><td colspan="4">核心期刊论文(篇)[以第一作者发表，须注明“广东省软科学研究计划项目(项目编号：)资助”]</td><td></td></tr>
<tr><td colspan="4">培养人才(人)</td><td></td></tr>
<tr><td colspan="4"></td><td></td></tr>
</table>

20150020919

	获国家级奖项(项)	
	获省级奖项(项)	
	其他（具体形式：用户填)	
其他成果及形式说明：		
2. 主要技术经济指标及社会效益		
累计新增销售收入（万元）		
累计新增利税（万元）	30.00	
其他主要技术经济指标及社会效益说明：		
项目负责人（签章）：杨磊 2015年 11月 15日		

2015A020209

三、项目进度和阶段目标

开始日期	结束日期	主要工作内容
2015-09-01	2015-11-30	成立项目领导小组，召开项目启动会议，明确项目工作内容和目标，项目前期调研；
2015-12-01	2016-03-31	动物疫病免疫检测数据采集规范研究、系统架构总体设计，项目关键技术的研究和攻关，Bayes分类算法及智能算法的改进；
2016-04-01	2016-06-30	建立基于大数据的动物疫病免疫检测信息智能分析模型；
2016-07-01	2017-03-31	基于大数据的动物疫病免疫检测信息智能分析系统设计与开发，进行该系统的功能和性能测试，以及联调，完善系统的各项功能指标；
2017-04-01	2017-06-30	在广州市广良畜牧有线公司部署该系统的基地运营环境，搭建运营平台进行系统试运行，对各个模块进行测试修改和完善；
2017-07-01	2017-09-01	将该项目进一步推广应用，准备总结验收相关材料，组织项目验收。

2015A020209110

四、承担、参与单位工作分工及经费分配情况

承担/参与单位名称（盖章）	工作分工	总经费分摊（万元）	省科技厅经费分配（万元）
华南农业大学	项目申报单位华南农业大学负责动物疫病分类规则挖掘技术研究、智能分析系统原型开发、用户测试、知识产权申请、负责项目的结题与验收	9.00	9.00
广东省农业科学院动物卫生研究所	动物疫病免疫监测数据采集、动物疫病免疫检测数据标准提供、协助用户测试	4.50	4.50
广州市广良畜牧有限公司	负责项目开发系统的应用示范	1.50	1.50
	合计	15.00	15.00

2015A020209119

五、项目总经费及省科技厅经费预算

1.省科技厅经费下达总额： （大写）壹拾伍万圆整；（小写 ）15.00万元;						
2.省科技厅经费年度下达计划：（第一期）15.00万元；（余额）0.00万元						
3.总经费开支预算计划：						
经费筹集情况：						（单位：万元）
总投入经费：15.00						
	省科技厅经费	自筹资金				合计
		自有资金	贷款	地方政府投入	其它	
已投入经费：						
新增经费：	15.00					15.00
政府部门、境外资金及其他资金投入情况说明：						

新增经费预算：					（单位：万元）
	新增经费总额		省科技厅经费		
支出经费	经费额	用途说明	经费额	用途说明	
基建费：					
1、直接费用：	14.25		14.25		

2015A020209119

(1)设备费：	3.00	用于购置动物疫病免疫检测数据采集物联网设备，按每套RFID扫描器1.1万元计算，购置RFID扫描器2台、RFID标签若干及高性能传感器若干，费用约需2.5万元；购置疫病大数据挖掘仿真软件2套约0.5万	3.00	用于购置动物疫病免疫检测数据采集物联网设备，按每套RFID扫描器1.1万元计算，购置RFID扫描器2台、RFID标签若干及高性能传感器若干，费用约需2.5万元；购置疫病大数据挖掘仿真软件2套约0.5万
(2)材料费：	2.00	用于购买数据存储专用硬盘、大容量闪存、条形码打印机、光学存储设备等消耗材料等	2.00	用于购买数据存储专用硬盘、大容量闪存、条形码打印机、光学存储设备等消耗材料等
(3)测试化验加工外协费：				
(4)燃料动力费：	0.80	用于项目实验示范及推广应用的电力、汽油等费用	0.80	用于项目实验示范及推广应用的电力、汽油等费用
(5)差旅费：	1.25	用于项目应用推广的交通费、住宿费、伙食补助费、长途电话费以及其他各种杂费等	1.25	用于项目应用推广的交通费、住宿费、伙食补助费、长途电话费以及其他各种杂费等
(6)会议费：	2.00	用于项目日常会议、中期会议和结题会务费、租用会议场所费用、会议资料费、交通费、茶水费、餐费、住宿费等	2.00	用于项目日常会议、中期会议和结题会务费、租用会议场所费用、会议资料费、交通费、茶水费、餐费、住宿费等
(7)国际合作与交流费：	2.00	用于项目组成员出国参加动物疫病免疫检测和大数据国际会议和邀请项目组以外的相关领域外国专家短期来访的费用	2.00	用于项目组成员出国参加动物疫病免疫检测和大数据国际会议和邀请项目组以外的相关领域外国专家短期来访的费用
(8)出版/文献/信息传播/知识产权事务费：	2.00	用于资料费、论文出版费、文献检索费、专业通信费、软件著作权申请及其他知识产权事务等费用	2.00	用于资料费、论文出版费、文献检索费、专业通信费、软件著作权申请及其他知识产权事务等费用
(9)租赁费：				
(10)人员费：	1.20	用于研究生及临聘人员开发应用推广的补贴	1.20	用于研究生及临聘人员开发应用推广的补贴
(11)专家咨询费：				
(12)直接费用其他支出：				
(13)科技金融服务体系其他费用：	0.00		0.00	
①信用评级补贴：				
②大赛场租：				
③特派员奖励与补贴：				
2、间接费用：	0.75		0.75	
科研管理费：	0.75	5%的科研管理费	0.75	5%的科研管理费

2015A020091

合计：	15.00		15.00	

2015A020209119

六、人员信息

项目负责人情况

姓名	年龄	性别	职称	职务	学历	在项目中承担的任务	所在单位	签名
杨磊	37	男	讲师	教研室副主任	硕士研究生	项目总负责、方案设计、项目日常管理和协调	华南农业大学	杨磊

2015A020209119

主要研究开发人员

姓名	年龄	性别	职称	职务	学历	在项目中承担的任务	所在单位	签名
李康顺	53	男	教授	院长	博士	Bayes分类算法及群体智能算法设计	华南农业大学	
马勇江	41	男	副教授	系主任	博士	免疫数据采集标准研究	华南农业大学	
陈琰	38	女	讲师	教师	博士	数据挖掘算法及系统平台研发	华南农业大学	
钟亮	25	男	未取得	硕士生	本科	项目软件开发与测试	华南农业大学	
杨舒玲	24	女	未取得	硕士生	本科	动物养殖电子档案开发	华南农业大学	
魏文康	44	男	研究员	主任	博士	动物疫病免疫技术、检测数据采集规范研究	广东省农业科学院动物卫生研究所	
翟少伦	32	男	助理研究员	兽医师	硕士	动物疫病防治知识处理、数据采集	广东省农业科学院动物卫生研究所	
陈琴苓	46	女	助理研究员	兽医师	硕士	动物疫病防治技术研究	广东省农业科学院动物卫生研究所	
陈永波	37	男	工程师	工程师	本科	系统管理与项目的应用推广	广东省农业科学院动物卫生研究所	
李泽流	50	男	兽医师	兽医师	本科	项目的应用示范	广州市广良畜牧有限公司	

七、承担、参与单位合作协议（须与申报书中合作协议或意向书相一致）

2015年广东省公益研究与能力建设专项资金项目

“基于大数据的动物疫病免疫检测信息智能分析系统研发与应用示范”

合 作 协 议 书

甲方：华南农业大学

乙方：广东省农业科学院动物卫生研究所

丙方：广州市广良畜牧有限公司

经甲乙丙三方共同协商，决定联合申报2015年广东省科技计划项目，项目名称“基于大数据的动物疫病免疫检测信息智能分析系统研发与应用示范”，并达成如下合作协议，三方共同恪守。

第一条 项目研究工作分工

甲方(主持方)：分类规则挖掘技术研究、智能分析系统原型开发、用户测试、知识产权申请、负责项目的结题与验收；

乙方(参与方)：动物疫病免疫监测数据采集、动物疫病免疫检测数据标准提供、协助用户测试；

丙方(参与方)：负责项目开发系统的应用示范。

第二条 经费管理与分配

华南农业大学负责科研项目管理工作，严格按照国家的有关规定进行，并建立行之有效的项目管理、财务管理制度。由专门的财务、审计部门负责对项目经费的管理，审核各项开支，以保证资金的合理使用，专款专用和课题顺利完成。如果本申报项目获批立项，按政府下达的资助经费，甲方、乙方、丙方同意此经费分别按政府资助经费的甲方：60% 乙方：30%丙方：10% 进行分配。

第三条 知识产权

各方独立完成的成果，其知识产权归各方单独享有，三方共同完成的成果，其知识产权归参与各方共同所有。

第四条 各方责任、权利、义务

在项目申报成功后经三方协商后另行签定协议。各方对各自提供的与项目申报相关资料的真实性和合法性承担全部责任。

第五条 项目合作时间

本项目合作期限为：2015年9月1日至2017年9月1日。

第六条 合作研究内容

三方合作的项目名称：基于大数据的动物疫病免疫检测信息智能分析系统研发与应用示范。

第七条 其它

1. 此协议在实施过程中如有其它需补充完善的内容，三方可协商另签订补充协议。
2. 此协议一式五份，甲、乙、丙三方各执一份。
3. 此协议自三方签字之日起生效。

八、合同条款

第一条 甲方与乙方根据《中华人民共和国合同法》及国家有关法规和规定，为顺利完成（2015）年**基于大数据的动物疫病免疫检测信息智能分析系统研发与应用示范** 专项项目（项目编号： 2015A020209119 ）经协商一致，特订立本合同，作为甲乙双方在项目实施管理过程中共同遵守的依据。

第二条 甲方的权利义务：

1.按合同书规定进行经费核拨的有关工作协调。

2.根据甲方需要，在不影响乙方工作的前提下，定期或不定期对乙方项目的实施情况和经费使用情况进行检查或抽查。

3.根据《广东省科技计划项目信用管理办法(试行)》对乙方进行科技计划信用管理。

第三条 乙方的权利义务：

1.确保落实自筹经费及有关保障条件。

2.按合同书规定，对甲方核拨的经费实行专款专用，单独列账，并随时配合甲方进行监督检查。

3.使用财政资金采购设备、原材料等，按照《广东省实施〈中华人民共和国招标投标法〉办法》有关规定，符合招标条件的须进行招标。

4.项目实施完成或实施到一定程度，须按照《广东省省级科技计划项目结题管理的实施细则（试行）》提出验收或终止结题的申请，并按甲方要求做好项目结题工作。

5.在每年1月向甲方如实提交上年度工作情况报告，报告内容包含上年度项目进展情况、经费决算和取得的效果等。

6.按照国家和省有关规定，每年须提交年度科技报告；项目验收时，须提交验收科技报告。

第四条 在履行本合同的过程中，如出现广东省相关政策法规重大改变等不可抗力情况，甲方有权对所核拨经费的数量和时间进行相应调整。

第五条 在履行本合同过程中，需要对项目起止时间、项目经费使用（包括自筹经费、经费分配及经费支出预算等）、项目内容（包括研发内容、技术指标、经济指标及成果指标等）、项目名称、项目承担单位（包括承担单位更名、承担单位替换）、参与单位、项目负责人和成员等进行变更的，甲乙双方按照《广东省省级科技计划项目合同书管理的
实施细则（试行）》有关规定执行。

第六条 在履行本合同的过程中，当事人一方发现可能导致项目整体或部分失败的情形时，应及时通知另一方，并采取适当措施减少损失，没有及时通知并采取适当措施，致使损失扩大的，应当就扩大的损失承担责任。

第七条 本项目技术成果的归属、转让和实施技术成果所产生的经济利益的分享，除双方另有约定外，按国家和广东省有关法规执行。

2015A020209119

第八条 属技术保密的项目，甲乙双方应另行订立技术保密条款，作为本合同正式内容的一部分，与本合同具有同等效力。

第九条 根据项目具体情况，经双方另行协商订立的附加条款，作为本合同正式内容的一部分，与本合同具有同等效力。

第十条 本合同的争议应由双方本着协商一致的原则解决，如双方协商不成的，则应向甲方所在地法院提起诉讼。

第十一条 保密条款：

1.本合同保密内容范围为：

/

2.本合同保密期限为：

/

3.乙方应与可能知悉保密内容的人员签订技术秘密保护协议。

4.各方应建立技术秘密保护制度。

5.属技术保密的项目必须经省负责技术保密部门审查后，确定可否发表或用于国际合作和交流。

第十二条 甲方可根据具体情况决定乙方是否需要单位担保，若需要保证单位，应订立担保条款，作为本合同正式内容一部分。当乙方不履行或不完全履行本合同，以及没有或没有完全承担违约责任时，乙方的保证单位承担连带保证责任。

第十三条 本合同一式六份，各份具有同等效力。甲方存三份，乙方存二份，丙方存一份，本合同自签字之日起生效，有效期至项目结题后一年内。各方均应负合同的法律责任，不应受机构、人事变动的影响。

说明：本合同书中，凡是当事人约定无需填写的内容，应在空白处划（/）。

2015A020209119

九、本合同签约各方

管理单位（甲方）：　广东省科学技术厅　（盖章）

单位地址：　广州市连新路171号大院信息大楼

法定代表人（或授权代表）：　黄宁生　（签章）

联系人（经办人）姓名：　林振亮　（签章）

Email：　linzl@gdstc.gov.cn

电话：　020-83163905

年　月　日

承担单位（乙方）：　华南农业大学　（盖章）

二级部门：　华南农业大学数学与信息（软件）学院

单位地址：　广东省广州市天河区五山路483号

法定代表人（或法人代理）：　陈晓阳　（签章）

联系人（项目主管）姓名：　石睿　（签章）

Email：　77909213@qq.com

电话：　020-85283435

开户单位名称：　华南农业大学

开户银行及帐号：　广东广州工行五山支行　3602002609000310520

年　月　日

乙方主管部门（丙方）：　华南农业大学　（盖章）

单位地址：　广东省广州市天河区五山路483号

法定代表人（或法人代理）：　陈晓阳　（签章）

联系人（项目主管）姓名：　石睿　（签章）

Email：　77909213@qq.com

电话：　020-85283435

开户单位名称：　华南农业大学

开户银行及帐号：　广东广州工行五山支行　3602002609000310520

年　月　日

受理编号：c1630550100064

项目编号：2016A020212020

文件编号：粤科规财字〔2016〕47号



广东省省级科技计划项目

合同书

项目名称：东源县特色农产品可溯源移动电商平台研发及示范应用

计划类别：农村科技领域

项目起止时间：2016-01-01　至　2017-12-31

管理单位(甲方)：广东省科学技术厅

承担单位(乙方)：华南农业大学

乙方主管部门(丙方)：华南农业大学

通讯地址：广东省广州市天河区五山路483号

邮政编码：510642　　单位电话：020-38632819

项目负责人：杨磊　　联系电话：020-85280320-612

项目联系人：杨磊　　联系电话：020-85280320-612

2016A020212020

广东省科学技术厅
二〇一四年制

一、项目实施内容

本项目拟建设东源县特色农产品可溯源移动电子商务平台，并在东源县小径种养专业合作社示范应用，项目探索农产品溯源技术、移动电子商务技术与O2O本地生活等新的商务模式融合，使消费者能够通过智能手机便捷购买所需农产品，并保障消费者所购农产品的质量安全。项目拟采用基于Android 的JAVA编程技术、ORACLE数据库结合Web service技术完成该平台的研发并在粤东贫困地区推广应用。

2016A02021202O

二、项目考核指标

<table>
<tr><td colspan="6">1.项目完成后提供的研究开发成果及形式（须明确产品、专利、版权、标准等成果的类型及数量）</td></tr>
<tr><td colspan="2">成果形式</td><td>成果数量</td><td colspan="2">成果形式</td><td>成果数量</td></tr>
<tr><td rowspan="2">发明专利</td><td>申请</td><td></td><td colspan="2">引进人才(人)</td><td></td></tr>
<tr><td>授权</td><td></td><td colspan="2">培养人才(人)</td><td>5</td></tr>
<tr><td rowspan="2">实用新型专利</td><td>申请</td><td></td><td colspan="2">科技人才奖励(人)</td><td></td></tr>
<tr><td>授权</td><td></td><td rowspan="2">技术标准制定</td><td>牵头(个)</td><td></td></tr>
<tr><td rowspan="2">外观设计专利</td><td>申请</td><td></td><td>参与(个)</td><td></td></tr>
<tr><td>授权</td><td></td><td colspan="2">科技报告(篇)</td><td></td></tr>
<tr><td rowspan="2">国外专利</td><td>PCT受理</td><td></td><td colspan="2">软件著作权(项)</td><td>1</td></tr>
<tr><td>授权</td><td></td><td colspan="2">论文论著(篇)</td><td>1</td></tr>
<tr><td colspan="2">获得国家级奖项(项)</td><td></td><td rowspan="3">其中：被收录论文数(篇)</td><td>SCI</td><td></td></tr>
<tr><td colspan="2">获得省级奖项(项)</td><td></td><td>EI</td><td>1</td></tr>
<tr><td colspan="2">新服务(项)</td><td></td><td>ISTP</td><td></td></tr>
<tr><td colspan="2">新产品（或新材料、新装备、新品种（系））</td><td></td><td colspan="2">新工艺（或新方法、新模式、新技术）</td><td></td></tr>
<tr><td colspan="2" rowspan="2">创新载体项目必填</td><td colspan="3">技术服务数量（项）</td><td></td></tr>
<tr><td colspan="3">服务企业数量（家）</td><td>1</td></tr>
<tr><td colspan="2" rowspan="4">科技金融项目必填</td><td colspan="3">开展培训宣讲活动场次(次)</td><td></td></tr>
<tr><td colspan="3">服务企业数量(家)</td><td></td></tr>
<tr><td colspan="3">帮助企业融资(万元)</td><td></td></tr>
<tr><td colspan="3">引进专业机构(家)</td><td></td></tr>
<tr><td colspan="2" rowspan="4">院士工作站项目必填</td><td colspan="3">引进院士及其团队科技成果转化数量</td><td></td></tr>
<tr><td colspan="3">院士开展的战略咨询和技术指导次数</td><td></td></tr>
<tr><td colspan="3">院士年进站次数</td><td></td></tr>
<tr><td colspan="3">院士及院士团队年进站时间</td><td></td></tr>
<tr><td colspan="2" rowspan="8">软科学项目必填</td><td colspan="3">决策咨询报告(篇)(至少1篇)</td><td></td></tr>
<tr><td colspan="3">研究总报告(篇)(至少1篇)</td><td></td></tr>
<tr><td colspan="3">研究中期报告(篇)</td><td></td></tr>
<tr><td colspan="3">研究分报告(篇)</td><td></td></tr>
<tr><td colspan="3">调研报告(篇)</td><td></td></tr>
<tr><td colspan="3">专著(篇)[须注明“广东省软科学研究计划项目(项目编号：)资助”]</td><td></td></tr>
<tr><td colspan="3">核心期刊论文(篇)[以第一作者发表，须注明“广东省软科学研究计划项目(项目编号：)资助”]</td><td></td></tr>
<tr><td colspan="3">培养人才(人)</td><td></td></tr>
</table>

20160021220

	获国家级奖项(项)	
	获省级奖项(项)	
	其他（具体形式：用户填）	
其他成果及形式说明：		
2. 主要技术经济指标及社会效益		
累计新增销售收入（万元）	40.20	
累计新增利税（万元）	15.38	
其他主要技术经济指标及社会效益说明：		
1、进一步增强农民专业合作社的移动电子商务的应用能力，大大提高工作质量和效率，为农业信息的发布和获取提供更便利的途径，缩窄信息鸿沟，缩小城乡差距、推动农村发展。2、加快农村信息化进程，引导农业结构调整、提高农业现代化水平、提升我国农产品的国际市场竞争力、促进农民增收和推进农村改革与发展。3、整合各类农业信息资源，减少农业信息的发布和获取的时间成本、资金成本，提高农民专业合作社移动电子商务应用的深度和广度，为农民专业合作社提供全面、权威、及时的各类资讯，为合作社特色品牌宣传、招商引资创造有利条件。4、推动农业产业改革与发展，加快农业信息化、管理系统化的进程。		
项目负责人（签章）：杨磊　2016年 9月 1日		

三、项

开始日
2016-01-
2016-03-
2016-05-
2016-09-
2017-06-
2017-09-

三、项目进度和阶段目标

开始日期	结束日期	主要工作内容
2016-01-01	2016-02-29	研究国内外最新参考文献和发展动态，到参与单位实地考察，充分调研，并进行问卷调查，统计特色农产品移动电子商务平台的农产品信息需求，抽象出农产品追溯系统数据模型；
2016-03-01	2016-04-30	对电子商务前沿技术进行调研，召开项目小组会议，确定特色农产品可溯源移动电商平台的整体架构、确定项目所采用的技术线路及关键技术，完成项目整体解决方案的讨论及定稿；
2016-05-01	2016-08-31	完成特色农产品移动电子商务平台的需求分析及总体设计；完成安全农产品溯源信息查询系统的总体设计；
2016-09-01	2017-05-31	完成特色农产品移动电子商务平台的开发，并无缝集成开发的安全农产品溯源查询系统；
2017-06-01	2017-08-31	完成东源县特色农产品可溯源移动电商平台的测试，部署及在参与单位上线应用；
2017-09-01	2017-12-31	继续完成特色农产品可溯源移动电商平台的应用示范及网络推广，优化、商务模式创新等工作；项目总结与验收；在粤东贫苦地区大规模推广应用该平台。

2016A020212020

四、承担、参与单位工作分工及经费分配情况

承担/参与单位名称（盖章）	工作分工	总经费分摊（万元）	省科技厅经费分配（万元）
华南农业大学	移动电子商务与溯源新技术及模式研究、东源县特色农产品可溯源移动电子商务平台原型设计与开发、用户测试、知识产权申请、技术培训、负责项目的结题与验收	5.00	5.00
东源县小径种养专业合作社	协助项目申报、东源县特色农产品全程溯源数据采集、协助进行移动电子商务平台测试、东源县特色农产品可溯源移动电商平台的部署、运营及应用示范、推广应用	5.00	5.00
	合计	10.00	10.00

五、项目总经费及省科技厅经费预算

1.省科技厅经费下达总额： （大写）壹拾万圆整；（小写 ）10.00万元;						
2.省科技厅经费拨付方式： **一次性拨款**						
3.省科技厅经费年度下达计划：**总额10.00(万元)**						
分期			经费(万元)			
第1期			10			
4.总经费开支预算计划：						
经费筹集情况：						（单位：万元）
总投入经费：10.00						
	省科技厅经费	自筹资金				合计
		自有资金	贷款	地方政府投入	其它	
已投入经费：						
新增经费：	10.00					10.00
政府部门、境外资金及其他资金投入情况说明：						

新增经费预算：				（单位：万元）
	新增经费总额		省科技厅经费	
支出经费	经费额	用途说明	经费额	用途说明
基建费：				
1、直接费用：	9.50		9.50	

2016A020212020

(1)设备费：	0.80	用于购置东源县特色农产品可溯源移动电商平台用高性能计算机打印设备、移动终端设备、标签等设备；	0.80	用于购置东源县特色农产品可溯源移动电商平台用高性能计算机打印设备、移动终端设备、标签等设备；
(2)材料费：	1.00	用于购买硒鼓、墨盒、打印纸、标签、锡箔、存储设备等消耗材料；	1.00	用于购买硒鼓、墨盒、打印纸、标签、锡箔、存储设备等消耗材料；
(3)测试化验加工外协费：				
(4)燃料动力费：	1.00	用于项目调研、交流、示范及推广应用的电力、汽油等费用；	1.00	用于项目调研、交流、示范及推广应用的电力、汽油等费用；
(5)差旅费：	1.00	用于项目的交通费用、住宿费、伙食补助费、长途电话费及其他各种杂费；	1.00	用于项目的交通费用、住宿费、伙食补助费、长途电话费及其他各种杂费；
(6)会议费：	0.70	用于项目日常会议、中期会议和结题会务费、租用会议场所费用、会议资料费、交通费、茶水费、餐费、住宿费等；	0.70	用于项目日常会议、中期会议和结题会务费、租用会议场所费用、会议资料费、交通费、茶水费、餐费、住宿费等；
(7)国际合作与交流费：				
(8)出版/文献/信息传播/知识产权事务费：	1.00	用于资料费、论文出版费、文献检索费、专业通信费、知识产权申请费及其他知识产权事务等费用；	1.00	用于资料费、论文出版费、文献检索费、专业通信费、知识产权申请费及其他知识产权事务等费用；
(9)租赁费：				
(10)人员费：	4.00	用于研究生及临聘人员设计与开发、测试、部署及应用推广的补贴。	4.00	用于研究生及临聘人员设计与开发、测试、部署及应用推广的补贴。
(11)专家咨询费：				
(12)直接费用其他支出：				
(13)科技金融服务体系其他费用：	0.00		0.00	
①信用评级补贴：				
②大赛场租：				
③特派员奖励与补贴：				
2、间接费用：	0.50		0.50	
科研管理费：	0.50	管理费	0.50	管理费
合计：	10.00		10.00	

20160321202

六、人员信息

项目负责人情况

姓名	年龄	性别	职称	职务	学历	在项目中承担的任务	所在单位	签名
杨磊	38	男	讲师	教研室副主任	硕士研究生	项目总负责、技术方案设计、日常管理和协调	华南农业大学	

主要研究开发人员

姓名	年龄	性别	职称	职务	学历	在项目中承担的任务	所在单位	签名
李康顺	53	男	教授	院长	博士研究生	平台规划及技术指导	华南农业大学	
吴理华	39	男	讲师	教研室副主任	博士研究生	移动电商平台架构设计、溯源信息标准设计	华南农业大学	
陈琰	38	女	讲师	教师	博士研究生	项目软件测试及系统上线部署	华南农业大学	
钟亮	25	男	未取得	研究生	本科	软件开发与测试	华南农业大学	
杨舒玲	24	女	未取得	研究生	本科	平台原型设计与开发	华南农业大学	
张树金	43	男	农艺师	理事长	本科	平台的运营及示范应用	东源县小径种养专业合作社	
涂伟强	44	男	农艺技术员	无	其他	协助进行特色农产品溯源信息标准制	东源县小径种养专业合作社	
张水平	43	男	技术员	无	其他	特色农产品全程数据采集、协助平台测试运营	东源县小径种养专业合作社	
张光荣	37	男	技术员	无	其他	协助进行网络营销、平台推广	东源县小径种养专业合作社	

七、承担、参与单位合作协议（须与申报书中合作协议或意向书相一致）

2016年广东省公益研究与能力建设专项项目申报

合 作 协 议 书

甲方：华南农业大学

乙方：东源县小径种养专业合作社

经甲乙双方共同协商，决定联合申报2016年广东省公益研究与能力建设专项项目，项目名称“东源县特色农产品可溯源移动电商平台研发及示范应用”，并达成如下合作协议，双方共同恪守。

第一条 项目研究工作分工

甲方(主持方)：项目申报、技术研究、软件原型开发、用户测试、知识产权申请、项目结题

乙方(参与方)： 协助项目申报、科研成果部署、推广应用

第二条 经费管理与分配

华南农业大学负责科研项目管理工作，严格按照国家的有关规定进行，并建立行之有效的项目管理、财务管理制度。由专门的财务、审计部门负责对项目经费的管理，审核各项开支，以保证资金的合理使用，专款专用和课题顺利完成。如果本申报项目获批立项，按政府下达的资助经费，甲方、乙方同意此经费分别按政府资助经费的甲方：50%、乙方：50% 进行分配。

第三条 知识产权

各方独立完成的成果，其知识产权归各方单独享有，双方共同完成的成果，其知识产权归参与双方共同所有。

第四条 双方责任、权利、义务

在项目申报成功后经双方协商后另行签定协议。双方对各自提供的与课题申报相关资料的真实性和合法性承担全部责任。

第五条 项目合作时间

本项目合作期限为：2016年1月1日至2017年12月31日。

第六条 合作研究内容

双方合作的项目名称：东源县特色农产品可溯源移动电商平台研发及示范应用。

第七条 其它

1. 此协议在实施过程中如有其它需补充完善的内容，双方可协商另订补充协议。
2. 此协议一式五份，甲、乙双方各执一份。
3. 此协议自双方签字之日起生效。

八、合同条款

第一条 甲方与乙方根据《中华人民共和国合同法》及国家有关法规和规定，为顺利完成（2016）年**东源县特色农产品可溯源移动电商平台研发及示范应用** 专项项目（项目编号： 2016A020212020 ）经协商一致，特订立本合同，作为甲乙双方在项目实施管理过程中共同遵守的依据。

第二条 甲方的权利义务：

1.按合同书规定进行经费核拨的有关工作协调。

2.根据甲方需要，在不影响乙方工作的前提下，定期或不定期对乙方项目的实施情况和经费使用情况进行检查或抽查。

3.根据《广东省科技计划项目信用管理办法(试行)》对乙方进行科技计划信用管理。

第三条 乙方的权利义务：

1.确保落实自筹经费及有关保障条件。

2.按合同书规定，对甲方核拨的经费实行专款专用，单独列账，并随时配合甲方进行监督检查。

3.使用财政资金采购设备、原材料等，按照《广东省实施〈中华人民共和国招标投标法〉办法》有关规定，符合招标条件的须进行招标。

4.项目实施完成或实施到一定程度，须按照《广东省省级科技计划项目结题管理的实施细则（试行）》提出验收或终止结题的申请，并按甲方要求做好项目结题工作。

5.在每年1月向甲方如实提交上年度工作情况报告，报告内容包含上年度项目进展情况、经费决算和取得的效果等。

6.按照国家和省有关规定，每年须提交年度科技报告；项目验收时，须提交验收科技报告。

第四条 在履行本合同的过程中，如出现广东省相关政策法规重大改变等不可抗力情况，甲方有权对所核拨经费的数量和时间进行相应调整。

第五条 在履行本合同过程中，需要对项目起止时间、项目经费使用（包括自筹经费、经费分配及经费支出预算等）、项目内容（包括研发内容、技术指标、经济指标及成果指标等）、项目名称、项目承担单位（包括承担单位更名、承担单位替换）、参与单位、项目负责人和成员等进行变更的，甲乙双方按照《广东省省级科技计划项目合同书管理的
实施细则（试行）》有关规定执行。

第六条 在履行本合同的过程中，当事人一方发现可能导致项目整体或部分失败的情形时，应及时通知另一方，并采取适当措施减少损失，没有及时通知并采取适当措施，致使损失扩大的，应当就扩大的损失承担责任。

第七条 本项目技术成果的归属、转让和实施技术成果所产生的经济利益的分享，除双方另有约定外，按国家和广东省有关法规执行。

2016A020212020

第八条 属技术保密的项目，甲乙双方应另行订立技术保密条款，作为本合同正式内容的一部分，与本合同具有同等效力。

第九条 根据项目具体情况，经双方另行协商订立的附加条款，作为本合同正式内容的一部分，与本合同具有同等效力。

第十条 本合同的争议应由双方本着协商一致的原则解决，如双方协商不成的，则应向甲方所在地法院提起诉讼。

第十一条 保密条款：

1.本合同保密内容范围为：

/

2.本合同保密期限为：

/

3.乙方应与可能知悉保密内容的人员签订技术秘密保护协议。

4.各方应建立技术秘密保护制度。

5.属技术保密的项目必须经省负责技术保密部门审查后，确定可否发表或用于国际合作和交流。

第十二条 甲方可根据具体情况决定乙方是否需要单位担保，若需要保证单位，应订立担保条款，作为本合同正式内容一部分。当乙方不履行或不完全履行本合同，以及没有或没有完全承担违约责任时，乙方的保证单位承担连带保证责任。

第十三条 本合同一式六份，各份具有同等效力。甲方存三份，乙方存二份，丙方存一份，本合同自签字之日起生效，有效期至项目结题后一年内。各方均应负合同的法律责任，不应受机构、人事变动的影响。

说明：本合同书中，凡是当事人约定无需填写的内容，应在空白处划（/）。

2016A020120

九、本合同签约各方

管理单位（甲方）：　广东省科学技术厅　（盖章）

单位地址：　广东省广州市连新路171号

法定代表人（或授权代表）：　黄宁生　（签章）

联系人（经办人）姓名：　叶毓峰　（签章）

Email：　yeyf@gdstc.gov.cn

电话：

2016 年 9 月 1 日

承担单位（乙方）：　华南农业大学　（盖章）

二级部门：　华南农业大学数学与信息（软件）学院

单位地址：　广东省广州市天河区五山路483号

法定代表人（或法人代理）：　陈晓阳　（签章）

联系人（项目主管）姓名：　石睿　（签章）

Email：　77909213@qq.com

电话：　020-85283435

开户单位名称：　华南农业大学

开户银行及帐号：　广东广州工行五山支行　3602002609000310520

2016 年 9 月 1 日

乙方主管部门（丙方）：　华南农业大学　（盖章）

单位地址：　广东省广州市天河区五山路483号

法定代表人（或法人代理）：　陈晓阳　（签章）

联系人（项目主管）姓名：　石睿　（签章）

Email：　77909213@qq.com

电话：　020-85283435

开户单位名称：　华南农业大学

开户银行及帐号：　广东广州工行五山支行　3602002609000310520

2016 年 9 月 1 日

华南农业大学 2018 年省级农村科技特派员项目

项目编号	姓 名	服务内容	服务地区
2018A0110	吴伟斌	丘陵山区林果茶园运输机械化技术示范和推广	平安村、绿水村、竹坑村
2018A0111	闫国琦	精准对接扶贫脱贫农渔业机械化科技成果推广与示范	孔美村、巴东村、五里村
2018A0112	罗明珠	稻田养鱼防控病虫害技术集成在紫金县的示范和推广应用	洋头村、礼坑村、璜光村
2018A0113	邹记兴	稻田养鱼之适宜鱼种的筛选与应用	水口村、鱼水村、五爱村
2018A0114	肖德琴	智能养蜂技术推广与应用	南星村、罗东村、西潭村
2018A0115	高用顺	畜禽废水在枇杷优良品种种植中的高效利用技术推广及应用	轮源村、隆岗村、新坡村
2018A0116	薛月菊	农产品溯源电子商务平台推广应用	浦兴村、黄塘村、明星村
2018A0117	王瑞龙	水稻与水生蔬菜间作技术集成在作物病虫害防控中的示范应用	坡平村、联川村、联北村
2018A0118	周胜	石斑鱼健康养殖技术示范推广	高螺村、田寮村、合港村
2018A0119	邢明	梅州金柚品牌提升及生态种植集成技术推广应用	园岭村、径口村、湾溪村
2018A0120	彭桂香	百香果健康种植施肥及病害防控技术	金溪村、黄洞村、金史村
2018A0121	徐铮	生猪规范养殖技术及良种推广示范	罗城村、轮源村、新坡村
2018A0122	曾山	水稻机械化高效种植技术集成与示范	火岗村、隔坑村、新圩村
2018A0123	曾志雄	果蔬采后保质贮运节能技术的应用推广	廖施村、崆峒村、三丰村
2018A0124	杨磊	粤东特色农产品种植技术服务及可溯源电子商务平台建设及运营规划	凹头村、龙江村、龙利村
2018A0125	谭志远	百香果种质培育与种植技术	隆兴村、下洞村、留潭村
2018A0126	向慧敏	鸭稻共作绿色稻米生产技术集成及其示范推广应用	斜周村、厚塘村、紫岭村
2018A0127	刘永柱	优质抗病超级稻新品种示范推广	高二村、光明村、黄河村

2018A0128	许细薇	畜禽粪便水热资源化处理及其在种植业的应用	新坡村、黄竹村、隆岗村
2018A0129	黄君	优质、广适型高端水果玉米示范与推广	群星村、合村、杜塘村
2018A0130	熊俊涛	现代化农业种植管理示范与农产品的电商平台建设	高二村、在上村、阳西村
2018A0131	沈万宽	黑皮果蔗提质增效关键技术集成推广	光明村、前锋村、陈村村
2018A0132	苗建银	油茶、花生等油料作物低温连续萃油技术研究及应用	龙江村、新民村、苏杨村
2018A0133	牟英辉	优质高产大豆品种华春 6 号与华夏 9 号及配套栽培技术的推广	白石村、联一村、由坪村
2018A0134	刘少群	单丛茶生态栽培，优质加工及品牌包装的技术服务	黄正村、中段村、五祉村
2018A0135	岑伊静	柑橘种植及以黄龙病为重点的病虫害综合防治技术示范推广	黄岗村、西南村、园岭村
2018A0136	邹湘军	互联网+全生命周期的绿色生态农产品管理及电商平台搭建	龙塘村、主固村、升平村
2018A0137	陈科伟	翁源县果蔬主要病虫害绿色防控技术应用示范	青山村、李洞村、联盟村
2018A0138	王叶元	高效优质的蚕桑生产技术推广与应用	沙寮村、鱼水村、和平村
2018A0139	何晓芳	良种桃树种植与病虫害防治技术研究示范	新八村、田心村、东陂村
2018A0140	田兴国	基于多光谱融合的竹笋及其制品在线质量监控应用于示范	赤米村、花田村、连樟村
2018A0141	杨文武	水稻种植合技术和适用农机装备的推广和应用	路外村、见龙村、京陇村
2018A0142	纪春艳	香蕉健康生产和病害绿色防控技术研究示范	三丰村、潮观村、良垌村
2018A0143	张林	华香 1 号和华香 2 号草莓品种种苗繁育和无公害栽培技术师范推广	柘陂村、东升村、枧岭村
2018A0144	李耀坤	肉牛优质高效生产关键技术示范推广	中埔村、新华村、璜光村
2018A0145	赵力超	基于现场分子检测的水产病害快速诊断技术	新风村、大沟村、崆峒村
2018A0146	王丽	基于精准分子检测的水产致病菌高通量快速诊断技术推广与应用	盘新村、凤来村、水口村
2018A0147	张光辉	农业产业化发展与农产品电商平台建设应用示范	横岗村、枧岭村、料洞村
2018A0148	杨秋妹	家畜养殖健康状况自动化监测	南星村、罗东村、石崇村

2018A0149	彭红星	互联网+农业绿色生态产品可追溯电商平台构建与应用	马催村、上洋村、彭村村
2018A0150	徐民俊	鱼鳖混养生态养殖技术	礼堂村、米贝村、新渡村
2018A0151	兰雅淇	基于低温连续相变设备的米糠高直化利用技术援助与示范	敬里村、塘社村、溪上村
2018A0152	赵会宏	河源市东源县贫困村水产养殖通识技术推广服务与特色养殖品种推介	小水村、群星村、鹊田村
2018A0153	连腾祥	高产优质黑大豆品种华春17号及膜侧施肥技术示范推广	联一村、白石村、由坪村
2018A0154	种云霄	粤东西北欠发达村镇水环境治理的低成本生态技术推广应用	轮源村、孔美村、天井岗村
2018A0155	朱勇文	广东夏季三黄鸡高效健康养殖技术的应用示范	樟村村、平安村、华南村
2018A0156	王林川	水禽优质安全健康养殖技术的应用示范	梅东村、海埕村、石河村
2018A0157	钟南	果树家禽生态循环种养优化规划，电商物流平台搭建	大南村、南星村、罗东村
2018A0158	骈瑞琪	油茶高效丰产栽培技术的研究与示范推广	大塘面村、茶坑村、宫前村
2018A0159	张庆	秸秆添加剂青贮技术推广应用	浮美村、向阳村、锡水村
2018A0160	刘天湖	轻便型竹制品和竹笋绿色生态食品野外初加工设备，技术与应用	东鹊村、连溪村、葸岭村
2018A0161	孙雄松	肥水一体化技术种植牧草饲养鱼和养肉牛（羊）	礼堂村、新渡村、亨渡村
2018A0162	奚如春	油茶标准示范园建设技术	礼堂村、浮美村、黄石村
2018A0163	李敏慧	香蕉枯萎病的防控	三丰村、潮观村、双凤村
2018A0164	何业华	三华李优良品种及配套栽培技术推广	钱新村、新洲村、陂蓬村
2018A0165	张轶婷	设施优质蔬菜高效生产技术服务	马山村、黄河村、阳西村
2018A0166	范兰芬	凡纳滨对虾高效节能精准养殖技术研究与开发	水口村、鱼水村、五爱村
2018A0167	吕辉雄	洪流村乡村旅游建设探索	洪流村、军船头村、沙坑村
2018A0168	邓铭	种养一体化家庭生态农场建设	方湖村、中埔村、璜光村
2018A0169	王红军	岭南特色水果生产机械化及绿色生态管理系统研究	龙塘村、主固村、升平村

2018A0170	罗哲辉	扶贫点区域化农业品牌设计技术应用示范	红花村、五祉村、乐岛村
2018A0171	石睿	优质茶叶栽培及客家炒茶加工技术的推广及应用	龙华村、罗山村、仓前村
2018A0172	程雄	蔬菜优质、高产、安全种植技术	天安村、洪山村、烧酒村
2018A0173	郁书君	绣球化在韶关地区的引种试验与产业化推广应用	安岗村、董联村、江头村
2018A0174	廖飞雄	特色乡土花卉的开发	高岗村、石门村、沈南村

广东省农业科技特派员项目

合 同 书

*项目名称：粤东特色农产品种植技术服务及可溯源电子商务平台建设及运营规划

*起止时间：2018 年 6 月 1 日至 2020 年 6 月 1 日

*二级单位：数学与信息学院

*项目负责人：杨磊 *联系电话：020-85280320-612 *手机：[redacted]

*电子邮箱：yanglei_s@scau.edu.cn

华南农业大学
二零一八年制

一、主要实施内容和项目目标

该项目的建设能够满足河源市东源县船塘镇凹头村砂糖桔、百香果等果树种植技术服务、电商及产品营销技术等需求；满足河源市东源县船塘镇龙江村板栗、水晶梨、油茶种植技术、电子商务平台搭建、物流与信息等技术需求；满足河源市东源县仙塘镇龙利村搭建电商平台的技术需求。

本项目拟建设的粤东特色农产品种植技术服务及可溯源电子商务平台主要包括特色农产品种植技术服务子平台和可溯源电子商务子平台，其中特色农产品种植技术服务子平台可以为贫困村提供农产品种植技术服务，农产品专家可以在线指导贫困村农民科学种植农产品，保障农产品种植的高效高产；特色农产品电子商务子平台集成安全溯源系统，可以促使贫困村所产特色农产品的销售渠道通畅，并保障消费者所购特色农产品质量安全，形成动态良性循环，帮助贫困村顺利脱贫。

本项目设计并开发一个粤东特色农产品种植技术服务平台，实现对贫困村农民、种植技术专家及相关管理部门提供特色农产品种植在线技术咨询服务支持。本项目设计并开发一个粤东特色农产品可溯源电子商务平台。拟开发的平台可以实现特色农产品的互联网上展示、在线下单、在线支付、溯源查询及在线咨询等功能。提供一套面向贫困村的区域农产品电子商务运营规划方案，初步完成贫困村特色农产品电子商务化，以贫困村本地特色农产品和粤东周边地区优质农产品相结合，整合农产品供应链，保障农产品的质量，建立特色农产品的优质品牌，使贫困村的特色农产品增加发力，体现更高的商业价值和社会价值，通过电子商务的运营，提升贫困村农民的收入，以产品质量保障农产品销售渠道通畅，从而形成良性循环，促使贫困村顺利脱贫，并保持可持续发展。

本项目拟完成的总目标为:

1.设计并研发粤东特色农产品种植技术服务及可溯源电子商务平台 1 套;

2.项目专家拟进村指导 1-2 次，开展 1-2 次培训，培训贫困户 80 人次以上，提供技术咨询/技术服务等 80 人次；帮助解决农产品电子商务等技术难题，形成项目研究报告 1 份。

（项目实施内容及目标以合同书为准，原则上不予调整。）

二、项目实施绩效

（选填，所填报内容作为项目中期检查和结题验收依据）

	一级指标	二级指标	三级指标	指标值
绩效指标	产出指标	数量指标	培训从事技术创新服务人员（人次）	
			培训和指导农业科技服务（人次）	80
			提供技术咨询/技术服务等（人次）	80
			开展创业辅导活动（场）	
		质量指标	科研仪器设备利用率（%）	
			技术帮扶贫困人数（人）	
			支持地方小微企业/机构/创新团队数	
	效益指标	经济效益指标	技术合同成交额（万元）	
			新增在孵企业（家）	
			培育高新技术企业（家）	
			促进科技投融资金额（万元）	
		社会效益指标	开放共享仪器设备数	
			科技成果转化数	
	满意度指标	服务对象满意度	被服务企业满意度（%）	
			被服务农民满意度（%）	100
其他说明（限300字）	完成平台原型1套；形成项目研究报告1份。			

三、项目进度和阶段目标

*起止时间	*主要工作内容
2018 年 06 月 - 2018 年 12 月	研究国内外最新参考文献和发展动态，到贫困村实地考察，充分调研，并进行问卷调查，统计粤东特色农产品种植技术服务及可溯源电子商务平台的特色农产品信息需求，抽象出粤东特色农产品种植技术服务及可溯源电子商务系统数据模型；联系特色农产品种植技术专家对特色农产品种植技术进行调研，召开项目小组会议，确定粤东特色农产品种植技术服务及可溯源电子商务平台的整体架构、确定项目所采用的技术线路及关键技术，完成项目整体解决方案的讨论及定稿；
2019 年 01 月 - 2019 年 06 月	完成粤东特色农产品种植技术服务及可溯源电子商务平台的需求分析及总体设计；完成粤东特色农产品种植技术服务子平台的总体设计；完成粤东特色农产品种植技术服务子平台及可溯源电商子平台的研发，对该粤东特色农产品种植技术服务及可溯源电子商务平台进行测试；完成平台原型 1 套；
2019 年 07 月 - 2019 年 12 月	完成粤东特色农产品种植技术服务及可溯源电子商务平台的测试，部署及在对接贫困村上线应用；为贫困村农民提供种植技术服务，完成农产品电商化及电商运营方案的试运行；
2020 年 01 月 - 2020 年 06 月	继续完成粤东特色农产品种植技术服务及可溯源电子商务平台的应用示范，完善农产品电子商务运营等工作；继续推广应用该粤东特色农产品种植技术服务及可溯源电子商务平台；完成项目报告 1 份，项目总结与验收。

四、经费情况表

经费预算：（单位：万元）		
支出经费	经费额	用途说明
（一）直接费用		
1、设备费	1	为建设贫困村农技服务及电商平台，需购置粤东特色农产品种植技术服务及电子商务平台高性能电子计算机 1-2 台，用以满足该平台在线运营的硬件需求。
2、材料费	0.8	用于购买平台培训材料打印所需的打印纸、光盘、存储设备等项目所需的消耗材料。
3、测试化验加工费		
4、差旅费/会议费	2.0	用于项目农产品种植技术及可溯源电子商务技术培训和推广应用的交通费用、住宿费、伙食补助费、长途电话费及其他各种杂费；用于项目日常会议、中期会议和结题及特色农产品种植技术培训和农产品电商平台运营培训等会务费、租用会议场所费用、会议资料费、交通费、茶水费、餐费、住宿费等。
5、出版/文献/信息传播/知识产权事务费	2.0	用于资料费、论文出版费、文献检索费、专业通信费、知识产权申请费及其他知识产权事务等费用。
6、劳务费	3.6	用于研究生及临聘人员在粤东特色农产品种植技术服务及可溯源电子商务平台设计、开发、测试、运维等过程的劳务费用及农产品种植技术和电子商务平台运营培训相关临聘人员的劳务费用等。
7、专家咨询费	0.6	用于项目建设过程及项目结题评审的专家咨询费用。
合计	10	

注：如需购买设备，须详细说明设备名称及金额，原则上不超过总经费的 40%；劳务费不超过总经费的 40%。本项目不扣管理费。经费不外拨，如有合作单位，采取报账制。

五、项目组人员情况

项目负责人									
序号	*姓名	*职称	*职务	*最高学位	*现从事专业	*所在单位	*身份证件号码	*在本项目中承担的工作任务	签名
1	杨磊	讲师	教研室副主任	博士	计算机科学与技术	数学与信息学院	410711197809240099	项目负责人，统筹整个项目的申报，执行与结题	
主要参与人员									
序号	*姓名	职称	职务	学位	现从事专业	*所在单位	*身份证件号码	在本项目中承担的工作任务	签名
1	李康顺	教授		博士	计算机科学与技术	数学与信息学院	362101196203110035	系统平台的整体规划，平台推广应用	
2	陈琰	副教授		博士	计算机科学与技术	数学与信息学院	642101197704260025	特色农产品种植技术专家在线咨询技术支持，协助进行电子商务技术培训	
3	杜治国	副教授		博士	计算机科学与技术	数学与信息学院	610422198012090518	特色农产品电商平台运营规划设计，协助平台推广	
4	吴理华	讲师	教研室副主任	博士	计算机科学与技术	数学与信息学院	362222197609243032	项目需求调研、制定粤东特色农产品电商化标准	
5	朱凯	讲师		硕士	计算机科学与技术	数学与信息学院	420302197908221217	平台需求分析与整体设计	
6	胡鑫	硕士生		学士	计算机科学与技术	数学与信息学院	500382199510174837	粤东特色农产品种植技术服务及可溯源电子商务平台研发与测试	

7	黄康	硕士生		学士	计算机科学与技术	数学与信息学院	430405199304281011	粤东特色农产品种植技术服务及可溯源电子商务平台研发与测试	

六、本合同签约各方

管理单位（甲方）：华南农业大学（盖章）

法定代表人（或法人代理）：陈晓阳（签章）

2018 年 8月31日

依托单位（乙方）：华南农业大学数学与信息学院（盖章）

单位负责人：（签章）

2018 年 8 月 31 日

联系人（项目负责人）姓名：（签名）

Email：yanglei_s@scau.edu.cn

电话：[redacted]

2018 年 8 月 31 日

项目编号： 20212100036

广州市农村科技特派员项目

合同书

项目名称： 基于数据挖掘的精准施肥决策系统的研发及推广应用

项目类别： 广州市农村科技特派员项目

特 派 员： 杨磊

承担单位： 华南农业大学

组织单位： 华南农业大学

责任处室： 农村和社会发展科技处

起止时间： 2021年09月01日 至 2023年08月31日

填表日期： 2021年07月29日

20212100036

广州市科学技术局制

（2021年版）

填 写 说 明

一、本合同书的项目编号由市科学技术局（以下简称市科技局）统一确定。

二、本合同书由申报书在后台自动转换生成，如有错漏之处需修正，请联系市科技局项目责任处室退回承担单位修正。

三、2021年市农村科技特派员项目经费实行“包干制”，承担单位建立健全相应的内部财务管理制度，实行项目经费决算内部公开。

四、本项目涉及两家单位参加，乙方应在签订本合同书前与合作单位就任务分工、经费和知识产权分配等问题签订有关合同或协议，作为本合同书的附件。

五、本合同书适用于广州市事前资助类科技计划项目，有特殊要求另行制定的除外。

202121000036

一、项目基本信息

项目名称	基于数据挖掘的精准施肥决策系统的研发及推广应用				
技术领域	科技服务				
承担单位	名　　称	华南农业大学			
	通信地址	广东省广州市天河区五山路483号			
	邮政编码	510642	传　　真	85281885	
	单位类型	高等院校			
	统一社会信用代码或组织机构代码	124400004554165634			
	法定代表人	刘雅红	电子邮箱	gale@scau.edu.cn	
	联系人	倪慧群	联系电话	02038632413	

服务单位	序号	名称	单位类型	联系人	联系电话	所属地区
	1	广州天适立农生态农业发展有限公司	其它	刘友梅	020-87879981	广东省广州市从化区

202121000036

二、特派员及团队成员信息

特派员	姓名	杨磊	证件类型	身份证	证件号码	410711197809240099	性别	男
	出生年月	1978-09-24	民族	汉族	国籍	中国	学历	博士研究生
	学位	博士	学位授予国家（或地区）	中国	职务	教研室副主任	职称	讲师(高校)
	所学专业	计算机科学与技术	手机号码	15918597385	办公电话	020-85280320	电子邮箱	yanglei_s@126.com

特派员团队成员（含特派员本人）

序号	姓名	证件类型	证件号码	年龄	性别	职务	职称	学历	现从事专业	分工	所在单位	签　名
1	杨磊	身份证	410711197809240099	42	男	教研室副主任	讲师(高校)	博士研究生	计算机科学与技术	项目负责人	华南农业大学	杨磊
2	李康顺	身份证	362101196203110035	59	男	教师	教授	博士研究生	计算机科学与技术	数据挖掘算法研究，系统整体架构设计	华南农业大学	
3	陈琰	身份证	642101197704260025	44	女	教师	副教授	博士研究生	计算机科学与技术	需求分析调研、系统概要设计	华南农业大学	陈琰
4	姚金涛	身份证	372822197806303836	42	男	教师	副教授	博士研究生	测土配方技术、农业电气化与自动化	精准施肥技术研究、建模与优化	华南农业大学	

20212100096

5	吴理华	身份证	362222197609243032	44	男	教师	讲师(高校)	博士研究生	精准施肥、农业信息化	精准施肥智能决策技术研究、系统开发	华南农业大学	吴理华
6	彭利民	身份证	350211197608060055	44	男	教师	副教授	博士研究生	生态肥料建模、计算机科学与技术	数据库设计，数据挖掘算法分析，土壤养分建模	华南农业大学	
7	朱凯	身份证	420302197908221217	41	男	教师	讲师(高校)	硕士研究生	计算机科学与技术	系统需求分析、详细设计，编码与测试	华南农业大学	
8	司国东	身份证	220104197610103116	44	男	教师	副教授	硕士研究生	土壤养分研究、计算机科学与技术	系统设计与研发，系统测试与部署	华南农业大学	司国东
9	梁淑敏	身份证	142601199708164020	23	女	硕士研究生	未取得	本科	计算机科学与技术	精准施肥决策系统设计与研发	华南农业大学	梁淑敏
10	祝彬杰	身份证	440902199710220011	23	男	硕士研究生	未取得	本科	计算机科学与技术	智能决策系统建模及优化，系统研发	华南农业大学	祝彬杰
11	宛敏洋	身份证	342622198908174375	31	男	硕士研究生	未取得	本科	计算机科学与技术	系统研发，辅助项目成果推广应用	华南农业大学	宛敏洋

20210100086

			445122199			硕士研究			计算机科	系统设计与研发、	华南农业	徐泽金

12	徐泽鑫	身份证	445122199805024714	23	男	硕士研究生	未取得	本科	计算机科学与技术	系统设计与研发、测试与部署	华南农业大学	徐泽鑫

20212100036

三、实施内容及工作进度安排

1.需要实施的技术和内容

本项目主要设计并研发基于数据挖掘的精准施肥决策系统，测试部署上线后，对该系统进行推广及应用。项目拟采集土壤采样点养分信息与田间试验数据，基于数据挖掘技术建立主流作物的精准施肥模型，动态监控土壤环境，提供合理施肥方案，实现精准施肥，土壤及肥料数据可以进行处理和挖掘，采用数据挖掘方法，建立数据模型，数据挖掘的结果用于远程控制，用于智能决策及生产预警等。

2.项目实施进度安排

序号	开始日期	结束日期	主要工作内容
1	2021-09-01	2022-02-28	成立项目领导小组，召开项目启动会议，明确项目工作内容和目标，项目前期调研，针对广州天适立农生态农业发展有限公司(从化区)的技术需求、实地考察，对该公司目前的微生物肥料的生产、销售及使用情况进行调研，并开展基于数据挖掘的精准施肥决策系统的需求分析，形成可行性分析报告，同时明确该系统建设的具体内容和形式；
2	2022-03-01	2022-08-31	接着进入技术分析与方案制定阶段，完成系统架构总体设计，项目关键技术的研究和攻关，主要包括：深入调研基于数据挖掘的精准施肥当前发展现状，进行系统总体设计，开展技术实施可行性分析，确定开展技术研发方式；通过数据库设计、系统总体设计和技术分析，制定基于数据挖掘技术的精准施肥决策支持系统的设计，研究测土配方及土壤环境模型的构建及智能算法的分布式技术体系，明确各个技术环节的实施方案，制定具体的实施任务；
3	2022-09-01	2023-02-28	基于数据挖掘的精准施肥决策系统研究与开发应用，进行该系统的功能和性能测试，以及联调，完善系统的各项功能指标。具体如下：拟采用基于数据挖掘的JAVA 编程技术和ORACLE 数据库结合Web service 技术开展精准施肥关键技术的研究与基于数据挖掘的精准施肥决策系统的开发，对技术成果进行集成，形成可以稳定运行的基于数据挖掘的精准施肥决策系统，实现研发目标；
4	2023-03-01	2023-08-31	建立基于数据挖掘的精准施肥决策系统示范基地，部署该系统的基地运营环境，搭建运营平台进行系统试运行，具体如下：在技术需求方及其基地等微生物肥料应用真实环境中应用本系统，验证该基于数据挖掘的精准施肥决策系统的有效性与稳定性，收集并分析精准施肥过程中出现的问题，寻找更优化的解决方案。最后进行项目的推广和组织示范应用，准备总结验收相关材料，组织项目验收。

注： 以半年为单位填报

四、特派员工作目标及验收指标

1. 工作目标

拟完成的总目标为：
1.设计并研发基于数据挖掘的精准施肥决策系统1套；
2.提供基于数据挖掘的精准施肥决策系统使用说明1套，并协助技术需求方运营该平台；
3.形成有自主知识产权的软著或专利1-2项；
4.建立基于数据挖掘的精准施肥决策系统示范基地1个；
5.培养本土农业信息化科技人才3-5名；
6.完成项目研究报告1份。

2. 验收指标

序号	成果形式		数量
1	技术培训	次	1
		人	20
2	技术服务	次	1
3	宣传报道	次	0
4	推广新品种	个	0
5	推广新技术	项	0
6	推广新设备	个	0
7	建立示范基地	个	1

其他成果及形式说明：

无

20212100036

3. 主要经济指标及社会效益

序号	指标名称	指标值
1	实施期内项目销售收入（万元）	0.00
2	实施期内项目利税（万元）	0.00
3	实施期内项目出口创汇（万美元）	0.00
4	实施期内项目新增就业人数（人）	0.00

其他经济指标及社会效益说明：

无

202121000036

五、项目经费

本项目经费¥ 10.00万元，实行“包干制”。

20212100036

六、共同条款

第一条　甲、乙、丙三方根据《中华人民共和国科学技术进步法》《广东省自主创新促进条例》《广州市科技创新促进条例》及《中华人民共和国民法典》等国家有关法规和规定，经协商一致，特订立本合同，作为甲、乙、丙三方在合同执行中共同遵守的依据。

第二条　甲、乙、丙三方应当严格履行《广州市科技计划项目管理办法》《广州市级财政科研项目资金绩效提升和管理监督办法》《广州市科技创新发展专项资金管理办法》的规定要求。

第三条　甲方应：

1.在项目执行期满时按相关管理办法组织项目验收；

2.根据财政经费预算安排，及时拨付项目经费。

第四条　乙方应：

1.为本单位提供的与本项目有关的全部材料真实、合法、有效性负责，同意甲方向行业协会等第三方机构直接调取乙方与本项目相关的数据、信息、材料，包括但不限于工商登记信息、审计报告等；

2.按照《合同书》规定的内容组织实施项目，接受并配合甲方、丙方以及各级财政、审计部门，或上述部门委托的机构进行评估、稽查、审计、检查和绩效评价，并按要求提供项目任务与预算执行情况和有关财务资料；

3.按照科技经费管理相关要求对项目经费单独设账，专款专用；

4.保证自筹资金按时到位和其它配套条件的落实；

5.在项目研究开发过程中优先考虑使用“广东省科技资源共享服务平台”的仪器设备，项目购置的设备仪器若符合入网条件应及时办理入网手续对社会共用共享，提高设备仪器的使用率。按照《中华人民共和国采购法》要求，对符合政府采购范围的设备仪器，执行政府采购；

6.项目合同执行期内需进行变更的，按照《广州市科技计划项目管理办法》《广州市级财政科研项目资金绩效提升和管理监督办法》《广州市科技创新发展专项资金管理办法》相关程序办理；

7.项目合同执行期满后3个月内向甲方提出验收申请，提前完成合同规定任务的可提前申请验收；

8.按照相关规定，在项目验收时提交科技报告，办理《验收证书》和科技成果登记手续；

9.配合甲方开展对财政资金绩效的跟踪，在项目实施期内及实施期结束后按照甲方要求提供相关信息和数据；

10.对合作单位承担监管责任，与合作单位签署合作协议，作为本合同的附件，因合作单位违反合作协议或其他导致本合同书项目建设未能按约定完成的行为，应向甲方承担违约责任。

第五条　丙方应：

1.协助甲方对项目的实施过程进行跟踪、检查和提供相关信息，并对所提供信息的客观真实性负责；

2.负责监管乙方严格遵守《合同书》规定的任务；

3.督促乙方按时到位自筹资金并保证和落实其他配套条件。

第六条　甲方同意给予乙方人民币（¥10.00万）元的资助，立项后一次性拨付；

第七条　合同终止：

1.项目因故无法继续进行的，按照相关规定实施合同终止。

2.发现存在以下情况之一的，立即启动终止程序：

①因不可抗拒因素导致项目无法继续进行、没有必要继续进行或无法完成合同预期目标任务的；

②不接受项目监督检查、检查不合格限期整改后仍未通过的或拒不配合项目验收工作的；

③无正当理由项目合同执行期满后3个月以后仍未提交验收申请的；

④项目承担单位已迁出本市，或已停止经营活动，或已注销的；

⑤发现在项目申报、实施过程中有违法、欺骗等事实的；

⑥存在其他导致项目不能正常实施的原因。

3.合同终止由乙方或丙方提出申请，也可由甲方强制实施。乙方提出合同终止，应先经丙方同意。

4.合同终止后，乙方应停止使用该项目财政经费；上缴尚未使用和使用不符合规定的财政经费。

第八条 对合同正常执行期及项目整改期之外的经费开支，不属于财政项目经费列支范围。

第九条 在履行本合同的过程中，乙方发现可能导致项目失败或部分失败的情形时，应及时通知甲方和丙方，并采取适当措施减少损失，没有及时通知并采取适当措施，致使损失扩大的，应当就扩大的损失承担责任。

第十条 在履行本合同的过程中，如遇到市财政计划改变等不可抗力情况，甲方对所核拔经费的数量和时间可进行相应变更。

第十一条 成果转化：

1.本项目技术成果及知识产权的归属、转让和实施技术成果所产生的经济利益的分享，除另有约定外，按国家和省、市有关规定执行；正式发表的论文、论著应标注“广州市科技计划项目资助”字样及项目编号；项目所取得的技术成果和知识产权应优先广州产业化或推广转让。

第十二条 属技术保密的项目，经协商订立如下技术保密条款：

1.本合同书保密内容范围为：本合同及其补充协议和附件、乙方因履行本合同所接触或知晓的甲方工作秘密（包括但不限于甲方的任何技术性资料、以及甲方为完成本合同提供的任何其他信息资料并且在提供时未说明是公开信息的）；

2.本合同书保密期限为 ：\；

3.乙方（包括但不限于乙方雇员、代理人、顾问等人员，下同）采取有效的保密措施以避免泄露给任何第三方；在本合同有效存续期间及合同终止后，未经甲方事先的书面同意，不得以任何方式公布、发表、公开、披露、散播、复制此种保密信息的任何部分，或对其加以任何形式的利用或使用；如甲方要求，乙方必须签署甲方提供的保密协议。乙方应与可能知悉保密内容的人员签订技术保密保护协议，保密义务不得低于本合同书的约定；

4.双方应建立技术保密制度；

5.属技术保密的项目必须经市负责技术保密部门审查后，方可确定可否发表或用于国际合作与交流。

第十三条 廉洁责任

甲方、丙方、评审机构及其工作人员不得索取、收受利益相关方财物或其他不正当利益，严格遵守中央八项规定精神及其实施细则。

乙方应严格遵守国家、省、市关于科技专项经费使用的有关法律、法规，相关政策以及廉洁建设的各项规定，积极开展人员廉洁从业教育，防范科技项目组成员在科研活动中出现出现“法律、行政法规、部门规章或规范性文件规定的其他相关违规行为。

第十四条 科研诚信和科技伦理要求

乙方应建立健全促进科研诚信和科技伦理的规章制度，落实以下职责：

1.建立健全本单位学术论文发表诚信承诺制度、科研过程可追溯制度、科研成果检查和报告制度等成果管理制度。对本项目形成的科研成果的署名、研究数据真实性、实验可重复性等进行诚信审核和学术把关。防范科技项目组成员在项目申报、研发过程中提供虚假信息或材料，抄袭、剽窃他人科研成果，捏造、变造或篡改科研数据；

2.加强对科技项目参加人员的科研诚信和科技伦理教育，督促科技项目组成员恪守科学道德准则，遵守科研活动规范。对在科研诚信和科技伦理方面存在问题情节较严重的，应及时调整出项目团队并及时以书面形式报告甲方；

3.加强对项目合作单位的科研诚信管理,正确履行管理、指导、监督职责,全面落实科研诚信和科技伦理要求；

4.乙方或项目合作单位及其相关人员被纳入科研严重失信行为记录或相关社会领域信用“黑名单”， 乙方应及时以书面形式报告甲方；

5.其他；\

在项目实施过程中,对乙方或项目合作单位及其相关人员有严重违背科研诚信和科技伦理要求的行为,甲方和相关部门可对乙方采取约谈主要负责人、停拨或核减经费、记入科研诚信严重失信行为数据库、将不良行为向社会公开、移送至有管理权限的纪检监察部门等处理处罚措施。

第十五条 争议解决

因本合同书所产生的争议，各方应友好协商解决；协商不成的，各方同意由本合同签订地人民法院管辖。

第十六条 书面通知与送达

甲方在本合同履行过程中向乙方或丙方发出或者提供的所有书面通知、文件、文书、资料等，均以本合同所列明的乙方或丙方地址送达。乙方或丙方如果迁址，应当书面通知甲方；未履行书面通知义务的，甲方按原地址邮寄相关材料即视为已履行送达义务。

第十七条 其他

\

本合同一式四份，各份具有同等效力。甲方和丙方各存一份，乙方存二份。本合同签订各方均负有相应的法律责任，不受机构、人事变动而影响。

说明：本《合同书》中，凡是三方约定无需填写的条款，在该条款的空白处划（\）。

20212100036

七、合同书各方签章

签订地点：广州市越秀区

广州市科学技术局（甲方）：

项目经办人（签章）：

责任处室负责人（签章）：

联系电话：

（公　章）

年　月　日

项目承担单位（乙方）：华南农业大学

二级部门：华南农业大学数学与信息学院

项目负责人（签章）：

项目经费汇入账号：

账户名：华南农业大学　　账号：3602002609000310520

开户银行：广东广州工行五山支行

财务负责人（签章）：　　财务负责人联系电话：02085287402

法定代表人（签章）：

（公　章）

2021年 8 月 10 日

组织单位（丙方）：华南农业大学

项目经办人（签章）：

（公　章）

2021年 8 月 10 日

承诺书

本单位/本人作为广州市农村科技特派员项目负责人，将严格遵守广州市科技计划管理相关规定，严格履行自身责任，加强对项目组人员及合作单位的管理，在此郑重承诺：

（一）确保与本项目有关的全部材料真实、合法、有效，未侵犯其他方知识产权等权利；

（二）严格遵守《广州市科技计划项目管理办法》《广州市级财政科研项目资金绩效提升和管理监督办法》《广州市科技创新发展专项资金管理办法》相关规定，实施项目和经费管理。

（三）严格遵守国家、省、市关于科研诚信和科技伦理的有关法律、法规，相关政策以及各项规定，加强项目实施过程中的科研诚信及科技伦理管理，恪守科研道德准则。

（四）_____

_____

如有违反，本单位/本人愿意接受相关部门做出的各项处理决定，包括但不限于终止项目，停拨或核减经费，追回项目经费，取消一定期限广州市科技计划项目申报资格，记入科研诚信严重失信行为数据库，将不良行为向社会公开以及主要责任人接受相应党纪政纪处理等。

项目承担单位签章：

日期：2021.8.10

项目负责人签章：

日期：2021.8.10

国家级星火计划项目证书

批准文号：国科发资〔2015〕436号

项目名称：基于智能挖掘算法的畜禽疫病动态分析与远程诊断系统

项目编号：2015GA780062

承担单位：华南农业大学

项目负责人：杨磊

科学技术部星火计划办公室

二〇一五年十二月二十八日

1871436

国家级星火计划项目证书

批准文号：国科发计〔2013〕571号

项目名称：动植物医院安全药物配送与监管信息网络平台的开发应用

项目编号：2013GA780044

承担单位：华南农业大学

项目负责人：杨磊

科学技术部星火计划办公室

二〇一三年十月十八日

受理编号：230919167974762

项目编号：SDZX2023032

文件编号：阳科通【2023】39号

省科技创新专项资金（“大专项+任务清单”）项目

任务书

项目名称：	基于区块链技术的稻米溯源云平台的研发与应用示范（技术研发类）		
计划类别：	专题六：支持乡村振兴科技创新和绿色发展项目		
项目起止时间：	2023-01-01 至 2025-06-30		
管理单位（甲方）：	阳江市科学技术局		
承担单位（乙方）：	阳江市漠阳香农业发展有限公司		
通讯地址：	阳江市阳东区红丰镇潮观村委会瓜地咀村（住所申报）		
邮政编码：	529800	单位电话：	0662-6280672
项目负责人：	杨磊	联系电话：	0662-6280672
项目联系人：	何水莲	联系电话：	0662-6280672

SDZX2023032

阳江市科学技术局

二零二三年

一、研发内容和关键技术

1.主要研究内容：
(1) 研发一套基于信任值的关键区块溯源技术。拟开发的系统对稻米溯源数据存储环境安全性较高，因此选用扩展性强、去中心化程度较高的Pos共识机制，引入信任值属性，同时拟设计相应的信任奖惩机制以限制恶意节点出现的概率，从而进一步提高稻米溯源数据存储的安全性和区块链网络中各节点在参与信息共享过程中的公平性。
(2) 设计并构建一个稻米溯源的云平台系统，并与基于信任值的关键区块溯源技术无缝集成。分析构建稻米供应链溯源的标准过程方案，贯穿水稻农作物的种植、运输、存储和销售等环节，分析与质量相关的关键业务过程中稻米质量特征以及特征之间的内在联系。拟开发的平台利用基于信任值的关键区块溯源系统，采用二维码追溯技术，实现一物一码防伪溯源。
(3) 完成基于区块链技术的稻米溯源云平台系统的示范应用。将基于区块链技术的稻米溯源云平台系统在项目申报单位进行示范应用。
2.拟解决关键性问题：
(1) 稻米溯源数据采集规范的制定及数据的采集；
(2) 阳江市稻米可溯源云平台的设计与开发；
(3) 融合区块链技术、智能合约技术等新的商务模式于该电商平台。
3.技术路线：
根据阳江市专业合作社稻米产品电商需求，按照软件系统设计的原则和开放性设计的思想来进行设计和实现，主要分为：云平台系统需求分析，技术分析，方案确定，软件系统研发，应用示范，反馈优化，验收结题等几个阶段。项目拟采用基于Web Serive编程技术、区块链技术结合智能合约技术完成该平台的设计与开发，Web Serive技术实现功能模块的设计与研发，区块链技术实现可溯源移动电子商务平台数据及溯源数据的存储，并利用智能合约技术实现简单请求到复杂响应的平台协同功能。
4.创新点：
(1)研究一种基于信任值的关键区块溯源技术，在原有区块链共识机制中引入信任值属性和相应的奖惩机制，进一步提高稻米溯源数据存储的安全性和区块链网络中各节点在参与信息共享过程中的公平性。
(2)建立一个覆盖稻米食品生产、加工、流通、检测、销售等各个阶段追溯信息的分类与编码标准体系，统一追溯编码标准，实现一物一码防伪溯源，并统一追溯规范，保证追溯链条的完整性和兼容性。
(3)研究一种基于演化算法的二维码的生成技术，以保证稻米追溯码的保密性、安全性以及追溯码的不可重构性。
(4)提出一种基于信息系统的分析方法构建信息记录标准库，完善标准化的信息记录。

SDZX2022032

二、项目考核指标

<table>
<tr><td colspan="6">（一）项目完成后提供的研究开发成果及形式（须明确产品、专利、版权、标准等成果的类型及数量）</td></tr>
<tr><td colspan="2">成果形式</td><td>成果数量</td><td colspan="2">成果形式</td><td>成果数量</td></tr>
<tr><td rowspan="2">发明专利</td><td>申请</td><td>0</td><td colspan="2">引进人才(人)</td><td>0</td></tr>
<tr><td>授权</td><td>0</td><td colspan="2">培养人才(人)</td><td>0</td></tr>
<tr><td rowspan="2">实用新型专利</td><td>申请</td><td>0</td><td colspan="2">科技人才奖励(人)</td><td>0</td></tr>
<tr><td>授权</td><td>0</td><td rowspan="2">技术标准制定</td><td>牵头(个)</td><td>0</td></tr>
<tr><td rowspan="2">外观设计专利</td><td>申请</td><td>0</td><td>参与(个)</td><td>0</td></tr>
<tr><td>授权</td><td>0</td><td colspan="2">科技报告(篇)</td><td>0</td></tr>
<tr><td rowspan="2">国外专利</td><td>PCT受理</td><td>0</td><td colspan="2">软件著作权(项)</td><td>2</td></tr>
<tr><td>授权</td><td>0</td><td colspan="2">论文论著(篇)</td><td>1</td></tr>
<tr><td colspan="2">获国家级奖项(项)</td><td>0</td><td rowspan="3">其中：被收录论文数(篇)</td><td>SCI</td><td>0</td></tr>
<tr><td colspan="2">获省家级奖项(项)</td><td>0</td><td>EI</td><td>1</td></tr>
<tr><td colspan="2">新服务(项)</td><td>0</td><td>ISTP</td><td>0</td></tr>
<tr><td colspan="2">新产品(或新材料、新装备、新品种(系))</td><td>1</td><td colspan="2">新工艺(或新方法、新模式、新技术)</td><td>0</td></tr>
<tr><td colspan="2" rowspan="2">服务企业数量(家)</td><td colspan="3">技术服务数量(项)</td><td>0</td></tr>
<tr><td colspan="3">服务企业数量(家)</td><td>0</td></tr>
<tr><td colspan="2" rowspan="4">科技金融项目必填</td><td colspan="3">开展培训宣讲活动场次(次)</td><td>0</td></tr>
<tr><td colspan="3">服务企业数量(家)</td><td>0</td></tr>
<tr><td colspan="3">帮助企业融资(万元)</td><td>0</td></tr>
<tr><td colspan="3">引进专业机构(家)</td><td>0</td></tr>
<tr><td colspan="2" rowspan="4">院士工作站项目必填</td><td colspan="3">引进院士及其团队科技成果转化数量</td><td>0</td></tr>
<tr><td colspan="3">院士开展的战略咨询和技术指导次数</td><td>0</td></tr>
<tr><td colspan="3">院士年进站次数</td><td>0</td></tr>
<tr><td colspan="3">院士及院士团队年进站时间</td><td></td></tr>
<tr><td colspan="2" rowspan="4">软科学项目必填</td><td colspan="3">决策咨询报告(篇)(至少1篇)</td><td>0</td></tr>
<tr><td colspan="3">研究总报告(篇)</td><td>0</td></tr>
<tr><td colspan="3">研究中期报告(篇)</td><td>0</td></tr>
<tr><td colspan="3">研究分报告(篇)</td><td>0</td></tr>
<tr><td colspan="2"></td><td colspan="3"></td><td></td></tr>
</table>

SDZK2025032

	调研报告(篇)	0
	专著(篇)	0
	培养人才(人)	0
	获国家级奖项(项)	0
	获省级奖项(项)	0
	其他	0

其他成果及形式说明：

向企业（合作社）推广基于区块链技术的稻米追溯云平台1个，对阳江市稻米种植及加工产业的发展具有较好的带动示范作用。

（二）主要技术经济指标及社会效益

累计新增销售收入(万元)	150
累计新增利税(万元)	15

其他主要技术经济指标及社会效益说明：

（1）进一步增强农民专业合作社的电子商务的应用能力，大大提高工作质量和效率，为农业信息的发布和获取提供更便利的途径，缩窄信息鸿沟，缩小城乡差距、推动农村发展。
（2）加快农村信息化进程，引导农业结构调整、提高农业现代化水平、提升我国农产品的国际市场竞争力、促进农民增收和推进农村改革与发展。
（3）整合各类农业信息资源，减少农业信息的发布和获取的时间成本、资金成本，提高农民专业合作社移动电子商务应用的深度和广度，为农民专业合作社提供全面、权威、及时的各类资讯，为合作社特色品牌宣传、招商引资创造有利条件。
（4）推动农业产业改革与发展，加快农业信息化、管理系统化的进程。

项目负责人（签章）：　　年　　月　　日

SDZX2021-03

三、项目进度和阶段目标

开始日期-结束日期	主要工作内容(限500字)
2023-01-01至2023-04-30	成立项目领导小组，召开项目启动会议，明确项目工作内容和目标，项目前期调研，实施方案编制。
2023-05-01至2023-12-31	完成稻米追溯数据标准、食品安全追溯规范研究，以及基于区块链技术的稻米溯源系统需求分析、总体设计，项目关键技术研究和攻关，区块链技术的选取和改进。
2024-01-01至2024-06-30	完成基于信任值的关键区块溯源技术的开发工作，溯源系统前端数据采集标准化接口的研发，稻米生产过程监控与追溯技术研发，及生产过程数据采集设备的研制。
2024-07-01至2024-11-30	完成稻米追溯云平台的搭建，并与基于信任值的关键区块溯源技术集成，完成云平台部署。
2024-12-01至2024-12-31	完成基于区块链技术的稻米追溯云平台的测试。
2025-01-01至2025-06-30	完成云平台的应用示范及推广，项目总结及验收。

SDZX2023032

四、项目经费情况

(一)市财政科技资金投入总额:(大写)	壹拾伍万圆整	;(小写):	15.00	万元		
(二)市科技局经费年度下达计划:(此为正常情况下预计拨付计划，中期评估或验收结题不通过的，甲 方有权停止或核减拨付后续资金)						
分期			经费(万元)			
(三)总经费及财政科技资金投入情况:						(单位：万元)
项目总经费投入	市级财政科技资金	自筹经费				合计
		自有资金	贷款	地方政府投入	其它	
	15.00	15	0	0	0	30.00
自筹资金投入情况说明：						
企业自筹资金15万元用于：业务费3万元（测试化验加工（系统技术开发）3万元），项目组成员劳务费11万元（企业项目人员人工费用11万元），间接费用1万元。						
是否为数学等纯理论基础研究项目： 否						
项目经费预算：						(单位：万元)
	项目总经费		市级财政科技资金			
支出经费	经费额	用途说明	经费额	用途说明		
1、直接费用	29.00	/	15.00	/		
(1)设备费	0	/	0	/		
(2)业务费	13	系统检测费、文献及出版费、知识产权申请费、差旅费、测试化验加工、材料费、技术咨询费	10	系统检测费、差旅费、文献及出版费、知识产权申请费、材料费、技术咨询费		
(3)直接人力资源成本	16	企业项目组人员人工费	5	企业项目组人员人工费		
2、间接费用	1.00	/	0.00	/		
(1)绩效支出	0	/	0	/		
(2)管理费用	1	项目管理相关费用	0	/		
(3)其他间接费用	0	/	0	/		
合计	30.00		15.00			
其他需说明的情况：						

SDZX2023032

财政补助资金15万元用于：业务费10元（企业知识产权申请费1万元，企业系统检测费1万元，企业差旅费2万元，华南农业大学产学研经费4.5万元（软著申请费及文献出版费1.5万元、材料费1.2万元、参与项目研究生人工费1.8万元）、新智农公司技术咨询费1.5万元），直接人力成本费用5万元（企业项目人员人工费用5万元。

SDZX2023032

单价50万元以上购置/试制设备预算明细表

序号	设备名称	单价(万元)	数量	金额(万元)
1				

单价50万元以上购置设备合计 数量：		金额	
单价50万元以上试制设备合计 数量：		金额	

填表说明：

1.设备分类：购置、试制；

2.设备购置类型：通用、专用；

3.试制设备不需要填写本表“购置设备类型”、“主要生产厂家及国别”、“规格型号”、“拟开放共享范围”列；

4.设备单价的单位为万元/台套，设备数量的单位为台套；

5.50万元及50万元以下的设备不用填写明细；

6.本表只填写市级财政专项资金购置（试制）的设备。

SDZX2023032

五、承担、参与单位工作分工及经费分配情况

承担/参与单位名称（盖章）	工作分工	总经费分摊(万元)	市级财政科技资金分配(万元)
阳江市漠阳香农业发展有限公司	负责系统业务需求分析、示范应用和带动合作社发展、推广，项目申报、管理和验收等工作。	24	9
项目参与单位信息			
单位名称	工作分工	总经费分摊(万元)	市科技局经费分配（万元）
华南农业大学	负责系统架构分析、总体及详细设计、系统研发，协助项目申报和验收。	4.5	4.5
广东新智农信息科技有限公司	负责项目系统平台的需求调研、进行部分技术研发、系统部署和运维，项目推广培训和技术服务，协助项目申报和验收。	1.5	1.5

SDZX2023032

六、人员信息

项目负责人：								
姓名	性别	年龄	职务	职称	学历	在项目中承担的任务	所在单位	签名
杨磊	男	45	教研室副主任	中级,讲师	博士研究生	项目总负责人，负责项目总体设计，规划，申报，项目执行。	华南农业大学	
黄伯初	男	45	总经理	未取得	其他	企业技术负责人，负责项目示范推广及落地	阳江市漠阳香农业发展有限公司	
主要研究开发人员：								
姓名	性别	年龄	职务	职称	学历	在项目中承担的任务	所在单位	签名
刘晓君	女	42	项目总监	助理研究员	本科	示范推广培训和技术服务	广东新智农信息科技有限公司	
何水莲	女	42	副总经理	未取得	其他	项目需求分析、项目实施、示范推广	阳江市漠阳香农业发展有限公司	
孙玉光	男	40	市场总监	未取得	本科	项目需求分析、项目执行、示范推广	阳江市漠阳香农业发展有限公司	
李康顺	男	61	实验室主任	教授	博士研究生	项目架构设计、区块链技术研究、项目测试	华南农业大学	
彭利民	男	47	教师	副教授	博士研究生	项目需求分析，总体设计，详细设计	华南农业大学	
吴理华	男	47	教师	讲师	博士研究生	项目编码及测试	华南农业大学	
徐瑞	男	24	技术工程师	未取得	本科	系统研发及测试	华南农业大学	
潘瑞群	女	33	项目经理	未取得	本科	示范推广培训和技术服务	广东新智农信息科技有限公司	

SDZX202303

谢顺娴	女	33	项目经理	未取得	本科	示范推广培训和技术服务	广东新农信科技有限公司智息	

SDZX2023032

七、承担、参与单位合作协议（须与申报书中合作协议或意向书相一致）

SDZX2023032

八、任务书条款

第一条　　甲方与乙方根据《中华人民共和国民法典》及国家有关法规和规定，为顺利完成（2023）年基于区块链技术的稻米溯源云平台的研发与应用示范（技术研发类）专项项目（项目编号：SDZX2023032）经协商一致，特订立本任务书，作为甲乙双方在项目实施管理过程中共同遵守的依据。
第二条　　甲方的权利义务：1.按任务书规定进行经费核拨的有关工作协调。2.根据甲方需要，在不影响乙方工作的前提下，定期或不定期对乙方项目的实施情况和经费使用情况进行检查或抽查。
第三条　　乙方的权利义务：1.确保落实自筹经费及有关保障条件。2.按任务书规定，对甲方核拨的经费实行专款专用，单独列账，并随时配合甲方进行监督检查。3.使用财政资金采购设备、原材料等，按照《广东省实施〈中华人民共和国招标投标法〉办法》有关规定，符合招标条件的须进行招标。4.项目实施完成或实施到一定程度，须按照《广东省省级科技计划项目结题管理的实施细则(试行)》，《阳江市科学技术局关于市科技计划项目验收结题管理的实施细则》提出验收或终止结题的申请，并按甲方要求做好项目结题工作。5.按规定向甲方报告项目工作情况，报告内容包含项目进展情况、经费决算和取得的效果等。6.按照国家、广东省和阳江市有关规定，提交科技报告及其他材料。
第四条　　在履行本任务书的过程中，如出现本地区相关政策法规重大改变等不可抗力情况，甲方有权对所核拨经费的数量和时间进行相应调整。
第五条　　在履行本任务书过程中，需要对项目起止时间、项目经费使用（包括自筹经费、经费分配及经费支出预算等）、项目内容（包括研发内容、技术指标、经济指标及成果指标等）、项目名称、项目承担单位（包括承担单位更名、承担单位替换）、参与单位、项目负责人和成员等进行变更的，具体按照《关于优化财政科研资金管理提升科研资金绩效的通知》（粤财教〔2018〕394号）、《省级科技计划项目任务书管理细则》（ 粤科规范字[2022] 8号）、《阳江市科学技术局关于市科技计划项目任务书管理的实施细则》（阳科通〔2022〕48号）等有关规定执行。其中，科研经费直接费用中所有科目费用调剂权全部下放给项目承担单位，项目承担单位应建立完善的内部管理制度，及时为科研人员办理调剂手续。
第六条　　在履行本任务书的过程中，当事人一方发现可能导致项目整体或部分失败的情形时，应及时通知另一方，并采取适当措施减少损失，没有及时通知并采取适当措施，致使损失扩大的，应当就扩大的损失承担责任。
第七条　　本项目技术成果的归属、转让和实施技术成果所产生的经济利益的分享，除双方另有约定外，按国家、广东省和阳江市有关法规执行。
第八条　　属技术保密的项目，甲乙双方应另行订立技术保密条款，作为本任务书正式内容的一部分，与本任务书具有同等效力。
第九条　　根据项目具体情况，经双方另行协商订立的附加条款，作为本任务书正式内容的一部分，与本任务书具有同等效力。
第十条　　本任务书的争议应由双方本着协商一致的原则解决，如双方协商不成的，则应向甲方所在地法院提起诉讼。
第十一条　　保密条款：
1.　本任务书保密内容范围为：/
2.　本任务书保密期限为：：/
3.乙方应与可能知悉保密内容的人员签订技术秘密保护协议。
4.各方应建立技术秘密保护制度。
5.属技术保密的项目必须经省负责技术保密部门审查后，确定可否发表或用于国际合作和交流。
第十二条　　甲方可根据具体情况决定乙方是否需要单位担保，若需要保证单位，应订立担保条款，作为本任务书正式内容一部分。当乙方不履行或不完全履行本任务书，以及没有或没有完全承担违约责任时，乙方的保证单位承担连带保证责任。
第十三条　　本任务书一式五份，各份具有同等效力。甲方存两份，乙方存三份，本任务书自签字之日起生效，有效期至项目结题后一年内。各方均应负任务书的法律责任，不应受机构、人事变动的影响。
说明：本任务书中，凡是当事人约定无需填写的内容，应在空白处划（/）。

SDZX2023032

九、本任务书签约各方

阳江市科学技术局	（盖章）
单位地址： 广东省阳江市江城区安宁路38号 法定代表人（或授权代表）： 莫家强 （盖章） 联系人（经办人）姓名： 黄君 （盖章） E-mail: 6973756@qq.com 电话: 13926342444 年 月 日	
阳江市漠阳香农业发展有限公司	（盖章，单位法人章或单位法人授权章）
单位地址： 阳江市阳东区红丰镇潮观村委会瓜地咀村（住所申报） 法定代表人（或法人代理）： 黄伯初 （盖章） 联系人（项目主管）姓名： 何水莲 （盖章） E-mail: 597136202@qq.com 电话： 0662-6280672 开户单位名称： 阳江市漠阳香农业发展有限公司 开户银行: 中国农业银行 开户帐号： 44546901040004178 年 月 日	

SDZX2023032

结项证书

项目类别：全国教育科学规划 国家一般 项目（BKA180233）

项目名称：乡村振兴背景下新型职业农民培育云平台研究

负 责 人：潘军　　证书号：38648

主要参加人：杨磊、陈然、雷丽珍、张程、肖春承、黄文勇、柯雅莉、李国豪

此项目经审核准予结项，鉴定等级（**合格**），特发此证。

全国教育科学规划领导小组办公室

2024 年 4 月 16 日

项目批准号	61703170
申请代码	F030507
归口管理部门	
依托单位代码	51064208A0499-0932



国家自然科学基金委员会

资助项目计划书

资助类别：青年科学基金项目

亚类说明：

附注说明：

项目名称：基于世代距离的高维多目标并行进化算法研究及其应用

直接费用：25万元　　执行年限：2018.01-2020.12

负 责 人：陈琰

通讯地址：广东省广州市天河区五山路483号华南农业大学信息学院615室

邮政编码：510642　　电　　话：020-85280320

电子邮件：cheny@scau.edu.cn

依托单位：华南农业大学

联 系 人：全锋　　电　　话：020-85280070

填表日期：2017年08月29日

国家自然科学基金委员会制

Version：1.003.409

项目组主要成员

编号	姓名	出生年月	性别	职称	学位	单位名称	电话	证件号码	项目分工	每年工作时间（月）
1	陈琰	1977.04	女	讲师	博士	华南农业大学	020-85280320	642101197704260025	项目负责人	10
2	李康顺	1962.03	男	教授	博士	华南农业大学	020-85280320	362101196203110035	进化算法分析	6
3	杨磊	1978.09	男	讲师	博士	华南农业大学	020-85280320	410711197809240099	进化算法设计	8
4	方永美	1971.03	女	讲师	硕士	华南农业大学	020-85280320	320202197103063523	农产品价格体系研究	8
5	熊璐	1987.08	女	博士生	硕士	华南农业大学	020-85280320	362502198708220229	进化算法实现	10
6	杨舒玲	1991.06	女	硕士生	学士	华南农业大学	020-85280320	440902199106254063	进化算法实现	10
7	陈卫广	1992.01	男	硕士生	学士	华南农业大学	020-85280320	445321199201294312	平台实现	10
8	梁卓智	1993.09	男	硕士生	学士	华南农业大学	020-85280320	440681199309252331	平台实现	10

总人数	高级	中级	初级	博士后	博士生	硕士生
8	1	3			1	3

课题编号：2023YFF1105101　　**密　级：公开**

国家重点研发计划
课题任务书

课题名称： 食品安全数据治理和智慧移动监督执法系统构建

所属项目： 食品安全智慧监管与控制关键技术研究与应用示范

所属专项： 食品营养与安全关键技术研发

项目牵头承担单位： 江南大学

课题承担单位： 清华大学

课题负责人： 唐彦嵩

执行期限： 2023 年 12 月 至 2027 年 12 月

中华人民共和国科学技术部制

2023 年 11 月 17 日

0003YF 2023YFF1105101 2023-11-17 16:22:18

16	朱凯	男	1979-08-22	身份证	420302197908221217	中级	无	硕士	计算机软件与理论	24	其他研究人员	数据库设计、架构设计、进度管理、质量管理	是	华南农业大学数学与信息学院
17	杨磊	男	1978-09-24	身份证	410711197809240099	中级	无	博士	计算机技术	23	其他研究人员	数据库设计、架构设计、数据分析	是	华南农业大学数学与信息学院
18	陈浩淇	男	2000-01-23	身份证	362201200001234819	其他	无	学士	计算机技术	24	其他研究人员	系统开发与测试	否	华南农业大学数学与信息学院
19	宁辰飞	男	2000-05-25	身份证	420921200005254954	其他	无	学士	计算机技术	24	其他研究人员	系统开发与测试	否	华南农业大学数学与信息学院
20	郑綮燎	男	2000-11-25	身份证	441523200011256310	其他	无	学士	计算机技术	24	其他研究人员	系统开发与测试	否	华南农业大学数学与信息学院
21	王文豹	男	1998-11-02	身份证	445281199811027079	其他	无	学士	计算机技术	24	其他研究人员	系统开发与测试	否	华南农业大学数学与信息学院
固定研究人员合计										703	/	/	/	/
流动人员或临时聘用人员合计										0	/	/	/	/
累计										703	/	/	/	/

课题编号：2023YFF1104201　　**密　级：公开**

国家重点研发计划
课题任务书

课题名称： 中式膳食营养数据库构建

所属项目： 个性化膳食数字化设计与智能制造关键技术研究与产业化示范

所属专项： 食品营养与安全关键技术研发

项目牵头承担单位： 火星人厨具股份有限公司

课题承担单位： 中国疾病预防控制中心营养与健康所

课题负责人： 张继国

执行期限： 2023 年 12 月 至 2027 年 12 月

中华人民共和国科学技术部制

2023 年 11 月 18 日

0003YF 2023YFF1104201 2023-11-18 19:50:02

5	白晶	女	1983-06-18	身份证	142730198306180346	副高级	无	博士	营养学	24	其他研究人员	基于现场调查构建家庭和餐馆菜肴膳食营养数据库	是	中国疾病预防控制中心营养与健康所
6	朱凯	男	1979-08-22	身份证	420302197908221217	中级	无	博士	计算机软件与理论	24	其他研究人员	中式膳食营养数据集成研究	是	华南农业大学数学与信息学院
7	杨磊	男	1978-09-24	身份证	410711197809240099	中级	无	博士	计算机科学与技术	24	其他研究人员	中式膳食营养数据集成研究	是	华南农业大学数学与信息学院
8	董小辉	男	1999-12-29	身份证	411426199912298051	其他	无	学士	公共卫生	24	其他研究人员	基于现场调查构建家庭和餐馆菜肴膳食营养数据库	否	中国疾病预防控制中心营养与健康所
9	董孟茹	女	1999-09-28	身份证	412821199909285728	其他	无	学士	营养与食品卫生学	24	其他研究人员	基于现场调查构建家庭和餐馆菜肴膳食营养数据库	否	中国疾病预防控制中心营养与健康所
10	俞峰峰	男	1988-05-26	身份证	330184198805260017	中级	中级结构工程师	学士	机械制造及其自动化	24	其他研究人员	中式膳食营养数据库的示范应用	是	火星人厨具股份有限公司
11	卜玲娟	女	1990-03-30	身份证	330411199003305669	中级	中级烹饪营养研究工程师	硕士	食品工程	24	其他研究人员	中式膳食营养数据库的示范应用	是	火星人厨具股份有限公司

广东省科学技术厅文件

粤科农字〔2024〕200号

广东省科学技术厅关于下达“百千万工程”农村科技特派员第二轮重点派驻人员名单和任务清单的通知

各有关地市科技局，各农村科技特派员派出单位:

为深入贯彻落实省委关于实施“百县千镇万村高质量发展工程”有关决策部署，进一步推动农村科技特派员下乡助力城乡区域协调发展，按照《广东省农村科技特派员科技助力百县千镇万村高质量发展行动计划（2023-2026）》《广东省科学技术厅关于落实“百千万工程”开展新一轮农村科技特派员重点派驻任务（2024-2026年）选派管理工作的通知》要求，在第一轮农村科技特派员3年帮扶重点派驻任务即将到期的情况下，按照“镇村

发榜+地市组织选派+省级认定支持”的新型组织管理方式，第二轮共选派2960名农村科技特派员组建984个团队，“一对一”结对科技帮扶全省涉农县（市、区）辖内984个乡镇。现将“百千万工程”农村科技特派员第二轮重点派驻人员名单和任务清单印发给你们:

一、各地市科技管理部门、派出单位应按照《广东省科学技术厅关于落实“百千万工程”开展新一轮农村科技特派员重点派驻任务（2024-2026年）选派管理工作的通知》（粤科函农字〔2023〕1649号）、《广东省科学技术厅关于印发〈农村科技特派员助力“百千万工程”管理工作指引（2024-2026年）〉的通知》（粤科函农字〔2024〕192号）有关要求，做好本辖区、本单位农村科技特派员组织、管理、考核和验收相关工作。

二、各农村科技特派员团队应聚焦落实省委实施“百千万工程”决策部署，在省、市科技管理部门指导下，扎根基层一线，配合驻镇帮扶工作队开展科技帮扶工作，农村科技特派员团队纳入驻镇帮扶工作队（乡镇人民政府）统一管理，本轮帮扶任务周期为3年。

三、农村科技特派员承担重点派驻任务经费保障，按年度以科技支撑“百千万工程”专项资金下达到各地市，各地市科技管理部门要加强管理，压实责任，专款专用，提高资金使用效率，应将专项资金拨付到相关派出单位，用于开展科技帮扶工作。

附件：“百千万工程”农村科技特派员第二轮重点派驻人员名单和任务清单

省科技厅

2024年9月5日

（联系人及电话：赵清泉，020-83163909）

133	KTP20240133	东源县船塘镇	广东省科学院（负责人、成员 1）、广东食品药品职业学院（成员 2）	卢颖林、杨欣妍、倪明龙	板栗优质丰产栽培及加工关键技术示范推广
134	KTP20240134	东源县双江镇	广东省农业科学院	史亮亮、曹海顺、严博方	西瓜产业提质增效关键技术示范推广
135	KTP20240135	东源县涧头镇	华南农业大学	王瑞龙、贺鸿志、马红彦	绿色种养循环农业关键技术与模式示范应用
136	KTP20240136	东源县灯塔镇	中国水产科学研究院珠江水产研究所	巩华、朱涛、杨志群	工厂化循环水（RAS）健康养殖技术示范
137	KTP20240137	东源县顺天镇	广东省农业科学院（负责人、成员 1）、广东工业大学（成员 2）	魏鑫钰、赵俊宏、陶志华	蓝莓高效种植与精深加工技术服务
138	KTP20240138	东源县柳城镇	河源职业技术学院	陈胜利、龙淑嫔、谢智阳	创新型专业镇内涵建设与服务
139	KTP20240139	东源县黄村镇	华南农业大学	李雷鸣、杨翠钰、陆珊	数智化 AI 视角的农文旅多模态传播与应用
140	KTP20240140	东源县康禾镇	广东省农业科学院（负责人、成员 2）、河源职业技术学院（成员 1）	凌彩金、胡国辉、郜礼阳	康禾贡茶品质提升关键技术及农旅融合示范
141	KTP20240141	东源县半江镇	华南农业大学	石娟娟、张鹏、梁雅晶	深化文旅融合发展，提升文化产业综合实力
142	KTP20240142	东源县仙塘镇	仲恺农业工程学院（负责人、成员 2）、华南农业大学（成员 1）	俞湘珍、陈佩、黄丽璇	稻米产业精深加工与品牌提升技术服务
143	KTP20240143	东源县黄田镇	仲恺农业工程学院	杨永、刘松梅、张金凤	黑花生、黑米高产栽培关键技术示范与推广
144	KTP20240144	东源县曾田镇	仲恺农业工程学院	钟振强、周冠怡彤、廖烨岷	农文旅融合发展与乡村振兴建设
145	KTP20240145	东源县新回龙镇	华南农业大学（负责人、成员 1）、广东农工商职业技术学院（成员 2）	朱贺、杨磊、周玮	数字化定制农业民宿系统助力乡村振兴农文旅应用研究
146	KTP20240146	东源县新港镇	华南农业大学	赵娜、肖媚燕、江涛	农文旅融合发展助力乡村振兴
147	KTP20240147	东源县叶潭镇	华南农业大学	钟国华、刘家莉、刘婕	叶潭柚提质增产、病虫害防控关键技术集成与示范推广

SCAULIB202625746

检索证明

根据委托人提供的论文材料，委托人**华南农业大学数学与信息学院 杨磊(学科类型:自然科学)** 5 篇论文收录情况如下表。

序号	论文名称	发表刊物及发表的年月卷期/页码等	作者排名	论文等级	作者文中单位	收录情况	影响因子	中科院大类分区
1	A many-objective evolutionary algorithm based on interaction force and hybrid optimization mechanism	SWARM AND EVOLUTIONARY COMPUTATION 出版年：2024 出版日期：OCT 卷期：90 页码：- 文献号：101667 文献类型：Article	第一作者	A 类	华南农业大学数学与信息学院	SCI	IF2-year=8.5 IF5-year=8.8 （2024）	计算机科学 2 区 Top 期刊：否 OA 期刊：否 （2025）
2	A many-objective evolutionary algorithm based on reference vector guided selection and two diversity and convergence enhancement strategies	APPLIED SOFT COMPUTING 出版年：2024 出版日期：MAR 卷期：154 页码：- 文献号：111369 文献类型：Article	第一作者	A 类	华南农业大学数学与信息学院	SCI	IF2-year=6.6 IF5-year=6.9 （2024）	计算机科学 2 区 Top 期刊：是 OA 期刊：否 （2025）
3	Many-objective evolutionary algorithm based on spatial distance and decision vector self-learning	INFORMATION SCIENCES 出版年：2023 出版日期：MAY 卷期：624 页码：94-109 文献类型：Article	第一作者	T2 类	华南农业大学数学与信息学院	SCI	IF2-year= IF5-year= （2023）	计算机科学 1 区 Top 期刊：是 OA 期刊：否 （2023）

华南农业大学图书馆 信息检索专用章

4	A vector angles-based many-objective particle swarm optimization algorithm using archive	APPLIED SOFT COMPUTING 出版年：2021 出版日期：JUL 卷期：106 页码：- 文献号：107299 文献类型：Article	第一作者	A 类	华南农业大学 数学与信息学院	SCI	IF2-year=8.263 IF5-year=7.595 （2021）	计算机科学 2区 Top 期刊：是 OA 期刊：否 （2021）
5	Ant colony classification mining algorithm based on pheromone attraction and exclusion	SOFT COMPUTING 出版年：2017 出版日期：OCT 卷期：21 19 页码：5741-5753 文献类型：Article	第一作者	B 类	华南农业大学 数学与信息学院	SCI	IF2-year=2.367 IF5-year=2.204 （2017）	工程技术 3区 Top 期刊：否 （2017）

说明：论文等级和中科院大类分区按《华南农业大学学术论文评价方案（试行）》划分。

报告免责声明:如未盖章,报告无效

检索员：田成

华南农业大学图书馆

2026-03-10

华南农业大学图书馆 信息检索专用章

华南农业大学图书馆SCAULIB20262374

SCAULIB202625816

检索证明

根据委托人提供的论文材料，委托人华南农业大学数学与信息学院 杨磊(学科类型:自然科学) 4 篇论文收录情况如下表。

序号	论文名称	发表刊物及发表的年月卷期/页码等	作者排名	论文等级	作者文中单位	收录情况	影响因子	中科院大类分区
1	An enhanced diversity indicator-based many-objective evolutionary algorithm with shape-conforming convergence metric	APPLIED SOFT COMPUTING 出版年：2024 出版日期：NOV 卷期：166 页码：- 文献号：112161 文献类型：Article	通讯作者	A 类	华南农业大学数学与信息学院	SCI	IF2-year=6.6 IF5-year=6.9 （2024）	计算机科学 2 区 Top 期刊：是 OA 期刊：否 （2025）
2	面向复杂约束多目标优化问题的双种群双阶段进化算法	计算机应用 出版年：2025 出版日期：2024-11-20 15:20 卷期：45 08 页码：- 文献号： 文献类型：期刊论文	通讯作者	C 类	华南农业大学数学与信息学院	北大核心	无	无
3	面向高维多目标优化的双阶段双种群进化算法	计算机工程与应用 出版年：2024 出版日期：2023-10-10 10:34 卷期：60 09 页码：-	通讯作者	C 类	华南农业大学数学与信息学院	北大核心	无	无

华南农业大学图书馆 信息检索专用章

		文献号： 文献类型：期刊论文						
4	较短的长序列时间序列预测模型	计算机应用 出版年：2024 出版日期：2023-08-17 16:47 卷期：44 06 页码：- 文献号： 文献类型：期刊论文	通讯作者	C类	华南农业大学数学与信息学院	北大核心	无	无

说明：论文等级和中科院大类分区按《华南农业大学学术论文评价方案（试行）》划分。

报告免责声明:如未盖章,报告无效

检索员：刘汉忠

华南农业大学图书馆

2026-03-11

华南农业大学图书馆 信息检索专用章

华南农业大学图书馆SCAU1820625816

Swarm and Evolutionary Computation 90 (2024) 101667

Contents lists available at ScienceDirect

Swarm and Evolutionary Computation

journal homepage: www.elsevier.com/locate/swevo

A many-objective evolutionary algorithm based on interaction force and hybrid optimization mechanism

Lei Yang [a,*], Jiale Cao [a], Kangshun Li [a], Yuanye Zhang [a], Rui Xu [a], Ke Li [b]

[a] College of Mathematics and Informatics, South China Agricultural University, Guangzhou, 510642, Guangdong, China
[b] Department of Computer Science, University of Exeter, Exeter, EX4 4QF, Devon, UK

ARTICLE INFO

Keywords:
Many-objective evolutionary algorithm
Interaction force
Hybrid evolutionary mechanism
Dominance resistance solutions
Perturbation

ABSTRACT

In many-objective optimization, both convergence and diversity are equally important. However, in high-dimensional spaces, traditional decomposition-based many-objective evolutionary algorithms struggle to ensure population diversity. Conversely, traditional Pareto dominance-based many-objective evolutionary algorithms face challenges in ensuring population convergence. In this paper, we propose a novel many-objective evolutionary algorithm based on interaction force and hybrid optimization mechanism (MaOEAIH) for effectively addressing the difficulty in balancing convergence and diversity. First, we use the concept of interaction force to simulate the convergence (akin to gravity) and diversity (repulsion) of the population. Subsequently, we design an optimization mechanism that combines decomposition and Pareto dominance to enhance the convergence and diversity of the population separately. Simultaneously, to eliminate dominance resistance solutions, we propose a quartile method based on boundary solutions. Additionally, Random perturbations are also introduced to certain individuals within the population to facilitate their escape from local optima. MaOEAIH is compared with some state-of-the-art algorithms on 31 well-known test problems with 3-15 objectives. The experimental results show that, compared to other algorithms, MaOEAIH not only obtains solution sets of higher quality when dealing with different types of many-objective optimization problems, but also effectively addresses key challenges including insufficient selection pressure, difficulty balancing convergence and diversity, and susceptibility to population entrapment in local optima within many-objective optimization scenarios.

1. Introduction

In reality, there are many optimization problems, such as sensor configuration [1], design of robot neuro-motion-controllers [2], and job-shop scheduling [3], in which in most cases there are two or more conflicting objectives. Improving the performance of one objective is likely to lead to a decrease in the performance of other objectives. Therefore, it is necessary to optimize these conflicting objectives as much as possible to achieve the optimal state of the overall objective. When the number of objectives in these problems is less than three, they are called multi-objective problems (MOPs) [4,5]. Otherwise, they are called many-objective problems (MaOPs) [6]. A MOP (MaOPs) can be expressed by (1):

$$\begin{cases} Minimize\ F(x) = \left(f_1(x), f_2(x), \ldots, f_M(x)\right)^T \\ Subject\ to\ x \in \Omega \end{cases} \tag{1}$$

where $x = \left(x_1, x_2, \ldots, x_n\right)^T$ is an n-dimensional decision vector in the decision space Ω. M is the number of objectives, and $F(x)$ is an M-dimensional objective vector. For two given decision vectors x_a and x_b, if x_a dominates x_b ($x_a \prec x_b$), then $\forall i \in \{1, 2, \ldots, M\}$, $f(x_a)_i \leq f(x_b)_i$ and $\exists i \in \{1, 2, \ldots, M\}$, $f(x_a)_i < f(x_b)_i$. A solution that is not dominated by any other solutions is called a non-dominated solution. The set of non-dominated solutions is called the Pareto-optimal set (PS), and the graph formed by the Pareto optimal solutions is called the Pareto-optimal front (PF).

As the number of objectives in MaOPs increases, the performance of traditional multi-objective evolutionary algorithms (MOEAs) in solving MaOPs gradually deteriorates, making it difficult to maintain a balance between population diversity and convergence [7], and solving MaOPs becomes increasingly challenging. To effectively address MaOPs, many excellent many-objective evolutionary algorithms (MaOEAs) [8–10] have been proposed. These algorithms can be roughly categorized into four types:

* Corresponding author.
E-mail address: yanglei_s@scau.edu.cn (L. Yang).

https://doi.org/10.1016/j.swevo.2024.101667
Received 19 June 2023; Received in revised form 14 April 2024; Accepted 12 July 2024
Available online 25 July 2024
2210-6502/© 2024 Elsevier B.V. All rights are reserved, including those for text and data mining, AI training, and similar technologies.

The first category is Pareto dominance-based MaOEAs. These algorithms generally employ two strategies for individual selection. The first strategy is to select individuals by modifying the Pareto dominance relation, such as GPO dominance [11], CSDR-dominance [12], and localized dominance [13]. These methods essentially relax the dominance relationship, allowing for the comparison of solutions that cannot be directly compared, thus maintaining selection pressure. Although these methods enhance the selection pressure of MaOEAs, they heavily rely on parameter settings and often struggle to find suitable parameters. The second strategy is to select individuals through novel diversity selection criteria. For instance, Xu et al. improve the selection pressure by choosing solutions with the best convergence index value [14]. Zhou et al. utilize a diversity maintenance mechanism based on global and local diversity to manage the population's diversity [15]. Chen et al. enhance the diversity of the population on different types of PFs through a diversity ranking method [16]. While these methods are effective in increasing selection pressure, they may fall slightly short in balancing diversity and convergence.

Decomposition-based MaOEAs belong to the second category, where the principle of these algorithms is to decompose an MaOPs into several subproblems using a set of weight vectors and simultaneously optimize these subproblems. MOEA/D [17] is a representative algorithm of this category. However, for decomposition-based MaOEAs that use fixed weights, the initial problem is that the number of individuals in the population must be the same as the number of weight vectors. Moreover, when faced with irregular-shaped PF such as disconnected, degenerate [18], reversed [19,20], constrained, severely scaled [21], and complex fronts [22], the performance of the algorithm deteriorates. This deterioration leads to the inability to generate uniformly distributed solutions and also results in wasted weight vectors. To address this problem, several methods for adaptive weight vectors have been proposed. For example, SRV [23] applies an improved k-means clustering method to extract weight vectors from the population. DEAdas [24] utilizes a dual-adjustment strategy to adjust the weight vectors. In MOEA/D-UR [25], a metric that detects improvements is employed to adjust the weight vectors when necessary. However, even though adjusting the weight vectors enables the decomposition-based MaOEAs to handle problems with irregular PF effectively, the number of weight vectors is often not arbitrary, and designing a reasonable and effective weight generation strategy still poses certain difficulties.

Indicator-based MaOEAs form the third category. Performance evaluation indicators can evaluate the comprehensive performance of candidate solutions, so introducing performance indicators can select candidate solutions and transform MaOPs into single-objective problems judged by performance indicators. Algorithms such as HyPE [26], MaOEA/IGD [27] and R2HCA-EMOA [28] use accurate indicators or estimated indicator values such as hypervolume(HV) [29], inverted generational distance(IGD) [30], and R2 [31] to guide the selection process of many-objective optimization. However, the computation cost of accurate indicator values is very expensive for indicator-based many-objective optimization algorithms. Secondly, the solutions generated are difficult to ensure the uniformity of distribution. Finally, it is still a difficult problem to select the most suitable reference point for various algorithms of this type.

The fourth category of MaOEAs is based on alternative evolutionary mechanisms. These algorithms employ unique evolutionary mechanisms distinct from the three common mechanisms mentioned above. For instance, LM-DAS [32], based on the duality analysis of the objective space and decision space, reduces problem complexity by prioritizing resource allocation to variables that are relevant to important objectives. However, incorrect resource allocation may lead to instability in the results. Another example is S3-CMA-ES [33], which utilizes a series of small subpopulations to approximate the PF, thereby improving the evolutionary speed of the population. However, the population is prone to getting trapped in local optima and fails to converge to the PF. Additionally, DVC-MOEA [34], based on decision variable classification, adopts a novel method to generate promising solutions. However, variations in the contribution of decision variables can lead to incorrect classification, thereby affecting the algorithm's performance. Du et al. [35] have bridged evolutionary algorithms and network science, proposing a networked evolutionary algorithm framework that significantly enhances the performance of evolutionary algorithms. Nonetheless, the complexity of the network structure may lead to increased implementation difficulty. Fister et al. [36] integrated novelty search with the differential evolution algorithm, enhancing the algorithm's global optimization performance. However, this approach requires careful parameter tuning.

In summary, existing MaOEAs exhibit several advantages, such as effectively maintaining diversity or convergence in high-dimensional spaces, generating a set of optimal solutions in a single run, deriving global approximate optimal solutions without requiring additional assumptions, high universality, strong robustness, and fast computational speed, among others. These attributes enable them to perform well in handling MaOPs. However, there are still some shortcomings. Firstly, in decomposition-based MaOEAs, the methods for adjusting weight vectors cannot effectively handle MaOPs with both regular and irregular PF simultaneously. Secondly, most MaOEAs, to some extent, prioritize either convergence or diversity, and fail to strike a good balance between the two. Thirdly, In Pareto-dominance-based MaOEAs, the presence of dominance resistance solutions [37] reduces the selection pressure of the algorithm, severely affecting the evolution of the population. Fourthly, In high-dimensional spaces, the search capability of evolutionary operators in MaOEAs is greatly constrained, making the population get trapped in local optima easily.

Inspired by the fact that physical systems with multiple bodies and interactions in nature tend to reach an ordered and homogeneous state, and the applicability of MaOEAs based on decomposition and Pareto dominance in various problems [38], we propose a many-objective evolutionary algorithm based on interaction force and hybrid optimization mechanism aiming to address the four aforementioned problems. Specifically, we use interaction forces in the Pareto dominance optimization mechanism to select a population that is close to the PF and roughly conforms to it, and then use this population as weight vectors in the decomposition-based optimization mechanism to emphasize the convergence of the population. Next, we use interaction forces again to select a population with good diversity. While using the quartile method based on boundary solutions to eliminate dominance resistance solutions, ensuring the convergence of the solutions. Finally, we use the obtained population as weight vectors to guide the population search for solutions that exhibit both convergence and diversity. Additionally, when the population gets trapped in local optima, we apply random perturbation to some individuals. The main contributions of this paper are as follows:

- This paper proposes Gravity and Repulsion-Interaction Force as measures for assessing the diversity of populations and selecting populations with good convergence and diversity as weight vectors.
- A hybrid optimization mechanism that combines decomposition and Pareto dominance is proposed to enhance the convergence and diversity of populations, while maintaining a balance between the two.
- We employ the quartile method and the boundary solutions of the population to roughly estimate the range of PF to identify solutions outside this range as dominance resistance solutions and eliminate them.
- Some offspring will be generated by randomly perturbing certain alleles of the parents, aiming to increase the probability of exploring regions far from the parent's area, thus allowing the population to escape local optima.

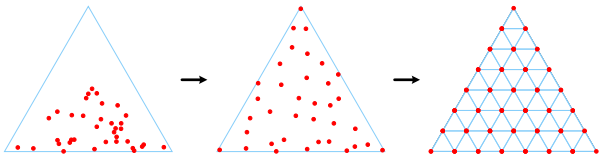


Fig. 1. Particles gradually transition from a chaotic and disordered state to a uniform and ordered state under the influence of Riesz's s-energy.

The remainder of this paper is organized as follows. In Section 2, we will review related work. In Section 3, we will provide a detailed description of our new algorithm. Then, experimental settings and results will be presented in Section 4. Finally, in Section 5, we summarize this paper and discuss future work.

2. Related work

In this section, we will introduce the concept of interaction force and the principle of Riesz s-energy, followed by an explanation of the quartile method.

2.1. Interaction forces and Riesz s-energy

Interaction forces [39] refer to the forces that an object exerts on other objects while also being subject to forces exerted by those objects. The effects of such forces may lead to a state of static or dynamic equilibrium between objects. Common types of Interaction forces include gravities, repulsions, elastic forces, and nuclear forces, among others.

Riesz s-energy [40] is essentially a type of energy that describes the interaction between particles and also represents repulsion, a type of interaction force. The principle behind it is that in natural physical systems consisting of multiple particles and interactions, the system will eventually reach a state of minimum total potential energy. In brief, by continuously selecting the point farthest from other points in the point set, a set of uniformly spaced points will eventually be obtained. In the homogeneous particle equilibrium system shown in Fig. 1, the initial distances between the particles are very close to each other, and because of the strong repulsion between them, they begin to separate from each other, making the distance between them increase gradually while their potential energy decrease at the same time. Eventually, the particles will reach an equilibrium state, and distribute uniformly on the plane. The mathematical definition of Riesz s-energy is as follows:

$$E = \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n} \frac{1}{\left\| x_i - x_j \right\|^s} \quad x \in R \tag{2}$$

where E represents the total energy of all points, and energy is represented by the Euclidean distance between two points, such that the greater the distance, the smaller the energy and the more uniform the points. n is the number of points, x_i and x_j represent the ith and jth points of the point set R, and $s \geq 0$ is a parameter that controls the emphasis on uniform distribution.

Recently, some articles in the field of many-objective optimization have also used Riesz s-energy. For example, in [41], the author used Riesz s-energy to select a set of points of a specified size and uniformity from the test suits to test the performance of MaOEAs. In [42], the author used Riesz s-energy to generate initially uniform reference points in the unit simplex. However, the application of Riesz s-energy in the field of many-objective optimization is still relatively limited, and it has great potential for development. With reasonable improvements, Riesz s-energy can be applied to select individuals with good convergence and diversity in many-objective optimization.

2.2. Quartile method

The quartile method [37] is a statistical technique used to describe the distribution of a dataset. It is commonly employed in exploratory data analysis to effectively identify the central tendency and dispersion of the dataset. Compared to traditional statistical measures such as mean and standard deviation, the quartile method exhibits stronger robustness and can effectively handle the influence of outliers and extreme values. By computing the interquartile range (IQR) of the dataset and using multiples of the IQR, the quartile method enables the determination of threshold values for detecting outliers. The quartile method is defined as:

$$\begin{cases} Q_1 = \mathbf{X}_{\left\lfloor \left(\frac{\|\mathbf{X}\|}{4} \right) \right\rfloor + 1} \left(\frac{\|\mathbf{X}\|}{4} - \left\lfloor \left(\frac{\|\mathbf{X}\|}{4} \right) \right\rfloor \right) + \\ \quad \mathbf{X}_{\left\lfloor \left(\frac{\|\mathbf{X}\|}{4} \right) \right\rfloor} \left(1 - \left(\frac{\|\mathbf{X}\|}{4} - \left\lfloor \left(\frac{\|\mathbf{X}\|}{4} \right) \right\rfloor \right) \right) \\ Q_3 = \mathbf{X}_{\left\lfloor \left(\frac{3\|\mathbf{X}\|}{4} \right) \right\rfloor + 1} \left(\frac{3\|\mathbf{X}\|}{4} - \left\lfloor \left(\frac{3\|\mathbf{X}\|}{4} \right) \right\rfloor \right) + \\ \quad \mathbf{X}_{\left\lfloor \left(\frac{3\|\mathbf{X}\|}{4} \right) \right\rfloor} \left(1 - \left(\frac{3\|\mathbf{X}\|}{4} - \left\lfloor \left(\frac{3\|\mathbf{X}\|}{4} \right) \right\rfloor \right) \right) \end{cases} \tag{3}$$

$$\begin{cases} UB = Q_3 + k \left(Q_3 - Q_1 \right) \\ LB = Q_1 - k \left(Q_3 - Q_1 \right) \end{cases} \tag{4}$$

where Q_1 is the first quartile, Q_3 is the third quartile, X is a set of ordered one-dimensional data, LB is the lower bound, UB is the upper bound, $k = 1.5$ indicates moderately extreme outliers, and $k = 3$ indicates highly extreme outliers.

3. Proposed algorithm

First, we will introduce the overall framework of MaOEAIH. Then, we will elaborate on our proposed Gravity and Repulsion-Interaction Force method and the process of using it to select individuals and weight vectors. Next, we will provide a detailed description of the hybrid evolution mechanism. Afterwards, we will explain the process of eliminating domination resistance. Finally, we will describe our mutation operation in detail.

3.1. The overall framework of MaOEAIH

Algorithm 1 presents the overall framework of our proposed MaOEAIH. First, we initialize a population $\mathbf{P}$ of size N and M objectives. Simultaneously, we initialize the parameters C, V, H, and $\mathbf{HP}$, and the details of these parameters, as well as those mentioned subsequently, are described in Table 1. Then, the population $\mathbf{P}$ starts to iteratively evolve. In each generation, a random subset of parents $\mathbf{P}'$ is selected from $\mathbf{P}$ to generate offspring $\mathbf{F}$ through crossover and mutation or perturbation. It is worth noting that our algorithm is different from most MaOEAs in that we also apply a perturbation operation to $\mathbf{F}$ to help the population escape from local optima. Finally, we employed the interaction forces and hybrid optimization mechanism to select N individuals from a total of $2N$ individuals in $\mathbf{P}'$ and $\mathbf{F}$ as the next generation population. Simultaneously return the next generation of $\mathbf{PSET}$. This evolution process is repeated until the stopping criterion is met. In the following sections, we will describe the main components of MaOEAIH in detail.

Algorithm 1 Framework of the Proposed MaOEAIH

Input: N (Population size), M (Number of objectives)
Output: **P** (Population)
1: **P** ← Initialize Population(N, M)
2: $V, C \leftarrow 0$
3: $H \leftarrow$ inf
4: **HP** ← **P**
5: **PSET** ← V, C, H, **HP**
6: **while** termination criterion not fulfilled **do**
7: **P**′ ← MatingSelection(**P**)
8: **F** ← VariationOrPerturbation(N, **P**′, V)
9: **P**, **PSET** ← MixedSelection(N, M, **P**, **F**, **PSET**)
10: **end while**

Table 1
Pseudocode common variables.

Variable	Description	Type
C	Parameter that determines whether the current population should employ an optimization mechanism based on decomposition or one based on Pareto dominance	Scalar
V	Parameter that decides if the current population needs perturbation	Scalar
H	Records the optimal values of population convergence and diversity	Scalar
HP	Stores historical populations	Set
PSET	A set of variables containing C, V, H, **HP**	Set
P	Parent population	Set
F	Offspring population	Set
P′	A mixed population of offspring and parent populations	Set

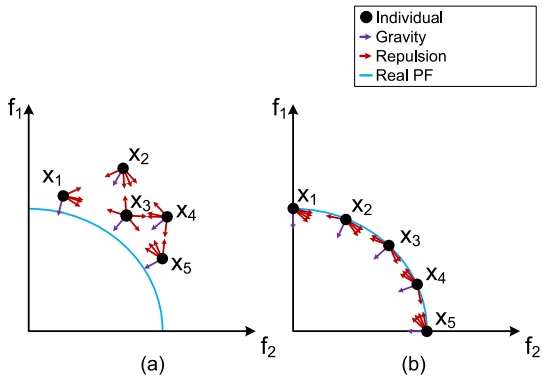


Fig. 2. Under GaRIF's influence, individuals repel each other and are gradually attracted towards PF, transitioning from (a) initial chaotic state to (b) final state of high diversity and convergence.

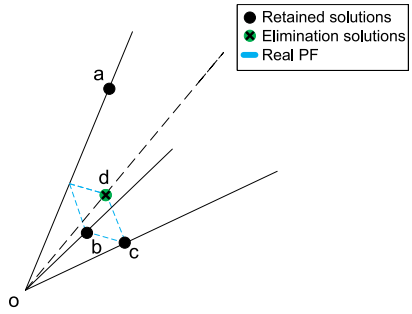


Fig. 3. Using the Manhattan distance to calculate the repulsion in the case of the same angle between individuals will tend to select individuals far from the PF.

3.2. Gravity and repulsion-interaction force

The PF in MaOPs is a high-dimensional hypersurface, making the task of maintaining solution diversity a challenging endeavor. Inspired by the effectiveness of Riesz s-energy in promoting point set uniformity, we incorporate it into a Pareto dominance-based MaOEAs as a criterion for diversity preservation. However, as the number of objectives in MaOPs increases, the Pareto dominance relationship gradually loses its effectiveness, leading to a deterioration in population convergence. Furthermore, Riesz s-energy, being a repulsion, tends to favor individuals with larger Euclidean distances from other individuals, which can result in the selection of individuals far away from the PF and further worsen population convergence.

To address these issues, we introduce the concept of gravity based on the inspiration from interaction forces and enhance the Riesz s-energy (repulsion) by employing different distance metrics. Finally, we propose the Gravity and Repulsion-Interaction Force (GaRIF), aiming to improve population convergence while maintaining diversity. Specifically, GaRIF is a method that simulates gravity and repulsion to drive population individuals closer to the PF while ensuring uniform diffusion across the entire PF. To further clarify GaRIF, a conceptual illustration is provided in Fig. 2.

Fig. 2(a) illustrates that initially, population individuals are in a chaotic and disordered state, with repulsion acting between each pair of individuals, pushing them away from each other. At the same time, they are also subject to gravity from the PF, pulling them closer to the PF. Over time, the distance between individuals increases, the repulsion gradually decreases, reaching its minimum value, no longer forcing individuals away from each other but maintaining a state of equilibrium. Similarly, as the gravity attracts individuals to the PF, the distance between individuals and the PF also reaches its minimum value, causing individuals to stop moving and remain in a state of equilibrium. As shown in Fig. 2(b), ultimately, these two forces will cause individuals to approach the PF infinitely while uniform spreading across the entire PF, achieving an orderly balanced state for the population. In other words, GaRIF maintains population diversity by simulating repulsion and ensures population convergence by simulating gravity. Its specific expression is shown in Eqs. (5):

$$\begin{cases} E_{GaRIF} = G \cdot R \\ G = \left(\sum_{i=1}^{n} \sum_{k=1}^{m} \left| x_k^i \right| \right)^{h_1} \\ R = \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n} (MD \cdot CD)^s \\ MD = \left(\frac{1}{\sum_{k=1}^{m} \left| x_k^i - x_k^j \right|} \right)^{h_2} \\ CD = \left(\frac{1}{1 - \cos\left(x^i, x^j\right)} \right)^{h_3} \\ x \in P \end{cases} \tag{5}$$

where n is the population size, m is the number of objectives, **P** is the current population, x_k^i is the kth objective value of the ith individual in **P**, the parameter s ($s \geq 0$) controls the uniform distribution and is set as $m-1$, following the Ref. [41], h_1 is the weight coefficient of the gravity term, h_2 is the weight coefficient of the reciprocal of the Manhattan distance between individuals, and h_3 is the weight coefficient of the reciprocal of the difference between one and Cosine similarity between individuals. G represents the Manhattan distance from all individuals in the population to the origin. Since in minimization problems a smaller G value indicates better convergence of the population [43], it can be used as gravity to maintain the convergence of the population. R is the

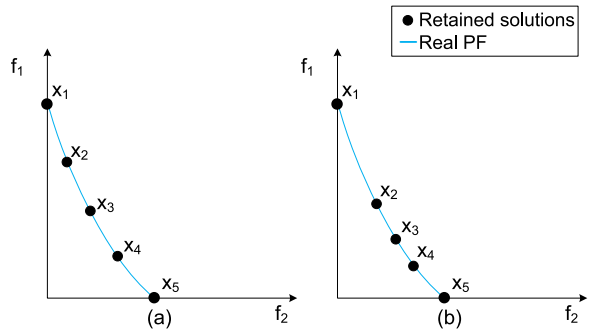


Fig. 4. Using (b) Cosine similarity to calculate repulsion in problems with convex PF results in uneven distribution of individuals, while adopting (a) Manhattan distance for repulsion calculation maintains a uniform distribution of individuals.

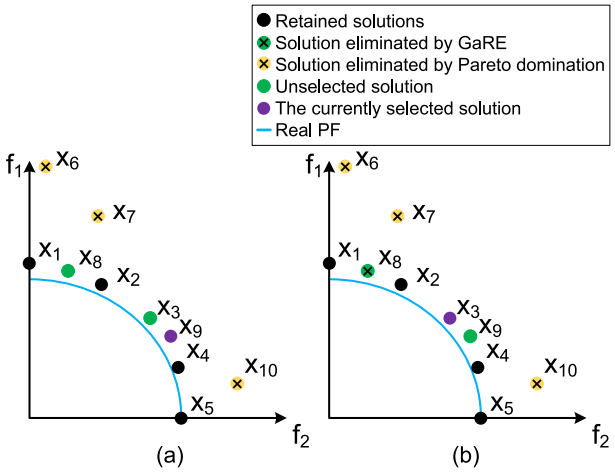


Fig. 5. (a) Roughly select a population with the minimum GaRIF by choosing individuals with the current minimum GaRIF. (b) Achieve a more precise selection of a population with the minimum GaRIF by sequentially replacing individuals obtained in (a) with the remaining individuals.

sum of the reciprocal s powers of the distance between each individual in the population and other individuals, representing repulsion used to maintain population diversity. The smaller R, the greater the distance between individuals in the population, and the better the diversity of the population. E_{GaRIF} represents GaRIF, which is a product of population gravity and repulsion. Therefore, a smaller E_{GaRIF} value indicates better balance between diversity and convergence within the population.

It is worth noting that the calculation of the repulsion term R, differs from the computation of Riesz s-energy. Instead of using $1/\|x_i - x_j\|$ in Riesz s-energy, we employ $MD \cdot CD$. This substitution is motivated by the following reasons: Firstly, in high-dimensional spaces, using Euclidean distance to measure the distance between points is not sufficiently accurate [44]. Therefore, we substitute Euclidean distance with Manhattan distance and Cosine similarity. Secondly, as shown in Fig. 3, in the case where the angles between individuals are the same, calculating R using Manhattan distance would select individual a with a large Manhattan distance to other individuals, instead of individual d, which is closer to the PF. Employing Cosine similarity might preserve d, but it may fail to ensure diversity, as demonstrated in Fig. 4(b), where using Cosine similarity to compute R could select individuals with equal angles within the convex PF, but the distances between them are not equal. Conversely, in Fig. 4(a), calculating R with Manhattan distance results in equal distances between the selected individuals. To combine the advantages of Manhattan distance and Cosine similarity, we use h_2 and h_3 to represent their respective proportions in computing

Algorithm 2 GaRIFSelection1

Input: N (Population size), M (Number of objectives), **P** (Population), **F** (Offspring), h_1 (Control the parameters of gravity), h_2, h_3 (Control the parameters of repulsion)
Output: **P** (Population), E_{GaRIF} (GaRIF of **P**)

To perform non-dominated sorting on $\mathbf{P} \cup \mathbf{F}$, obtaining **Q** (the last non-dominated layer individuals) and $\mathbf{P}'$ (non-dominated layers individuals except the last layer)
GM ← GaRIFMatrix($N, M, \mathbf{P} \cup \mathbf{F}, h_2, h_3$)
for $i = 1 \rightarrow (N - |\mathbf{P}'|)$ **do**
  for $j = 1 \rightarrow |\mathbf{Q}|$ **do**
    Calculate E_{GaRIF} of the current population using Eqs (5), h_1, and **GM**, and store this value in $\mathbf{EM}(j)$
  end for
  Add the individual a corresponding to the minimum value in $\mathbf{EM}(j)$ to $\mathbf{P}'$, and remove a from **Q**
  $\mathbf{O} \leftarrow \mathbf{a} \cup \mathbf{O}$
end for
for $i = 1 \rightarrow |\mathbf{O}|$ **do**
  Calculate E_{GaRIF} of $\mathbf{P}'$ using Eqs (5), h_1, and **GM**
  for $j = 1 \rightarrow |\mathbf{Q}|$ **do**
    Calculate E_{GaRIF} of the current population using Eqs (5), h_1, and **GM**, and store this value in $\mathbf{EM}(j)$
  end for
  $[\mathbf{EM}_{min}, l] \leftarrow \mathbf{EM}$
  if $E_{GaRIF} > E^{min}_{GaRIF}$ **then**
    $\mathbf{P}' \leftarrow \mathbf{P}' \cup \mathbf{Q}(l) - \mathbf{O}(i)$
    $\mathbf{Q} \leftarrow \mathbf{Q} - \mathbf{Q}(l) + \mathbf{O}(i)$
    $E_{GaRIF} \leftarrow E^{min}_{GaRIF}$
  end if
end for
$\mathbf{P} \leftarrow \mathbf{P}'$

Algorithm 3 GaRIFMatrix

Input: N (Population size), M (Number of objectives), **P** (Population), h_2, h_3 (Control the parameters of repulsion)
Output: **GM** (The distance matrix between two individuals in the storage population)

Calculate the difference between the one and Cosine similarities of each pair of individuals in **P**, and store the results in the matrix **OneCos**.
for $i = 1 \rightarrow N$ **do**
  for $j = 1 \rightarrow N$ **do**
    if $i = j$ **then**
      continue
    end if
    for $l = 1 \rightarrow M$ **do**
      $u_1 \leftarrow u_1 + |f(i)_l - f(j)_l|$
    end for
    $\mathbf{GM}(i,j) \leftarrow \frac{1}{((u_1)^{h_2} \cdot (\mathbf{OneCos}(i,j))^{h_3})^{M-1}}$
  end for
end for

R. Finally, since the distance measure should be inversely proportional to R, we calculate the Cosine similarity by subtracting the Cosine distance from 1.

The search space for finding a population of size N with the minimum GaRIF value from a set containing $2N$ individuals comprising both parents and offspring, is $\binom{2N}{N}$ [41], which incurs a significantly

high time complexity. To address this issue, this paper employs a simplified approach for selecting populations of size N with the smallest possible GaRIF value.

As shown in Algorithm 2, if the selected non-dominated individuals do not fulfill the population size after non-dominated sorting, the individuals with the minimum GaRIF value among the remaining non-dominated individuals and the already selected individuals are chosen to form the population. This process resembles a greedy algorithm (steps 3–9 of Algorithm 2). For example, in Fig. 5(a), if 5 individuals need to be chosen and assumes that x_9 has a smaller GaRIF value with the selected individuals compared to any other unselected individual, then it will be selected. However, this selection may not be accurate enough. Therefore, we individually replace the selected individuals chosen by GaRIF with the unselected non-dominated individuals. If the replacement does not decrease the GaRIF value of the population, the replacement is canceled (Steps 10–20 of Algorithm 2). For example, in Fig. 5(b), if replacing x_9 with x_3 decreases the GaRIF value of the population, x_3 will be retained. Although the method cannot find populations with the smallest GaRIF values but populations with the smallest possible GaRIF values, its time complexity is only $O(N^2)$. Additionally, if the GaRIF value is computed for each individual during the selection process, the total time complexity of this method would be $O(N^4M)$. To avoid redundant calculations, a matrix is employed to store the distances between previously computed individuals, similar to the approach described in [41]. This reduces the overall time complexity to $O(N^3M)$, as shown in Algorithm 3.

3.3. Hybrid optimization mechanism

Although GaRIF can improve the convergence and diversity of the population, there is still room for improvement for problems that are difficult to converge. Decomposition-based MaOEAs can effectively converge to the PF. Therefore, the population selected by GaRIF can be used as the weight vector for decomposition-based MaOEAs (this paper adopts MOEA/D) to guide the search for solutions and further improve convergence. Fig. 6(a), (b), and (c) illustrate this process. However, balancing gravity and repulsion is not straightforward, which leads to a lack of diversity in the population selected by GaRIF. For example, in Fig. 6(c), the distance between x_3 and x_4 is significantly smaller than the distances between other individuals. It is worth noting that the population selected through the above steps has already approximated the range of the PF. By constraining the offspring within this range (Section 3.4), we can eliminate gravity and its impact on diversity, select a population with good diversity through GaRIF, and avoid the concern that repulsion and dominance resistance solutions deviate the population from the PF which significantly reduces convergence, as shown in Fig. 6(d). However, the determined range of the PF is only an approximate range, and the population may still deviate slightly from the PF, leading to reduced convergence of the population. To address this, we once again use the population as the weight vector to guide the search for solutions and obtain a population with both good convergence and diversity, as shown in Fig. 6(e).

Furthermore, Algorithm 4 presents the implementation and details of the above steps and provides the transition conditions of the optimization mechanism and the setting of some coefficients. Since the initial value of C is 0, Algorithm 4 first adopts a Pareto dominance-based optimization mechanism to evolve the population. (steps 1 to 2 of Algorithm 4). When the historical minimum value of GaRIF in the population remains unchanged for a certain number of generations and the population has already undergone perturbation, C is set to 1 or 3 (steps 12 to 31 of Algorithm 4). Subsequently, we employ a decomposition-based optimization mechanism as a replacement for the Pareto dominance-based mechanism(steps 3 to 8 of Algorithm 4). This substitution is motivated by the stability of the GaRIF value in the population, which signifies a certain degree of stability in both convergence and diversity. Similarly, when the historical minimum

Algorithm 4 MixedSelection

Input: N (Population size), M (Number of objectives), **P** (Population), **F** (Offspring), **PSET** (The parameter set containing the parameters V, C, H, and **HP**)
Output: **P** (Population), **PSET** (The parameter set containing the parameters V, C, H, and **HP**)

1: **if** $C = 0$ **then**
2: **P**, E_{GaRIF} ←GaRIFSelection1(N, M, **P**, **F**, 1, 1, 1)
3: **else if** $C = 1 \parallel C = 3$ **then**
4: Using the population obtained from a Pareto dominance-based optimization mechanism as the weight vector **W**.
5: Set the ideal point as the coordinate origin
6: The next generation population **P**′ was selected from **P** and **F** using the same method as MOEA/D
7: **P**← **P**′
8: Calculate the Manhattan distance from the origin to each individual in **P**, and store the results in E_{GaRIF}
9: **else if** $C = 2$ **then**
10: **P**,E_{GaRIF} ←GaRIFSelection2(N, M, **P**, **F**, **HP**, 0, 1, 0)
11: **end if**
12: **if** $E_{GaRIF} < H \parallel (C = 1$ and $E_{GaRIF} < H + 10^{-6})$ **then**
13: $H \leftarrow E_{GaRIF}$
14: **else**
15: **if** H remains unchanged for a certain number of generations **then**
16: **if** $V = 0$ **then**
17: $V \leftarrow 1$ /*Start perturbation*/
18: Counting the number of generations with unchanged H from 0
19: **else**
20: **if** $C = 0$ **then**
21: $C \leftarrow 1$
22: **else if** $C = 1$ **then**
23: $C \leftarrow 2$
24: **HP**← **P**
25: **else if** $C = 2$ **then**
26: $C \leftarrow 3$
27: **end if**
28: Counting the number of generations with unchanged H from 0 and V is set to 0
29: **end if**
30: **end if**
31: **end if**
32: **PSET**← V, C, H, **HP**

value of the sum of distances from each individual to the origin remains constant for a specified number of generations and the population has already undergone perturbation, C is set to 2 (steps 12 to 31 of Algorithm 4), and we switch back to the Pareto dominance-based optimization mechanism (steps 9 to 10 of Algorithm 4). This constancy in the minimum sum of distances from the origin represents a certain level of stability in population convergence. The "a certain number of generations" will be introduced in Section 4.6. Moreover, in the initial usage of the Pareto dominance-based optimization mechanism, we consider both gravity and repulsion to be equally important. Therefore, we set the GaRIF coefficients, h_1, h_2, and h_3, to 1, 1, 1. However, in the second usage of the Pareto dominance-based optimization mechanism, we prioritize the diversity of the population. Thus, we set the GaRIF coefficients, h_1, h_2, and h_3, to 0, 1, 0.

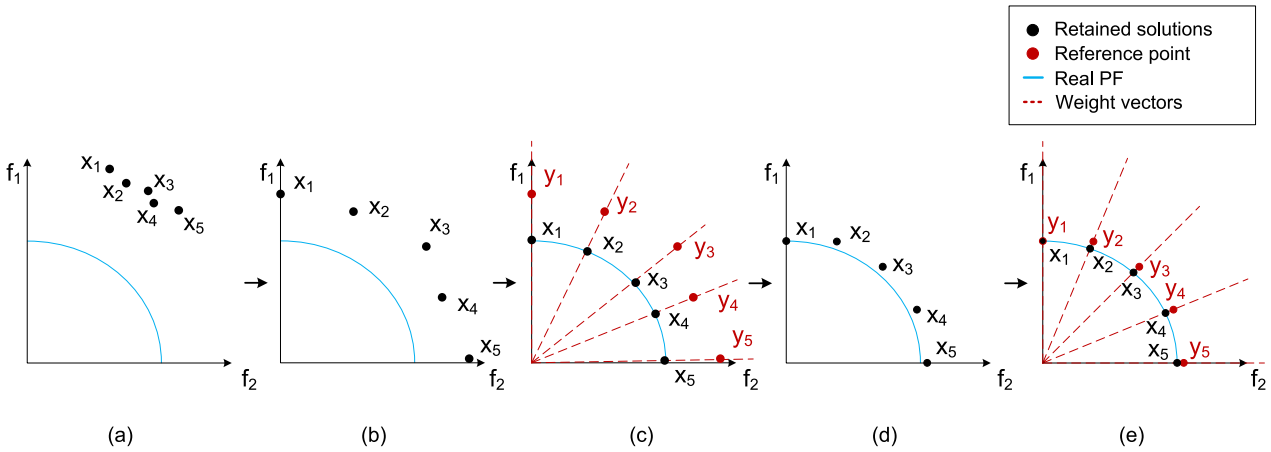


Fig. 6. Hybrid optimization mechanism. The population transitions from (a) to (b) and from (c) to (d) using a Pareto dominance-based optimization mechanism to enhance diversity. The shift from (b) to (c) and (d) to (e) employs a decomposition-based optimization mechanism to enhance convergence.

3.4. Eliminating dominance resistance solution

Algorithm 5 SearchDRS

Input: N (Population size), M (Number of objectives), $\mathbf{P}(x)$ (Population individual x), **HP** (Historical population)
Output: *DRS* (Dominance Resistance Solution Discriminant Parameters)

1: Select the M individuals closest to the M coordinate axes from **HP** as the boundary solutions **Bs**
2: **for** $i = 1 \rightarrow N$ **do**
3: **HPS**$(i) \leftarrow$sum(**HP**(i))
4: **end for**
5: Sort **HPS** in ascending order.
6: **if** $N \geq 4$ **then**
7: Calculate Q_1, Q_3 and UB by Eqs. (3) and (4)
8: **end if**
9: **for** $i = 1 \rightarrow M$ **do**
10: **BsS**$(i) \leftarrow$sum(**Bs**(i))
11: **end for**
12: $maxUB \leftarrow$ max(**BsS**(i))
13: **if** $maxUB > UB$ **then**
14: $UB \leftarrow maxUB$
15: **end if**
16: **if** sum(**P**(x)) **then** $> UB$
17: $DRS \leftarrow$ true
18: **else**
19: $DRS \leftarrow$ false
20: **end if**

In order to make the generated offspring as close as possible to the PF, we employ the quartile method based on boundary solutions to eliminate dominance resistance solutions and restrict the range of offspring generation. In Algorithm 5, we first save the final population **HP** obtained from the initial use of the decomposition-based optimization mechanism. Next, we calculate the sum of each individual on each objective value and store it in *HPS*. Subsequently, we compute the upper bound UB of *HPS* using formulas (3) and (4), and then use UB as the upper bound for the PF. In steps 16–20 of Algorithm 5, by comparing the sum of each objective value in the offspring individual with UB, We restrict offspring generation to the vicinity of PF. If the sum of each objective value in the offspring exceeds UB, it is considered a dominance resistance solution and needs to be eliminated. Otherwise, it is retained.

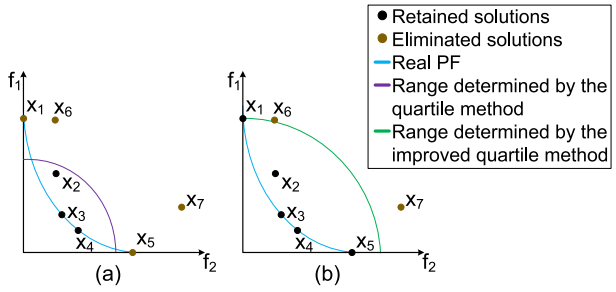


Fig. 7. (b)The improved quartile method expands the detection range near boundary solutions compared to (a) the unimproved quartile method.

In this paper, according to [37], the parameter k in the quartile method is set to 1.5. However, if the distribution of the **HP** population is uneven and the value of k is small, as shown in Fig. 7(a), the dense region in the middle and sparse regions on the sides, there is a possibility of erroneously identifying boundary solutions outside the purple region as dominance resistance solutions and eliminating them, although these solutions are not actually dominance resistance. This not only fails to improve the algorithm's performance but may also reduce it. To address this issue, in the first step of Algorithm 5, we select the M individuals closest to the M coordinate axes from **HP** as the boundary solutions. Then, in steps 9–12, we calculate the maximum sum of objective values, $maxUB$, among these M individuals and compare it with UB. If $maxUB$ is greater than UB, we replace UB with $maxUB$ to expand the range of offspring generation and avoid erroneously eliminating useful solutions, as shown in Fig. 7(b).

Algorithm 6 provides specific steps for eliminating dominance resistance solutions. For each offspring, we first determine whether it is a dominance resistance solution using Algorithm 5. If it is, no further operation is performed. Otherwise, we compare the dominance relationship between the offspring individual and the parent individual. If they are mutually non-dominating, we compare the change in GaRIF value after replacing the parent individual with the offspring individual. If the GaRIF value does not decrease, the replacement is canceled. The method of selecting the population with the minimum GaRIF value is similar to steps 10–20 in Algorithm 2. At this stage, the population has undergone several iterations and is no longer in the initial chaotic and unordered state. Instead, it exhibits good convergence and diversity. Therefore, steps 3–9 of Algorithm 2 are not required here.

Algorithm 6 GaRIFSelection2

Input: N (Population size), M (Number of objectives), **P** (Population), **F** (Offspring), **HP** (Historical population), h_1 (Control the parameters of gravity), h_2, h_3 (Control the parameters of repulsion)
Output: **P** (Population), E_{GaRIF} (GaRIF of **P**)

GM←GaRIFMatrix(N, M, **P** ∪ **F**, h_2, h_3)
for $i \leftarrow 1$ to N **do**
  DRS ←SearchDRS(N, M, **F**(i), **HP**)
  if DRS = true **then**
    continue
  end if
  if **F**(i) ≺ **P** **then**(i)
    P(i) ← **F**(i)
  else if **P**(i) ≺ **F** **then**(i)
    continue
  else
    Compute the number of elements in **P** that dominate **P**(i) as $OldBeDom$ and the number of elements in **P** that dominate **F**(i) as $NewBeDom$
    if $OldBeDom = NewBeDom$ **then**
      Calculate the GaRIF values PE and FE for **P** and **F**, respectively, using Eqs (5), h_1, and **GM**
      if $FE < PE$ **then**
        P(i) ← **F**(i)
      end if
    else if $OldBeDom > NewBeDom$ **then**
      P(i) ← **F**(i)
    else
      continue
    end if
  end if
end for
Calculate E_{GaRIF} of **P** using Eqs (5), h_1, and **GM**

3.5. Perturbation strategy

Most MaOEAs commonly employ simulated binary crossover (SBX) [45] to perform crossover on parents, followed by Gaussian perturbation [46] to mutate the resulting offspring. However, this approach can often lead to a significant proximity between the generated offspring and their parents, thereby restricting the search space and making the population susceptible to getting trapped in local optima. To address this issue, we propose a random perturbation method in Algorithm 7. When the historical minimum of the GaRIF value based on Pareto dominance remains unchanged for a certain number of generations, or when the historical minimum of the sum of distances from each individual in the population to the origin remains unchanged for a certain number of generations in a decomposition-based evolution mechanism, we randomly select a portion of the parent individuals for perturbation and treat the perturbed results as offspring. The perturbation method resembles polynomial mutation (PM) [47], but we replace the Gaussian perturbation in PM with Eqs. (6). The definition of Eqs. (6) is as follows:

$$x_i = x_i \pm \text{random}(lower, upper), \quad i \in (1, D) \tag{6}$$

where $x = \left(x_1, x_2, \ldots, x_D\right)^T$ is an D-dimensional decision vector in the decision space Ω, x_i represents the ith decision variable of the parent individual that has been selected for perturbation, $lower$ represents the lower bound of the decision variable range, while $upper$ represents the upper bound of the decision variable range.

Algorithm 7 VariationOrPerturbation

Input: N (Population size), **P** (Population), V (Perturbation parameter)
Output: **F** (Offspring)

for $i = 1 \rightarrow N$ **do**
  r_1=Random(1)
  if $V = 0 \parallel r_1 = 1$ **then**
    r_2=Random(N)+1
    F(i)′ ← Crossover(**P**(i), **P**(r_2))
    F(i)″ ← Variation(**F**(i)′)
    F← **F** ∪ **F**(i)″
  else
    Using Eqs. (6) to replace Gaussian perturbation in polynomial variation to perturb **P**(i) and generate **F**(i)
    If the decision variables are outside the valid range, they will be perturbed again.
    F← **F** ∪ **F**(i)
  end if
end for

Due to the significant randomness in our perturbation, the generated offspring may exhibit substantial differences from their parents, increasing the diversity of the search and aiding in the discovery of potential global optima. To avoid excessive perturbation that could slow down the evolution of the population, we still utilize PM and SBX to generate offspring for the unselected parent individuals.

3.6. Computational complexity

Given a MaOP with M objectives, in the Pareto dominance-based optimization mechanism, the time complexity for non-dominated sorting of a population of size N is $O(N^2M)$, selecting the population with the minimum GaRIF value takes $O(N^2)$ time complexity, and calculating the distance between each pair of individuals in the population requires $O(N^2M)$ time complexity. Therefore, the time complexity for calculating the GaRIF value of the population is $O(N^3M)$, and the overall time complexity of the dominance-based optimization mechanism is $O(N^2M+N^2+N^3M) = O(N^3M)$. In the decomposition-based optimization mechanism, this paper adopts MOEA/D, whose time complexity is $O(MTN)$, where T represents the number of neighboring weight vectors adjacent to a weight vector, and $T < N$. Therefore, the total time complexity of MaOEAIH is $O(N^3M)$.

4. Experimental study

In this section, to verify the effectiveness of MaOEAIH in handling MaOPs, we compared it with several state-of-the-art MaOEAs of different types on a benchmark test suites. These representatives include MaOEAIBP [48], MaOEAIGD [27], ARMOEA [49], HEA [50], tDEA [51], TSNSGAII [52], EFRRR [53], and RVEA [54]. The aforementioned experiments were conducted using the Evolutionary Many-Objective Optimization platform (PlatEMO) [55]. Furthermore, the source code for MaOEAIH and supplementary materials for some experiments are available for access at https://github.com/ASmallChestnut/MaOEAIH.

4.1. Experimental settings

4.1.1. Test problems

In this paper, we employ a set of 31 scalable test problems from widely-used benchmark test suites, namely DTLZ [56], WFG [57],

MAF [58], and IDTLZ [59], to verify the performance of our proposed algorithm on various types of MaOPs. This test suites cover a wide range of MaOP types, including but not limited to unimodal, multimodal, deceptive, hard-to-converge, biased, concave, convex, severely scaled, linear, degenerate, discontinuous, and problems with highly expanded PF. Since the algorithm in this paper focuses on solving different types of MaOPs, MAF14 and MAF15 are primarily used to assess the performance of MaOEAs on problems with large-scale decision variables. Therefore, these two test problems were not adopted in this paper. For the 31 test problems DTLZ1-DTLZ7, WFG1-WFG9, MAF1-MAF13, IDTLZ1-IDTLZ2, we set the number of objectives M as 3, 5, 8, 10, and 15. Except for MAF8 and MAF9, where the decision variable dimensions were set as 2, and MAF13, where the decision variable dimensions were set as 5, the decision variable dimensions for the remaining test problems were set as $D = M + r - 1$. In DTLZ1 and IDTLZ1, r was set as 5, in DTLZ7, r was set as 20, and for the remaining test problems, r was set as 10.

4.1.2. Performance indicators

In this paper, we employ IGD as an evaluation Indicator to assess the overall performance of different algorithms on the aforementioned test suites. IGD provides an approximate assessment of the convergence and diversity of the final solutions by calculating the average distance between each reference point on the true PF and the nearest solution on the approximated PF obtained by the MaOEA. A smaller value of IGD indicates a better overall performance of an algorithm, i.e., a better convergence and diversity. The mathematical expression for IGD is as follows:

$$\mathrm{IGD} = \frac{\sum_{p \in P_{true}} \min_{q \in P_{known}} \|p - q\|}{|P_{true}|} \tag{7}$$

where P_{true} represents the set of reference points obtained from the true PF, P_{known} represents the final solution set obtained by the MaOEA, p denotes a solution from P_{true}, q denotes a solution from P_{known}, $\|p - q\|$ represents the Euclidean distance between p and q, and $|P_{true}|$ represents the number of reference points on the true PF.

Additionally, this paper also employed the DeltaP [60], DM [61], PD [62], and Spread [61] performance Indicators to comprehensively evaluate MaOEAIH's performance in handling various MaOPs. However, given the constraints of space in the paper, these experimental results will be uploaded to the same link as the source code.

4.1.3. Parameter settings

(1) Crossover and Mutation: The crossover operator used by all algorithms in the comparative experiments is SBX, while the mutation operator is PM. For SBX, the crossover probability is set to 1, and the distribution index is set to 20. For PM, the expected number of mutated variables is set to 1, and the distribution index is set to 20.

(2) Population Size: To ensure a fair comparison, the population size in all experiments is uniformly set to 100.

(3) Termination Condition and Number of Runs: In Sections Section 4.2, 4.5, and 4.6, we set the maximum number of function evaluations to 600,000, while in Sections 4.3 and 4.4, it was set to 200,000 and 100,000, respectively. Furthermore, to ensure the reliability of the experimental results, we independently ran each algorithm 30 times on each test problem.

(4) Significance test: We employed the Wilcoxon rank sum [63] test at a significance level of 0.05 to perform statistical analysis on the experimental results. The symbols "+ ", "−", and "≈" indicate that the compared algorithm's results are significantly better than, significantly worse than, or not significantly different from the results of MaOEAIH, respectively. Additionally, the best performing results will be highlighted in dark.

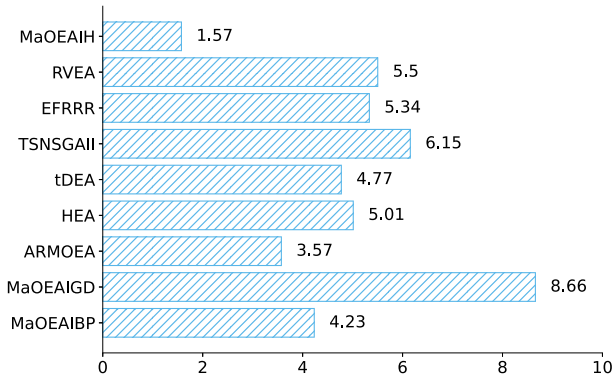


Fig. 8. Average performance score. Smaller scores indicate that the algorithm has better performance on IGD.

4.2. Experimental results and analysis of overall performance of MaOEAIH

The experimental results of all the algorithms in various test suites with different objectives are shown in Tables 2–4. Additionally, we calculated the average performance scores of all algorithms across all test suites, as shown in Fig. 8. Based on these results, it can be observed that MaOEAIH performs the best in terms of IGD values in most of the test problems, exhibiting significant advantages over other competing algorithms. The specific details are as follows:

When dealing with difficult convergence problems such as DTLZ1 and DTLZ3, MaOEAIH adopts a decomposition-based optimization mechanism and a quartile method based on boundary solutions, which effectively assists the population in converging to the PF, thus outperformed other algorithms. It only slightly lags behind EFRRR in the 8-dimensional DTLZ1 problem. To visually demonstrate this result, Fig. 9 presents the parallel coordinate plot of the final populations obtained by each algorithm on the 10-dimensional DTLZ3. From the figure, it is evident that MaOEAIGD, tDEA, and TSNSGAII have objective values exceeding 10 on each objective, failing to converge to the PF. This phenomenon is due to these three algorithms losing selection pressure in high-dimensional spaces, causing individuals to remain distributed far from the PF and unable to approach it. Although ARMOEA, HEA, EFRRR, and RVEA can converge to the PF, their populations' distribution is similar, as they all employ reference points to maintain diversity, resulting in most individuals clustered in certain areas of the PF, with many regions, like the 0.2 to 0.6 objective value range, lacking individual, indicating poor diversity. Similarly, while MaOEAIBP employs a boundary penalty strategy, resulting in a denser distribution in the 0.2 to 0.6 objective value range, it too lacks individual distribution in many PF regions (such as the region with objective values between 0.2 and 0.4), leading to poor diversity. In contrast, MaOEAIH not only converges to the PF but also achieves an even distribution across the entire PF, demonstrating its effective handling of difficult convergence in MaOPs.

In the case of problems like DTLZ2 and DTLZ4, where maintaining population diversity is challenging, MaOEAIH achieves significantly better population diversity compared to other algorithms, thanks to the good performance of GaRIF in preserving population diversity.

In scenarios where problems like DTLZ5, DTLZ6, WFG3, MAF6, MAF8, MAF9, and MAF13 have degenerate PFs, MaOEAIH's results are superior in 65.7% of cases, which can be attributed to GaRIF and the perturbation strategy that enables the population to accurately discover the PF. Fig. 10 displays the population distribution of each algorithm on the 3-dimensional MAF6, and it can be observed that MaOEAIH achieves a more uniform and extensive population distribution, while EFRRR and RVEA fail to converge to the PF due to a lack of intersection between most weight vectors and the PF. Although ARMOEA has a similar population distribution to MaOEAIH, careful observation reveals

Table 2
Mean and standard deviation of the IGD values obtained by MaOEAIH and other MaOEAs for DTLZ test suit.

Problem	M	MaOEAIBP	MaOEAIGD	ARMOEA	HEA	tDEA	TSNSGAII	EFRRR	RVEA	MaOEAIH
DTLZ1	3	2.3002e−2	5.8918e−1	2.0557e−2	2.0558e−2	2.0557e−2	2.9228e−2	2.0557e−2	2.0556e−2	2.0214e−2
		(4.20e−4) −	(3.64e−1) −	(3.94e−7) −	(6.20e−6) −	(6.57e−7) −	(1.40e−2) −	(1.81e−7) −	(8.92e−8) −	(1.32e−4)
	5	7.9549e−2	7.5436e−1	6.8059e−2	6.8060e−2	6.8060e−2	8.5187e−2	6.8058e−2	6.8059e−2	6.6017e−2
		(1.58e−3) −	(6.00e−1) −	(1.28e−6) −	(2.73e−6) −	(1.42e−6) −	(1.56e−2) −	(1.27e−6) −	(4.73e−7) −	(1.20e−3)
	8	1.4086e−1	6.9820e−1	1.0868e−1	1.0870e−1	1.0869e−1	1.6198e−1	1.0858e−1	1.0870e−1	1.0977e−1
		(2.55e−3) −	(9.99e−1) −	(9.35e−6) +	(1.49e−6) +	(1.47e−6) +	(4.29e−2) −	(3.50e−5) +	(1.32e−4) +	(1.91e−3)
	10	1.7945e−1	4.6919e−1	1.5414e−1	1.5416e−1	1.5406e−1	2.3380e−1	1.6026e−1	1.5411e−1	1.2806e−1
		(5.39e−3) −	(2.57e−1) −	(1.82e−4) −	(1.19e−5) −	(4.81e−5) −	(3.97e−2) −	(2.58e−3) −	(6.28e−5) −	(2.84e−3)
	15	1.9927e−1	8.1833e−1	1.7104e−1	1.9532e−1	3.1328e−1	3.8975e−1	2.9480e−1	1.8884e−1	1.5804e−1
		(1.76e−2) −	(6.35e−1) −	(1.40e−2) −	(3.53e−2) −	(5.30e−2) −	(5.14e−2) −	(3.99e−2) −	(5.11e−5) −	(8.18e−3)
DTLZ2	3	7.6659e−2	1.7095e−1	5.4464e−2	5.5213e−2	5.4465e−2	5.4600e−2	5.4465e−2	5.4464e−2	5.2470e−2
		(2.75e−3) −	(1.70e−4) −	(4.30e−7) −	(4.15e−4) −	(5.35e−6) −	(6.98e−5) −	(3.73e−7) −	(2.44e−7) −	(3.25e−4)
	5	2.3207e−1	2.2244e−1	2.1222e−1	2.1222e−1	2.1222e−1	2.1261e−1	2.1221e−1	2.1221e−1	1.9912e−1
		(1.82e−3) −	(2.70e−3) −	(1.24e−5) −	(4.49e−7) −	(1.01e−5) −	(2.35e−4) −	(2.12e−6) −	(2.41e−7) −	(1.09e−3)
	8	4.0331e−1	4.0810e−1	3.8691e−1	3.8698e−1	3.8691e−1	3.8745e−1	3.8680e−1	3.8694e−1	3.7412e−1
		(5.44e−3) −	(1.56e−2) −	(2.74e−5) −	7.10e−4) −	(2.24e−5) −	(1.06e−3) −	(2.36e−4) −	(4.35e−6) −	(1.85e−3)
	10	5.1565e−1	5.9496e−1	4.9214e−1	5.3022e−1	5.0025e−1	5.2575e−1	5.1279e−1	5.0027e−1	4.6382e−1
		(4.63e−3) −	(7.87e−2) −	(6.81e−3) −	(4.21e−3) −	(6.26e−5) −	(4.41e−3) −	(2.25e−3) −	(3.79e−5) −	(1.47e−3)
	15	6.3427e−1	8.9954e−1	6.8944e−1	7.1601e−1	7.0343e−1	7.7475e−1	7.0959e−1	6.9665e−1	5.9439e−1
		(2.30e−3) −	(2.25e−1) −	(1.20e−2) −	(4.94e−3) −	(1.70e−2) −	(7.50e−3) −	(1.25e−2) −	(2.04e−3) −	(1.72e−3)
DTLZ3	3	1.0680e−1	1.4055e+1	5.4467e−2	5.5161e−2	5.4466e−2	7.2548e−2	5.4467e−2	5.4466e−2	5.2627e−2
		(1.71e−1) −	(7.17e+0) −	(5.83e−6) −	(4.47e−4) −	(2.09e−6) −	(4.31e−2) −	(2.71e−6) −	(3.01e−6) −	(5.09e−4)
	5	2.3362e−1	1.2930e+1	2.1223e−1	2.1222e−1	2.1223e−1	2.8723e−1	2.1223e−1	2.1223e−1	2.0135e−1
		(2.27e−3) −	(5.89e+0) −	(2.13e−5) −	(8.42e−6) −	(1.22e−5) −	(3.91e−2) −	(2.01e−5) −	(1.29e−5) −	(2.42e−3)
	8	4.0724e−1	7.9158e+0	3.8780e−1	3.8654e−1	3.9726e−1	6.6207e−1	3.9525e−1	3.8700e−1	3.7992e−1
		(7.01e−3) −	(7.00e+0) −	(1.34e−3) −	(6.17e−4) −	(5.62e−2) −	(1.18e−1) −	(4.48e−2) −	(7.10e−5) −	(1.70e−2)
	10	5.2073e−1	5.8299e+0	5.2648e−1	5.2736e−1	5.2308e−1	1.0323e+0	5.1477e−1	5.0028e−1	4.7096e−1
		(6.97e−3) −	(3.40e+0) −	(1.47e−2) −	(3.88e−3) −	(6.96e−2) −	(7.73e−2) −	(2.07e−3) −	(6.38e−5) −	(7.82e−3)
	15	6.4530e−1	5.6688e+0	7.1025e−1	7.4733e−1	9.4108e−1	1.2509e+2	9.4658e−1	6.9364e−1	6.0326e−1
		(6.74e−3) −	(4.61e+0) −	(3.02e−2) −	(1.15e−1) −	(5.66e−2) −	(6.72e+1) −	(4.81e−2) −	(6.90e−3) −	(9.66e−3)
DTLZ4	3	2.5758e−1	2.6170e−1	3.2737e−1	2.0117e−1	1.0049e−1	5.4639e−2	5.4465e−2	5.4464e−2	5.2850e−2
		(2.79e−1) −	(1.69e−1) −	(2.70e−1) −	(2.27e−1) −	(1.83e−1) −	(6.83e−5) −	(5.91e−7) −	(8.14e−8) −	(5.48e−4)
	5	3.1876e−1	3.5262e−1	2.3978e−1	4.0124e−1	2.1221e−1	2.1264e−1	2.1224e−1	2.2668e−1	2.0216e−1
		(1.12e−1) −	(1.89e−1) −	(7.14e−2) −	(2.56e−1) −	(8.39e−6) −	(1.12e−4) −	(1.30e−4) −	(7.92e−2) −	(1.68e−3)
	8	4.2631e−1	5.0040e−1	3.8691e−1	4.1862e−1	3.8690e−1	3.8727e−1	3.8757e−1	4.2918e−1	3.7725e−1
		(4.74e−2) −	(1.06e−1) −	(4.10e−5) −	(7.33e−2) −	(4.67e−5) −	(4.77e−4) −	(6.70e−4) −	(5.85e−2) −	(1.80e−3)
	10	5.2890e−1	5.9452e−1	5.0178e−1	5.8088e−1	5.0023e−1	5.4773e−1	5.1944e−1	5.3510e−1	4.6783e−1
		(4.18e−2) −	(8.89e−2) −	(3.69e−3) −	(5.62e−2) −	(9.66e−5) −	(4.10e−3) −	(3.37e−3) −	(5.33e−2) −	(1.32e−3)
	15	6.3760e−1	8.3126e−1	6.8935e−1	7.9229e−1	6.9624e−1	1.1736e+0	7.1215e−1	7.6129e−1	5.9563e−1
		(9.81e−3) −	(5.19e−2) −	(9.57e−3) −	(8.17e−2) −	(5.59e−5) −	(2.71e−1) −	(1.37e−2) −	(4.85e−2) −	(1.84e−3)
DTLZ5	3	1.0147e−2	5.6065e−1	5.3590e−3	3.3193e−2	3.2433e−2	1.9252e−2	3.6381e−2	6.2392e−2	4.2210e−3
		(1.32e−3) −	(2.00e−1) −	(1.29e−4) −	(1.88e−3) −	(2.38e−3) −	(4.81e−3) −	(3.78e−3) −	(9.75e−4) −	(8.02e−5)
	5	6.8633e−2	5.7666e−1	7.3456e−2	1.0785e−1	1.8171e−1	1.7016e−1	2.2562e−1	2.2250e−1	5.8045e−2
		(1.27e−2) −	(1.57e−1) −	(1.06e−2) −	(1.93e−2) −	(6.83e−2) −	(5.96e−2) −	(4.92e−2) −	(6.48e−3) −	(1.30e−2)
	8	3.0729e−1	6.4907e−1	1.0610e−1	2.2056e−1	1.9243e−1	6.4882e−1	2.3133e−1	6.7860e−1	6.1577e−2
		(6.24e−2) −	(1.35e−1) −	(2.67e−2) −	(4.43e−2) −	(7.52e−2) −	(8.73e−2) −	(7.31e−2) −	(7.24e−2) −	(4.07e−2)
	10	3.4242e−1	6.5382e−1	1.1405e−1	2.0536e−1	3.1893e−1	6.2932e−1	1.8935e−1	2.2252e−1	5.2282e−2
		(6.99e−7) −	(1.34e−1) −	(2.50e−2) −	(2.92e−2) −	(6.87e−2) −	(8.58e−2) −	(4.14e−2) −	(5.53e−2) −	(2.45e−2)
	15	3.4242e−1	7.1294e−1	1.1649e−1	3.3246e−1	2.4104e−1	4.7108e−1	3.2320e−1	5.5025e−1	4.8561e−2
		(9.36e−7) −	(1.55e−5) −	(2.59e−2) −	(6.75e−2) −	(7.79e−2) −	(2.60e−1) −	(8.82e−2) −	(2.37e−1) −	(2.60e−2)
DTLZ6	3	9.7762e−3	6.7590e−1	5.0647e−3	3.9913e−2	4.6850e−2	3.4961e−2	4.7657e−2	1.1437e−1	4.1203e−3
		(1.28e−3) −	(1.92e−1) −	(6.91e−5) −	(8.48e−4) −	(1.18e−2) −	(2.64e−3) −	(8.83e−3) −	(1.55e−2) −	(3.94e−5)
	5	8.7059e−2	7.1050e−1	7.6135e−2	1.6668e−1	2.9094e−1	3.7612e−1	2.5009e−1	2.3351e−1	9.9003e−2
		(1.37e−2) ≈	(2.14e−1) −	(1.19e−2) ≈	(3.98e−2) −	(8.85e−2) −	(8.64e−2) −	(9.47e−2) −	(4.63e−2) −	(7.20e−2)
	8	3.3750e−1	8.5039e−1	1.1548e−1	3.9543e−1	3.8481e−1	7.2314e−1	2.1736e−1	2.7571e−1	4.3107e−2
		(2.68e−2) −	(3.47e−1) −	(2.69e−2) −	(1.19e−1) −	(9.48e−2) −	(6.47e−2) −	(6.97e−2) −	(8.12e−2) −	(1.67e−2)
	10	3.4242e−1	7.4058e−1	9.7603e−2	4.2196e−1	3.7142e−1	6.2729e−1	2.0585e−1	1.9893e−1	4.3281e−2
		(2.76e−7) −	(1.64e−1) −	(2.58e−2) −	(1.15e−1) −	(8.77e−2) −	(1.07e−1) −	(4.29e−2) −	(5.54e−2) −	(1.81e−2)
	15	3.4242e−1	7.1829e−1	1.1200e−1	6.4578e−1	3.5220e−1	6.3851e+0	2.8090e−1	4.0027e−1	3.9805e−2
		(3.27e−7) −	(1.34e−2) −	(2.47e−2) −	(8.27e−2) −	(1.17e−1) −	(3.10e+0) −	(7.53e−2) −	(1.99e−1) −	(1.92e−2)
DTLZ7	3	1.1639e−1	1.0551e+0	1.7630e−1	2.5084e−1	1.2733e−1	1.0330e−1	1.0629e−1	1.0568e−1	5.8012e−2
		(1.20e−1) ≈	(5.37e−1) −	(1.75e−1) −	(2.06e−1) −	(9.33e−2) −	(6.55e−2) −	(8.07e−3) −	(8.04e−4) −	(1.17e−3)
	5	3.7999e−1	2.0851e+0	3.5130e−1	3.6587e−1	5.3043e−1	3.5486e−1	5.1745e−1	5.0890e−1	2.8988e−1
		(1.25e−1) ≈	(1.12e+0) −	(7.86e−3) −	(1.06e−1) −	(2.51e−2) −	(5.96e−3) −	(3.11e−2) −	(2.00e−3) −	(7.41e−3)
	8	8.7655e−1	3.6858e+0	1.7965e+0	1.1093e+0	1.4518e+0	1.2068e+0	2.1489e+0	1.8555e+0	6.8905e−1
		(1.28e−1) −	(2.02e+0) −	(9.54e−2) −	(3.01e−3) −	(2.12e−1) −	(1.92e−2) −	(4.73e−1) −	(2.71e−2) −	(4.70e−3)
	10	1.3023e+0	4.4274e+0	3.4997e+0	2.1200e+0	1.6480e+0	2.5004e+0	2.0873e+0	3.6403e+0	9.4470e−1
		(3.23e−1) −	(2.42e+0) −	(1.22e−1) −	(1.27e−2) −	(3.07e−1) −	(3.62e−1) −	(5.37e−1) −	(8.75e−2) −	(9.40e−3)
	15	3.3876e+0	2.8895e+0	7.3830e+0	8.2001e+0	1.1100e+1	8.9713e+0	7.9929e+0	7.0858e+0	1.5673e+0
		(7.82e−1) −	(3.45e−1) −	(2.95e−1) −	(1.17e+0) −	(5.45e−1) −	(7.69e−1) −	(5.57e−1) −	(3.08e−1) −	(1.25e−2)
+/−/≈		0/32/3	0/35/0	1/33/1	1/34/0	1/34/0	0/35/0	1/34/0	1/34/0	

a lack of individuals in the central region of its PF. The remaining algorithms fail to completely cover the PF.

In the case of problems with disconnected PFs like DTLZ7 and MAF7, MaOEAIH achieves all the optimal results. This is because

Table 3
Mean and standard deviation of the IGD values obtained by MaOEAIH and other MaOEAs for WFG test suit.

Problem	M	MaOEAIBP	MaOEAIGD	ARMOEA	HEA	tDEA	TSNSGAII	EFRRR	RVEA	MaOEAIH
WFG1	3	1.6193e−1	2.2889e+0	1.4413e−1	1.4501e−1	1.3939e−1	1.5679e−1	1.4209e−1	1.4769e−1	1.6019e−1
		(4.11e−3) −	(5.86e−2) −	(2.90e−3) +	(1.65e−3) +	(1.89e−3) +	(6.43e−3) ≈	(1.62e−3) +	(3.85e−3) +	(9.75e−3)
	5	6.2547e−1	3.3256e+0	4.7412e−1	4.6317e−1	4.4298e−1	5.5745e−1	4.7704e−1	4.4786e−1	4.8527e−1
		(2.37e−2) −	(6.60e−1) −	(3.39e−3) ≈	(4.54e−3) +	(4.05e−3) +	(2.43e−2) −	(1.34e−3) ≈	(9.79e−3) +	(2.61e−2)
	8	1.3562e+0	6.5126e+0	1.0263e+0	1.6722e+0	1.0103e+0	1.4171e+0	9.9490e−1	1.2372e+0	9.7039e−1
		(6.24e−2) −	(2.90e+0) −	(8.78e−3) −	(1.05e−1) −	(3.08e−2) −	(7.47e−2) −	(4.14e−2) −	(1.51e−1) −	(7.27e−2)
	10	1.8482e+0	8.7759e+0	1.2866e+0	1.8211e+0	1.2908e+0	1.8517e+0	1.4422e+0	1.3652e+0	1.1551e+0
		(1.01e−1) −	(4.18e+0) −	(6.45e−3) −	(2.79e−1) −	(4.81e−2) −	(8.23e−2) −	(9.15e−2) −	(1.04e−1) −	(1.08e−1)
	15	2.7299e+0	1.4265e+1	2.0345e+0	3.5698e+0	2.1642e+0	3.2245e+0	2.1556e+0	2.2719e+0	1.8531e+0
		(1.84e−1) −	(5.48e+0) −	(1.60e−2) −	(3.56e−1) −	(8.82e−2) −	(1.78e−1) −	(1.12e−1) −	(6.85e−2) −	(2.24e−1)
WFG2	3	2.2818e−1	1.5063e+0	1.6514e−1	1.5562e−1	1.5829e−1	1.7406e−1	1.7102e−1	1.7397e−1	1.6935e−1
		(1.23e−2) −	(1.71e−1) −	(9.65e−4) +	(1.78e−3) +	(1.09e−3) +	(5.93e−3) −	(2.64e−3) −	(2.21e−3) −	(4.53e−3)
	5	6.2982e−1	1.9751e+0	5.0745e−1	4.9581e−1	4.7278e−1	5.8217e−1	5.1887e−1	4.7875e−1	5.4737e−1
		(1.62e−2) −	(4.48e−1) −	(1.90e−3) +	(8.45e−3) +	(9.01e−4) +	(2.06e−2) −	(1.32e−2) +	(6.66e−3) +	(2.53e−2)
	8	1.3590e+0	2.9085e+0	1.0883e+0	1.8655e+0	1.8210e+0	1.3896e+0	1.1242e+0	1.2923e+0	1.0628e+0
		(3.14e−2) −	(6.77e−1) −	(1.49e−2) −	(3.15e−1) −	(4.34e−1) −	(7.90e−2) −	(5.92e−2) −	(3.14e−2) −	(3.56e−2)
	10	1.9126e+0	5.3011e+0	1.3547e+0	2.1929e+0	3.3610e+0	1.9081e+0	1.4514e+0	1.5087e+0	1.3360e+0
		(8.28e−2) −	(3.06e+0) −	(1.50e−2) ≈	(1.85e−1) −	(5.00e−1) −	(7.27e−2) −	(8.69e−2) −	(1.22e−2) −	(7.83e−2)
	15	2.2712e+0	8.2560e+0	2.0633e+0	3.4293e+0	9.2874e+0	3.4713e+0	3.9870e+0	2.3463e+0	2.1733e+0
		(2.15e−1) ≈	(6.56e+0) −	(3.19e−2) ≈	(3.84e−1) −	(2.14e+0) −	(1.42e−1) −	(9.25e−1) −	(9.20e−3) −	(2.57e−1)
WFG3	3	6.4201e−2	3.1817e+0	1.1622e−1	7.1260e−2	1.2970e−1	1.3271e−1	1.2460e−1	2.2287e−1	5.3865e−2
		(5.14e−3) −	(2.62e−2) −	(7.35e−3) −	(7.99e−3) −	(1.80e−2) −	(2.31e−2) −	(9.23e−3) −	(6.59e−3) −	(2.43e−3)
	5	3.8656e−1	5.4261e+0	6.8676e−1	5.2535e−1	6.3846e−1	7.3887e−1	6.4743e−1	7.1141e−1	3.4749e−1
		(6.02e−2) −	(3.46e−2) −	(4.84e−2) −	(3.57e−2) −	(2.76e−2) −	(1.31e−1) −	(4.34e−2) −	(3.34e−2) −	(3.82e−2)
	8	1.0664e+0	8.8757e+0	2.1489e+0	1.8901e+0	1.8506e+0	2.6711e+0	1.3349e+0	2.4152e+0	1.0756e+0
		(1.87e−1) ≈	(5.35e−2) −	(2.19e−1) −	(9.97e−2) −	(5.14e−1) −	(3.54e−1) −	(3.02e−1) −	(2.91e−1) −	(1.45e−1)
	10	1.6166e+0	1.1191e+1	3.3693e+0	2.6049e+0	2.6522e+0	3.2899e+0	2.2716e+0	3.4125e+0	1.6532e+0
		(2.27e−1) ≈	(4.28e−2) −	(1.83e−1) −	(1.60e−1) −	(8.88e−1) −	(4.59e−1) −	(4.56e−1) −	(7.03e−2) −	(2.87e−1)
	15	3.1522e+0	1.6905e+1	6.4406e+0	7.2867e+0	4.3628e+0	9.5269e+0	4.7111e+0	7.7079e+0	4.2414e+0
		(9.23e−1) +	(1.16e−1) −	(9.06e−1) −	(2.33e−1) −	(5.15e−1) ≈	(5.92e−1) −	(7.22e−1) −	(5.29e−1) −	(9.47e−1)
WFG4	3	3.0289e−1	3.9407e+0	2.2087e−1	2.2286e−1	2.2087e−1	2.2120e−1	2.2091e−1	2.2115e−1	2.0439e−1
		(9.74e−3) −	(3.52e−1) −	(5.52e−6) −	(2.17e−3) −	(3.53e−6) −	(2.81e−4) −	(8.05e−6) −	(3.92e−4) −	(9.38e−4)
	5	1.4128e+0	6.2788e+0	1.2250e+0	1.2251e+0	1.2250e+0	1.2246e+0	1.2262e+0	1.2265e+0	1.1131e+0
		(2.58e−2) −	(5.76e−1) −	(5.38e−5) −	(2.38e−4) −	(7.87e−5) −	(1.11e−3) −	(5.41e−4) −	(1.47e−3) −	(3.25e−3)
	8	3.5379e+0	9.8145e+0	3.5275e+0	3.5330e+0	3.5223e+0	3.5439e+0	3.5609e+0	3.5070e+0	3.1575e+0
		(5.03e−2) −	(1.22e+0) −	(4.60e−3) −	(7.99e−3) −	(1.11e−3) −	(1.14e−2) −	(8.29e−3) −	(1.54e−2) −	(1.19e−2)
	10	5.3858e+0	1.3135e+1	5.8687e+0	6.1211e+0	5.8596e+0	6.0045e+0	5.9145e+0	5.8428e+0	4.8125e+0
		(1.15e−1) −	(2.36e+0) −	(9.87e−3) −	(8.34e−2) −	(2.83e−3) −	(7.56e−2) −	(1.02e−2) −	(9.88e−2) −	(1.75e−2)
	15	9.5276e+0	2.5029e+1	1.2041e+1	1.2717e+1	1.2005e+1	1.3242e+1	1.2033e+1	1.2846e+1	9.4634e+0
		(1.28e−1) −	(3.56e+0) −	(5.39e−2) −	(2.86e−1) −	(1.28e−2) −	(8.73e−2) −	(1.77e−1) −	(4.37e−1) −	(4.05e−2)
WFG5	3	3.0568e−1	7.9349e−1	2.2987e−1	2.3104e−1	2.2987e−1	2.2995e−1	2.3038e−1	2.3000e−1	2.1185e−1
		(1.10e−2) −	(5.61e−1) −	(1.53e−6) −	(9.04e−4) −	(2.74e−6) −	(2.11e−4) −	(5.65e−4) −	(1.90e−4) −	(8.05e−4)
	5	1.4110e+0	6.2667e+0	1.2153e+0	1.2153e+0	1.2153e+0	1.2128e+0	1.2260e+0	1.2158e+0	1.0979e+0
		(2.17e−2) −	(1.05e+0) −	(1.28e−5) −	(1.11e−5) −	(6.27e−6) −	(9.91e−4) −	(1.38e−2) −	(5.65e−4) −	(2.30e−3)
	8	3.5491e+0	1.2887e+1	3.5269e+0	3.5353e+0	3.5279e+0	3.5281e+0	3.5736e+0	3.5029e+0	3.1670e+0
		(4.11e−2) −	(2.35e+0) −	(2.40e−3) −	(5.66e−3) −	(6.29e−5) −	(7.00e−3) −	(2.04e−2) −	(9.38e−3) −	(1.03e−2)
	10	5.4190e+0	1.6466e+1	5.8128e+0	6.0313e+0	5.8201e+0	5.8801e+0	6.1714e+0	5.7981e+0	4.8047e+0
		(1.27e−1) −	(2.86e+0) −	(9.76e−3) −	(5.73e−2) −	(3.78e−4) −	(3.89e−2) −	(9.44e−2) −	(2.23e−2) −	(1.67e−2)
	15	9.6080e+0	2.7812e+1	1.1868e+1	1.2225e+1	1.1940e+1	1.3101e+1	1.2031e+1	1.1433e+1	9.4201e+0
		(1.45e−1) −	(2.94e+0) −	(1.08e−1) −	(1.16e−1) −	(4.25e−2) −	(1.67e−1) −	(1.69e−1) −	(2.28e−1) −	(4.92e−2)
WFG6	3	3.1686e−1	2.7652e+0	2.3496e−1	2.3938e−1	2.3985e−1	2.4285e−1	2.3350e−1	2.3507e−1	2.2220e−1
		(1.00e−2) −	(1.32e+0) −	(6.97e−3) −	(1.03e−2) −	(9.96e−3) −	(1.09e−2) −	(9.31e−3) −	(9.90e−3) −	(8.22e−3)
	5	1.4186e+0	5.6896e+0	1.2141e+0	1.2145e+0	1.2143e+0	1.2135e+0	1.2154e+0	1.2151e+0	1.1104e+0
		(2.21e−2) −	(1.28e+0) −	(7.88e−4) −	(1.20e−3) −	(9.53e−4) −	(1.36e−3) −	(3.56e−3) −	(1.24e−3) −	(2.81e−3)
	8	3.6292e+0	9.4138e+0	3.5314e+0	3.5499e+0	3.5331e+0	3.5507e+0	3.5500e+0	3.5917e+0	3.1677e+0
		(4.00e−2) −	(5.08e+0) −	(5.58e−3) −	(9.71e−3) −	(4.85e−3) −	(1.98e−2) −	(5.77e−3) −	(4.60e−2) −	(1.12e−2)
	10	5.7019e+0	8.9150e+0	5.7876e+0	6.2010e+0	5.8043e+0	6.1258e+0	5.8571e+0	6.0978e+0	4.8138e+0
		(7.86e−2) −	(4.77e+0) −	(2.11e−2) −	(1.03e−1) −	(1.26e−2) −	(8.12e−2) −	(2.01e−2) −	(1.71e−1) −	(1.83e−2)
	15	9.7708e+0	2.1076e+1	1.2015e+1	1.2828e+1	1.1914e+1	1.3583e+1	1.1948e+1	1.3026e+1	9.4432e+0
		(2.06e−1) −	(9.56e+0) −	(1.97e−1) −	(2.43e−1) −	(2.24e−2) −	(8.88e−2) −	(1.93e−1) −	(3.72e−1) −	(5.11e−2)
WFG7	3	3.0883e−1	2.5716e+0	2.2090e−1	2.2377e−1	2.2089e−1	2.2210e−1	2.2089e−1	2.2102e−1	2.0772e−1
		(1.09e−2) −	(8.79e−1) −	(2.00e−5) −	(1.87e−3) −	(5.98e−6) −	(6.09e−4) −	(7.17e−6) −	(4.74e−5) −	(1.60e−3)
	5	1.4338e+0	5.8209e+0	1.2264e+0	1.2268e+0	1.2258e+0	1.2236e+0	1.2292e+0	1.2310e+0	1.1227e+0
		(1.93e−2) −	(6.87e−1) −	(6.14e−4) −	(1.39e−3) −	(3.82e−4) −	(1.36e−3) −	(2.82e−3) −	(3.30e−3) −	(4.49e−3)
	8	3.6012e+0	1.0736e+1	3.5337e+0	3.5473e+0	3.5317e+0	3.5536e+0	3.5958e+0	3.7109e+0	3.1924e+0
		(4.61e−2) −	(2.21e+0) −	(7.85e−3) −	(8.32e−3) −	(1.04e−2) −	(2.41e−2) −	(1.01e−2) −	(7.60e−2) −	(1.51e−2)
	10	5.5732e+0	1.3798e+1	5.8842e+0	6.2353e+0	5.8722e+0	6.0813e+0	5.9478e+0	6.1690e+0	4.8348e+0
		(7.52e−2) −	(2.05e+0) −	(5.82e−2) −	(8.07e−2) −	(1.11e−2) −	(5.42e−2) −	(1.30e−2) −	(1.12e−1) −	(2.11e−2)
	15	9.4888e+0	2.4122e+1	1.1706e+1	1.2620e+1	1.1999e+1	1.3522e+1	1.3495e+1	1.2719e+1	9.4874e+0
		(9.16e−2) ≈	(2.35e+0) −	(1.97e−1) −	(1.98e−1) −	(4.97e−2) −	(2.17e−1) −	(1.64e+0) −	(3.35e+0) −	(7.57e−2)

(*continued on next page*)

MaOEAIH uses the populations with PF shape information as the weight vector, effectively avoiding the waste of weight vectors and the issue of uneven coverage of weight vectors on the PF.

In problems with convex PFs such as WFG1, WFG2, MAF3, MAF10, and MAF11, MaOEAIH only obtains approximately half of the optimal results. This may attribute to the failure of quartile method based on

Table 3 (*continued*).

WFG8	3	3.5120e−1	3.6732e+0	2.6394e−1	2.7339e−1	2.7335e−1	3.0022e−1	2.8369e−1	2.8151e−1	2.5585e−1
		(1.16e−2) −	(2.22e−1) −	(2.38e−3) −	(2.79e−3) −	(3.63e−3) −	(5.79e−3) −	(4.60e−3) −	(4.30e−3) −	(3.09e−3)
	5	1.3516e+0	5.4034e+0	1.2219e+0	1.2263e+0	1.2415e+0	1.2312e+0	1.3374e+0	1.2391e+0	1.1468e+0
		(1.82e−2) −	(1.80e+0) −	(8.11e−4) −	(4.21e−3) −	(1.06e−2) −	(2.91e−3) −	(2.08e−2) −	(8.98e−3) −	(4.82e−3)
	8	3.5232e+0	1.2010e+1	3.5985e+0	3.7501e+0	3.5812e+0	3.6797e+0	3.5799e+0	3.9253e+0	3.2796e+0
		(2.89e−2) −	(2.30e+0) −	(2.52e−2) −	(2.45e−2) −	(2.02e−2) −	(1.92e−2) −	(8.73e−2) −	(1.10e−1) −	(2.06e−2)
	10	5.4949e+0	1.4874e+1	5.8950e+0	6.0394e+0	5.7271e+0	6.0662e+0	5.8898e+0	6.0830e+0	4.9222e+0
		(1.30e−1) −	(1.62e+0) −	(1.12e−1) −	(4.94e−2) −	(5.37e−2) −	(7.04e−2) −	(1.31e−1) −	(1.97e−1) −	(7.27e−2)
	15	9.5207e+0	2.7044e+1	1.2005e+1	1.2947e+1	1.2310e+1	1.2947e+1	1.3031e+1	1.2232e+1	9.6363e+0
		(1.97e−1) +	(2.49e+0) −	(3.82e−1) −	(1.10e−1) −	(4.41e−1) −	(1.71e−1) −	(3.77e−1) −	(4.36e−1) −	(1.09e−1)
WFG9	3	2.9857e−1	2.0939e+0	2.2051e−1	2.2183e−1	2.2040e−1	2.2204e−1	2.2989e−1	2.2110e−1	2.0074e−1
		(1.31e−2) −	(5.41e−1) −	(3.46e−4) −	(1.49e−3) −	(2.70e−4) −	(1.02e−3) −	(2.56e−3) −	(7.70e−4) −	(1.10e−3)
	5	1.3648e+0	4.8164e+0	1.2149e+0	1.2154e+0	1.2142e+0	1.2088e+0	1.3605e+0	1.2188e+0	1.1053e+0
		(3.28e−2) −	(1.16e+0) −	(2.98e−3) −	(2.37e−3) −	(1.98e−3) −	(7.61e−3) −	(1.94e−2) −	(2.92e−3) −	(5.05e−3)
	8	3.4308e+0	1.1188e+1	3.5357e+0	3.5501e+0	3.5144e+0	3.5868e+0	3.5581e+0	3.5116e+0	3.2215e+0
		(2.95e−2) −	(3.66e+0) −	(1.21e−2) −	(1.57e−2) −	(1.24e−2) −	(2.52e−2) −	(7.68e−2) −	(2.23e−2) −	(2.34e−2)
	10	5.1881e+0	1.5208e+1	5.8126e+0	5.8813e+0	5.8293e+0	5.9208e+0	6.2385e+0	5.8113e+0	4.8333e+0
		(1.03e−1) −	(3.96e+0) −	(1.26e−2) −	(4.54e−2) −	(3.65e−2) −	(6.67e−2) −	(7.58e−2) −	(6.54e−2) −	(3.98e−2)
	15	9.1811e+0	2.6112e+1	1.1596e+1	1.2039e+1	1.1938e+1	1.2775e+1	1.1632e+1	1.1303e+1	9.5022e+0
		(8.81e−2) +	(6.40e+0) −	(2.78e−1) −	(5.57e−2) −	(2.68e−1) −	(2.35e−1) −	(5.73e−1) −	(4.38e−1) −	(1.06e−1)
+/−/≈		3/38/4	0/45/0	3/39/3	4/41/0	4/40/1	0/44/1	2/42/1	3/42/0	

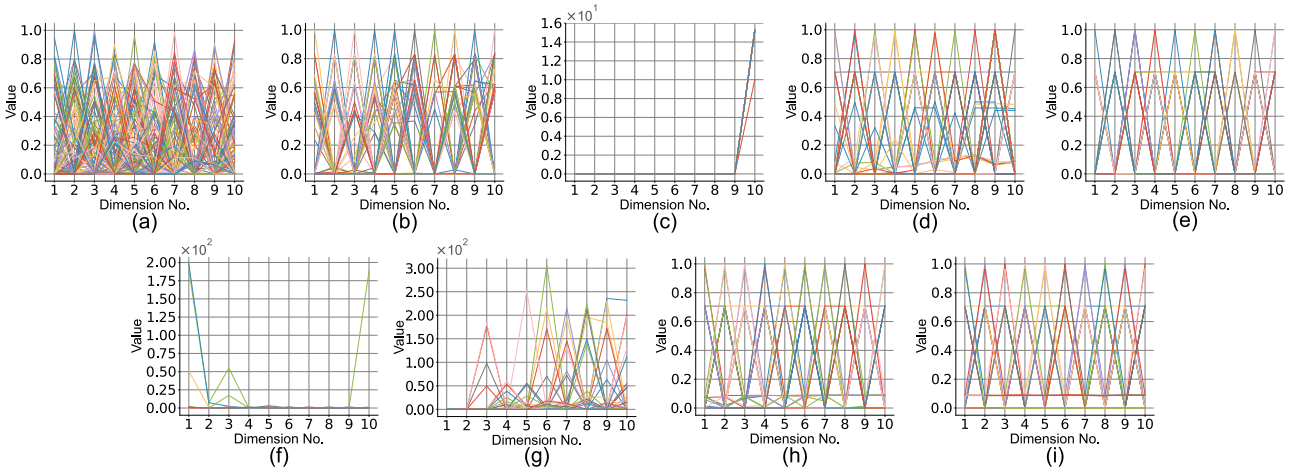


Fig. 9. Distribution of the final population for all algorithms on DTLZ3 problem with 10 objectives. The population obtained by MaOEAIH exhibits superior convergence and diversity compared to other algorithms. (a)MaOEAIH. (b)MaOEAIBP. (c)MaOEAIGD. (d)ARMOEA. (e)HEA. (f)tDEA. (g)TSNSGAII. (h)EFRRR. (i)RVEA.

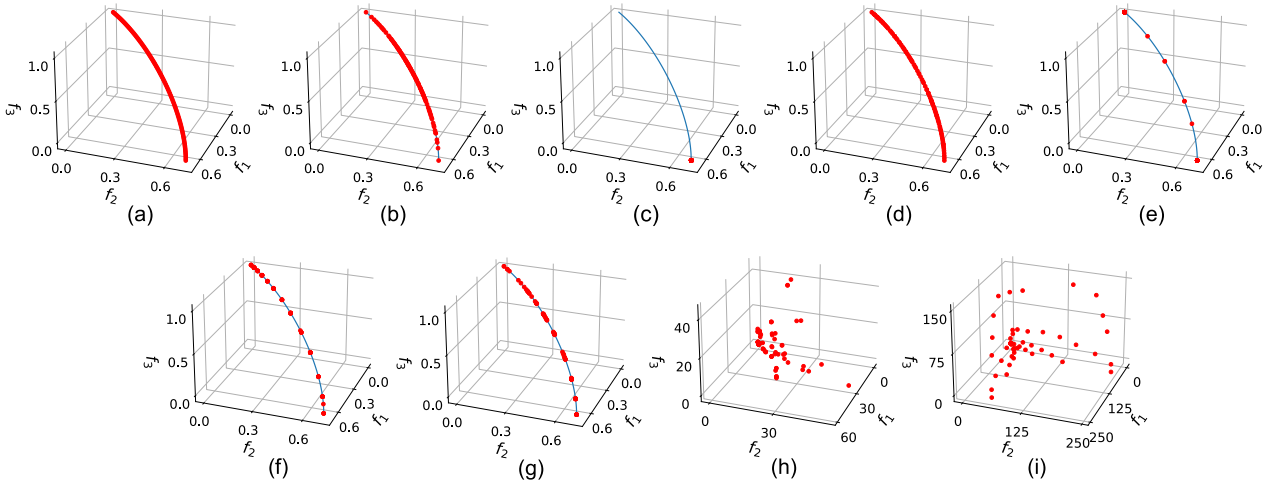


Fig. 10. Distribution of the final population for all algorithms on MaF6 problem with 3 objectives. The population obtained by MaOEAIH exhibits superior coverage and uniformity compared to other algorithms. (a)MaOEAIH. (b)MaOEAIBP. (c)MaOEAIGD. (d)ARMOEA. (e)HEA. (f)tDEA. (g)TSNSGAII. (h)EFRRR. (i)RVEA.

boundary solutions in accurately identifying the range of the PF, resulting in compromised population diversity. Nevertheless, MaOEAIH's results are mostly superior to the other compared algorithms.

For WFG4 to WFG9 and MAF12 with characteristics of multimodality, large basin sizes, deception, separable variables, and nonseparable variables in the search space, except for the 15-dimensional WFG8,

Table 4
Mean and standard deviation of the IGD values obtained by MaOEAIH and other MaOEAs for MAF and IDTLZ test suits.

Problem	M	MaOEAIBP	MaOEAIGD	ARMOEA	HEA	tDEA	TSNSGAII	EFRRR	RVEA	MaOEAIH
MaF1	3	4.4589e−2	1.6193e−1	4.3539e−2	7.0720e−2	8.0826e−2	7.1340e−2	7.7803e−2	8.2142e−2	4.0410e−2
		(7.02e−4) −	(4.61e−4) −	(1.88e−4) −	(2.29e−4) −	(1.10e−3) −	(7.89e−4) −	(3.69e−4) −	(1.28e−4) −	(1.19e−4)
	5	1.4909e−1	2.9193e−1	1.4860e−1	2.2812e−1	5.8844e−1	2.1666e−1	2.5535e−1	4.3712e−1	1.3113e−1
		(2.18e−3) −	(6.66e−3) −	(3.24e−3) −	(5.69e−4) −	(1.75e−1) −	(2.75e−3) −	(2.04e−2) −	(1.32e−1) −	(3.24e−4)
	8	2.6383e−1	3.7260e−1	2.6524e−1	3.4513e−1	3.2485e−1	3.5083e−1	4.5968e−1	6.6904e−1	2.1862e−1
		(4.45e−3) −	(4.01e−3) −	(1.34e−3) −	(6.30e−3) −	(1.29e−2) −	(1.10e−2) −	(7.70e−3) −	(7.73e−2) −	(3.14e−4)
	10	3.2051e−1	3.7113e−1	3.0245e−1	3.4325e−1	3.6306e−1	3.5632e−1	4.7007e−1	7.1447e−1	2.5467e−1
		(7.39e−3) −	(1.85e−2) −	(5.18e−4) −	(5.91e−3) −	(1.65e−2) −	(1.20e−2) −	(1.87e−2) −	(7.94e−2) −	(8.22e−4)
	15	4.0021e−1	4.0315e−1	4.4023e−1	4.1330e−1	3.9415e−1	4.6409e−1	5.8125e−1	7.7056e−1	3.0401e−1
		(1.29e−2) −	(2.36e−2) −	(5.41e−2) −	(1.35e−2) −	(2.10e−2) −	(2.80e−2) −	(2.38e−2) −	(7.80e−2) −	(9.35e−4)
MaF2	3	3.1420e−2	2.7048e−1	3.3238e−2	3.6444e−2	3.6442e−2	4.6275e−2	3.7112e−2	4.0009e−2	2.9211e−2
		(6.16e−4) −	(1.77e−1) −	(7.82e−4) −	(1.08e−4) −	(3.93e−4) −	(2.22e−3) −	(4.15e−4) −	(4.04e−4) −	(3.27e−4)
	5	1.2926e−1	1.4906e−1	1.2189e−1	1.3592e−1	1.4441e−1	1.4811e−1	1.4724e−1	1.4576e−1	1.1828e−1
		(3.80e−3) −	(5.18e−2) −	(1.44e−3) −	(8.44e−4) −	(2.70e−3) −	(1.27e−3) −	(5.33e−3) −	(9.43e−4) −	(1.40e−3)
	8	2.0269e−1	3.9577e−1	2.0042e−1	1.8077e−1	2.0928e−1	1.8381e−1	2.3934e−1	5.0894e−1	1.7210e−1
		(9.85e−3) −	(1.99e−2) −	(4.48e−3) −	(1.64e−3) −	(1.10e−2) −	(8.56e−4) −	(2.01e−2) −	(2.26e−1) −	(2.41e−3)
	10	2.3948e−1	4.1771e−1	2.4284e−1	2.1012e−1	3.0614e−1	2.1506e−1	2.5383e−1	6.5393e−1	1.9873e−1
		(3.11e−2) −	(1.83e−2) −	(1.01e−2) −	(2.19e−3) −	(3.21e−2) −	(1.89e−3) −	(1.89e−2) −	(1.80e−1) −	(2.57e−3)
	15	4.1890e−1	4.2886e−1	3.8133e−1	2.2375e−1	5.3500e−1	2.4045e−1	6.8898e−1	8.4207e−1	2.3376e−1
		(1.44e−2) −	(2.32e−2) −	(3.51e−2) −	(5.34e−4) +	(8.95e−2) −	(8.18e−3) −	(3.62e−2) −	(3.45e−2) −	(4.78e−3)
MaF3	3	4.0278e−2	2.6135e+2	4.6488e−2	3.9784e−2	5.0037e−2	1.4308e−1	4.6358e−2	5.9056e−2	3.1995e−2
		(1.18e−3) −	(2.12e+2) −	(6.26e−5) −	(2.75e−4) −	(4.00e−5) −	(7.62e−2) −	(1.66e−5) −	(6.89e−2) −	(2.71e−4)
	5	9.0986e−2	3.6916e+1	9.8598e−2	8.0785e−2	1.1019e−1	1.7801e−1	9.8640e−2	8.1630e−2	8.3555e−2
		(2.80e−3) −	(5.48e+1) −	(2.42e−4) −	(2.21e−3) +	(1.35e−4) −	(4.69e−2) −	(5.74e−5) −	(5.39e−3) ≈	(2.51e−3)
	8	1.4587e−1	2.8851e+1	1.4150e−1	1.6639e−1	3.1120e−1	5.6779e+5	1.8414e−1	1.1020e−1	1.2158e−1
		(5.93e−3) −	(4.81e+1) −	(8.17e−4) −	(4.59e−3) −	(2.95e−1) −	(2.06e+6) −	(4.29e−2) −	(2.27e−2) +	(1.11e−2)
	10	1.7262e−1	5.0830e+1	1.2118e−1	1.7522e−1	4.6567e−1	3.1849e+6	2.2786e−1	9.9087e−2	1.3119e−1
		(3.49e−2) −	(1.23e+2) −	(1.10e−3) +	(6.77e−3) −	(3.27e−1) −	(1.07e+7) −	(5.98e−2) −	(5.33e−3) +	(9.68e−3)
	15	1.1687e−1	3.3237e+1	1.2708e−1	1.8336e−1	7.9379e−1	2.8111e+8	3.6519e−1	1.2223e−1	1.5026e−1
		(7.68e−3) +	(3.61e+1) −	(5.06e−3) +	(1.31e−2) −	(1.94e−1) −	(1.44e+9) −	(1.54e−1) −	(4.97e−3) +	(1.16e−2)
MaF4	3	3.2256e−1	8.2167e+0	3.3946e−1	3.3922e−1	3.2337e−1	4.1327e−1	3.8067e−1	4.1322e−1	2.4795e−1
		(1.36e−2) −	(7.32e+0) −	(1.80e−3) −	(5.21e−3) −	(1.44e−2) −	(3.62e−2) −	(2.02e−2) −	(9.68e−2) −	(1.32e−2)
	5	2.4349e+0	4.4789e+1	2.9880e+0	2.8725e+0	4.1436e+0	3.4602e+0	4.0326e+0	4.4791e+0	1.9693e+0
		(6.12e−2) −	(3.93e+1) −	(2.17e−1) −	(5.11e−2) −	(5.71e−1) −	(3.97e−1) −	(2.85e−1) −	(1.21e+0) −	(1.18e−2)
	8	1.7440e+1	2.0899e+2	3.0201e+1	3.2914e+1	4.0393e+1	3.9342e+1	4.5481e+1	5.9446e+1	1.6887e+1
		(1.12e+0) −	(2.47e+1) −	(2.02e+0) −	(2.01e+0) −	(6.83e+0) −	(1.70e+0) −	(5.51e+0) −	(1.59e+1) −	(1.16e+0)
	10	6.9016e+1	9.6578e+2	1.4429e+2	1.4009e+2	1.7957e+2	1.4396e+2	1.5426e+2	2.2986e+2	6.7293e+1
		(5.74e+0) ≈	(2.81e+2) −	(1.73e+1) −	(3.63e+0) −	(1.48e+1) −	(3.48e+0) −	(1.67e+1) −	(4.85e+1) −	(3.96e+0)
	15	2.2534e+3	8.4171e+4	7.0742e+3	5.3771e+3	5.6267e+3	5.7033e+3	8.2495e+3	9.5027e+3	2.4019e+3
		(2.66e+2) ≈	(6.24e+4) −	(1.24e+3) −	(3.24e+2) −	(3.50e+2) −	(2.44e+2) −	(1.48e+3) −	(2.50e+3) −	(3.69e+2)
MaF5	3	1.1069e+0	1.5570e+0	1.1028e+0	1.2017e+0	3.1915e−1	2.6041e−1	2.5976e−1	3.0117e−1	2.3366e−1
		(1.22e+0) −	(7.17e−1) −	(1.28e+0) −	(1.45e+0) −	(3.25e−1) −	(6.03e−4) −	(2.32e−6) −	(2.27e−1) −	(2.44e−3)
	5	3.3244e+0	5.9378e+0	2.4997e+0	3.6409e+0	2.3735e+0	2.3758e+0	2.3744e+0	3.0815e+0	2.0173e+0
		(1.41e+0) −	(2.25e+0) −	(6.36e−1) −	(2.01e+0) −	(6.12e−4) −	(6.73e−3) −	(2.05e−3) −	(1.31e+0) −	(1.84e−2)
	8	2.1506e+1	4.2269e+1	2.8482e+1	2.7974e+1	2.8236e+1	2.7799e+1	2.7748e+1	2.9877e+1	1.6225e+1
		(5.13e+0) −	(6.69e+0) −	(3.53e−1) −	(3.29e+0) −	(1.18e−2) −	(4.03e−1) −	(3.84e−1) −	(3.81e+0) −	(5.46e−1)
	10	8.4867e+1	2.9783e+2	1.6678e+2	1.2346e+2	1.3717e+2	1.4085e+2	1.4021e+2	1.3191e+2	6.7021e+1
		(1.08e+1) −	(3.70e+1) −	(7.02e+0) −	(1.62e+1) −	(1.63e−1) −	(3.70e+0) −	(1.67e+0) −	(1.70e+1) −	(9.68e+0)
	15	2.4997e+3	7.3234e+3	5.8753e+3	3.6731e+3	4.8127e+3	5.3679e+3	4.9498e+3	6.6090e+3	1.9825e+3
		(3.78e+2) −	(1.02e+1) −	(2.72e+2) −	(4.74e+2) −	(2.10e+0) −	(5.18e+2) −	(7.16e+1) −	(1.02e+3) −	(1.30e+2)
MaF6	3	9.6296e−3	6.7058e−1	5.1340e−3	3.9256e−2	3.6147e−2	3.3861e−2	3.7227e−2	3.5524e−2	4.0351e−3
		(9.80e−4) −	(1.05e−1) −	(1.33e−4) −	(1.32e−3) −	(5.04e−3) −	(4.05e−3) −	(1.10e−2) −	(1.42e−3) −	(2.98e−5)
	5	9.8685e−3	6.8324e−1	5.0810e−3	7.9791e−2	1.4659e−1	6.5538e−2	1.0936e−1	8.1554e−2	4.0852e−3
		(1.13e−3) −	(3.92e−2) −	(6.43e−5) −	(3.61e−3) −	(2.11e−2) −	(1.01e−2) −	(2.41e−2) −	(1.30e−2) −	(4.26e−5)
	8	7.6379e−2	7.0808e−1	6.3019e−3	1.2281e−1	1.5180e−1	1.2153e−1	1.6648e−1	5.1535e−1	4.4796e−3
		(1.35e−1) −	(2.64e−2) −	(3.27e−4) −	(1.77e−2) −	(6.94e−2) −	(1.02e−2) −	(3.04e−2) −	(2.76e−1) −	(1.72e−3)
	10	1.6526e−1	7.1319e−1	9.4521e−3	1.3389e−1	2.3817e−1	2.6595e−1	1.8880e−1	1.3144e−1	3.8410e−2
		(1.69e−1) −	(2.08e−2) −	(4.58e−3) ≈	(3.27e−2) −	(7.35e−2) −	(1.45e−1) −	(3.57e−2) −	(4.26e−4) −	(7.24e−2)
	15	3.0914e−1	7.1299e−1	4.8725e−2	2.7436e−1	2.6753e−1	3.2419e−1	3.5369e−1	5.9375e−1	9.4281e−2
		(1.01e−1) −	(1.44e−4) −	(2.19e−2) ≈	(5.82e−2) −	(7.32e−2) −	(3.88e−2) −	(6.42e−2) −	(2.03e−1) −	(9.07e−2)
MaF7	3	1.0716e−1	9.0481e−1	1.7478e−1	1.5811e−1	1.2992e−1	1.0379e−1	1.0695e−1	1.0532e−1	5.7637e−2
		(1.12e−1) ≈	(5.05e−1) −	(2.55e−1) −	(1.25e−1) −	(9.26e−2) −	(6.57e−2) −	(6.70e−3) −	(2.68e−4) −	(1.19e−3)
	5	3.5717e−1	1.9242e+0	3.4645e−1	5.8827e−1	5.2898e−1	3.5593e−1	5.1688e−1	5.0918e−1	2.8967e−1
		(1.19e−1) ≈	(1.15e+0) −	(5.48e−3) −	(5.25e−1) −	(2.48e−2) −	(5.67e−3) −	(2.62e−2) −	(4.06e−4) −	(7.14e−3)
	8	8.2739e−1	3.8206e+0	1.8084e+0	1.1242e+0	1.4042e+0	1.2123e+0	2.0829e+0	1.8280e+0	6.8838e−1
		(9.91e−2) −	(1.99e+0) −	(5.17e−2) −	(7.83e−2) −	(2.52e−1) −	(2.21e−2) −	(4.77e−1) −	(1.41e−1) −	(3.61e−3)
	10	1.2774e+0	4.4074e+0	3.4751e+0	2.1207e+0	1.7420e+0	2.6453e+0	1.9900e+0	3.6522e+0	9.4205e−1
		(2.90e−1) −	(2.45e+0) −	(1.23e−1) −	(1.23e−2) −	(4.31e−1) −	(3.66e−1) −	(4.10e−1) −	(2.48e−2) −	(9.65e−3)
	15	3.2246e+0	3.1876e+0	7.3758e+0	8.0627e+0	1.1100e+1	8.9916e+0	8.1645e+0	7.1575e+0	1.5692e+0
		(8.03e−1) −	(1.70e+0) −	(3.24e−1) −	(8.23e−1) −	(5.49e−1) −	(5.99e−1) −	(4.66e−1) −	(1.73e−1) −	(1.29e−2)

(*continued on next page*)

WFG9, and MAF12, MaOEAIH achieves all the optimal results. To showcase this outstanding result, Fig. 11 presents the parallel coordinate plot of the final populations obtained by each algorithm on the 10-dimensional WFG5. From the figure, it can be seen that MaOEAIH exhibits a wider and more uniformly distributed region compared to other algorithms. Although the population distribution obtained by

Table 4 (*continued*).

MaF8	3	6.5136e−2 (1.37e−3) +	5.7543e−1 (2.21e−1) −	7.6668e−2 (2.29e−3) −	2.2909e−1 (3.40e−1) −	1.9392e−1 (5.80e−2) −	1.4783e−1 (1.26e−2) −	1.3977e−1 (1.67e−2) −	1.4060e−1 (7.85e−3) −	6.8220e−2 (1.32e−3)
	5	1.1554e−1 (2.63e−3) −	7.4477e−1 (1.56e−1) −	1.3856e−1 (5.35e−3) −	2.6330e−1 (2.79e−1) −	4.1522e−1 (2.10e−2) −	2.4935e−1 (2.11e−2) −	3.6984e−1 (1.21e−2) −	4.6734e−1 (5.08e−2) −	1.1122e−1 (1.50e−3)
	8	1.5862e−1 (3.88e−3) −	1.3575e+0 (2.98e−1) −	2.1529e−1 (1.01e−2) −	2.7587e−1 (2.35e−3) −	7.1531e−1 (1.01e−1) −	2.7966e−1 (1.47e−2) −	9.0911e−1 (8.66e−2) −	9.7908e−1 (1.09e−1) −	1.4661e−1 (1.48e−3)
	10	1.7711e−1 (3.83e−3) −	1.4657e+0 (2.22e−1) −	2.4192e−1 (5.78e−3) −	4.0508e−1 (2.78e−2) −	1.0347e+0 (1.47e−1) −	4.5049e−1 (5.30e−2) −	8.7934e−1 (1.66e−1) −	1.1321e+0 (1.37e−1) −	1.6333e−1 (1.51e−3)
	15	2.1556e−1 (2.73e−3) −	2.0019e+0 (2.60e−1) −	5.0385e−1 (3.61e−2) −	5.6157e−1 (5.58e−2) −	1.4715e+0 (1.77e−1) −	5.9553e−1 (5.38e−2) −	1.2557e+0 (1.65e−1) −	1.5852e+0 (2.16e−1) −	1.9907e−1 (1.40e−3)
MaF9	3	6.9543e−2 (1.70e−3) −	7.8781e−1 (3.55e−1) −	6.2000e−2 (6.87e−5) −	6.1988e−2 (9.42e−6) −	6.1992e−2 (9.09e−7) −	4.2021e−1 (5.71e−2) −	6.6023e−2 (5.74e−4) −	6.1989e−2 (2.33e−6) −	6.0692e−2 (3.71e−4)
	5	1.1501e−1 (1.77e−3) −	9.2055e−1 (4.21e−1) −	1.4580e−1 (7.93e−3) −	1.5849e−1 (1.34e−2) −	8.1010e−1 (2.22e−1) −	6.1751e−1 (1.93e−1) −	3.8870e−1 (5.96e−2) −	4.2101e−1 (9.85e−2) −	1.0781e−1 (3.67e−3)
	8	1.5656e−1 (1.90e−3) +	1.2707e+0 (5.69e−1) ≈	2.5974e−1 (1.24e−2) +	2.2230e−1 (2.16e−2) +	1.2268e+0 (8.88e−1) ≈	2.3992e+0 (2.00e+0) −	5.4955e−1 (8.11e−2) +	9.9538e−1 (2.29e−1) ≈	1.0777e+0 (3.87e−1)
	10	1.8424e−1 (3.03e−3) +	1.7338e+0 (9.56e−1) ≈	3.2110e−1 (2.44e−2) +	4.6984e−1 (1.81e−2) +	1.0978e+0 (1.24e−1) +	1.2997e+0 (3.65e−1) +	7.3699e−1 (1.08e−1) +	1.3284e+0 (4.13e−1) +	1.8774e+0 (8.67e−1)
	15	2.2086e−1 (3.24e−3) +	7.0181e+0 (5.39e+0) −	5.1097e−1 (3.82e−2) −	1.1867e+0 (2.21e−1) −	1.8377e+0 (5.11e−1) −	1.8914e+0 (2.10e+0) −	1.3581e+0 (2.11e−1) −	2.9038e+0 (3.17e+0) −	2.2225e−1 (5.23e−2)
MaF10	3	1.6083e−1 (5.83e−3) ≈	2.2668e+0 (1.33e−1) −	1.4481e−1 (2.73e−3) +	1.4533e−1 (1.59e−3) +	1.3968e−1 (1.52e−3) +	1.5625e−1 (8.00e−3) ≈	1.4183e−1 (1.49e−3) +	1.4543e−1 (3.31e−3) +	1.6109e−1 (1.30e−2)
	5	6.3411e−1 (2.22e−2) −	3.3187e+0 (6.97e−1) −	4.7436e−1 (4.28e−3) +	4.6253e−1 (3.96e−3) +	4.4383e−1 (6.51e−3) +	5.5099e−1 (1.81e−2) −	4.7681e−1 (1.51e−3) +	4.4681e−1 (4.88e−3) +	4.9232e−1 (2.93e−2)
	8	1.3554e+0 (6.54e−2) −	7.0777e+0 (2.38e+0) −	1.0190e+0 (8.65e−3) −	1.6900e+0 (1.49e−1) −	1.0099e+0 (5.90e−2) −	1.4458e+0 (7.46e−2) −	9.9164e−1 (3.35e−2) −	1.2782e+0 (1.46e−1) −	9.6382e−1 (6.04e−2)
	10	1.8399e+0 (8.68e−2) −	7.4322e+0 (3.32e+0) −	1.2879e+0 (8.26e−3) −	1.8072e+0 (2.99e−1) −	1.2771e+0 (2.91e−2) −	1.8886e+0 (1.28e−1) −	1.4397e+0 (1.08e−1) −	1.3768e+0 (8.33e−2) −	1.1363e+0 (7.75e−2)
	15	2.7222e+0 (2.04e−1) −	1.2930e+1 (6.94e+0) −	2.0356e+0 (1.38e−2) −	3.5118e+0 (3.96e−1) −	2.2123e+0 (1.42e−1) −	3.2306e+0 (1.95e−1) −	2.1757e+0 (1.33e−1) −	2.2723e+0 (5.80e−2) −	1.8487e+0 (2.17e−1)
MaF11	3	2.2847e−1 (1.67e−2) −	1.5486e+0 (2.05e−1) −	1.6505e−1 (9.61e−4) +	1.5604e−1 (2.10e−3) +	1.5822e−1 (1.04e−3) +	1.7475e−1 (5.42e−3) −	1.7007e−1 (8.49e−4) ≈	1.7288e−1 (2.35e−3) −	1.6920e−1 (3.02e−3)
	5	6.2698e−1 (1.25e−2) −	1.9458e+0 (2.91e−1) −	5.0795e−1 (1.87e−3) +	4.9422e−1 (7.10e−3) +	4.7303e−1 (9.91e−4) +	5.7551e−1 (2.18e−2) −	5.1830e−1 (1.55e−2) +	4.7977e−1 (7.72e−3) +	5.5237e−1 (2.26e−2)
	8	1.3644e+0 (3.87e−2) −	2.6011e+0 (4.24e−1) −	1.0845e+0 (7.90e−3) −	1.7865e+0 (2.84e−1) −	1.8763e+0 (4.85e−1) −	1.3816e+0 (4.96e−2) −	1.1378e+0 (6.70e−2) −	1.2964e+0 (3.19e−2) −	1.0539e+0 (3.13e−2)
	10	1.9412e+0 (8.07e−2) −	5.0873e+0 (3.83e+0) −	1.3509e+0 (4.09e−3) ≈	2.2929e+0 (1.26e−1) −	2.9055e+0 (9.03e−1) −	1.9005e+0 (6.54e−2) −	1.4622e+0 (1.21e−1) −	1.5024e+0 (1.23e−2) −	1.3252e+0 (7.77e−2)
	15	2.3155e+0 (2.34e−1) ≈	7.7070e+0 (7.35e+0) −	2.0512e+0 (3.99e−2) +	3.7182e+0 (6.49e−1) −	8.6313e+0 (2.37e+0) −	3.5141e+0 (1.48e−1) −	3.6591e+0 (8.64e−1) −	2.3468e+0 (8.47e−3) ≈	2.2457e+0 (3.29e−1)
MaF12	3	3.0004e−1 (8.98e−3) −	2.1917e+0 (5.69e−1) −	2.2036e−1 (2.77e−4) −	2.2985e−1 (2.98e−2) −	2.2052e−1 (2.32e−4) −	2.3069e−1 (3.05e−2) −	2.2950e−1 (2.89e−3) −	2.2088e−1 (4.04e−4) −	2.0103e−1 (1.33e−3)
	5	1.3610e+0 (2.52e−2) −	4.6976e+0 (1.27e+0) −	1.2141e+0 (1.86e−3) −	1.2161e+0 (3.13e−3) −	1.2139e+0 (1.93e−3) −	1.2071e+0 (5.49e−3) −	1.3625e+0 (2.41e−2) −	1.2192e+0 (2.80e−3) −	1.1060e+0 (4.80e−3)
	8	3.4289e+0 (4.36e−2) −	1.1109e+1 (2.66e+0) −	3.5311e+0 (1.04e−2) −	3.5495e+0 (1.45e−2) −	3.5251e+0 (1.72e−2) −	3.5821e+0 (3.10e−2) −	3.5514e+0 (2.34e−2) −	3.5220e+0 (2.51e−2) −	3.2251e+0 (2.48e−2)
	10	5.1842e+0 (8.16e−2) −	1.5212e+1 (4.37e+0) −	5.8112e+0 (2.43e−2) −	5.8747e+0 (3.62e−2) −	5.8312e+0 (3.87e−2) −	5.9181e+0 (5.82e−2) −	6.2083e+0 (8.01e−2) −	5.8335e+0 (4.62e−2) −	4.8281e+0 (3.34e−2)
	15	9.1462e+0 (9.54e−2) +	2.5515e+1 (7.06e+0) −	1.1592e+1 (3.17e−1) −	1.2052e+1 (5.67e−2) −	1.1962e+1 (1.88e−1) −	1.2766e+1 (2.39e−1) −	1.1784e+1 (5.67e−1) −	1.1221e+1 (4.32e−1) −	9.4846e+0 (1.08e−1)
MaF13	3	8.5605e−2 (2.64e−3) −	6.0225e−1 (2.41e−1) −	6.4233e−2 (4.53e−3) +	6.3039e−2 (2.00e−3) +	6.0801e−2 (2.77e−3) +	1.3238e−1 (1.64e−2) −	6.8878e−2 (4.48e−3) +	6.2834e−2 (2.79e−3) +	7.8803e−2 (9.13e−3)
	5	1.0720e−1 (8.39e−3) −	7.9455e−1 (7.92e−2) −	1.4219e−1 (5.83e−3) −	1.8322e−1 (1.02e−2) −	4.4621e−1 (5.95e−2) −	3.8182e−1 (1.09e−1) −	3.1489e−1 (2.84e−2) −	4.3114e−1 (2.69e−2) −	1.0062e−1 (7.51e−3)
	8	1.2289e−1 (9.13e−3) ≈	1.1440e+0 (5.81e−2) −	1.9096e−1 (9.26e−3) −	4.2561e−1 (3.49e−2) −	6.4498e−1 (9.33e−2) −	1.0589e+0 (6.40e−1) −	5.9450e−1 (1.40e−1) −	1.2387e+0 (1.28e+0) −	1.2225e−1 (9.42e−3)
	10	1.2992e−1 (8.66e−3) ≈	1.2571e+0 (1.54e−1) −	2.2303e−1 (1.94e−2) −	5.5895e−1 (5.25e−2) −	7.3375e−1 (9.08e−2) −	1.9093e+0 (3.59e+0) −	1.0169e+0 (1.90e−1) −	1.0651e+0 (2.48e−1) −	1.2907e−1 (6.95e−3)
	15	1.4160e−1 (5.95e−3) +	1.6269e+0 (2.38e−1) −	4.0537e−1 (3.84e−2) −	7.6555e−1 (1.32e−1) −	1.2150e+0 (2.20e−1) −	1.7355e+0 (3.02e−1) −	1.4065e+0 (1.09e−1) −	5.3653e+0 (2.16e+1) −	1.5057e−1 (1.12e−2)
IDTLZ1	3	2.2388e−2 (4.07e−4) −	1.2345e−1 (9.25e−2) −	2.1744e−2 (2.29e−5) −	3.5132e−2 (4.34e−5) −	4.0429e−2 (5.11e−4) −	3.5932e−2 (4.25e−4) −	3.8869e−2 (2.47e−4) −	4.4658e−2 (1.04e−2) −	1.9962e−2 (1.15e−4)
	5	7.4181e−2 (9.47e−4) −	1.7459e−1 (1.18e−1) −	7.5202e−2 (1.78e−3) −	1.1631e−1 (3.02e−3) −	3.7727e−1 (7.77e−2) −	1.0568e−1 (2.79e−3) −	1.2878e−1 (1.06e−2) −	1.5959e−1 (2.13e−2) −	6.7092e−2 (4.98e−4)
	8	1.3140e−1 (1.96e−3) −	3.0139e−1 (1.39e−1) −	1.3253e−1 (1.36e−3) −	1.8263e−1 (6.18e−2) −	1.6467e−1 (4.27e−3) −	1.7573e−1 (5.38e−3) −	2.6989e−1 (1.32e−2) −	2.7704e−1 (3.06e−2) −	1.1839e−1 (5.88e−3)
	10	1.5695e−1 (2.76e−3) −	3.5220e−1 (1.57e−1) −	1.5101e−1 (7.36e−4) −	2.2153e−1 (1.17e−1) −	1.9160e−1 (1.05e−2) −	1.8900e−1 (1.33e−2) −	2.8916e−1 (8.22e−3) −	3.2031e−1 (4.26e−2) −	1.2784e−1 (2.40e−3)
	15	1.9501e−1 (5.23e−3) ≈	4.4624e−1 (1.22e−1) −	2.2088e−1 (1.49e−2) −	2.3610e−1 (9.71e−2) −	2.0667e−1 (3.03e−2) −	1.9751e−1 (1.07e−2) −	3.5219e−1 (1.64e−2) −	3.6402e−1 (4.65e−2) −	1.7252e−1 (2.69e−2)

(*continued on next page*)

MaOEAIBP is similar to MaOEAIH, the distribution is not uniform, with larger gaps between individuals in the 0 to 2.5 range of objectives 6 to 10. Meanwhile, As an indicator-based MaOEA, MaOEAIGD struggles to maintain population diversity, thus obtaining the poorest result where all individuals converge at a single point. For the remaining algorithms, although their populations can cover the entire PF, these populations are not uniformly distributed and are mainly concentrated on the boundaries of the PF, leaving a large number of gaps in the

Table 4 (*continued*).

IDTLZ2	3	7.3682e−2	3.3274e−1	7.7457e−2	7.4857e−2	7.2105e−2	8.1145e−2	8.3395e−2	7.9669e−2	5.2057e−2
		(3.40e−3) −	(4.66e−3) −	(8.10e−5) −	(1.19e−3) −	(1.09e−3) −	(1.87e−3) −	(2.63e−3) −	(9.04e−4) −	(2.67e−4)
	5	2.3643e−1	4.9316e−1	2.3953e−1	2.5570e−1	3.3392e−1	2.7264e−1	3.3470e−1	3.6306e−1	1.9750e−1
		(4.17e−3) −	(1.53e−2) −	(5.07e−3) −	(3.51e−3) −	(2.67e−2) −	(2.03e−3) −	(1.99e−2) −	(1.09e−2) −	(1.03e−3)
	8	4.1933e−1	7.6873e−1	5.2711e−1	6.3207e−1	6.3923e−1	6.5265e−1	7.1084e−1	7.7445e−1	3.7413e−1
		(4.61e−3) −	(9.53e−3) −	(1.33e−2) −	(1.20e−2) −	(1.03e−2) −	(3.59e−3) −	(2.29e−2) −	(4.68e−2) −	(1.67e−3)
	10	4.7855e−1	7.9123e−1	5.2540e−1	7.2351e−1	7.5591e−1	7.3831e−1	7.5370e−1	7.4956e−1	4.5602e−1
		(3.50e−3) −	(2.43e−2) −	(1.22e−2) −	(1.25e−2) −	(1.25e−2) −	(3.19e−3) −	(2.15e−2) −	(1.82e−2) −	(2.00e−3)
	15	5.9912e−1	8.8669e−1	7.3698e−1	8.3192e−1	8.6624e−1	8.6286e−1	1.0123e+0	9.3189e−1	5.9153e−1
		(6.01e−3) −	(7.19e−4) −	(1.80e−2) −	(8.77e−3) −	(1.48e−2) −	(4.41e−3) −	(4.48e−2) −	(2.67e−2) −	(2.57e−3)
+/−/≈		7/59/9	0/73/2	10/62/3	4/69/2	6/68/1	6/66/3	6/67/1	8/64/3	

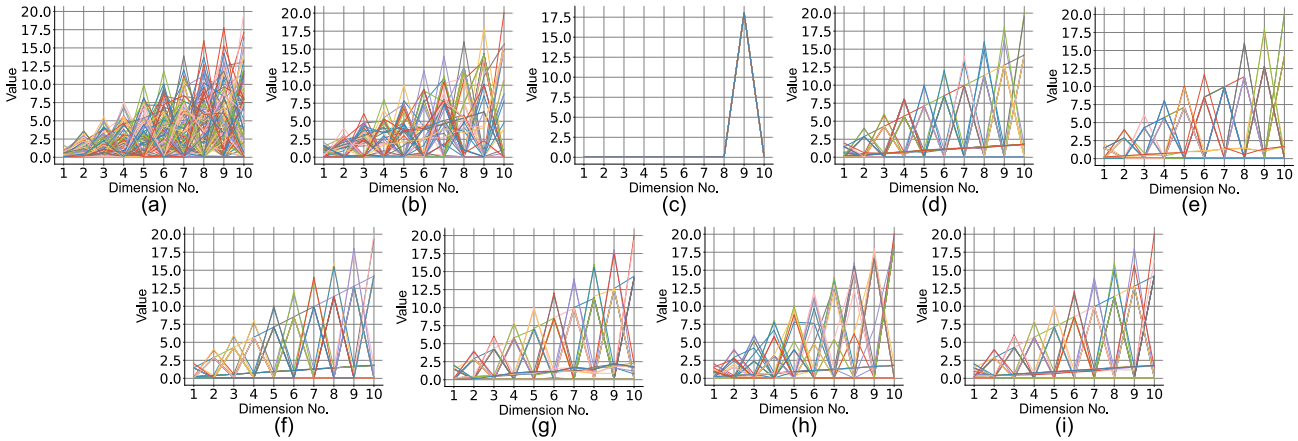


Fig. 11. Distribution of the final population for all algorithms on WFG5 problem with 10 objectives. The population obtained by MaOEAIH exhibits superior uniformity compared to other algorithms. (a)MaOEAIH. (b)MaOEAIBP. (c)MaOEAIGD. (d)ARMOEA. (e)HEA. (f)tDEA. (g)TSNSGAII. (h)EFRRR. (i)RVEA.

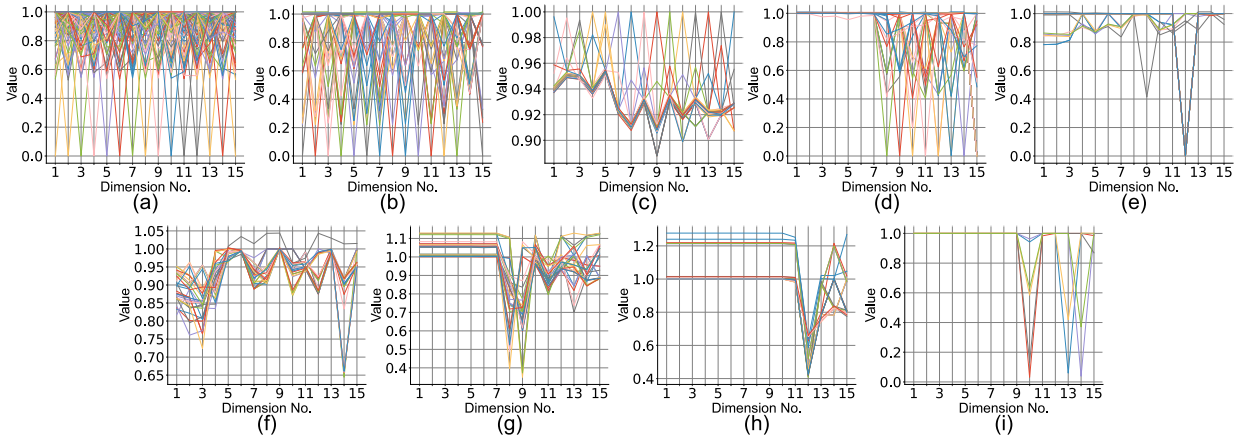


Fig. 12. Distribution of the final population for all algorithms on MAF1 problem with 15 objectives. The population obtained by MaOEAIH exhibits superior coverage and uniformity compared to other algorithms. (a)MaOEAIH. (b)MaOEAIBP. (c)MaOEAIGD. (d)ARMOEA. (e)HEA. (f)tDEA. (g)TSNSGAII. (h)EFRRR. (i)RVEA.

center of the PF. Overall, MaOEAIH is more effective at maintaining population diversity when dealing with MaOPs that have features like multimodality and large basin scales, compared to other algorithms.

Similarly, apart from achieving optimal results on 15-dimensional MAF4, where it is on par with MaOEAIBP, MaOEAIH also attained nearly all optimal results on MAF4 and MAF5 with severe scaling features. This is because GaRIF employs the principle of energy balance, enabling the population to uniformly spread across the entire PF regardless of how it is scaled. Consequently, MaOEAIH can effectively handle MaOPs with severe scaling features.

In the inversion problems of IDTLZ1, IDTLZ2, MAF1, and MAF2 under different objectives, MaOEAIH obtained 19 optimal results and 1 suboptimal result, demonstrating its effective handling of such problems. To visually demonstrate this result more intuitively, Fig. 12 shows the final population distribution of these algorithms under the 15-dimensional MAF1. From Fig. 12(e), it can be observed that although HEA enhanced selection pressure through hyper-dominance, its diversity maintenance method based on reference points led the population to converge to several points in the PF. Similarly, other algorithms using reference points also failed to maintain diversity. Although tDEA enhanced selection pressure through a new dominance relation, it lacked a diversity maintenance strategy, resulting in population diversity like algorithms using reference points. The population uniformity of MaOEAIGD is relatively good, but as shown in Fig. 12(c), the population distribution below the objective value of 0.94 is sparse. For MaOEAIBP, its diversity is better than the algorithms mentioned above, but as shown in Fig. 12(b), its distribution is sparse on the 14th objective. In contrast, as shown in Fig. 12(a), MaOEAIH maintains population diversity better when dealing with inversion problems, with a uniform and extensive population distribution.

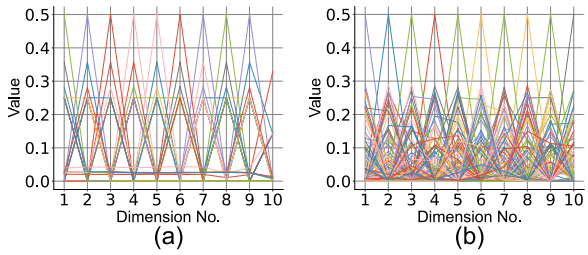


Fig. 13. Distribution of the final population for RVEA and RVEAGaRIF algorithms on the DTLZ1 problem with 10 objectives. The population obtained by (b)RVEAGaRIF is more uniform than that obtained by (a)RVEA.

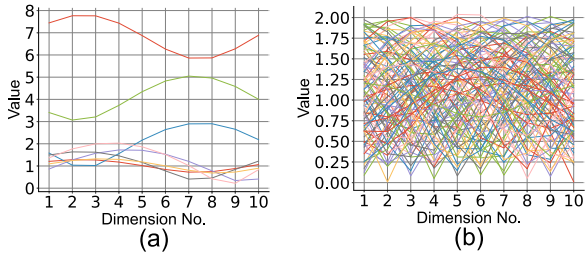


Fig. 14. Distribution of the final population for RVEA and RVEAGaRIF algorithms on the MAF8 problem with 10 objectives. The population obtained by (b)RVEAGaRIF exhibits superior convergence and diversity compared to the population obtained by (a)RVEA.

So far, we have demonstrated the effectiveness of MaOEA-IH for various MaOPs.

4.3. Effectiveness of GaRIF

To verify the effectiveness of weight vectors generated by MaOEAIH in handling MaOPs with regular PF and irregular PF, we replaced the weight vectors of RVEA with the weight vectors generated by MaOEAIH in the 31 test problems mentioned above. The algorithm with the replaced weight vectors is denoted as RVEAGaRIF. It is important to note that the weight vectors generated in MaOEAIH are extracted during the second use of the Pareto dominance-based evolution mechanism, and the ideal point for RVEAGaRIF was set as the coordinate origin. Subsequently, experiments were conducted on these test problems using RVEAGaRIF and RVEA.

Fig. 13 presents the parallel coordinate plot of the final populations obtained by RVEA and RVEAGaRIF on the 10-dimensional test problem DTLZ1, which has a regular PF. From the figure, it can be observed that both RVEAGaRIF and RVEA effectively converge to the PF. However, the final population obtained by RVEA does not cover the region of objective values between 0.05 and 0.25, whereas RVEAGaRIF can effectively cover these regions. This indicates that RVEAGaRIF exhibits better population diversity compared to RVEA. Fig. 14 depict the parallel coordinate plots of the final populations obtained by RVEA and RVEAGaRIF on the 10-dimensional test problem MAF8, which has irregular PF. In MAF8, the population obtained by RVEA fails to converge to the PF, while only retaining a small number of individuals in the population. However, the population obtained by RVEAGaRIF not only converges to the PF but also effectively covers the entire PF. This phenomenon is caused by the mismatch between the weight vectors used by RVEA and the shape of the PF, resulting in the waste of many weight vectors. As a result, individuals can only converge towards the remaining weight vectors, ultimately leading to their clustering together and the inability to completely cover the entire PF.

Furthermore, due to space limitations, we only provide the statistical results of the comparison between RVEAGaRIF and RVEA using the IGD indicator on the 3, 5, 8, and 10-objective experimental test suites in Table 5. From Table 5, it can be observed that in the DTLZ, WFG, MAF, and IDTLZ problem series with regular and irregular PFs, RVEAGaRIF outperforms RVEA in 103 out of 124 cases, approximately 83.1%. This demonstrates the competitive advantage of the algorithm that utilizes the weight vectors generated by MaOEAIH compared to the original algorithm when dealing with MaOPs with regular and irregular PFs.

Table 5
The statistical results of the comparison between RVEAGaRIF and RVEA using IGD (+ , −, ≈ respectively represent that RVEAGaRIF is worse, better, and no significant difference).

Comparisons		RVEA vs. RVEAGaRIF		
		+	−	≈
Test problems	DTLZ1	1	3	0
	DTLZ2	0	4	0
	DTLZ3	0	4	0
	DTLZ4	0	4	0
	DTLZ5	0	3	1
	DTLZ6	0	4	0
	DTLZ7	0	4	0
	WFG1	2	2	0
	WFG2	1	3	0
	WFG3	0	4	0
	WFG4	1	3	0
	WFG5	1	3	0
	WFG6	2	2	0
	WFG7	1	3	0
	WFG8	1	3	0
	WFG9	1	3	0
	MAF1	0	4	0
	MAF2	0	4	0
	MAF3	0	4	0
	MAF4	0	4	0
	MAF5	2	2	0
	MAF6	0	4	0
	MAF7	0	4	0
	MAF8	0	4	0
	MAF9	2	2	0
	MAF10	2	2	0
	MAF11	1	3	0
	MAF12	1	3	0
	MAF13	1	3	0
	IDTLZ1	0	4	0
	IDTLZ2	0	4	0
$No.(M)$	3	3	28	0
	5	4	27	0
	8	4	27	0
	10	9	21	1
	All	20	103	1

4.4. Analysis of perturbation strategy

To investigate the impact of perturbation strategies on algorithm performance, we compared MaOEAIH with and without perturbation strategies. The experimental results are presented in Figs. 15 and 16. Fig. 15(a) displays a potential population obtained by the unperturbed MaOEAIH on the 3-dimensional DTLZ4 test problems. It can be observed that this population is concentrated on one boundary of the PF. In contrast, Fig. 15(b) shows the population obtained by the MaOEAIH with perturbation strategy, which covers the entire PF. This phenomenon may be attributed to the significant density differences in the point sets of the DTLZ4 test problem's PF. The population is likely to converge to areas with higher point density, unable to spread to regions with lower density, resulting in being trapped in local optima. This demonstrates that appropriate random perturbation helps the population spread into low-density regions, enabling escape from local optima. Fig. 16 illustrates the final populations obtained by the unperturbed and perturbed MaOEAIH strategies on the 10-dimensional DTLZ6 test problem. In Fig. 16(a), the unperturbed MaOEAIH fails to converge to the PF, while in Fig. 16(b), the perturbed MaOEAIH

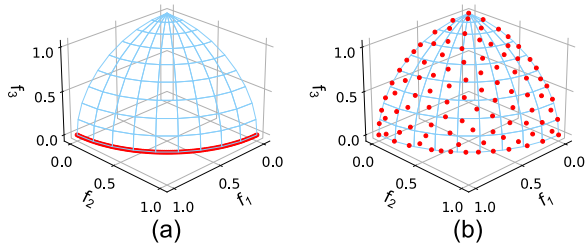


Fig. 15. Distribution of the final population for unperturbed and perturbed MaOEAIH on the DTLZ4 problem with 3 objectives. The population obtained by perturbed MaOEAIH demonstrates superior diversity compared to the population obtained by unperturbed MaOEAIH.

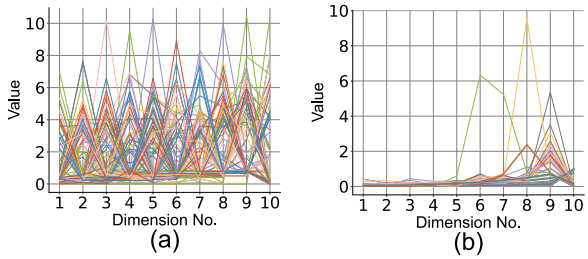


Fig. 16. Distribution of the final population for unperturbed and perturbed MaOEAIH on the DTLZ6 problem with 10 objectives. The population obtained by perturbed MaOEAIH demonstrates superior convergence compared to the population obtained by Unperturbed MaOEAIH.

achieves a population that approximately converges to the PF. If we appropriately increase the maximum number of evaluations, the unperturbed MaOEAIH strategy can also achieve a reasonable convergence to the PF. This indicates that perturbation strategies can improve the convergence rate of our algorithm on problems similar to DTLZ6.

4.5. The effect of eliminating dominant resistance solutions

To evaluate the effectiveness of the quartile method based on boundary solutions in eliminating dominance resistance solutions, we conducted comparative experiments between MaOEAIH and its variant without the quartile method based on boundary solutions, referred to as MaOEAIHDRS. We used a set of test suites with 15 objectives for the experiments. The experimental results, shown in Table 6, indicate that out of the 31 test problems, MaOEAIH significantly outperformed MaOEAIHDRS in 16 problems. This improvement can be attributed to the effective elimination of domination resistance solutions through the quartile method based on boundary solutions, particularly in difficult convergence problems like DTLZ1. This prevented a significant decrease in solution convergence when MaOEAIH pursued diversity. Additionally, 12 results were approximately comparable to MaOEAIHDRS. However, as the number of objectives increased, resulting in more domination resistance solutions, MaOEAIH might outperform MaOEAIHDRS in such cases. The three problems where MaOEAIH performed worse than MaOEAIHDRS were likely due to imprecise selection of boundary solutions using the coarse method, resulting in an incorrect estimation of the PF range and inadvertent elimination of useful solutions. This compromise compromised the algorithm's performance.

4.6. Research on optimization mechanism transformation parameters

The specific value for "a certain number of generations" in the context of "the minimum historical value of GaRIF of the population remains unchanged for a certain number of generations or when the minimum historical value of the sum of distances from each individual in the population to the origin remains unchanged" from Section 3.3 is determined for the following experiments. We conducted tests to evaluate the impact of different values for the "certain number of generations" on the algorithm and obtained the maximum "certain number of generations" required for three optimization mechanism transitions that yielded the overall best performance. Fig. 17(a) illustrates the source of the maximum "certain number of generations" required for the first transition, which was obtained from the 10-dimensional test problem WFG1. As the "certain number of generations" increases, the IGD value generally decreases, with a minimal decrease observed between 80 and 100 generations. Therefore, we set the "certain number of generations" for the first transition to 100. Fig. 17(b) presents the source of the maximum "certain number of generations" required for the second transition, which was obtained from the 10-dimensional test problem MAF6. Increasing the "certain number of generations" reduces the IGD value, but after 20 generations, the IGD value starts to increase. Hence, we set the "certain number of generations" for the second transition to 20. Fig. 17(c) displays the source of the maximum "certain number of generations" required for the third transition, obtained from the 10-dimensional test problem WFG3. The IGD value reaches its minimum at 60 generations. Therefore, we set the "certain number of generations" for the third transition to 60. It is important to note that in most test problems, such large values for the "certain number of generations" are not required, and only a few generations are sufficient. The value we selected is to balance all test problems, but due to the complexity and diversity of real-world problems, these values are rough estimates rather than precise ones. However, we chose them to maximize the possibility of producing superior results.

Table 6
Mean and standard deviation of the IGD values obtained by MaOEAIH and MaOEAIHDRS for DTLZ, WFG, MAF, and IDTLZ test suits.

Problem	M	MaOEAIHDRS	MaOEAIH
DTLZ1	15	1.8273e−1 (9.57e−3) −	1.5804e−1 (8.18e−3)
DTLZ2	15	5.9325e−1 (2.16e−3) +	5.9439e−1 (1.72e−3)
DTLZ3	15	6.1146e−1 (9.63e−3) −	6.0326e−1 (9.66e−3)
DTLZ4	15	6.0427e−1 (2.17e−3) −	5.9563e−1 (1.84e−3)
DTLZ5	15	1.1041e−1 (4.64e−1) −	4.8561e−2 (2.60e−2)
DTLZ6	15	3.8671e−2 (2.24e−2) ≈	3.9805e−2 (1.92e−2)
DTLZ7	15	1.6754e+0 (3.36e−2) −	1.5673e+0 (1.25e−2)
WFG1	15	1.7884e+0 (2.24e−1) ≈	1.8531e+0 (2.24e−1)
WFG2	15	2.2829e+0 (3.10e−1) ≈	2.1733e+0 (2.57e−1)
WFG3	15	4.3559e+0 (8.08e−1) ≈	4.2414e+0 (9.47e−1)
WFG4	15	9.4612e+0 (4.68e−2) ≈	9.4634e+0 (4.05e−2)
WFG5	15	9.4456e+0 (5.00e−2) −	9.4201e+0 (4.92e−2)
WFG6	15	9.4659e+0 (6.28e−2) ≈	9.4432e+0 (5.11e−2)
WFG7	15	9.4975e+0 (5.71e−2) ≈	9.4914e+0 (6.57e−2)
WFG8	15	9.6968e+0 (1.09e−1) −	9.6363e+0 (1.09e−1)
WFG9	15	9.5457e−1 (1.27e−1) −	9.5022e−1 (1.06e−1)
MaF1	15	3.2362e−1 (4.56e−3) −	3.0401e−1 (9.35e−4)
MaF2	15	2.3414e−1 (4.18e−3) ≈	2.3376e−1 (4.78e−3)
MaF3	15	2.0160e−1 (1.61e−2) −	1.5026e−1 (1.16e−2)
MaF4	15	2.0745e+3 (1.63e+2) +	2.4019e+3 (3.69e+2)
MaF5	15	2.1064e+3 (1.07e+2) −	1.9825e+3 (1.30e+2)
MaF6	15	6.9896e−2 (7.47e−2) ≈	9.4281e−2 (9.07e−2)
MaF7	15	1.6638e+0 (3.59e−2) −	1.5692e+0 (1.29e−2)
MaF8	15	2.0203e−1 (3.00e−3) −	1.9907e−1 (1.40e−3)
MaF9	15	2.5064e−1 (5.28e−2) −	2.2225e−1 (5.23e−2)
MaF10	15	1.8181e+0 (2.41e−1) ≈	1.8487e+0 (2.17e−1)
MaF11	15	2.3520e+0 (3.44e−1) ≈	2.2457e+0 (3.29e−1)
MaF12	15	9.5140e+0 (6.69e−2) ≈	9.4846e+0 (1.08e−1)
MaF13	15	1.6494e−1 (1.11e−2) −	1.5057e−1 (1.12e−2)
IDTLZ1	15	1.8292e−1 (2.23e−2) −	1.7252e−1 (2.69e−2)
IDTLZ2	15	5.7985e−1 (3.46e−3) +	5.9153e−1 (2.57e−3)
+/ − / ≈		3/16/12	

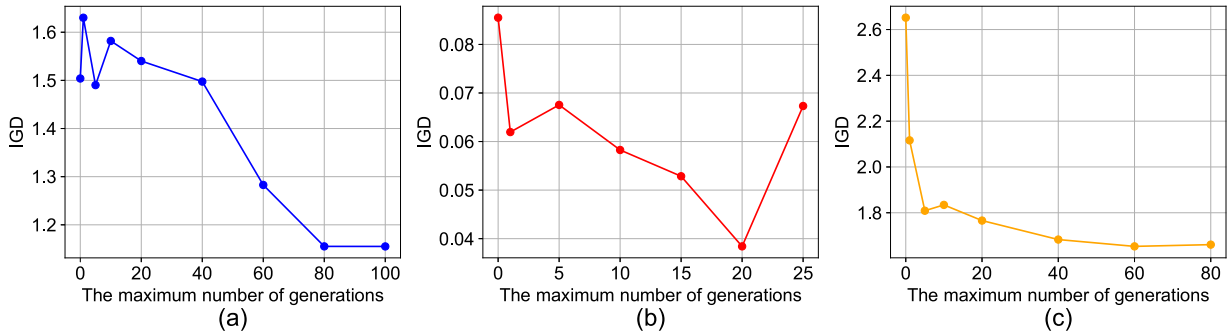


Fig. 17. The source of the maximum "certain number of generations". A smaller IGD value indicates that "certain number of generations" is more appropriate. (a)First transition in 10-dimensional WFG1. (b)Second transition in 10-dimensional MAF6. (c)Last transition in 10-dimensional WFG3.

Table 7
Running time of all algorithms.

Algorithm	MaOEAIBP	MaOEAIGD	ARMOEA	HEA	tDEA	TSNSGAII	EFRRR	RVEA	MaOEAIH
Total time	11 265.44	8456.31	46 211.385	6727.249	5194.235	11 469.973	6214.766	3484.68	52 763.07
Rank	6	5	8	4	2	7	3	1	9

4.7. Comparison of algorithms' running times

To evaluate the efficiency of MaOEAIH in handling MaOPs, this section summarizes the total time required by MaOEAIH and its comparative algorithms to process all test problems (measured in seconds), as shown in Table 7. The results indicate that RVEA has the shortest runtime. In contrast, MaOEAIBP, ARMOEA, TSNSGAII, and MaOEAIH take much longer, all exceeding 10^4 seconds, with MaOEAIH taking the longest because selecting the population with the minimum GaRIF requires a significant amount of time. Despite MaOEAIH's higher time complexity, its time consumption is acceptable given its superior performance.

In summary, MaOEAIH is suitable for solving problems that are complex but not extremely time-sensitive. From another perspective, it is also applicable to scenarios where the objective function evaluation is very time-consuming because, in such cases, the evaluation time of the objective function far exceeds the algorithm running time, making the running time differences between algorithms negligible. For example, in real-world applications like vehicle structure design in automotive crash safety [64], and pipeline systems with a large number of decision variables [65], rapid response may not be the primary concern, but improvements in the quality of the solution set can have a more significant impact.

5. Conclusion

In this paper, a many-objective evolutionary algorithm based on interaction force and hybrid optimization mechanism (MaOEAIH) is proposed to balance convergence and diversity. In MaOEAIH, a population selected based on Pareto dominance and the Gravity and Repulsion-Interaction Force is employed as the weight vectors in the decomposition-based optimization mechanism to obtain a population with good convergence and diversity. Additionally, a quartile method based on boundary solutions is used to maintain convergence, and a random perturbation method is applied to help the population escape local optima.

Comparing with 8 state-of-the-art algorithms on 31 test problems, MaOEAIH shows competitive performance compared to other algorithms. Furthermore, experiments conducted on the weight vectors generated by MaOEAIH show that these weight vectors effectively handle problems with both regular and irregular Pareto fronts. The experiments on the methods for eliminating dominance resistance solutions and the perturbation strategy also validate their effectiveness.

When dealing with most MaOPs, MaOEAIH can effectively improve the diversity and convergence of the population, enhance the selection pressure on the population, maintain a balance between convergence and diversity, and help the population escape local optima. However, MaOEAIH lacks the means to handle MaOPs with convex PF, leading to relatively poor results in these problems. Additionally, MaOEAIH spends a considerable amount of time when using GaRIF to select individuals, resulting in a higher time complexity. Finally, MaOEAIH only undergoes performance verification on the test suites, and its effectiveness in real-world applications remains to be studied. In future work, we will focus on researching a method that can accurately identify boundary solutions to handle problems with convex PF, while also using determinant point processes to reduce the selection time of GaRIF. Furthermore, recent constrained MaOPs have received widespread attention, and MaOEAIH will be applied to constrained real-world applications such as unmanned aircraft path detection to enhance its practical value. However, MaOEAIH was not designed with constraint problems in mind, making it challenging to improve MaOEAIH to handle constraint problems. At the same time, tuning certain parameters of MaOEAIH in handling real-world applications is also a challenge.

CRediT authorship contribution statement

Lei Yang: Conceptualization, Funding acquisition, Investigation, Methodology, Supervision, Writing – review & editing. **Jiale Cao:** Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Kangshun Li:** Funding acquisition, Supervision. **Yuanye Zhang:** Investigation, Visualization, Writing – review & editing. **Rui Xu:** Investigation, Visualization. **Ke Li:** Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

This work was partially supported by Natural Science Foundation of Guangdong Province of China (Grant No. 2020A1515010691), Science and Technology Innovation Special Project of Guangdong Province, China (Grant No. SDZX2023032), Agricultural Science and Technology Commissioner Project of Guangzhou City, China (Grant No. 20212100036), and National Natural Science Foundation of China (Grant Nos.61573157 and 61703170). The authors also gratefully acknowledge the reviewers for their helpful comments and suggestions that helped to improve the presentation.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.swevo.2024.101667.

References

[1] J. Liu, L. Xu, Y. Hu, H. Jahanshahi, Flow measurement data quality improvement-oriented optimal flow sensor configuration, Swarm Evol. Comput. 80 (2023) 101325, http://dx.doi.org/10.1016/j.swevo.2023.101325.

[2] A. Salih, A. Moshaiov, Promoting transfer of robot neuro-motion-controllers by many-objective topology and weight evolution, IEEE Trans. Evol. Comput. 27 (2) (2023) 385–395, http://dx.doi.org/10.1109/TEVC.2022.3172294.

[3] S.-C. Liu, Z.-G. Chen, Z.-H. Zhan, S.-W. Jeon, S. Kwong, J. Zhang, Many-objective job-shop scheduling: A multiple populations for multiple objectives-based genetic algorithm approach, IEEE Trans. Cybern. 53 (3) (2023) 1460–1474, http://dx.doi.org/10.1109/TCYB.2021.3102642.

[4] L. Miguel Antonio, C.A. Coello Coello, Coevolutionary multiobjective evolutionary algorithms: Survey of the state-of-the-art, IEEE Trans. Evol. Comput. 22 (6) (2018) 851–865, http://dx.doi.org/10.1109/TEVC.2017.2767023.

[5] C.A. Coello Coello, S. González Brambila, J. Figueroa Gamboa, M.G. Castillo Tapia, R. Hernández Gómez, Evolutionary multiobjective optimization: open research areas and some challenges lying ahead, Complex Intell. Syst. 6 (2) (2020) 221–236, http://dx.doi.org/10.1007/s40747-019-0113-4.

[6] M. Farina, P. Amato, On the optimal solution definition for many-criteria optimization problems, in: 2002 Annual Meeting of the North American Fuzzy Information Processing Society Proceedings, IEEE, 2002, pp. 233–238, http://dx.doi.org/10.1109/NAFIPS.2002.1018061.

[7] B. Li, J. Li, K. Tang, X. Yao, Many-objective evolutionary algorithms: A survey, ACM Comput. Surv. 48 (1) (2015) 1–35, http://dx.doi.org/10.1145/2792984.

[8] X. Wang, Z. Xie, X. Zhou, X. Gu, A two-stage adaptive reference direction guided evolutionary algorithm with modified dominance relation for many-objective optimization, Swarm Evol. Comput. 78 (2023) 101272, http://dx.doi.org/10.1016/j.swevo.2023.101272.

[9] T. Liu, Z. Wang, M. Wei, A many-objective optimization algorithm using a two-space interactive evolutionary framework, Swarm Evol. Comput. 75 (2022) 101185, http://dx.doi.org/10.1016/j.swevo.2022.101185.

[10] Z. Mao, M. Liu, A local search-based many-objective five-element cycle optimization algorithm, Swarm Evol. Comput. 68 (2022) 101009, http://dx.doi.org/10.1016/j.swevo.2021.101009.

[11] S. Zhu, L. Xu, E.D. Goodman, Z. Lu, A new many-objective evolutionary algorithm based on generalized Pareto dominance, IEEE Trans. Cybern. 52 (8) (2022) 7776–7790, http://dx.doi.org/10.1109/TCYB.2021.3051078.

[12] J. Shen, P. Wang, X. Wang, A controlled strengthened dominance relation for evolutionary many-objective optimization, IEEE Trans. Cybern. 52 (5) (2022) 3645–3657, http://dx.doi.org/10.1109/TCYB.2020.3015998.

[13] G. Yu, Y. Jin, M. Olhofer, A multiobjective evolutionary algorithm for Finding Knee Regions using two localized dominance relationships, IEEE Trans. Evol. Comput. 25 (1) (2021) 145–158, http://dx.doi.org/10.1109/TEVC.2020.3008877.

[14] Y. Xu, H. Zhang, X. Zeng, Y. Nojima, An adaptive convergence enhanced evolutionary algorithm for many-objective optimization problems, Swarm Evol. Comput. 75 (2022) 101180, http://dx.doi.org/10.1016/j.swevo.2022.101180.

[15] Y. Zhou, S. Li, W. Pedrycz, G. Feng, ACDB-EA: Adaptive convergence-diversity balanced evolutionary algorithm for many-objective optimization, Swarm Evol. Comput. 75 (2022) 101145, http://dx.doi.org/10.1016/j.swevo.2022.101145.

[16] G. Chen, J. Li, A diversity ranking based evolutionary algorithm for multi-objective and many-objective optimization, Swarm Evol. Comput. 48 (2019) 274–287, http://dx.doi.org/10.1016/j.swevo.2019.03.009.

[17] Q. Zhang, H. Li, MOEA/D: A multiobjective evolutionary algorithm based on decomposition, IEEE Trans. Evol. Comput. 11 (6) (2007) 712–731, http://dx.doi.org/10.1109/TEVC.2007.892759.

[18] D.K. Saxena, K. Deb, Non-linear dimensionality reduction procedures for certain large-dimensional multi-objective optimization problems: Employing correntropy and a novel maximum variance unfolding, in: Evolutionary Multi-Criterion Optimization, Springer, 2007, pp. 772–787, http://dx.doi.org/10.1007/978-3-540-70928-2_58.

[19] H. Ishibuchi, Y. Setoguchi, H. Masuda, Y. Nojima, Performance of decomposition-based many-objective algorithms strongly depends on Pareto front shapes, IEEE Trans. Evol. Comput. 21 (2) (2017) 169–190, http://dx.doi.org/10.1109/TEVC.2016.2587749.

[20] H. Ishibuchi, R. Imada, N. Masuyama, Y. Nojima, Use of two reference points in hypervolume-based evolutionary multiobjective optimization algorithms, in: International Conference on Parallel Problem Solving from Nature, Springer, 2018, pp. 384–396, http://dx.doi.org/10.1007/978-3-319-99253-2_31.

[21] M. Li, X. Yao, What weights work for you? Adapting weights for any Pareto front shape in decomposition-based evolutionary multi-objective optimisation, Evol. Comput. 28 (2) (2017) 227–253, http://dx.doi.org/10.1162/evco_a_00269.

[22] Y. Qi, X. Ma, F. Liu, L. Jiao, J. Sun, J. Wu, MOEA/D with adaptive weight adjustment, Evol. Comput. 22 (2) (2014) 231–264, http://dx.doi.org/10.1162/EVCO_a_00109.

[23] S. Liu, Q. Lin, K.-C. Wong, C.A. Coello Coello, J. Li, Z. Ming, J. Zhang, A self-guided reference vector strategy for many-objective optimization, IEEE Trans. Cybern. 52 (2) (2022) 1164–1178, http://dx.doi.org/10.1109/TCYB.2020.2971638.

[24] C. Zhao, Y. Zhou, Y. Hao, Decomposition-based evolutionary algorithm with dual adjustments for many-objective optimization problems, Swarm Evol. Comput. 75 (2022) 101168, http://dx.doi.org/10.1016/j.swevo.2022.101168.

[25] L.R. de Farias, A.F. Araújo, A decomposition-based many-objective evolutionary algorithm updating weights when required, Swarm Evol. Comput. 68 (2022) 100980, http://dx.doi.org/10.1016/j.swevo.2021.100980.

[26] J. Bader, E. Zitzler, Hype: An algorithm for fast hypervolume-based many-objective optimization, Evol. Comput. 19 (1) (2011) 45–76, http://dx.doi.org/10.1162/EVCO_a_00009.

[27] Y. Sun, G.G. Yen, Z. Yi, IGD indicator-based evolutionary algorithm for many-objective optimization problems, IEEE Trans. Evol. Comput. 23 (2) (2019) 173–187, http://dx.doi.org/10.1109/TEVC.2018.2791283.

[28] K. Shang, H. Ishibuchi, A new hypervolume-based evolutionary algorithm for many-objective optimization, IEEE Trans. Evol. Comput. 24 (5) (2020) 839–852, http://dx.doi.org/10.1109/TEVC.2020.2964705.

[29] L. While, P. Hingston, L. Barone, S. Huband, A faster algorithm for calculating hypervolume, IEEE Trans. Evol. Comput. 10 (1) (2006) 29–38, http://dx.doi.org/10.1109/TEVC.2005.851275.

[30] Q. Zhang, A. Zhou, Y. Jin, RM-MEDA: A regularity model-based multiobjective estimation of distribution algorithm, IEEE Trans. Evol. Comput. 12 (1) (2008) 41–63, http://dx.doi.org/10.1109/TEVC.2007.894202.

[31] D. Brockhoff, T. Wagner, H. Trautmann, On the properties of the R2 indicator, in: Proceedings of the 14th Annual Conference on Genetic and Evolutionary Computation, ACM, 2012, pp. 465–472, http://dx.doi.org/10.1145/2330163.2330230.

[32] J. Zhang, L. Wei, R. Fan, H. Sun, Z. Hu, Solve large-scale many-objective optimization problems based on dual analysis of objective space and decision space, Swarm Evol. Comput. 70 (2022) 101045, http://dx.doi.org/10.1016/j.swevo.2022.101045.

[33] H. Chen, R. Cheng, J. Wen, H. Li, J. Weng, Solving large-scale many-objective optimization problems by covariance matrix adaptation evolution strategy with scalable small subpopulations, Inform. Sci. 509 (2020) 457–469, http://dx.doi.org/10.1016/j.ins.2018.10.007.

[34] Q. Liu, J. Zou, S. Yang, J. Zheng, A multiobjective evolutionary algorithm based on decision variable classification for many-objective optimization, Swarm Evol. Comput. 73 (2022) 101108, http://dx.doi.org/10.1016/j.swevo.2022.101108.

[35] W. Du, M. Zhang, W. Ying, M. Perc, K. Tang, X. Cao, D. Wu, The networked evolutionary algorithm: A network science perspective, Appl. Math. Comput. 338 (2018) 33–43, http://dx.doi.org/10.1016/j.amc.2018.06.002.

[36] I. Fister, A. Iglesias, A. Galvez, J. Del Ser, E. Osaba, I. Fister, M. Perc, M. Slavinec, Novelty search for global optimization, Appl. Math. Comput. 347 (2019) 865–881, http://dx.doi.org/10.1016/j.amc.2018.11.052.

[37] Y. Liu, N. Zhu, M. Li, Solving many-objective optimization problems by a Pareto-based evolutionary algorithm with preprocessing and a penalty mechanism, IEEE Trans. Cybern. 51 (11) (2021) 5585–5594, http://dx.doi.org/10.1109/TCYB.2020.2988896.

[38] K. Li, K. Deb, Q. Zhang, S. Kwong, An evolutionary many-objective optimization algorithm based on dominance and decomposition, IEEE Trans. Evol. Comput. 19 (5) (2015) 694–716, http://dx.doi.org/10.1109/TEVC.2014.2373386.

[39] A. Ikai, Chapter four - interaction forces, in: The World of Nano-Biomechanics (Second Edition), Elsevier, 2017, pp. 63–76, http://dx.doi.org/10.1016/B978-0-444-63686-7.00004-3.

[40] D. Hardin, E. Saff, Minimal Riesz energy point configurations for rectifiable d-dimensional manifolds, Adv. Math. 193 (1) (2005) 174–204, http://dx.doi.org/10.1016/j.aim.2004.05.006.

[41] J.G. Falcón-Cardona, H. Ishibuchi, C.A.C. Coello, Riesz s-energy-based reference sets for multi-objective optimization, in: 2020 IEEE Congress on Evolutionary Computation, IEEE, 2020, pp. 1–8, http://dx.doi.org/10.1109/CEC48606.2020.9185833.

[42] J. Blank, K. Deb, Y. Dhebar, S. Bandaru, H. Seada, Generating well-spaced points on a unit simplex for evolutionary many-objective optimization, IEEE Trans. Evol. Comput. 25 (1) (2021) 48–60, http://dx.doi.org/10.1109/TEVC.2020.2992387.

[43] Y. Liu, D. Gong, J. Sun, Y. Jin, A many-objective evolutionary algorithm using a one-by-one selection strategy, IEEE Trans. Cybern. 47 (9) (2017) 2689–2702, http://dx.doi.org/10.1109/TCYB.2016.2638902.

[44] C.C. Aggarwal, A. Hinneburg, D.A. Keim, On the surprising behavior of distance metrics in high dimensional space, in: International Conference on Database Theory, Springer, 2001, pp. 420–434, http://dx.doi.org/10.1007/3-540-44503-X_27.

[45] K. Deb, Multi-objective optimisation using evolutionary algorithms: An introduction, in: Multi-Objective Evolutionary Optimisation for Product Design and Manufacturing, Springer London, 2011, pp. 3–34, http://dx.doi.org/10.1007/978-0-85729-652-8_1.

[46] H.-G. Beyer, H.-P. Schwefel, Evolution strategies –a comprehensive introduction, Nat. Comput. 1 (1) (2002) 3–52, http://dx.doi.org/10.1023/A:1015059928466.

[47] K. Deb, Geneas: A robust optimal design technique for mechanical component design, in: Evolutionary Algorithms in Engineering Applications, Springer Berlin Heidelberg, 1997, pp. 497–514, http://dx.doi.org/10.1007/978-3-662-03423-1_27.

[48] Z. Liang, T. Luo, K. Hu, X. Ma, Z. Zhu, An indicator-based many-objective evolutionary algorithm with boundary protection, IEEE Trans. Cybern. 51 (9) (2021) 4553–4566, http://dx.doi.org/10.1109/TCYB.2019.2960302.

[49] Y. Tian, R. Cheng, X. Zhang, F. Cheng, Y. Jin, An indicator-based multiobjective evolutionary algorithm with reference point adaptation for better versatility, IEEE Trans. Evol. Comput. 22 (4) (2018) 609–622, http://dx.doi.org/10.1109/TEVC.2017.2749619.

[50] Z. Liu, F. Han, Q. Ling, H. Han, J. Jiang, A many-objective optimization evolutionary algorithm based on hyper-dominance degree, Swarm Evol. Comput. 83 (2023) 101411, http://dx.doi.org/10.1016/j.swevo.2023.101411.

[51] Y. Yuan, H. Xu, B. Wang, X. Yao, A new dominance relation-based evolutionary algorithm for many-objective optimization, IEEE Trans. Evol. Comput. 20 (1) (2016) 16–37, http://dx.doi.org/10.1109/TEVC.2015.2420112.

[52] F. Ming, W. Gong, L. Wang, A two-stage evolutionary algorithm with balanced convergence and diversity for many-objective optimization, IEEE Trans. Syst. Man Cybern.: Syst. 52 (10) (2022) 6222–6234, http://dx.doi.org/10.1109/TSMC.2022.3143657.

[53] Y. Yuan, H. Xu, B. Wang, B. Zhang, X. Yao, Balancing convergence and diversity in decomposition-based many-objective optimizers, IEEE Trans. Evol. Comput. 20 (2) (2016) 180–198, http://dx.doi.org/10.1109/TEVC.2015.2443001.

[54] R. Cheng, Y. Jin, M. Olhofer, B. Sendhoff, A reference vector guided evolutionary algorithm for many-objective optimization, IEEE Trans. Evol. Comput. 20 (5) (2016) 773–791, http://dx.doi.org/10.1109/TEVC.2016.2519378.

[55] Y. Tian, R. Cheng, X. Zhang, Y. Jin, Platemo: A MATLAB platform for evolutionary multi-objective optimization [educational forum], IEEE Comput. Intell. Mag. 12 (4) (2017) 73–87, http://dx.doi.org/10.1109/MCI.2017.2742868.

[56] K. Deb, L. Thiele, M. Laumanns, E. Zitzler, Scalable test problems for evolutionary multiobjective optimization, in: Evolutionary Multiobjective Optimization: Theoretical Advances and Applications, Springer London, 2005, pp. 105–145, http://dx.doi.org/10.1007/1-84628-137-7_6.

[57] S. Huband, P. Hingston, L. Barone, L. While, A review of multiobjective test problems and a scalable test problem toolkit, IEEE Trans. Evol. Comput. 10 (5) (2006) 477–506, http://dx.doi.org/10.1109/TEVC.2005.861417.

[58] R. Cheng, M. Li, Y. Tian, X. Zhang, S. Yang, Y. Jin, X. Yao, A benchmark test suite for evolutionary many-objective optimization, Complex Intell. Syst. 3 (1) (2017) 67–81, http://dx.doi.org/10.1007/s40747-017-0039-7.

[59] H. Jain, K. Deb, An evolutionary many-objective optimization algorithm using reference-point based nondominated sorting approach, part II: Handling constraints and extending to an adaptive approach, IEEE Trans. Evol. Comput. 18 (4) (2014) 602–622, http://dx.doi.org/10.1109/TEVC.2013.2281534.

[60] O. Schutze, X. Esquivel, A. Lara, C.A. Coello Coello, Using the averaged hausdorff distance as a performance measure in evolutionary multiobjective optimization, IEEE Trans. Evol. Comput. 16 (4) (2012) 504–522, http://dx.doi.org/10.1109/TEVC.2011.2161872.

[61] Y. Cui, Z. Geng, Q. Zhu, Y. Han, Review: Multi-objective optimization methods and application in energy saving, Energy 125 (2017) 681–704, http://dx.doi.org/10.1016/j.energy.2017.02.174.

[62] H. Wang, Y. Jin, X. Yao, Diversity assessment in many-objective optimization, IEEE Trans. Cybern. 47 (6) (2017) 1510–1522, http://dx.doi.org/10.1109/TCYB.2016.2550502.

[63] J. Derrac, S. García, D. Molina, F. Herrera, A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms, Swarm Evol. Comput. 1 (1) (2011) 3–18, http://dx.doi.org/10.1016/j.swevo.2011.02.002.

[64] X. Liao, Q. Li, X. Yang, W. Zhang, W. Li, Multiobjective optimization for crash safety design of vehicles using stepwise regression model, Struct. Multidiscip. Optim. 35 (6) (2008) 561–569, http://dx.doi.org/10.1007/s00158-007-0163-x.

[65] S. Mahdavi, M.E. Shiri, S. Rahnamayan, Metaheuristics in large-scale global continues optimization: A survey, Inform. Sci. 295 (2015) 407–428, http://dx.doi.org/10.1016/j.ins.2014.10.042.

Applied Soft Computing Journal 154 (2024) 111369

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

A many-objective evolutionary algorithm based on reference vector guided selection and two diversity and convergence enhancement strategies

Lei Yang [a,*], Yuanye Zhang [a], Jiale Cao [a], Kangshun Li [a], Dongya Wang [b]

[a] School of Mathematics and Informatics, South China Agricultural University, Guangzhou 510642, China
[b] University of Exeter, College of Engineering, Mathematics and Physical Sciences, Exeter EX4 4QF, UK

ARTICLE INFO

Keywords:
Many-objective optimization
Reference vector
Convergence and diversity enhancement

ABSTRACT

Achieving the balance between convergence and diversity is a key and challenging issue in many-objective optimization. Reference vector guided selection is an exemplary method for decomposition-based many-objective evolutionary algorithms (MaOEAs). However, there are some problems with it such as insufficient number of obtained solutions and inefficient convergence evaluation metric. Aiming at solving or alleviating these problems, this paper proposes a many-objective evolutionary algorithm based on reference vector guided selection and two diversity and convergence enhancement strategies. The proposed algorithm introduces two new strategies namely adaptive sparse region detection and convergence-only selection. The former is to adaptively detect sparse regions of current elite population, while the latter is to prevent the elimination of solutions with prominent convergence performance. Together with a newly proposed elite retention strategy, these two strategies can achieve diversity and convergence enhancement on the basis on reference vector guided selection. Besides, A new selection criterion for reference vector guided selection is proposed to better measure the convergence of solutions in high dimensionality. Experimental results on widely used test problem suites up to 15 objectives indicate that the proposed algorithm is highly competitive in comparison with seven state-of-the-art MaOEAs.

1. Introduction

Multi-objective optimization problems (MOPs) can be formulated as follows:

$$\begin{aligned} &min \quad F(x) = \{f_1(\boldsymbol{x}), f_2(\boldsymbol{x}), \ldots, f_m(\boldsymbol{x})\} \\ &s.t. \quad \boldsymbol{x} \in \Omega \end{aligned} \tag{1}$$

where $\Omega \subseteq R^n$ is the decision space, $\boldsymbol{x} = (x_1, x_2, \ldots, x_n)$ is the decision vector and $F(\boldsymbol{x}) \in R^m$ is the corresponding objective vector consisting of m objective values. If more than three objectives are considered, these problems are termed as many-objective optimization problems (MaOPs) [1]. MaOPs are widespread in the real world, such as car side impact bar crashworthiness problem [2], hybrid recommendation system design [3] and hyperparameter optimization of machine learning [4–7].

Since the objectives conflict with each other under most circumstances, finding a solution that optimizes all the objectives simultaneously is impossible. Hence a set of solutions which achieve the best trade-off among all objectives are what multi-objective optimization seeks. These solutions are known as Pareto optimal solutions and any improvement of a Pareto optimal solution in one objective must lead to a deterioration in at least one other objective. The set of all Pareto optimal solutions in decision space and objective space are Pareto Set (PS) and Pareto Front (PF) respectively.

Evolutionary algorithms (EAs) have proven to be an efficient way solving MOPs since they are able to obtain a set of solutions in a single run owing to the population-based nature. Thus, research area of multi-objective evolutionary algorithms (MOEAs) has attracted much attention and numerous MOEAs have been developed over the past three decades. These MOEAs can be mainly categorized into three categories based on the environmental selection strategy, i.e., dominance-based MOEAs, decomposition-based MOEAs and indicator-based MOEAs.

Many MOEAs that perform well on MOPs with two or three objectives encounter difficulties in many-objective scenarios [8,9]. As the number of objective increases, the proportion of non-dominated solutions in population increases dramatically. The probability of any two solutions being comparable is $1/2^{m-1}$ in an m-dimensional objective space [10], which already drops to 0.0625 when $m = 5$, not to mention a larger m. Affected by this situation, dominance-based MOEAs loss selection pressure as the major selection criteria Pareto dominance fails to compare solutions. Thus the secondary selection criteria designed for diversity maintenance has to consider convergence and diversity simultaneously during environmental selection, which unfortunately beyond

* Corresponding author.
E-mail address: yanglei_s@scau.edu.cn (L. Yang).

https://doi.org/10.1016/j.asoc.2024.111369
Received 20 September 2023; Received in revised form 3 January 2024; Accepted 3 February 2024
Available online 12 February 2024
1568-4946/© 2024 Elsevier B.V. All rights reserved.

its capabilities as dominance resistant solutions are what it prefers. R.C. Purshouse et al. presents a detailed discussion about this phenomenon in [11]. To alleviate this problem, many modified dominance relation were designed, e.g., θ-dominance [12], fractional dominance [13] and GPO (generalized Pareto optimality) [14]. These approaches enhance selection pressure and improve convergence effectively, but tend to result in the loss of diversity.

Indicator-based MOEAs usually integrate convergence and diversity into scalar performance indicators like hypervolume (HV) [15] and inverted generational distance (IGD) [16] to evaluate solutions. Although they successfully avoid the loss of selection pressure as the number of objective increases, exponentially increased computation cost of some indicators often makes them time-consuming [17]. Some new performance indicators were proposed recently including the ratio-based indicator with infinite norm in PREA [18] and the adaptive scalarizing function based fitness assessment in [19] to balance performance and computation cost.

Decomposition-based MOEAs crystallized in [20] share a general framework. They decompose an MOP into a number of single-objective subproblems using scalarization approaches like Tchebycheff approach then optimize them simultaneously and cooperatively through an iterative way. Each subproblem is characterized by the weight vector embedded in problem expression, and the diversity of weight vectors leads to the diversity of solutions naturally. Traditional decomposition-based MOEAs represented by MOEA/D [20] are capable of dealing with MaOPs since no additional difficulties like dominance resistance or high computation cost emerge, but their unstable performance observed from previous researches [21–23] and low search efficiency [24] are not satisfying. In recent years, another decomposition strategy has been proposed which decomposes the objective space into a set of subspaces using reference vectors [25]. This is equivalent to dividing an MOP into a set of multi-objective subproblems and solving them separately but simultaneously. Based on this strategy, some MOEAs are proposed to deal with MOPs [26] or MaOPs [27,28] and achieve competitive results. Reference vector guided evolutionary algorithm (RVEA) [27] is one of the most representative algorithms on this branch and presents a paradigm for solving MaOPs using reference vector guided selection. We will give a brief introduction about objective space decomposition and reference vector guided selection in Section 2.

There are some improvement researches toward the inefficiency of RVEA. Qiu et al. [29] indicates that the selection pressure posed by RVEA with respect to the convergence performance of solutions is mainly from the length of translated objective vectors, while this metric is poor in many-objective scenarios. To solve this issue, a new parameter inspired by fractional dominance relation is constructed to replace the aforementioned metric. Besides, an adaptive reference vector adjustment strategy is designed to cope with MOPs with irregular PF since the reference vector regeneration strategy RVEA employs is naive. In [30], a new search engine based on differential evolution (DE) is combined with RVEA to achieve further performance enhancement. This search engine is implemented based on a cooperative scheme of local and global search strategies. Besides, some researches combine reference vector guided selection with other techniques for many-objective optimization. In [31], modified inverted generational distance (IGD^+) indicator is combined with reference vector guided selection to form a two-stage selection strategy, which can balance convergence and diversity well when solving MaOPs. In [32], reference vectors are adjusted according to the distribution of solutions after reference vector guided selection to make sure that most reference vectors are associated with solutions.

Adaptive reference vector adjustment strategy seems indispensable for decomposition-based MOEAs when solving problems with irregular PF shapes [33], such as disconnected, degenerate or inverted. Many researches have been carried out toward this issue in both multi-objective and many-objective fields [34–38]. However, this strategy is not going to be studied in this paper. Instead, we focus on some other problems RVEA or reference vector guided selection strategy confronts. Reference vector guided selection strategy selects one elite solution from each subspace, which often results in insufficient number of solutions in final elite population as there may exist some empty subspaces containing no solution especially in the early evolutionary stage. This problem occurs more and severely when handling MOPs with irregular PF, making the number of solutions in final population much smaller than the preset population size. Although this problem was mentioned in [27,29], it was either unresolved or resolved sloppily. While in [32], a secondary selection criterion based on the dominance relationship is adopted so that a sufficient number of solutions can survive to the next generation. Further on this problem, if there exist empty subspaces, there will naturally be crowded subspaces. Selecting only one solution from each of these crowded subspaces probably lose some superior candidate solutions. These solutions may have better convergence performance but locate further from the associated reference vector compared to the optimal solution in their subspace. Retaining these solutions is beneficial to the subsequent evolutionary process. Even if there is no empty subspace, the distribution of elite solutions may not be as uniform as reference vectors. There may be some sparse regions with fewer solutions and the existence of empty subspaces will worsen this. Although we do not concern adaptive reference vector adjustment, finding a proper way to add solutions into these sparse regions is helpful for enhancing diversity. Apart from this, the length of objective vectors RVEA uses is a poor metric for evaluating convergence in many-objective scenarios as mentioned in [29]. This problem does exist since Euclidean distance as well as other distance metrics suffers from the curse of dimensionality [39].

Aiming at solving or alleviating the above issues and improving the overall performance of RVEA as well as other MOEAs using reference vector guided selection strategy, this paper proposes a many-objective evolutionary algorithm based on reference vector guided selection and two diversity and convergence enhancement strategies termed RVEA-2DCES. The main contributions are summarized as follows:

1. Two new strategies for diversity and convergence enhancement namely adaptive sparse region detection and convergence-only selection are proposed. They will be conducted after reference vector guided selection. In adaptive sparse region detection strategy, an adaptive approach is applied to remaining solutions not selected by reference vector guided selection to detect sparse regions of current final elite population. Some solutions will be added into elite population EP_1 to fill these sparse regions later. While during convergence-only selection, remaining solutions with prominent convergence performance will be retained into elite population EP_2.
2. An elite retention strategy is proposed together with the two strategies above to add solutions of EP_1 and EP_2 into final elite population methodically. Any vacancies in final elite population brought by reference vector guided selection will be filled while improving its convergence and diversity.
3. A new selection criterion for reference vector guided selection, termed HD-APD is proposed. Manhattan distance (L_1 norm) between candidate solutions and ideal point is utilized to replace the Euclidean distance (L_2 norm) RVEA uses to better measure the convergence of solutions in high dimensionality, since Manhattan distance is likely to be a preferable metric in high dimensionality.

The remainder of this paper is organized as follows. Section 2 introduces some background knowledge as preliminaries. We then elaborate the details of the proposed RVEA-2DCES in Section 3. Comparative studies with seven state-of-the-art MaOEAs are carried out in Section 4 followed by discussions about experimental results, statistical analysis and other experiments. Finally, we conclude this paper and present some future research issues.

2. Preliminaries

In this section, we introduce the reference vector set used in this study and then briefly review the design of reference vector guided selection strategy.

2.1. Reference vector

Generating a uniformly distributed reference vector set is essential for most decomposition-based MOEAs. Das and Dennis's systematic approach [40] that generates uniformly distributed points on a unit simplex is the most commonly used method to achieve this. However, as pointed out in [41], Das-Dennis's approach faces obvious issues especially in high dimensionality. First of all, the number of generated points $N = \binom{p+m-1}{m-1}$ is totally determined by p, the number of gaps between consecutive points along each objective axis and m, the number of objectives, which means that only fixed number of points can be obtained instead of arbitrary number. Besides, the number of generated points increases dramatically as p increases in high dimensionality. For instance, when $m = 10$, a reasonable range of p from 2 to 6 results in a jump of N from 55, 220, 715 to 2002, 5005. Since the population size of most decomposition based-MOEAs is the same as the number of reference points, a small value of p (e.g., 2 or 3) is employed in most cases for practical consideration. However, another severe problem conflicts with this. When $p < m$, all the generated points lie on the boundary of unit simplex and when $p = m$, only one interior point exists. To obtain more interior points, $p > m$ is necessary, which is however unacceptable in high dimensionality according to the above analysis, not to mention even if $p > m$, interior points still only occupy a tiny part of all generated points. A layer-wise construction strategy is suggested to alleviate these two conflicting issues above and obtain more interior points [42]. Nevertheless, this strategy is still not capable of generating arbitrary number of points, and the uniformity of points cannot be guaranteed either.

To generate an arbitrary number of well-spaced points on a unit simplex in up to 15-dimension space, Blank et al. [41] propose a number of viable methods based on sampling, construction, reduction or Riesz s-Energy. Comparative results concerning a number of performance metrics indicate that s-Energy method is the most efficient one among these proposed methods and Das-Dennis's approach. Multibody and interacting physical systems eventually settle on a state corresponding to the minimum overall potential energy. Motivated by this, Blank et al. use a generalization of potential energy called Riesz s-Energy [43] dealing with high dimensional spaces, and minimize the overall s-Energy of a point set initialized by reduction method using a gradient-based optimization approach iteratively. Once the convergence criteria is met or maximum number of iterations is reached, the final point set will be a well-spaced one on the unit simplex.

In this study, the above Riesz s-Energy method will be used for generating reference points. Originating from the coordinate origin and connecting to these reference points, we can get the reference vector set. It is worth noting that converting these obtained reference vectors into unit vectors is convenient for subsequent calculation, so we conduct unitization beforehand by dividing each reference vector by its norm.

2.2. Reference vector guided selection

Objective space decomposition is a prerequisite for reference vector guided selection. Commonly used objective space decomposition strategy proposed by [25] divides the objective space into a number of subspaces using an uniformly distributed reference vector set $V = \{\boldsymbol{v_0}, \boldsymbol{v_1}, \ldots, \boldsymbol{v_N}\}$. Specifically, each solution will be allocated into a subspace according to the acute angles between its objective vector and all reference vectors. Subspaces are defined as $\Omega^i = \{\boldsymbol{s} | \langle \boldsymbol{s}, \boldsymbol{v_i} \rangle \leq \langle \boldsymbol{s}, \boldsymbol{v_j} \rangle, \forall j \in 1, 2, \ldots, N\}$, where $i = 1, 2, \ldots, N$ and $\langle \boldsymbol{s}, \boldsymbol{v_i} \rangle$ represents the acute angle between solution $\boldsymbol{s}$ and ith reference vector $\boldsymbol{v_i}$. This angle can be calculated as:

$$\langle \boldsymbol{s}, \boldsymbol{v_i} \rangle = arccos \frac{\boldsymbol{s} \cdot \boldsymbol{v_i}}{\|\boldsymbol{s}\| \|\boldsymbol{v_i}\|} \tag{2}$$

According to the definition of subspace, each solution will associate a reference vector $\boldsymbol{v_i}$ if and only if it has the smallest vector angle between $\boldsymbol{v_i}$ compared with other reference vectors. Afterwards, all solutions associated with $\boldsymbol{v_i}$ constitute Ω^i. Apart from acute angle, perpendicular distance from solution to reference vector is alternative for objective space decomposition [42]. Either way, they divide objective space according to the similarity between solution and reference vector.

Since solutions distribute in different subspaces after decomposition, solving the original MOP using solutions of each subspace constitutes a series of different multi-objective subproblems, and the diversity of reference vectors ensures the diversity of obtained solutions from each subproblem. Different strategies can be applied to solve these subproblems simultaneously. For example, RVEA designs a scalarization approach to convert these multi-objective subproblems into single-objective subproblems, then selects one solution from each subspace that is optimal to the corresponding subproblem. NSGA-III [42] utilizes non-dominated sorting to select solutions with better convergence in each subspace. The strategy RVEA employs is called reference vector guided selection.

3. Proposed RVEA-2DCES

3.1. Main framework

The main framework of the proposed RVEA-2DCES is presented in Algorithm 1. A set of N reference vectors are predefined to provide search directions. The upper bound of population size N' is set larger than N and the excess part is mainly for two elite retention strategies. After initializing the population with random individuals, commonly used genetic operations including selection, crossover and mutation are conducted to generate offspring population. Specifically, binary tournament selection is employed to select parents for reproduction and like most start-of-the-art MOEAs do, simulated binary crossover (SBX) [44] and polynomial mutation (PM) [45] are employed to generate offspring solutions. Following the widely used elitism strategy, offspring population is combined with parent population to undergo environmental selection, during which elite solutions are selected to constitute an elite population for next iteration. Repeat the above procedures until termination condition, i.e., maximal function evaluations is met.

Algorithm 1 Main framework of the proposed RVEA-2DCES

Input: upper bound of population size N', maximal function evaluations FEs, a set of reference vectors V={$\boldsymbol{v_0}$,$\boldsymbol{v_1}$,...,$\boldsymbol{v_N}$}
Output: final population P

1: **Initialization:** create the initial population P with N random individuals, set $evaluations = 0$
2: **while** $evaluations < FEs$ **do**
3: $Q \leftarrow$ offspring-generation(P)
4: $FE \leftarrow |P|$
5: $U \leftarrow P \cup Q$
6: $P \leftarrow$ environmental selection(U, N, N')
7: $evaluations \leftarrow evaluations + FE$
8: **end while**
9: **return** P

3.2. High-dimensional Angle-Penalized distance

RVEA designs a scalarization approach Angle-Penalized Distance (APD) for many-objective optimization to balance convergence and diversity in each subspace. We propose a new selection criterion named

High-Dimensional Angle-Penalized Distance (HD-APD) by replacing the Euclidean distance (L_2 norm) between candidate solution and ideal point with Manhattan distance (L_1 norm). HD-APD is defined as:

$$d_{i,j} = (1 + P(\theta_{i,j})) \cdot \left\| \boldsymbol{f}_i' \right\|_1 \tag{3}$$

where $\boldsymbol{f}_i' = \boldsymbol{f}_i - \boldsymbol{z}^{\boldsymbol{min}}$ is the translated objective vector of solution i ($\boldsymbol{z}^{\boldsymbol{min}}$ consists of minimal objective values of current population, also known as ideal point) and $\left\| \boldsymbol{f}_i' \right\|_1$ represents the Manhattan distance (L_1 norm) from $\boldsymbol{f}_i'$ to the ideal point. $P(\theta_{i,j})$ is a penalty function related to $\theta_{i,j}$, the acute angle between $\boldsymbol{f}_i'$ and $\boldsymbol{v}_j$ to measure the consistency between the direction of i and its associated reference vector:

$$P(\theta_{i,j}) = m \cdot (\frac{evaluations}{FEs})^2 \cdot \frac{\theta_{i,j}}{\gamma_{v_j}}$$

$$\gamma_{v_j} = min \left\langle \boldsymbol{v}_i, \boldsymbol{v}_j \right\rangle, \quad i \in 1, 2, \ldots, N, i \neq j \tag{4}$$

where m is the number of objectives and γ_{v_j} is the smallest acute angle between $\boldsymbol{v}_j$ and other reference vectors, which is used to normalize angles in the subspace specified by $\boldsymbol{v}_j$ in case of dense or sparse distribution of reference vectors.

In the definition of HD-APD, Manhattan distance evaluates the convergence performance of a solution while penalty function measures the diversity performance. It is obvious that a smaller HD-APD indicates a better overall performance, that is to say this solution balances convergence and diversity better.

The motivation behind the replacement of L_2 norm by L_1 norm is that the concept of proximity, distance or nearest neighbor might not be qualitatively meaningful in high dimensional space because the data becomes sparse, which is also known as the curse of dimensionality [46]. Thus distance metric used to measure the similarity between candidate solutions and ideal point will inevitably suffer dimensionality curse more as the number of objectives increases. According to [46], the meaningfulness of commonly used L_k norm worsens faster with increasing dimensionality for higher values of k, thus for a given problem with fixed dimensionality, a smaller k is probably preferable. According to this, Manhattan distance (L_1 norm) is a more promising distance metric in many-objective scenarios. We will verify this in Section 4.7.

3.3. Environmental selection

Algorithm 2 provides the pseudocode of environmental selection. Line 1 to Line 19 are reference vector guided selection strategy referring to RVEA. Specifically, objective value translation is executed first to set ideal point the origin of coordinate system and guarantee that all the translated objective values are inside the first quadrant. Concrete embodiment of the importance of objective value translation is presented in [27]. After that, the objective space is divided into a set of subspaces by associating each solution with its nearest reference vector. The details of objective space decomposition have already been introduced in Section 2. Based on the results of population partition, HD-APDs of all solutions in each subspace are calculated and every solution with the smallest HD-APD among its own subspace will be selected into population P for next generation.

According to the analysis in Section 1, selecting one solution from each subspace often results in insufficient population size of P because of the existence of the empty subspaces. To better solve this problem while improving diversity and convergence of P, adaptive sparse region detection strategy and convergence-only selection will be executed sequentially after reference vector guided selection.

3.3.1. Adaptive sparse region detection

Although uniformly distributed reference vectors provide uniform search directions, actual distribution of elite solutions selected from each subspace may not be the same, Fig. 1 (left part) is an illustration. In this two-objective minimization problem, $\boldsymbol{v_0}$, $\boldsymbol{v_1}$, …, $\boldsymbol{v_5}$ are

Algorithm 2 Environmental Selection Strategy of the Proposed RVEA-2DCES

Input: combined population U, the number of reference vectors N, upper bound of population size N'
Output: final elite population P for next generation

1: $P, EP_1, EP_2 \leftarrow \emptyset$
2: /* Objective value translation */
3: Calculate ideal point $\boldsymbol{z}^{\boldsymbol{min}}$ of U
4: **for** $i = 1$ to $|U|$ **do**
5: $\quad \boldsymbol{f}_i' \leftarrow \boldsymbol{f}_i - \boldsymbol{z}^{\boldsymbol{min}}$
6: **end for**
7: /* Objective space decomposition */
8: **for** $i = 1$ to N **do**
9: $\quad P_i \leftarrow \emptyset$
10: **end for**
11: **for** $i = 1$ to $|U|$ **do**
12: $\quad k \leftarrow argmin_{j \in 1,2,\ldots,N} \left\langle \boldsymbol{f}_i', \boldsymbol{v}_j \right\rangle$
13: $\quad P_k \leftarrow P_k \cup U_i$
14: **end for**
15: /* Reference vector guided selection */
16: **for** $k = 1$ to N **do**
17: $\quad$ **for** $i = 1$ to $|P_k|$ **do**
18: $\quad\quad d_{i,k} = (1 + P(\theta_{i,k})) \cdot \left\| \boldsymbol{f}_i' \right\|_1$
19: $\quad$ **end for**
20: $\quad s \leftarrow argmin_{i \in 1,2,\ldots,|P_k|} d_{i,k}$
21: $\quad P \leftarrow P_{k_s}$
22: **end for**
23: /* Get the remaining combined population */
24: $R \leftarrow \complement_U P$
25: $EP_1 \leftarrow$ Adaptive sparse region detection(P, R)
26: $EP_2 \leftarrow$ Convergence-only selection(P, R)
27: elite retention(P, R, EP_1, EP_2, N')
28: **return** P

five uniformly distributed reference vectors and after reference vector guided selection, solutions represented by solid circles are selected into P for next generation as they are elite solutions in subspaces specified by $\boldsymbol{v_1}$ to $\boldsymbol{v_4}$ separately, while solutions represented by hollow circles are abandoned. The convergence performance of solution A and B are similar to elite solutions, and their absence lead to the emergence of two sparse regions surrounded by dotted lines. The absence of A and B are caused by their closeness to angle bisector of two reference vectors, which makes them far from both reference vectors. But this phenomenon can be further divided into two cases: (1) For A exactly on the angle bisector, no matter which subspace it is divided into, its HD-APD will be larger than elite solutions of that subspace owing to the penalty function, thus fails to be selected as an elite solution. (2) For B close to the angle bisector, it will not be selected as elite solution in its subspace for the same reason as A, and the subspace close to it (specified by $\boldsymbol{v_5}$) is empty.

If we can figure out a way to retain A and B into population P, the distribution will undoubtfully become better, hence to improve diversity (right part of Fig. 1). This is the purpose of adaptive sparse region detection strategy and Algorithm 3 describes the details of it.

Adaptive sparse region detection is inspired by the maximum-vector-angle-first strategy in VaEA [10]. First associate each solution R_i in R with a solution P_j in P, satisfying that P_j has the smallest angle with R. Record this smallest angle as $\theta(R_i)$. The association procedure is illustrated in Fig. 2 following the example in Fig. 1. It is not difficult to analyze that the large $\theta(R_i)$ is, the better can R_i fill the sparse regions of P. Thus we put solutions in R with larger $\theta(R_i)$ into elite population EP_1 to retain them into P in subsequent procedures. To limit the amount of solutions added into P, an angle threshold is set to $(m-1)^2 * \frac{\pi/2}{2(N-1)}$. This threshold is set intuitively

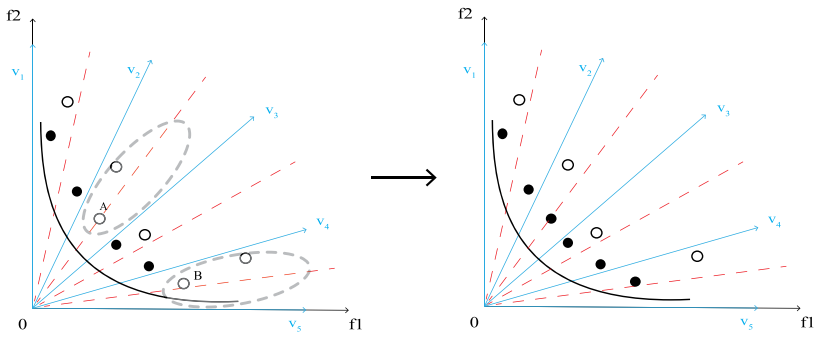


Fig. 1. An illustration to demonstrate the effect of adaptive sparse region detection strategy.

Algorithm 3 Adaptive sparse region detection

Input: population P and remaining combined population R after reference vector guided selection
Output: elite population EP_1

```
/* Association */
for i = 1 to |R| do
    θ(R_i) ← ∞
    for j = 1 to |P| do
        Calculate α = ⟨f'_{R_i}, f'_{P_j}⟩
        if α < θ(R_i) then
            θ(R_i) ← α
        end if
    end for
end for
ρ ← argmax_{i∈1,2,...,|R|} θ(R_i)
while θ(R_ρ) ≥ (m − 1)^2 * π/2(N−1) do
    EP_1 ← EP_1 ∪ R_ρ
    ρ ← argmax_{i∈1,2,...,|R|} θ(R_i)
end while
return EP_1
```

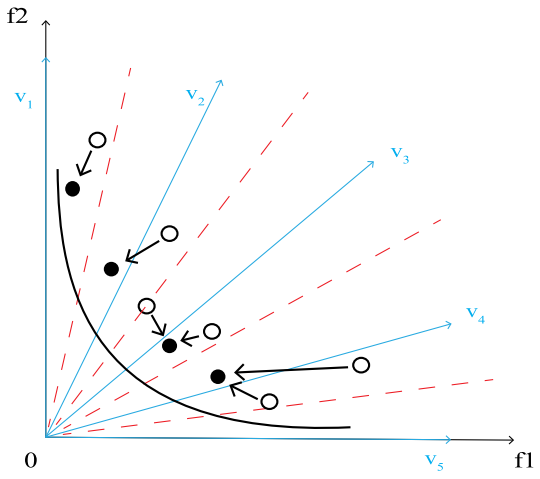


Fig. 2. Association procedure in adaptive sparse region detection.

according to the situation in two-dimensional space and extended to higher dimensionalities.

Adaptive sparse region detection strategy makes reference to the maximum-vector-angle-first strategy in VaEA, but their scenes to be used and effects are different. In VaEA, maximum-vector-angle-first strategy is conducted after non-dominated-sorting and applied on the last non-dominated front to be included to improve diversity. It is well known that non-dominated-sorting only concerns convergence, thus maximum-vector-angle-first strategy is used to improve general diversity of elite population non-dominated-sorting obtains. While in, reference vector guided selection has already guaranteed convergence and diversity to a great extent. On the basis of that, improving diversity using adaptive sparse region detection strategy is more purposeful, that is to fill sparse regions and improve uniformity. Besides, set an angle threshold while VaEA does not.

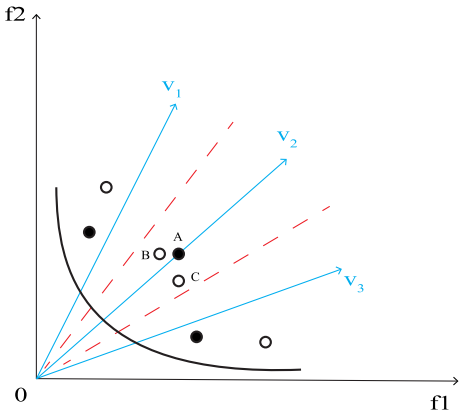


Fig. 3. A scenario where convergence-only selection works.

3.3.2. Convergence-only selection

Solutions that best balance convergence and diversity in their own subspace are selected during reference vector guided selection and adaptive sparse region detection strategy gives the remaining solutions a second chance to survive regardless of their convergence. Nevertheless, some solutions with prominent convergence performance may still be discarded regrettably and a possible case is shown in Fig. 3. Solution A, B and C densely distribute in the subspace specified by v_2 and the ascending order of their HD-APDs is A, C, B where HD-APDs of B and C are just a little bit larger than A. Since only one solution in this subspace can survive as an elite, B and C will be eliminated despite they are more convergent than A. Retaining B and C will improve the convergence and benefit subsequent evolutionary process apparently as they may produce promising offspring solutions. This is what the second elite retention strategy convergence-only selection aims. Algorithm 4 presents the procedure of convergence-only selection.

As can be seen from Algorithm 4, convergence-only selection is simple to implement as calculations it needs have already been done in reference vector guided selection. By comparing convergence performance only between remaining solutions in R and elite solutions in their own subspaces, solutions in R with outstanding convergence (e.g., B and C in Fig. 3) will be put into elite population EP_2.

Algorithm 4 Convergence-only selection

Input: population P and remaining combined population R after reference vector guided selection
Output: elite population EP_2

for $i = 1$ to $|R|$ **do**
  Determine the subspace R_i locates and elite solution es of this subspace selected in reference vector guided selection.
  if $\left\| f'_{R_i} \right\|_1 < \left\| f'_{es} \right\|_1$ **then**
    $EP_2 \leftarrow EP_2 \cup R_i$
  end if
end for
return EP_2

3.3.3. Elite retention

After conducting adaptive sparse region detection and convergence-only selection, two elite population EP_1 and EP_2 are obtained. Finally, an elite retention strategy is proposed to put solutions of EP_1 and EP_2 into final elite population P as parent population for next generation. Algorithm 5 presents the details. First, put solutions in both EP_1 and EP_2 into P as they can improve diversity and convergence of P simultaneously. After that, remove these solutions from EP_1 and EP_2 and update the associated smallest angles of remaining solutions in EP_1, i.e., $\theta(EP_{1_i})$ of EP_{1_i} since P has more solutions now and $\theta(EP_{1_i})$ may decrease. Update procedure is presented in Algorithm 6 which is very similar to adaptive sparse region detection strategy. Line 10 to Line 22 can be summarized as selecting solutions from EP_1 and EP_2 in turn into P until the size of P reaches N' or EP_1 and EP_2 are empty. It is worth noting that the update procedure should be conducted once adding new solutions into P.

As population size of EP_1 and EP_2 are both unknown, population size of final elite population P is not sure and dynamic. We then set an upper bound for it and details will be discussed in Section 4.3.

Algorithm 5 Elite retention

Input: population P and remaining combined population R after reference vector guided selection, elite population EP_1 and EP_2, upper bound of population size N'
Output: population P for next generation

$EP = EP_1 \cap EP_2$
for $i = 1$ to $|EP|$ **do**
  if $|P| + 1 \leq N'$ **then**
    $P \leftarrow P \cup EP_i$
  end if
end for
$EP_1 \leftarrow \complement_{EP_1} EP$
$EP_2 \leftarrow \complement_{EP_2} EP$
UpdateAssociation(EP_1, EP)
Sort EP_1 in descending order according to $\theta(EP_{1_i})$
Sort EP_2 in ascending order according to L_1 norm.
while $EP_1 \neq \emptyset \cap (|P| + 1 \leq N')$ **do**
  Put the first solution s_1 of EP_1 into P and delete it from EP_1.
  if $EP_2 \neq \emptyset \cap (|P| + 1 \leq N')$ **then**
    Put the first solution s_2 of EP_2 into P and delete it from EP_2
  end if
  UpdateAssociation($EP_1, \{s_1, s_2\}$)
  Sort EP_1 in descending order according to $\theta(EP_{1_i})$
end while
while $EP_2 \neq \emptyset \cap (|P| + 1 \leq N')$ **do**
  Put the first solution of EP_2 into P and delete it from EP_2
end while
return P

Algorithm 6 UpdateAssociation

Input: elite population EP_1, solution set S new added into P
Output: updated elite population EP_1

for $i = 1$ to $|EP_1|$ **do**
  for $j = 1$ to $|S|$ **do**
    Calculate $\alpha = \left\langle f'_{EP_{1_i}}, f'_{S_j} \right\rangle$
    if $\alpha < \theta(EP_{1_i})$ **then**
      $\theta(EP_{1_i}) \leftarrow \alpha$
    end if
  end for
  if $\theta(EP_{1_i}) < (m-1)^2 * \frac{\pi/2}{2(N-1)}$ **then**
    Remove EP_{1_i} from EP_1
  end if
end for
return EP_1

4. Comparative studies

To compare the proposed RVEA-2DCES with 7 state-of-the-art MaOEAs, i.e., RVEA-iGNG [47], RVEA [27], NSGA-II/SDR [48], oneby-oneEA [49], HEA [50], MaOEA-IT [51] and hpaEA [52], comprehensive experiments are conducted on 20 benchmark test problems taken from DTLZ test suite [53], WFG test suite [54] and MaF test suite [55]. Each problem is tested on $3, 5, 8, 10, 15$ objectives with 20 independent runs. To have statistically sound conclusions, Wilcoxon rank sum test is adopted to test significance of differences among the results obtained by each algorithm at a significance level of 0.05. According to the results of Wilcoxon rank sum test, "-" means that RVEA-2DCES significantly outperforms the compared algorithm, "+" indicates that RVEA-2DCES is significantly surpassed by the compared algorithm and "≈" represents that there is no statistically significant difference.

4.1. Benchmark test problems

In the comprehensive experiments, DTLZ1-4, WFG1-9 and MaF1-7 are taken as benchmark test problems. For DTLZ test problems, the number of decision variables is set to $n = m + k - 1$, where m is the number of objectives and $k = 5$ for DTLZ1, $k = 10$ for DTLZ2-4. Among these decision variables, k variables are distance-related and other $m - 1$ are position-related. For WFG test problems, the number of decision variables is set to $n = K + L$, where $K = m - 1$ is the number of position-related working parameters and $L = 10$ is the number of distance-related working parameters. These working parameters will be mapped into $m - 1$ underlying position parameters and 1 underlying distance parameter via transformation functions. For MaF test problems, the number of decision variables is set to $n = m + k - 1$, $k = 10$ for MaF1-6 and 20 for MaF7.

4.2. Performance indicator

A widely used performance indicator HV is employed to evaluate the comprehensive performance of final non-dominated solution set obtained by each MaOEA. HV concerns convergence and diversity simultaneously and a larger HV indicates a better overall performance.

HV represents the volume of the region which is dominated by final solution set but dominates the reference point. To calculate HV, reference point is set to $(1, \ldots, 1)^T$ and all objective values are normalized by point $1.1 \times z^{nad}$ before calculation, where z^{nad} denotes the nadir point of the PF. For 3-objective problems, accurate HVs are calculated. While for problems with more than 3 objectives, Monte Carlo method [56] with 1,000,000 sampling points is adopted to calculate approximate HVs considering the computation cost.

Table 1
Settings of the number of reference vectors (N) and population size (upper bound for RVEA-2DCES) for compared MaOEAs.

M	N	Other MaOEAs	RVEA-2DCES
3	91	91	100
5	210	210	250
8	240	240	300
10	300	300	350
15	400	400	450

4.3. Parameter settings

In this subsection, we present the general parameter settings of experiments.

- *Population Size*: Some of the compared MaOEAs use reference vectors to provide uniform search directions, their population size is then set the same to the number of reference vectors. Other compared algorithms do not utilize reference vectors and their population size is set the same to above MaOEAs. RVEA-2DCES use the same number of reference vectors as other compared MaOEAs, however, the population size of RVEA-2DCES should be larger for elite retention. As introduced in Section 3.3.3, population size of final elite population is dynamic and we set an upper bound for it according to the number of reference vectors and objectives. The detailed settings of population size are summarized in Table 1. In general, more objectives corresponds to larger population size since more solutions are needed to search higher dimensional objective space and the gap of population size between RVEA-2DCES and other MaOEAs is approximately 50 except on 3-objective problems.
- *Termination Condition*: All experimental runs terminate when the function evaluations reach FEs, the maximal function evaluations. FEs are set the same for different benchmark problems but vary according to m. Specifically, 50 000 for 3-objective, 100 000 for 5-objective, 150 000 for 8- objective, 210 000 for 10-objective and 240 000 for 15-objective. It is worth mentioning that although RVEA-2DCES holds a larger population size, the same FEs ensure the fairness of comparative experiments to some extent since larger population size corresponds to less iterations.
- *General Parameter Settings for Genetic Operators*: As mentioned above, simulated binary crossover (SBX) and polynomial mutation (PM) are used to generate offspring population. For SBX, the distribution index η_c and crossover probability p_c are set to 20 and 1.0 respectively. For PM, the distribution index is set to $\eta_m = 20$ and mutation probability $p_m = 1/n$.

The proposed RVEA-2DCES was implemented in JMetal [57] and comparative experiments were carried out in PlatEMO [58], both of which are popular evolutionary multi-objective optimization (EMO) platforms.

4.4. Results of comparative studies on different test suites

4.4.1. Results on DTLZ1 to DTLZ4

The average and standard deviation of HV on DTLZ1-4 over 20 independent runs obtained by each algorithm are summarized in Table 2. The best and second best results of each test problem are highlighted in gray and light gray background respectively.

It can be observed from Table 2 that RVEA-2DCES obtained the best overall performance on DTLZ test suite as it obtained 8 best results and 6 s best results out of 20 test problems. Besides, the results of Wilcoxon rank sum test indicate that RVEA-2DCES significantly outperformed other algorithms on most test problems. Specifically, RVEA-2DCES performed better than most competitors on DTLZ1, DTLZ2 and DTLZ4. However, its performance on 3-, 5- and 8-objective DTLZ3 lagged behind most compared algorithms and there was a significant performance degradation compared to RVEA on 5- and 8-objective. Considering that DTLZ3 is a highly multimodal problem and its search space contains $3^r - 1$ local optima, this degradation may be mainly attributed to the convergence-only selection strategy, as retaining more solutions with superior convergence makes it easier for the population to fall into local optimum. RVEA-iGNG, RVEA, onebyoneEA and HEA obtained similar overall results with RVEA-2DCES as DTLZ is a relatively easy test suite to convergence to the PF. Slight lead of RVEA-2DCES is mainly due to the diversity improvement brought by adaptive sparse region detection strategy. MaOEA-IT did not show any competitiveness on most test problems while hpaEA performed worse than the above algorithms especially on 10- and 15-objective benchmarks, indicating its method of selecting prominent solutions based on the hyperplane formed by their neighboring solutions suffers serious performance degradation when the number of objectives increases. NSGA-II/SDR obtained competitive results on DTLZ3, mediocre results on DTLZ1, DTLZ2 and poor results on DTLZ4. This is because its strengthened dominance relation (SDR) improves convergence effectively while leading to the loss of diversity. Thus it tends to perform well on test problems focusing on convergence but perform poorly on test problems focusing on diversity.

To analyze the results more intuitively, we visualize the final non-dominated solution sets obtained by each algorithm on 10-objective DTLZ3 by plotting the parallel coordinates in Fig. 4. These results are from typical runs with median HV values. It can be observed from Fig. 4 that MaOEA-IT and hpaEA failed to converge to the PF, and most solutions were far away from the PF. Their 0 HV values fit the visualization result. RVEA-2DCES, RVEA and HEA are all reference vector-based MaOEAs, their final non-dominated solution sets distributed similarly to reference vectors, mainly concentrating on the middle parts or boundaries of the PF. Thus their HV values were very close. Compared with RVEA and HEA, RVEA-2DCES obtained more solutions near the middle of PF. This is attributed to the adaptive sparse region detection strategy for adding solutions into these regions. RVEA-iGNG trains a GNG network and adapts the reference vectors to the weights of nodes in the GNG every generation. Therefore, the distribution of its final non-dominated solution set was different from the above three reference vector-based MaOEAs since reference vectors they used were constant. Besides, is worth mentioning that several solutions of RVEA-iGNG did not converge. The middle parts of approximate PFs obtained by NSGA-II/SDR and onebyoneEA seemed crowded and messy, but near the boundaries (e.g., (0.9,1) of both algorithms), the distribution of solutions is quite sparse. This indicated that their diversity preservation mechanism are inefficient in high dimensionality.

4.4.2. Results on WFG1 to WFG9

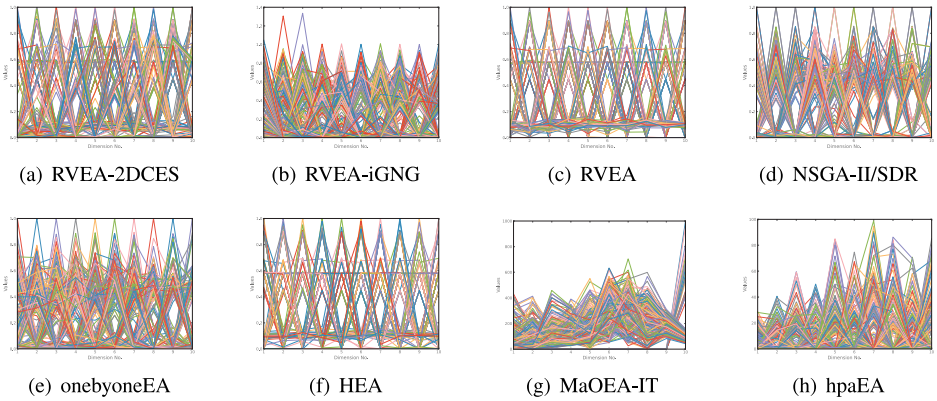
The average and standard deviation of HV on WFG1 to WFG9 over 20 independent runs obtained by each algorithm are presented in Table 3. HEA obtained the best overall performance on WFG test suite as it obtained 15 best results out of 45 test problems followed by NSGA-II/SDR and RVEA-2DCES which obtained 11 and 9 best results separately. Overall, the performance of reference vector-based MaOEAs on WFG test suite was not as good as their performance on DTLZ test suite. One possible reason for this is that test problems of WFG test suite have differently-scaled objectives while DTLZ not. Commonly used objective space normalization strategies are not suited for RVEA as they change actual objective values, which will influence the calculation of APD. Thus RVEA proposed an reference vector scaling strategy [27] to tackle scaled test problems. This strategy periodically scales the reference vectors according to the range of solutions. RVEA-2DCES and RVEA-iGNG also use this strategy. However, the frequency of using this strategy has a significant impact on performance, and commonly used frequency was obtained from experiments instead of theoretical analysis. Therefore, the effect of normalization may affect the performance of reference vector-based MaOEAs to a certain extent.

Table 2
Comparison of HV average and standard deviation on DTLZ test problems.

Problem	M	RVEA-2DCES	RVEA-iGNG	RVEA	NSGA-II/SDR	onebyoneEA	HEA	MaOEA-IT	hpaEA
DTLZ1	3	8.4155e−1 (6.67e−4)	8.3905e−1 (8.53e−4)−	8.4138e−1 (3.53e−4)≈	7.9220e−1 (2.49e−2)−	7.5714e−1 (1.57e−1)−	8.4097e−1 (4.84e−4)−	6.2543e−1 (2.99e−1)−	8.4227e−1 (1.16e−3)≈
	5	9.7980e−1 (4.21e−4)	9.7841e−1 (5.00e−4)−	9.7972e−1 (1.61e−4)≈	9.4217e−1 (1.04e−2)−	9.3935e−1 (6.36e−3)−	9.7942e−1 (3.88e−4)−	3.6641e−1 (4.04e−1)−	9.8084e−1 (2.84e−4)≈
	8	9.9764e−1 (1.11e−4)	9.9767e−1 (2.48e−4)≈	9.9756e−1 (5.19e−5)≈	9.5676e−1 (1.35e−2)−	9.8267e−1 (2.72e−3)−	9.9618e−1 (8.88e−4)−	5.1364e−4 (2.30e−3)−	9.9267e−1 (1.43e−2)−
	10	9.9968e−1 (3.06e−5)	9.9905e−1 (2.47e−4)−	9.9944e−1 (2.32e−5)≈	9.3706e−1 (2.21e−2)−	9.9198e−1 (1.58e−3)≈	9.9965e−1 (3.58e−5)−	0.0000e+0 (0.00e+0)−	9.7015e−1 (1.06e−1)−
	15	9.9991e−1 (1.54e−5)	8.1731e−1 (2.20e−1)−	9.9989e−1 (8.08e−4)≈	8.9796e−1 (4.29e−2)−	9.9854e−1 (3.54e−4)−	9.9966e−1 (1.19e−4)−	0.0000e+0 (0.00e+0)−	7.9276e−1 (3.20e−1)−
DTLZ2	3	5.6025e−1 (2.09e−4)	5.5865e−1 (9.18e−4)−	5.5956e−1 (3.59e−5)≈	2.5662e−1 (2.22e−2)−	5.5495e−1 (1.67e−3)−	5.5942e−1 (2.12e−4)−	2.3594e−1 (1.05e−1)−	5.6035e−1 (3.67e−4)+
	5	8.1204e−1 (4.86e−4)	8.0681e−1 (1.26e−3)−	8.1251e−1 (4.43e−4)≈	7.9469e−1 (2.98e−3)−	8.0098e−1 (2.16e−3)−	8.1263e−1 (4.26e−4)+	2.1164e−1 (1.15e−1)−	8.1558e−1 (4.87e−4)+
	8	9.2968e−1 (6.79e−4)	9.3517e−1 (9.32e−4)+	9.2590e−1 (2.06e−4)−	9.2461e−1 (3.97e−3)−	9.2201e−1 (2.67e−3)−	9.2625e−1 (3.21e−4)−	1.8469e−1 (6.22e−2)−	9.2363e−1 (2.77e−3)−
	10	9.7278e−1 (2.13e−4)	9.6710e−1 (9.43e−4)−	9.6966e−1 (1.72e−4)−	9.6256e−1 (2.71e−3)−	9.5551e−1 (1.69e−3)−	9.6983e−1 (2.01e−4)−	1.5788e−1 (6.94e−2)−	9.4837e−1 (1.35e−2)−
	15	9.9457e−1 (1.02e−4)	9.8578e−1 (7.77e−4)−	9.9123e−1 (1.08e−4)−	9.9450e−1 (7.66e−4)≈	9.8731e−1 (9.27e−4)−	9.9138e−1 (9.97e−5)−	2.0904e−1 (6.89e−2)−	9.2264e−1 (1.36e−2)−
DTLZ3	3	4.9319e−1 (1.29e−1)	5.4836e−1 (5.35e−3)+	4.6530e−1 (1.62e−1)≈	2.4346e−1 (1.62e−2)−	5.4797e−1 (3.26e−3)+	5.4383e−1 (8.66e−3)+	2.4537e−2 (1.10e−1)−	5.3709e−1 (9.69e−3)+
	5	7.6495e−1 (1.48e−2)	8.0466e−1 (4.23e−3)+	7.9085e−1 (1.12e−2)≈	7.9397e−1 (4.87e−3)+	7.9801e−1 (3.01e−3)+	8.0306e−1 (5.60e−3)+	0.0000e+0 (0.00e+0)−	7.8320e−1 (2.03e−2)+
	8	9.1148e−1 (5.95e−3)	9.3234e−1 (2.28e−3)+	9.2181e−1 (1.93e−3)+	9.2527e−1 (3.23e−3)+	9.1986e−1 (2.93e−3)+	9.2002e−1 (4.10e−3)+	0.0000e+0 (0.00e+0)−	2.5043e−3 (9.48e−3)−
	10	9.6582e−1 (1.98e−3)	9.4916e−1 (1.30e−2)−	9.6856e−1 (8.57e−4)+	9.6326e−1 (1.94e−3)−	9.5347e−1 (3.24e−3)−	9.6702e−1 (2.06e−3)+	0.0000e+0 (0.00e+0)−	0.0000e+0 (0.00e+0)−
	15	9.9255e−1 (3.87e−4)	9.6515e−3 (3.57e−2)−	9.9057e−1 (6.88e−4)≈	9.9312e−1 (3.44e−3)≈	9.8660e−1 (1.13e−3)−	9.9103e−1 (3.01e−4)−	0.0000e+0 (0.00e+0)−	0.0000e+0 (0.00e+0)−
DTLZ4	3	5.6031e−1 (2.23e−4)	5.4403e−1 (4.89e−2)−	5.5955e−1 (5.18e−5)−	2.6502e−1 (5.62e−2)−	5.5572e−1 (1.84e−3)−	4.5779e−1 (1.58e−1)−	1.3027e−1 (6.87e−2)−	3.2528e−1 (1.43e−1)−
	5	8.1279e−1 (5.22e−4)	8.0307e−1 (1.95e−2)−	8.1251e−1 (3.73e−4)≈	3.5465e−1 (8.63e−2)−	8.0314e−1 (2.02e−2)−	7.9420e−1 (6.28e−2)≈	1.7686e−1 (1.48e−1)−	7.8091e−1 (6.55e−2)−
	8	9.3049e−1 (5.53e−4)	9.3684e−1 (1.54e−3)+	9.2610e−1 (3.12e−4)−	5.0439e−1 (4.86e−2)−	9.3213e−1 (1.34e−3)+	9.2646e−1 (2.79e−4)−	7.2340e−2 (5.61e−2)−	9.1162e−1 (1.96e−2)−
	10	9.7371e−1 (2.33e−4)	9.6983e−1 (2.91e−3)−	9.6986e−1 (1.52e−4)−	5.9459e−1 (1.11e−1)−	9.6474e−1 (3.07e−3)−	9.6943e−1 (1.93e−3)−	4.2550e−2 (5.74e−2)−	9.6296e−1 (3.47e−3)−
	15	9.9519e−1 (6.38e−5)	9.8888e−1 (7.59e−4)−	9.9121e−1 (8.25e−5)−	8.0984e−1 (8.42e−2)−	9.9325e−1 (4.14e−4)≈	9.9143e−1 (1.12e−4)−	9.9961e−2 (7.59e−2)−	9.7112e−1 (7.36e−3)−
+/ − / ≈			5/14/1	2/7/11	2/16/2	4/14/2	5/14/1	0/20/0	3/15/2

Table 3
Comparison of HV average and standard deviation on WFG test problems.

Problem	M	RVEA-2DCES	RVEA-iGNG	RVEA	NSGA-II/SDR	onebyoneEA	HEA	MaOEA-IT	hpaEA
WFG1	3	6.6844e−1 (3.95e−2)	9.4066e−1 (1.88e−3)+	9.2044e−1 (2.02e−2)+	9.2000e−1 (7.04e−3)+	9.0225e−1 (7.04e−3)+	9.4116e−1 (9.46e−4)+	1.7916e−1 (5.37e−2)−	6.1614e−1 (1.45e−1)−
	5	6.1875e−1 (3.48e−2)	9.9628e−1 (5.63e−4)+	9.8741e−1 (2.23e−2)+	9.8181e−1 (5.67e−3)+	9.8488e−1 (1.96e−2)+	9.9079e−1 (3.10e−2)+	2.3309e−1 (8.72e−2)−	9.2958e−1 (6.10e−2)+
	8	7.8064e−1 (2.59e−2)	9.9775e−1 (4.90e−4)+	9.8335e−1 (3.49e−2)+	9.9042e−1 (7.44e−3)+	9.9645e−1 (1.03e−3)+	9.9416e−1 (1.77e−3)+	1.7328e−1 (9.88e−2)−	9.8433e−1 (3.65e−2)+
	10	8.5737e−1 (2.03e−2)	9.9790e−1 (5.06e−4)+	9.9714e−1 (5.89e−4)+	9.8755e−1 (1.17e−2)+	9.9791e−1 (6.01e−4)+	9.9047e−1 (3.12e−2)+	1.3887e−1 (8.00e−2)−	9.9874e−1 (9.80e−4)+
	15	9.4186e−1 (5.30e−3)	9.9797e−1 (4.91e−4)+	9.9835e−1 (6.20e−4)+	9.8729e−1 (2.00e−2)+	9.9887e−1 (1.69e−4)+	9.8964e−1 (3.20e−3)+	5.4786e−2 (9.01e−3)−	9.9425e−1 (2.43e−2)+
WFG2	3	9.2422e−1 (2.34e−3)	9.3247e−1 (1.53e−3)+	9.2404e−1 (1.62e−3)≈	9.0754e−1 (9.96e−3)−	8.9226e−1 (8.15e−3)−	9.3401e−1 (7.61e−4)+	5.9047e−1 (5.06e−2)−	9.2533e−1 (6.29e−3)≈
	5	9.8975e−1 (2.13e−3)	9.9154e−1 (1.21e−3)≈	9.8911e−1 (1.68e−3)≈	9.7380e−1 (3.96e−3)−	9.7803e−1 (5.24e−3)−	9.8768e−1 (7.26e−4)−	6.0085e−1 (3.25e−2)−	9.8917e−1 (1.52e−3)≈
	8	9.9051e−1 (3.00e−3)	9.9369e−1 (1.15e−3)+	9.8083e−1 (4.51e−3)−	9.8296e−1 (4.95e−3)−	9.9011e−1 (2.73e−3)≈	9.8798e−1 (2.62e−3)−	6.1130e−1 (3.67e−2)−	9.8370e−1 (2.77e−3)−
	10	9.9388e−1 (2.48e−3)	9.9550e−1 (7.36e−4)≈	9.8560e−1 (4.06e−3)−	9.8576e−1 (3.19e−3)−	9.9382e−1 (1.83e−3)≈	9.9365e−1 (2.79e−3)≈	5.9518e−1 (4.54e−2)−	9.9164e−1 (1.44e−3)−
	15	9.8863e−1 (2.45e−3)	9.9628e−1 (8.66e−4)+	9.6871e−1 (7.13e−3)−	9.9225e−1 (2.38e−3)+	9.9486e−1 (1.09e−3)+	9.9138e−1 (6.32e−3)+	5.8966e−1 (1.09e−1)−	9.8958e−1 (2.31e−3)≈
WFG3	3	3.2500e−1 (1.81e−2)	3.9389e−1 (2.95e−3)+	3.3870e−1 (9.34e−3)+	3.8794e−1 (4.74e−3)+	2.5353e−1 (1.84e−2)−	4.0278e−1 (1.87e−3)+	1.3404e−1 (1.93e−2)−	3.6690e−1 (1.49e−2)+
	5	1.9980e−1 (1.11e−2)	1.6803e−1 (1.27e−2)−	1.4649e−1 (2.04e−2)−	1.9950e−1 (1.07e−2)−	5.9976e−2 (1.11e−2)−	2.1849e−1 (7.56e−3)+	1.7099e−4 (6.69e−4)−	1.4331e−1 (2.08e−2)−
	8	1.9644e−2 (2.23e−2)	7.6628e−3 (9.36e−3)−	0.0000e+0(0.00e+0)−	4.0748e−2 (1.73e−2)+	0.0000e+0 (0.00e+0)−	7.0162e−2 (7.51e−3)+	0.0000e+0 (0.00e+0)−	7.1207e−3 (1.18e−2)−
	10	0.0000e+0(0.00e+0)	0.0000e+0(0.00e+0)≈	0.0000e+0(0.00e+0)≈	2.1844e−3 (6.74e−3)≈	0.0000e+0(0.00e+0)≈	5.6742e−2 (1.43e−2)+	0.0000e+0 (0.00e+0)≈	0.0000e+0 (0.00e+0)≈
	15	0.0000e+0(0.00e+0)	0.0000e+0(0.00e+0)≈	0.0000e+0(0.00e+0)≈	0.0000e+0(0.00e+0)≈	0.0000e+0(0.00e+0)≈	1.1274e−2(1.94e−2)+	0.0000e+0(0.00e+0)≈	0.0000e+0(0.00e+0)≈
WFG4	3	5.4887e−1 (1.58e−3)	5.5403e−1 (1.05e−3)≈	5.4842e−1 (1.45e−3)−	5.4478e−1 (2.75e−3)−	5.0617e−1 (1.14e−2)−	5.5748e−1 (6.31e−4)+	2.5380e−1 (6.79e−2)−	5.5311e−1 (3.56e−3)+
	5	8.0135e−1 (1.57e−3)	7.8916e−1 (2.17e−3)−	7.9709e−1 (2.12e−3)−	7.8462e−1 (3.38e−3)−	6.7897e−1 (1.31e−2)−	7.9859e−1 (1.53e−3)−	3.2526e−1 (8.19e−2)−	7.6079e−1 (1.89e−2)−
	8	9.2425e−1 (1.85e−3)	9.0005e−1 (2.71e−3)−	8.9809e−1 (4.40e−3)−	9.1865e−1 (3.83e−3)−	7.6893e−1 (8.54e−3)−	9.1110e−1 (2.31e−3)−	3.3976e−1 (3.66e−2)−	7.2611e−1 (3.10e−2)−
	10	9.4463e−1 (3.02e−3)	9.2429e−1 (2.95e−3)−	9.5142e−1 (3.16e−3)+	9.5629e−1 (3.06e−3)+	8.0994e−1 (9.85e−3)−	9.5858e−1 (2.22e−3)+	2.8472e−1 (5.96e−2)−	7.5754e−1 (3.61e−2)−
	15	9.7684e−1 (4.87e−3)	9.3515e−1 (5.84e−3)−	9.7462e−1 (4.19e−3)≈	9.8908e−1 (1.29e−3)+	8.7663e−1 (8.54e−3)−	9.8889e−1 (8.48e−4)+	3.7286e−1 (7.58e−2)−	7.1136e−1 (2.37e−2)−
WFG5	3	5.1536e−1 (1.05e−3)	5.1619e−1 (9.55e−4)≈	5.1604e−1 (4.28e−4)≈	5.1143e−1 (1.53e−3)−	4.7039e−1 (1.62e−2)−	5.1823e−1 (2.58e−4)≈	2.2308e−1 (5.64e−2)−	5.1735e−1 (1.18e−3)≈
	5	7.5986e−1 (8.53e−4)	7.4682e−1 (2.15e−3)−	7.5864e−1 (1.15e−3)≈	7.4712e−1 (1.98e−3)−	6.4878e−1 (1.22e−2)−	7.6068e−1 (5.03e−4)≈	2.7780e−1 (3.11e−2)−	7.5893e−1 (2.39e−3)≈
	8	8.7004e−1 (6.69e−4)	8.5063e−1 (2.52e−3)−	8.5813e−1 (1.50e−3)−	8.6485e−1 (3.09e−3)−	7.2225e−1 (1.33e−2)−	8.6252e−1 (8.13e−4)−	2.6617e−1 (2.20e−2)−	8.3182e−1 (1.15e−2)−
	10	8.8919e−1 (2.94e−3)	8.7628e−1 (3.13e−3)−	9.0122e−1 (7.96e−4)+	8.9628e−1 (1.98e−3)+	7.6274e−1 (1.22e−2)−	8.8986e−1 (3.63e−4)≈	2.3130e−1 (1.20e−2)−	8.5240e−1 (1.54e−2)−
	15	9.0797e−1 (1.94e−3)	8.8246e−1 (4.02e−3)−	9.1589e−1 (3.78e−4)+	9.2052e−1 (5.40e−4)+	8.2086e−1 (1.08e−2)−	9.1760e−1 (1.44e−4)+	2.9092e−1 (2.61e−2)−	7.4595e−1 (1.38e−2)−
WFG6	3	4.9347e−1 (2.07e−2)	5.0174e−1 (1.69e−2)+	4.9539e−1 (1.25e−2)≈	5.0047e−1 (1.30e−2)≈	4.2868e−1 (2.54e−2)−	5.0760e−1 (1.48e−2)+	1.7019e−1 (2.83e−2)−	5.0387e−1 (1.12e−2)+
	5	7.3974e−1 (1.14e−2)	7.2954e−1 (1.51e−2)−	7.3721e−1 (1.23e−2)≈	7.3080e−1 (1.22e−2)−	5.8526e−1 (2.03e−2)−	7.3442e−1 (1.68e−2)−	2.7465e−1 (2.43e−2)−	7.3192e−1 (1.23e−2)−
	8	8.5282e−1 (1.29e−2)	8.2726e−1 (2.25e−2)−	8.3284e−1 (2.36e−2)−	8.5004e−1 (1.39e−2)−	6.3253e−1 (2.21e−2)−	8.3594e−1 (1.75e−2)−	2.6338e−1 (2.28e−2)−	7.9509e−1 (2.08e−2)−
	10	8.6057e−1 (1.54e−2)	8.5312e−1 (2.00e−2)−	8.7281e−1 (2.08e−2)+	8.8085e−1 (1.78e−2)+	6.6452e−1 (2.20e−2)−	8.7815e−1 (1.38e−1)+	2.0214e−1 (2.09e−2)−	8.2436e−1 (1.82e−2)−
	15	8.6283e−1 (2.43e−2)	8.4681e−1 (2.15e−2)−	7.3981e−1 (5.79e−2)−	9.0265e−1 (2.03e−2)+	6.9891e−1 (2.29e−2)−	9.0129e−1 (2.72e−2)+	3.2097e−1 (5.56e−2)−	7.2783e−1 (1.65e−2)−
WFG7	3	5.5648e−1 (1.22e−3)	5.5563e−1 (1.03e−3)≈	5.4987e−1 (1.06e−3)≈	5.5041e−1 (1.67e−3)≈	4.6335e−1 (1.43e−2)−	5.5202e−1 (6.15e−4)−	2.5496e−1 (1.96e−2)−	5.5625e−1 (9.27e−4)≈
	5	8.0272e−1 (9.27e−4)	7.9859e−1 (1.39e−3)−	8.0261e−1 (9.67e−4)≈	7.9536e−1 (2.23e−3)−	6.2798e−1 (1.52e−2)−	8.0256e−1 (5.82e−4)≈	3.3457e−1 (2.76e−2)−	8.0033e−1 (2.66e−3)−
	8	9.2069e−1 (2.08e−3)	9.1494e−1 (1.97e−3)−	8.9611e−1 (5.73e−3)−	9.2236e−1 (3.46e−3)≈	7.3382e−1 (1.20e−2)−	9.1899e−1 (1.01e−3)−	3.6428e−1 (3.89e−2)−	8.3268e−1 (2.70e−2)−
	10	9.5349e−1 (1.82e−3)	9.4418e−1 (1.63e−3)−	9.5279e−1 (2.30e−3)≈	9.6045e−1 (2.72e−3)+	7.7837e−1 (1.54e−2)−	9.6582e−1 (4.95e−4)+	2.7336e−1 (3.78e−2)−	8.6208e−1 (2.12e−2)−
	15	9.8301e−1 (1.83e−3)	9.5316e−1 (3.84e−3)−	9.8272e−1 (3.46e−3)≈	9.9306e−1 (1.39e−3)+	8.7134e−1 (9.51e−3)−	9.9075e−1 (1.09e−4)+	3.7847e−1 (3.82e−2)−	8.0735e−1 (1.53e−2)−
WFG8	3	4.6140e−1 (3.71e−3)	4.7526e−1 (1.97e−3)+	4.6471e−1 (2.02e−3)+	4.6267e−1 (1.75e−3)≈	3.8878e−1 (1.07e−2)−	4.7584e−1 (1.47e−3)+	1.7923e−1 (1.20e−2)−	4.6951e−1 (5.07e−3)+
	5	6.7819e−1 (2.58e−3)	6.8136e−1 (2.54e−3)≈	6.8897e−1 (2.11e−3)+	6.7612e−1 (3.49e−3)−	5.3629e−1 (1.06e−2)−	7.0114e−1 (1.67e−3)+	2.7749e−1 (2.23e−2)−	6.8835e−1 (2.65e−3)+
	8	8.4173e−1 (4.02e−2)	8.1487e−1 (2.21e−2)−	7.3059e−1 (9.06e−2)−	8.2878e−1 (3.05e−2)−	5.3307e−1 (5.61e−2)−	8.1404e−1 (2.11e−2)−	2.4934e−1 (2.91e−2)−	7.4475e−1 (5.66e−3)−
	10	8.7247e−1 (4.09e−2)	8.6294e−1 (2.76e−2)−	7.5879e−1 (7.32e−2)−	9.1565e−1 (2.67e−2)+	5.9881e−1 (6.73e−2)−	8.8483e−1 (2.28e−2)≈	1.5329e−1 (2.76e−2)−	8.1729e−1 (1.95e−2)−
	15	8.9911e−1 (5.60e−2)	8.8263e−1 (8.48e−3)−	7.2683e−1 (1.19e−1)−	9.6426e−1 (4.07e−2)+	6.3369e−1 (1.02e−1)−	9.2808e−1 (3.99e−3)+	3.5057e−1 (2.64e−2)−	8.4212e−1 (1.44e−2)−
WFG9	3	5.3215e−1 (4.75e−3)	5.3620e−1 (3.09e−3)+	5.3048e−1 (3.32e−3)≈	5.3137e−1 (2.36e−3)−	4.8016e−1 (1.50e−2)−	5.3208e−1 (3.86e−3)≈	1.7827e−1 (2.56e−2)−	5.2952e−1 (3.88e−3)−
	5	7.6197e−1 (4.30e−3)	7.5522e−1 (3.39e−3)−	7.5402e−1 (5.66e−3)−	7.6002e−1 (3.60e−3)≈	6.4458e−1 (1.45e−2)−	7.5952e−1 (5.50e−3)−	2.7032e−1 (1.80e−2)−	7.5325e−1 (4.23e−3)−
	8	8.7428e−1 (6.53e−2)	8.4372e−1 (1.10e−2)−	8.4113e−1 (1.02e−2)−	8.7717e−1 (4.48e−3)≈	7.1503e−1 (4.13e−2)−	8.5243e−1 (5.72e−3)−	2.8716e−1 (2.41e−2)−	8.1043e−1 (1.70e−2)−
	10	8.9447e−1 (7.72e−2)	8.6880e−1 (5.34e−3)−	8.8436e−1 (1.08e−2)≈	9.1242e−1 (2.78e−3)+	7.5785e−1 (2.75e−2)−	9.0385e−1 (4.86e−3)+	2.1301e−1 (3.15e−2)−	8.4467e−1 (1.25e−2)−
	15	9.0238e−1 (3.83e−2)	8.5071e−1 (3.71e−2)−	8.5204e−1 (6.18e−2)−	9.4034e−1 (5.06e−3)+	8.0247e−1 (3.93e−2)−	9.1695e−1 (7.28e−3)+	3.6756e−1 (1.92e−2)−	7.4690e−1 (1.04e−2)−
+/ − / ≈			12/25/8	12/18/15	20/17/8	6/35/4	26/12/7	0/43/2	9/28/8



(a) RVEA-2DCES (b) RVEA-iGNG (c) RVEA (d) NSGA-II/SDR

(e) onebyoneEA (f) HEA (g) MaOEA-IT (h) hpaEA

Fig. 4. Parallel coordinates of final non-dominated solution sets obtained by each algorithm on 10-objective DTLZ3.

Specific to each test problem, WFG1 is designed to investigate an MOEA's ability coping with bias and mixed PF geometries. The performance of RVEA-2DCES on WFG1 was only better than MaOEA-IT. Obvious performance degradation compared to RVEA reveals that Manhattan distance is less capable of handling polynomial and flat bias than Euclidean distance. WFG2 has a disconnected PF while WFG3 is difficult with a degenerate PF. RVEA-iGNG and HEA were the best algorithms on these two problems separately. For RVEA-iGNG, this can be attributed to the reference vector adjustment strategy specially designed for irregular problems. While the performance of HEA benefited from the improved reference vectors-based diversity preservation strategy which makes solutions well-distributed in the degenerate PF. Without specially designed approach handling irregular PFs, RVEA-2DCES obtained competitive results especially on WFG2. Irregular PFs will invalidate some reference vectors as subspaces specified by them are always empty, which reduces the diversity of obtained population. Disconnected segments account for a small proportion of the PF of WFG2, thus invalid reference vectors account for a small proportion of the reference vector set. This reduces the impact of irregular PF on the diversity of solution set obtained by RVEA-2DCES. Besides, considering that solutions tend to distribute crowdedly near the segments of irregular PFs, convergence-only selection together with elite retention strategy can improve the diversity by adding more of these solutions into final elite population. WFG4-9 have the same concave PFs with different problem properties. Their objectives are either separable or non-separable, either unimodal or multimodal (incluing the special case deceptive multimodality). Besides, WFG7-9 are parameter dependent while WFG4-6 are not. RVEA-2DCES, NSGA-II/SDR and HEA showed clear advantages over other algoritms on WFG4 to WFG9, demonstrating their comprehensive ability dealing with concave MaOPs. According to the results of Wilcoxon rank sum test, NSGA-II/SDR obtained similar performance with RVEA-2DCES and the performance of HEA was slightly better.

WFG4 is a multimodal and concave test problem. Its 8-objective parallel coordinates are presented in Fig. 5. RVEA-2DCES, RVEA-iGNG, RVEA, NSGA-II/SDR and HEA were capable of covering the whole range of PF. Solution distributions of RVEA and HEA were similar because they used the same reference vector set as search directions. RVEA-2DCES and RVEA-iGNG obtained more solutions in the middle of PF, attributed to the adaptive sparse region detection and adaptive reference vector adjustment respectively. These two strategies both improve diversity based on the distribution of current solutions. NSGA-II/SDR also obtained a competitive solution set as WFG4 is easy to converge to the PF. On the basis of this, crowding distance for diversity preservation worked well to make the distribution more uniform. The overall range of approximate PFs obtained by MaOEA-IT and hpaEA were smaller than true PF, especially on the first four objectives. As for onebyoneEA, it maintained diversity on the first three objectives, but on other objectives, the range of solutions was much smaller than PF. Only some boundary solutions were obtained. Similar results occurred on 15-objective WFG8, a more difficult test problem than WFG4 with non-separable property and significant bias. Fig. 6 shows that compared to 8-objective WFG4, RVEA failed to cover the last three objectives while onebyoneEA failed to obtain the extreme point on the eleventh objective and sufficient coverage on most objectives, indicating their performance degradation as the number of objectives increases. RVEA-2DCES, RVEA-iGNG, NSGA-II/SDR and HEA covered the PF well, but the distribution of NSGA-II/SDR and HEA were obviously sparser than RVEA-2DCES and RVEA-iGNG especially near the boundary of PF. For WFG8, distance related parameters are dependent on position related parameters, meaning that an algorithm cannot simply find a good set of distance parameters, and then use that set to spread out along the PF [54]. This puts higher requirements on the diversity preservation mechanism of MOEAs and results in the difference of diversity.

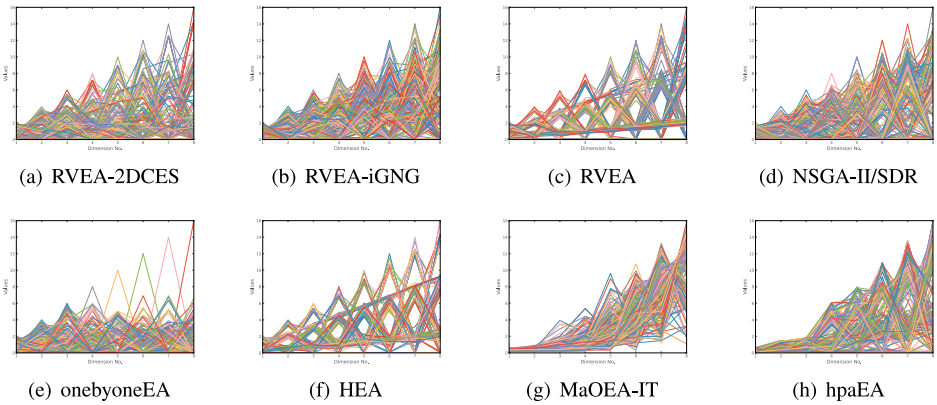
4.4.3. Results on MaF1 to MaF7

The average and standard deviation of HV on MaF1 to MaF7 over 20 independent runs obtained by each algorithm are presented in Table 4. RVEA-2DCES obtained the best overall performance on MaF test suite since it obtained 17 best results among 35 test problems. According to the results of Wilcoxon rank sum test, RVEA-iGNG was also a competitive algorithm followed by NSGA-II/SDR and hpaEA.

MaF test suite is constructed to promote the research of evolutionary many-objective optimization via suggesting a set of test problems with a good representation of various real-world scenarios. It covers different problem features such as being multimodal, disconnected, degenerate and having a complex Pareto set or a large number of decision variables [55]. MaF1 is the modified version of inverted DTLZ1 to assess whether an MaOEA is capable of dealing with inverted PF. For reference vector-based MaOEAs, nonconformity between the shape of inverted PF and the distribution of reference vectors will result in poor diversity. Reference vector adjustment strategy of RVEA-iGNG alleviated this problem, thus the performance of RVEA-iGNG was better than RVEA-2DCES and RVEA. NSGA-II/SDR and onebyoneEA were the best two algoritms on MaF1 as they did not use reference vectors for diversity management and solutions are easy to converge to the linear PF of MaF1. MaF2 is modified from DTLZ2 to increase the difficulty of convergence. RVEA-2DCES was the best algorithm on MaF2 attributed to its convergence enhancement strategy. MaF3 is convex DTLZ3, a test problem with convex PF and a large number of local fronts. No algorithm was significantly better than the others on MaF3, indicating that there is no method particularly suitable for dealing with convexity. MaF4 is designed to assess whether algorithms are capable of dealing with badly scaled PFs, especially when the fitness landscape is highly multimodal. It can be observed from the results that MaF4 is difficult to converge since HVs were quite small. Convergence-only selection together with elite retention strategy of RVEA-2DCES improved the convergence of RVEA-2DCES, making its performance obviously better

Table 4
Comparison of HV average and standard deviation on MaF test problems.

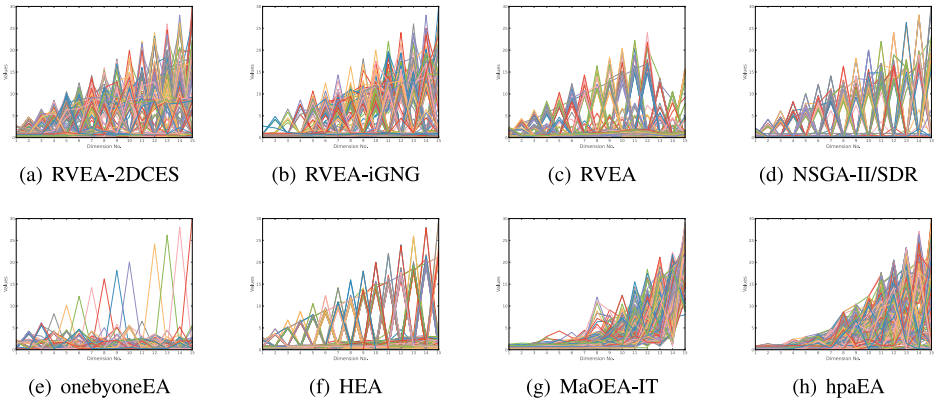
Problem	M	RVEA-2DCES	RVEA-iGNG	RVEA	NSGA-II/SDR	onebyoneEA	HEA	MaOEA-IT	hpaEA
MaF1	3	1.9939e−1 (2.68e−3)	2.1916e−1 (3.86e−4)+	1.8646e−1 (4.76e−4)−	1.1584e−1 (9.05e−2)−	2.1429e−1 (1.44e−3)+	1.9741e−1 (5.05e−4)−	6.6351e−2 (3.57e−2)−	2.1891e−1 (5.67e−4)+
	5	9.5000e−3 (7.42e−4)	1.2432e−2 (1.58e−4)+	3.4599e−3 (2.88e−4)−	1.2959e−2 (1.26e−4)+	1.3279e−2 (8.05e−5)+	6.9008e−3 (2.18e−4)−	1.9562e−3 (1.81e−3)−	1.2496e−2 (1.44e−4)+
	8	2.6753e−5 (3.51e−6)	3.6063e−5 (3.03e−6)+	1.5321e−6 (1.47e−6)−	4.1835e−5 (2.31e−6)+	4.5358e−5 (9.83e−6)+	2.2182e−5 (6.82e−7)+	1.7453e−6 (2.65e−6)−	3.5971e−5 (6.26e−6)+
	10	3.1704e−7 (4.23e−7)	3.8054e−7 (1.87e−7)+	8.4045e−9 (4.08e−9)≈	7.1649e−7 (2.63e−7)+	4.8497e−7 (2.56e−7)≈	3.5936e−7 (1.29e−8)+	1.8459e−8 (2.83e−8)−	5.4783e−7 (5.37e−7)+
	15	0.0000e+0 (0.00e+0)	1.0883e−12 (4.60e−12)+	2.5697e−14 (1.40e−14)+	0.0000e+0 (0.00e+0)≈	5.2254e−12 (6.83e−12)+	3.4062e−12 (1.15e−13)+	6.2785e−14 (1.14e−13)+	0.0000e+0 (0.00e+0)≈
MaF2	3	2.3697e−1 (1.51e−3)	2.4478e−1 (3.59e−4)+	2.2829e−1 (1.77e−3)−	2.4327e−1 (7.04e−4)+	2.3040e−1 (2.50e−3)−	2.4376e−1 (2.70e−4)+	1.3193e−1 (2.01e−2)−	2.4110e−1 (1.05e−3)+
	5	2.3694e−1 (2.01e−3)	2.0286e−1 (7.04e−4)−	1.7639e−1 (1.90e−3)−	2.0307e−1 (1.40e−3)−	1.8801e−1 (2.04e−3)−	1.8990e−1 (1.80e−3)−	1.4379e−1 (2.31e−2)−	1.9165e−1 (1.55e−3)−
	8	2.2137e−1 (6.95e−3)	2.3469e−1 (1.91e−3)+	1.5566e−1 (6.37e−3)−	2.3239e−1 (2.40e−3)+	2.1866e−1 (2.68e−3)−	2.1211e−1 (1.64e−3)−	1.1679e−1 (2.09e−2)−	2.1205e−1 (2.11e−3)−
	10	2.3092e−1 (3.34e−3)	2.2551e−1 (2.42e−3)−	1.6826e−1 (4.47e−3)−	2.2271e−1 (2.59e−3)−	2.0880e−1 (3.22e−3)−	2.0622e−1 (1.20e−3)−	8.8313e−2 (1.08e−2)−	2.2387e−1 (1.39e−3)−
	15	2.1592e−1 (2.11e−3)	2.0580e−1 (2.67e−3)−	6.2749e−2 (2.11e−2)−	2.0900e−1 (4.26e−3)−	1.9526e−1 (3.79e−3)−	1.7774e−1 (2.48e−3)−	1.3698e−1 (3.21e−2)−	2.0008e−1 (3.55e−3)−
MaF3	3	8.2583e−1 (2.86e−1)	9.1080e−1 (2.14e−1)+	7.3866e−1 (3.41e−1)≈	9.2587e−1 (9.14e−3)+	7.9844e−1 (6.29e−2)+	9.3836e−2 (3.97e−2)−	2.2070e−1 (3.92e−1)−	9.5654e−1 (1.75e−3)+
	5	9.9786e−1 (1.30e−3)	9.9870e−1 (4.46e−4)+	9.1715e−1 (2.21e−1)−	9.8300e−1 (4.52e−3)−	9.7641e−1 (1.36e−2)−	9.9783e−1 (1.26e−3)+	0.0000e+0 (0.00e+0)−	9.9917e−1 (4.32e−4)+
	8	9.9977e−1 (5.51e−4)	9.9957e−1 (1.60e−4)≈	9.9165e−1 (2.31e−2)−	9.9024e−1 (5.64e−3)−	9.9890e−1 (4.55e−4)≈	9.9405e−1 (2.22e−3)−	0.0000e+0 (0.00e+0)−	1.0008e−1 (3.08e−1)−
	10	9.9907e−1 (3.94e−4)	9.9987e−1 (1.21e−4)≈	9.9061e−1 (2.91e−2)−	9.9229e−1 (3.06e−3)−	9.9966e−1 (2.60e−4)≈	9.9861e−1 (1.70e−3)≈	0.0000e+0 (0.00e+0)−	0.0000e+0 (0.00e+0)−
	15	9.9998e−1 (4.74e−5)	3.8557e−1 (4.59e−1)−	9.9930e−1 (6.12e−4)≈	9.9720e−1 (1.46e−3)−	9.9991e−1 (8.21e−5)≈	9.8671e−1 (9.40e−3)−	0.0000e+0 (0.00e+0)−	0.0000e+0 (0.00e+0)−
MaF4	3	4.6887e−1 (3.93e−2)	5.2658e−1 (3.96e−3)+	4.8158e−1 (2.95e−2)+	4.9551e−1 (5.61e−2)+	3.7004e−1 (3.43e−2)−	5.0945e−2 (4.50e−3)+	4.0721e−2 (9.95e−2)−	5.1914e−1 (6.57e−3)+
	5	3.5082e−1 (1.39e−2)	1.2162e−1 (3.66e−3)−	4.0899e−2 (1.57e−2)−	1.3120e−1 (1.45e−3)−	6.9817e−2 (1.27e−2)−	9.5693e−2 (4.20e−3)−	1.8720e−5 (8.37e−5)−	1.1327e−1 (3.66e−3)−
	8	6.8364e−2 (1.52e−2)	3.8428e−3 (5.11e−4)−	1.2314e−5 (7.69e−6)−	8.6514e−4 (1.10e−4)−	1.8262e−4 (8.30e−5)−	4.4273e−3 (3.46e−4)−	3.6671e−5 (1.64e−4)−	1.4546e−3 (2.25e−4)−
	10	1.3869e−2 (4.13e−3)	2.8005e−4 (5.67e−5)−	1.0626e−7 (7.08e−8)−	1.4940e−5 (3.88e−6)−	1.6360e−6 (5.49e−7)−	2.9742e−4 (2.86e−5)−	0.0000e+0 (0.00e+0)−	1.2230e−4 (2.80e−5)−
	15	2.9112e−5 (9.92e−6)	1.5522e−7 (4.71e−8)−	6.6308e−12 (2.81e−11)−	5.7852e−10 (3.20e−10)−	1.8597e−11 (1.54e−11)−	1.8226e−7 (2.75e−8)−	0.0000e+0 (0.00e+0)−	1.3161e−7 (1.88e−7)−
MaF5	3	5.4895e−1 (4.91e−2)	5.3397e−1 (6.52e−2)−	5.3608e−1 (1.05e−1)≈	2.6793e−1 (4.25e−2)−	4.8740e−1 (3.99e−2)−	4.2693e−1 (1.35e−1)−	9.3193e−2 (9.57e−3)−	4.0724e−1 (1.69e−1)≈
	5	9.9703e−1 (5.98e−5)	8.0264e−1 (1.72e−3)−	8.0229e−1 (3.11e−2)−	1.7169e−1 (9.05e−2)−	6.7760e−1 (1.69e−2)−	7.9416e−1 (6.25e−2)−	1.4341e−1 (1.07e−1)−	7.9308e−1 (4.13e−2)−
	8	1.0000e+0 (1.15e−5)	9.1193e−1 (4.80e−3)−	9.1187e−1 (6.14e−3)−	1.1768e−1 (5.19e−2)−	7.6342e−1 (1.27e−2)−	9.2658e−1 (2.12e−4)−	6.1537e−2 (6.09e−2)−	9.2143e−1 (5.64e−3)−
	10	1.0000e+0 (4.24e−6)	9.5006e−1 (2.51e−3)−	9.5307e−1 (1.90e−3)−	1.0510e−1 (3.46e−2)−	8.0392e−1 (1.01e−2)−	9.6987e−1 (1.74e−4)−	9.9258e−2 (6.33e−2)−	9.6476e−1 (3.16e−3)−
	15	1.0000e+0 (1.82e−12)	9.6709e−1 (4.23e−3)−	9.4177e−1 (1.02e−2)−	9.7605e−2 (3.00e−2)−	8.9015e−1 (6.26e−3)−	9.9142e−1 (9.32e−5)−	8.0803e−2 (5.40e−2)−	9.7353e−1 (5.33e−3)−
MaF6	3	1.8018e−1 (3.84e−3)	1.9971e−1 (1.20e−4)+	1.7547e−1 (5.38e−3)−	1.9836e−1 (3.92e−4)+	1.9943e−1 (1.30e−4)+	1.8248e−1 (2.80e−3)≈	4.8219e−2 (1.02e−2)−	1.9963e−1 (8.46e−5)+
	5	1.3834e−1 (2.90e−3)	1.2995e−1 (3.70e−4)−	1.1753e−1 (1.61e−3)−	1.2344e−1 (4.41e−3)−	1.2982e−1 (3.61e−4)−	1.1498e−1 (1.72e−3)−	1.2133e−1 (2.58e−2)−	1.3003e−1 (2.76e−4)−
	8	1.0838e−1 (1.08e−3)	1.0636e−1 (2.05e−4)−	9.1368e−2 (1.49e−2)−	1.0384e−1 (1.13e−3)−	1.0630e−1 (3.61e−4)−	9.3122e−2 (1.51e−2)−	4.7515e−3 (2.03e−2)−	1.0649e−1 (3.39e−4)−
	10	1.0024e−1 (1.54e−3)	1.0088e−1 (2.84e−4)≈	9.4757e−2 (9.54e−4)−	9.9531e−2 (5.92e−4)−	1.0082e−1 (2.81e−4)≈	4.3644e−2 (4.15e−2)−	2.9491e−2 (2.92e−2)−	0.0000e+0 (0.00e+0)−
	15	8.8564e−2 (5.53e−3)	7.9554e−2 (3.49e−2)−	9.1759e−2 (7.62e−4)+	9.4959e−2 (2.95e−4)+	9.5425e−2 (2.80e−4)+	3.3688e−2 (3.41e−2)−	3.6501e−2 (4.59e−2)−	0.0000e+0 (0.00e+0)−
MaF7	3	2.5687e−1 (4.94e−3)	2.7292e−1 (1.85e−2)+	2.6495e−1 (1.25e−3)+	2.6956e−1 (1.57e−3)+	2.5381e−1 (1.03e−2)≈	2.3698e−1 (5.85e−2)≈	1.1719e−1 (2.36e−2)−	2.6763e−1 (1.18e−2)+
	5	2.9448e−1 (8.88e−3)	2.6852e−1 (2.67e−2)−	2.1980e−1 (3.34e−3)−	2.5675e−1 (2.24e−3)−	1.9138e−1 (1.64e−2)−	2.5536e−1 (6.84e−3)−	1.5122e−2 (2.64e−2)−	2.6565e−1 (5.78e−3)−
	8	1.9750e−1 (7.98e−3)	2.0364e−1 (3.37e−3)+	1.6693e−1 (1.23e−2)−	2.0534e−1 (3.01e−3)+	7.7801e−2 (2.55e−2)−	2.1046e−1 (7.09e−3)+	0.0000e+0 (0.00e+0)−	2.0332e−1 (3.20e−3)+
	10	8.9280e−3 (9.13e−3)	1.5175e−1 (9.29e−3)+	1.3886e−1 (1.82e−2)+	1.5933e−1 (3.70e−2)+	6.7490e−2 (1.61e−2)+	1.9104e−1 (1.45e−3)+	0.0000e+0 (0.00e+0)−	1.6897e−1 (6.13e−3)+
	15	8.3780e−3 (2.46e−2)	5.8376e−2 (3.21e−2)+	2.5457e−2 (3.84e−2)+	1.3861e−1 (6.77e−2)+	1.2265e−3 (2.68e−3)−	1.5166e−1 (4.03e−3)+	0.0000e+0 (0.00e+0)−	1.2854e−1 (1.20e−2)+
+/−/≈			15/17/3	6/25/4	13/21/1	8/21/6	9/23/3	1/34/0	13/20/2



(a) RVEA-2DCES (b) RVEA-iGNG (c) RVEA (d) NSGA-II/SDR

(e) onebyoneEA (f) HEA (g) MaOEA-IT (h) hpaEA

Fig. 5. Parallel coordinates of final non-dominated solution sets obtained by each algorithm on 8-objective WFG4.



(a) RVEA-2DCES (b) RVEA-iGNG (c) RVEA (d) NSGA-II/SDR

(e) onebyoneEA (f) HEA (g) MaOEA-IT (h) hpaEA

Fig. 6. Parallel coordinates of final non-dominated solution sets obtained by each algorithm on 15-objective WFG8.

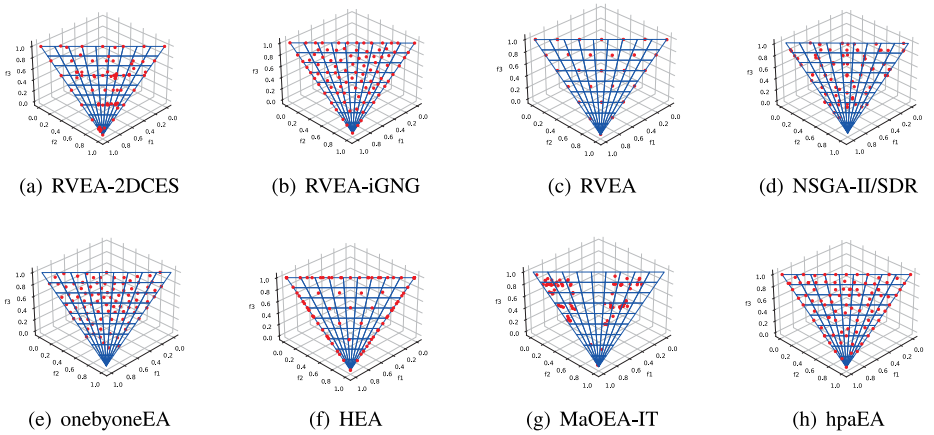
than other algorithm. MaF5 is convex badly scaled DTLZ4. The majority of Pareto optimal solutions are crowded in a small subregion as the PS of MaF5 has a highly biased distribution. RVEA-2DCES obtained all the best results on MaF5. This may be because solutions with prominent convergence retained by convergence-only selection were concentrated in this subregion, hence improved the diversity. MaF6 has a degenerate PF and MaF7 has a disconnected PF where the number of disconnected segments is 2^{m-1}. The performance of RVEA-2DCES on 10- and 15-objective MaF7 deteriorated seriously. This is probably because that as the number of disconnected segments increased exponentially, most reference vectors were invalid. Thus diversity and convergence enhancement strategies lost their function and misled the evolution to non-convergent regions.

Fig. 7 presents the 3-D coordinate graphs of final non-dominated solution sets on MaF1. For reference vector-based MaOEAs, three-dimensional reference points distribute on a unit simplex. As can be observed in Fig. 7(c) and (f), RVEA obtained uniformly but sparsely distributed solution set and the size of it was much smaller than population size as analyzed in Section 1. While solutions obtained by HEA mainly distributed on the boundary of PF, which is a common phenomenon for reference vector-based MOEAs when handling irregular PFs [33]. RVEA-2DCES obtained a better solution set with sufficient solutions on the basis of reference vector guided selection, thus its HV value was better than RVEA. While most of the extra solutions were concentrated near those solutions obtained by reference vector guided selection, providing little help in improving diversity. This shows that on relatively easy 3-objective problems, improvement brought by the proposed two diversity and convergence enhancement strategies is not obvious. Also as a reference vector-based algorithm, RVEA-iGNG performed quite well as its solutions distributed uniformly and extensively on the PF, demonstrating the superiority of its adaptive reference vector adjustment strategy on irregular PFs. The diversity of solutions obtained by MaOEA-IT and NSGA-II/SDR were not satisfying. The former only concentrated on limited parts of the PF while the latter only realized insufficient coverage of PF. Besides, hpaEA and onebyoneEA obtained superior solution sets with uniform and extensive distribution owing to the angle-based niche technique and interval-based diversity preservation mechanism separately.

Fig. 8 presents the parallel coordinates of final non-dominated solution sets on 10-objective MaF3. MaF3 is convex DTLZ3, a test problem with multimodal and convex PF. The PF of MaF3 range from 0 to 1 on all objectives, thus none of these algorithms could cover the whole PF. onebyoneEA obtained many boundary solutions on the PF along each objective since it uses corner solutions to enhance the spread of the solutions, but other solutions distributed inside a narrow range. RVEA was quite close to cover the whole PF except on the fifth and seventh objectives. Besides, some solutions RVEA obtained did not converge. MaOEA-IT and hpaEA did not converge at all and their objective values were too large to accept. Apart from this, RVEA-2DCEA, RVEA-iGNG and HEA maintained diversity in the range of 0 to 0.2, and RVEA-iGNG presented better potential to find extreme points. It can be seen from the results of these algorithms that MaF3 is a difficult testing problem.

4.5. Statistical analysis

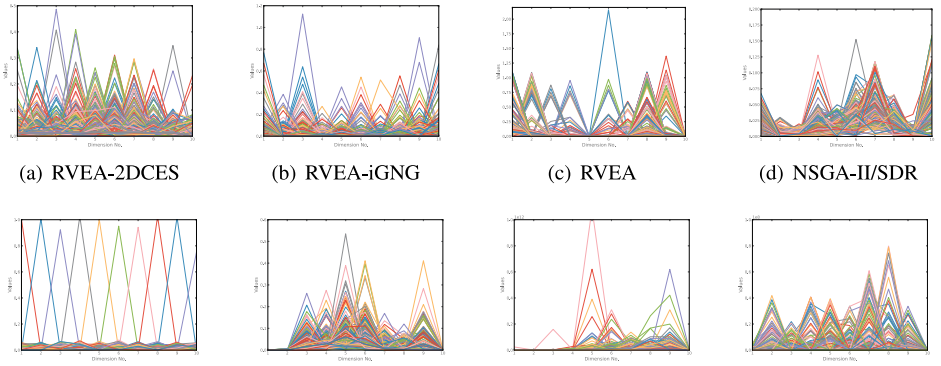
For a thorough statistical analysis of the results in Section 4.4, a ranking analysis using the Friedman test was conducted and the average rank of Friedman test are presented in Table 5. It can be observed that on 3-objective test problems, RVEA-2DCES ranked behind RVEA-iGNG, hpaEA, HEA and its ranking was close to RVEA. The reason behind is that HD-APD is mainly designed for high dimensional



(a) RVEA-2DCES (b) RVEA-iGNG (c) RVEA (d) NSGA-II/SDR

(e) onebyoneEA (f) HEA (g) MaOEA-IT (h) hpaEA

Fig. 7. 3-D coordinate graph of final non-dominated solution sets obtained by each algorithm on 3-objective MaF1.



(a) RVEA-2DCES (b) RVEA-iGNG (c) RVEA (d) NSGA-II/SDR

(e) onebyoneEA (f) HEA (g) MaOEA-IT (h) hpaEA

Fig. 8. Parallel coordinates of final non-dominated solution sets obtained by each algorithm on 10-objective MaF3.

Table 5
Average rank of Friedman test on test problems with different number of objectives.

M	RVEA-2DCES	RVEA-iGNG	RVEA	NSGA-II/SDR	onebyoneEA	HEA	MaOEA-IT	hpaEA
3	4	2.3	4.6	4.9	5.6	3.45	7.95	3.2
5	2.45	3.45	4.35	4.75	5.7	3.55	7.9	3.85
8	2.5	2.7	5.45	3.5	5.2	3.35	7.8	5.25
10	3.175	3.775	4.425	3.75	5.125	2.85	7.725	5.175
15	3.2	4.45	4.55	3.2	4.35	2.95	7.45	5.85

MOPs. Therefore, its effect is not obvious on 3-objective scenario. Besides, there is little room in the final elite population for elite retention strategy in most instances, thus the performance of RVEA-2DCES should be close to RVEA. Apart from this, RVEA-2DCES obtained the best average rank on 5-, 8-objective test problems and second best average rank on 10-, 15-objective test problems, demonstrating its superior competitiveness. It is worth mentioning that HEA obtained the best average rank on 10- and 15-objective test problems owing to its solution selection method based on hyper-dominance degree and the population reselection strategy that ensures enough selection pressure for convergence as the number of objectives increases.

Then, the Friedman statistics τ_F is calculated according to the following formulas:

$$\chi_F^2 = \frac{12K_f}{K_a(K_a+1)}[\sum_{i=1}^{K_a} R_i^2 - \frac{K_a(K_a+1)^2}{4}] \tag{5}$$

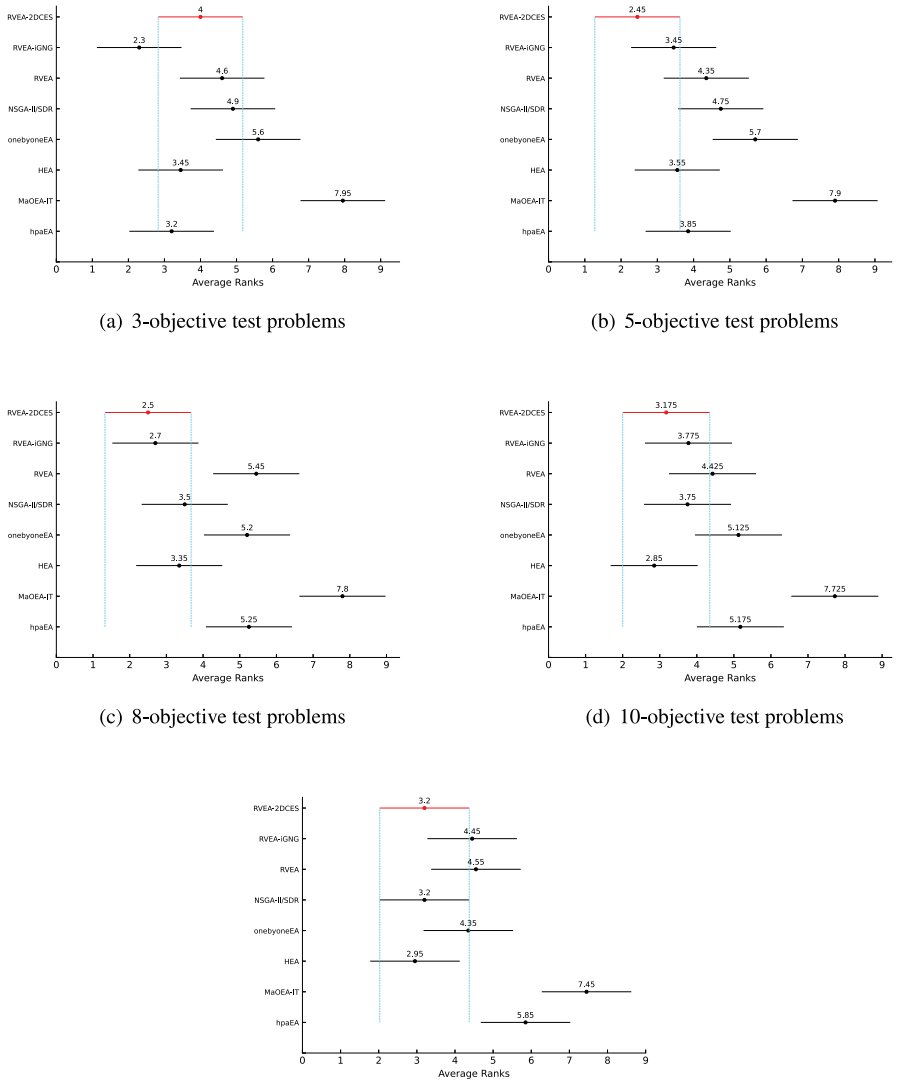
$$\tau_F = \frac{(K_f-1)\chi_F^2}{K_f(K_a-1)-\chi_F^2} \tag{6}$$

where K_a is the number of compared algorithms, K_f is the number of test problems and R_i is the average rank of the ith algorithm. If τ_F is greater than the critical value τ_c, it indicates the hypothesis that all compared algorithms performed equally is rejected and their performance is significantly different. Specific to our experiments, the significance level α is set to 0.05, K_a and K_f are 8 and 20 separately. Thus, it can be calculated that τ_F is 19.301 on 3-objective, 16.81 on 5-objective, 17.534 on 8-objective, 14.406 on 10-objective and 12.093 on 15-objective. Since τ_c is 2.079 under such condition, the hypothesis that all compared algorithms performed equally is rejected.

To verify which algorithm is significantly superior to others, Nemenyi test is adopted as a post-hoc test. If the difference between the average ranks of two algorithms is greater than the critical difference CD, it indicates that their performance is significantly different. CD is defined as follows:

$$CD = q_\alpha * \sqrt{\frac{K_a(K_a+1)}{6K_f}} \tag{7}$$

where q_α is 3.031 when the significance level $\alpha = 0.05$ and $K_a = 20$, thus it can be calculated that CD is 2.348. The results of Friedman test and Nemenyi test are presented in Fig. 9. There is no significant difference between RVEA-2DCES and a compared algorithm if its result intersects



(a) 3-objective test problems

(b) 5-objective test problems

(c) 8-objective test problems

(d) 10-objective test problems

(e) 15-objective test problems

Fig. 9. Results of Friedman and Nemenyi test on test problems with different number of objectives.

with dotted lines. It can be observed from Fig. 9 that RVEA-2DCES significantly outperforms MaOEA-IT in all situations. Besides, RVEA-2DCES significantly outperforms onebyoneEA on 5- and 8-objective, hpaEA on 8- and 15-objective and RVEA on 8-objective.

4.6. Comparison of computational complexity and running time

In this subsection, we analyze the computational complexity of the proposed RVEA-2DCES and compare its computational complexity and running time with other algorithms.

To analyze the computational complexity of RVEA-2DCES, main steps within one generation in the main loop of Algorithm 2 are considered. The main loop consists of four parts: reference vector guided selection, adaptive sparse region detection, convergence-only selection and elite retention strategy. For reference vector guided selection, it includes the following components: objective value translation with a complexity of $O(mN)$, objective space decomposition with a complexity of $O(mN^2)$, calculation of HD-APD with a complexity of $O(mN^2)$ and elitism selection with a complexity of $O(N^2)$, where m is the number of objectives and N is the population size. Thus, worst case computational complexity of reference vector guided selection is $O(mN^2)$ [27]. For adaptive sparse region detection, computational complexity comes from association with a complexity of $O(mN^2)$ and traversals of remaining combined population with the worst case complexity of $O(N^2)$. Convergence-only selection only needs to traverse the remaining combined population once, bringing a computational complexity of $O(N)$. Computational complexity of elite retention strategy mainly results from the update procedure and sorting. Worse case complexity of update procedure is $O(mN^2)$ and complexity of sorting is $O(NlogN)$. Considering that sorting is repeated in while loop, worse case complexity will become $O(N^2logN)$. To summarize, the worst overall computation complexity of RVEA-2DCES in one generation is $O(mN^2)+O(mN^2)+O(N)+O(N^2logN)=max\{O(mN^2),O(N^2logN)\}$.

Table 6 presents the computational complexity of all compared algorithms. RVEA-iGNG needs to train the GNG network, making it time consuming and its computational complexity difficult to analyze. In addition to this, it can be observed that $O(mN^2)$ is a common computational complexity of mainstream MaOEAs.

To compare the time complexity of these algorithms more intuitively, running times of each algorithm on DTLZ3, WFG7 and MaF4 are listed in Table 7. There is a general trend that algorithms with

Table 6
Computational complexity of compared algorithms.

Algorithms	Computational complexity
RVEA-2DCES	$max\{O(mN^2), O(N^2 logN)\}$
RVEA-iGNG	–
RVEA	$O(mN^2)$
NSGA-II/SDR	$O(mN^2)$
onebyoneEA	$O(mN^2)$
HEA	$O(mN^2)$
MaOEA-IT	$max\{O((mTN)^2), O(N^3)\}$
hpaEA	$O(N \log_{m-1} N + mN^2 + m^3 N)$

better performance take longer time to run. RVEA-2CDES and HEA with the best overall performance have the third and fourth longest average running time respectively. Although RVEA-iGNG is a competitive algorithm, its running time is one or two orders of magnitude longer than other algorithms. While MaOEA-IT with the shortest running time performed worst on most test problems. Compared with the performance improvement compared to RVEA, extra running time of RVEA-2DCES is completely acceptable.

4.7. Ablation experiments

In this subsection, ablation experiments are conducted to investigate the effectiveness of the main contributions of this paper, i.e., High-Dimensional Angle-Penalized Distance and two diversity and convergence enhancement strategies.

4.7.1. Effectiveness of HD-APD

To verify the effectiveness of HD-APD, i.e., the efficiency improvement brought by Manhattan distance (L_1 norm) in high dimensionality, we compared the performance of RVEA and RVEA with HD-APD instead of APD (denoted as RVEA-HD) on 15-objective benchmark problems. All parameter settings were the same to above comprehensive experiments except population size, which was set to 400 for both algorithms.

The average and standard deviation of HV over 20 independent runs are presented in Table 8. It can be observed that RVEA-HD showed obvious advantages on MaF test suite. Noticeable performance degradation only appeared on WFG1, while on other test problems RVEA-HD performed similarly to RVEA, except on WFG6 and WFG8 where advantages of RVEA-HD were obvious. The results of Wilcoxon rank sum test also indicated that HD-APD is a more effective metric than APD in high dimensionality.

4.7.2. Effectiveness of two diversity and convergence enhancement strategies

To verify the effectiveness of two diversity and convergence enhancement strategies, i.e., adaptive sparse region detection and convergence-only selection, two new versions of RVEA-2DCES are designed: (1) Using solutions from EP_1 only to conduct elite retention (denoted as RVEA-ASRD). (2) Using solutions from EP_2 only to conduct elite retention (denoted as RVEA-COS). Experiments were conducted on 20 15-objective test problems among RVEA-HD, RVEA-ASRD, RVEA-COS and RVEA-2DCES. Population size was set to 400 for RVEA-HD. While for others, upper bound of population size was set to 450.

Table 9 presents the average and standard deviation of HV over 20 independent runs obtained by four algorithms. It can be observed that the overall performance of RVEA-2DCES was significantly better than RVEA-HD, demonstrating the effectiveness of two diversity and convergence enhancement strategies together with the proposed elite retention strategy. Only using convergence-only selection could enhance the performance on test problems focusing on convergence like DTLZ3 and MaF4, but also encountered significant performance degradation on test problems with irregular PF (MaF2 and MaF7) or bias (WFG8). Interestingly, RVEA-ASRD obtained best results on these test problems. However, it also encountered performance degradation on WFG4-7 with concave PFs. To sum up, conducting these two diversity and convergence enhancement strategies simultaneously can tackle MOPs with different problem features better.

4.8. Discussions about elite population size and parameter sensitivity

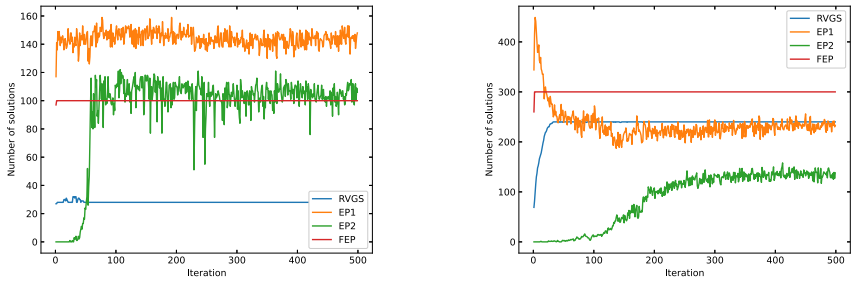
As the final population size of in each iteration is dynamic and affected by two elite population EP_1 and EP_2, we will further explore their changing trend during evolutionary process in this subsection.

Elite solutions selected from reference vector guided selection (RVGS), EP_1 obtained by adaptive sparse region detection strategy, EP_2 obtained by convergence-only selection strategy and final elite population (FEP) are all taken into consideration. Fig. 10 presents the number of solutions in them during evolutionary process of 3-objective MaF1 and 8-objective DTLZ3, which are representatives of problems with regular PF and irregular PF separately.

It can be observed from Fig. 10(a) that only about 30 of 91 reference vectors are valid to intersect with the PF of 3-objective MaF1, which is consistent with the results of Fig. 7(c). Given that only a small number of solutions existed in final elite population after RVGS, adaptive sparse region detection strategy put most of solutions in remaining combined population into EP_1 although some of them may be redundant and would be eliminated from EP_1 soon by Algorithm 6. The number of

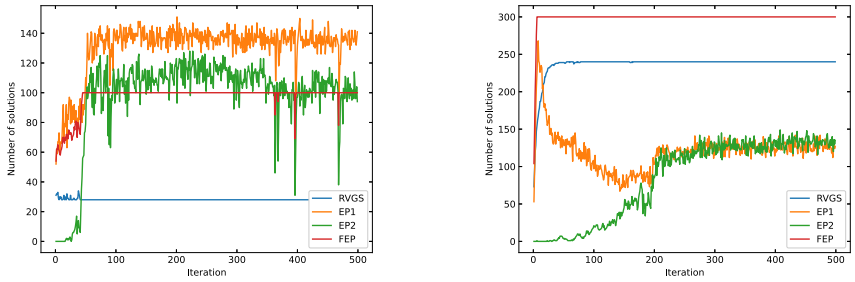
Table 7
Comparison of average running times on DTLZ3, WFG7 and MaF4.

Problem	M	RVEA-2DCES	RVEA-iGNG	RVEA	NSGA-II/SDR	onebyoneEA	HEA	MaOEA-IT	hpaEA
DTLZ3	3	2.9400e+0	2.2982e+1	2.1512e+0	2.4943e+0	3.1302e+0	4.2695e+0	1.4074e+0	4.3402e+0
	5	1.1010e+1	9.9927e+1	4.1764e+0	4.9008e+0	5.8549e+0	8.5182e+0	1.8539e+0	8.5280e+0
	8	1.7059e+1	2.1358e+2	6.4309e+0	7.6829e+0	8.9842e+0	1.5052e+1	3.0744e+0	1.5918e+1
	10	2.2070e+1	4.6488e+2	8.8124e+0	1.1699e+1	1.4071e+1	2.1990e+1	3.6828e+0	2.6404e+1
	15	3.0125e+1	1.0877e+3	9.9988e+0	1.6074e+1	1.9953e+1	2.7420e+1	4.1734e+0	5.7629e+1
WFG7	3	2.9914e+0	3.6855e+1	2.1336e+0	2.3488e+0	3.0336e+0	2.8348e+0	3.7039e+0	6.2712e+0
	5	1.1012e+1	1.6036e+2	4.0625e+0	4.7256e+0	5.9785e+0	6.5883e+0	3.2488e+0	1.4353e+1
	8	1.6269e+1	3.0656e+2	6.2832e+0	7.5992e+0	9.4019e+0	1.2734e+1	3.9182e+0	2.3854e+1
	10	2.1380e+1	6.0956e+2	9.1259e+0	1.1714e+1	1.4810e+1	2.0819e+1	4.3879e+0	3.5086e+1
	15	3.0607e+1	1.1650e+3	1.1167e+1	1.7208e+1	2.1421e+1	2.8883e+1	4.9024e+0	8.8167e+1
MaF4	3	2.9041e+0	2.3882e+1	2.3268e+0	2.7886e+0	3.7234e+0	4.2750e+0	2.1281e+0	5.4468e+0
	5	1.0095e+1	1.0178e+2	2.9614e+0	5.0620e+0	6.2039e+0	9.6316e+0	2.5509e+0	1.0337e+1
	8	1.4132e+1	1.9969e+2	4.5830e+0	7.9376e+0	1.0112e+1	2.3231e+1	4.0895e+0	2.2275e+1
	10	1.7479e+1	4.1988e+2	6.4169e+0	1.2542e+1	1.6018e+1	3.3527e+1	3.4480e+0	3.9219e+1
	15	2.2097e+1	8.4308e+2	6.5130e+0	1.5884e+1	2.0787e+1	4.2459e+1	3.7291e+0	6.9425e+1
Average ranking		5.53	8	1.93	2.93	4.2	5.27	1.33	6.8



(a) 3-objective MaF1 (b) 8-objective DTLZ3

Fig. 10. Curves of the number of solutions in different populations during evolutionary process.



(a) 3-objective MaF1 (b) 8-objective DTLZ3

Fig. 11. Curves of the number of solutions in different populations during evolutionary process after doubling angle threshold.

Table 8
Comparison of HV average and standard deviation between RVEA-HD and RVEA on 15-objective test problems.

Problem	RVEA-HD	RVEA
DTLZ1	9.9993e−1 (1.62e−5)	9.9989e−1 (8.08e−4)≈
DTLZ2	9.9458e−1 (9.44e−5)	9.9123e−1 (1.08e−4)−
DTLZ3	9.9143e−1 (3.88e−3)	9.9057e−1 (6.88e−4)≈
DTLZ4	9.9518e−1 (6.81e−5)	9.9121e−1 (8.25e−5)−
WFG1	9.4100e−1 (3.76e−3)	9.9835e−1 (6.20e−4)+
WFG2	9.8856e−1 (2.76e−3)	9.6871e−1 (7.13e−3)−
WFG3	0.0000e+0 (0.00e+0)	0.0000e+0 (0.00e+0)≈
WFG4	9.7089e−1 (3.26e−3)	9.7462e−1 (4.19e−3)+
WFG5	9.0801e−1 (1.89e−3)	9.1589e−1 (3.78e−4)+
WFG6	8.5803e−1 (2.36e−2)	7.3981e−1 (5.79e−2)−
WFG7	9.8128e−1 (1.58e−3)	9.8272e−1 (3.46e−3)≈
WFG8	8.8231e−1 (6.17e−2)	7.2683e−1 (1.19e−1)−
WFG9	8.5745e−1 (5.11e−2)	8.5204e−1 (6.18e−2)−
MaF1	0.0000e+0 (0.00e+0)	2.5697e−14 (1.40e−14)+
MaF2	2.1541e−1 (1.91e−3)	6.2749e−2 (2.11e−2)−
MaF3	9.9998e−1 (1.98e−5)	9.9930e−1 (6.12e−4)≈
MaF4	7.0012e−6 (1.87e−6)	6.6308e−12 (2.81e−11)−
MaF5	9.4804e−1 (3.15e−5)	9.4177e−1 (1.02e−2)−
MaF6	9.6094e−2 (1.78e−3)	9.1759e−2 (7.62e−4)−
MaF7	1.2581e−1 (8.70e−3)	2.5457e−2 (3.84e−2)−
+/ − / ≈		4/11/5

solutions in EP_2 was small in early stage and experienced a surge. It fluctuated sharply around 100 after this surge, and this instability may be brought by the small number of objectives. As a result, final elite population size always reached 100 except for the first iteration, rather than changing dynamically we expected. This exception may be due to poor quality of the randomly generated initial population.

While in Fig. 10(b), situation was somewhat different. The number of elite solutions obtained by RVGS gradually increased and stabilized to 240 as the evolutionary process proceeded. The number of reference vectors 8-objective benchmark problems used was exactly 240, which means that there was no empty subspace. The changing trend of EP_1 corresponded with that of RVGS: the more solutions selected by RVGS, the fewer remaining solutions put into EP_1. The number of solutions in EP_1 was still quite a lot after reaching a stable level. This is probably because the angle threshold we set is small for high-dimensional objective space. The number of solutions in EP_2 also increased gradually and eventually maintained around a stable value. This is explainable as the design of HD-APD pays more attention to convergence in the early stage and more and more attention to the balance of convergence and diversity as the evolutionary process proceeds (see equation in 3.2). Thus in the early stage, solutions selected by RVGS are basically the best convergent in their own subspaces, so that few solutions are put into EP_2. Later, these convergent solutions fail to be selected by RVGS due to diversity concerns, which makes them selected into EP_2 by convergence-only selection strategy.

Finally, we will perform a sensitivity analysis on the angle threshold by doubling it. It can be seen from Fig. 11 that for 3-objective MaF1, the parameter change brought no noticeable change. The number of solutions in EP_1 was fewer in early stage but increased to about 140 soon. The number of solutions in FEP did not reach 100 at the beginning accordingly. Besides, occasional fluctuations appeared in FEP. While for 8-objective DTLZ3, the number of solutions in EP_1 decreased significantly to about half of its original value when the evolution stabilized, but FEP was not influenced.

Table 10 presents the average and standard deviation of HV on DTLZ3 and MaF1 over 20 independent runs obtained by RVEA-2DCES with original angle threshold (denoted as θ_{min}) and doubled θ_{min}. There was no obvious difference and original θ_{min} seemed a little better. A larger θ_{min} may reduce the size of EP_1 in high dimensionality to improve computational efficiency while maintaining similar performance, but a θ_{min} widely applicable for MOPs with different objective numbers is hard to design, which is worthy of a further study.

5. Conclusion

In this paper, a many-objective evolutionary algorithm based on reference vector guided selection and two diversity and convergence

Table 9
Comparison of HV average and standard deviation among RVEA-HD, RVEA-ASRD, RVEA-COS and RVEA-2DCES on 15-objective test problems.

Problem	RVEA-HD	RVEA-ASRD	RVEA-COS	RVEA-2DCES
DTLZ1	9.9993e−1 (1.62e−5)	9.9981e−1 (3.51e−5)≈	9.9990e−1 (2.24e−5)≈	9.9991e−1 (1.54e−5)≈
DTLZ2	9.9458e−1 (9.44e−5)	9.9465e−1 (6.86e−5)≈	9.9459e−1 (7.30e−5)≈	9.9457e−1 (1.02e−4)≈
DTLZ3	9.9143e−1 (3.88e−3)	9.9122e−1 (7.61e−4)≈	9.9304e−1 (4.25e−4)+	9.9255e−1 (3.87e−4)+
DTLZ4	9.9518e−1 (6.81e−5)	9.9549e−1 (8.67e−5)+	9.9517e−1 (1.24e−4)≈	9.9519e−1 (6.38e−5)≈
WFG1	9.4100e−1 (3.76e−3)	9.5361e−1 (8.24e−3)+	9.3576e−1 (2.67e−3)−	9.4186e−1 (5.30e−3)≈
WFG2	9.8856e−1 (2.76e−3)	9.9079e−1 (2.15e−3)+	9.8859e−1 (3.00e−3)≈	9.8863e−1 (2.45e−3)≈
WFG3	0.0000e+0 (0.00e+0)	0.0000e+0(0.00e+0)≈	0.0000e+0(0.00e+0)≈	0.0000e+0(0.00e+0)≈
WFG4	9.7089e−1 (3.26e−3)	9.5638e−1 (5.26e−3)−	9.6612e−1 (7.63e−3)−	9.7684e−1 (4.87e−3)+
WFG5	9.0801e−1 (1.89e−3)	9.0315e−1 (2.93e−3)−	9.0873e−1 (1.85e−3)≈	9.0797e−1 (1.94e−3)≈
WFG6	8.5803e−1 (2.36e−2)	8.4707e−1 (1.99e−2)−	8.5864e−1 (2.45e−2)≈	8.6283e−1 (2.43e−2)+
WFG7	9.8128e−1 (1.58e−3)	9.7327e−1 (3.40e−3)−	9.8498e−1 (2.67e−3)+	9.8301e−1 (1.83e−3)+
WFG8	8.8231e−1 (6.17e−2)	9.0014e−1 (1.83e−2)+	8.2203e−1 (7.03e−2)−	8.9911e−1 (5.60e−2)+
WFG9	8.5745e−1 (5.11e−2)	8.6224e−1 (4.88e−2)+	8.6647e−1 (5.30e−2)+	9.0238e−1 (3.83e−2)+
MaF1	0.0000e+0 (0.00e+0)	0.0000e+0 (0.00e+0)≈	0.0000e+0 (0.00e+0)≈	0.0000e+0 (0.00e+0)≈
MaF2	2.1541e−1 (1.91e−3)	2.1656e−1 (2.68e−3)≈	2.0013e−1 (3.95e−2)−	2.1592e−1 (2.11e−3)≈
MaF3	9.9998e−1 (1.98e−5)	9.9999e−1 (1.00e−5)≈	9.9995e−1 (3.72e−5)≈	9.9998e−1 (4.74e−5)≈
MaF4	7.0012e−6 (1.87e−6)	8.6011e−6 (1.69e−6)+	2.1746e−5 (6.29e−6)+	2.9112e−5 (9.92e−6)+
MaF5	9.4804e−1 (3.15e−5)	1.0000e+0(2.14e−12)+	1.0000e+0 (1.35e−11)+	1.0000e+0 (1.82e−12)+
MaF6	9.6094e−2 (1.78e−3)	8.5851e−1 (6.79e−3)+	9.5323e−2 (2.58e−3)≈	8.8564e−2 (5.53e−3)−
MaF7	1.2581e−1 (8.70e−3)	1.3624e−1 (8.52e−3)+	7.8985e−6 (1.71e−5)−	8.3780e−3 (2.46e−2)−
+/ − / ≈		9/4/7	5/5/10	8/2/10

Table 10
Comparison of HV average and standard deviation between with original θ_{min} and doubled θ_{min} on DTLZ3 and MaF1.

Problem	Original θ_{min}	Doubled θ_{min}
DTLZ3(3)	4.9319e−1 (1.29e−1)	4.9252e−1 (1.19e−2)≈
DTLZ3(5)	7.6495e−1 (1.48e−2)	7.6466e−1 (4.22e−2)≈
DTLZ3(8)	9.1148e−1 (5.95e−3)	9.1108e−1 (5.59e−3)≈
DTLZ3(10)	9.6582e−1 (1.98e−3)	9.6667e−1 (1.48e−3)≈
DTLZ3(15)	9.9255e−1 (3.87e−4)	9.9222e−1 (7.83e−4)≈
MaF1(3)	1.9939e−1 (2.68e−3)	1.9710e−1 (2.81e−3)≈
MaF1(5)	9.5000e−3 (7.42e−4)	8.5078e−3 (1.26e−3)−
MaF1(8)	2.6753e−5 (3.51e−6)	1.6089e−5 (7.06e−6)−
MaF1(10)	3.1704e−7 (4.23e−7)	9.4010e−8 (6.21e−8)−
MaF1(15)	0.0000e+0 (0.00e+0)	4.8205e−13 (0.00e+0)≈
+/ − / ≈		0/3/7

enhancement strategies, termed RVEA-2DCES, is proposed for many-objective optimization. Two strategies namely adaptive sparse region detection and convergence-only selection are proposed to detect sparse regions and find solutions with superior convergence performance after reference vector guided selection. They will obtain two elite population EP_1 and EP_2. Then, an elite retention strategy is designed to add solutions of EP_1 and EP_2 into final elite population methodically, which will fill any vacancies of final elite population brought by reference vector guided selection and improve diversity and convergence. Finally, a new selection criterion for reference vector guided selection, termed HP-APD, is proposed to better measure the convergence of solutions in high dimensionality. Experimental results of RVEA-2DCES on DTLZ, WFG and MaF test suites against seven state-of-the-art MaOEAs demonstrated its superior competitiveness and capacity dealing with many-objective problems, indicating RVEA-2DCES a preferable choice for many-objective optimization.

How to tackle MOPs with irregular PF is a common problem for decomposition-based MOEAs. RVEA-2DCES has not taken this into consideration specifically, thus its performance on WFG3, MaF1 and MaF7 was struggling. In the future, we are going to add adaptive reference vector adjustment strategy into RVEA-2DCES and combine it with our proposed diversity and convergence enhancement strategies properly. Besides, a completer convergence evaluation metric will be investigated to improve the performance of convergence-only selection strategy and reference vector guided selection.

CRediT authorship contribution statement

Lei Yang: Conceptualization, Funding acquisition, Investigation, Supervision, Writing – review & editing, Resources. **Yuanye Zhang:** Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft. **Jiale Cao:** Investigation, Visualization, Writing – review & editing. **Kangshun Li:** Funding acquisition, Supervision. **Dongya Wang:** Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

This work was partially supported by Natural Science Foundation of Guangdong Province of China (Grant No. 2020A1515010691), Agricultural Science and Technology Commissioner Project of Guangzhou City, China (Grant No. 20212100036), and National Natural Science Foundation of China (Grant No. 61573157 and 61703170).

References

[1] M. Farina, P. Amato, On the optimal solution definition for many-criteria optimization problems, in: 2002 Annual Meeting of the North American Fuzzy Information Processing Society Proceedings. NAFIPS-FLINT 2002 (Cat. No. 02TH8622), IEEE, 2002, pp. 233–238.
[2] G. Dhiman, A. Kaur, HKn-RVEA: a novel many-objective evolutionary algorithm for car side impact bar crashworthiness problem, Int. J. Veh. Des. 80 (2–4) (2019) 257–284.
[3] X. Cai, Z. Hu, P. Zhao, W. Zhang, J. Chen, A hybrid recommendation system with many-objective evolutionary algorithm, Expert Syst. Appl. 159 (2020) 113648.

[4] I. Nurhidayat, B. Pimpunchat, S. Noeiaghdam, U. Fernández-Gámiz, Comparisons of SVM kernels for insurance data clustering, Emerg. Sci. J. 6 (4) (2022) 866–880.
[5] B.T. Khoa, T.T. Huynh, Predicting exchange rate under uirp framework with support vector regression, assessment 12 (2022) 13.
[6] A. Morales-Hernández, I. Van Nieuwenhuyse, S. Rojas Gonzalez, A survey on multi-objective hyperparameter optimization algorithms for machine learning, Artif. Intell. Rev. 56 (8) (2023) 8043–8093.
[7] I.A. Alexandrov, A.V. Kirichek, V.Z. Kuklin, L.M. Chervyakov, Development of an algorithm for multicriteria optimization of deep learning neural networks, HighTech Innov. J. 4 (1) (2023) 157–173.
[8] T. Wagner, N. Beume, B. Naujoks, Pareto-, aggregation-, and indicator-based methods in many-objective optimization, in: International Conference on Evolutionary Multi-Criterion Optimization, Springer, 2007, pp. 742–756.
[9] H. Ishibuchi, N. Tsukamoto, Y. Nojima, Evolutionary many-objective optimization: A short review, in: 2008 IEEE Congress on Evolutionary Computation (IEEE World Congress on Computational Intelligence), IEEE, 2008, pp. 2419–2426.
[10] Y. Xiang, Y. Zhou, M. Li, Z. Chen, A vector angle-based evolutionary algorithm for unconstrained many-objective optimization, IEEE Trans. Evol. Comput. 21 (1) (2016) 131–152.
[11] R.C. Purshouse, P.J. Fleming, On the evolutionary optimization of many conflicting objectives, IEEE Trans. Evol. Comput. 11 (6) (2007) 770–784.
[12] Y. Yuan, H. Xu, B. Wang, X. Yao, A new dominance relation-based evolutionary algorithm for many-objective optimization, IEEE Trans. Evol. Comput. 20 (1) (2015) 16–37.
[13] W. Qiu, J. Zhu, G. Wu, M. Fan, P.N. Suganthan, Evolutionary many-objective algorithm based on fractional dominance relation and improved objective space decomposition strategy, Swarm Evol. Comput. 60 (2021) 100776.
[14] C. Zhu, L. Xu, E.D. Goodman, Generalization of Pareto-optimality for many-objective evolutionary optimization, IEEE Trans. Evol. Comput. 20 (2) (2015) 299–315.
[15] L. While, P. Hingston, L. Barone, S. Huband, A faster algorithm for calculating hypervolume, IEEE Trans. Evol. Comput. 10 (1) (2006) 29–38.
[16] Y. Sun, G.G. Yen, Z. Yi, IGD indicator-based evolutionary algorithm for many-objective optimization problems, IEEE Trans. Evol. Comput. 23 (2) (2018) 173–187.
[17] J. Luo, X. Huang, Y. Yang, X. Li, Z. Wang, J. Feng, A many-objective particle swarm optimizer based on indicator and direction vectors for many-objective optimization, Inform. Sci. 514 (2020) 166–202.
[18] J. Yuan, H.-L. Liu, F. Gu, Q. Zhang, Z. He, Investigating the properties of indicators and an evolutionary many-objective algorithm using promising regions, IEEE Trans. Evol. Comput. 25 (1) (2020) 75–86.
[19] L. Li, G.G. Yen, A. Sahoo, L. Chang, T. Gu, On the estimation of pareto front and dimensional similarity in many-objective evolutionary algorithm, Inform. Sci. 563 (2021) 375–400.
[20] Q. Zhang, H. Li, MOEA/D: A multiobjective evolutionary algorithm based on decomposition, IEEE Trans. Evol. Comput. 11 (6) (2007) 712–731.
[21] Y. Xu, H. Zhang, X. Zeng, Y. Nojima, An adaptive convergence enhanced evolutionary algorithm for many-objective optimization problems, Swarm Evol. Comput. 75 (2022) 101180.
[22] Z.-Z. Liu, Y. Wang, P.-Q. Huang, And: A many-objective evolutionary algorithm with angle-based selection and shift-based density estimation, Inform. Sci. 509 (2020) 400–419.
[23] W. Zhong, X. Hu, F. Lu, J. Wang, X. Liu, Y. Chen, A two-stage adjustment strategy for space division based many-objective evolutionary optimization, IEEE Access 8 (2020) 197249–197262.
[24] H. Ishibuchi, H. Sato, Evolutionary many-objective optimization, in: Proceedings of the Genetic and Evolutionary Computation Conference Companion, 2019, pp. 614–661.
[25] H.-L. Liu, F. Gu, Q. Zhang, Decomposition of a multiobjective optimization problem into a number of simple multiobjective subproblems, IEEE Trans. Evol. Comput. 18 (3) (2013) 450–455.
[26] H. Chen, G. Wu, W. Pedrycz, P.N. Suganthan, L. Xing, X. Zhu, An adaptive resource allocation strategy for objective space partition-based multiobjective optimization, IEEE Trans. Syst. Man Cybern.: Syst. 51 (3) (2019) 1507–1522.
[27] R. Cheng, Y. Jin, M. Olhofer, B. Sendhoff, A reference vector guided evolutionary algorithm for many-objective optimization, IEEE Trans. Evol. Comput. 20 (5) (2016) 773–791.
[28] H. Bai, J. Zheng, G. Yu, S. Yang, J. Zou, A Pareto-based many-objective evolutionary algorithm using space partitioning selection and angle-based truncation, Inform. Sci. 478 (2019) 186–207.
[29] W. Qiu, J. Zhu, H. Yu, M. Fan, L. Huo, An adaptive reference vector adjustment strategy and improved angle-penalized value method for RVEA, Complexity 2021 (2021).
[30] J. Lin, S. Zheng, Y. Long, Improved reference vector guided differential evolution algorithm for many-objective optimization, in: Proceedings of the 2020 5th International Conference on Mathematics and Artificial Intelligence, 2020, pp. 43–49.
[31] F. Li, Z. Shang, H. Shen, Y. Liu, P.-Q. Huang, Combining modified inverted generational distance indicator with reference-vector-guided selection for many-objective optimization, Appl. Intell. 53 (10) (2023) 12149–12162.
[32] Q. Liu, Y. Jin, M. Heiderich, T. Rodemann, Adaptation of reference vectors for evolutionary many-objective optimization of problems with irregular Pareto fronts, in: 2019 IEEE Congress on Evolutionary Computation, CEC, 2019, pp. 1726–1733.
[33] H. Ishibuchi, Y. Setoguchi, H. Masuda, Y. Nojima, Performance of decomposition-based many-objective algorithms strongly depends on Pareto front shapes, IEEE Trans. Evol. Comput. 21 (2) (2016) 169–190.
[34] C. Zhang, L. Gao, X. Li, W. Shen, J. Zhou, K.C. Tan, Resetting weight vectors in MOEA/D for multiobjective optimization problems with discontinuous Pareto front, IEEE Trans. Cybern. (2021).
[35] X. Ma, Y. Yu, X. Li, Y. Qi, Z. Zhu, A survey of weight vector adjustment methods for decomposition-based multiobjective evolutionary algorithms, IEEE Trans. Evol. Comput. 24 (4) (2020) 634–649.
[36] M. Li, X. Yao, What weights work for you? Adapting weights for any Pareto front shape in decomposition-based evolutionary multiobjective optimisation, Evol. Comput. 28 (2) (2020) 227–253.
[37] L.R. de Farias, A.F. Araújo, A decomposition-based many-objective evolutionary algorithm updating weights when required, Swarm Evol. Comput. 68 (2022) 100980.
[38] M. Zhang, L. Wang, W. Li, B. Hu, D. Li, Q. Wu, Many-objective evolutionary algorithm with adaptive reference vector, Inform. Sci. 563 (2021) 70–90.
[39] E.M. Mirkes, J. Allohibi, A. Gorban, Fractional norms and quasinorms do not help to overcome the curse of dimensionality, Entropy 22 (10) (2020) 1105.
[40] I. Das, J.E. Dennis, Normal-boundary intersection: A new method for generating the Pareto surface in nonlinear multicriteria optimization problems, SIAM J. Optim. 8 (3) (1998) 631–657.
[41] J. Blank, K. Deb, Y. Dhebar, S. Bandaru, H. Seada, Generating well-spaced points on a unit simplex for evolutionary many-objective optimization, IEEE Trans. Evol. Comput. 25 (1) (2020) 48–60.
[42] K. Deb, H. Jain, An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part I: solving problems with box constraints, IEEE Trans. Evol. Comput. 18 (4) (2013) 577–601.
[43] D. Hardin, E. Saff, Minimal Riesz energy point configurations for rectifiable d-dimensional manifolds, Adv. Math. 193 (1) (2005) 174–204.
[44] K. Deb, R.B. Agrawal, et al., Simulated binary crossover for continuous search space, Complex Syst. 9 (2) (1995) 115–148.
[45] K. Deb, M. Goyal, et al., A combined genetic adaptive search (GeneAS) for engineering design, Comput. Sci. Inform. 26 (1996) 30–45.
[46] C.C. Aggarwal, A. Hinneburg, D.A. Keim, On the surprising behavior of distance metrics in high dimensional space, in: International Conference on Database Theory, Springer, 2001, pp. 420–434.
[47] Q. Liu, Y. Jin, M. Heiderich, T. Rodemann, G. Yu, An adaptive reference vector-guided evolutionary algorithm using growing neural gas for many-objective optimization of irregular problems, IEEE Trans. Cybern. 52 (5) (2022) 2698–2711.
[48] Y. Tian, R. Cheng, X. Zhang, Y. Su, Y. Jin, A strengthened dominance relation considering convergence and diversity for evolutionary many-objective optimization, IEEE Trans. Evol. Comput. 23 (2) (2018) 331–345.
[49] Y. Liu, D. Gong, J. Sun, Y. Jin, A many-objective evolutionary algorithm using a one-by-one selection strategy, IEEE Trans. Cybern. 47 (9) (2017) 2689–2702.
[50] Z. Liu, F. Han, Q. Ling, H. Han, J. Jiang, A many-objective optimization evolutionary algorithm based on hyper-dominance degree, Swarm Evol. Comput. 83 (2023) 101411.
[51] Y. Sun, B. Xue, M. Zhang, G.G. Yen, A new two-stage evolutionary algorithm for many-objective optimization, IEEE Trans. Evol. Comput. 23 (5) (2018) 748–761.
[52] H. Chen, Y. Tian, W. Pedrycz, G. Wu, R. Wang, L. Wang, Hyperplane assisted evolutionary algorithm for many-objective optimization problems, IEEE Trans. Cybern. 50 (7) (2019) 3367–3380.
[53] K. Deb, L. Thiele, M. Laumanns, E. Zitzler, Scalable test problems for evolutionary multiobjective optimization, in: Evolutionary Multiobjective Optimization, Springer, 2005, pp. 105–145.
[54] S. Huband, P. Hingston, L. Barone, L. While, A review of multiobjective test problems and a scalable test problem toolkit, IEEE Trans. Evol. Comput. 10 (5) (2006) 477–506.
[55] R. Cheng, M. Li, Y. Tian, X. Zhang, S. Yang, Y. Jin, X. Yao, A benchmark test suite for evolutionary many-objective optimization, Complex Intell. Syst. 3 (1) (2017) 67–81.
[56] J. Bader, E. Zitzler, Hype: An algorithm for fast hypervolume-based many-objective optimization, Evol. Comput. 19 (1) (2011) 45–76.
[57] A.J. Nebro, J.J. Durillo, M. Vergne, Redesigning the jmetal multi-objective optimization framework, in: Proceedings of the Companion Publication of the 2015 Annual Conference on Genetic and Evolutionary Computation, 2015, pp. 1093–1100.
[58] Y. Tian, R. Cheng, X. Zhang, Y. Jin, Platemo: A MATLAB platform for evolutionary multi-objective optimization [educational forum], IEEE Comput. Intell. Mag. 12 (4) (2017) 73–87.

Information Sciences 624 (2023) 94–109

Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

Many-objective evolutionary algorithm based on spatial distance and decision vector self-learning

Lei Yang [a], Kangshun Li [a,*], Chengzhou Zeng [a], Shumin Liang [a], Binjie Zhu [a], Dongya Wang [b]

[a] School of Mathematics and Informatics, South China Agricultural University, Guangzhou 510642, China
[b] University of Exeter, College of Engineering, Mathematics and Physical Sciences, Exeter EX4 4QF, UK

ARTICLE INFO

Article history:
Received 22 December 2021
Received in revised form 20 July 2022
Accepted 3 November 2022
Available online 9 December 2022

Keywords:
Many-objective optimization
Spatial distance
Self-learning
Environmental selection
Distributive vector

ABSTRACT

In this paper, a new many-objective optimization evolutionary algorithm (MaOEA), namely Many-Objective Evolutionary Algorithm Based on Spatial Distance and Decision Vector Self-Learning (DVSLEA), is proposed for many-objective optimization. The core idea of the algorithm is to use spatial distance to influence the value of disturbance ratio and then affect the generation of offspring. In order to make the algorithm have a good distribution, distribution vector is introduced for the procedure of disturbance. Moreover, a self-learning process is corporated to ascertain the value of disturbance ratio. To evaluate the performance of DVSLEA, the DTLZ and WFG test suites with 3, 5, 8, 10, and 15 objectives are adopted. The experimental results indicate that DVSLEA shows superior performance over nine competitive evolutionary algorithms(MOEA/DD, NSGA-III, VaEA, SPEA2, SPEA2-SDE, MOEADAWA, onebyoneEA, PREA, RVEA), when solving most of the test problems used.

© 2022 Published by Elsevier Inc.

1. Introduction

Multi-objective optimization problems (MOPs) which involve more than one conflicting objectives to be optimized exist in many industries. When the objective number of the optimization problems is less than three, they are called multi-objective optimization problems. Otherwise, these optimization problems are called many-objective optimization problems (MaOPs). Without loss of generality, taking the objective function minimization as an example, the MOP is defined as follows:

$$minimize \quad F(x) = \{f_1(x), f_2(x), \ldots, f_m(x)\} \tag{1}$$

where $x = [x_1, x_2, \ldots, x_n]^T \in X \subset R^n$is a n dimensional decision vector, X is the decision space, $F(x)$ consists of m objective functions which need to be optimized.

MOPs can be seen everywhere in our life, which has attracted many scholars to study and discuss [17,31]. In 1985, David Schaffer proposed the vector estimation genetic algorithm, which meant the birth of multi-objective optimization algorithm, and realized the combination of EA and MOPs for the first time. In 1989, David Goldberg applied Pareto related theory in economics to EA. Since then, relevant researchers have successively used Multi-objective Evolutionary Algorithm(MOEA) to solve multi-objective optimization problems. After decades of evolution, MOEA can now be divided into three main classes: MOEA based on Pareto dominance relations, MOEA based on decomposition methods, and MOEA based on performance indicator. In addition to the above evolutionary algorithms, by merging neural networks and evolutionary algorithms,

* Corresponding author.
E-mail address: likangshun632@sina.com (K. Li).

https://doi.org/10.1016/j.ins.2022.11.002
0020-0255/© 2022 Published by Elsevier Inc.

several researchers have improved the evolutionary algorithm [6,46,47]. Many scholars have also conducted in-depth studies on optimization problems with mixed variables [30,32].

Multi-objective Evolutionary Algorithms based on decomposition decompose the objective space into a number of subspace without changing the objective number, and transform the MOP into single-objective sub-problems or multi-objective sub-problems. In addition, these sub-problems evolve in a cooperative way, which not only converges fast, but also has high solving accuracy. In [15], a multi-objective genetic local search algorithm is proposed, which is the first algorithm to apply decomposition method to multi-objective optimization problems. The most widely used decomposition based MOEA is MOEA/D [44], whose convergence performance is significantly better than NSGA-II at low dimensions. Nonetheless, in the high-dimensional objective space, evenly distributed weight vectors could not generate a uniformly distributed solution set because the final population may not be close to the direction of weight vectors, leading to the deterioration of distribution. Later, many algorithms made many improvements on the basis of the original MOEA/D framework to solve the problems in the procedure of MOEA/D processing MOPs and MaOPs: For some optimization problems with irregular Pareto front (PF), it is not guaranteed that the weight vectors are evenly distributed on the PF, which results in the ineffectiveness of weight vectors guiding the evolution of the population. Some adaptive change methods offer solutions to some of these issues [20,21].

Deb K et al. proposed a multi-objective optimization algorithm NSGA-III based on non-dominated ranking of reference points [8], which significantly improved the distribution of population by using preset evenly distributed weight vectors, combined with decomposition mechanism in MOEA/D algorithm and non-dominated solution stratified mechanism. The algorithm greatly alleviates the degradation problem caused by Pareto domination, and thus outperforms MOEA/D [44] and NSGA-II [9]. However, because it adopts Pareto dominance relation with lower selection pressure, the convergence needs to be further strengthened. MaOEA-RNM [42] presents a relative non-dominance matrix, on which a fitness formula is defined to address the issue of selective pressure loss caused by dominant resistance. in order to further ensure the diversity, the relative non-dominance matrix is paired with the k-means clustering approach for a novel design of the environmental selection. In 2017 [10], Doi et al. proposed to use the inverted triangular weight vector to minimize the influence of PF shape on the algorithm. Xiang Y et al. proposed the VaEA algorithm [34] in 2017. Individuals with poor convergence within the Angle threshold range will be replaced, and the convergence is greatly improved while maintaining the diversity of the population. Therefore, the algorithm can balance the convergence and diversity of the population in the high-dimensional space to some extent. In 2019, Xiang Y et al. [35] proposed an algorithm which uses the ratio between the average Euclidean distance between m(m is the object number) nearest solutions and reference points and the Euclidean distance between reference points and hyperplane to estimate the approximate shape of PF, and divides the shape of PF into concave, convex and linear. This algorithm has an advantage dealing with MaOPs with irregular PF shape. Recently, some experts concentrated on decision vectors. [25] proved that some dimensional variables in the decision vector influence the diversity of solutions, and some dimensional variables play an important role in convergence. [45] proposed a modified decomposition-based many objective ant colony optimization (ACO) algorithm and employed an adaptive reference point mechanism that chooses the ideal point or nadir point as the reference point according to the distribution of the candidate solutions. This mechanism is utilized to improve the selection operator, accelerate the convergence speed and enhance the optimization ability. [4] utilizes historical solutions and proposes a new evolution operator for decomposition-based many-objective optimization.

Many-objective optimization algorithms are also widely used in practical life, such as budget management and [1,16,36]. [1] tested 18 evolutionary many-objective algorithms against well-known combinatorial optimization problems, including knapsack problem (MOKP), traveling salesman problem (MOTSP), and quadratic assignment problem (mQAP), all up to 10 objectives. To address problems such as high-speed train head shape design, overlapping community detection, power dispatch, and unmanned aerial vehicle formation, [11] proposes a many-objective evolutionary algorithm based on decomposition with dynamic resource allocation (MaOEA/D-DRA) for irregular optimization. An efficient many-objective optimization system was proposed in [33], and this system was utilized to improve the aerodynamics of a Vista-class cruise ship at four crucial wind angles.

The goal of MOPs is to obtain a set of Pareto-optimal solutions with good trade-off among the multiple conflicting objectives. The difficulty of dealing with MOPs is that different objectives contradict with each other. At the same time, it will be difficult for the algorithm to balance the distribution and convergence of the population. As the number of objectives increases, most of the individuals in the population are not dominated by each other, leading to the dramatic increase of non-dominated solutions and making the performance of MaOEAs based on traditional Pareto dominance relationship worse and ineffective [14]. In [37], a combining angle-based selection strategy and clustering strategy was used to balance the convergence and diversity. Angle-based selection strategy can ensure the convergence of the population, and the clustering strategy helps to describe the population distribution. A Two-Stage Adjustment Strategy was proposed for pace division based many-objective evolutionary optimization to deal with the irregular PFs [48]. In the first stage, the diversity of the population was guaranteed, while in the second stage, the sparse sub-space was explored by reference vectors. Similarly, MaOEA-MS suggests a multistage MaOEA, where convergence and diversity are treated independently at various stages of optimization [28]. Dong also suggested MaOEA/D-DRA for irregular optimization, which can dynamically assign computer resources to different search areas based on the Pareto front of the issue [11]. To achieve spread and convergence simultaneously, MaOEA-ARV [43] employs an adaptive reference vector approach that dynamically modifies the reference vector in accordance with the distribution of current candidate solutions. [38] proposes a new dominance relation to better balance the convergence and diversity. In the proposed dominance relation, a convergence indicator and a niching technique based

adaptive parameter are adopted to ensure the convergence and diversity of the nondominated solution set. Dimensionality reduction is also a good strategy in addition to employing reference vectors and new dominance relations. By clustering and aggregating the objective functions based on their correlation, [39] effectively reduces the dimension of the objective.

Some traditional methods for solving MaOPs, such as NSGA-II [9] and SPEA2 [50], can already achieve good results when solving low-dimensional MOPs. However, these traditional multi-objective evolutionary algorithms may face significant challenges when encountering MaOPs with four and more objectives. A variety of evolutionary algorithms have been proposed for many-objective optimization in recent years. However, the difficulties in balancing the convergence and diversity of the population and selecting promising parents for offspring reproduction remain. Zhou presented a many-objective evolutionary optimization selection technique based on niches and angles. Individual diversity is estimated using the niche-based density estimation approach, and individuals with poor convergence are eliminated using the angle-based selection strategy [49]. A decomposition method is utilized in [27] to ensure population diversity, and ideal points on each reference vector allow for faster population convergence to the optimal front. [3] uses a multioperator and multiparameter strategy to improve adaptability and diversity of the population, and a bidirectional local search strategy to prevent the decrease of exploration capability during the early stage and increase the exploitation capability during the later stage of the search process. [12] propose a computationally efficient dropout neural network (EDN) to replace the Gaussian process and a new model management strategy to achieve a good balance between convergence and diversity for assisting evolutionary algorithms to solve high-dimensional multiobjective and many-objective expensive optimization problems. A region division based decomposition approach for evolutionary many-objective optimization is proposed in [23], two attributions of regions can better guarantee population diversity.

To further address issues about how to balance the convergence and distribution, this paper proposes a Many-Objective Evolutionary Algorithm Based on Spatial Distance and Decision Vector Self- Learning(DVSLEA). In this proposal, the disturbing ratio is self-learning updated according to the spatial distance, which is calculated based on Euclidean distances. The main contributions and novelty of this work include the following:

- A distribution vector is proposed for generation of offspring by disturbing individuals, intuitively showing the dimension of variables that could affect the distribution.
- A spatial distance based disturbing ratio self-learning strategy is designed in this paper, which can help to ascertain the appropriate value of the disturbing ratio.
- A new mechanism of offspring generation. This paper proposes to use distribution vector and disturbing ratio to generate offspring, which improves the distribution of the population.

The rest of this article is organized as follows. Section 2 presents the details of the DVSLEA algorithm. The experimental results and some discussions are provided in Section 3. Finally, our conclusion and future work are presented in Section 4.

2. Proposed DVSLEA

2.1. General framework

The framework of the proposed method is shown in Algorithm 1. First, N individuals are randomly generated in the entire decision space to form the initial population. In the step of generating offspring, DVSLEA uses a new strategy. $2/3N$ individuals are generated using crossover and mutation methods. Two parent individuals are randomly selected from P. By using variation operations(i.e. crossover and mutation) to the parents, we can obtain two children solutions each time [25]. Repeat the above procedure $1/3$ N times to generate $2/3$ N individuals. The remaining $1/3$ N individuals are generated by disturbing the decision vectors with low crowding degree in the non-dominated solution set of the population. A population consisting of $2/3$ N and $1/3$ N individuals can be obtained. Finally, N individuals are selected from the set $U(P \cup P' = U)$ to construct the next generation population P. The above procedures are repeated until the termination condition is reached.

Algorithm 1: General Framework

Input: Population Size N
Output: Final Population P
1: $P \leftarrow initialization(N)$
2: Initialize various parameters /*Initialize parameters */
3: $Div - V$ and $Mix - V = ConstructVectors(P_{nd})$ /*Get distribution vector and mixd vector*/
4: **while** evaluations < maxEvaluations **do**
5: $Radius = constructRadius(P_{nd})$ /*Construct radius */
6: $P' = createOffspringPopulation(P_{nd}, P_d)$
7: $U = P' \cup P$
8: $P = environmentalSelection(U)$
9: **end while**
10: **return** P

2.2. Classification of decision variables

Algorithm 2 gives pseudo codes for constructing distributed vector and mixed vector. The categorization notion from data mining has been used to optimization and related topics by certain people [13,29,41]. In MOPs, some decision variables control the convergence of the solutions obtained, while others determine the distribution of the solutions obtained [35]. DVSLEA divides decision variables into three categories. The first type of decision variables is convergence variable: Changing the value of only one dimension of $X_1 = (x_1, x_2, \ldots, x_n)$at a time, there simply exists almost two relationships between $X_1 = (x_1, x_2, \ldots, x_n)$and generated decision vector $X_2 = (x_1, x_2, \ldots, x_n)$ in the objective space: In the first case, X_1 dominates X_2.Otherwise, X_2 dominates X_1, and the decision variable at this position is called the convergence variable. Changing the convergence variable alone will hardly result in a non-dominant relationship between the generated decision vector and the original decision vector in the objective space. The second type of decision variable is distribution variable: Changing the value of only one dimension of $X_1 = (x_1, x_2, \ldots, x_n)$at a time, there exists only one relationship between $X_1 = (x_1, x_2, \ldots, x_n)$and generated decision vector $X_2 = (x_1, x_2, \ldots, x_n)$ in the objective space: X_1 and X_2 non-dominate each other in the objective space, so the decision variable at this position is called distribution variable. Changing the distribution variable alone will almost never lead to the dominated relationship between the decision vector and the original decision vector in the objective space. The third type of decision variable is mixed variable: Changing the value of only one dimension of $X_1 = (x_1, x_2, \ldots, x_n)$at a time, the decision vector X_1 and X_2 in the objective space have nearly both non-matching relationship, so the decision variable at this position is called mixed variable. Changing mixed variables alone will lead to the existence of non-dominated and dominated relationship between the decision vector and the original decision vector in the objective space. DVSLEA uses the non-dominated solution set P_{nd} of the initial population P to construct the distribution vector. The size of P_{nd} is N, and the value range of each dimension of its decision vector is [a,b]. First, we need to set a disturbing ratio c. The value range of c is set between 0.05 and 0.1(the value of c can be set arbitrarily). The result of multiplying c by the value of (b-a) is used to make a positive or negative disturbance on the i-th dimension of the decision vector for the solution X (positive and negative disturbances,i.e.to add or subtract the previous result from the value of the i dimension). A positive disturbance of X yields the solution X_1 and a negative disturbance yields the solution X_2. X is compared with X_1 and X_2 using Pareto dominance in the objective space. And then we do the statistics. If it's a dominant relationship, dominateNumplus one. If it's a non-dominant relationship, nondominateNum plus one. In order to ensure accuracy, DVSLEA will delete the individuals whose decision variables are the smallest or biggest bound of the decision variables in the decision vector at first. After all comparisons, if the dominateNum of the i-th dimension accounts for more than 90% of the total statistic times, i-th dimensional decision variable is considered to be a convergence variable, and $Div - V[i]$ is ($Div - V$ is the distribution vector) set to 0. If the non-dominateNum statistics of the i-th dimension accounts for more than 90% of the total number of statistics, i-th dimensional decision variable is considered to be a distribution variable, and the distribution vector $Div - V[i]$ is set to 1. If neither of the above two situations is true, the decision variable of this dimension is considered to be a mixed variable, and the $Mix - V[i]$($Mix - V$ is the mixed vector) is set to 1. When $Div - V = (0, 0, \ldots, 0)$, the mixed vector is used to generate offsprings.

Algorithm 2: ConstructVectors(P_{nd}, n)

Input: non-dominated solution set P_{nd}, the dimension number of decision vector n
Output: distribution vector $Div - V$,mix vector $Mix - V$
1: $Div - V = 0, Mix - V = 0$
2: $Q_{nd} = delete(P_{nd})$ /*Delete the non-dominated solutions whose value exceed bound*/
3: **while** $i = 0 < Q_{nd}.size$ **do**
4: p_1 and $p_2 = change(p)$ /*Disturb p in positive and negative way*/
5: **if** $p \prec p_1$ or $p_1 \prec p$ **then**
6: $dominateNum[i] + +$
7: **else**
8: $nondominateNum[i] + +$ 9: **end if** 10: **if** $p \prec p_2$ or $p_2 \prec p$ **then**
11: $dominateNum[i] + +$
12: **else**
13: $nondominateNum[i] + +$ 14: **end if** 15: **end while**
16: **while** $i = 0 < Q_{nd}.size$ **do**
17: **if** $nondominateNum[i] \geqslant 0.9 * 2 * Q_{nd}.size$ **then**
18: $Div - V[i] = 1$
19: **else if** $dominateNumi \geqslant 0.9 * 2 * Q_{nd}.size$ **then**
20: $Div - V[i] = 0$
21: **else**
22: $Mix - V[i] = 1$ 23: **end if** 24: **end while**
25: **return** $Div - V, Mix - V$

2.3. Construct radius

Algorithm 3 is used to calculate the radius(spatial distance). DVSLEA uses weight vectors in the calculation of radius distance. The method for generating weight vectors in this paper is the method proposed in [8] for generating a two-layer weight vector [8]. Using Euclidean distance to compute spatial distance in this process is beneficial to an even distribution of population. The specific process is as follows: Firstly, the weight vectors and the non-dominated sulutions of the population are normalized. The normalization function is to unify the value range of the objective functions and the reference points, so as to avoid the influence brought by different orders of magnitude of each objective function. The normalization process is as follows.

$$f_i'(x) = f_i(x) - z_i^{min} \tag{2}$$

$$ASF(x, w) = max_{i=1}^{M} f_i'/w^i \tag{3}$$

$$f_i^n(x) = f_i'(x)/(a_i - z_i^{min}) \tag{4}$$

Where $z^{min} = (z_1^{min}, z_2^{min}, \ldots, z_M^{min})$, Eq. 2 can be used to obtain the transformed objective value first. After that, m extreme value points can be obtained according to Eq. 3. The extreme points are used to create an m-dimensional hyperplane. As a result, we may get the intersection of the hyperplane with each objective axis, also known as the dimension's intercept. Finally, Eq. 4 performs the normalized objective function. NSGA-III [8] contains more information of the normalizing procedure. After normalization, extremum solutions of each objective axis direction can be obtained, and line, plane or hyperplane determined by these solutions can be obtained, which is convenient for subsequent calculation. Here, the nondominated solutions of population are used to construct the radius(spatial distance), which needs to be updated every generation. Firstly, the nearest solution of the nondominated solutions with the smallest Angle to the m-dimensional vector $v = (1, 1, \ldots, 1)$ is found. In Fig. 1, point E is the least angular solution to the vector v. After that find the two weight vectors closest to E and the intersection of the vertical mapping between point E and these two weight vectors, then calculate the distance between the two intersection points. As shown in Fig. 2, the intersection points of vertical projection from point E to the nearest two weight vectors $w3$ and $w4$ are points A and B respectively. First,we need to compute the Euclidean distance AB between point A and point B. Then calculate the ratio of the average Euclidean distance from point E to the extreme points of each objective direction of the current population and to the extreme points of each objective direction of the weight vectors. The radius distance is the product of the length of AB and the ratio. Since the range covered by the weight vectors is different from that of the real PF for each test question, this paper will scale the radius distance obtained above roughly by calculating the ratio between the estimated PF and the range covered by the weight vectors.

Algorithm 3: ConstructRadius(P_{nd}, n)

Input: non-dominated solution setP_{nd}, the dimension number of decision vector n
Output: radius *Radius*
1: $P_{nd} = normalization(P_{nd})$
2: $E = findMinAngle(P_{nd})$ /*Find the solution E */
3: $vector[2] = findWeightVector(E)$
4: $Radius = computeDistance(E, vector)$
5: **return** Radius

For example,in the three-objective test problem,as shown in Fig. 3, The inner red triangle is the plane formed by the current population at some convergence level, and the outer large black triangle is the plane formed by the weight vector of the current convergence level. The average Euclidean distance between point E and the extreme points of each objective direction of the current population (points D, F and G in the Fig. 3) was calculated, and the average Euclidean distance between point E and the extreme points of each objective direction of the weight vector (points A, B and C in the Fig. 3) was calculated, and finally the ratio of the two was calculated. And the final radius is the result of multiplying the distance between AB by this ratio.

2.4. Generate offspring

Algorithm 4 gives pseudocodes to generate offspring population. First, $2/3N$ individuals are generated from the parent population using variation operations. The last $1/3N$ offsprings are generated by positively and negatively disturbing distributive variables controlling distribution of the non-dominated solutions with low crowding degree in the decision vector. Several studies have shown that genetic interventions should target the dominant region of the gene more frequently, which is better for sustaining population variety [18]. After many experiments, the result of 2/3 and 1/3 ratios is better than those of other ratios in performance.These two parameters are not discussed deeply in this paper, so whether they are the best

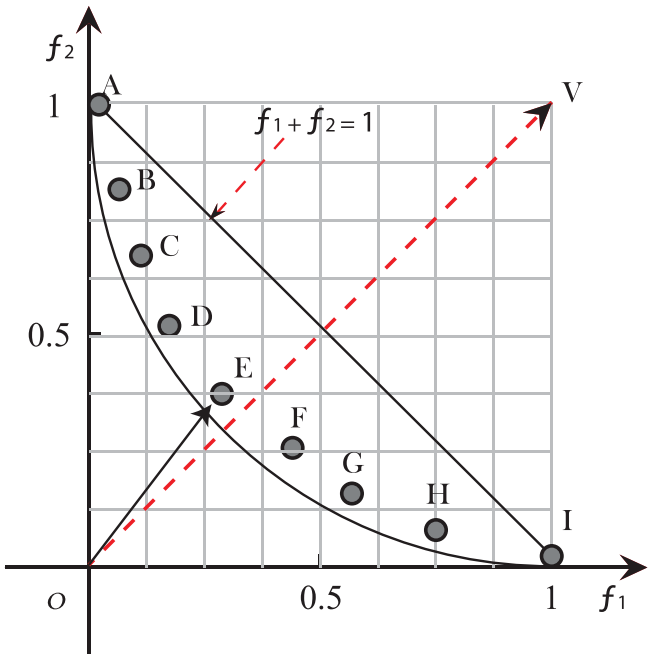


Fig. 1. Find the least angular solution.

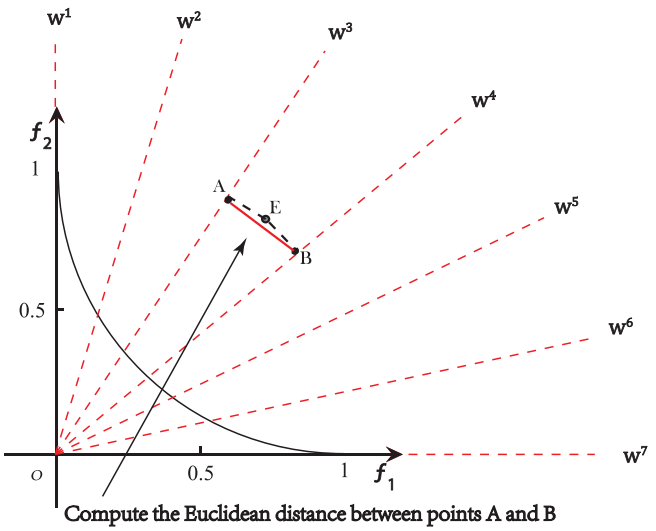


Fig. 2. Compute the Euclidean distance.

value remains to be verified. For DVSLEA, this value can well enhance the distribution and convergence of the population. When the decision variable of the i-th dimension in the individual decision vector is disturbed (when the $Div - V[i]$=1, the disturbance ratio of the current dimension needs to be determined through the self-learning of the decision variable), the other dimensions of decision variables remain unchanged. The initial disturbance value is the product of *disturbingRatioV*[i] and the range of the current dimensional decision variable. For example, the value of the first dimension decision variable of individual X is 0.5 and the whole range of the first dimension decision variable is [0,1], *disturbingratioV*[0]=0.1. Through positive disturbance, the value of the first dimension decision variable of individual X becomes 0.5 + 1*0.1 = 0.6, while the decision variables of other dimensions remain unchanged. And we got a new decision vector. If the Euclidean distance is less than the spatial distance, it indicates that the disturbance proportion is too small and should be enlarged. If the Euclidean distance is less than the radius distance, it indicates that the disturbance proportion is too small and should be enlarged. The self-adaptive disturbance ratio can make the decision variable self-learn until the Euclidean distance between the offspring and the parent set to roughly equals to the spatial distance. After a lot of experiments, the initial value of disturbance ratio is 0.1. For most of the test problems, the Euclidean distance between the parent

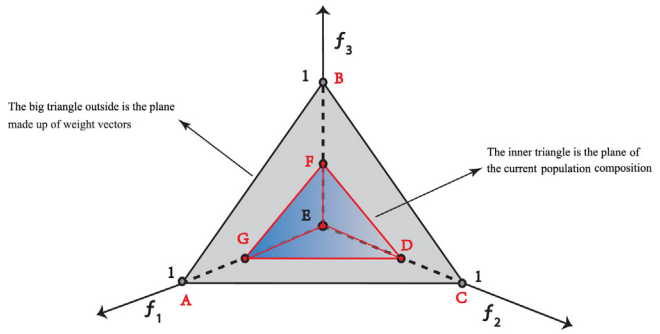


Fig. 3. Consruct radius.

and offspring generated by using the disturbance ratio at the beginning is appropriate, which is convenient for faster convergence when the value of the disturbing ratio is adaptively updated.

Algorithm 4: CreateOffspringPopulation(P, P_{nd}, P_d, N, n)

Input: population$P$, non-dominated solution setP_{nd}, population size N,dimension number of dicision vector n
Output: disturbing ratio *disturbingRatioV*, next population P'

```
for 1 to 2/3 N do
    variation(P)        /*Create offsprings by using variable opreation*/
end for
crowding[P_nd.size] = computeCrowding(P_nd)
sortByCrowding(P_nd, crowding[P_nd.size])        /*Sort solution depend on crowding degree in ascending order*/
for 1 to N/3 do
    p_1 and p_2 = change(p)
    computeDistance(p, p_1, p_2)
    updateDisturbingRatioV(disturbingRatioV)
end for
return P', disturbingRatioV
```

The *disturbingRatioV*[n] is updated in the following ways: Firstly, the initial disturbance ratio of 0.1 in each dimension is reduced by 0.01. We restore the changed disturbance ratio 0.09. And then the ratio of positive and negative disturbance to distributive variables in this dimension is going to be 0.09. There are mainly the following situations: (1) if the Euclidean distance between the offspring disturbed by this proportion and the original parent is larger than the spatial distance, the range of the disturbing ratio is (0,0.09). In the future, when the positive and negative dimension is disturbed, the binary search method can be constantly used to find the appropriate value of the disturbance ratio. (2) If the Euclidean distance between the offspring disturbed by this ratio and the original parent is smaller than the spatial distance, then we should record the current disturbance ratio and enlarge the current disturbance ratio by 10%, and perform the disturbance again. If the Euclidean distance between the offspring and the parent is larger than the spatial distance, the binary search method can be used in the range of the previously recorded disturbance proportion and the present disturbance proportion. (3) In spite of changing the value of the disturbing ratio of the current dimension, the Euclidean distance between the progenitor and the original parent generated during the positive and negative perturbation of the distribution variable of this dimension is always much larger or much smaller than the radius distance. In addition, if the Euclidian distance difference between the offspring and the original parent generated by positive and negative perturbation of other dimensional distributive variables is too large, the if the Euclidean distance between the offspring and the original parents is always much larger or much smaller than the radius distance in spite of the value of the disturbance ratio changed in any way. In addition, if the Euclidean distance differs greatly from the values of the children and parents of other dimensions, the offspring will not be generated by positive and negative disturbance of this dimensional distributive variable after a certain number of comparisons, and the value of the distribution vector of the corresponding dimension will also be set to 0.

2.5. Environmental selection

PF shape estimation is needed: the PF shape was estimated at each iteration, which is very helpful to improve the convergence of the population. Accurat prediction of PF shape can guide the population to search the real PF, so that the convergence of the population becomes better. The population P was cleared, and the union population U was classified according to pareto dominance and divided into two sets of solutions, one was non-dominated solution set S_{nd} and the other

was dominated solution set S_d. $U = S_{nd} \cup S_d$. All the solutions of S_{nd} will be used to estimate the shape of PF [25]. The specific process was as follows: Normalize all the solutions in S_{nd} and calculate the sum of their function values in each objective, respectively, then classify them according to the sum.

$$sum(x) = f'_1(x) + f'_2(x) + \ldots + f'_m(x) \tag{5}$$

- If sum $\in$ (0,0.9), the shape is convex;
- If sum $\in$ [0.9,1.1], the shape is linear;
- If sum > 1.1, the shape is concave;

If the estimated PF shape is convex or concave, the individual fitness value can be calculated by the following formula:

$$c(x) = \sqrt{\sum_{i=q}^{m} (f_i(x) - z^*)^2} \tag{6}$$

where $z^* = (0, 0 \ldots m)$ is the ideal point,namely,the coordinate origin point O after adaptive normalization.

If the estimated PF shape is linear, the individual fitness value can be calculated by the following formula:

$$c(x) = \sum_{i=1}^{m} f_i(x) \tag{7}$$

The reason for choosing these fitness estimators is that they are beneficial for problems whose PFs fit the contour lines formed by these estimators [24]. Above, we have mentioned that the union population U is classified into dominated solution set S_d and non-dominated solution set S_{nd} according to Pareto dominance. And then we need to figure out if the size of S_{nd} is bigger than N. If the size of S_{nd} is less than N, the solutions of S_{nd} participate in the population P, the algorithm also need to choose solutions from S_d, whose fitness value ranks the first N - —S_{nd}—, then added them to the P. Otherwise, the hypercube classification mentioned in [35] is used to classify S_{nd}. After adaptive normalization of the non-dominated solution S_{nd}, a hypercube is constructed with the origin $(0, 0, .., 0)$ and the points $(1, 1, .., m)$ formed by the lines, planes or hyperplanes formed by the extremum solutions of each coordinate axis and the intercepts of each coordinate axis. The hypercube divides the nondominant solution S_{nd} into S_{in}, which is inside the hypercube, and S_{out}, which is outside the hypercube. If the size of S_{in} is still bigger than N, the Euclidean distance between each solution and other solutions should be calculated in S_{in}, this method selects the two solutions with the smallest Euclidean distance, deletes individual with the smallest fitness value until the size is equal to N, and finally adds the remaining solutions in S_{in} to population P. When the number of iterations reaches the maximum, ended the loop and return the final population P.

Algorithm 5: EnvironmentalSelection(U)

Input: union population U
Output: new population P

```
clear(P)
U = normalization(U)
{S_d, S_nd} = classificationByDominance(U)
estimatePFShape(S_nd)
if S_nd.size == N then
    P ← S_nd
else if S_nd.size < N then
    P ← S_nd andP ← S_d        /*Add all solutions in S_nd into P and select solutions from S_d*/
else
    {S_in, S_out} = classificationByHypercube(S_nd)
    if S_in.size == N then
        P ← S_in
    else if S_in.size < N then

        P ← S_in andP ← S_out
    else
        P = select(S_in,N)
    end if
end if
return P
```

3. Experimental studies

3.1. Benchmark problems and performance indicator

In this article, the DTLZ1-7 test problems and the WFG1-9 test problems were used. Test problems with irregular PFs are suitable for evaluating the distribution and convergence of algorithms. For each problem, the number of objectives m varied from 3 to 15, that is, $m \in 3, 5, 8, 10, 15$. The dimension number of decision vector D was set by $D = m + r - 1$ for DTLZ1-7 (here, r was set to 5 for DTLZ1, to 10 for DTLZ2-6, to 20 for DTLZ7). For WFG1-9, $D = l + k$. Especially, decision vectors have k position-related parameters and l distance-related parameters(here, k was set to $2 * (m - 1)$ and l was set to 20). The inverted generation distance(IGD) and hypervolume(HV) were chosen as the indicators for this paper's solution set performance evaluation because they may assess both the distribution and the convergence of the final solution set [19].

3.2. Parameter settings

In our experiments, DVSLEA is compared to five competitive algorithms, that is, MOEA/DD [2], NSGA-III [8], VaEA [34], SPEA2 [50], SPEA2 + SDE [22], MOEADAWA [26], onebyoneEA [24], PREA [40] and RVEA [5]. MOEA/DD combines the advantages of both Pareto dominance and decomposition-based methods; NSGA-III uses two layers of reference points to maintain distribution of the population and guide the direction of the population evolutionary search; SPEA2 + SDE is an improvement on the Pareto dominance-based algorithm SPEA2 that uses SDE instead of the original density estimation; MOEADAWA adjusts weight vectors periodically so that the weights of subproblems can be redistributed adaptively to obtain better uniformity of solutions. In PREA, an approach based on the parallel distance is used to select individuals in the promising region, ensuring population variety. In the high-dimensional objective space, RVEA employs a scalarization strategy to balance convergence and divesity of the solutions. The settings of population size and number of weight vectors are listed in Table 1. For test problems with 3 and 5 objectives, we use the weight vector generation method proposed by Das et al. [7] which generates only one layer of weight vectors. For the test problems with 8, 10 and 15 objectives,a two-layer weight vector generation method was used to generate the weight vectors [8]. P_1 and P_2, representing the number of outer and inner divisions respectively, are taken in integers. NGSA-III suggested the population size for NSGA-III should be a multiple of 4, which would result in a larger population size than the number of weight vectors in some cases, as well as VaEA, which also uses the same framework as NSGA-III. For all other algorithms, population size is set the same with the number of weight vectors. In order to ensure accuracy of the experiments,the population sizes of all the algorithms in this paper should not differ too much from the number of objectives. The settings of all parameters for algorithms are listed in Table 2. Only the experimental results of MOEA/DD, NSGA-III, VaEA, SPEA2 and SPEA2SDE are presented in this article. The comprehensive HV and IGD results of MOEADAWA, onebyoneEA, PREA, and RVEA may be found in the supplementary file due to page limits. All algorithms use simulated binary crossover (SBX) and polynomial variation (PM) to generate new offspring populations, where η_c and η_m denote the distribution indices of SBX and PM, respectively, and p_c and p_m are the variance probability and crossover probability. For the algorithm MOEA/DD, T is the size of the neighbourhood and δ is the probability of neigh-

Table 1
Set values of weight vector parameters $P1$ and $P2$ and population size N.

m	P_1, P_2	NSGA-III,VaEA N	Others N
3	12,0	92	91
5	6,0	212	210
8	3,2	156	156
10	3,2	276	275
15	2,1	136	135

Table 2
Parameter Settings for all algorithms.

algorithm	Parameter setting
DVSLEA	$p_m = 1/D, p_c = 1.0, \eta_c = 30, \eta_m = 20$
MOEA/DD	$p_m = 1/D, p_c = 1.0, \eta_m = 20, \delta = 0.9, T = 20$
NSGA-III	$p_m = 1/D, p_c = 1.0, \eta_c = 30, \eta_m = 20$
VaEA	$p_m = 1/D, p_c = 1.0, \eta_c = 30, \eta_m = 20$
SPEA2	$p_m = 1/D, p_c = 1.0, \eta_c = 30, \eta_m = 20$
SPEA2 + SDE	$p_m = 1/D, p_c = 1.0, \eta_c = 30, \eta_m = 20$
MOEADAWA	$p_m = 1/D, p_c = 1.0, \eta_c = 20, \eta_m = 20$
onebyoneEA	$p_m = 1/D, p_c = 1.0, \eta_c = 30, \eta_m = 20$
PREA	$P_s = 0.7$
RVEA	$p_m = 1/D, p_c = 1.0, \eta_c = 30, \eta_m = 20, f_r = 0.1$

bourhood selection. All the algorithms are independently run 30 times in each test instance for each problem and the average results of the 30 experiments are compared. The same maximum number of function evaluations was used for all algorithms as a condition for termination. (see Table 3).

Table 4, 5 and Table 6, 7 respectively list the mean and standard deviation of HV and IGD for DVSLEA and the other five algorithms with the DTLZ and WFG test problems set at 3, 5, 8, 10 and 15 objectives(values in brackets are standard deviations). In the tables below, +, -, and ≈ are the results of the Wilcoxon signed-rank test, representing the results generated by the other algorithms as better than, worse than, and approximately equal to the results generated by DVSLEA. In addition, the best and second best results are marked in dark and light grey in the following tables.

3.3. Experimental results of DTLZ1-7

As shown in Table 4, DVSLEA significantly outperforms MOEA/DD, NSGA-III, VaEA, SPEA2, and SPEA2 + SDE in 17/35 ≈ 48.6%, 21/35 ≈ 60%, 30/35 ≈ 85.7%, 32/35 ≈ 91.4%, and 22/35 ≈ 62.8% in solving DTLZ test instances, respectively. As we can see, the smallest and the largest percentage are 48.6% and 91.4%, respectively. Regarding the HV and IGD results, DVSLEA would be the most competitive algorithm handling DTLZ test problems. For the IGD results, as shown in Table 5, DVSLEA is competitive with MOEA/DD, NSGA-III, VaEA, SPEA2 and SPEA2 + SDE, but significantly better than other algorithms in at least 21 out of 35 test instances. We can find that the largest ratio is 32/35 ≈ 91.4%, which is detected in the pairwise comparison between DVSLEA and SPEA2. As evidenced by statistical results summarized in Table 4 and 5, DVSLEA has shown the most competitive performance on DTLZ4-DTLZ7. In the HV of DTLZ1, MOEA/DD show the best performance, while in the IGD of DTLZ1, SPEA2SDE is the best. DVSLEA perturbs the decision variables that regulate distributivity to generate offspring, hence outperforms other algorithms in the high dimensional DTLZ4 test problem, which assesses the algorithm's capacity to main-

Table 3
Set maximum number of function evaluations.

m	maxEvaluateNum
3	92000
5	265000
8	234000
10	552000
15	408000

Table 4
Comparison of HV average and standard deviation on DTLZ test problems.

	m	DVSLEA	MOEA/DD	NSGAIII	VaEA	SPEA2	SPEA2SDE
DTLZ1	3	8.3612e-1 (2.52e-4)	8.4165e-1 (8.99e-5)+	8.4154e-1 (2.60e-4)+	8.0285e-1 (4.09e-2) -	8.4076e-1 (5.46e-4)+	8.3150e-1 (3.37e-3)-
	5	9.7588e-1 (1.41e-3)	9.7984e-1 (1.30e-4)+	9.7987e-1 (1.50e-4)+	9.1138e-1 (4.70e-2) -	9.7416e-1 (1.21e-3)-	9.6976e-1 (2.42e-3)-
	8	9.9490e-1 (5.55e-5)	9.9759e-1 (5.19e-5)+	9.9169e-1 (2.84e-2)-	9.0114e-1 (4.29e-2) -	0.0000e+0 (0.00e+0)-	9.8617e-1 (2.09e-3)-
	10	9.9769e-1 (2.08e-5)	9.9968e-1 (1.93e-5)+	9.9760e-1 (1.10e-2) =	9.5863e-1 (2.27e-2)-	0.0000e+0 (0.00e+0)-	9.9588e-1 (7.21e-4)-
	15	9.9967e-1 (9.50e-6)	9.9992e-1 (9.74e-6)=	9.9941e-1 (1.71e-3)=	9.7470e-1 (8.89e-3)-	0.0000e+0 (0.00e+0)-	9.9155e-1 (2.52e-3)-
DTLZ2	3	5.5577e-1 (1.34e-3)	5.5962e-1 (2.25e-6)+	5.5961e-1 (5.55e-6)+	5.5500e-1 (1.43e-3) =	5.5283e-1 (1.53e-3)-	5.5866e-1 (1.23e-3)+
	5	7.8651e-1 (4.48e-4)	8.1266e-1 (5.48e-4)+	8.1265e-1 (3.45e-4)+	7.9340e-1 (2.42e-3) +	7.4773e-1 (8.90e-3)-	8.1154e-1 (1.94e-3)+
	8	9.2119e-1 (2.37e-4)	9.1409e-1 (2.17e-4)-	9.1935e-1 (1.79e-2)-	9.0852e-1 (2.42e-3)-	0.0000e+0 (0.00e+0)-	9.2837e-1 (1.78e-3)+
	10	9.6510e-1 (1.68e-4)	9.6979e-1 (1.71e-4) +	9.6802e-1 (6.91e-3) +	9.4963e-1 (1.98e-3)-	0.0000e+0 (0.00e+0)-	9.7185e-1 (7.88e-4)+
	15	9.9169e-1 (3.92e-2)	9.9065e-1 (9.55e-5)-	9.8310e-1 (7.66e-3)-	9.5897e-1 (2.64e-3)-	0.0000e+0 (0.00e+0)-	9.8186e-1 (2.07e-3)-
DTLZ3	3	5.5503e-1 (2.54e-2)	5.5604e-1 (2.80e-3)=	5.5476e-1 (3.94e-3)=	5.4921e-1 (1.02e-2) -	5.5627e-1 (2.16e-3) =	5.5789e-1 (1.86e-3)=
	5	8.0226e-1 (1.13e-3)	8.1222e-1 (5.84e-4) +	8.1185e-1 (7.82e-4) +	6.3182e-1 (6.26e-2)-	7.7610e-1 (7.27e-3)-	8.1311e-1 (1.61e-3)+
	8	9.2753e-1 (1.23e-2)	9.2342e-1 (6.91e-4)-	8.8073e-1 (9.97e-2)-	4.5374e-1 (3.41e-1)-	0.0000e+0 (0.00e+0)-	9.2638e-1 (3.43e-3)-
	10	9.6981e-1 (2.08e-4)	9.6979e-1 (1.87e-4)=	9.3740e-1 (5.27e-2)-	7.2272e-1 (2.61e-1)-	0.0000e+0 (0.00e+0)-	9.7208e-1 (1.28e-3)+
	15	9.9163e-1 (4.15e-1)	9.9065e-1 (9.83e-5)-	9.3417e-1 (4.67e-2)-	3.6484e-2 (6.67e-2)-	0.0000e+0 (0.00e+0)-	9.7846e-1 (2.90e-3)-
DTLZ4	3	5.5307e-1 (1.09e-3)	5.5962e-1 (2.19e-6)+	5.1559e-1 (8.93e-2)-	5.5434e-1 (1.17e-3)=	4.5771e-1 (1.51e-1)-	4.5897e-1 (1.26e-1)-
	5	8.0817e-1 (6.37e-2)	8.1272e-1 (3.57e-4)+	8.0837e-1 (2.18e-2)=	7.8934e-1 (2.47e-3)-	7.3393e-1 (1.40e-2)-	8.0904e-1 (1.69e-2)=
	8	9.2951e-1 (4.12e-2)	9.2402e-1 (2.90e-4)-	9.0157e-1 (3.95e-2)-	9.0114e-1 (4.80e-3)-	0.0000e+0 (0.00e+0)-	9.2783e-1 (6.32e-3)-
	10	9.6931e-1 (2.17e-2)	9.6981e-1 (1.55e-4)=	9.6151e-1 (1.67e-2)-	9.4216e-1 (4.68e-3)-	0.0000e+0 (0.00e+0)-	9.7187e-1 (7.32e-4)+
	15	9.9525e-1 (1.35e-2)	9.9049e-1 (7.84e-4)-	9.8009e-1 (9.51e-3)-	9.6417e-1 (2.00e-3)-	0.0000e+0 (0.00e+0)-	9.8725e-1 (1.60e-3)-
DTLZ5	3	1.9941e-1 (6.52e-3)	1.8282e-1 (5.06e-4)-	1.9381e-1 (1.05e-3)-	1.9919e-1 (1.96e-4)-	1.9933e-1 (1.52e-4)-	1.9921e-1 (2.73e-4)-
	5	1.1024e-1 (2.82e-4)	1.1528e-1 (4.17e-4)+	1.1513e-1 (2.77e-3)+	9.8481e-2 (4.55e-3)-	5.3675e-2 (2.38e-2)-	1.1261e-1 (3.44e-3)+
	8	9.9406e-2 (3.07e-4)	9.6040e-2 (3.57e-4)-	9.4484e-2 (2.67e-3)-	9.0881e-2 (2.58e-4)-	0.0000e+0 (0.00e+0)-	9.2090e-2 (1.14e-3)-
	10	9.9942e-2 (2.39e-4)	9.4320e-2 (2.92e-4)-	9.1323e-2 (1.21e-3)-	9.0859e-2 (2.55e-4)-	0.0000e+0 (0.00e+0)-	9.1122e-2 (4.60e-4)-
	15	9.1250e-2 (2.83e-4)	9.1798e-2 (1.41e-3)+	9.1213e-2 (4.41e-4) =	9.0907e-2 (3.54e-5)-	0.0000e+0 (0.00e+0)-	9.0994e-2 (3.10e-4)-
DTLZ6	3	1.8537e-1 (2.60e-4)	1.8192e-1 (1.28e-4)-	1.9062e-1 (1.50e-3)+	1.9957e-1 (6.20e-5)+	1.9984e-1 (5.24e-5)+	1.9932e-1 (2.03e-4)+
	5	1.1164e-1 (3.51e-3)	1.1514e-1 (2.77e-4)+	1.0186e-1 (8.74e-3)-	9.1193e-2 (4.43e-4)-	4.6907e-2 (3.86e-2)-	1.1130e-1 (3.44e-3)=
	8	1.0424e-1 (3.65e-2)	9.5777e-2 (2.12e-4)-	9.0974e-2 (3.36e-4)-	5.4501e-2 (4.53e-2)-	0.0000e+0 (0.00e+0)-	9.1048e-2 (6.42e-4)-
	10	9.7661e-2 (2.50e-4)	9.4230e-2 (2.89e-4)-	9.0999e-2 (2.44e-4)-	5.7526e-2 (4.45e-2)-	0.0000e+0 (0.00e+0)-	9.0830e-2 (3.42e-4)-
	15	9.1482e-2 (3.04e-4)	9.2083e-2 (2.77e-4)+	9.0973e-2 (2.39e-4)-	9.0857e-2 (2.05e-4)-	0.0000e+0 (0.00e+0)-	9.0916e-2 (2.44e-4)-
DTLZ7	3	2.7763e-1 (7.05e-2)	2.1618e-1 (2.10e-2)-	2.7000e-1 (1.63e-3)-	2.7390e-1 (9.25e-3)-	2.7453e-1 (6.30e-3) -	2.7401e-1 (9.36e-3)-
	5	2.6799e-1 (6.35e-2)	1.0833e-1 (3.11e-2)-	2.5787e-1 (2.99e-3)-	2.4712e-1 (3.34e-3)-	2.4520e-1 (3.37e-3)-	2.7618e-1 (2.49e-3)+
	8	1.6140e-1 (2.84e-4)	1.7954e-2 (2.51e-2) -	2.0306e-1 (2.90e-3)+	1.6727e-1 (5.46e-3)+	1.1113e-2 (1.23e-2) -	9.2052e-2 (1.56e-2)-
	10	1.9372e-1 (1.97e-4)	6.0136e-5 (6.86e-5)-	1.9010e-1 (3.59e-3)-	1.4011e-1 (5.56e-3)-	1.3018e-3 (3.23e-3)-	3.1541e-2 (1.04e-2)-
	15	1.3042e-1 (3.10e-2)	3.7675e-7 (8.32e-8)-	1.2945e-1 (1.17e-2)-	1.0150e-1 (4.62e-3)-	8.4992e-9 (3.27e-8)-	1.6389e-3 (2.15e-3)-
+/-/≈			14/17/4	9/21/5	3/30/2	2/32/1	10/22/3

Table 5
Comparison of IGD average and standard deviation on DTLZ test problems.

	m	DVSLEA	MOEA/DD	NSGAIII	VaEA	SPEA2	SPEA2SDE
DTLZ1	3	2.1356e-2 (2.03e-3)	2.0562e-2 (6.38e-6)+	2.0570e-2 (2.00e-5)+	3.4442e-2 (1.59e-2) -	2.1087e-2 (2.21e-4)+	2.1462e-2 (2.62e-4)-
	5	5.1712e-2 (1.47e-5)	5.2711e-2 (8.44e-6)-	5.2709e-2 (7.31e-6)-	9.7609e-2 (2.75e-2)-	6.2616e-2 (1.69e-3)-	5.0256e-2 (3.30e-4)+
	8	1.0224e-1 (9.06e-5)	9.7232e-2 (4.23e-5)+	1.0574e-1 (2.85e-2)-	2.0512e-1 (2.19e-2)-	1.1605e+2 (3.58e-1)-	9.5946e-2 (5.87e-4)+
	10	1.3699e-1 (6.73e-5)	1.0958e-1 (2.31e-5)+	1.1528e-1 (2.35e-2)+	1.9558e-1 (1.46e-2)-	1.5206e+2 (2.84e-1)-	1.0080e-1 (4.77e-4)+
	15	1.5385e-1 (3.16e-3)	1.8309e-1 (6.22e-4)-	1.8647e-1 (9.28e-3)-	2.2322e-1 (1.34e-2)-	2.3807e+2 (3.01e+1)-	1.3338e-1 (9.21e-4)+
DTLZ2	3	5.5539e-2 (1.88e-2)	5.4464e-2 (2.91e-7)+	5.4465e-2 (9.28e-7)+	5.7303e-2 (7.89e-4)-	5.6682e-2 (6.24e-4)-	8.0156e-2 (2.79e-3)-
	5	1.6845e-1 (5.22e-7)	1.6514e-1 (6.60e-7)+	1.6513e-1 (4.57e-6)+	1.6729e-1 (1.10e-3)=	1.8810e-1 (5.09e-3)-	1.8974e-1 (2.13e-3)-
	8	3.1289e-1 (4.84e-3)	3.1478e-1 (4.76e-6)-	3.2504e-1 (4.08e-2)-	3.6375e-1 (2.18e-3)-	2.4081e+0 (2.12e-2)-	3.6140e-1 (2.22e-3)-
	10	4.1027e-1 (5.88e-5)	4.2207e-1 (3.49e-5)-	4.2683e-1 (2.05e-2) -	4.1192e-1 (1.65e-3)-	2.4884e+0 (1.43e-2)-	4.2410e-1 (2.16e-3)-
	15	6.0128e-1 (2.14e-4)	6.1960e-1 (1.40e-4)-	6.3186e-1 (1.34e-2)-	5.8452e-1 (1.85e-3)+	2.6472e+0 (1.35e-2)-	6.0771e-1 (4.79e-3)-
DTLZ3	3	5.6653e-2 (2.21e-4)	5.4742e-2 (3.47e-4)+	5.4863e-2 (5.60e-4)+	6.0202e-2 (6.78e-3)-	5.5734e-2 (5.02e-4)+	7.8481e-2 (2.30e-3)-
	5	1.6899e-1 (1.04e-4)	1.6518e-1 (3.70e-5)+	1.6521e-1 (9.26e-5)+	3.2737e-1 (6.41e-2) -	1.8314e-1 (4.26e-3)-	1.8915e-1 (2.12e-3)-
	8	3.1600e-1 (3.62e-3)	3.1512e-1 (2.27e-4)+	3.6347e-1 (1.10e-1)-	9.0991e-1 (6.16e-1)-	1.2676e+3 (1.75e+2)-	3.6841e-1 (1.14e-2)-
	10	4.3199e-1 (4.97e-4)	4.2197e-1 (1.30e-4)+	4.6725e-1 (7.51e-2)-	7.7294e-1 (6.44e-1)-	1.4441e+3 (1.53e+2)-	4.2426e-1 (3.44e-3)+
	15	6.1652e-1 (2.76e-1)	6.1987e-1 (3.14e-4)-	6.7203e-1 (4.07e-2)-	2.1127e+0 (8.18e-1)-	1.7356e+3 (1.23e+2)-	6.1767e-1 (1.11e-2)-
DTLZ4	3	5.6362e-2 (2.43e-1)	5.4464e-2 (2.88e-7)+	1.5188e-1 (1.98e-1)-	5.7625e-2 (6.58e-4)-	2.5894e-1 (3.10e-1)-	2.9332e-1 (2.59e-1)-
	5	1.6776e-1 (1.37e-1)	1.6514e-1 (5.95e-7)+	1.7341e-1 (4.52e-2)-	1.6992e-1 (1.01e-3)-	2.0537e-1 (3.82e-2) -	1.9767e-1 (4.09e-2)-
	8	3.1259e-1 (8.83e-2)	3.1489e-1 (9.73e-6)-	3.7039e-1 (9.56e-2)-	3.6350e-1 (2.67e-3)-	2.4374e+0 (3.06e-2)-	3.6259e-1 (1.64e-2)-
	10	4.1347e-1 (5.84e-2)	4.2199e-1 (1.08e-4)-	4.4662e-1 (5.11e-2)-	4.2028e-1 (5.01e-3)-	2.5016e+0 (1.39e-2)-	4.1703e-1 (1.76e-3)-
	15	5.9653e-1 (3.18e-2)	6.2119e-1 (3.71e-3)-	6.4448e-1 (2.04e-2)-	5.8882e-1 (2.05e-3)+	2.6550e+0 (1.28e-2)-	6.0526e-1 (7.28e-3)-
DTLZ5	3	5.1755e-3 (1.19e-3)	3.1452e-2 (1.00e-3)-	1.2557e-2 (1.55e-3)-	5.4376e-3 (2.39e-4)-	4.8019e-3 (1.35e-4)+	1.0592e-2 (1.22e-3)-
	5	7.4270e-2 (4.32e-3)	1.1281e-1 (1.07e-2) -	8.3476e-2 (2.37e-2) -	1.1561e-1 (2.69e-2)-	1.7442e-1 (3.33e-2)-	6.0413e-2 (9.39e-3)+
	8	1.1252e-1 (6.68e-6)	1.5298e-1 (2.64e-2)-	2.6376e-1 (7.25e-2)-	3.1549e-1 (7.83e-2)-	2.3981e+0 (4.89e-2)-	1.1794e-1 (1.69e-2)-
	10	1.1339e-1 (1.57e-6)	1.2686e-1 (2.23e-2)-	3.7475e-1 (7.69e-2)-	4.3810e-1 (1.28e-1)-	2.4332e+0 (3.02e-2)-	1.4481e-1 (2.33e-2)-
	15	1.6215e-1 (3.83e-4)	1.5574e-1 (1.56e-2)+	2.3766e-1 (5.39e-2)-	5.4825e-1 (1.66e-1)-	2.5212e+0 (2.90e-2)-	1.6224e-1 (2.90e-2)=
DTLZ6	3	5.2650e-3 (4.60e-3)	3.3775e-2 (1.85e-4)-	1.9319e-2 (2.31e-3)-	5.0615e-3 (1.66e-4)+	4.4531e-3 (3.07e-5)+	1.0378e-2 (9.98e-4)-
	5	1.2198e-1 (5.41e-5)	1.1932e-1 (1.19e-2) +	1.7758e-1 (5.95e-2)-	2.5419e-1 (4.02e-2)-	3.7738e-1 (1.92e-1)-	7.0383e-2 (8.87e-3)+
	8	2.5379e-2 (5.23e-3)	1.5986e-1 (2.65e-2)-	3.6030e-1 (1.61e-1)-	6.3927e-1 (4.42e-1)-	9.9928e+0 (2.18e-2)-	1.9057e-1 (3.24e-2)-
	10	1.1461e-1 (4.80e-4)	1.2215e-1 (1.92e-2)-	3.9612e-1 (1.45e-1)-	6.8806e-1 (4.30e-1)-	1.0008e+1 (1.69e-2)-	2.2453e-1 (5.32e-2)-
	15	1.7237e-1 (7.43e-2)	1.6329e-1 (1.63e-6)+	4.0450e-1 (1.18e-1)-	4.3135e-1 (1.67e-1)-	1.0100e+1 (3.61e-2)-	3.4242e-1 (2.26e-16)-
DTLZ7	3	5.8458e-2 (1.74e-3)	4.7901e-1 (2.37e-1)-	7.7254e-2 (3.28e-3)-	8.3475e-2 (7.29e-2)-	7.2570e-2 (5.14e-2)-	8.2512e-2 (7.64e-2)-
	5	2.3344e-1 (8.17e-3)	2.3742e+0 (1.06e+0)-	2.8546e-1 (1.13e-2)-	2.7028e-1 (6.82e-3)-	2.4167e-1 (4.78e-3)-	2.7077e-1 (2.67e-2)-
	8	7.1711e-1 (2.46e-1)	1.7297e+0 (4.14e-1)-	7.8317e-1 (2.40e-2) -	7.0413e-1 (1.22e-2)+	1.0383e+0 (4.17e-2)-	7.4314e-1 (1.16e-2)-
	10	8.9834e-1 (4.83e-1)	2.4544e+0 (4.59e-1)-	9.2673e-1 (3.99e-2)-	9.3109e-1 (9.74e-3)-	1.5191e+0 (4.63e-2)-	8.8668e-1 (5.72e-2)+
	15	1.1542e+0 (2.19e-1)	3.4460e+0 (7.17e-2)-	6.8582e+0 (9.02e-1)-	2.3418e+0 (1.67e-1)-	2.3552e+0 (8.28e-2)-	1.5490e+0 (2.70e-2)-
+/-/≈			14/21/0	6/29/0	4/30/1	4/31/0	8/26/1

Table 6
Comparison of HV average and standard deviation on WFG test problems

	m	DVSLEA	MOEA/DD	NSGAIII	VaEA	SPEA2	SPEA2SDE
WFG1	3	8.8210e-1 (3.13e-2)	7.9090e-1 (6.67e-2) -	9.2390e-1 (1.94e-2)+	9.0892e-1 (1.63e-2) +	9.3690e-1 (1.02e-2)+	9.3787e-1 (5.46e-3)+
	5	8.4812e-1 (3.34e-2)	9.3037e-1 (3.64e-2) +	9.8445e-1 (1.43e-2)+	9.2120e-1 (2.62e-2) +	9.7755e-1 (2.47e-2)+	9.9393e-1 (8.05e-3)+
	8	9.8759e-1 (1.18e-2)	8.9621e-1 (6.53e-2) -	9.8778e-1 (2.05e-2)=	9.0750e-1 (5.42e-2) -	9.4116e-1 (3.32e-2)-	9.8594e-1 (2.01e-2)-
	10	9.9558e-1 (3.70e-3)	9.7487e-1 (1.81e-2) -	9.9561e-1 (1.47e-2)=	9.5846e-1 (5.10e-2)-	9.8085e-1 (2.40e-2)-	9.9518e-1 (1.19e-2)=
	15	9.9962e-1 (4.77e-2)	9.7886e-1 (5.52e-3) -	9.9812e-1 (9.36e-4)-	9.5564e-1 (5.70e-2)-	9.9997e-1 (2.90e-5)=	9.8877e-1 (2.44e-2)-
WFG2	3	9.2522e-1 (6.14e-3)	8.6794e-1 (7.12e-2)-	8.8449e-1 (6.41e-2)-	8.6426e-1 (6.71e-2)-	8.5574e-1 (6.95e-2)-	8.5302e-1 (7.21e-2)-
	5	9.9262e-1 (4.93e-2)	9.4137e-1 (6.35e-2) -	9.7874e-1 (4.45e-2)-	9.7987e-1 (2.41e-3)-	9.8890e-1 (2.89e-3)-	9.4149e-1 (7.41e-2)-
	8	9.9335e-1 (4.21e-2)	8.9111e-1 (7.67e-2) -	9.6135e-1 (6.77e-2)-	9.7986e-1 (3.21e-2)-	9.8346e-1 (3.63e-3)-	9.4556e-1 (7.01e-2)-
	10	9.9707e-1 (4.88e-2)	9.2104e-1 (5.83e-2) -	9.6427e-1 (6.78e-2)-	9.8953e-1 (2.00e-3)-	9.8570e-1 (2.43e-3)-	9.7854e-1 (4.51e-2)-
	15	9.9534e-1 (5.33e-2)	8.6943e-1 (6.89e-2) -	9.1992e-1 (8.72e-2)-	9.7843e-1 (4.58e-2)-	9.8273e-1 (1.03e-2)-	9.3926e-1 (7.95e-2)-
WFG3	3	4.3272e-1 (2.84e-2)	2.7947e-1 (3.34e-2)-	3.8898e-1 (7.88e-3)-	3.6430e-1 (7.69e-3)-	3.7479e-1 (5.11e-3)-	3.8857e-1 (1.01e-2)-
	5	1.8169e-1 (1.15e-2)	1.0064e-1 (1.90e-2)-	1.4068e-1 (1.47e-2)-	1.0010e-1 (1.18e-2)-	1.2011e-1 (2.70e-2)-	5.6332e-2 (2.45e-2)-
	8	4.6287e-1 (2.35e-2)	4.7276e-1 (1.17e-2)+	7.0276e-3 (1.06e-2)-	9.7342e-3 (3.27e-2)-	4.7346e-1 (1.22e-2)+	4.9359e-1 (4.29e-2)+
	10	6.3376e-1 (1.62e-2)	5.2415e-1 (2.33e-2)-	5.7415e-1 (1.19e-2)-	5.6731e-2 (4.12e-3)-	5.6941e-1 (1.18e-3)-	6.9845e-1 (1.53e-2)+
	15	5.0256e-1 (1.56e-2)	4.8746e-1 (1.41e-2)-	4.4347e-1 (3.39e-2)-	4.5821e-1 (1.21e-2)-	4.9581e-1 (6.78e-2)-	4.9833e-1 (1.69e-2)-
WFG4	3	5.5772e-1 (2.51e-3)	5.3780e-1 (2.00e-3) -	5.4971e-1 (1.63e-3)-	5.3661e-1 (3.93e-3)-	5.2407e-1 (3.30e-3)-	5.4893e-1 (2.09e-3)-
	5	8.0352e-1 (1.86e-2)	7.6427e-1 (3.28e-3)-	7.7570e-1 (2.43e-2)-	7.4044e-1 (4.48e-3)-	6.8412e-1 (6.92e-3)-	7.6964e-1 (3.97e-3)-
	8	9.0996e-1 (3.46e-2)	6.9420e-1 (2.28e-2)-	8.5289e-1 (3.19e-2)-	8.4854e-1 (8.24e-3)-	6.7183e-1 (1.78e-2)-	8.3105e-1 (9.31e-3)-
	10	9.6249e-1 (4.32e-2)	7.2750e-1 (1.60e-2)-	9.2874e-1 (6.88e-3)-	8.8427e-1 (6.76e-3)-	7.1617e-1 (1.32e-2)-	8.9470e-1 (8.08e-3)-
	15	9.5842e-1 (6.31e-2)	5.2218e-1 (5.61e-2)-	9.7003e-1 (7.46e-3)+	8.9992e-1 (7.81e-3)-	5.8694e-1 (4.16e-2)-	9.2715e-1 (1.58e-2)-
WFG5	3	5.1289e-1 (2.10e-3)	5.0153e-1 (2.67e-3)-	5.1307e-1 (2.43e-3)=	5.0853e-1 (3.22e-3)-	4.9770e-1 (4.44e-3)-	5.1183e-1 (4.15e-3)=
	5	7.4550e-1 (9.56e-3)	7.2336e-1 (3.54e-3)-	7.5195e-1 (1.74e-3)+	7.2291e-1 (3.62e-3)-	6.6975e-1 (5.91e-3)-	7.2414e-1 (4.32e-3)-
	8	8.4424e-1 (2.72e-2)	7.0014e-1 (3.02e-2) -	8.4392e-1 (1.44e-2)-	8.1088e-1 (5.18e-3)-	6.4230e-1 (2.03e-2)-	7.8476e-1 (8.78e-3)-
	10	9.0041e-1 (2.44e-2)	7.1032e-1 (1.81e-2)-	8.8860e-1 (1.20e-2)-	8.4538e-1 (6.17e-3)-	6.6458e-1 (2.11e-2)-	8.4208e-1 (4.90e-3)-
	15	9.1220e-1 (5.51e-2)	5.5408e-1 (2.98e-2) -	9.0462e-1 (8.75e-3)-	8.4429e-1 (5.62e-3)-	5.1779e-1 (4.47e-2)-	7.6603e-1 (2.97e-2)-
WFG6	3	5.1027e-1 (9.42e-3)	5.0731e-1 (8.04e-3)-	5.2016e-1 (6.60e-3)+	5.1097e-1 (5.42e-3)=	5.0457e-1 (6.39e-3)-	5.1940e-1 (4.98e-3)+
	5	7.6151e-1 (8.07e-2)	7.3471e-1 (9.40e-3)-	7.5529e-1 (6.73e-3)-	7.2911e-1 (6.59e-3)-	6.7878e-1 (1.22e-2)-	7.4475e-1 (6.93e-3)-
	8	8.6311e-1 (3.44e-2)	6.9521e-1 (2.51e-2) -	8.6241e-1 (8.00e-3)-	8.4683e-1 (6.92e-3)-	6.6123e-1 (2.22e-2)-	8.2306e-1 (8.23e-3)-
	10	9.1580e-1 (4.45e-2)	7.0996e-1 (2.27e-2)-	9.0639e-1 (8.65e-3)-	8.8375e-1 (8.38e-3)-	6.6375e-1 (1.97e-2)-	8.7741e-1 (8.23e-3)-
	15	9.1608e-1 (3.54e-2)	5.1747e-1 (4.95e-2)-	9.2137e-1 (1.56e-2)+	8.9131e-1 (9.89e-3)-	5.6030e-1 (4.71e-2)-	8.2475e-1 (2.50e-2)-
WFG7	3	5.5647e-1 (5.16e-3)	5.4109e-1 (5.89e-3) -	5.5707e-1 (5.23e-4)=	5.4899e-1 (1.46e-3)-	5.4222e-1 (2.30e-3)-	5.5320e-1 (2.22e-3)-
	5	8.0663e-1 (1.39e-2)	7.7839e-1 (2.20e-3)-	8.0652e-1 (9.45e-4)=	7.7820e-1 (3.82e-3)-	6.6352e-1 (4.28e-2)-	7.8534e-1 (3.16e-3)-
	8	9.1663e-1 (2.30e-2)	7.3705e-1 (2.01e-2)-	8.7285e-1 (4.16e-2)-	8.9749e-1 (3.42e-3)-	5.9740e-1 (2.66e-2)-	8.5700e-1 (9.66e-3)-
	10	9.6609e-1 (1.84e-2)	7.5191e-1 (2.19e-2)-	9.3391e-1 (1.87e-2)-	9.4141e-1 (2.91e-3)-	6.3610e-1 (2.73e-2)-	9.3028e-1 (2.35e-3)-
	15	9.8725e-1 (6.20e-3)	5.6541e-1 (4.91e-2)-	9.8191e-1 (3.16e-3)-	9.5281e-1 (3.90e-3)-	5.4367e-1 (4.64e-2)-	9.5093e-1 (6.84e-3)-
WFG8	3	4.7814e-1 (4.86e-3)	4.2756e-1 (3.97e-2)-	4.7519e-1 (3.12e-3)-	4.5787e-1 (4.25e-3)-	4.5291e-1 (3.05e-3)-	4.7908e-1 (2.23e-3)=
	5	6.5475e-1 (7.67e-2)	6.8124e-1 (7.92e-3)+	6.9259e-1 (3.24e-3)+	6.3998e-1 (5.50e-3)-	5.9095e-1 (1.28e-2)-	6.8200e-1 (2.70e-3)+
	8	7.2982e-1 (6.95e-2)	5.0948e-1 (5.55e-2)-	7.7329e-1 (5.75e-3) +	6.9276e-1 (1.29e-2) -	6.1361e-1 (2.28e-2) -	7.7730e-1 (7.15e-3)+
	10	8.6711e-1 (2.79e-2)	5.2297e-1 (6.62e-2) -	8.5996e-1 (6.64e-3)-	7.6607e-1 (1.30e-2)-	6.3940e-1 (2.06e-2)-	8.4129e-1 (4.53e-3)-
	15	9.0551e-1 (3.86e-1)	8.3099e-1 (1.39e-1)-	9.0359e-1 (2.69e-2)-	8.4360e-1 (1.35e-2)-	5.0531e-1 (7.94e-2)-	9.0181e-1 (4.56e-3)-
WFG9	3	5.0809e-1 (2.16e-2)	4.6896e-1 (2.45e-2)-	4.6887e-1 (1.74e-2)-	4.7996e-1 (2.44e-2)-	4.5858e-1 (1.50e-2)-	4.8415e-1 (2.98e-2)-
	5	7.4652e-1 (3.62e-2)	6.6119e-1 (2.25e-2)-	6.6245e-1 (1.09e-2)-	6.4534e-1 (8.34e-3)-	6.2170e-1 (1.06e-2)-	6.7901e-1 (3.08e-2)-
	8	7.2135e-1 (1.08e-1)	6.3655e-1 (2.71e-2)-	7.1222e-1 (3.10e-2)-	7.0092e-1 (1.16e-2)-	6.1004e-1 (3.04e-2)-	7.2149e-1 (3.27e-2)=
	10	7.5551e-1 (1.14e-1)	6.4316e-1 (2.07e-2)-	7.5313e-1 (2.60e-2)-	7.2782e-1 (1.00e-2)-	6.5844e-1 (2.13e-2)-	7.9133e-1 (2.51e-2)+
	15	7.3775e-1 (9.10e-2)	4.6978e-1 (5.26e-2)-	7.7350e-1 (4.55e-2)+	6.8478e-1 (1.64e-2)-	4.7887e-1 (1.12e-1)-	7.3883e-1 (2.33e-2)=
+/-/≈			3/42/0	9/31/5	2/42/1	3/41/1	8/32/5

Table 7
Comparison of IGD average and standard deviation on WFG test problems.

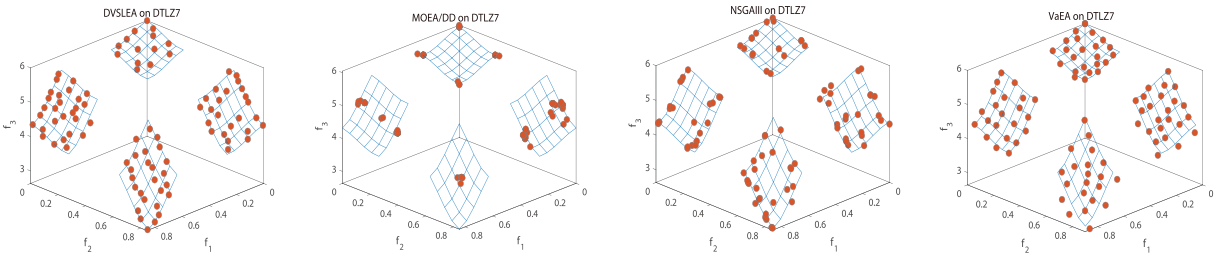
	m	DVSLEA	MOEA/DD	NSGAIII	VaEA	SPEA2	SPEA2SDE
WFG1	3	3.3840e-1 (3.63e-4)	3.5243e-1 (1.04e-1) -	1.5393e-1 (1.65e-2)+	1.7639e-1 (1.64e-2)+	1.5972e-1 (7.36e-3)+	1.5571e-1 (6.19e-3)+
	5	4.2567e-1 (3.16e-2)	4.3504e-1 (1.97e-2)-	3.7174e-1 (8.51e-3)+	4.2468e-1 (2.51e-2)=	4.4548e-1 (2.50e-2)-	3.6325e-1 (9.78e-3)+
	8	8.9326e-1 (2.43e-2)	9.7116e-1 (4.39e-2)-	9.1891e-1 (1.48e-1)-	9.1244e-1 (4.54e-2)-	1.1716e+0 (3.66e-2)-	8.7510e-1 (1.62e-2)+
	10	1.0491e+0 (3.16e-2)	1.2621e+0 (8.66e-2)-	1.0919e+0 (2.83e-1)-	9.7723e-1 (4.47e-2)+	1.3885e+0 (5.30e-2)-	9.7565e-1 (1.35e-2)+
	15	1.6090e+0 (5.42e-2)	1.8896e+0 (3.19e-2)-	1.8949e+0 (1.31e-1)-	1.6530e+0 (4.63e-2)-	3.0226e+0 (4.41e-1)-	1.6462e+0 (2.67e-2)-
WFG2	3	1.8329e-1 (1.76e-1)	3.0843e-1 (1.84e-1)-	2.5760e-1 (1.47e-1)-	2.9946e-1 (1.62e-1)-	3.3445e-1 (1.55e-1)-	3.6629e-1 (1.50e-1)-
	5	4.7792e-1 (2.38e-2)-	6.6116e-1 (3.28e-1)-	4.4620e-1 (2.18e-1)+	3.8778e-1 (5.24e-3)+	5.8788e-1 (1.84e-2)-	6.8183e-1 (3.54e-1)-
	8	1.0309e+0 (3.31e-1)	1.8526e+0 (7.12e-1)-	1.5036e+0 (5.43e-1)-	9.7866e-1 (3.01e-1)+	1.7439e+0 (1.03e-1)-	1.4281e+0 (6.43e-1)-
	10	1.1647e+0 (6.95e-1)	1.9298e+0 (8.69e-1)-	1.7047e+0 (7.96e-1)-	1.0008e+0 (8.63e-3)+	2.1612e+0 (1.03e-1)-	1.2949e+0 (6.05e-1)-
	15	1.8734e+0 (1.51e+0)	4.0577e+0 (1.94e+0)-	3.5002e+0 (1.83e+0)-	2.0098e+0 (1.03e+0)-	5.4924e+0 (6.20e-1)-	3.0597e+0 (1.82e+0)-
WFG3	3	2.4547e-2 (7.95e-2)	3.8467e-1 (9.97e-2)-	8.8038e-2 (1.83e-2)-	1.3692e-1 (1.29e-2)-	1.1794e-1 (1.04e-2)-	7.3151e-2 (2.20e-2)-
	5	2.7571e-1 (1.31e-1)	5.5204e-1 (3.99e-2)-	4.3988e-1 (4.14e-2)-	5.6576e-1 (3.87e-2)-	5.3623e-1 (6.91e-2)-	6.6415e-1 (1.46e-1)-
	8	1.3699e+0 (1.61e-2)	2.0071e+0 (7.46e-2)-	1.2940e+0 (4.57e-1)+	1.3769e+0 (1.42e-1)=	2.5823e+0 (4.11e-1)-	2.0120e+0 (9.20e-1)-
	10	1.2322e+0 (1.35e-1)	2.6985e+0 (6.21e-2)-	1.2624e+0 (6.02e-1)-	1.8317e+0 (2.16e-1)-	3.0856e+0 (3.48e-1)-	2.0610e+0 (7.25e-1)-
	15	2.0063e+0 (1.43e-1)	7.0296e+0 (5.98e-2)-	2.0634e+0 (2.53e-1)-	3.4636e+0 (3.32e-1)-	5.6211e+0 (4.42e-1)-	1.8393e+0 (5.07e-1)+
WFG4	3	2.3087e-1 (2.94e-3)	2.4265e-1 (1.77e-3)-	2.2144e-1 (2.82e-4)+	2.3179e-1 (3.41e-3)=	2.2873e-1 (3.31e-3)+	3.2508e-1 (1.70e-2)-
	5	9.5708e-1 (1.05e-1)	1.0540e+0 (4.48e-3)-	9.9440e-1 (1.17e-1)-	9.3970e-1 (5.32e-3)+	9.2911e-1 (6.35e-3)+	1.1312e+0 (1.82e-2)-
	8	3.0576e+0 (1.64e-1)	4.7183e+0 (1.17e-1)-	3.1890e+0 (3.85e-1)-	3.0837e+0 (3.17e-2)-	3.0729e+0 (3.92e-2)-	3.2459e+0 (5.57e-2)-
	10	4.1490e+0 (4.64e-1)	6.9522e+0 (7.28e-2)-	4.5297e+0 (1.73e-1)-	4.0168e+0 (2.45e-2)+	4.1793e+0 (3.81e-2)-	4.3675e+0 (3.80e-2)-
	15	8.0053e+0 (4.99e-1)	1.3923e+1 (3.27e-1)-	9.2797e+0 (1.92e-1)-	8.0067e+0 (8.12e-2)=	9.7036e+0 (1.54e-1)-	9.2297e+0 (6.69e-1)-
WFG5	3	2.4759e-1 (2.06e-3)	2.4615e-1 (2.73e-3)=	2.3176e-1 (1.28e-3)+	2.3925e-1 (2.72e-3)+	2.3273e-1 (3.37e-3)+	3.3553e-1 (1.74e-2)-
	5	9.5212e-1 (5.92e-2)	1.0294e+0 (3.30e-3)-	9.5696e-1 (4.88e-3)-	9.3807e-1 (6.20e-3)+	9.1907e-1 (5.26e-3)+	1.1278e+0 (1.78e-2)-
	8	3.1310e+0 (2.23e-1)	4.3244e+0 (2.13e-1)-	2.9533e+0 (8.28e-2)+	3.2132e+0 (2.14e-2)-	3.9628e+0 (3.27e-2)-	3.1888e+0 (3.95e-2)-
	10	4.2082e+0 (3.55e-1)	6.6132e+0 (1.62e-1)-	4.5052e+0 (4.75e-2)-	3.9827e+0 (2.87e-2)+	4.1316e+0 (3.67e-2)+	4.3235e+0 (4.57e-2)-
	15	7.8071e+0 (4.36e-1)	1.3101e+1 (2.68e-1)-	9.1920e+0 (1.06e-1)-	7.9144e+0 (8.39e-2)-	9.4548e+0 (2.10e-1)-	1.1911e+1 (7.19e-1)-
WFG6	3	2.4879e-1 (1.74e-2)	2.5333e-1 (6.26e-3)-	2.3007e-1 (3.50e-3)+	2.4611e-1 (5.06e-3)+	2.4263e-1 (4.74e-3)+	3.4119e-1 (1.23e-2)-
	5	9.5176e-1 (2.93e-1)	1.0512e+0 (3.60e-3)-	9.5961e-1 (4.62e-4)-	9.5676e-1 (1.05e-2)-	9.4336e-1 (8.32e-3)+	1.1755e+0 (2.33e-2)-
	8	3.1216e+0 (2.63e-1)	4.5112e+0 (1.54e-1)-	2.9509e+0 (3.07e-3)+	3.1378e+0 (6.73e-2)=	3.3566e+0 (2.85e-2)-	3.3557e+0 (4.21e-2)-
	10	4.0620e+0 (3.24e-1)	6.8373e+0 (9.87e-2)-	4.5657e+0 (1.57e-1)-	4.0648e+0 (3.81e-2)=	4.0797e+0 (3.35e-2)-	4.5524e+0 (3.68e-2)-
	15	8.1360e+0 (2.92e-1)	1.3526e+1 (1.74e-1)-	9.5905e+0 (6.02e-1)-	7.9037e+0 (7.51e-2)+	8.9520e+0 (1.77e-1)-	1.1269e+1 (7.26e-1)-
WFG7	3	2.2477e-1 (1.73e-2)	2.4506e-1 (5.21e-3)-	2.2097e-1 (6.27e-5)+	2.2821e-1 (2.68e-3)-	2.2264e-1 (2.53e-3)+	3.3726e-1 (1.60e-2)-
	5	9.3603e-1 (4.87e-2)	1.0587e+0 (5.00e-3)-	9.6660e-1 (1.01e-3)-	9.4693e-1 (8.95e-3)-	9.5955e-1 (3.35e-2)-	1.1588e+0 (1.97e-2)-
	8	3.2075e+0 (1.17e-1)	4.4755e+0 (1.22e-1)-	3.5576e+0 (6.95e-1)-	3.0707e+0 (5.46e-2)+	3.0612e+0 (3.70e-2)+	3.1086e+0 (3.46e-2)+
	10	4.1899e+0 (2.56e-1)	6.7216e+0 (1.47e-1)-	5.1359e+0 (4.91e-1) -	4.2138e+0 (2.58e-2)-	4.1958e+0 (4.15e-2)-	4.3287e+0 (4.70e-2)-
	15	8.9108e+0 (4.60e-2)	1.3683e+1 (3.29e-1)-	9.2771e+0 (1.24e-1)-	8.0044e+0 (7.05e-2)+	9.6851e+0 (2.10e-1)-	8.9293e+0 (1.62e-1)-
WFG8	3	2.7459e-1 (5.80e-3)	3.4253e-1 (5.60e-2)-	2.7401e-1 (5.27e-3)=	3.0811e-1 (7.72e-3)-	3.0598e-1 (4.22e-3)-	3.4562e-1 (1.22e-2)-
	5	1.0069e+0 (1.62e-1)	1.0517e+0 (7.00e-3)-	9.8712e-1 (7.22e-3)+	1.0746e+0 (9.91e-3)-	1.0519e+0 (1.05e-2)-	1.1604e+0 (1.66e-2)-
	8	3.1556e+0 (3.32e-1)	4.1155e+0 (3.15e-1)-	3.5451e+0 (1.25e-1)-	3.2700e+0 (3.32e-2)-	3.2531e+0 (4.54e-2)-	3.4010e+0 (3.39e-2)-
	10	3.9974e+0 (2.07e-1)	6.4365e+0 (3.09e-1)-	4.8229e+0 (9.18e-2)-	4.3108e+0 (2.40e-2)-	4.4686e+0 (5.17e-2)-	4.5791e+0 (3.99e-2)-
	15	8.8294e+0 (2.51e+0)	9.6344e+0 (8.45e-1)-	9.3661e+0 (2.67e-1)-	8.5025e+0 (1.05e-1)+	9.7636e+0 (2.15e-1)-	9.1206e+0 (2.53e-1)-
WFG9	3	2.2937e-1 (2.45e-2)	2.6683e-1 (2.06e-2)-	2.5455e-1 (1.47e-2)-	2.5139e-1 (2.09e-2)-	2.6404e-1 (1.59e-2)-	3.2115e-1 (1.58e-2)-
	5	9.3051e-1 (7.93e-2)	1.0111e+0 (6.48e-3)-	9.3190e-1 (4.83e-3)-	9.5459e-1 (8.43e-3)-	9.6567e-1 (1.61e-2)-	1.0707e+0 (2.28e-2)-
	8	3.0876e+0 (2.20e-1)	3.7216e+0 (1.56e-1)-	3.1176e+0 (3.09e-1)-	3.0382e+0 (2.08e-2)+	3.1660e+0 (6.81e-2)-	3.1959e+0 (4.25e-2)-
	10	3.8870e+0 (7.03e-1)	5.9546e+0 (1.82e-1)-	4.4867e+0 (1.78e-1)-	3.9472e+0 (2.92e-2)-	4.2593e+0 (5.04e-2)-	4.3127e+0 (4.46e-2)-
	15	7.5442e+0 (1.99e+0)	1.0925e+1 (8.20e-1)-	8.6728e+0 (1.82e-1)-	7.5261e+0 (8.24e-2)+	9.1858e+0 (2.36e-1)-	1.0689e+1 (7.27e-1)-
+/-/≈			0/44/1	11/33/1	17/22/6	10/35/0	6/39/0

tain distributivity. DVSLEA performs better on test problems with irregular PFs, such as DTLZ6 with degenerate PFs, and DTLZ7 with discontinuous PFs, since it adaptively selects the fitness value calculation method depending on the PF shape estimation. We can see that DVSLEA has a clear advantage in these problems. DVSLEA has good performance for both HV and IGD. In order to understand the experiment in many ways and facilitate observation, 3D coordinate plots and parallel coordinate diagrams of some test problems are given. Due to page limitations,Figs. 4 and 5 are three dimensional and parallel coordinates of the last generation generated on the three-objectives DTLZ7 and ten-objectives DTLZ5 by five algorithms: DVSLEA, MOEA/DD, NSGA-III, VaEA, SPEA2, and SPEA2SDE, respectively. It can be seen from Fig. 4 that the population individuals of MOEA/DD only converge in two parts of the true PF, while the population individuals of NSGA-III and SPEA2SDE are distributed in all four parts of the true PF, but there is more overlap among individuals and the convergence and distribution are poor. The best performance of DVSLEA can be seen in the Table 4 and 5.

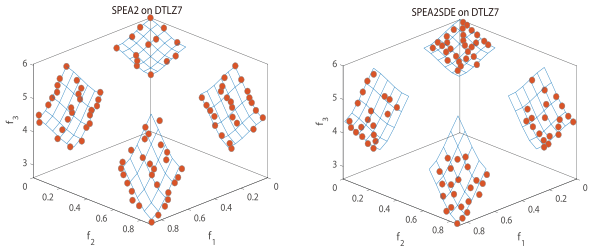
3.4. Experimental results of WFG1-9

Tables 6 and 7 show the HV and IGD means and standard deviations for the experiments with DVSLEA and the other five algorithms with the WFG test problem set at 3, 5, 8, 10 and 15 objectives, respectively. Compared with DTLZ test problems, WFG test problems are more challenging. Test problems results on the WFG1-9 test problems are summarized in 6 and 7. According to the HV results, DVSLEA shows a significant improvement over MOEA/DD, NSGA-III, VaEA, SPEA2, and SPEA2 + SDE in 42/45 ≈ 93.3%, 31/45 ≈ 68.9%, 42/45 ≈ 93.3%, 41/45 ≈ 91.1%, and 32/45 ≈ 71.1% WFG test instances, respectively. As we can see, the smallest and the largest percentage are 68.9% and 93.3%, respectively. Regarding the HV and IGD results, DVSLEA would be a competitive algorithm in handling WFG test problems. For the IGD results, as shown in Table 7, DVSLEA is competitive with other algorithms in solving WFG test problems with high-dimensional objective.

Based on the experimental results of DVSLEA in HV and IGD, DVSLEA shows a competitive advantage in the WFG test problems. Table 6 shows the HV values of the five algorithms on the WFG test problems, and we can see that DVSLEA performs best. Table 7 shows the IGD values of the five algorithms on the WFG test problems. Significantly, DVSLEA shows a

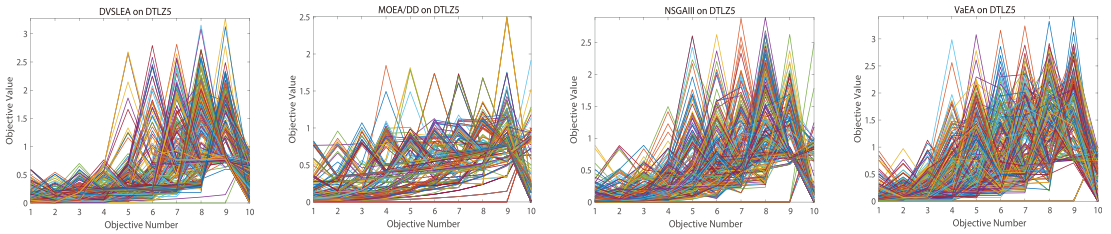


(a) DVSLEA (b) MOEA/DD (c) NSGA-III (d) VaEA

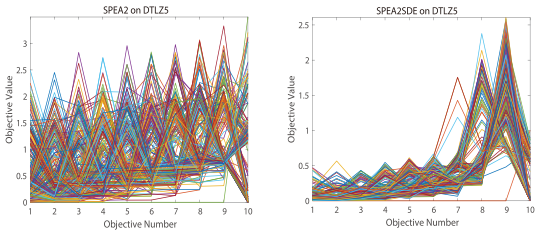


(e) SPEA2 (f) SPEA2SDE

Fig. 4. 3D coordinate diagram of DTLZ7.



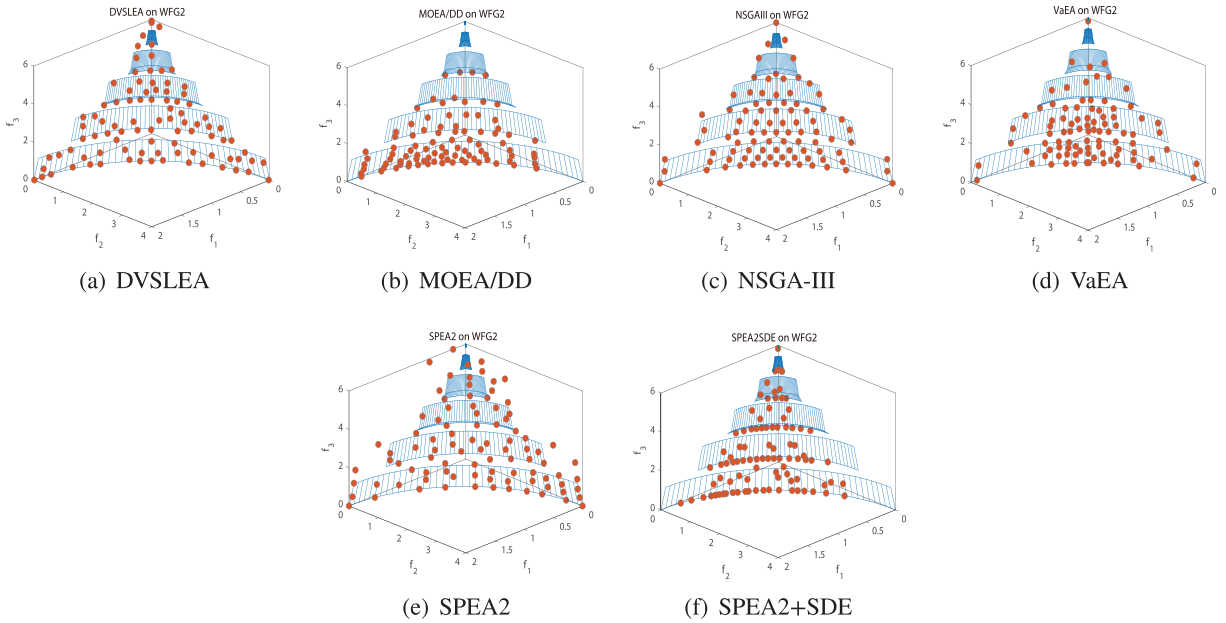
(a) DVSLEA (b) MOEA/DD (c) NSGA-III (d) VaEA



(e) SPEA2 (f) SPEA2SDE

Fig. 5. Parallel coordinates of DTLZ5 with 10 objects.

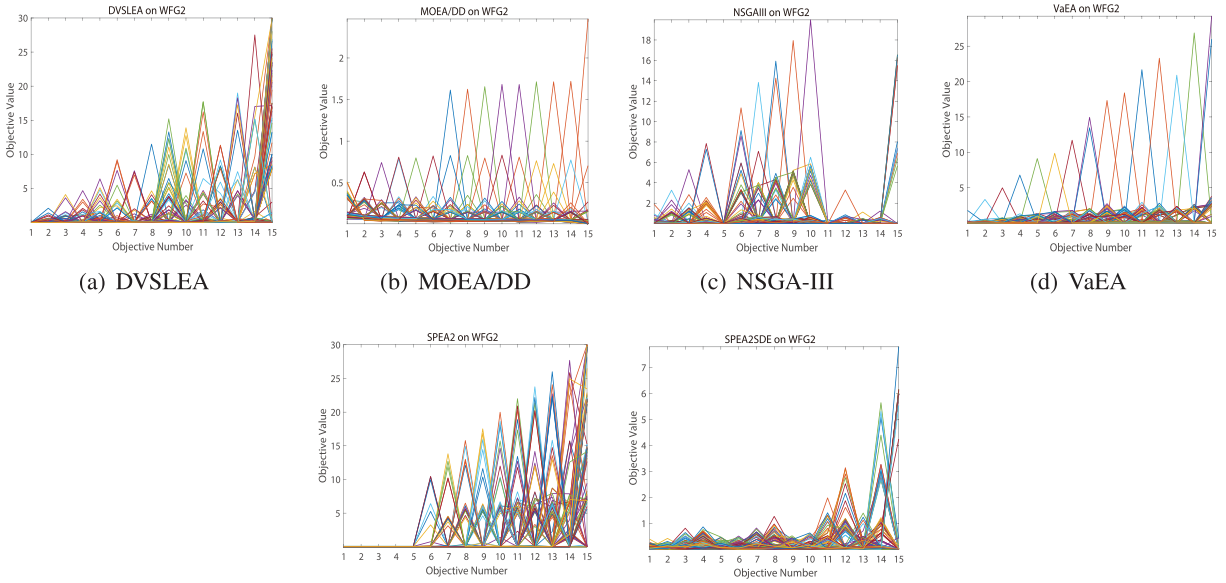
better performance in WFG1-8 test problems with high-dimensional objectives. For the concave, non-separable test problems WFG9 with deceptive and multimodal properties PF, DVSLEA achieves the best results for IGD values at 3, 5 and 10 objectives. Fig. 6 shows a parallel coordinate plot of the experimental results of the six algorithms in WFG2 with fifteen objectives. The true PF ranges for the fifteen objectives of the test problem WFG2 are roughly [0, 2 × number of objective dimensions] from the first dimension to the fifteenth dimension, roughly between 0 and 4 in the 2- dimension, and roughly between 0 and 30 in the 15- dimension. It is clear from the plot that only DVSLEA, VaEA and SPEA2 satisfy the range of objective value, while the solution set of SPEA2 does not have any objective values in the first to seventh dimensions and VaEA has most of its solutions in the range of [0, 3] in the first to fifteenth dimensions. The graph shows that DVSLEA has a better convergence and distributivity than other algorithms in covering the true PF. (See Fig. 7).



(a) DVSLEA (b) MOEA/DD (c) NSGA-III (d) VaEA

(e) SPEA2 (f) SPEA2+SDE

Fig. 6. 3D coordinate diagram of WFG2.



(a) DVSLEA (b) MOEA/DD (c) NSGA-III (d) VaEA

(e) SPEA2 (f) SPEA2+SDE

Fig. 7. Parallel coordinates of WFG2 with 15 objects.

3.5. Computational complexity analysis of DVSLEA

The computational complexity for the DVSLEA are analyzed as follows.In line2 of Algorithm 5, the normalization of solutions in union population U with 2 N solutions requires a time complexity of $O(m^2N)$, where m is the objective number and N is the population size. Then, to obtain the classification of U, the nondominated sort runs on the U in line3, which requires $O(m^2N)$. To estimate the PF shape, $O(m * |S_{nd}|)$is required to calculate the sum of the function values of each objective after normalization of each non-dominated solution, where S_{nd} denotes the number of non-dominated solutions. And $O(mN)$ is needed to run the hypercube classify process in line 10 of Algorithm 5. In Algorithm 4, positive and negative disturbance are performed on the non-dominated solutions with low crowding degree to generate N solutions in the descendant individ-

uals, which need the time complexity of $O(mNd \times max\{m, d\})$, where d is the dimension of the decision vector.For the stage of solutions selection,the time for complexity is $O(N^2 logN)$. Taking all the above calculations into account,the overall worst-case time complexity of an iteration is $max\{O(N^2 logN), O(mNd \times max\{m, d\}), O(mN^2)\}$.

4. Conclusions

In this paper, DVSLEA is proposed to solve more complex MaOPs. The algorithm focuses on two major challenges in designing many-objective optimisation algorithms: (1) how to make the population converge to the true Pareto front as far as possible; (2) how to maintain the distribution of the population during evolution. DVSLEA proposes a simple and effective method for PF shape estimation, which is classified as convex, concave and linear. Different metrics are used to calculate individual fitness values for the different types of Pareto frontal shapes estimated, and individuals with good fitness values are retained during the selection phase. By comparing Pareto dominance with the method described above for continuous screening of individuals, the convergence of the population is maintained. A new method for calculating radius distances is also proposed, where the radius calculated by DVSLEA is used to self-learn the proportion of perturbations in the decision vector that controlling the distributional variables, which plays an important role in maintaining the population's distributional properties. In our future work, we hope to improve the approximate values of radius distances currently used to more accurate values of radius distances needed for the algorithm.Later, we will be more precise in the error range between the Euclidean distance between the offspring and the original and the radius distance.

CRediT authorship contribution statement

Lei Yang: Conceptualization, Methodology. **Kangshun Li:** Supervision, Writing - original draft. **Chengzhou Zenga:** Visualization, Investigation. **Shumin Liang:** Data curation. **Binjie Zhu:** Software, Validation. **Dongya Wang:** Writing - review & editing.

Data availability

I have shared the experimental result data on the manuscript and supplement file

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was partially supported by Key Realm R&D Program of GuangDong Province with (Grant No. 2019B020219003), Natural Science Foundation of Guangdong Province of China (Grant No. 2020A1515010691), Agricultural Science and Technology Commissioner Project of Guangzhou City (Grant No. 20212100036), and National Natural Science Foundation of China (Grant Nos. 61573157 and 61703170). The authors also gratefully acknowledge the reviewers for their helpful comments and suggestions that helped to improve the presentation.

References

[1] R. Behmanesh, I. Rahimi, A.H. Gandomi, Evolutionary many-objective algorithms for combinatorial optimization problems: a comparative study, Arch. Comput. Methods Eng. 28 (2021) 673–688, https://doi.org/10.1007/s11831-020-09415-3.
[2] P.A. Bosman, D. Thierens, The balance between proximity and diversity in multiobjective evolutionary algorithms, IEEE Trans. Evolut. Comput. 7 (2003) 174–188, https://doi.org/10.1109/TEVC.2003.810761.
[3] Chen, J., Ding, J., Tan, K.C., Chen, Q., 2021. A decomposition-based evolutionary algorithm for scalable multi/many-objective optimization. Memetic Comput., 1–20.https://doi.org/10.1007/s12293-021-00330-z.
[4] Z. Chen, Y. Zhou, X. Zhao, Y. Xiang, J. Wang, A historical solutions based evolution operator for decomposition-based many-objective optimization, Swarm Evolut. Comput. 41 (2018) 167–189, https://doi.org/10.1016/j.swevo.2018.02.008.
[5] R. Cheng, Y. Jin, M. Olhofer, B. Sendhoff, A reference vector guided evolutionary algorithm for many-objective optimization, IEEE Trans. Evol. Comput. 20 (2016) 773–791.
[6] Y. Cui, Y. Sun, M. Jian, X. Zhang, T. Yao, X. Gao, Y. Li, Y. Zhang, A novel underwater image restoration method based on decomposition network and physical imaging model, Int. J. Intell. Syst. (2021).
[7] I. Das, J.E. Dennis, Normal-boundary intersection: A new method for generating the pareto surface in nonlinear multicriteria optimization problems, SIAM J. Optimiz. 8 (1998) 631–657, https://doi.org/10.1137/S1052623496307510.
[8] K. Deb, H. Jain, An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part i: solving problems with box constraints, IEEE Trans. Evolut. Comput. 18 (2013) 577–601, https://doi.org/10.1109/TEVC.2013.2281535.
[9] K. Deb, A. Pratap, S. Agarwal, T. Meyarivan, A fast and elitist multiobjective genetic algorithm: Nsga-ii, IEEE Trans. Evol. Comput. 6 (2002) 182–197, https://doi.org/10.1109/4235.996017.
[10] K. Doi, R. Imada, Y. Nojima, H. Ishibuchi, Use of inverted triangular weight vectors in decomposition-based many-objective algorithms, Asia-Pacific Conference on Simulated Evolution and Learning (2017) 321–333, https://doi.org/10.1007/978-3-319-68759-927.

[11] M.G. Dong, B. Liu, C. Jing, A many-objective evolutionary algorithm based on decomposition with dynamic resource allocation for irregular optimization, Front. Inform. Technol. Electron. Eng. 21 (2020) 1171–1190, https://doi.org/10.1631/FITEE.1900321.
[12] D. Guo, X. Wang, K. Gao, Y. Jin, J. Ding, T. Chai, Evolutionary optimization of high-dimensional multiobjective and many-objective expensive problems assisted by a dropout neural network, IEEE Trans. Syst., Man, Cybern.: Syst. (2021) 1–14, https://doi.org/10.1109/TSMC.2020.3044418.
[13] T. Han, L. Zhang, S. Jia, Bin similarity-based domain adaptation for fine-grained image classification, Int. J. Intell. Syst. (2022).
[14] Ishibuchi, H., Tsukamoto, N., Nojima, Y., 2008. Evolutionary many-objective optimization: A short review, in: 2008 IEEE Congress on Evolutionary Computation (IEEE World Congress on Computational Intelligence), pp. 2419–2426. DOI:10.1109/CEC.2008.4631121.
[15] A. Jaszkiewicz, Genetic local search for multi-objective combinatorial optimization, Eur. J. Oper. Res. 137 (2002) 50–71, https://doi.org/10.1016/S0377-2217(01)00104-7.
[16] W. Jiang, Z. Ma, S. Li, H. Xiao, J. Yang, Privacy budget management and noise reusing in multichain environment, Int. J. Intell. Syst. (2021).
[17] W. Jiang, S. Pan, C. Lu, Z. Zhao, S. Lin, M. Xiong, Z. He, Label entropy-based cooperative particle swarm optimization algorithm for dynamic overlapping community detection in complex networks, Int. J. Intell. Syst. 37 (2022) 1371–1407.
[18] K. Li, Y. Chen, W. Li, J. He, Y. Xue, Improved gene expression programming to solve the inverse problem for ordinary differential equations, Swarm Evolut. Comput. 38 (2018) 231–239.
[19] K. Li, K. Deb, Q. Zhang, S. Kwong, An evolutionary many-objective optimization algorithm based on dominance and decomposition, IEEE Trans. Evol. Comput. 19 (2014) 694–716, https://doi.org/10.1109/TEVC.2014.2373386.
[20] K. Li, Z. Liang, S. Yang, Z. Chen, H. Wang, Z. Lin, Performance analyses of differential evolution algorithm based on dynamic fitness landscape, Int. J. Cognit. Inform. Natural Intell. (IJCINI) 13 (2019) 36–61.
[21] K. Li, H. Wang, S. Li, A mobile node localization algorithm based on an overlapping self-adjustment mechanism, Inf. Sci. 481 (2019) 635–649.
[22] M. Li, S. Yang, X. Liu, Shift-based density estimation for pareto-based algorithms in many-objective optimization, IEEE Trans. Evol. Comput. 18 (2013) 348–365, https://doi.org/10.1109/TEVC.2013.2262178.
[23] R. Liu, J. Liu, R. Zhou, C. Lian, R. Bian, A region division based decomposition approach for evolutionary many-objective optimization, Knowl.-Based Syst. 194 (2020), https://doi.org/10.1016/j.knosys.2020.105518 105518.
[24] Y. Liu, D. Gong, J. Sun, Y. Jin, A many-objective evolutionary algorithm using a one-by-one selection strategy, IEEE Trans. Cybern. 47 (2017) 2689–2702.
[25] X. Ma, F. Liu, Y. Qi, X. Wang, L. Li, L. Jiao, M. Yin, M. Gong, A multiobjective evolutionary algorithm based on decision variable analyses for multiobjective optimization problems with large-scale variables, IEEE Trans. Evol. Comput. 20 (2015) 275–298, https://doi.org/10.1109/TEVC.2015.2455812.
[26] Y. Qi, X. Ma, F. Liu, L. Jiao, J. Sun, J. Wu, Moea/d with adaptive weight adjustment, Evolut. Comput. 22 (2014) 231–264.
[27] S. Qin, C. Sun, G. Zhang, X. He, Y. Tan, A modified particle swarm optimization based on decomposition with different ideal points for many-objective optimization problems, Complex Intell. Syst. 6 (2020) 263–274.
[28] J. Shen, P. Wang, H. Dong, J. Li, W. Wang, A multistage evolutionary algorithm for many-objective optimization, Inf. Sci. 589 (2022) 531–549, https://www.sciencedirect.com/science/article/pii/S0020025521013177, https://doi.org/10.1016/j.ins.2021.12.096..
[29] Su, Q., Zhang, X., Wang, H., A blind color image watermarking algorithm combined spatial domain and SVD. Int. J. Intell. Syst.
[30] F. Wang, Y. Li, A. Zhou, K. Tang, An estimation of distribution algorithm for mixed-variable newsvendor problems, IEEE Trans. Evol. Comput. 24 (2020) 479–493, https://doi.org/10.1109/TEVC.2019.2932624.
[31] F. Wang, F. Liao, Y. Li, H. Wang, A new prediction strategy for dynamic multi-objective optimization using gaussian mixture model, Inf. Sci. 580 (2021) 331–351.
[32] F. Wang, H. Zhang, A. Zhou, A particle swarm optimization algorithm for mixed-variable optimization problems, Swarm Evolut. Comput. 60 (2021) 100808.
[33] P. Wang, F. Wang, Z. Chen, Y. Dai, Aerodynamic optimization of a luxury cruise ship based on a many-objective optimization system, Ocean Eng. 236 (2021), https://doi.org/10.1016/j.oceaneng.2021.109438 109438.
[34] Y. Xiang, Y. Zhou, M. Li, Z. Chen, A vector angle-based evolutionary algorithm for unconstrained many-objective optimization, IEEE Trans. Evol. Comput. 21 (2016) 131–152, https://doi.org/10.1109/TEVC.2016.2587808.
[35] Y. Xiang, Y. Zhou, X. Yang, H. Huang, A many-objective evolutionary algorithm with pareto-adaptive reference points, IEEE Trans. Evol. Comput. 24 (2019) 99–113, https://doi.org/10.1109/TEVC.2019.2909636.
[36] H. Xiao, H. Zeng, W. Jiang, Y. Zhou, X. Tu, Hmm-tcn-based health assessment and state prediction for robot mechanical axis, Int. J. Intell. Syst. (2021).
[37] Z. Xiong, J. Yang, Z. Hu, Z. Zhao, X. Wang, Evolutionary many-objective optimization algorithm based on angle and clustering, Appl. Intell. 51 (2021) 2045–2062, https://doi.org/10.1007/s10489-020-01874-2.
[38] Yang, F., Xu, L., Chu, X., Wang, S., 2021. A new dominance relation based on convergence indicators and niching for many-objective optimization. Appl. Intell., 1–18. https://doi.org/10.1007/s10489-020-01976-x.
[39] X. Yao, Q. Zhao, D. Gong, S. Zhu, Solution of large-scale many-objective optimization problems based on dimension reduction and solving knowledge guided evolutionary algorithm, IEEE Trans. Evol. Comput. (2021).
[40] J. Yuan, H.L. Liu, F. Gu, Q. Zhang, Z. He, Investigating the properties of indicators and an evolutionary many-objective algorithm using promising regions, IEEE Trans. Evol. Comput. 25 (2020) 75–86.
[41] L. Zhang, W. Jiang, Z. Zhao, Short-text feature expansion and classification based on non-negative matrix factorization, International Conference on Machine Learning for Cyber Security, Springer (2020) 347–362.
[42] M. Zhang, L. Wang, W. Guo, W. Li, D. Li, B. Hu, Q. Wu, Many-objective evolutionary algorithm based on relative non-dominance matrix, Inf. Sci. 547 (2021) 963–983, https://www.sciencedirect.com/science/article/pii/S0020025520309713, https://doi.org/10.1016/j.ins.2020.09.061..
[43] M. Zhang, L. Wang, W. Li, B. Hu, D. Li, Q. Wu, Many-objective evolutionary algorithm with adaptive reference vector, Inf. Sci. 563 (2021) 70–90, https://www.sciencedirect.com/science/article/pii/S0020025521000347, https://doi.org/10.1016/j.ins.2021.01.015..
[44] Q. Zhang, H. Li, Moea/d: A multiobjective evolutionary algorithm based on decomposition, IEEE Trans. Evolut. Comput. 11 (2007) 712–731, https://doi.org/10.1109/TEVC.2007.892759.
[45] H. Zhao, C. Zhang, B. Zhang, A decomposition-based many-objective ant colony optimization algorithm with adaptive reference points, Inf. Sci. 540 (2020) 435–448, https://doi.org/10.1016/j.ins.2020.06.028.
[46] X. Zheng, X. Liu, Y. Zhang, L. Cui, X. Yu, A portable hci system-oriented eeg feature extraction and channel selection for emotion recognition, Int. J. Intell. Syst. 36 (2021) 152–176.
[47] X. Zheng, X. Yu, Y. Yin, T. Li, X. Yan, Three-dimensional feature maps and convolutional neural network-based emotion recognition, Int. J. Intell. Syst. 36 (2021) 6312–6336.
[48] W. Zhong, X. Hu, F. Lu, J. Wang, X. Liu, Y. Chen, A two-stage adjustment strategy for space division based many-objective evolutionary optimization, IEEE Access 8 (2020) 197249–197262, https://doi.org/10.1109/ACCESS.2020.3034754.
[49] J. Zhou, J. Zou, S. Yang, J. Zheng, D. Gong, T. Pei, Niche-based and angle-based selection strategies for many-objective evolutionary optimization, Inf. Sci. 571 (2021) 133–153.
[50] E. Zitzler, M. Laumanns, L. Thiele, Spea 2: Improving the strength pareto evolutionary algorithm, TIK-Report 103 (2001), https://doi.org/10.3929/ethz-a-004284029.

Applied Soft Computing Journal 106 (2021) 107299

Contents lists available at ScienceDirect

Applied Soft Computing Journal

journal homepage: www.elsevier.com/locate/asoc

A vector angles-based many-objective particle swarm optimization algorithm using archive

Lei Yang [a,*], Xin Hu [a], Ke Li [b]

[a] School of Mathematics and Informatics, South China Agricultural University, Guangzhou 510642, China
[b] University of Exeter, College of Engineering, Mathematics and Physical Sciences, Exeter EX4 4QF, UK

ARTICLE INFO

Article history:
Received 12 June 2020
Received in revised form 24 January 2021
Accepted 3 March 2021
Available online 16 March 2021

Keywords:
Many-objective optimization
Particle swarm optimization
Vector angle
Archive maintenance

ABSTRACT

Because of the easy implement and fast convergence speed in single objective optimization problems, the particle swarm optimization algorithm has been extended to many-objective optimization problems. When designing a many-objective particle swarm optimization algorithm, archive maintenance strategy and selection of leaders are two crucial issues. To addressing these two problems, this paper proposed a vector angles-based many-objective particle swarm optimization algorithm using archive. In this algorithm, a new method was proposed to make the external archive getting a balance between convergence and diversity, based on the values of vector angles of each solution. Also, we designed a novel strategy based on vector angle and decomposition to select *gbest* and *pbest* from the archive to promote evolution of the population. Besides, the shift-based density estimation was used as the standard to clone elite solutions to strengthen the quality of the external archive. The experiment results indicate that our algorithm has competitive performance comparing with the six state-of-the-art many-objective optimization algorithms on three widely used benchmarks DTLZ, WFG, and MaF.

© 2021 Elsevier B.V. All rights reserved.

1. Introduction

There are many optimization problems with multiple objectives in the natural sciences, social sciences, and engineering fields. When the number of objectives for these optimization problems is no more than three, they are called with multi-objective optimization problems (MOPs). Else, those problems are termed with many-objective optimization problems (MaOPs) [1]. In MaOPs, the number of objectives is large, the different objectives are mutually coupled and conflict with each other, which makes the complexity of problem-solving and searching difficulty increases sharply. With the objective numbers grows, traditional optimization algorithms based on Pareto dominance relationship has become worse and worse, because most of solutions in the population become non-dominated [2]. Looking for efficient new algorithms to solve MaOPs has become a frontier and hot spot in the field of multi-objective optimization.

Increasing the performance of one objective may degrade the performance of another objective in MOPs. Finding trade-off solutions among multiple conflicting objectives is the primary purpose in MOPs. Such a trade-off solution is achieved by finding a solution that cannot improve any objectives performance without degrading other objectives performance, known as the non-dominated solution. There may be existing multiple such non-dominated solutions for one MOP. The task of MOPs is to find a set of well-balanced solutions. This set is called non-dominated set or Pareto optimal set (PS), where the corresponding objective value in the objective space is called Pareto optimal frontier (PF). Finding an exact PF is usually not feasible, so goal of MOPs is to find approximate solutions of the true PF, making the distance to the true PF is smallest and causing solutions more dispersed. Therefore, there are two critical difficulties in solving MOPs. One is that the non-dominated solutions should be as much as possible approximating the true PF: known as convergence of the solutions. Another one is that the obtained non-dominated solutions are preferably evenly distributed over the entire PF surface: known as diversity of the solutions distribution.

In 1984, the vector-evaluated genetic algorithms (VEGA) was proposed in machine learning by David Schaffer [3]. It is the first time to accomplish a combination between evolutionary algorithm (EA) and MOPs. Since 1989, David Goldberg introduced the Pareto theory in economics to EA [4]. More and more multi-objective evolutionary algorithms (MOEAs) for dealing with MOPs have been proposed, such as NSGA-II [5] and SPEA2 [6]. These two algorithms mainly use the Pareto dominate relationship as the primary selection strategy, and it can effectively handle MOPs. But regarding MaOPs, finding a set of well trade-off solutions become harder than in MOPs, due to the traditional MOEAs based on

* Corresponding author.
E-mail address: yanglei_s@scau.edu.cn (L. Yang).

https://doi.org/10.1016/j.asoc.2021.107299
1568-4946/© 2021 Elsevier B.V. All rights reserved.

Pareto dominated relationship loss the selection pressure to make the population approach the true PF. With the target dimension increases, the difficulty of optimization increases exponentially, and the relationship between solutions becomes more strenuous to evaluate. At the same time, the complexity of the search also increases with the number of objectives increase, and it is more challenging to maintain the even distribution of solutions. Therefore, MaOPs are recognized as relatively severe research problems by the public; its difficulty in solving is more complicated than other optimization problems. However, with the rapid development of production and scientific research, more and more MaOPs have been needing to be addressed, and this made research of MaOPs become an urgent need.

To effectively handle the MaOPs, over the past few years, many researchers used different methods and techniques from different perspectives to solve critical problems in MaOPs. Those methods can mainly divide into four categories: (1) Pareto-based methods; (2) decomposition-based methods; (3) indicator-based methods; (4) other methods.

(1) Pareto-based methods: Modifying the Pareto dominance relationship is the most immediate way to handle the poor performance of traditional Pareto dominance relationships in MaOPs. In [7], a α-domination strategy is defined for handling MaOPs, and this strategy are based on the relationship between 0 and the weighted summation of the difference between objective values. In [8], a ε-dominance strategy is proposed, which objective values of each solution will be shrunk by $1-e$ times before the comparison between solutions by Pareto dominance relations. But it may conduct more difficult to judge the difference of each solution. A Grid-Based Evolutionary Algorithm (GrEA) [9] introduced grid dominance, which utilizes the grid to help the population to converge. Furthermore, some MaOEAs adopted effective maintain diversity strategy as the second selection, such as a newly shifted-based density estimation method (SDE) [10] and NSGA-III [11], which is an enhanced edition of NSGA-II by using of the reference points to maintain diversity.

(2) Decomposition-based methods: Decomposition-based algorithms are a kind of algorithms that combines mathematical programming with evolutionary algorithms. The most widely used decomposition-based algorithm is MOEA/D [12], through a set of uniformly distributed weight vectors, the MOPs are converted to multiple scalar single-objective optimization problems (SOPs) and simultaneously optimized. The MOEA/D was originally designed for solving MOPs, but a large number of decomposition-based algorithms have been proposed to solve MaOPs recently, due to its effectiveness in handling MOPs. Also, the decomposition-based methods exit drawbacks when tackling MaOPs. When solving problems with irregular Pareto front, the uniformly distribute of weight vector in Pareto front cannot be guaranteed, because it may conduct the weight vector cannot guide population evolution efficiently [13]. To solve this issue, some methods based on tuning weight vector have be investigated recently. One study by Doi [14] proposed to use inverted triangular weight vectors to reduce impacts brought by irregular Pareto front. In [15], the authors demonstrated a new method about regularly adjusting weight vector to make it cover the PF as possible as wide. Recently, Xiang et al. [16] designed a MaOEAs with adaptive references points, which is adapted by shape of current PF. In addition, a large and growing body of literature have investigated search ability of decomposition-based MaOEAs in many-objective scenario. Examples include applying WS method in a local manner in MOEA/D-LWS [17], exploiting the perpendicular distance between a solution and a weight vector in the objective space in MOEA/D-DU [18].

(3) Indicator-based methods: Hypervolume (HV) [19] is an indicator that can measure the convergence and diversity of a Pareto front approximation simultaneously. Some MOEAs use HV as the selection method of solutions, like IBEA [20] and HypE [21]. And the indicator-based algorithms have been experimentally verified to be able to deal with MaOPs [22] effectively. However, with the number of objectives increase, the computational complexities for calculating HV are significantly increased, which may hinder the use of this kind of algorithms in MaOPs. Although, some study about improving speed of HV calculation have been proposed recently [23,24], they still cannot handle MaOPs with large number of objective effectively. To date, several studies (e.g., MOMBI-II [25] and TS-R2EA [26]) employed R2 indicator [27] to replace HV as the population selection strategy to solve MaOPs. R2 indicator is similar to HV, which can simultaneously evaluate all desired aspects of a Pareto front approximation [28]. Compared to HV, calculating R2 does not require colossal time expenditure, but it requires a set of well-distributed weight vectors like used in MOEA/D. Because of weight vectors, R2-based MOEAs may face the same issue mentioned before as decomposition-based algorithms.

(4) Other methods: Apart from the above three types, there are some studies about the approaches of preference-based and dimensionality reduction. Preference-based MaOEAs [29,30] only focus on getting a subset of PF based on user's preference, which solved by variety of preference models. The dimensionality reduction approaches [31,32] give a different way to tackle MaOPs, this kinds of methods aim to reduce problem's objectives through analyze correlation between objectives to determine which objective could be reduced, but none of the objectives can be eliminated in some complex problems. Furthermore, some algorithms did not belong to the above categories, they still can solve MaOPs effectively, such as MOEA/DD [33], AnD [34], and Two_Arch2 [35]. MOEA/DD combines dominance and decomposition to balance diversity and convergence of the population. AnD use an angle-based strategy with SDE to eliminate solutions in environmental selection. Two_Arch2 have two archives which one updated by Pareto dominance, the other one updated by the indicator. In addition, there are some other types of MaOEA. Considering the research content of this paper, we will not introduce other algorithms here, interested readers can refer to the literatures [36, 37].

Particle swarm optimization originally proposed for solving SOPs, due to its fast convergence speed and easy implement in SOPs, researchers extend PSO to tackle MOPs and MaOPs [38–40]. However, there have two critical issues that need to be solved when applying PSO into MOPs/MaOPs. First one, unlike in SOPs, MOPs/MaOPs do not have an overall optimal solution. So how to select the leader is a crucial issue of MOPSO algorithm. Another one is that due to the fast speed of convergence, the diversity of population loss quickly, and this may lead to premature. To address this, majority of current MOPSOs used a external archive to keep diversity, so how to efficiently maintain diversity in external archive is another critical issue of MOPSOs. Current MOPSOs is still cannot meet the requirement of society, and it still has room for improvement in dealing with MaOPs. In this paper, we mainly focus on address the above two issues in MOPSOs, then a new MOPSO is proposed for solving MaOPs (VaPSO). The contributions of this paper can be summarized as follows:

- A novel external archive maintaining method based on vector angle is designed, effectively making a balance between diversity and convergence in the external archive and the additional time cost is relatively low.
- A new method based on vector angle and decomposition to select *gbest*, *pbest* in the external archive are proposed. Besides, the velocity update equation also had been changed to improve the performance of this algorithm.

- An SDE-based clone strategy is used to reproduce a new external archive, which can improve the quality of solutions in external archive to better guide population evolution.

The rest of this paper is organized as follows. Background knowledge are summarized in Section 2. Section 3 introduces the details of our proposed algorithms. In Section 4, systematic experiments are conducted to verify the effects of the proposed algorithm. Finally, Section 5 is conclusion of whole paper.

2. Background

2.1. Vector angle

In this paper, the vector angle is the angle between two solutions in the normalized objective space. The way to calculate the vector angle as follows. At first, objectives in all solutions should be normalized to eliminate the impacts of difference amplitudes on multiple objectives. In this paper, the normalization method is the same way as in NSGA-III [11]. The objectives normalized as follows:

$$f_i'(x) = \frac{f_i(x) - z_i^*}{\alpha_i}, \quad i = 1, 2, \ldots, m. \tag{1}$$

where $f_i(x)$ is the ith objective value of solution x, m is the number of objective, z_i^* is minimum value of the ith objective in the population P. α_i is the intercepts of each objective, which can be calculated after finding out the extreme point e_i by Achievement Scalarizing Function (ASF). The extreme point e_i is a solution with minimum value of ASF in the ith objective. The ASF is defined by the following way:

$$ASF(x_i, \omega_i) = max_{j=1}^{m} \frac{f_j(x_i) - z_j^*}{w_{i,j}} \tag{2}$$

where $\omega_i = (w_{i,1}, w_{i,2}, \ldots, w_{i,m})$ represents the axis direction of f_i, which can be calculated by following principle: if $i \neq j$, then $w_{i,j} = 0$, otherwise $w_{i,j} = 1$. A m-D hyperplane is constructed by m number of extreme points after getting all ASF values, and α_i is the intercept in the ith objective axis. Finally, through the intercepts all of the solutions can be normalized. Due to the limitation of page size, for more details about the normalization, please refer to the [11].

After the normalization, the vector angle $\angle_{x,y}$ between x and y can be calculated as follows [41]:

$$\angle_{x,y} = arccos|\frac{f'(x) \bullet f'(y)}{\|f'(x)\| \times \|f'(y)\|}| \tag{3}$$

where $\bullet$ denotes the inner product, and $\|\cdot\|$ is the L^2 norm of a solution. Obviously the $\angle_{x,y} \in [0, \frac{\pi}{2}]$. In this paper, only the vector angle in Eq. (15) is represented by degree, and the others are represented by radians.

2.2. The decomposition method

There are three popular decomposition methods adopted in multi or many-objective optimization problems, including the weighted sum, Tchebycheff, and penalty-based boundary intersection method (PBI). The decomposition method can decompose a MaOP into several subproblems and optimize them simultaneously. In this paper, we used the PBI method to select the leader to guide the population approaching true PF in each subproblem. This method is defined as follows [12]:

$$\begin{aligned} &\text{minimize} \quad g(x|\lambda, z^*) = d_1 + \theta d_2 \\ &\text{subject to} \quad x \in \Omega \end{aligned} \tag{4}$$

Algorithm 1 The general framework of VaPSO

Input: population P, population size N, external archive A, a set of weight vector $\lambda = \{\lambda_1, \lambda_2, \ldots, \lambda_N\}$
Output: Non-dominate solutions in the A

```
t = 0
[A, P] = initialize()
while t < maxgen do
    S = cloneOperation(A)
    A = archiveUpdate(A, S)
    P = PSO(A, P)
    A = archiveUpdate(A, P)
    t + 2
end while
return A
```

where

$$d_1 = \frac{\|(f'(x) - z^*)^T \lambda\|}{\|\lambda\|} \tag{5}$$

$$d_2 = \|f'(x) - (z^* + d_1 \frac{\lambda}{\|\lambda\|})\| \tag{6}$$

The z^* is defined in Eq. (1), and the λ is uniformly distributed weight vector in objective space like the same in MOEA/D [12]. The penalty factor θ is used to balance the d_1 and d_2, which represented convergence and diversity of population, respectively. It is inspiring from [42], setting proper values of θ based on the vector angle between solutions and weight vectors. It can make the population keep the right balance with convergence and diversity.

2.3. Shift-based density estimation

Shift-based density estimation (SDE) [10] is proposed to handle MaOPs. Unlike the traditional density estimation only estimated the diversity, the SDE can measure the solution's convergence and diversity simultaneously. The calculation method of SDE is also straightforward, as follows:

$$SDE(x) = \min_{y \in P, x \neq y} \sqrt{\sum_{k=1}^{m} sde(f_k'(x), f_k'(y))} \tag{7}$$

where

$$sde(f_k'(x), f_k'(y)) = \begin{cases} f_k'(x) - f_k'(y) \text{ if } f_k'(x) > f_k'(y) \\ 0 \end{cases} \tag{8}$$

where $f_k'(x)$ is the kth normalized objective of x as defined in Eq. (1).

3. The proposed approach

3.1. General framework

The pseudocode of the proposed VaPSO is shown in Algorithm 1. We can see the whole framework of VaPSO. At first, a set of uniformly distributed weight vectors should be generated by Das and Dennis's weight vector generation method [43]. In population $P(0)$ of the first turn, the position $x_i, i \in 1, 2, \ldots, m$ are initialized randomly in the feasible space Ω, and the velocity $v_i, i \in 1, 2, \ldots, m$ are initialized as 0. Moreover, the first archive $A(0)$ is placed non-dominate solutions from $P(0)$.

At the tth iteration, a new solution set S can be obtained by applying the cloning strategy to archive A. Then we used the *archiveUpdate* strategy to update the union of A and S to a new

Algorithm 2 $S = cloneOperation(A)$

Input: external archive A
Output: new temp solution set S
1: $B = A$
2: $C = \emptyset$
3: $SDEassignment(B)$
4: $sort(B)$ // sort B according to SDE distance.
5: **if** $|B| > NC$ **then**
6: $B = B[:, NC]$
7: **end if**
8: **for** $i = 1$ to $|B|$ **do**
9: calculate n_i according to (9)
10: reproduce n_i solutions of b_i then add them to C
11: **end for**
12: $S = variation(C)$
13: return S

Algorithm 3 $A = archiveUpdate(A, P)$

Input: external archive A, population P, population size N
Output: new archive A
1: $C = A \cup P$
2: $A = \emptyset$
3: $C = normalization(C)$
4: $C = computeFitness(C)$
5: $C_{nd} = selectByDominance(C)$ // only left the non-dominated solutions C_{nd} in C
6: **if** $|C_{nd}| > N$ **then**
7: $A = maxMinAngleSelection(C_{nd}, A)$
8: **else**
9: $A = C$
10: **end if**
11: return A

archive A. The leaders can be selected from A to update the population P by *PSO* search. After updating the population, continue to update the collection of P and A by using the *archiveUpdate* strategy. The above procedures are repeated until the down-time condition reached. This algorithm mainly uses three main key components: *archiveUpdate* strategy, *PSO* search process, and *cloneOperation*. In the following section, we will describe the details of the three key components.

3.2. Clone operation

From [44], it is indicated that clone operation can accelerate convergence, especially for MOP without parameter dependencies. Also the experiment in AgMOPSO [40] has shown the cloning strategy's effectiveness. Unlike AgMOPSO, this paper uses the SDE instead of the crowding-distance [5] as the standard for cloning to handle MaOPs effectively. As mention before the SDE can measure the solution's quality not only convergence but also diversity, it is suited to be used as the density estimation for clone operation. The original intention of the cloning operation is to breed solutions as good as possible according to SDE distance. This means that solutions with larger SDE distances have greater reproductive opportunities than others. Through the clone operator, making the external archive A have good diversity and convergence, to better guide the evolution of the population P in PSO, and avoiding to stuck in local optimal.

The flow of the clone operation can be seen from Algorithm 2. Suppose the number of solutions after cloning in S is N, and the number of solutions that should be used to clone is NC. Usually, the NC should be $N/5$ according to [40]. At first, copy archive A to a temporary archive B and initialize temporary archive C as empty. In each solution $b_i, i \in 1, 2, \ldots, |B|$ in B, the SDE distance should be calculated. Then NC solutions in B are selected to reproduce C. The reproduce procedures are introduced as follows:

$$C = \bigcup_{i=1}^{NC} \bigcup_{j=1}^{n_i} b_i \tag{9}$$

where b_i is the ith solution in B, and the n_i is the number of copies of b_i calculated by

$$n_i = \lceil N \times \frac{SDE(b_i)}{\sum_{j=1}^{NC} SDE(b_i)} \rceil \tag{10}$$

where $SDE(b_i)$ is the SDE distance of b_i calculated by Eq. (7).

When the new reproduced population C has generated, the evolutionary search strategy is further conducted in C. Two widely used evolutionary operator simulated binary crossover (SBX) and polynomial-based mutation (PM) [45] have been used in the VaPSO. In VaPSO, the evolutionary search strategy is the same way applied in AgMOPSO and NSGA-III. Due to page limitations, please refer to [11,40] for using this operator.

3.3. archive update

The *archiveUpdate* section decided which solutions should be placed into the archive A. The performance of this algorithm is directly related to which solutions are selected for storage in this section. So how to choose solutions with good convergence and diversity is the key to this part.

The pseudocode of the *archiveUpdate* is shown in Algorithm 3, First, the union set C of A and P (S is the same) is normalized by the function *normalization*, and how to normalize have been discussed in Eq. (1). After the *normalization* procedure, the fitness value of each solution in C is calculated as follows:

$$fit(c_j) = \sqrt{\sum_{i=1}^{m} f_i'(c_j)^2} \tag{11}$$

where $fit(c_j)$ is the jth solution's fitness value in the union set C. The fitness value is also a kind of measurement, used to judge which solution is better in convergence. Then the *selectByDominance* function is used to select the non-dominance solutions C_{nd} in C according the Pareto dominance criterion. However, most of solutions are non-dominated in MaOP [2], a new *maxMinAngleSelection* strategy has been used when Pareto dominance criterion is invalid. The *maxMinAngleSelection* strategy is mainly divided into three parts, which are described as follows.

(1) *Eliminate the DRSs*: In Pareto-based MOEA, dominance resistant solutions (DRSs) can easily appear, but it is difficult to find and eliminate them in time, thereby reducing the performance of the evolutionary algorithm. DRS can be defined as (i) DRSs are extremely inferior to others in at least one objective, therefore they are far from Pareto optimal; (ii) solutions that dominate a DRS are scarcely found [7]. Such solutions generally do not have substantial help for the evolutionary process even bring disadvantages. So, identifying DRSs and eliminating them will improve the performance of MaOEA methods. As described in Algorithm 4 (line 1–8), the DRSs will be eliminated firstly according to the normalized objective values. According to [16], the solution with the normalized objective value larger than 1 can be deemed as dominance resistant solutions (DRSs). The DRSs usually have a terrible performance of convenience, which is far-away from the true PF. In the light of [16], if the number of C_{nd} is larger than N, It is necessary to remove DRSs in C_{nd} when

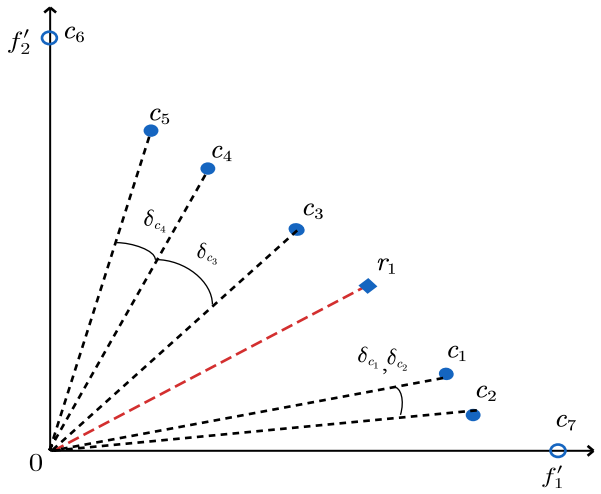


Fig. 1. Illustration of remove the minimum vector angle solution.

experiments on problems with a vast local optimal PF such as DTLZ1 and DTLZ3 [46].

(2) *Remove solutions with minimum vector angle*: Before the elimination procedure starts, the angle $\angle_{c_i,c_j}$ of every two solutions in the C_{nd} should be calculated and stored in the matrix $M_{|C_{nd},C_{nd}|}$. In this way, the algorithm does not need to recalculate the angle each time when deletes or adds any solutions. Then, the minimum vector angle δ_{c_i} of each solution in C_{nd} can be calculated easily with the help of angle matrix M. We assume the c_k has a minimum angle solution with c_j in C_{nd}, the c_k is defined as a partner of c_j denotes as $c_k = \mu(c_j)$. The mathematical definition of δ_{c_k} and $\mu(c_k)$ are as follows:

$$\mu(c_k) = c_j, \quad j = \underset{s=1,s\neq k}{\overset{|C_{nd}|}{argmin}}(\angle(c_j, c_s)|c_s \in C_{nd}) \tag{12}$$

$$\delta_{c_k} = \underset{s=1}{\overset{|C_{nd}|}{min}}(\angle(c_k, c_s)) \tag{13}$$

where the $\angle(c_k, c_s)$ is the vector angle between c_k and c_s calculated by Eq. (3). While two solutions have a small vector angle, it is indicated those two solutions have similar search directions. If existing too many solutions with similar search direction in the population, it will not only slow the search speed of the algorithm but also waste precious computing resources. So the strategy in this part was designed to remove solutions in the external archive according to the minimum vector angle. In line (11–20) of Algorithm 4, it demonstrates the process of deleting the minimum angle individually. First, m extreme solutions should be added into archive A (A was empty before this operation). The extreme solutions in C_{nd} are defined as solutions that have the minimum angle to m vectors $(1, 0, \ldots, 0), (0, 1, \ldots, 0), \ldots, (0, 0, \ldots, 1)$ reference to [41]. The extreme solutions are represented by e_i. The extreme solutions are a bit like the boundary solution in NSGA-II [5]. Whether it is an extreme solution in VaPSO or a boundary solution in NSGA-II, the area around them is a potential area that should be searched. However, extreme solutions maybe have a bad convergence; it may affect the algorithm's performance. The above step has removed the DRSs; hence, the influence of the convergence may be alleviated.

After adding extreme solutions to archive A, the algorithm begins to delete solutions in C_{nd} with the minimum vector angle. Similar to [47], in all solutions pairs of C_{nd} we choose a pair of solutions c_k and c_j with a minimum δ_{c_k}, c_j is $\mu(c_k)$. Then select an solution with weak convergence from this pair according to fitness value calculated by Eq. (11). The above procedure will

Algorithm 4 $A = maxMinAngleSelection(C_{nd}, A)$

```
1: while |C_nd|> N do
2:   [MaxV, c_ind] = findMax(C_nd)   // find the maximum objective value Max and its corresponding solution c_ind in C_nd
3:   if MaxV > 1 then
4:     remove(c_ind)   // remove the c_ind from C_nd
5:   else
6:     break
7:   end if
8: end while
9: if |C_nd|> N then
10:  A ∪ e_i, i ∈ 1, 2, ..., m   // add m extreme solution e_i to A
11:  while |C_nd|< 0.9N − m do
12:    [c_k, c_j] = findMinAngle(C_nd)   // find two solutions c_k and c_j with a minimum δ_{c_k} in C_nd
13:    if fit(c_k) < fit(c_j) then
14:      R = R ∪ c_j
15:      remove(c_j)   // remove the c_j from C_nd
16:    else
17:      R = R ∪ c_k
18:      remove(c_k)   // remove the c_k from C_nd
19:    end if
20:  end while
21:  A = A ∪ C_nd
22:  while |A|< N do
23:    r_k = findMaxAngle(A, R)   // find the solution r_k with a maximum δ_{r_k} in R
24:    A = A ∪ r_k
25:    remove(r_k)   // remove the r_k from R
26:  end while
27: end if
28: return A
```

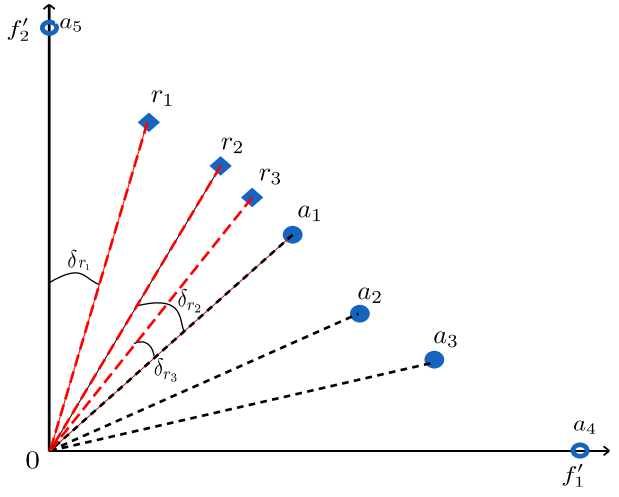


Fig. 2. Illustration of add the maximum vector angle solution.

repeat until the number of C_{nd} reach $0.9N - m$ (there are already m extreme solutions in the A). Finally, all the removed solutions deleted from C_{nd} are migrated to the removed set R and combining A and C_{nd}. As shown in Fig. 1, one of the solution should be selected from c_1 and c_2 to delete due to the δ_{c_1} is minimum.

(3) *Add solutions with maximum vector angle*: As shown in Fig. 2, the diamond point ♦ represents the solutions in R, and both the solid circles • and hollow circles ∘ points belong to A. The better distributed solution r_1 was deleted in the above steps.

This situation indicates that some well-distributed solutions may be deleted. For this reason, the VaPSO will give the deleted solutions in R another chance to put it back into A. The process of *adding the maximum solution* is relatively simple as follows. Find the solution with maximum δ_{r_i}. The δ_{r_i} is minimum vector angle between r_i and a_j calculated as follows:

$$\delta_{r_i} = \min_{j=1}^{|A|}(angle(r_i, a_j)), \quad i = 1, 2, \ldots, |R| \tag{14}$$

where the $r_i \in R$, $a_j \in A$. Different with δ_{c_j} in Eq. (13), the δ_{r_i} is the minimum vector angle of each solutions between R and A. Then, the index of solution r_k with maximum δ_{r_i} can be find easily as follows: $k = argmax(\delta_{r_i}), i \in 0, 1, \ldots, |R|$. At last, some solutions with proper diversity will be put back into A, so the r_1 in Fig. 2 will put into A due to δ_{r_2} is bigger than δ_{r_1} and δ_{r_3}. Verification of this process through Section 4.6 of the experiment can make the final result of the algorithm have a better convergence and diversity.

3.4. PSO-based search

The population P are updated by the *PSO* method. In this method, the *pbest* and *gbest* are needed to be found before updating the position information of solutions. In MOPs, solutions cannot be compared directly by the values of a single objective, but comparing by Pareto dominate relationships is feasible. However, in MaOPs most of the solutions are non-dominated that made how to select suitable solutions as *pbest* and *gbest* to update the population getting harder. Here a novel velocity update strategy and selection of *pbest* and *gbest* is proposed to handle the above situation. The pseudocode of the *PSO* method is shown Algorithm 5. Just like the general PSO is divided into three parts: the selection of *pbest* and *gbest*, update the velocities and update the positions(line 2–4 of Algorithm 5). Next, we will explain the details of each step above.

(1) Selection of *pbest* and *gbest*: Inspiration from [42], a proper penalty factor θ, found by the adaptive PBI selection method, can balance diversity and convergence of population properly. The adaptive PBI selection method is used to select *pbest* with a minimum PBI value in each subproblem. It is well-known that a large θ encourages diversity. Conversely, a small θ promotes convergence. The penalty factor θ_i for subproblem i is calculated as follows:

$$\theta_i = k \times \angle(p_i, \lambda_i) \quad i \in 1, 2, \ldots, N \tag{15}$$

where k is a scaling parameter and the $\angle(p_i, \lambda_i)$ is the vector angle between p_i and λ_i; N is the population size. The vector angle $\angle(p_i, \lambda_i)$ in this formula is measured by degrees. It is obvious that the vector angle is normalized to $[0°, 90°]$.

Fig. 3 illustrates the selection of *pbest*. The solid circles ● and triangles ▲ represent the solutions in P and A respectively, and the λ_1 and λ_2 is the weight vector. The vector angle $\angle(p_1, \lambda_1)$ between p_1 and λ_1 is relatively small, which means the solution p_1 have a good diversity. According the value of θ_1 calculated by Eq. (15), PBI values of each solution $A(a_1, a_2, \ldots, a_5)$ with λ_1 is calculated by Eq. (4). The p_1 has a good diversity, and now convergence should be considered at first. Choosing the a_3 as the $pbest_1$ to guide p_1 according to the value of PBI, instead of a_2 which maybe have a better diversity. In the same way, diversity is the first consideration because of lack of it in p_2. So the a_5 should be selected as the $pbest_2$, not the a_4 which may have a good convergence instead of the diversity which is needed. As mentioned before, there are not exist a overall optimal in MaOP. In view of this situation, the solution in A which is closed to λ_i will be picked as $gbest_i$ to improve diversity. In Fig. 3, the a_2 and a_5 will be picked as $gbest_1$ and $gbest_2$ respectively. In some cases, the

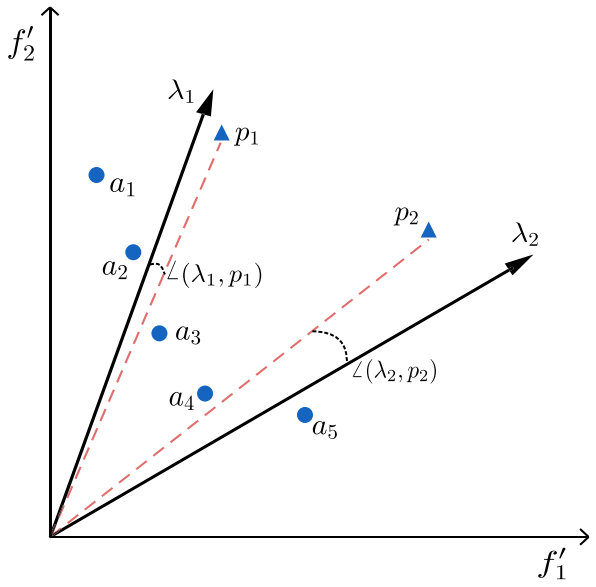


Fig. 3. Illustration of selection of *pbest* in bi-objective scenario.

Algorithm 5 $A = PSO(A, P)$

Input: population P, external archive A, population size N
Output: a new population P
1: **for** $i = 1$ to N **do**
2: select the $pbest_i$ by using adaptive PBI method in A
3: select the $gbest_i$ based on vector angle in A
4: update the velocity v_i by Eq. (16)
5: update the position x_i by Eq. (19)
6: **end for**
7: return P

$gbest_i$ and $pbest_i$ are equal, indicated it can give a search direction with both diversity and convergence simultaneously.

(2) Update the velocities and positions: After finding the $pbest_i$ and $gbest_i$, the velocity v_i is updated as follows:

$$\begin{aligned} v_i(t+1) = {} & \omega v_i(t) + cr_1(x_{pbest_i}(t) - x_i(t)) \\ & + sgn(fit(gbest_i) - fit(p_i))F_i r_2(x_{gbest_i}(t) - x_i(t)) \end{aligned} \tag{16}$$

where x_i is the position information of ith solution in P; r_1 and r_2 are two random number evenly distributed in $[0, 1]$; ω is the initial weight; c is called learning factor; t indicates the number of iteration; F_i balanced search direction around both $pbest_i$ and $gbest_i$, the F_i is worked out as follows:

$$F_i = \frac{\frac{\pi}{2} - \angle(gbest_i, \lambda_i)}{\frac{\pi}{2}} + \frac{fit(pbest_i)}{fit(gbest_i)} \tag{17}$$

The F_i can divide into two part, the first part is main control the diversity and the last part is concern about convergence. In the first part of F_i, the $\angle(gbest_i, \lambda_i)$ is normalized to $[0, 1]$ for measure the diversity. And the last part, it is the ratio of the fitness of $pbest_i$ and $gbest_i$. The larger the F_i indicated the better convergence and diversity of $gbest_i$, and the solution p_i can learn more information from $gbest_i$ according to Eq. (16). And the $sgn(fit(gbest_i) - fit(p_i))$ is expressed as follows:

$$sgn(fit(gbest_i) - fit(p_i)) = \begin{cases} 1 & \textbf{if } fit(gbest_i) - fit(p_i) > 0 \\ -1 & \textbf{if } fit(gbest_i) - fit(p_i) < 0 \end{cases} \tag{18}$$

According to Eq. (16), the overall search direction was mainly affected by $pbest_i$ and $gbest_i$. The branch search direction of $gbest_i$ is mainly controlled by $fit(gbest_i) - fit(p_i)$, tended to diversity

Table 1
Setting of the population size N and H_1, H_2 parameter of weight vector.

m	H_1, H_2	NSGA-III VaEA	Others
5	5,0	126	126
8	3,2	156	156
10	3,2	276	275
15	2,1	136	135

instead of convergence. If the fitness of $gbest_i$ is bigger than p_i's, it indicates p_i is closer to PF than $gbest_i$, so the branch search direction is from $gbest_i$ to p_i. Otherwise, a opposite direction will be searched.

When the above step finished, the position information of x_i is updated as follows:

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{19}$$

When the positions in some dimensions fly out to the boundary, it will be converted into the boundary, and the velocity will be reset as 0 on the corresponding dimension.

3.5. Algorithm time complexity analysis

This section analyzes the main time complexity of VaPSO at one generation. The *SDEassignment* procedure (line 3 of Algorithm 3) deal with a archive with N solutions having m objectives requires $O(mN^2)$ multiplications. In *archiveUpdate*, the *normalization* and *computeFitness* (line 3 and 4 in Algorithm 3) both need $O(mN^2)$ additions. The time complexity of *selectByDominance* (line 5 in Algorithm 3) is $O(mN^2)$. For the remove and add solutions procedure (line 11–27 in Algorithm 4) require $O(mN^2)$ and $O(N^2 \log N)$ [47] respectively. In summary, the general time complexity of one generation of VaPSO is $max(mN^2, N^2 \log N)$.

4. Experimental study

4.1. Test problem

To test the performance of our proposed algorithm, seven test problems from the DTLZ test suite (DTLZ1 to DTLZ7) [5], nine test problems from the WFG test suite (WFG1 to WFG9) [48], and seven test problems from the MaF test suite (MaF1 to MaF7) [49] have been selected as the test problems. According [5,48], and [49], and the above problems have linear, convex, concave, mixed, degenerated, discontinuous, or scaled PF, that make it extremely difficult for the algorithm to find final solutions with good diversity and convergence. For each DTLZ, WFG, and MaF problem, the number of objectives is set as $m \in \{5, 8, 10, 15\}$. As suggest in [5], the number of decision variables is set as $n = m + r - 1$ for all DTLZ problems, where $r = 5$ for DTLZ1, $r = 20$ for DTLZ7, and $r = 10$ for others. According recommendation from [48], the number of decision variables is set to $n = k + l$, where the position variables $k = 2 \times (m - 1)$ and the distance-related variables $l = 20$ for all WFG problems. About the MaF problems, the number of decision variables is set by $n = m+k-1$, where k is set to 10 for MaF1 to MaF6 and to 20 for MaF7, as suggested by its author [49].

4.2. Performance measures

According to the [50], each indicator has its own optimal distribution type for each Pareto front. Inverted generational distance (IGD) [51], hypervolume (HV) [52], and IGD plus (IGD+) [53] are widely used indicators to measure performance of MaOEAs. Comparing with IGD and IGD+, the calculation process of HV did not need the reference points on the real Pareto front but requiring a substantial time consumption. IGD+ is a weakly Pareto compliant version of IGD, but it is not always as a good indicator to evaluate the uniformity of solutions [54]. To limit the influence about indicator in our experiments, both of three indicators was used to measure performance in our experimental study.

The IGD indicator measures the average distance between the final solutions obtained by the algorithm and reference points on the true Pareto front, which are calculated as follows:

$$IGD(A, P^*) = \frac{\sum_{x \in P*} min_{a \in A}(distance(x, a))}{|P^*|} \tag{20}$$

where A is the final approximated solution set obtained by algorithms; P^* is the reference points on the true Pareto front; $distance(x, A)$ is the Euclidean distances between x and the point from A. The biggest drawback of IGD is that it needs the reference points. The number of reference points also impacts the performance of IGD. The formula for calculating IGD+ is similar with IGD, the only difference is how to calculate *distance* in Eq. (20). The distance in IGD+ is calculated by using following function: $distance_{IGD+}(x, a) = \sqrt{\sum_{i=1}^{m} (\max(a_i - r_i, 0))^2}$. The more reference points, the more accurate the calculation of IGD and IGD+, but the time complexity will be increased. To balance the time complexity and accuracy, 200,000 reference points were generated by [55,56] to measure the IGD and IGD+ in the experiments.

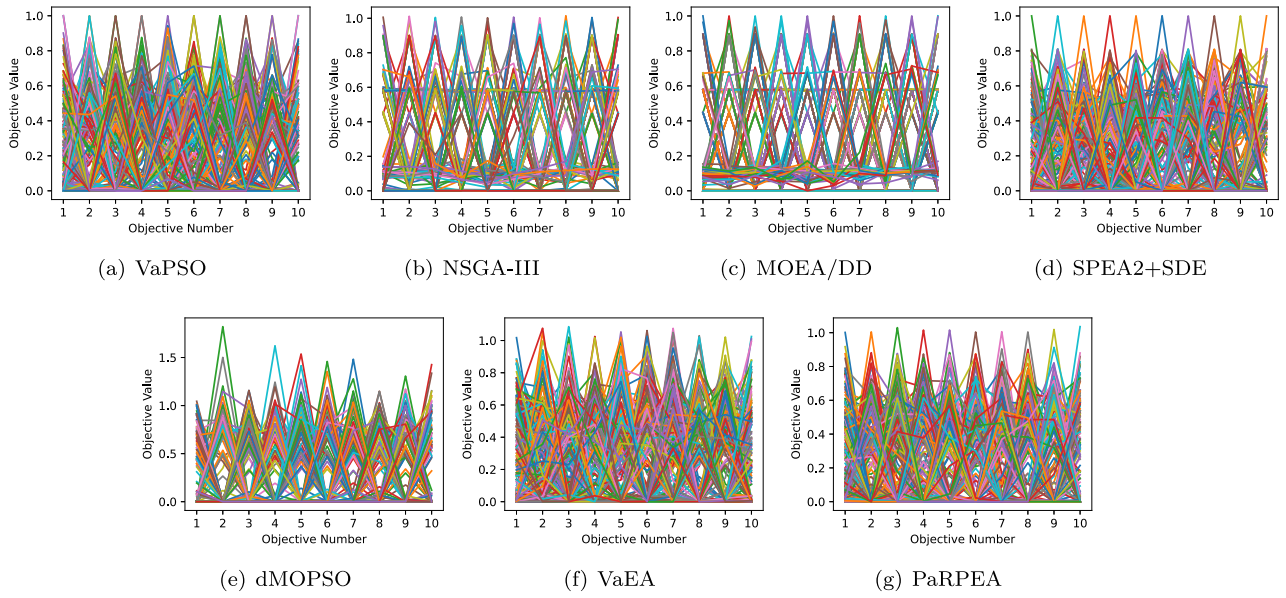
The HV indicator measures the size of the objective space, which is dominated by the obtained final solutions. Let $z = z_1, z_2, \ldots, z_m$ be the reference point dominated by all the Pareto optimal points, and the HV is calculated as follows:

$$HV(A, z) = Lebesgue(\bigcup_{x \in A}[f_1(x), z_1], \times, \ldots, [f_m(x), z_m]) \tag{21}$$

where $Lebesgue(\cdot)$ is the Lebesgue measure. Before the calculation of HV, the objective values of final solutions in all test problems are normalized by the $1.1 \times (f_1^{max}, f_2^{max}, \ldots, f_m^{max})$, where $f_i^{max} (i \in 1, 2, \ldots, m)$ is the maximum value of ith objective in the real Pareto front, then, the reference point is set as $[1, 1, \ldots, 1]$. In this work, the recently proposed method [23] to calculate HV is used when the number of objectives no more than eight. To save the computing resource, the approximate value of HV is calculated by the Monte Carlo method with $1,000,000$ sample points when the number of objectives is more than eight.

4.3. Competitor algorithms

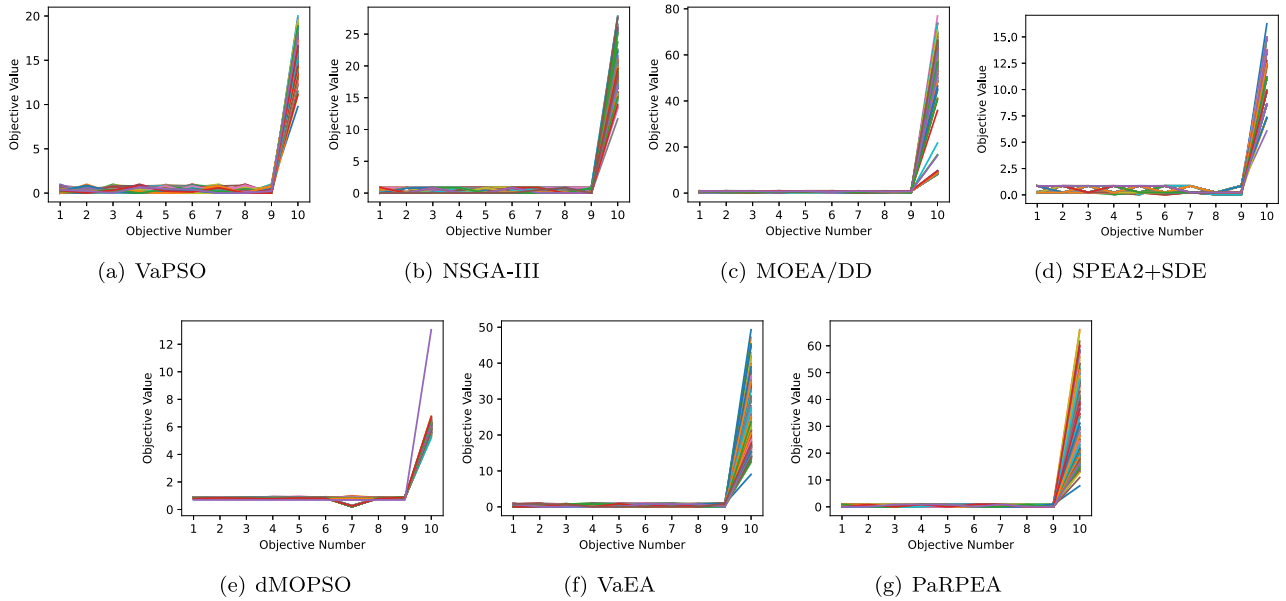
In this work, six state-of-the-art algorithms are used to study the performance of VaPSO, i.e., NSGA-III [11], MOEA/DD [33], SPEA2+SDE [10], dMOPSO [57], VaEA [41], PaRPEA [16]. NSGA-III uses reference points to manage the diversity of population and provide guidance for the evolutionary direction of the population. MOEA/DD combines the advantages of Pareto dominance and decomposition. SPEA2+SDE is an algorithm for replacing the original density estimator by SDE in the classic Pareto-based algorithm SPEA2. The decomposition method is used to selection of leaders in dMOPSO [57]. VaEA [41] is an algorithm based on the vector angle for environmental selection. PaEPEA can dynamically adjust reference points dynamically based on the type of current PF shape. The VaPSO is implemented by a well-known framework called jMetal [58], and the source code of VaPSO and true Pareto front can be find on https://github.com/Gxinhu/VaPSO.



(a) VaPSO (b) NSGA-III (c) MOEA/DD (d) SPEA2+SDE

(e) dMOPSO (f) VaEA (g) PaRPEA

Fig. 4. The parallel coordinates of final results obtained by seven algorithms on the ten-objective DTLZ4 with the median HV value.



(a) VaPSO (b) NSGA-III (c) MOEA/DD (d) SPEA2+SDE

(e) dMOPSO (f) VaEA (g) PaRPEA

Fig. 5. The parallel coordinates of final results obtained by seven algorithms on the ten-objective DTLZ7 with the median HV value.

Table 2
Parameter settings of all the compared algorithm.

Algorithm	Parameter settings
NSGA-III	$p_c = 1.0, p_m = 1/D, \eta_c = 30, \eta_m = 20$
MOEA/DD	$p_c = 1.0, p_m = 1/D, \eta_c = 30, \eta_m = 20, T = 20, \delta = 0.9$
SPEA2 + SDE	$p_c = 1.0, p_m = 1/D, \eta_c = 30, \eta_m = 20$
dMOPSO	$\omega \in [0.1, 0.5], c_1, c_2 \in [1.5, 2.0]$
VaEA	$p_c = 1.0, p_m = 1/D, \eta_c = 30, \eta_m = 20$
VaPSO	$p_c = 1.0, p_m = 1/D, \eta_c = 30, \eta_m = 20, \omega \in [0.1, 0.5], c \in [1.5, 2.0], k = 0.06$
PaRPEA	$p_c = 1.0, p_m = 1/D, \eta_c = 30, \eta_m = 20$

4.4. Parameter setting

The population size and number of weight vectors are presented in Table 1. For test problems with 8, 10, and 15 objectives, the two-layer generation method is applied to generate weight vectors [11]. H_1 and H_2 are two integer parameters, representing the number of divisions for boundary layer and inside layer, respectively. According to [11], the population size of NSGA-III must

Table 3
IGD comparison of the seven algorithms on DTLZ and WFG problems.

Problem	M	VaPSO	NSGA-III	MOEA/DD	SPEA2+SDE	dMOPSO	VaEA	PaRPEA
DTLZ1	5	6.032e−02(6.2e−04)	6.570e−02(2.2e−03)+	6.509e−02(1.1e−04)+	5.665e−02(7.1e−04)−	6.314e−02(1.7e−03)+	6.180e−02(1.1e−03)+	6.068e−02(5.7e−04)+
	8	9.504e−02(3.9e−03)	9.571e−02(8.1e−04)+	9.418e−02(2.0e−04)≈	8.881e−02(7.3e−04)−	1.303e−01(1.3e−02)+	1.023e−01(7.0e−03)+	9.910e−02(6.7e−03)+
	10	1.055e−01(7.1e−03)	1.064e−01(7.6e−04)+	1.017e−01(3.1e−04)−	9.646e−02(3.4e−04)−	1.823e−01(1.4e−02)+	1.242e−01(1.7e−02)+	5.830e−01(1.1e+00)+
	15	1.558e−01(1.9e−02)	1.777e−01(3.4e−03)+	1.662e−01(2.0e−03)+	1.291e−01(1.1e−03)−	1.854e−01(1.5e−02)+	1.541e−01(9.2e−03)≈	4.578e+00(3.5e+00)+
DTLZ2	5	1.938e−01(1.3e−03)	2.033e−01(6.4e−05)+	2.033e−01(1.8e−06)+	2.207e−01(2.2e−03)+	2.129e−01(2.0e−03)+	1.958e−01(1.1e−03)+	1.957e−01(1.5e−03)+
	8	3.544e−01(2.3e−03)	3.463e−01(1.9e−04)−	3.449e−01(3.0e−05)−	3.788e−01(3.3e−03)+	3.593e−01(3.9e−03)+	3.711e−01(3.0e−03)+	3.686e−01(2.9e−03)+
	10	3.955e−01(1.4e−03)	4.049e−01(5.2e−04)+	4.025e−01(2.2e−04)+	4.124e−01(1.5e−03)+	4.071e−01(2.5e−03)+	4.225e−01(3.5e−03)+	4.095e−01(2.7e−03)+
	15	5.910e−01(3.7e−03)	5.992e−01(1.8e−03)+	5.947e−01(1.1e−03)+	6.204e−01(4.4e−03)+	6.128e−01(5.4e−03)+	6.120e−01(2.7e−03)+	6.081e−01(2.7e−03)+
DTLZ3	5	1.937e−01(1.6e−03)	2.100e−01(9.4e−03)+	2.038e−01(5.6e−04)+	2.230e−01(1.2e−02)+	2.155e−01(5.3e−03)+	1.978e−01(2.9e−03)+	1.970e−01(2.2e−03)+
	8	6.533e−01(6.9e−01)	4.581e−01(3.6e−01)≈	3.473e−01(2.1e−03)−	3.962e−01(1.8e−02)≈	4.791e−01(5.3e−02)≈	2.353e+00(1.4e+00)+	6.569e−01(1.2e+00)≈
	10	7.143e−01(5.1e−01)	5.395e−01(3.8e−01)≈	4.034e−01(2.1e−03)−	4.261e−01(1.4e−02)≈	6.647e−01(5.4e−02)≈	9.958e+00(5.5e+00)+	2.094e+00(6.3e+00)≈
	15	1.295e+00(9.2e−01)	7.051e−01(2.0e−01)−	6.045e−01(3.6e−03)−	6.387e−01(1.1e−02)−	7.522e−01(4.5e−02)−	1.060e+01(6.7e+00)+	6.282e−01(5.8e−03)−
DTLZ4	5	1.975e−01(1.8e−03)	2.033e−01(5.0e−05)+	2.033e−01(1.2e−06)+	2.690e−01(8.7e−02)+	3.082e−01(1.8e−02)+	1.976e−01(1.1e−03)≈	1.980e−01(1.7e−03)+
	8	3.603e−01(1.8e−03)	3.459e−01(2.9e−04)−	3.450e−01(9.3e−05)−	3.833e−01(2.7e−02)+	4.796e−01(1.3e−02)+	3.687e−01(2.0e−03)+	3.615e−01(2.1e−03)+
	10	4.022e−01(8.8e−04)	4.031e−01(5.2e−04)+	4.025e−01(3.0e−04)+	4.103e−01(1.4e−03)+	5.270e−01(1.4e−02)+	4.293e−01(5.2e−03)+	4.048e−01(1.6e−03)+
	15	6.040e−01(2.8e−03)	6.029e−01(1.7e−03)−	6.002e−01(2.2e−03)−	6.140e−01(1.2e−02)+	6.849e−01(8.2e−03)+	6.134e−01(3.1e−03)+	5.997e−01(2.2e−03)−
DTLZ5	5	7.920e−02(1.4e−02)	1.892e−01(6.7e−02)+	1.212e−01(1.3e−02)+	6.769e−02(1.3e−02)−	3.157e−02(2.7e−04)−	1.032e−01(1.8e−02)+	1.733e−01(4.1e−02)+
	8	1.177e−01(2.6e−02)	3.208e−01(7.8e−02)+	1.745e−01(1.1e−02)+	1.161e−01(2.0e−02)≈	2.419e−02(4.7e−04)−	3.307e−01(1.1e−01)+	1.180e+00(3.6e−01)+
	10	1.021e−01(1.9e−02)	4.000e−01(1.1e−01)+	1.506e−01(1.8e−02)+	1.439e−01(2.3e−02)+	1.849e−02(1.9e−04)−	6.582e−01(4.1e−01)+	1.954e+00(2.2e−01)+
	15	1.601e−01(3.0e−02)	2.602e−01(8.2e−02)+	1.529e−01(6.5e−03)≈	1.634e−01(3.0e−02)+	9.567e−02(4.2e−04)−	5.431e−01(1.8e−01)+	1.711e+00(3.4e−01)+
DTLZ6	5	9.973e−02(3.0e−02)	1.821e+00(1.4e−01)+	2.980e−01(3.3e−02)+	8.991e−02(1.5e−02)−	3.203e−02(1.3e−05)−	3.543e+00(2.4e−01)+	1.726e+00(6.1e−01)+
	8	1.200e−01(2.9e−02)	3.938e+00(2.3e−01)+	9.087e−01(3.8e−02)+	1.961e−01(2.4e−02)+	2.433e−02(6.8e−06)−	6.614e+00(4.9e−01)+	9.659e+00(3.4e−01)+
	10	1.010e−01(3.2e−02)	5.442e+00(2.5e−01)+	1.537e+00(4.9e−02)+	3.264e−01(2.3e−02)+	1.889e−02(2.9e−04)−	7.214e+00(5.8e−01)+	9.851e+00(7.8e−02)+
	15	1.438e−01(5.4e−02)	4.367e+00(3.0e−01)+	6.931e−01(2.2e−02)+	2.744e−01(4.0e−02)+	9.573e−02(5.9e−06)−	5.759e+00(9.1e−01)+	9.939e+00(1.1e−01)+
DTLZ7	5	2.657e−01(7.5e−03)	3.184e−01(9.9e−03)+	5.553e−01(1.1e−02)+	2.841e−01(7.5e−02)≈	6.534e−01(1.2e−02)+	3.288e−01(7.6e−03)+	3.268e−01(8.4e−03)+
	8	6.399e−01(1.7e−02)	8.125e−01(3.8e−02)+	1.569e+00(1.1e−01)+	7.406e−01(2.2e−02)+	1.873e+00(7.2e−03)+	7.033e−01(1.3e−02)+	8.239e−01(7.8e−02)+
	10	9.766e−01(7.8e−02)	1.236e+00(1.3e−01)+	1.799e+00(2.5e−01)+	9.371e−01(3.1e−02)−	2.152e+00(2.3e−01)+	1.045e+00(5.7e−02)+	1.245e+00(6.2e−02)+
	15	3.561e+00(7.2e−01)	8.030e+00(9.8e−01)+	3.761e+00(1.2e+00)≈	1.553e+00(4.2e−02)−	4.007e+00(1.3e+00)+	2.501e+00(2.7e−01)−	2.889e+00(4.8e−01)−
WFG1	5	1.295e+00(1.6e−01)	1.381e+00(1.2e−01)+	1.061e+00(1.1e−01)−	8.807e−01(2.6e−02)−	1.962e+00(1.5e−02)+	1.405e+00(1.2e−01)+	1.533e+00(1.4e−01)+
	8	1.846e+00(2.6e−01)	1.372e+00(8.4e−02)−	1.720e+00(1.0e−01)−	1.189e+00(3.4e−02)−	2.546e+00(1.2e−02)+	1.273e+00(6.0e−02)−	1.592e+00(1.5e−01)−
	10	2.076e+00(2.8e−01)	1.717e+00(9.8e−02)−	2.474e+00(8.5e−02)+	1.414e+00(4.8e−02)−	2.895e+00(1.3e−02)+	1.606e+00(7.1e−02)−	1.744e+00(1.1e−01)−
	15	1.573e+00(9.9e−02)	1.758e+00(3.1e−02)+	2.081e+00(7.2e−02)+	2.012e+00(8.9e−02)+	3.710e+00(4.0e−02)+	1.730e+00(4.1e−02)+	1.618e+00(3.2e−02)+
WFG2	5	6.974e−01(2.3e−01)	6.416e−01(3.4e−01)≈	6.274e−01(2.9e−01)≈	8.553e−01(3.9e−01)+	6.717e−01(3.9e−02)≈	6.861e−01(3.9e−01)≈	1.050e+00(3.8e−01)+
	8	9.218e−01(1.4e−01)	1.171e+00(6.9e−01)≈	1.013e+00(4.4e−01)≈	1.100e+00(6.7e−01)≈	1.132e+00(3.9e−02)+	8.991e−01(4.5e−01)−	1.252e+00(6.3e−01)+
	10	9.364e−01(8.9e−02)	1.453e+00(9.5e−01)+	1.091e+00(2.6e−02)+	1.438e+00(9.9e−01)+	1.458e+00(6.1e−02)+	1.032e+00(4.5e−01)+	1.181e+00(4.4e−01)+
	15	1.894e+00(2.8e−01)	4.156e+00(1.9e+00)+	1.882e+00(7.0e−01)≈	2.437e+00(1.6e+00)≈	2.155e+00(9.9e−02)+	2.564e+00(1.8e+00)≈	2.096e+00(9.4e−01)≈
WFG3	5	6.325e−01(1.4e−01)	5.017e−01(9.7e−02)−	7.356e−01(5.0e−02)+	7.350e−01(1.6e−01)+	7.307e−01(4.5e−02)+	8.147e−01(1.0e−01)+	9.329e−01(9.0e−02)+
	8	1.082e+00(4.0e−01)	8.558e−01(1.5e−01)−	1.416e+00(5.0e−02)+	1.205e+00(3.1e−01)+	2.408e+00(5.7e−01)+	1.712e+00(2.3e−01)+	2.138e+00(2.5e−01)+
	10	1.298e+00(4.3e−01)	8.577e−01(9.9e−02)−	1.534e+00(4.4e−02)+	1.374e+00(2.4e−01)+	4.327e+00(5.2e−01)+	2.238e+00(2.5e−01)+	2.526e+00(3.4e−01)+
	15	1.009e+00(1.8e−01)	2.253e+00(4.3e−01)+	2.257e+00(9.5e−02)+	3.826e+00(1.1e+00)+	1.490e+01(3.3e+00)+	2.208e+00(5.7e−01)+	3.968e+00(8.1e−01)+
WFG4	5	1.096e+00(1.2e−02)	1.198e+00(3.3e−03)+	1.277e+00(2.5e−03)+	1.253e+00(2.5e−02)+	1.729e+00(1.0e−01)+	1.097e+00(1.1e−02)≈	1.090e+00(1.3e−02)−
	8	2.972e+00(2.9e−02)	3.058e+00(2.1e−02)+	3.827e+00(2.1e−01)+	3.177e+00(4.5e−02)+	6.936e+00(1.2e−01)+	2.970e+00(2.4e−02)≈	2.966e+00(3.1e−02)−
	10	4.130e+00(1.3e−01)	4.081e+00(3.1e−02)−	4.708e+00(2.4e−01)+	4.408e+00(7.9e−02)+	9.355e+00(1.8e−01)+	4.080e+00(1.8e−02)−	4.037e+00(1.9e−02)−
	15	9.066e+00(1.1e−01)	9.814e+00(1.5e−01)+	1.050e+01(4.8e−01)+	9.675e+00(1.6e−01)+	1.623e+01(9.8e−02)+	8.859e+00(6.6e−02)−	8.778e+00(5.6e−02)−
WFG5	5	1.072e+00(8.9e−03)	1.192e+00(5.0e−03)+	1.247e+00(1.4e−03)+	1.276e+00(1.9e−02)+	1.285e+00(7.4e−02)+	1.111e+00(9.6e−03)+	1.102e+00(8.9e−03)+
	8	2.934e+00(2.5e−02)	3.069e+00(1.3e−02)+	4.341e+00(2.3e−01)+	3.174e+00(4.1e−02)+	6.272e+00(3.4e−01)+	3.056e+00(3.1e−02)+	3.036e+00(2.7e−02)+
	10	4.008e+00(1.9e−02)	4.176e+00(3.6e−02)+	6.481e+00(3.7e−01)+	4.420e+00(6.7e−02)+	6.099e+00(5.3e−01)+	4.099e+00(1.6e−02)+	4.103e+00(2.1e−02)+
	15	9.213e+00(3.6e−01)	1.018e+01(5.1e−02)+	1.393e+01(1.4e−01)+	1.138e+01(4.7e−01)+	1.295e+01(1.1e+00)+	8.816e+00(3.9e−02)−	8.848e+00(4.0e−02)−
WFG6	5	1.106e+00(1.1e−02)	1.196e+00(2.4e−03)+	1.263e+00(3.8e−03)+	1.350e+00(3.6e−02)+	1.562e+00(1.1e−01)+	1.131e+00(1.0e−02)+	1.118e+00(9.3e−03)+
	8	3.073e+00(3.3e−02)	3.099e+00(7.8e−03)+	3.959e+00(2.1e−01)+	3.324e+00(4.7e−02)+	6.886e+00(8.2e−02)+	3.131e+00(4.0e−02)+	3.092e+00(4.2e−02)+
	10	4.144e+00(2.9e−02)	4.211e+00(1.6e−02)+	5.877e+00(5.3e−01)+	4.577e+00(5.7e−02)+	9.306e+00(6.1e−02)+	4.180e+00(2.5e−02)+	4.191e+00(2.6e−02)+
	15	9.327e+00(1.6e−01)	1.024e+01(1.8e−01)+	1.389e+01(1.9e−01)+	1.101e+01(3.4e−01)+	1.613e+01(4.7e−02)+	8.971e+00(4.4e−02)−	9.004e+00(7.1e−02)−
WFG7	5	1.110e+00(1.2e−02)	1.216e+00(3.7e−03)+	1.284e+00(2.4e−03)+	1.307e+00(2.5e−02)+	1.936e+00(1.0e−01)+	1.140e+00(1.3e−02)+	1.125e+00(8.0e−03)+
	8	3.078e+00(3.1e−02)	3.107e+00(8.5e−03)+	3.604e+00(1.5e−01)+	3.082e+00(4.5e−02)≈	6.959e+00(1.2e−01)+	3.099e+00(3.4e−02)+	3.051e+00(2.9e−02)−
	10	4.092e+00(3.6e−02)	4.125e+00(2.5e−02)+	4.337e+00(3.2e−02)+	4.330e+00(3.3e−02)+	9.294e+00(1.5e−01)+	4.071e+00(1.6e−02)−	4.053e+00(1.5e−02)−
	15	9.149e+00(9.5e−02)	9.806e+00(1.6e−01)+	9.783e+00(1.3e−01)+	9.628e+00(1.1e−01)+	1.616e+01(1.3e−01)+	8.957e+00(6.1e−02)−	8.989e+00(5.3e−02)−
WFG8	5	1.163e+00(1.4e−02)	1.166e+00(2.2e−03)≈	1.237e+00(3.2e−03)+	1.287e+00(2.2e−02)+	1.452e+00(4.7e−02)+	1.196e+00(9.7e−03)+	1.164e+00(1.3e−02)≈
	8	3.192e+00(6.6e−02)	3.177e+00(6.6e−02)−	3.711e+00(3.7e−01)+	3.349e+00(3.0e−02)+	7.734e+00(1.2e−01)+	3.163e+00(2.6e−02)−	3.104e+00(2.0e−02)−
	10	4.502e+00(1.4e−01)	4.364e+00(1.0e−01)−	4.460e+00(8.0e−02)−	4.700e+00(3.5e−02)+	1.019e+01(9.2e−02)+	4.450e+00(3.4e−02)−	4.407e+00(2.3e−02)−
	15	1.014e+01(2.3e−01)	9.945e+00(2.4e−01)−	1.054e+01(1.2e+00)≈	1.032e+01(2.4e−01)+	1.679e+01(1.3e−01)+	9.620e+00(7.8e−02)−	9.371e+00(9.0e−02)−
WFG9	5	1.061e+00(1.1e−02)	1.089e+00(4.3e−03)+	1.187e+00(4.9e−03)+	1.194e+00(2.7e−02)+	1.433e+00(1.1e−01)+	1.064e+00(8.1e−03)+	1.059e+00(1.2e−02)−
	8	2.881e+00(2.8e−02)	2.940e+00(2.0e−02)+	3.286e+00(1.4e−01)+	3.094e+00(2.5e−02)+	5.769e+00(4.8e−01)+	2.915e+00(2.6e−02)+	2.896e+00(2.5e−02)+
	10	4.099e+00(4.8e−02)	4.053e+00(4.1e−02)−	4.507e+00(2.3e−01)+	4.410e+00(5.6e−02)+	6.102e+00(5.4e−01)+	4.113e+00(2.8e−02)+	4.047e+00(2.4e−02)−
	15	8.869e+00(2.6e−01)	9.185e+00(7.7e−02)+	1.068e+01(6.4e−01)+	1.035e+01(3.9e−01)+	1.121e+01(7.3e−01)+	8.795e+00(6.5e−02)≈	8.613e+00(1.0e−01)−
+/≈/−			45/5/14	47/7/10	45/7/12	52/3/9	44/7/13	40/4/20

be multiple of four, it slightly larger than the number of weight vectors in some cases. The population size in VaEA keeps the same as in NSGA-III. Regarding other algorithms, the population size equal to the number of weight vectors, as recommended by their developers.

The parameter settings of all the algorithms are listed in Table 2. All the algorithm except dMOPSO uses the SBX and PM to generate new offsprings. η_c and η_m are distribute index for SBX and PM respectively, and p_c and p_m are the probability of crossover and mutation respectively. For dMOSPO, VaPSO, their learning factors c, c_1, c_2 are randomly sampled from $[1.5, 2.0]$, and the initial weight ω is randomly generated from $[0.1, 0.5]$. Regarding MOEA/DD, T and δ are the neighborhood size and neighborhood selection probability, respectively. The scaling factor k is required to Eq. (15) in VaPSO.

In order to reduce the randomness of evolutionary algorithm, all the algorithms were run 30 times independently. The same number of maximum fitness evaluation is set as $fe_{max} = max(100000, 10000 \times m)$, where m is the number of objectives. Therefore, the number of max iterations can be calculated easily by $maxgen = \lfloor fe_{max}/N \rfloor$, where N is the population size.

4.5. Comparisons results

Tables 3–5 list the mean and standard deviation of the indicator results in DTLZ, WFG, and MaF problems, respectively. The Wilcoxon's rank-sum test was used to investigate the results obtained by VaPSO and other peer algorithms, whether it exists a significant difference, where the significance level of $\alpha = 0.05$. In the following tables, the $+$, $-$, $\approx$ indicate the results generated

Table 4
HV comparison of the seven algorithms on DTLZ and WFG problems.

Problem	M	VaPSO	NSGA-III	MOEA/DD	SPEA2+SDE	dMOPSO	VaEA	PaRPEA
DTLZ1	5	9.618e−01(1.6e−03)	9.742e−01(1.1e−03)−	9.748e−01(1.4e−04)−	9.476e−01(4.8e−03)+	9.475e−01(7.2e−03)+	9.658e−01(2.7e−03)−	9.685e−01(1.7e−03)−
	8	9.921e−01(1.2e−03)	9.972e−01(2.2e−04)−	9.967e−01(2.9e−04)−	9.740e−01(4.4e−03)+	9.073e−01(2.0e−02)+	9.919e−01(1.8e−03)≈	9.930e−01(1.7e−03)−
	10	9.976e−01(1.0e−03)	9.993e−01(9.7e−05)−	9.979e−01(6.0e−04)−	9.889e−01(1.5e−03)+	8.837e−01(2.7e−02)+	9.894e−01(1.2e−02)+	7.615e−01(4.1e−01)+
	15	9.957e−01(3.0e−03)	9.999e−01(3.1e−05)−	9.984e−01(5.9e−04)−	9.787e−01(3.8e−03)+	8.899e−01(2.6e−02)+	9.931e−01(4.6e−03)+	1.996e−01(4.0e−01)+
DTLZ2	5	7.857e−01(1.6e−03)	7.939e−01(3.3e−04)−	7.948e−01(1.1e−05)−	7.922e−01(2.3e−03)−	7.590e−01(5.8e−03)+	7.736e−01(1.9e−03)+	7.721e−01(3.8e−03)+
	8	9.147e−01(2.8e−03)	9.203e−01(4.6e−04)−	9.235e−01(8.0e−05)−	9.251e−01(2.6e−03)−	8.709e−01(8.9e−03)+	8.975e−01(3.9e−03)+	8.971e−01(5.1e−03)+
	10	9.608e−01(1.7e−03)	9.634e−01(6.1e−04)−	9.689e−01(1.8e−04)−	9.662e−01(1.4e−03)−	9.266e−01(6.5e−03)+	9.269e−01(6.4e−03)+	9.463e−01(4.2e−03)+
	15	9.775e−01(1.7e−03)	9.897e−01(2.8e−04)−	9.906e−01(9.5e−05)−	9.829e−01(2.3e−03)−	9.774e−01(3.0e−03)≈	9.415e−01(5.0e−03)+	9.503e−01(6.3e−03)+
DTLZ3	5	7.849e−01(2.0e−03)	7.721e−01(1.7e−02)+	7.885e−01(4.1e−03)−	7.872e−01(4.5e−03)−	7.164e−01(1.7e−02)+	7.595e−01(1.4e−02)+	7.739e−01(7.4e−03)+
	8	7.368e−01(3.4e−01)	8.221e−01(2.2e−01)≈	9.143e−01(5.9e−03)−	9.155e−01(7.6e−03)−	6.362e−01(6.6e−02)≈	1.133e−01(2.2e−01)+	8.237e−01(2.7e−01)−
	10	6.793e−01(4.1e−01)	8.288e−01(2.4e−01)≈	9.610e−01(3.7e−03)−	9.583e−01(4.7e−03)−	5.456e−01(7.3e−02)≈	0.000e+00(0.0e+00)+	8.943e−01(2.4e−01)−
	15	5.314e−01(3.8e−01)	8.638e−01(2.7e−01)−	9.892e−01(1.5e−03)−	9.741e−01(3.8e−03)−	7.111e−01(5.4e−02)≈	3.333e−08(1.8e−07)+	9.822e−01(3.1e−03)−
DTLZ4	5	7.874e−01(1.7e−03)	7.945e−01(3.1e−04)−	7.949e−01(4.7e−06)−	7.718e−01(3.7e−02)≈	7.237e−01(1.4e−02)+	7.745e−01(2.7e−03)+	7.766e−01(3.3e−03)+
	8	9.188e−01(2.0e−03)	9.233e−01(2.4e−04)−	9.240e−01(3.0e−05)−	9.198e−01(9.9e−03)−	8.625e−01(1.2e−02)+	8.986e−01(4.2e−03)+	9.099e−01(2.6e−03)+
	10	9.662e−01(1.3e−03)	9.683e−01(3.5e−04)−	9.697e−01(1.5e−04)−	9.645e−01(1.3e−03)+	9.162e−01(1.0e−02)+	9.220e−01(7.7e−03)+	9.573e−01(2.1e−03)+
	15	9.831e−01(1.2e−03)	9.905e−01(1.4e−04)−	9.906e−01(7.0e−05)−	9.823e−01(2.8e−03)≈	9.475e−01(8.6e−03)+	9.517e−01(4.4e−03)+	9.710e−01(2.8e−03)+
DTLZ5	5	1.140e−01(1.9e−03)	3.245e−02(2.0e−02)+	1.119e−01(4.8e−04)+	1.102e−01(4.4e−03)+	1.264e−01(7.6e−05)−	1.019e−01(4.1e−03)+	8.034e−02(1.8e−02)+
	8	9.628e−02(1.6e−03)	7.200e−02(2.4e−02)+	8.418e−02(6.4e−03)+	9.093e−02(1.3e−03)+	1.043e−01(3.9e−05)−	8.981e−02(1.5e−03)+	0.000e+00(0.0e+00)+
	10	9.429e−02(9.4e−04)	2.713e−02(2.7e−02)+	6.602e−02(1.5e−02)+	7.950e−02(6.6e−03)+	1.001e−01(2.5e−04)−	3.849e−02(3.3e−02)+	0.000e+00(0.0e+00)+
	15	9.218e−02(3.4e−04)	6.949e−02(2.6e−02)+	7.988e−02(8.0e−03)+	8.999e−02(6.4e−04)+	9.443e−02(2.6e−04)−	8.064e−02(2.3e−02)+	0.000e+00(0.0e+00)+
DTLZ6	5	1.182e−01(2.7e−03)	0.000e+00(0.0e+00)+	1.746e−03(1.4e−03)+	8.653e−02(1.6e−02)+	1.261e−01(3.1e−06)−	0.000e+00(0.0e+00)+	0.000e+00(0.0e+00)+
	8	9.870e−02(1.7e−03)	0.000e+00(0.0e+00)+	0.000e+00(0.0e+00)+	4.009e−03(6.1e−03)+	1.042e−01(1.3e−06)−	0.000e+00(0.0e+00)+	0.000e+00(0.0e+00)+
	10	9.497e−02(8.9e−04)	0.000e+00(0.0e+00)+	0.000e+00(0.0e+00)+	4.493e−05(5.1e−05)+	1.000e−01(3.6e−04)−	0.000e+00(0.0e+00)+	0.000e+00(0.0e+00)+
	15	9.163e−02(6.5e−04)	0.000e+00(0.0e+00)+	0.000e+00(0.0e+00)+	8.396e−04(4.4e−03)+	9.447e−02(2.5e−04)−	0.000e+00(0.0e+00)+	0.000e+00(0.0e+00)+
DTLZ7	5	2.628e−01(1.8e−03)	2.280e−01(6.0e−03)+	1.252e−01(1.8e−03)+	2.483e−01(7.2e−03)+	1.286e−01(4.0e−03)+	2.385e−01(4.0e−03)+	2.325e−01(4.2e−03)+
	8	2.133e−01(2.2e−03)	1.854e−01(5.4e−03)+	1.115e−03(8.0e−04)+	9.952e−02(4.4e−02)+	4.946e−05(9.7e−07)+	1.557e−01(4.9e−03)+	9.554e−02(3.3e−02)+
	10	2.056e−01(4.1e−03)	1.662e−01(4.4e−03)+	5.400e−06(1.4e−05)+	2.986e−02(1.1e−02)+	1.048e−03(5.5e−03)+	8.596e−02(1.6e−02)+	3.825e−02(1.5e−02)+
	15	1.509e−01(6.3e−03)	1.473e−01(6.3e−03)+	1.000e−07(4.0e−07)+	1.606e−03(1.9e−03)+	6.685e−03(8.6e−03)+	8.788e−02(1.5e−03)+	9.772e−03(2.0e−02)+
WFG1	5	4.844e−01(5.0e−02)	3.820e−01(3.7e−02)+	5.293e−01(4.8e−02)−	7.183e−01(1.9e−02)−	2.972e−01(3.0e−03)+	3.688e−01(3.2e−02)+	3.431e−01(5.2e−02)+
	8	4.050e−01(6.4e−02)	4.755e−01(4.8e−02)−	3.619e−01(3.3e−02)+	7.973e−01(1.7e−02)−	2.405e−01(4.6e−03)+	5.252e−01(3.5e−02)−	3.925e−01(4.8e−02)+
	10	3.924e−01(6.7e−02)	4.129e−01(3.9e−02)−	2.241e−01(1.7e−02)+	7.336e−01(2.4e−02)−	2.205e−01(2.9e−03)+	4.660e−01(3.4e−02)−	4.071e−01(4.0e−02)−
	15	8.762e−01(4.9e−02)	8.385e−01(9.9e−03)+	6.681e−01(9.9e−02)+	8.317e−01(2.7e−02)+	1.859e−01(4.2e−03)+	8.306e−01(2.2e−02)+	8.366e−01(2.4e−02)+
WFG2	5	9.838e−01(6.2e−03)	9.383e−01(7.2e−02)+	9.274e−01(5.5e−02)+	8.937e−01(8.1e−02)+	8.886e−01(8.9e−03)+	9.225e−01(7.8e−02)+	9.146e−01(8.1e−02)+
	8	9.925e−01(3.9e−03)	9.413e−01(7.1e−02)+	9.023e−01(4.0e−02)+	9.454e−01(6.3e−02)+	8.681e−01(1.1e−02)+	9.632e−01(4.4e−02)+	9.508e−01(6.7e−02)+
	10	9.927e−01(2.8e−03)	9.364e−01(6.8e−02)+	9.006e−01(1.9e−02)+	9.435e−01(6.9e−02)+	8.619e−01(1.1e−02)+	9.682e−01(3.1e−02)+	9.644e−01(3.1e−02)+
	15	9.923e−01(4.5e−03)	8.631e−01(8.3e−02)+	8.930e−01(3.3e−02)+	9.417e−01(6.9e−02)+	8.781e−01(1.1e−02)+	9.358e−01(7.7e−02)+	9.718e−01(4.8e−02)+
WFG3	5	5.793e−01(3.3e−02)	6.083e−01(1.0e−02)−	5.641e−01(1.2e−02)+	5.615e−01(2.1e−02)+	5.662e−01(8.2e−03)+	5.659e−01(1.7e−02)+	5.238e−01(2.0e−02)+
	8	6.002e−01(3.6e−02)	5.988e−01(1.6e−02)≈	4.788e−01(1.1e−02)+	5.560e−01(3.4e−02)+	4.696e−01(2.5e−02)+	5.725e−01(1.3e−02)+	4.787e−01(2.6e−02)+
	10	5.984e−01(3.8e−02)	6.250e−01(1.3e−02)−	4.538e−01(1.0e−02)+	5.604e−01(1.7e−02)+	3.631e−01(3.7e−02)+	5.591e−01(2.2e−02)+	4.787e−01(3.6e−02)+
	15	6.665e−01(1.6e−02)	5.984e−01(2.6e−02)+	4.012e−01(7.9e−03)+	4.420e−01(7.0e−02)+	4.905e−02(2.0e−02)+	6.270e−01(2.4e−02)+	5.071e−01(6.5e−02)+
WFG4	5	7.546e−01(4.8e−03)	7.498e−01(5.0e−03)+	7.408e−01(4.0e−03)+	7.156e−01(6.4e−03)+	5.934e−01(1.7e−02)+	7.109e−01(6.8e−03)+	7.166e−01(6.3e−03)+
	8	8.190e−01(1.5e−02)	8.141e−01(1.2e−02)+	7.432e−01(2.1e−02)+	7.581e−01(1.4e−02)+	3.774e−01(3.6e−02)+	7.884e−01(1.3e−02)+	7.881e−01(1.0e−02)+
	10	8.214e−01(2.1e−02)	7.686e−01(1.4e−02)+	5.882e−01(3.3e−02)+	7.798e−01(7.3e−03)+	3.287e−01(3.9e−02)+	7.616e−01(1.4e−02)+	7.657e−01(1.6e−02)+
	15	8.640e−01(2.5e−02)	8.856e−01(1.4e−02)−	6.503e−01(4.9e−02)+	8.183e−01(1.3e−02)+	9.877e−02(6.4e−02)+	7.499e−01(1.7e−02)+	8.096e−01(1.8e−02)+
WFG5	5	7.002e−01(5.3e−03)	7.250e−01(2.5e−03)−	6.930e−01(2.9e−03)+	6.896e−01(4.6e−03)+	5.503e−01(2.0e−02)+	6.933e−01(3.9e−03)+	6.981e−01(5.6e−03)+
	8	7.986e−01(9.3e−03)	8.087e−01(6.1e−03)−	6.719e−01(2.0e−02)+	7.283e−01(8.9e−03)+	2.016e−01(3.8e−02)+	7.839e−01(7.2e−03)+	7.909e−01(7.0e−03)+
	10	8.119e−01(1.1e−02)	7.921e−01(7.7e−03)+	5.665e−01(2.1e−02)+	7.537e−01(5.9e−03)+	4.878e−02(3.3e−02)+	7.585e−01(9.1e−03)+	7.736e−01(5.6e−03)+
	15	8.508e−01(1.3e−02)	8.876e−01(3.7e−03)−	4.455e−01(2.4e−02)+	7.702e−01(2.5e−02)+	1.257e−02(8.6e−03)+	7.724e−01(1.1e−02)+	8.220e−01(8.3e−03)+
WFG6	5	6.867e−01(2.6e−03)	7.302e−01(6.5e−03)−	7.090e−01(8.6e−03)−	7.030e−01(7.5e−03)−	6.087e−01(1.8e−02)+	7.032e−01(8.8e−03)−	7.027e−01(7.5e−03)−
	8	8.007e−01(3.0e−03)	8.338e−01(8.5e−03)−	7.502e−01(1.6e−02)+	7.598e−01(1.1e−02)+	2.490e−01(4.9e−02)+	8.087e−01(1.1e−02)−	8.106e−01(1.0e−02)−
	10	8.389e−01(3.6e−03)	8.268e−01(1.3e−02)+	6.626e−01(2.5e−02)+	7.698e−01(1.0e−02)+	1.697e−01(4.2e−02)+	7.850e−01(1.3e−02)+	7.949e−01(1.0e−02)+
	15	8.586e−01(3.3e−02)	9.087e−01(9.7e−03)−	5.392e−01(3.4e−02)+	8.174e−01(1.8e−02)+	1.328e−01(3.4e−02)+	8.297e−01(1.1e−02)+	8.581e−01(1.2e−02)≈
WFG7	5	7.713e−01(3.9e−03)	7.741e−01(2.7e−03)−	7.507e−01(3.8e−03)+	7.375e−01(5.3e−03)+	4.199e−01(1.9e−02)+	7.433e−01(7.1e−03)+	7.458e−01(5.9e−03)+
	8	8.927e−01(6.0e−03)	8.641e−01(6.7e−03)+	7.998e−01(1.2e−02)+	7.789e−01(1.7e−02)+	2.169e−01(2.4e−02)+	8.619e−01(4.4e−03)+	8.567e−01(6.0e−03)+
	10	9.219e−01(8.3e−03)	8.460e−01(1.2e−02)+	6.770e−01(2.5e−02)+	8.355e−01(8.6e−03)+	1.709e−01(2.3e−02)+	8.264e−01(1.1e−02)+	8.244e−01(1.2e−02)+
	15	9.548e−01(4.6e−03)	9.605e−01(4.1e−03)−	8.680e−01(2.6e−02)+	8.744e−01(9.9e−03)+	1.045e−01(2.6e−02)+	8.619e−01(1.2e−02)+	8.978e−01(6.8e−03)+
WFG8	5	6.143e−01(8.2e−03)	6.512e−01(4.2e−03)−	6.320e−01(8.2e−03)−	6.392e−01(4.3e−03)−	4.106e−01(1.3e−02)+	5.913e−01(9.2e−03)+	6.184e−01(9.3e−03)−
	8	7.144e−01(2.8e−02)	6.989e−01(1.2e−02)+	6.256e−01(3.6e−02)+	7.305e−01(7.0e−03)−	1.023e−01(2.2e−02)+	6.114e−01(1.9e−02)+	6.515e−01(1.9e−02)+
	10	7.984e−01(2.8e−02)	7.058e−01(2.6e−02)+	5.802e−01(2.7e−02)+	7.488e−01(7.0e−03)+	7.526e−02(1.2e−02)+	5.850e−01(2.4e−02)+	6.087e−01(2.5e−02)+
	15	8.717e−01(6.4e−03)	8.175e−01(6.1e−02)+	5.941e−01(1.3e−01)+	8.401e−01(9.7e−03)+	8.278e−02(1.0e−02)+	7.720e−01(1.4e−02)+	7.938e−01(1.9e−02)+
WFG9	5	6.196e−01(6.6e−03)	6.415e−01(1.8e−02)−	6.295e−01(2.0e−02)−	6.530e−01(2.7e−02)−	5.571e−01(1.7e−02)+	6.218e−01(1.7e−02)+	6.165e−01(1.0e−02)+
	8	6.759e−01(8.2e−03)	6.921e−01(1.6e−02)−	5.644e−01(3.0e−02)+	7.050e−01(2.7e−02)−	2.894e−01(3.1e−02)+	6.767e−01(1.5e−02)≈	6.840e−01(1.6e−02)−
	10	6.833e−01(1.3e−02)	7.003e−01(1.2e−02)−	4.869e−01(3.4e−02)+	7.438e−01(1.4e−02)−	2.576e−01(8.7e−02)+	6.824e−01(1.5e−02)+	6.904e−01(1.1e−02)−
	15	6.662e−01(1.5e−02)	7.335e−01(2.6e−02)−	4.352e−01(5.9e−02)+	7.198e−01(2.3e−02)−	1.741e−01(6.6e−02)+	6.241e−01(2.1e−02)+	6.689e−01(2.6e−02)≈
+/≈/−			30/3/31	44/0/20	43/2/19	52/4/8	57/2/5	51/2/11

by VaPSO are significantly better than, worse than, equal to the results generated by other six peer algorithms, respectively. Moreover, in the following table, the best and second-best results are indicated by dark gray and light gray, respectively.

4.5.1. Comparisons on DTLZ problems

For problem DTLZ1 to DTLZ4, VaPSO performed better than others except for MOEA/DD in terms of IGD. In HV and IGD+, MOEA/DD wined the first place. However, in IGD of DTLZ2, the VaPSO can beat the MOEA/DD. Concerning the other DTLZ problem, the VaPSO had a competitive performance. For DTLZ5 and DTLZ6 with degenerate PFs, the dMOPSO and VaPSO are the best and the second-best respectively both on IGD and HV. The MOEA/DD and NSGA-III perform poorly on DTLZ5 and DTLZ6, due to the weight vectors were used to guide the evolution direction in those two algorithms. Regarding IGD+, the dMOPSO still performed best. These weight vector coverages space are much larger than real PFs, and this may mislead the direction of evolution. Although the weight vector was used in VaPSO, it was only used to select the leader in PSO, which does not significantly affect the direction of evolution. Regarding DTLZ7, our proposed algorithm VaPSO has excellent performance both on IGD and HV in DTLZ7, especially on HV; the VaPSO beat all the other competitors. Interestingly, the SPEA2+SDE was observed to win the first prize in IGD+. This phenomenon could be explained by IGD+ is a not good indicator to measure diversity of solutions [54]. However, the DTLZ7 with disconnected PF mainly measures the ability of algorithms to keep diversity of solutions.

To understand the experiment from visualization, Figs. 4 and 5 are the parallel coordinates of final solutions generated by the seven algorithms on the ten-objective DTLZ4 and DTLZ7, respectively. Seeing from Fig. 4, all the algorithms except for dMOPSO are converged into [0,1], which is the range of the true PF in DTLZ4. It is not difficult to understand this situation since the dMOPSO was not originally designed to solve MaOPs. Moreover, the SPEA2+SDE mainly distributed between [0,0.8]; the MOEA/DD

Table 5
IGD+ comparison of the seven algorithms on DTLZ and WFG problems.

Problem	M	VaPSO	NSGA-III	MOEA/DD	SPEA2+SDE	dMOPSO	VaEA	PaRPEA
DTLZ1	5	4.430e−02(6.1e−04)	4.862e−02(1.5e−03)+	4.788e−02(2.3e−04)+	3.843e−02(5.9e−04)−	4.728e−02(1.4e−03)+	4.326e−02(6.7e−04)−	4.305e−02(5.8e−04)−
	8	6.443e−02(1.3e−03)	6.463e−02(1.2e−03)+	6.261e−02(3.5e−04)−	5.788e−02(6.5e−04)−	8.134e−02(6.3e−03)+	7.039e−02(3.9e−03)+	6.721e−02(2.7e−03)+
	10	6.861e−02(3.5e−03)	7.084e−02(1.3e−03)+	6.539e−02(4.3e−04)−	6.081e−02(3.8e−04)−	1.122e−01(9.3e−03)+	8.976e−02(1.6e−02)+	5.533e−01(1.1e+00)+
	15	9.069e−02(1.3e−02)	1.283e−01(4.7e−03)+	1.146e−01(2.6e−03)+	7.745e−02(1.3e−03)−	1.095e−01(1.2e−02)+	1.020e−01(7.0e−03)+	4.563e+00(3.5e+00)+
DTLZ2	5	8.075e−02(8.4e−04)	7.559e−02(3.0e−04)−	7.466e−02(6.9e−06)−	7.982e−02(1.6e−03)−	9.970e−02(3.9e−03)+	8.799e−02(1.2e−03)+	8.995e−02(2.4e−03)+
	8	1.509e−01(2.1e−03)	1.401e−01(6.1e−04)−	1.354e−01(8.6e−05)−	1.394e−01(2.7e−03)−	1.855e−01(7.9e−03)+	1.680e−01(3.3e−03)+	1.702e−01(4.8e−03)+
	10	1.763e−01(2.6e−03)	1.664e−01(1.7e−03)−	1.528e−01(1.9e−04)−	1.628e−01(2.3e−03)−	2.172e−01(6.9e−03)+	2.175e−01(7.2e−03)+	1.956e−01(6.4e−03)+
	15	2.628e−01(2.8e−03)	2.410e−01(9.1e−04)−	2.357e−01(7.5e−05)−	2.449e−01(2.9e−03)−	2.713e−01(6.3e−03)+	3.025e−01(4.2e−03)+	3.018e−01(7.5e−03)+
DTLZ3	5	8.052e−02(1.0e−03)	9.145e−02(1.2e−02)+	7.972e−02(3.3e−03)≈	8.336e−02(2.9e−03)+	1.232e−01(1.0e−02)+	9.674e−02(9.1e−03)+	8.890e−02(5.0e−03)+
	8	4.639e−01(7.3e−01)	2.752e−01(4.0e−01)≈	1.468e−01(7.1e−03)−	1.478e−01(6.0e−03)−	3.331e−01(3.9e−02)≈	2.287e+00(1.5e+00)+	4.499e−01(1.3e+00)−
	10	5.287e−01(5.7e−01)	3.451e−01(4.2e−01)≈	1.664e−01(7.3e−03)−	1.704e−01(5.2e−03)−	4.641e−01(4.1e−02)≈	9.927e+00(5.5e+00)+	1.864e+00(6.4e+00)−
	15	1.002e+00(1.0e+00)	3.695e−01(2.3e−01)−	2.434e−01(7.4e−03)−	2.579e−01(5.8e−03)−	4.658e−01(3.1e−02)≈	1.057e+01(6.8e+00)+	2.460e−01(5.8e−03)−
DTLZ4	5	8.051e−02(6.7e−04)	7.500e−02(2.4e−04)−	7.464e−02(3.5e−06)−	9.921e−02(3.3e−02)+	1.134e−01(6.3e−03)+	8.860e−02(1.4e−03)+	8.826e−02(2.0e−03)+
	8	1.504e−01(1.8e−03)	1.361e−01(3.8e−04)−	1.349e−01(3.1e−05)−	1.490e−01(1.3e−02)−	1.819e−01(5.9e−03)+	1.702e−01(3.4e−03)+	1.600e−01(2.6e−03)+
	10	1.715e−01(2.4e−03)	1.551e−01(7.9e−04)−	1.514e−01(9.4e−05)−	1.713e−01(2.1e−03)≈	2.085e−01(5.9e−03)+	2.314e−01(7.5e−03)+	1.873e−01(3.9e−03)+
	15	2.566e−01(3.2e−03)	2.368e−01(5.7e−04)−	2.357e−01(7.5e−05)−	2.573e−01(8.6e−03)≈	2.899e−01(3.8e−03)+	2.987e−01(3.6e−03)+	2.793e−01(4.6e−03)+
DTLZ5	5	5.693e−02(1.7e−02)	1.551e−01(6.7e−02)+	9.086e−02(1.5e−02)+	2.035e−02(3.3e−03)−	8.108e−03(1.5e−04)−	5.568e−02(1.1e−02)≈	9.792e−02(2.7e−02)+
	8	7.654e−02(2.5e−02)	2.369e−01(6.3e−02)+	1.470e−01(7.5e−03)+	3.691e−02(6.4e−03)−	1.003e−02(1.1e−04)−	1.697e−01(9.0e−02)+	1.108e+00(3.8e−01)+
	10	6.142e−02(1.8e−02)	3.244e−01(1.1e−01)+	1.220e−01(1.8e−02)+	5.255e−02(8.6e−03)−	8.295e−03(8.1e−05)−	5.240e−01(4.3e−01)+	1.934e+00(2.3e−01)+
	15	1.031e−01(3.8e−02)	1.917e−01(8.3e−02)+	5.979e−02(4.3e−03)−	5.086e−02(1.0e−02)−	4.021e−02(8.2e−05)−	3.104e−01(1.7e−01)+	1.641e+00(3.6e−01)+
DTLZ6	5	5.807e−02(2.8e−02)	1.818e+00(1.4e−01)+	2.914e−01(3.4e−02)+	4.554e−02(1.7e−02)−	8.324e−03(5.9e−06)−	3.524e+00(2.4e−01)+	1.717e+00(6.1e−01)+
	8	6.775e−02(3.0e−02)	3.925e+00(2.3e−01)+	9.005e−01(3.8e−02)+	1.559e−01(2.2e−02)+	1.013e−02(4.7e−06)−	6.593e+00(4.9e−01)+	9.653e+00(3.4e−01)+
	10	4.722e−02(2.0e−02)	5.433e+00(2.5e−01)+	1.528e+00(5.0e−02)+	3.114e−01(2.4e−02)+	8.386e−03(3.5e−05)−	7.191e+00(5.8e−01)+	9.849e+00(7.9e−02)+
	15	6.711e−02(3.2e−02)	4.330e+00(3.2e−01)+	6.684e−01(2.3e−02)+	2.277e−01(3.2e−02)+	4.022e−02(1.5e−06)−	5.718e+00(9.2e−01)+	9.933e+00(1.1e−01)+
DTLZ7	5	1.366e−01(6.9e−03)	2.021e−01(1.1e−02)+	1.691e−01(1.2e−03)+	1.147e−01(5.0e−02)−	2.303e−01(5.6e−03)+	1.837e−01(1.1e−02)+	1.919e−01(1.1e−02)+
	8	4.406e−01(3.7e−02)	3.943e−01(4.9e−02)−	1.044e+00(6.4e−02)+	2.643e−01(1.2e−02)−	1.120e+00(7.0e−03)+	4.546e−01(2.5e−02)+	6.147e−01(7.6e−02)+
	10	6.435e−01(7.6e−02)	8.093e−01(1.6e−01)+	1.566e+00(2.3e−01)+	3.324e−01(1.3e−02)−	1.279e+00(1.0e−01)+	8.210e−01(6.1e−02)+	1.041e+00(5.9e−02)+
	15	3.133e+00(7.7e−01)	7.786e+00(1.0e+00)+	3.575e+00(1.3e+00)+	1.023e+00(6.0e−02)−	3.268e+00(1.6e+00)≈	1.675e+00(6.5e−02)−	1.892e+00(1.5e−01)−
WFG1	5	1.275e+00(1.6e−01)	1.307e+00(1.4e−01)+	9.034e−01(1.4e−01)−	4.390e−01(2.9e−02)−	1.935e+00(1.5e−02)+	1.347e+00(1.4e−01)+	1.484e+00(1.6e−01)+
	8	1.796e+00(2.8e−01)	1.089e+00(1.4e−01)−	1.472e+00(1.3e−01)−	3.731e−01(2.7e−02)−	2.470e+00(1.2e−02)+	9.951e−01(1.0e−01)−	1.447e+00(1.8e−01)−
	10	1.996e+00(3.1e−01)	1.431e+00(1.4e−01)−	2.248e+00(1.0e−01)+	5.395e−01(5.4e−02)−	2.747e+00(2.1e−02)+	1.263e+00(1.2e−01)−	1.492e+00(1.5e−01)−
	15	7.839e−01(1.8e−01)	4.696e−01(4.4e−02)−	7.556e−01(3.1e−01)≈	3.734e−01(5.9e−02)−	3.315e+00(5.1e−02)+	4.556e−01(5.4e−02)−	4.383e−01(4.8e−02)−
WFG2	5	2.276e−01(9.1e−02)	4.380e−01(4.1e−01)≈	2.768e−01(3.5e−01)≈	5.691e−01(5.2e−01)≈	1.881e−01(1.1e−02)−	4.919e−01(4.6e−01)+	6.097e−01(4.5e−01)+
	8	2.896e−01(5.6e−02)	6.925e−01(8.7e−01)≈	3.500e−01(5.5e−01)−	5.306e−01(8.4e−01)≈	2.596e−01(1.6e−02)−	4.053e−01(5.4e−01)−	6.737e−01(7.8e−01)+
	10	3.299e−01(7.1e−02)	8.618e−01(1.2e+00)≈	2.658e−01(3.5e−02)−	7.730e−01(1.2e+00)≈	3.454e−01(3.0e−02)+	3.576e−01(5.3e−01)−	4.568e−01(5.2e−01)+
	15	1.166e+00(4.0e−01)	3.548e+00(2.2e+00)+	4.213e−01(8.9e−01)−	1.211e+00(2.0e+00)≈	4.332e−01(1.0e−01)−	1.699e+00(2.1e+00)≈	9.181e−01(1.2e+00)−
WFG3	5	4.691e−01(1.5e−01)	4.069e−01(6.7e−02)−	6.711e−01(5.6e−02)+	4.244e−01(8.5e−02)−	5.560e−01(4.0e−02)+	6.107e−01(9.9e−02)+	8.028e−01(1.1e−01)+
	8	7.936e−01(2.8e−01)	6.871e−01(1.2e−01)−	1.390e+00(5.2e−02)+	7.821e−01(1.8e−01)≈	1.640e+00(1.9e−01)+	1.116e+00(1.9e−01)+	1.722e+00(2.7e−01)+
	10	9.500e−01(3.0e−01)	6.997e−01(7.5e−02)−	1.513e+00(4.4e−02)+	9.596e−01(1.3e−01)≈	2.590e+00(1.4e−01)+	1.492e+00(2.2e−01)+	1.855e+00(3.0e−01)+
	15	7.116e−01(1.2e−01)	1.510e+00(2.3e−01)+	2.202e+00(9.0e−02)+	2.274e+00(5.5e−01)+	4.072e+00(9.3e−02)+	1.528e+00(3.5e−01)+	2.534e+00(4.9e−01)+
WFG4	5	4.028e−01(6.9e−03)	3.940e−01(6.2e−03)−	4.409e−01(4.2e−03)+	4.560e−01(8.1e−03)+	6.377e−01(2.1e−02)+	4.655e−01(9.2e−03)+	4.525e−01(9.5e−03)+
	8	1.058e+00(4.2e−02)	9.416e−01(2.7e−02)−	1.070e+00(2.3e−02)+	1.223e+00(2.7e−02)+	1.280e+00(2.0e−02)+	1.083e+00(3.5e−02)+	1.070e+00(2.4e−02)+
	10	1.498e+00(7.8e−02)	1.911e+00(1.8e−01)+	3.304e+00(5.0e−01)+	1.969e+00(5.8e−02)+	1.452e+00(2.4e−02)−	1.702e+00(1.4e−01)+	1.658e+00(7.5e−02)+
	15	1.872e+00(1.4e−01)	2.119e+00(4.3e−01)+	6.368e+00(9.7e−01)+	4.753e+00(5.1e−01)+	1.771e+00(7.2e−02)−	3.926e+00(4.9e−01)+	2.398e+00(3.0e−01)+
WFG5	5	4.630e−01(8.9e−03)	4.142e−01(3.2e−03)−	4.776e−01(1.9e−03)+	4.694e−01(7.7e−03)+	7.356e−01(4.0e−02)+	4.652e−01(5.0e−03)+	4.569e−01(6.2e−03)−
	8	1.029e+00(2.5e−02)	9.030e−01(1.0e−02)−	1.068e+00(9.2e−03)+	1.178e+00(2.5e−02)+	1.619e+00(1.2e−01)+	1.026e+00(2.0e−02)−	9.959e−01(1.6e−02)−
	10	1.439e+00(6.1e−02)	1.295e+00(2.4e−02)−	1.366e+00(3.7e−02)−	1.742e+00(3.6e−02)+	2.875e+00(2.4e−01)+	1.506e+00(3.0e−02)+	1.419e+00(2.5e−02)−
	15	4.116e+00(1.4e+00)	1.460e+00(1.1e−02)−	1.554e+00(8.2e−03)−	2.596e+00(2.3e−01)−	3.491e+00(1.9e−01)−	2.075e+00(1.3e−01)−	1.782e+00(2.3e−02)−
WFG6	5	4.878e−01(4.6e−03)	4.155e−01(8.6e−03)−	4.806e−01(1.1e−02)−	4.823e−01(1.3e−02)−	6.411e−01(2.5e−02)+	4.753e−01(1.3e−02)−	4.738e−01(1.1e−02)−
	8	9.871e−01(1.7e−02)	8.736e−01(1.2e−02)−	1.065e+00(1.4e−02)+	1.174e+00(2.4e−02)+	1.370e+00(3.4e−02)+	1.006e+00(2.4e−02)+	9.951e−01(1.9e−02)+
	10	1.238e+00(3.1e−02)	1.194e+00(3.3e−02)−	1.401e+00(8.4e−02)+	1.689e+00(7.2e−02)+	1.555e+00(3.0e−02)+	1.420e+00(3.8e−02)+	1.385e+00(2.9e−02)+
	15	1.647e+00(3.7e−02)	1.415e+00(3.6e−02)−	1.545e+00(1.5e−02)−	2.490e+00(2.2e−01)+	1.725e+00(1.7e−02)+	1.814e+00(4.5e−02)+	1.721e+00(2.2e−02)+
WFG7	5	3.752e−01(5.3e−03)	3.616e−01(3.9e−03)−	4.328e−01(5.3e−03)+	4.299e−01(1.2e−02)+	8.590e−01(2.4e−02)+	4.128e−01(1.0e−02)+	4.082e−01(7.2e−03)+
	8	8.751e−01(2.6e−02)	8.621e−01(1.4e−02)−	1.019e+00(1.1e−02)+	1.080e+00(3.2e−02)+	1.410e+00(2.2e−02)+	9.272e−01(1.7e−02)+	9.362e−01(1.9e−02)+
	10	1.251e+00(1.2e−01)	1.579e+00(1.1e−01)+	1.966e+00(9.8e−02)+	1.715e+00(5.1e−02)+	1.607e+00(3.0e−02)+	1.514e+00(4.7e−02)+	1.526e+00(6.9e−02)+
	15	1.816e+00(6.4e−01)	2.051e+00(2.8e−01)+	3.020e+00(4.2e−01)+	4.448e+00(2.7e−01)+	1.801e+00(7.2e−02)≈	3.819e+00(2.7e−01)+	2.961e+00(2.1e−01)+
WFG8	5	7.267e−01(1.3e−02)	6.291e−01(9.7e−03)−	6.553e−01(2.3e−02)−	7.206e−01(1.1e−02)−	1.028e+00(4.2e−02)+	7.596e−01(1.4e−02)+	7.253e−01(1.8e−02)≈
	8	1.821e+00(1.5e−01)	1.765e+00(1.1e−01)−	1.299e+00(1.1e−01)−	1.930e+00(5.6e−02)+	1.543e+00(1.7e−02)−	1.919e+00(5.0e−02)+	1.897e+00(3.1e−02)+
	10	2.643e+00(4.2e−01)	2.555e+00(2.1e−01)≈	2.159e+00(1.9e−01)−	2.985e+00(8.9e−02)+	1.675e+00(2.1e−02)−	2.648e+00(8.3e−02)≈	2.689e+00(7.9e−02)≈
	15	6.943e+00(5.0e−01)	3.864e+00(1.2e+00)−	2.904e+00(9.3e−01)−	6.428e+00(4.1e−01)−	1.720e+00(2.2e−02)−	5.297e+00(4.4e−01)−	4.316e+00(2.7e−01)−
WFG9	5	5.743e−01(1.5e−02)	5.169e−01(2.9e−02)−	5.459e−01(3.1e−02)−	5.166e−01(4.4e−02)−	6.768e−01(3.0e−02)+	5.728e−01(3.0e−02)+	5.752e−01(2.3e−02)≈
	8	1.382e+00(4.1e−02)	1.313e+00(8.9e−02)−	1.468e+00(1.0e−01)+	1.390e+00(1.0e−01)≈	1.596e+00(8.1e−02)+	1.383e+00(7.5e−02)≈	1.351e+00(1.1e−01)−
	10	2.036e+00(9.3e−02)	2.209e+00(1.5e−01)+	2.942e+00(4.9e−01)+	2.155e+00(9.3e−02)+	2.525e+00(1.6e−01)+	2.086e+00(9.4e−02)+	2.048e+00(1.3e−01)≈
	15	3.899e+00(9.8e−01)	2.811e+00(3.8e−01)−	3.517e+00(1.7e+00)−	3.734e+00(4.2e−01)≈	3.846e+00(6.0e−01)≈	4.056e+00(4.7e−01)+	3.239e+00(5.2e−01)−
+/≈/−			24/6/34	32/3/29	23/10/31	41/6/17	49/4/11	43/4/17

and NSGA-III primarily concentrated on the border and center area. The VaPSO, VaEA and PaRPEA are uniformly distributed between [0,1], but in VaEA, the objective values are slightly bigger or smaller than the border of true PF in some dimensions. It can be seen from Fig. 4 that MOEA/DD is not as good as VaPSO, but the HV and IGD+ of MOEA/DD is still the best. These circumstances also confirm that the HV and IGD+sometimes cannot measure the distribution effectively, as mentioned in [54].

For ten-objective DTLZ7, the range of objective values from first to the ninth dimensions is [0, 1], and in the tenth dimension, it is [11.18, 20] according to the true PF of DTLZ7. It can be seen from Fig. 5, and only the dMOPSO do not well distribute into [0, 1] in the first to the ninth dimensions. Regarding the last dimension of DTLZ7, the objective values of NSGA-III, MOEA/DD, VaEA and PaRPEA have exceeded the border, and the dMOSPO is converging to a small area. The VaEA and SPEA2+SDE are relatively good compared with the other four algorithms, except that the former fails to cover the minimum boundary, and the latter is failing to cover the maximum edge. In general, all the compared algorithms cannot handle ten-objective DTLZ7 perfectly.

4.5.2. Comparisons on WFG problems

The WFG problems introduced some new features such as scaled, deceptive, non-separable, and mixed PF; this makes WFG more challenging than DTLZ. In combination with HV, IGD and IGD+, VaSPO presented a competitive performance on WFG problems.

Table 3 shows the IGD values of the seven algorithms. SPEA2+SDE shows the best performance on WFG1 on IGD. The WFG1 is a problem with the mixed PF included both concave and convex, so MOEA/DD and NSGA-III cannot efficiently handle problems like this type. Regarding WFG2, VaPSO shows the best general performance, while obtained one best in 8 objectives and second-best in 10, 15 objectives. For WFG3 to WFG8, VaSPO and

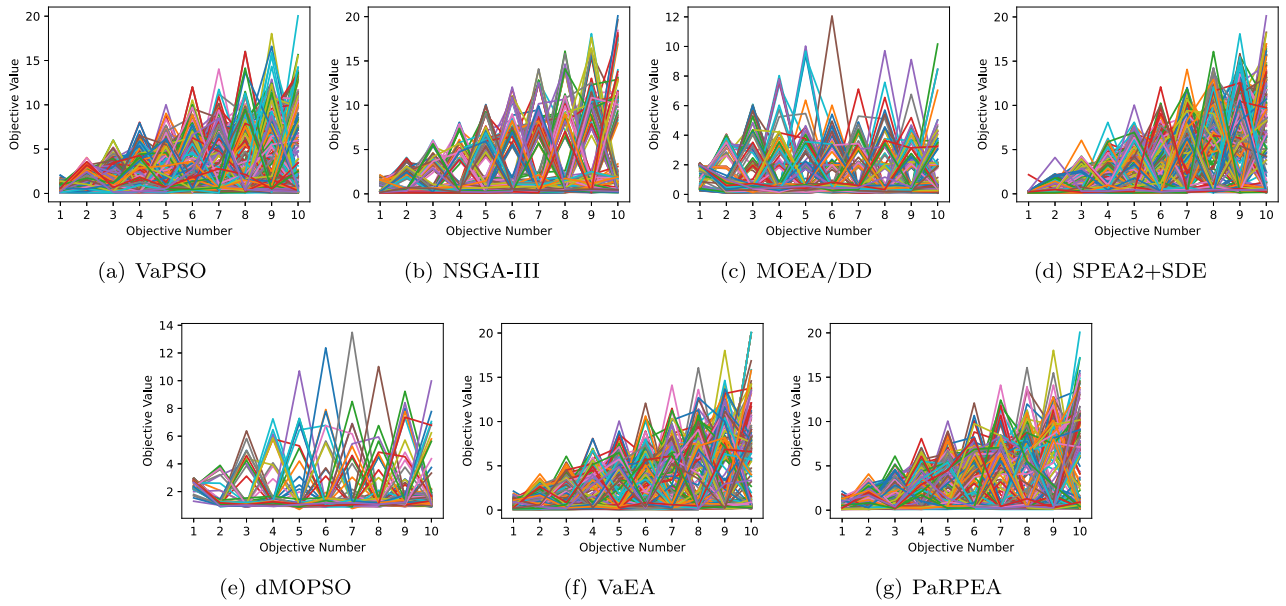


Fig. 6. The parallel coordinates of final results obtained by seven algorithms on the ten-objective WFG5 with the median HV value.

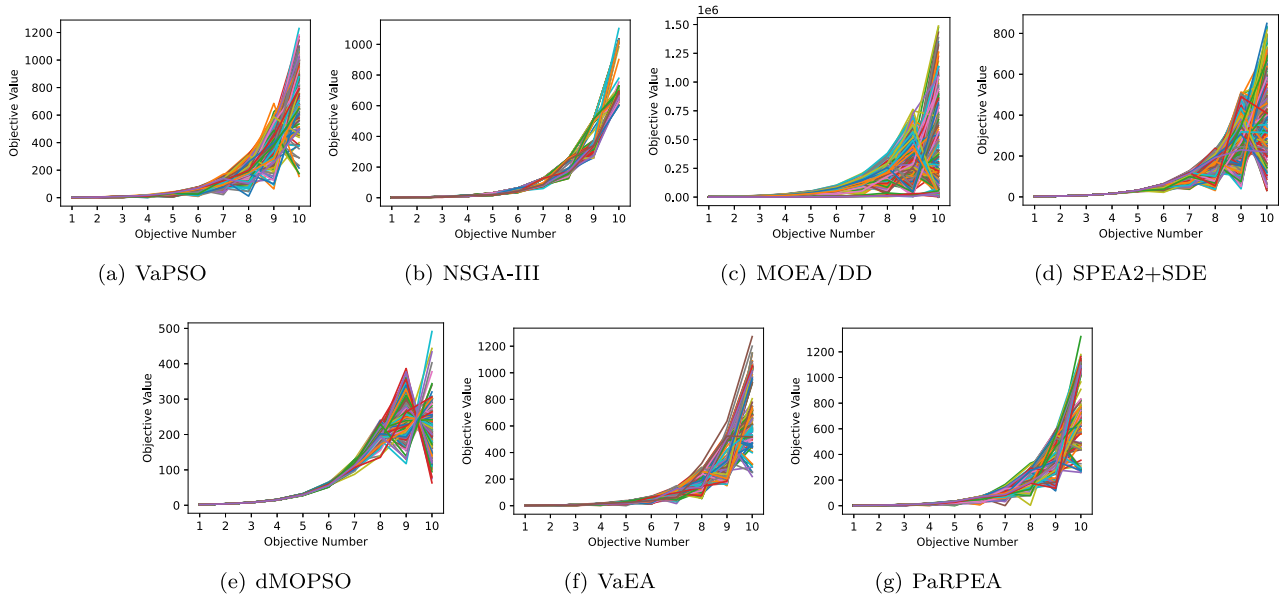


Fig. 7. The parallel coordinates of final results obtained by seven algorithms on the ten-objective MaF4 with the median HV value.

VaEA showed superior performance over its competitors, while VaEA has a good property on the higher objectives. Regarding WFG9 with a multi-modal and deceptive PF, VaPSO obtained two best results with 5 and 8 objectives, while NSGA-III and VaEA wined the first place in cases of 10 and 15 objectives, respectively.

The results of HV on WFG problems are list in Table 4. It can be seen, VaPSO and NSGA-III achieves top performance. Specifically, VaPSO got 16 best results and 10 second best results out of 36 test problems. Moreover, NSGA-III obtained 13 best results and 10 s results. It is also observed that VaPSO reaches the pretty good performance on WFG2, WFG4, WFG7, WFG8. However, regarding WFG9, VaPSO is worse than NSGA-III and SPEA2+SDE, of which SPEA2+SDE performs best.

For IGD+, NSGA-III and VaPSO still have an outstanding performance. More specifically, NSGA-III obtains 18 best and 1 second best out of 35 problems respectively. And, VaPSO obtains 3 best and 13 second best. Regarding MOEA/DD, SPEA2+SDE, dMOPSO and PaRPEA, they perform overall performance on WFG8, WFG1, WFG2, and WFG9, respectively.

Fig. 6 plots the results obtained by the seven algorithms on ten-objective WFG5 problems. All algorithms converge to true PF, but their distribution is different. dMOPSO and MOEA/DD have relatively bad performance with diversity. They used a reference vector but did not normalize the objective values, which may cause failure on the WFG5 problem with scale. In other words, the weight vectors cannot be evenly distributed on the Pareto front of WFG5. NSGA-III and SPEA2+SDE were failed to cover areas with center and boundary. Solutions values in 10 objective failed to cover the boundary of true Pareto front in VaPSO, and this situation also occurs in VaEA, but in 7, 8, 9 objective. PaEPEA looks like having an excellent performance with convergence and diversity, but it does not show an advantage in indicator results.

Table 6
IGD comparison of the seven algorithms on MaF problems.

Problem	M	VaPSO	NSGA-III	MOEA/DD	SPEA2+SDE	dMOPSO	VaEA	PaRPEA
MaF1	5	1.581e+00(2.4e−03)	1.597e+00(1.1e−02)+	1.582e+00(3.2e−03)+	1.573e+00(8.7e−04)−	1.575e+00(3.1e−03)−	1.581e+00(2.7e−03)≈	1.583e+00(3.1e−03)+
	8	2.312e+00(8.8e−04)	2.305e+00(1.4e−03)−	2.336e+00(2.2e−03)+	2.312e+00(1.2e−03)+	2.339e+00(8.7e−03)+	2.313e+00(3.4e−03)+	2.321e+00(4.0e−03)+
	10	2.702e+00(6.9e−04)	2.693e+00(3.2e−04)−	2.750e+00(1.2e−02)+	2.701e+00(1.0e−03)−	2.729e+00(7.6e−03)+	2.705e+00(4.1e−03)+	2.707e+00(3.5e−03)+
	15	3.502e+00(1.5e−03)	3.494e+00(1.8e−03)−	3.542e+00(1.1e−02)+	3.505e+00(1.5e−03)+	3.530e+00(7.7e−03)+	3.493e+00(1.9e−03)−	3.495e+00(1.9e−03)−
MaF2	5	1.135e−01(1.6e−03)	1.266e−01(2.0e−03)+	1.141e−01(1.8e−03)+	1.154e−01(1.8e−03)+	1.235e−01(7.7e−04)+	1.143e−01(2.4e−03)+	1.158e−01(2.1e−03)+
	8	1.541e−01(4.5e−03)	1.916e−01(1.2e−02)+	2.248e−01(3.7e−03)+	1.679e−01(6.5e−03)+	2.266e−01(3.2e−03)+	1.635e−01(4.2e−03)+	1.724e−01(4.3e−03)+
	10	1.649e−01(4.1e−03)	6.397e−01(7.4e−03)+	2.545e−01(4.5e−03)+	1.666e−01(3.5e−03)+	2.812e−01(4.4e−03)+	1.727e−01(5.4e−03)+	1.787e−01(4.8e−03)+
	15	2.773e−01(2.8e−02)	2.616e−01(2.2e−02)−	3.463e−01(2.2e−02)+	2.412e−01(3.0e−02)−	5.065e−01(1.4e−02)+	2.109e−01(2.7e−03)−	2.130e−01(2.5e−03)−
MaF3	5	1.667e−01(3.4e−01)	1.216e−01(5.1e−02)≈	9.655e−02(3.2e−03)−	8.562e−02(6.9e−03)−	1.681e−01(7.8e−02)+	1.250e−01(1.7e−02)+	8.262e−02(2.1e−03)−
	8	1.280e+03(4.0e+03)	5.292e+01(1.5e+02)−	9.128e−02(5.8e−03)−	9.249e−02(5.1e−03)−	2.030e−01(5.1e−02)−	4.090e−01(6.9e−01)−	2.027e+04(1.2e+04)+
	10	3.320e+03(7.0e+03)	8.985e+02(1.8e+03)≈	5.941e+00(7.6e+00)−	8.749e−02(3.8e−03)−	2.507e−01(5.9e−02)−	2.621e+03(6.1e+03)≈	6.806e+04(5.2e+04)+
	15	7.161e+02(2.8e+03)	1.042e+01(2.5e+01)−	8.993e−02(4.3e−03)−	9.681e−02(2.5e−03)−	1.391e−01(2.0e−02)−	4.226e+02(1.3e+03)+	8.791e+03(5.2e+03)+
MaF4	5	2.277e+00(8.9e−02)	3.026e+00(2.3e−01)+	9.645e+01(4.6e+01)+	3.498e+00(4.3e−01)+	8.505e+00(4.7e−01)+	2.236e+00(7.9e−02)−	2.357e+00(9.8e−02)+
	8	1.743e+01(5.5e−01)	3.123e+01(2.5e+00)+	2.202e+03(7.6e+02)+	3.885e+01(4.8e+00)+	9.698e+01(6.5e+00)+	1.832e+01(7.8e−01)+	2.054e+01(1.7e+00)+
	10	5.570e+01(2.7e+00)	6.652e+02(4.6e+01)+	2.714e+04(6.7e+03)+	1.455e+02(1.7e+01)+	4.455e+02(3.8e+01)+	5.790e+01(4.7e+00)+	6.319e+01(5.0e+00)+
	15	1.945e+03(1.4e+02)	3.679e+03(1.7e+02)+	5.078e+05(1.7e+05)+	7.036e+03(8.4e+02)+	1.656e+04(7.9e+02)+	1.792e+03(1.9e+02)−	1.774e+03(1.9e+02)−
MaF5	5	2.079e+00(3.1e−02)	2.541e+00(2.9e−03)+	5.263e+00(6.3e−03)+	2.746e+00(9.3e−01)+	1.021e+01(4.7e−01)+	2.092e+00(3.4e−02)+	2.104e+00(3.1e−02)+
	8	1.583e+01(4.5e−01)	2.199e+01(2.1e−01)+	8.171e+01(9.0e−01)+	2.738e+01(6.6e+00)+	8.655e+01(5.5e−01)+	1.646e+01(4.1e−01)+	1.597e+01(4.5e−01)+
	10	4.728e+01(8.1e−01)	1.539e+00(1.2e−02)−	2.957e+02(1.3e+01)+	1.200e+02(2.3e+01)+	3.064e+02(2.4e−01)+	4.872e+01(1.3e+00)+	4.998e+01(6.7e+00)+
	15	1.613e+03(7.2e+01)	3.573e+03(3.3e+02)+	7.019e+03(9.2e+02)+	4.039e+03(1.1e+03)+	7.577e+03(4.5e−01)+	1.634e+03(2.4e+02)−	2.078e+03(4.7e+02)+
MaF6	5	4.185e−03(2.0e−04)	4.753e−02(1.3e−02)+	8.467e−02(2.5e−03)+	8.082e−03(9.0e−04)+	3.125e−02(2.4e−04)+	6.985e−03(9.6e−04)+	4.354e−03(3.9e−04)+
	8	4.765e−03(6.0e−03)	1.021e−01(1.7e−01)+	1.648e−01(2.4e−02)+	1.894e−01(5.3e−01)+	2.384e−02(2.9e−04)+	1.259e−01(1.7e−01)+	1.008e+00(1.5e+00)+
	10	1.117e−02(3.8e−02)	7.696e−01(5.5e−01)+	7.056e−01(2.8e−01)+	1.549e+00(1.4e+00)+	1.843e−02(2.6e−04)+	5.804e−01(1.9e−01)+	5.301e+00(7.5e+00)+
	15	1.677e−01(2.5e−01)	3.969e−01(1.0e−01)+	3.103e−01(1.3e−01)+	9.438e−01(4.4e−01)+	9.572e−02(6.0e−04)≈	2.969e−01(5.6e−02)+	9.461e+01(6.4e+01)+
MaF7	5	2.661e−01(6.7e−03)	3.200e−01(1.2e−02)+	5.545e−01(8.0e−03)+	2.926e−01(6.6e−02)≈	6.539e−01(1.7e−02)+	3.275e−01(8.0e−03)+	3.286e−01(9.1e−03)+
	8	6.420e−01(2.4e−02)	8.068e−01(4.0e−02)+	1.566e+00(1.1e−01)+	7.325e−01(2.9e−02)+	1.835e+00(1.6e−01)+	6.999e−01(1.2e−02)+	8.127e−01(6.3e−02)+
	10	9.550e−01(6.4e−02)	1.223e+00(9.0e−02)+	1.924e+00(3.8e−01)+	9.292e−01(2.9e−02)−	2.173e+00(1.9e−01)+	1.061e+00(4.1e−02)+	1.246e+00(5.8e−02)+
	15	3.816e+00(5.9e−01)	8.276e+00(5.9e−01)+	4.104e+00(2.2e+00)≈	1.549e+00(3.5e−02)−	3.914e+00(1.4e+00)≈	2.535e+00(2.5e−01)−	3.108e+00(4.9e−01)−
+/≈/−			19/2/7	23/1/4	18/1/9	22/2/4	19/2/7	23/0/5

Table 7
HV comparison of the seven algorithms on MaF problems.

Problem	M	VaPSO	NSGA-III	MOEA/DD	SPEA2+SDE	dMOPSO	VaEA	PaRPEA
MaF1	5	9.370e−03(4.3e−04)	5.384e−03(5.3e−04)+	3.638e−03(2.0e−04)+	1.091e−02(1.2e−04)−	8.293e−03(9.1e−04)+	9.460e−03(2.6e−04)−	9.093e−03(2.7e−04)+
	8	2.884e−05(8.4e−07)	2.281e−05(1.3e−06)+	2.842e−06(3.6e−07)+	2.849e−05(8.6e−07)+	2.091e−06(3.9e−07)+	2.173e−05(1.1e−06)+	1.850e−05(1.1e−06)+
	10	4.667e−07(7.2e−07)	5.667e−07(7.6e−07)≈	6.667e−08(2.5e−07)+	5.333e−07(6.7e−07)≈	0.000e+00(0.0e+00)+	2.333e−07(5.0e−07)≈	1.667e−07(4.5e−07)+
	15	0.000e+00(0.0e+00)	0.000e+00(0.0e+00)≈	0.000e+00(0.0e+00)≈	0.000e+00(0.0e+00)≈	0.000e+00(0.0e+00)≈	0.000e+00(0.0e+00)≈	0.000e+00(0.0e+00)≈
MaF2	5	1.676e−01(4.9e−03)	1.700e−01(2.7e−03)−	1.729e−01(7.3e−04)−	1.946e−01(1.9e−03)−	1.737e−01(1.5e−03)−	1.654e−01(4.8e−03)+	1.663e−01(3.8e−03)+
	8	1.891e−01(1.0e−02)	2.025e−01(4.2e−03)−	1.934e−01(1.8e−03)−	2.261e−01(2.7e−03)−	1.922e−01(1.7e−03)≈	1.933e−01(7.9e−03)−	2.004e−01(6.1e−03)−
	10	2.010e−01(1.4e−02)	2.120e−01(4.1e−03)−	2.033e−01(2.0e−03)≈	2.294e−01(2.5e−03)−	1.948e−01(2.2e−03)+	2.011e−01(7.4e−03)≈	2.040e−01(4.9e−03)≈
	15	2.000e−01(3.8e−03)	1.620e−01(4.2e−03)+	1.575e−01(2.5e−03)+	2.074e−01(3.9e−03)−	1.465e−01(4.1e−03)+	1.784e−01(6.4e−03)+	1.624e−01(6.5e−03)+
MaF3	5	9.625e−01(1.8e−01)	9.811e−01(3.4e−02)+	9.893e−01(3.1e−03)+	9.876e−01(3.2e−03)+	9.365e−01(9.8e−02)+	9.961e−01(1.7e−03)≈	9.989e−01(1.4e−04)−
	8	2.592e−01(4.3e−01)	6.946e−01(4.6e−01)−	9.864e−01(6.2e−03)−	9.958e−01(1.5e−03)−	9.289e−01(7.2e−02)−	8.621e−01(3.4e−01)−	0.000e+00(0.0e+00)+
	10	3.864e−04(1.4e−03)	3.333e−02(1.8e−01)≈	1.815e−01(3.4e−01)−	9.987e−01(5.5e−04)−	8.662e−01(9.3e−02)−	0.000e+00(0.0e+00)≈	0.000e+00(0.0e+00)≈
	15	3.633e−01(4.7e−01)	3.638e−01(3.7e−01)≈	9.870e−01(2.3e−03)−	9.985e−01(5.3e−04)−	9.730e−01(1.9e−02)−	1.672e−01(3.4e−01)+	0.000e+00(0.0e+00)+
MaF4	5	1.086e−01(2.9e−03)	7.436e−02(7.9e−03)+	0.000e+00(0.0e+00)+	8.012e−02(1.1e−02)+	4.089e−02(3.9e−03)+	1.009e−01(3.6e−03)+	9.490e−02(6.5e−03)+
	8	3.371e−03(2.5e−04)	1.601e−03(2.7e−04)+	0.000e+00(0.0e+00)+	2.266e−04(8.7e−05)+	1.512e−04(7.3e−05)+	1.699e−03(2.5e−04)+	9.579e−04(3.8e−04)+
	10	2.738e−04(3.3e−05)	2.058e−04(3.6e−05)+	0.000e+00(0.0e+00)+	3.400e−06(2.0e−06)+	3.300e−06(3.0e−06)+	1.144e−04(2.6e−05)+	2.957e−05(1.4e−05)+
	15	6.667e−08(2.5e−07)	2.000e−07(4.0e−07)≈	0.000e+00(0.0e+00)≈	0.000e+00(0.0e+00)≈	0.000e+00(0.0e+00)≈	0.000e+00(0.0e+00)≈	0.000e+00(0.0e+00)≈
MaF5	5	7.879e−01(1.9e−03)	7.945e−01(2.6e−04)−	6.478e−01(1.0e−04)+	7.403e−01(3.5e−02)+	3.401e−01(5.9e−02)+	7.741e−01(2.5e−03)+	7.777e−01(2.1e−03)+
	8	9.192e−01(1.9e−03)	9.233e−01(1.9e−04)−	5.592e−01(1.5e−02)+	7.172e−01(7.6e−02)+	2.742e−01(4.6e−02)+	8.973e−01(4.7e−03)+	9.090e−01(3.3e−03)+
	10	9.666e−01(6.9e−04)	9.683e−01(2.6e−04)−	5.473e−01(1.8e−02)+	7.201e−01(7.7e−02)+	2.959e−01(4.2e−02)+	9.219e−01(9.9e−03)+	8.984e−01(2.1e−01)+
	15	9.833e−01(9.9e−04)	9.905e−01(2.0e−04)−	3.783e−01(6.2e−02)+	5.555e−01(1.1e−01)+	2.590e−01(3.8e−02)+	9.497e−01(5.1e−03)+	4.873e−01(3.9e−01)+
MaF6	5	1.289e−01(2.4e−04)	1.225e−01(2.6e−03)+	1.047e−01(6.5e−03)+	1.286e−01(1.9e−04)+	1.265e−01(7.7e−05)+	1.295e−01(1.4e−04)−	1.297e−01(3.4e−05)−
	8	1.055e−01(1.3e−03)	8.412e−02(3.9e−02)+	2.261e−02(2.4e−02)+	9.115e−02(3.6e−02)+	1.044e−01(7.5e−05)+	8.001e−02(4.0e−02)≈	5.345e−02(5.3e−02)+
	10	1.002e−01(1.5e−03)	2.274e−02(4.1e−02)+	4.533e−06(2.4e−05)+	2.880e−02(4.4e−02)+	1.002e−01(4.0e−04)+	3.375e−03(1.8e−02)+	3.367e−03(1.8e−02)+
	15	9.379e−02(1.7e−03)	2.848e−02(2.5e−02)+	1.501e−03(7.4e−03)+	0.000e+00(0.0e+00)+	9.440e−02(2.5e−04)≈	6.841e−02(2.1e−02)+	0.000e+00(0.0e+00)+
MaF7	5	2.628e−01(1.9e−03)	2.285e−01(5.7e−03)+	1.262e−01(1.8e−03)+	2.506e−01(5.5e−03)+	1.282e−01(2.7e−03)+	2.374e−01(4.3e−03)+	2.331e−01(4.1e−03)+
	8	2.123e−01(2.9e−03)	1.855e−01(5.2e−03)+	1.072e−03(7.5e−04)+	1.011e−01(4.0e−02)+	5.085e−03(1.9e−02)+	1.545e−01(5.8e−03)+	1.078e−01(1.5e−02)+
	10	2.052e−01(3.2e−03)	1.669e−01(5.1e−03)+	4.800e−06(7.7e−06)+	3.391e−02(1.9e−02)+	1.341e−03(7.2e−03)+	8.127e−02(1.5e−02)+	3.726e−02(2.0e−02)+
	15	1.523e−01(4.6e−03)	1.472e−01(6.7e−03)+	3.667e−07(1.6e−06)+	1.903e−03(3.5e−03)+	5.884e−03(9.5e−03)+	8.773e−02(1.0e−03)+	1.555e−03(5.6e−03)+
+/≈/−			15/5/8	20/3/5	17/3/8	20/4/4	17/7/4	21/4/3

4.5.3. Comparisons on maf problems

The results of MaF in IGD, HV and IGD+ shows in Tables 6–8, respectively. VaPSO obtains best performance in IGD and HV, and second best in IGD+, which demonstrates the competitive performance of VaPSO on these MaF problem. MaF1 is inverted version of DTLZ1, NSGA-III performs best in HV and IGD+, while SPEA2+SDE has a better result in IGD. How ever in case of 15 objective, VaEA seemed have best performance, as it has smallest IGD and IGD+ values. MaF2 is modified from DTLZ2 through increasing the difficulty to converge. VaPSO shows the best performance in IGD, while SPEA2+SDE is dominant in HV and IGD+, and VaEA still shows its advantage in MaF2 with 15 objective, which has smallest IGD and IGD+values. Regarding MaF3, it has a convex PF and large number of local PF. SPEA2+SDE and MOEA/DD shows to be advantageous for handling MaF3, as they both have 5 best in sum of IGD, HV and IGD+. Surprisingly, PaRPEA works quite well on MaF3 with 15 objective in terms of IGD and HV. For MaF4-7, our proposed algorithms obtains best performance in IGD and HV, while VaPSO is slightly worse than SPEA2+SDE in IGD+. Specifically, NGSA3 is superior on MaF5 in HV and IGD+, and SPEA2+SDE obtains smallest IGD+ values on MaF4 and MaF7 in terms of IGD+.

One interesting thing can be observed in here, the value of solutions in IGD, HV and IGD+ is inconsistent. For example in MaF4, SPEA2+SDE do not obtain any best or second best in IGD and HV, but it gets 4 full best in IGD+. A possible explanation for this might be that each indicator have their preference which has been mentioned in Section 4.2. And Fig. 7 shows the parallel coordinates on MaF4 with 10 objectives. According to true Pareto front of MaF4, the range of mth objective is $[0, 2^m]$. As can be seen from the figure, MOEA/DD do not converge into the expected

Table 8
IGD+ comparison of the seven algorithms on MaF problems.

Problem	M	VaPSO	NSGA-III	MOEA/DD	SPEA2+SDE	dMOPSO	VaEA	PaRPEA
MaF1	5	1.581e+00(2.4e−03)	1.597e+00(1.1e−02)+	1.582e+00(3.2e−03)+	1.573e+00(8.7e−04)−	1.575e+00(3.1e−03)−	1.581e+00(2.7e−03)≈	1.583e+00(3.1e−03)+
	8	2.312e+00(8.8e−04)	2.305e+00(1.4e−03)−	2.336e+00(2.2e−03)+	2.312e+00(1.2e−03)+	2.339e+00(8.7e−03)+	2.313e+00(3.4e−03)+	2.321e+00(4.0e−03)+
	10	2.702e+00(6.9e−04)	2.693e+00(3.2e−04)−	2.750e+00(1.2e−02)+	2.701e+00(1.0e−03)−	2.729e+00(7.6e−03)+	2.705e+00(4.1e−03)+	2.707e+00(3.5e−03)+
	15	3.502e+00(1.5e−03)	3.494e+00(1.8e−03)−	3.542e+00(1.1e−02)+	3.505e+00(1.5e−03)+	3.530e+00(7.7e−03)+	3.493e+00(1.9e−03)−	3.495e+00(1.9e−03)−
MaF2	5	6.758e−02(1.7e−03)	7.283e−02(1.1e−03)+	7.379e−02(8.3e−04)+	6.023e−02(6.9e−04)−	6.993e−02(9.4e−04)+	6.809e−02(2.4e−03)+	7.214e−02(2.0e−03)+
	8	1.023e−01(2.6e−03)	1.191e−01(6.9e−03)+	1.514e−01(3.3e−03)+	9.611e−02(3.0e−03)−	1.527e−01(2.3e−03)+	1.018e−01(2.8e−03)−	1.085e−01(3.1e−03)+
	10	1.077e−01(2.2e−03)	5.012e−01(2.6e−03)+	1.600e−01(5.0e−03)+	9.523e−02(1.8e−03)−	1.841e−01(2.6e−03)+	1.091e−01(3.9e−03)+	1.129e−01(3.1e−03)+
	15	1.465e−01(8.9e−03)	1.569e−01(1.1e−02)+	2.137e−01(1.5e−02)+	1.395e−01(1.4e−02)−	2.856e−01(8.8e−03)+	1.281e−01(1.4e−03)−	1.305e−01(1.3e−03)−
MaF3	5	1.012e−01(3.5e−01)	6.580e−02(4.2e−02)+	2.396e−02(9.9e−04)−	2.454e−02(1.2e−03)−	8.133e−02(8.0e−02)+	4.143e−02(4.9e−03)+	4.123e−02(2.7e−03)+
	8	1.280e+03(4.0e+03)	5.288e+01(1.5e+02)−	1.855e−02(4.9e−03)−	1.950e−02(7.5e−04)−	1.244e−01(6.0e−02)−	3.484e−01(7.1e−01)−	2.027e+04(1.2e+04)+
	10	3.320e+03(7.0e+03)	8.985e+02(1.8e+03)≈	5.931e+00(7.6e+00)−	1.534e−02(5.0e−04)−	1.876e−01(6.9e−02)−	2.621e+03(6.1e+03)≈	6.806e+04(5.2e+04)+
	15	7.161e+02(2.8e+03)	1.040e+01(2.5e+01)−	1.024e−02(3.6e−04)−	1.359e−02(6.2e−04)−	6.253e−02(3.0e−02)−	4.226e+02(1.3e+03)+	8.791e+03(5.2e+03)+
MaF4	5	8.309e−01(3.7e−02)	1.564e+00(2.9e−01)+	9.644e+01(4.6e+01)+	7.012e−01(5.1e−02)−	1.357e+00(6.7e−02)+	8.630e−01(4.2e−02)+	9.231e−01(8.0e−02)+
	8	5.036e+00(3.5e−01)	1.840e+01(2.8e+00)+	2.202e+03(7.6e+02)+	3.670e+00(3.0e−01)−	8.456e+00(5.3e−01)+	6.170e+00(4.4e−01)+	7.322e+00(9.6e−01)+
	10	1.390e+01(1.1e+00)	6.652e+02(4.6e+01)+	2.714e+04(6.7e+03)+	9.615e+00(3.6e−01)−	2.745e+01(1.7e+00)+	1.891e+01(2.7e+00)+	2.349e+01(3.3e+00)+
	15	4.050e+02(5.4e+01)	2.335e+03(1.8e+02)+	5.078e+05(1.7e+05)+	2.690e+02(3.9e+01)−	6.514e+02(6.4e+01)+	7.210e+02(1.6e+02)+	6.682e+02(1.0e+02)+
MaF5	5	4.380e−01(5.1e−03)	4.045e−01(1.5e−03)−	6.573e−01(2.1e−04)+	5.832e−01(1.8e−01)+	9.807e−01(5.5e−02)+	4.788e−01(8.6e−03)+	4.731e−01(7.2e−03)+
	8	1.042e+00(2.6e−02)	9.171e−01(3.4e−03)−	1.206e+00(2.1e−03)+	1.477e+00(2.2e−01)+	1.368e+00(2.7e−02)+	1.166e+00(2.8e−02)+	1.130e+00(3.1e−02)+
	10	1.272e+00(2.5e−02)	1.397e+00(1.8e−02)+	1.357e+00(5.1e−03)+	1.565e+00(3.0e−02)+	1.469e+00(2.3e−02)+	1.524e+00(6.4e−02)+	1.484e+00(1.8e−01)+
	15	1.572e+00(2.4e−02)	1.464e+00(2.1e−02)−	1.622e+00(2.8e−01)≈	1.690e+00(1.3e−02)+	1.635e+00(1.4e−02)+	1.649e+00(1.5e−02)+	2.106e+00(7.9e−01)+
MaF6	5	2.021e−03(9.3e−05)	2.273e−02(5.1e−03)+	3.381e−02(2.5e−03)+	1.829e−03(9.6e−05)−	7.958e−03(6.5e−05)+	3.028e−03(4.2e−04)+	1.900e−03(1.7e−04)−
	8	2.293e−03(2.6e−03)	5.684e−02(1.1e−01)+	1.104e−01(3.2e−02)+	1.712e−01(5.0e−01)−	9.948e−03(1.2e−04)+	6.017e−02(8.9e−02)+	9.539e−01(1.5e+00)+
	10	4.622e−03(1.5e−02)	6.748e−01(5.2e−01)+	6.889e−01(2.8e−01)+	1.488e+00(1.4e+00)+	8.299e−03(1.2e−04)+	4.641e−01(1.9e−01)+	5.245e+00(7.5e+00)+
	15	7.974e−02(1.4e−01)	2.137e−01(1.1e−01)+	2.778e−01(1.4e−01)+	8.295e−01(4.7e−01)+	4.021e−02(1.3e−04)≈	1.021e−01(2.0e−02)≈	9.460e+01(6.4e+01)+
MaF7	5	1.362e−01(6.9e−03)	2.015e−01(1.1e−02)+	1.695e−01(2.3e−03)+	1.170e−01(3.6e−02)−	2.316e−01(5.8e−03)+	1.855e−01(1.1e−02)+	1.912e−01(1.1e−02)+
	8	4.432e−01(3.2e−02)	3.856e−01(4.4e−02)−	1.071e+00(8.2e−02)+	2.585e−01(8.4e−03)−	1.097e+00(8.5e−02)+	4.612e−01(2.5e−02)+	6.056e−01(7.0e−02)+
	10	6.213e−01(7.2e−02)	8.030e−01(1.0e−01)+	1.593e+00(3.5e−01)+	3.329e−01(1.1e−02)−	1.300e+00(5.4e−02)+	8.285e−01(4.1e−02)+	1.055e+00(6.0e−02)+
	15	3.409e+00(6.3e−01)	8.043e+00(6.2e−01)+	3.894e+00(2.3e+00)≈	1.008e+00(6.6e−02)−	3.111e+00(1.7e+00)≈	1.685e+00(8.9e−02)−	1.956e+00(1.6e−01)−
+/≈/−			18/1/9	22/2/4	8/0/20	22/2/4	20/3/5	24/0/4

range. Although NSGA-III and dMOPSO converge into expected range, they only distribute among a small area. It can be seen from the fact that objective values in 8,9 and 10 objective do not reach 0, VaEA and PaRPEA failed to successfully cover the boundary. About VaPSO and SPEA2+SDE, they also fail to fully cover the true Pareto front. In 10 objective, the range of objective value obtained by VaPSO is around 200 to 1200, which exceeds the expected range. On the contrary, the range of SPEA2+SDE is 0 to 800. Maybe it is the difference in this place that caused the difference in indicators. In a word, analyzing the experiment result by three indicators is helpful for comprehensive study of our proposed algorithm.

Moreover, the Friedman test was used to rank all the compared algorithms on DTLZ, WFG and MaF problems in terms of IGD, HV and IGD+. Table 9 summarizes the average rank of the seven algorithms, the average rank of VaPSO are smallest both on IGD, HV and IGD+ indicator. NSGA-III, VaEA and SPEA2+SDE won second place in IGD, HV and IGD+, respectively. Through the average rank obtained by the Friedman test, it confirms the superiority of VaPSO when handling those MaOPs.

4.6. Effectiveness of adding solutions with maximum vector angle part

As can be seen from Section 3.3, the *maxMinAngleSelection* strategy consists of three parts, and the part three is first proposed in this paper. To verify the effectiveness of part three: adding solutions with maximum vector angle solutions (*Add* strategy for short), a modified version named VaPSO-NoAdd has been designed, which is removed part three compared to the original VaPSO. Specifically, after removing solutions with minimum vector angle until the size of C_{nd} reaches $N - m$ in Algorithm 4 line 9–21, the VaPSO-NoAdd would return a archive directly and do not give solutions with maximum vector angle another chances to come back into archive (inline 22–26). We selected DTLZ and WFG problems on 5 and 10 objectives to compare these two versions of VaPSO, and the parameter settings are as the same as used in the above experiments. Table 10 shows the

Table 9
Average rank of all the compared algorithm on all the problems in terms of IGD, HV, and IGD Plus.

Algorithms	IGD	HV	IGD+
VaPSO	2.48	2.63	3.23
NSGA-III	4.04	2.89	3.51
MOEA/DD	4.6	4.63	4.01
SPEA2+SDE	3.92	3.45	3.34
dMOPSO	5.57	5.70	4.79
VaEA	3.53	4.28	4.44
PaRPEA	3.87	4.41	4.66

results of IGD and HV obtained by 30 independently runs. We can see from the table, VaPSO shows competitive performance in the test problems. Among all the problems, VaPSO obtains 21/32 and 26/32 best in terms of IGD and HV, respectively. Those results fully evidence the effectiveness of *Add* strategy.

5. Conclusion

In this paper, a vector angles-based many-objective particle swarm optimization algorithm using archive is proposed, named VaPSO. In VaPSO, an original method with relatively low computational complexity was utilized to maintain archives by vector angle. Also, a new scheme for selecting the leader to update the positions of the population in PSO was proposed. Furthermore, the SDE density estimator was used in the cloning strategy for generating new offspring solutions of the external archive. To verify the effect of VaPSO, a series of experiments were conducted on WFG, DTLZ, and MaF problems. The results of this study indicate that VaPSO has a competitive performance compare with the other six algorithms.

In the future, we will continue to explore this algorithm from different perspectives, such as combining with other algorithms to further improve performance, extending the algorithm to solve problems with irregular PF or real-world problems.

Table 10
The IGD and HV results of VaPSO and VaPSONoAdd on WFG and DTLZ with 5 and 10 objectives.

Problem	m	IGD		HV	
		VaPSO	VaPSONoAdd	VaPSO	VaPSONoAdd
DTLZ1	5	6.055e−02(6.9e−04)	6.085e−02(7.2e−04)+	9.615e−01(1.9e−03)	9.592e−01(1.9e−03)+
	10	1.053e−01(7.2e−03)	1.054e−01(5.0e−03)+	9.978e−01(5.4e−04)	9.970e−01(8.3e−04)+
DTLZ2	5	1.939e−01(1.8e−03)	1.946e−01(1.8e−03)+	7.855e−01(2.4e−03)	7.815e−01(3.2e−03)+
	10	3.958e−01(1.2e−03)	3.969e−01(1.3e−03)+	9.613e−01(1.7e−03)	9.567e−01(2.5e−03)+
DTLZ3	5	1.929e−01(1.5e−03)	1.935e−01(1.9e−03)+	7.841e−01(2.6e−03)	7.801e−01(3.4e−03)+
	10	8.863e−01(7.8e−01)	9.370e−01(8.3e−01)≈	6.389e−01(4.1e−01)	6.121e−01(4.3e−01)≈
DTLZ4	5	1.977e−01(1.3e−03)	1.983e−01(2.0e−03)+	7.882e−01(1.7e−03)	7.833e−01(2.1e−03)+
	10	4.019e−01(1.0e−03)	4.040e−01(1.0e−03)+	9.664e−01(9.1e−04)	9.639e−01(1.3e−03)+
DTLZ5	5	7.932e−02(1.9e−02)	8.099e−02(2.0e−02)≈	1.146e−01(2.7e−03)	1.125e−01(2.5e−03)+
	10	1.060e−01(2.4e−02)	1.119e−01(2.3e−02)+	9.398e−02(8.5e−04)	9.352e−02(1.1e−03)+
DTLZ6	5	1.024e−01(2.8e−02)	1.166e−01(3.6e−02)+	1.185e−01(2.1e−03)	1.159e−01(4.2e−03)+
	10	9.715e−02(2.7e−02)	1.198e−01(4.7e−02)+	9.288e−02(1.3e−02)	9.393e−02(1.3e−03)+
DTLZ7	5	2.695e−01(6.5e−03)	2.841e−01(1.4e−02)+	2.617e−01(2.3e−03)	2.621e−01(2.0e−03)−
	10	9.564e−01(6.9e−02)	9.275e−01(5.3e−02)−	2.053e−01(3.1e−03)	2.017e−01(3.0e−03)+
WFG1	5	1.322e+00(1.1e−01)	1.316e+00(1.3e−01)≈	4.710e−01(3.3e−02)	4.766e−01(5.2e−02)≈
	10	2.061e+00(2.4e−01)	2.090e+00(2.7e−01)+	3.918e−01(6.7e−02)	3.836e−01(6.3e−02)≈
WFG2	5	7.636e−01(2.1e−01)	6.931e−01(2.3e−01)−	9.833e−01(6.1e−03)	9.817e−01(4.8e−03)+
	10	9.531e−01(9.9e−02)	9.363e−01(6.0e−02)≈	9.931e−01(3.4e−03)	9.933e−01(2.9e−03)≈
WFG3	5	5.819e−01(1.4e−01)	6.384e−01(2.0e−01)+	5.907e−01(3.1e−02)	5.784e−01(3.7e−02)+
	10	1.319e+00(5.0e−01)	1.085e+00(4.3e−01)−	5.899e−01(5.1e−02)	6.136e−01(3.9e−02)−
WFG4	5	1.101e+00(1.1e−02)	1.090e+00(1.1e−02)−	7.541e−01(4.3e−03)	7.411e−01(9.1e−03)+
	10	4.120e+00(3.0e−02)	4.158e+00(4.7e−02)+	8.229e−01(1.4e−02)	8.105e−01(2.2e−02)+
WFG5	5	1.072e+00(8.8e−03)	1.084e+00(1.1e−02)+	7.003e−01(4.4e−03)	6.926e−01(6.1e−03)+
	10	4.029e+00(2.1e−02)	4.035e+00(2.6e−02)+	8.156e−01(1.1e−02)	7.969e−01(1.5e−02)+
WFG6	5	1.105e+00(9.6e−03)	1.111e+00(1.1e−02)+	6.883e−01(9.9e−03)	6.825e−01(3.8e−03)+
	10	4.152e+00(4.0e−02)	4.146e+00(4.3e−02)−	8.374e−01(3.8e−03)	8.351e−01(4.5e−03)+
WFG7	5	1.108e+00(1.2e−02)	1.108e+00(1.2e−02)≈	7.722e−01(3.7e−03)	7.672e−01(4.4e−03)+
	10	4.092e+00(3.1e−02)	4.094e+00(3.1e−02)≈	9.224e−01(7.2e−03)	9.166e−01(1.1e−02)+
WFG8	5	1.162e+00(1.5e−02)	1.164e+00(1.3e−02)+	6.161e−01(9.3e−03)	6.084e−01(1.0e−02)+
	10	4.496e+00(8.4e−02)	4.549e+00(1.1e−01)+	7.970e−01(3.0e−02)	7.845e−01(3.8e−02)+
WFG9	5	1.064e+00(1.3e−02)	1.075e+00(1.1e−02)+	6.184e−01(6.5e−03)	6.085e−01(7.7e−03)+
	10	4.102e+00(6.6e−02)	4.132e+00(5.1e−02)+	6.865e−01(1.5e−02)	6.748e−01(1.3e−02)+
+/≈/−			21/6/5		26/4/2

CRediT authorship contribution statement

Lei Yang: Conceptualization, Methodology. **Xin Hu:** Writing - original draft, Software. **Ke Li:** Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was partially supported by Natural Science Foundation of Guangdong Province of China (Grant No. 2020A1515 010691), Science and Technology Project of Guangdong Province of China (Grant No. 2018A0124), and National Natural Science Foundation of China (Grant Nos. 61573157 and 61703170). The authors also gratefully acknowledge the reviewers for their helpful comments and suggestions that helped to improve the presentation.

References

[1] M. Farina, P. Amato, On the optimal solution definition for many-criteria optimization problems, in: 2002 Annual Meeting of the North American Fuzzy Information Processing Society Proceedings. NAFIPS-FLINT 2002 (Cat. No. 02TH8622), IEEE, 2002, http://dx.doi.org/10.1109/nafips.2002.1018061.

[2] H. Ishibuchi, N. Tsukamoto, Y. Nojima, Evolutionary many-objective optimization: A short review, in: 2008 IEEE Congress on Evolutionary Computation, IEEE World Congress on Computational Intelligence, 2008, pp. 2419–2426, http://dx.doi.org/10.1109/CEC.2008.4631121.

[3] J.D. Schaffer, Multiple objective optimization with vector evaluated genetic algorithms, in: Proceedings of the 1st International Conference on Genetic Algorithms, L. Erlbaum Associates Inc., Hillsdale, NJ, USA, 1985, pp. 93–100.

[4] D.E. Goldberg, Genetic Algorithms in Search, Optimization and Machine Learning, first ed., Addison-Wesley Longman Publishing Co., Inc., Boston, MA, USA, 1989.

[5] K. Deb, A. Pratap, S. Agarwal, T. Meyarivan, A fast and elitist multiobjective genetic algorithm: NSGA-II, IEEE Trans. Evol. Comput. (2002) http://dx.doi.org/10.1109/4235.996017.

[6] E. Zitzler, M. Laumanns, L. Thiele, SPEA2: Improving the Strength Pareto Evolutionary Algorithm, TIK-Report 103, Eidgenössische Technische Hochschule Zürich (ETH), Institut für Technische …, 2001.

[7] K. Ikeda, H. Kita, S. Kobayashi, Failure of Pareto-based MOEAs: Does non-dominated really mean near to optimal? in: Proceedings of the 2001 Congress on Evolutionary Computation (IEEE Cat. No.01TH8546), IEEE, 2001, http://dx.doi.org/10.1109/cec.2001.934293.

[8] M. Laumanns, L. Thiele, K. Deb, E. Zitzler, Combining convergence and diversity in evolutionary multiobjective optimization, Evol. Comput. 10 (3) (2002) 263–282, http://dx.doi.org/10.1162/106365602760234108.

[9] S. Yang, M. Li, X. Liu, J. Zheng, A grid-based evolutionary algorithm for many-objective optimization, IEEE Trans. Evol. Comput. 17 (5) (2013) 721–736, http://dx.doi.org/10.1109/tevc.2012.2227145.

[10] M. Li, S. Yang, X. Liu, Shift-based density estimation for pareto-based algorithms in many-objective optimization, IEEE Trans. Evol. Comput. 18 (3) (2014) 348–365, http://dx.doi.org/10.1109/TEVC.2013.2262178.

[11] K. Deb, H. Jain, An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, Part I: Solving problems with box constraints, IEEE Trans. Evol. Comput. 18 (4) (2014) 577–601, http://dx.doi.org/10.1109/TEVC.2013.2281535.

[12] Z. Qingfu, L. Hui, MOEA/D: A multiobjective evolutionary algorithm based on decomposition, IEEE Trans. Evol. Comput. 11 (6) (2007) 712–731, http://dx.doi.org/10.1109/TEVC.2007.892759, arXiv:1701.00879.
[13] H. Ishibuchi, Y. Setoguchi, H. Masuda, Y. Nojima, Performance of decomposition-based many-objective algorithms strongly depends on Pareto front shapes, IEEE Trans. Evol. Comput. 21 (2) (2016) 169–190.
[14] K. Doi, R. Imada, Y. Nojima, H. Ishibuchi, Use of inverted triangular weight vectors in decomposition-based many-objective algorithms, in: Lecture Notes in Computer Science, Springer International Publishing, 2017, pp. 321–333, http://dx.doi.org/10.1007/978-3-319-68759-9_27.
[15] Y. Qi, X. Ma, F. Liu, L. Jiao, J. Sun, J. Wu, MOEA/d with adaptive weight adjustment, Evol. Comput. 22 (2) (2014) 231–264, http://dx.doi.org/10.1162/evco_a_00109.
[16] Y. Xiang, Y. Zhou, X. Yang, H. Huang, A many-objective evolutionary algorithm with Pareto-adaptive reference points, IEEE Trans. Evol. Comput. (2019) 1–15, http://dx.doi.org/10.1109/TEVC.2019.2909636.
[17] R. Wang, Z. Zhou, H. Ishibuchi, T. Liao, T. Zhang, Localized weighted sum method for many-objective optimization, IEEE Trans. Evol. Comput. 22 (1) (2018) 3–18, http://dx.doi.org/10.1109/tevc.2016.2611642.
[18] Y. Yuan, H. Xu, B. Wang, B. Zhang, X. Yao, Balancing convergence and diversity in decomposition-based many-objective optimizers, IEEE Trans. Evol. Comput. 20 (2) (2016) 180–198, http://dx.doi.org/10.1109/TEVC.2015.2443001.
[19] E. Zitzler, Evolutionary Algorithms for Multiobjective Optimization: Methods and Applications, Vol. 63, Citeseer, 1999.
[20] E. Zitzler, S. Künzli, Indicator-based selection in multiobjective search, in: Lecture Notes in Computer Science, Springer Berlin Heidelberg, 2004, pp. 832–842, http://dx.doi.org/10.1007/978-3-540-30217-9_84.
[21] J. Bader, E. Zitzler, HypE: An algorithm for fast hypervolume-based many-objective optimization, Evol. Comput. 19 (1) (2011) 45–76, http://dx.doi.org/10.1162/evco_a_00009.
[22] G.G. Yen, Z. He, Performance metric ensemble for multiobjective evolutionary algorithms, IEEE Trans. Evol. Comput. 18 (1) (2014) 131–144, http://dx.doi.org/10.1109/TEVC.2013.2240687.
[23] L. While, L. Bradstreet, L. Barone, A fast way of calculating exact hypervolumes, IEEE Trans. Evol. Comput. 16 (1) (2012) 86–95, http://dx.doi.org/10.1109/TEVC.2010.2077298.
[24] L.S. Russo, A.P. Francisco, Quick hypervolume, IEEE Trans. Evol. Comput. 18 (4) (2014) 481–502, http://dx.doi.org/10.1109/TEVC.2013.2281525.
[25] R.H. Gómez, C.A.C. Coello, Improved metaheuristic based on the R2 indicator for many-objective optimization, in: Proceedings of the 2015 on Genetic and Evolutionary Computation Conference - GECCO '15, ACM Press, 2015, http://dx.doi.org/10.1145/2739480.2754776.
[26] F. Li, R. Cheng, J. Liu, Y. Jin, A two-stage R2 indicator based evolutionary algorithm for many-objective optimization, Appl. Soft Comput. J. 67 (2018) 245–260, http://dx.doi.org/10.1016/j.asoc.2018.02.048.
[27] M.P. Hansen, A. Jaszkiewicz, Evaluating the Quality of Approximations to the Non-Dominated Set, 1998.
[28] D.B. Wagner, R2 indicator based multiobjective search, Evol. Comput. 23 (3) (2015) 421–449, http://dx.doi.org/10.1162/EVCO.
[29] R. Wang, R.C. Purshouse, P.J. Fleming, Preference-inspired coevolutionary algorithms for many-objective optimization, IEEE Trans. Evol. Comput. 17 (4) (2013) 474–494, http://dx.doi.org/10.1109/TEVC.2012.2204264.
[30] F. Goulart, F. Campelo, Preference-guided evolutionary algorithms for many-objective optimization, Inform. Sci. 329 (2016) 236–255, http://dx.doi.org/10.1016/j.ins.2015.09.015, Special issue on Discovery Science, http://www.sciencedirect.com/science/article/pii/S0020025515006696.
[31] A.R. de Freitas, P.J. Fleming, F.G. Guimarães, Aggregation trees for visualization and dimension reduction in many-objective optimization, Inform. Sci. 298 (2015) 288–314, http://dx.doi.org/10.1016/j.ins.2014.11.044, http://www.sciencedirect.com/science/article/pii/S0020025514011347.
[32] A. López Jaimes, C.A. Coello Coello, D. Chakraborty, Objective reduction using a feature selection technique, in: Proceedings of the 10th Annual Conference on Genetic and Evolutionary Computation, GECCO '08, Association for Computing Machinery, New York, NY, USA, 2008, pp. 673–680, http://dx.doi.org/10.1145/1389095.1389228.
[33] K. Li, K. Deb, Q. Zhang, S. Kwong, An evolutionary many-objective optimization algorithm based on dominance and decomposition, IEEE Trans. Evol. Comput. 19 (5) (2015) 694–716, http://dx.doi.org/10.1109/TEVC.2014.2373386.
[34] Z.-z. Liu, Y. Wang, P.-q. Huang, AnD: A many-objective evolutionary algorithm with angle-based selection and shift-based density estimation, Inform. Sci. (2018) 1–20, http://dx.doi.org/10.1016/j.ins.2018.06.063.
[35] H. Wang, L. Jiao, X. Yao, Two arch2: An improved two-archive algorithm for many-objective optimization, IEEE Trans. Evol. Comput. 19 (4) (2015) 524–541, http://dx.doi.org/10.1109/TEVC.2014.2350987.
[36] B. Li, J. Li, K. Tang, X. Yao, Many-objective evolutionary algorithms: A survey, ACM Comput. Surv. 48 (1) (2015) http://dx.doi.org/10.1145/2792984.
[37] M. Li, Evolutionary Many-Objective Optimisation: Pushing the Boundaries, 2015.
[38] E.M. Figueiredo, T.B. Ludermir, C.J. Bastos-Filho, Many objective particle swarm optimization, Inform. Sci. 374 (2016) 115–134, http://dx.doi.org/10.1016/j.ins.2016.09.026, http://dx.doi.org/10.1016/j.ins.2016.09.026.
[39] Q. Lin, S. Liu, Q. Zhu, C. Tang, R. Song, J. Chen, C.A. Coello, K.C. Wong, J. Zhang, Particle swarm optimization with a balanceable fitness estimation for many-objective optimization problems, IEEE Trans. Evol. Comput. 22 (1) (2018) 32–46, http://dx.doi.org/10.1109/TEVC.2016.2631279.
[40] Q. Zhu, Q. Lin, W. Chen, K.C. Wong, C.A. Coello Coello, J. Li, J. Chen, J. Zhang, An external archive-guided multiobjective particle swarm optimization algorithm, IEEE Trans. Cybern. 47 (9) (2017) 2794–2808, http://dx.doi.org/10.1109/TCYB.2017.2710133.
[41] Y. Xiang, Y. Zhou, M. Li, Z. Chen, A vector angle-based evolutionary algorithm for unconstrained many-objective optimization, IEEE Trans. Evol. Comput. 21 (1) (2017) 131–152, http://dx.doi.org/10.1109/TEVC.2016.2587808.
[42] D. Han, W. Du, W. Du, Y. Jin, C. Wu, An adaptive decomposition-based evolutionary algorithm for many-objective optimization, Inform. Sci. 491 (2019) 204–222, http://dx.doi.org/10.1016/J.INS.2019.03.062.
[43] I. Das, J.E. Dennis, Normal-boundary intersection: A new method for generating the Pareto surface in nonlinear multicriteria optimization problems, SIAM J. Optim. 8 (3) (1998) 631–657.
[44] Q. Lin, J. Chen, Z. Zhan, W. Chen, C.A.C. Coello, Y. Yin, C. Lin, J. Zhang, A hybrid evolutionary immune algorithm for multiobjective optimization problems, IEEE Trans. Evol. Comput. 20 (5) (2016) 711–729, http://dx.doi.org/10.1109/TEVC.2015.2512930.
[45] K. Deb, R.B. Agrawal, Simulated binary crossover for continuous search space, Complex Syst. 9 (2) (1995) 115–148.
[46] K. Deb, L. Thiele, M. Laumanns, E. Zitzler, Scalable multi-objective optimization test problems, in: Proceedings of the 2002 Congress on Evolutionary Computation. CEC'02 (Cat. No.02TH8600), Vol. 1, 2002, pp. 825–830, http://dx.doi.org/10.1109/CEC.2002.1007032.
[47] Y. Zhou, Y. Xiang, Z. Chen, J. He, S. Member, J. Wang, A scalar projection and angle-based evolutionary algorithm for many-objective optimization problems, IEEE Trans. Cybern. 49 (6) (2019) 2073–2084, http://dx.doi.org/10.1109/TCYB.2018.2819360.
[48] S. Huband, P. Hingston, L. Barone, L. While, A review of multiobjective test problems and a scalable test problem toolkit, IEEE Trans. Evol. Comput. 10 (5) (2006) 477–506, http://dx.doi.org/10.1109/TEVC.2005.861417.
[49] R. Cheng, M. Li, Y. Tian, X. Zhang, S. Yang, Y. Jin, X. Yao, A benchmark test suite for evolutionary many-objective optimization, Complex Intell. Syst. 3 (1) (2017) 67–81, http://dx.doi.org/10.1007/s40747-017-0039-7.
[50] R. Tanabe, H. Ishibuchi, An analysis of quality indicators using approximated optimal distributions in a three-dimensional objective space, arXiv, (ISSN: 23318422) 2020, pp. 1–15.
[51] C.A.C. Coello, M.R. Sierra, A study of the parallelization of a coevolutionary multi-objective evolutionary algorithm, in: MICAI 2004: Advances in Artificial Intelligence, Springer Berlin Heidelberg, 2004, pp. 688–697, http://dx.doi.org/10.1007/978-3-540-24694-7_71.
[52] E. Zitzler, L. Thiele, Multiobjective evolutionary algorithms: A comparative case study and the strength Pareto approach, IEEE Trans. Evol. Comput. 3 (4) (1999) 257–271, http://dx.doi.org/10.1109/4235.797969.
[53] H. Ishibuchi, H. Masuda, Y. Tanigaki, Y. Nojima, Modified distance calculation in generational distance and inverted generational distance, in: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 9019, 2015, pp. 110–125, http://dx.doi.org/10.1007/978-3-319-15892-1_8.
[54] H. Ishibuchi, R. Imada, N. Masuyama, Y. Nojima, Comparison of hypervolume, IGD and IGD+ from the viewpoint of optimal distributions of solutions, in: Evolutionary Multi-Criterion Optimization - 10th International Conference, EMO 2019, East Lansing, MI, USA, March 10-13, 2019, Proceedings, 2019, pp. 332–345, http://dx.doi.org/10.1007/978-3-030-12598-1_27.
[55] Y. Tian, R. Cheng, X. Zhang, Y. Jin, PlatEMO: A MATLAB platform for evolutionary multi-objective optimization [educational forum], IEEE Comput. Intell. Mag. 12 (2017) 73–87.
[56] Y. Tian, X. Xiang, X. Zhang, R. Cheng, Y. Jin, Sampling reference points on the Pareto fronts of benchmark multi-objective optimization problems, in: 2018 IEEE Congress on Evolutionary Computation, CEC, 2018, pp. 1–6.
[57] S. Zapotecas Martínez, C.A. Coello Coello, A multi-objective particle swarm optimizer based on decomposition, in: Proceedings of the 13th Annual Conference on Genetic and Evolutionary Computation, GECCO '11, ACM, New York, NY, USA, 2011, pp. 69–76, http://dx.doi.org/10.1145/2001576.2001587, http://doi.acm.org/10.1145/2001576.2001587.
[58] A.J. Nebro, J.J. Durillo, M. Vergne, Redesigning the jMetal multi-objective optimization framework, in: Proceedings of the Companion Publication of the 2015 on Genetic and Evolutionary Computation Conference - GECCO Companion '15, ACM Press, 2015, http://dx.doi.org/10.1145/2739482.2768462.

Soft Comput
DOI 10.1007/s00500-016-2151-9

METHODOLOGIES AND APPLICATION

Ant colony classification mining algorithm based on pheromone attraction and exclusion

Lei Yang[1] · **Kangshun Li**[1] · **Wensheng Zhang**[2] · **Zhenxu Ke**[1]

© Springer-Verlag Berlin Heidelberg 2016

Abstract Ant colony optimization algorithms have been applied successfully in classification rule mining. However, basic ant colony classification mining algorithms generally suffer from problems, such as premature convergence and falling into local optimum easily. Simultaneously, the classification mining algorithms use sequential covering strategy to discover rules, and the interaction between rules is less considered. In this study, a new ant colony classification mining algorithm based on pheromone attraction and exclusion (Ant-Miner$_{PAE}$) is proposed, in which a new pheromone calculation method is designed and the search is guided by the new probability transfer formula. By contrast,the basic algorithm structure is modified, and the order of the iteration is adjusted. Thus, the problem of rule interaction is mitigated. Ant-Miner$_{PAE}$ can balance the relation of exploration and development of constructing rules, which can make the ants in the search process initially explore and develop in the later period. Our experiments, which use 12 publicly available data sets, show that the predictive accuracy obtained by Ant-Miner$_{PAE}$ implementing the proposed pheromone attraction and exclusion strategy is statistically significantly higher than the predictive accuracy of other rule induction classification algorithms, such as CN2, C4.5 rules, PSO/ACO2, Ant-Miner, and cAnt-Miner$_{PB}$. Furthermore, the rules discovered by Ant-Miner$_{PAE}$ are considerably simpler than those discovered by its counterparts.

Keywords Data mining · Classification rule · Ant colony algorithm · Pheromone attraction and exclusion

1 Introduction

Data is a source of knowledge form that can be structured, (e.g., data in a relational database), semi-structured (e.g., text, graphics and image data), or heterogeneous (e.g., data distributed in the network). Data mining (Han and Kamber 2001) is a method of extracting valuable knowledge from a large amount of data. It combines traditional data analysis method and a complex algorithm to process a large amount of data. Knowledge is widely used in market analysis, product control, decision support, scientific exploration, and other fields. Data mining is interdisciplinary, that is, it uses ideas from many fields, such as database systems, statistics, machine learning, and information science. As an important task in the field of data mining, data classification describes important data mining models and predicts the future trend of the data. Data classification problem has been studied widely in machine learning, pattern recognition, artificial intelligence, and other fields. Furthermore, numerous classification algorithms have been proposed. In various applications such as credit approval, medical diagnostics, and protein structure prediction, the comprehensibility of the model plays an important role (Dhar et al. 2000; Freitas et al. 2010). For instance, one of the main objectives of classification is to create a classification model to classify and maximize the accuracy of prediction. Correct predictions on the test set results in an accurate classification model.

Communicated by V. Loia.

✉ Lei Yang
yanglei_s@scau.edu.cn

Wensheng Zhang
wensheng.zhang@ia.ac.cn

[1] College of Mathematics and Informatics, South China Agricultural University, Guangzhou, China

[2] Institute of Automation, Chinese Academy of Sciences, Beijing, China

Published online: 26 April 2016

The ant colony algorithm proposed by Parpinelli et al. has been applied in classification rule mining. The algorithm simulates ant foraging to construct classification rules, calculate the coverage of rules, establish the classification model according to the coverage threshold, and optimize the constructed classification model. Furthermore, the algorithm obtains a list similar to the set of IF-THEN rules. Ant colony is a self-organizing system that can find the shortest path between the nest and food without visual information, center control, and active collaboration mechanism owing to the release of heuristic information about food source to call companions. Ants drop pheromone on the ground as they walk from a food source to the nest, thereby creating a pheromone trail on the path. The pheromone concentration of a path influences the choices that ants make. More pheromones on a path means the path is more attractive, and pheromones aggregate. Thus, the number of ants that walk on the path multiplies. This cooperation behavior caused by autocatalysis forms a positive feedback mechanism, which makes more ants choose the optimal foraging path (Dorigo 1994; Dorigo et al. 1996). Ultimately, the majority of the ants will follow the same path, which is most likely the shortest path between the food source and the nest.

Dorigo and Stützle (2004) provided a broad definition of ant colony optimization (ACO). To solve an optimization problem, the solution space of a finite set must first be defined to compile solutions to optimization problems. The ACO algorithm uses artificial ant colony. The ants build a solution for the optimization problem, which is selected by iteration based on their associated pheromone and heuristic information, corresponding to the assessment of the solution in the current (Otero et al. 2013). The pheromone model is a parametric probability model, which is a core module of an ant colony algorithm, used to generate solutions to a problem according to probability. The candidate solution is established after iteration according to the pheromone and heuristic information. Eventually, the ant colony converges to an optimal solution or near-optimal solution.

With reference to the traditional ant colony classification algorithms and other related optimization algorithms (Li and Zou 2007; Kaltenbacher 2001; Kaltenbacher and Schicho 2002; Keung and Zou 2000), this study proposes a new ant colony classification mining algorithm based on pheromone attraction and exclusion (Ant-Miner$_{\mathrm{PAE}}$), where a new pheromone calculation method is designed, and the search is guided by the new probability transfer formula. The basic algorithm structure has been modified, and the order of the iteration is adjusted to mitigate the problem of rule interaction. The pheromones of rule creation process by ants contain attractive parts and exclusive sections, which make the ants in the search rules process explore initially before developing in the later period. It can effectively improve the quality and accuracy of the search for the rules list. The study uses Java to implement the algorithm. The experiments use 12 publicly available data sets to show that the predictive accuracy obtained by Ant-Miner$_{\mathrm{PAE}}$ is statistically and significantly higher than the predictive accuracy of other rule induction classification algorithms, such as C4.5 rules, CN2, PSO/ACO2, Ant-Miner, and cAnt-Miner$_{\mathrm{PB}}$. Moreover, the rule lists discovered by Ant-Miner$_{\mathrm{PAE}}$ are considerably simple.

The remainder of this study is organized as follows. Section 2 presents a discussion of the traditional ant colony classification algorithms. Section 3 presents our new ant colony classification mining algorithm based on pheromone attraction and exclusion (Ant-Miner$_{\mathrm{PAE}}$). Section 4 presents the experimental results and discussion. Finally, Sect. 5 concludes this study and presents future research directions.

2 Traditional ant colony classification algorithms

Classification refers to a given data object, and the class of the object is determined by a specific classification model. Figure 1 shows the workflow of classification task.

Data classification is a two-stage process: first, a model for classification is built (corresponding to the vertical flow in Fig. 1), and then the data are classified based on the model (corresponding to the horizontal flow in Fig. 1). Data samples are usually required to determine the classification model, which is called the training data set where a classification algorithm builds the classifier by analyzing or "learning from" a training set made up of database tuples and their associated class labels. A tuple, X, is represented by an n-dimensional attribute vector, $X = (x_1, x_2, \ldots, x_n)$, depicting n measurements made on the tuple from n database attributes, respectively, $A_1, A_2, \ldots, A_n$. Each tuple, X, is assumed to belong to a predefined class as determined by another database attribute called, the class label attribute. This first step of the classification process can also be viewed as the learning of a mapping or function, $y = f(x)$, that can

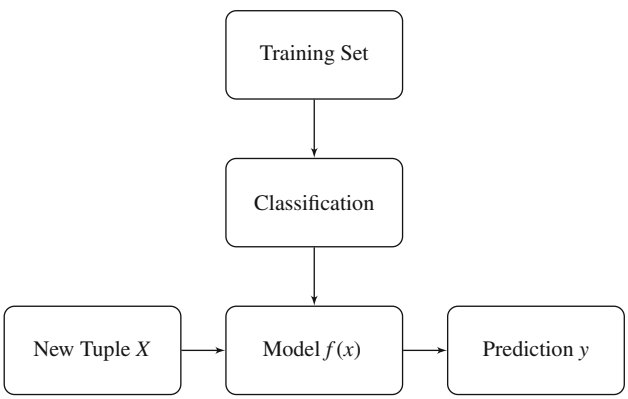


Fig. 1 Work flow of classification

predict the associated class label y of a given tuple X. The model based on training data sets cannot guarantee the accuracy of classification, yet it is needed to evaluate the accuracy of the model by testing data sets, which is the main task of the second stage. A good classification model helps people make the right decision. The general classification model is provided in the form of a classification rule.

The acquisition of classification rules is an important aspect of data mining. The general form of the classification rules is

IF⟨conditions⟩THEN⟨class⟩

where ⟨conditions⟩ is called rule antecedent. The rule antecedent (IF part) contains a set of conditions usually connected by a logical conjunction operator (AND). Each rule condition is referred to as a term. Thus, the rule antecedent is a logical conjunction of terms in the form IF $\langle$ term$_1$ AND $term_2$ AND $\cdots$ AND $term_n$ $\rangle$. Each term is triple $\langle$ attribute, operator, value $\rangle$, where the value belongs to the domain of attributes, and the operator is a relational operator. The current version of classification algorithm copes only with categorical attributes. Thus, the operator is always "=". The rule consequent specifies the class predicted for cases where the predictor attributes satisfy all the terms specified in the rule antecedent.

Data classification is widely used in artificial intelligence, machine learning, and pattern recognition. Many classification algorithms have been proposed, such as decision tree classification, Bayesian classification, classification based on the neural network, classification based on genetic algorithm, and classification based on the ant colony algorithm. These classification rule mining algorithms have their own internal defects. For example, the fault tolerance of noise performance of the decision tree method is poor, and Bayesian classification of requirements for prior probability is not theoretically convincing. Results obtained from neural network method are difficult to understand and verify because of the many nodes and connection weights. Furthermore, the training requires a long period of time. Genetic algorithms have difficulty in the iterative process from data classification problem to genetic groups. In addition, the ant colony algorithm is prone to premature and stagnation phenomenon. Although the classification algorithms of ACO have some shortcomings, the methods have received much attention because ant colony algorithms are better at finding good solutions. Parpinelli et al. (2002b) used the ant colony algorithm to obtain classification rules to propose a famous ant colony classification algorithm called Ant-Miner. The algorithm simulated ant foraging to construct classification rules, calculated the coverage of rules, established the classification model according to the coverage threshold, and optimized the constructed classification model.

The basic idea of Ant-Miner (Parpinelli et al. 2002a; Liu and Pan 2007) is as follows: at first, the list of discovered rules is empty, and the training set consists of all the training cases. Each search of the algorithm completes three basic tasks, that is, rule construction, rule pruning, and pheromone updating. The algorithm then discovers one classification rule. This rule is added to the list of discovered rules, and the training cases that are covered correctly by this rule are removed from the training set. This process is performed iteratively whenever the number of uncovered training cases is greater than a user-specified threshold called *MaximumUncovered*. The algorithm eventually obtains a set of classification rules as follows: Ant$_t$ starts with an empty rule, that is, a rule with no term in its antecedent and adds one term at a time to its current partial rule. At the beginning of each iteration of the external WHILE loop, the pheromone of all nodes is initialized with the same value. Once the loop is completed, the best rule called R_{best} among the rules constructed by all ants is added to the list of discovered rules named *DiscoveredRuleList*. At the end of the algorithm, the list of *DiscoveredRuleList* can be treated as the discovered rules. The training cases covered correctly by the R_{best} are then removed from the training set. This process is performed iteratively whenever the number of uncovered training cases is greater than *MaximumUncovered*. To improve the quality of the rules, the irrelevant terms need to be removed from the rule R_t constructed by Ant$_t$.

Different from other classification algorithms, the important feature of ant colony algorithm is its capability to update the pheromone according to the rules R_t after pruning, increase the pheromone in the trail followed by Ant$_t$ (according to the quality of rule R_t), and decrease the pheromone in the other trails (simulating the pheromone evaporation). Another ant then starts to construct its rule using the new amounts of pheromone to guide its search. This process is the positive feedback characteristic of the ant colony algorithm. Simultaneously, the convergence test must be conducted in the entire process of the discovery of the rules. The convergence threshold can be set as desired. If the rules found by ants meet the formula

$$R_t = R_{t+1} \quad (t > 1) \tag{1}$$

then the convergence threshold j is set to $j + 1$. If the discovered rule is the same as the last one or 1, then the next ant begins to rebuild the rules. The iteration of the inner loop is executed repeatedly until the following conditions are met: (1) any term to be added to the rule would make the rule cover fewer cases than a user-specified threshold called *MaximumUncovered*. (2) The convergence of the algorithm is greater than the preset threshold value in the process of constructing rules. The heuristic function in Ant-Miner is based on ant colony mechanism and information theory. Unlike other classification algorithms, the Ant-Miner is a global

search classification rule that is different from the greedy and local search of decision tree and rule reduction algorithm because of the introduction of the operation mechanism of ant colony. The pheromone and the heuristic factor are the two aspects of the decision factor of Ant-Miner, and the effective combination of these two factors determines the operating efficiency of Ant-Miner.

Ant-Miner is the first algorithm that was applied to a data classification problem by using ACO. Studies (Parpinelli et al. 2001, 2002a, b) have shown that compared with the classical classification algorithms C4.5 (Quinlan 2014) and CN2 (Clark and Niblett 1989; Clark and Boswell 1991), Ant-Miner simplifies the discovered rules and improves the comprehensibility and prediction accuracy of classification. In recent years, many researchers have worked on the ant colony classification algorithm, and many expansion and improvement methods for Ant-Miner have been proposed in the field of ant colony construction, state transition rule, heuristic strategies, rule pruning, pheromone updating, and processing continuous attributes. In the construction of ant colony, Meyer and Parpinelli (2012) proposed construction of multi-ant colony method. Jin et al. (2006) presented multi-swarm ant colony construction method. Liu et al. (2003) proposed the new state transfer rule that extended the exploration ability for Ant-Miner state transition rules and reduced the preferences for a discovered rule. Wang and Feng (2005) simplified the state transfer probability calculation method on the basis of research of Liu et al. (2002). In terms of heuristic strategy; Liu et al. (2002) presented an evaluation method based on density. Martens et al. (2007) made more effective ant-based assessment of the selected class of equations. Wang and Feng (2005) proposed a simple and effective heuristic function for the problem of prematurity. To improve the pruning speed of Ant-Miner in dealing with large data set of attributes, Chan and Freitas (2006b) proposed a hybrid pruning approach. Reference (Liu et al. 2003; Wang and Feng 2005) discussed pheromone updating to control the pheromone evaporation rate of an old trail. Liu et al. (2003) introduced the pheromone evaporation rate for the pheromone updating formula of Ant-Miner. Wang and Feng (2005) proposed the adaptive pheromone update rule method based on the method of Liu et al. (2003). In terms of dealing with continuous attributes, Otero et al. (2008, 2009) presented the processing method of the discretization of continuous attributes in the construction rules. These researchers later proposed a dynamic discretization method based on minimum description length. In addition, Chan and Freitas (2006a) proposed an improved algorithm for solving multi-label classification tasks. Smaldon and Freitas (2006) proposed an improved algorithm for generating a random classification rule.

On the basis of existing research on Ant-Miner algorithms, this study aims to find an algorithm that can improve the precision of prediction and the stability of the algorithm and simplify rules. Furthermore, the study aims to improve the performance of the classification of the mining algorithm and add advantages in massive data classification.

3 Ant colony classification mining algorithm based on pheromone attraction and exclusion

In this section, we discuss in detail our proposed algorithm for the discovery of classification rules; this algorithm is called Ant-Miner$_{\mathrm{PAE}}$. This section is divided into five subsections, namely, general description of Ant-Miner$_{\mathrm{PAE}}$, method of rule construction, rule pruning, improved method of pheromone updating, and process design of Ant-Miner$_{\mathrm{PAE}}$.

3.1 General description of Ant-Miner$_{\mathrm{PAE}}$

Ant-Miner aims to discover a list of classification rules by applying a sequential covering strategy, which creates one-rule-at-a-time until all the training examples are covered by one of the rules in the discovered list. The algorithm follows a sequential covering strategy, which has the drawback of not coping with the problem of rule interaction. The outcome of a rule affects the rules that can be discovered subsequently because the search space is modified by the removal of the examples covered by previous rules. Otero et al. (2013) proposed a new sequential covering strategy with ant colony mining algorithm called cAnt-Miner$_{\mathrm{PB}}$. An important feature of the algorithm is the number of rules of candidate list constructed by ants is not needed, and the length difference of the rule list is flexible. The number of rules constructed by each ant depends on the number of instances of each iteration of the rule list creation process, and the change is based on the instance of the previously created rule, which represents the interaction of the ants. cAnt-Miner$_{\mathrm{PB}}$ relies on a new sequential covering strategy to create a list of rules. An ant creates a complete list of rules at each iteration of the algorithm instead of a single rule. The algorithm has the ability to find the optimal solution; however, the algorithm is prone to prematurity and exhibits stagnation. On the basis of the basic structure of the approach of Otero et al. (2013), this study proposes a new pheromone attraction and exclusion method in the rule construction by ants. Pheromone updating uses a combination of global and local update methods. The pheromones of rule creation process by ants contain attractive parts as well as exclusive sections, the ratio of which balances the relationship of exploration and development. Increasing the weight of attraction and decreasing the weight of exclusion continuously makes the ants in the search rules process explore initially and develop in the later period. It can effectively improve the quality and accuracy of the search for rules list.

3.2 Rule construction

First, the algorithm is initialized with required parameters. The list of discovered rules is empty, and the training set consists of all the training cases. The attribute node path is established by the simulation of ants in the ant colony algorithm optimization model. Every node is initialized with the same amount of pheromone. Hence, when the first ant starts its search, all nodes have the same amount of pheromone. The initial amount of pheromone deposited at each position is inversely proportional to the number of values of all attributes and is defined by

$$\tau_{ij}(t=0) = \frac{1}{\sum_{i=1}^{\alpha} b_i}, \tag{2}$$

where α is the total number of attributes, and b_i is the number of possible values that can be taken by attribute A_i.

3.2.1 Method of rule construction

If the attribute nodes are random in the process of constructing the rules, then the calculation time is large, which should not happen (De López and Mántaras 1991). To avoid the blind choice of ants, the choice of the $term_{ij}$ to be added to the current partial rule depends on both problem-dependent heuristic function (η) and the amount of pheromone (τ) associated with each $term_{ij}$. Each ant starts with an empty rule, that is, a rule with no term in its antecedent, and adds one term at a time to its current partial rule until the stopping criteria is met. $term_{ij}$ is a rule condition of the form $A_i = V_{ij}$, where A_i is the ith attribute and V_{ij} is the jth value of the domain of A_i. The probability that $term_{ij}$ is chosen to be added to the current partial rule is

$$P_{ij}(t) = \frac{\tau_{ij}(t)\eta_{ij}}{\sum_{i=1}^{\alpha}\sum_{j=1}^{b_i}\tau_{ij}(t)\eta_{ij}}, \quad \forall i \in I, \tag{3}$$

where the variables are defined as η_{ij} value of a problem-dependent heuristic function for $term_{ij}$. A high value of η_{ij} means more relevance for classification of the $term_{ij}$. Thus, the probability of being chosen is higher. $\tau_{ij}(t)$ is the amount of pheromone associated with $term_{ij}$ at iteration t, corresponding to the amount of pheromone currently available in the position (i, j) of the rule, followed by the current ant. Better quality of the rule constructed by an ant means a higher amount of pheromone added to the trail segments visited by the ant. Eventually, the best trail segments to be followed, that is, the best terms (attribute–value pairs) to be added to a rule, will have higher amounts of pheromone, thereby increasing their probability of being chosen. α is the total number of attributes. b_i is the number of values in the domain of the ith attribute. I is the set of attributes not visited by the ants.

3.2.2 New method for calculating the pheromone

In this part, we propose a new calculation method of pheromone based on the pheromone attraction and exclusion, and we apply the method to the new transition probability. The pheromone contains both attractive and exclusive parts, and the released pheromone from different ants can be distinguished by the algorithm. The ants are attracted by their own released pheromones and are excluded by other ants. Therefore, we define a representation to attract the weight of Λ_{ij}^k and a representation of the exclusion of the weight of Φ_{ij}^k for each attribute node $term_{ij}$ of the ant k. The weight of representation to attract is defined as follows:

$$\Lambda_{ij}^k(t) = \frac{\tau_{ij}^k(t)}{\sum_{u\in N_i^k(t)}\tau_{iu}^k(t)}, \tag{4}$$

where $\tau_{ij}^k(t)$ is the pheromone of $term_{ij}$ for ant k, standardized with the sum of pheromones left on the other nodes by the ant. The weight of representation to exclude is defined as

$$\Phi_{ij}^k(t) = \frac{\Pi_{ij}^k(t)}{\sum_{u\in N_i^k(t)}\Pi_{iu}^k(t)}, \tag{5}$$

where

$$\Pi_{ij}^k(t) = \sum_{m=1,\ldots,n_k(m\neq k)} \tau_{ij}^m(t) \tag{6}$$

Formula (6) represents the amount of exclusion pheromone of $term_{ij}$ for ant k, namely, the sum of pheromone quantity released by other ants. According to the above definition, the method for calculating the pheromone of $term_{ij}$ is

$$\tau_{ij}(t) = \frac{(\Lambda_{ij}^k(t)/\Phi_{ij}^k(t))^{\alpha}}{\sum_{u\in N_i^k(t)}(\Lambda_{iu}^k(t)/\Phi_{iu}^k(t))^{\alpha}} \tag{7}$$

The ratio of attraction and exclusion in the formula balances the relationship between exploration and development. The algorithm tends to explore initially and then develop later in the search because of the constantly increasing weights of attraction and decreasing weights of exclusion. At the beginning of the search, the ant tends to walk on the unvisited road because the amount of pheromone released by other ants is greater than that which it released, which helps to explore a new path and discover new rules. Later, the pheromones left by the ant as well as the weight of attraction would increase for the ant to develop on its own and converge to the optimal solution to find the optimal rules.

3.2.3 Heuristic function

Ant-Miner$_{\mathrm{PAE}}$ computes the value η_{ij} of a heuristic function, which is an estimate of the quality of $term_{ij}$ with respect to its ability to improve the predictive accuracy of the rule. The heuristic function is defined by

$$\eta_{ij} = \frac{log_2(k) - infoT_{ij}}{\sum_{i=1}^{\alpha}\sum_{j=1}^{b_i}(log_2(k) - infoT_{ij})} \tag{8}$$

$$infoT_{ij} = -\sum_{w=1}^{k}\left[\frac{freqT_{ij}^{w}}{|T_{ij}|}\right] \times \log_2\left[\frac{freqT_{ij}^{w}}{|T_{ij}|}\right] \tag{9}$$

In $infoT_{ij}$, k is the number of category, $|T_{ij}|$ is the number of $term_{ij}$ of the form $A_i = V_{ij}$, A_i is the ith attribute, and V_{ij} is the jth value belonging to the domain of A_i. $freqT_{ij}^{w}$ is the number of observing class w conditioned on $A_i = V_{ij}$. (8) and (9) show that a higher value of infoT_{ij} results in a smaller probability that the current ant will choose to add $term_{ij}$ to its partial rule.

3.3 Rule pruning

To avoid over fitting to the training data, the rule pruning procedure is called immediately after the current ant completes the construction of its rule. The method iteratively removes one term at a time from the rule if this process improves the quality of the rule. The process is repeated until the rule has only one term or no term, whose removal will improve the quality of the rule.

Rule pruning potentially increases the predictive power of the rule, thereby helping to avoid its overfitting to the training data. Another motivation for rule pruning is its ability to simplify the rule because a shorter rule is usually easier to be understood by the user than a longer one.

The quality of a rule in this study is defined by the following formula:

$$Q = \begin{cases} 1 & (FP + FN + TN = 0) \\ \frac{TP}{TP+FN} & (FP + TN = 0) \\ \frac{TP}{TP+FP} & (TN + FN = 0) \\ \frac{TP}{TP+FN} \times \frac{TN}{FP+TN} & (\mathrm{ELSE}) \end{cases} \tag{10}$$

where TP is the number of cases covered by the rule that has the class predicted by the rule; FP is the number of cases covered by the rule that has a different class from the class predicted by the rule; TN is the number of cases not covered by the rule and has no class predicted by the rule; FN is the number of cases not covered by the rule but has the class predicted by the rule. A large Q means a high quality of the rule.

3.4 Improved method of pheromone updating

3.4.1 Pheromone updating on the attribute node in the rules

Pheromone updating for a $term_{ij}$ is performed according to (11) for all terms $term_{ij}$ that occur in the rule.

$$\tau_{ij}(t+1) = \tau_{ij}(t) + \tau_{ij}(t) \times Q, \quad \forall i, j \in \mathrm{Rule} \tag{11}$$

The pheromone will be increased for the terms that occur in the rule and reduced for the terms that do not occur in the rule because of evaporation. The following two basic characteristics of pheromone updating conditions must be met:

(1) For all $term_{ij}$ that occur in the rule found by the current ant, the amount of pheromone is increased by a fraction of the current amount of pheromone given by Q. A high Q means a high increase of the pheromone.
(2) The amount of pheromone associated with each $term_{ij}$ that does not occur in the rule found by the current ant has to be decreased to simulate pheromone evaporation in real ant colonies according to (12).

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) \tag{12}$$

3.4.2 Pheromone updating on the attribute node outside the rules

Pheromone evaporation on the attribute node $term_{ij}$ outside the rules is implemented by standardizing each attribute node pheromone value τ_{ij}. The standardization of the pheromone values for an attribute node $term_{ij}$ is calculated by the following formula (13).

$$\tau_{ij}(t+1) = \frac{\tau_{ij}(t)}{\sum_{i=1}^{\alpha}\sum_{j=1}^{b_i}\tau_{ij}(t)}, \quad \forall i, j \notin \mathrm{Rule}, \tag{13}$$

where $\sum_{i=1}^{\alpha}\sum_{j=1}^{b_i}\tau_{ij}(t)$ is the sum of pheromones on all attribute nodes, which also include the attribute nodes $term_{ij}$ in the rules found by the current Ant$_t$.

3.5 Process design of Ant-Miner$_{\mathrm{PAE}}$

The high-level pseudocode of the algorithm is as follows:

Algorithm 1 A high-level description of Ant-Miner$_{PAE}$

Require: training examples
Ensure: best discovered list of rules (list$_{gb}$)
  Initialize all trails with the same amount of pheromone;
  $list_{gb} = []$;
  $m = 0$;
  while $m <$ *maximum iterations* and *not stagnation* **do**
    $list_{ib} = []$;
    for $n = 1$ to $colony - size$ **do**
      $examples = \{all\ training\ cases\}$;
      $list_n = []$;
      while $|examples| > MaximumUncovered$ **do**
        $ComputeHeuristicInformation(examples)$;
        $Rule = CreateRule(examples)$;
        $Prune(rule)$;
        $examples = examples - Covered(rule, examples)$;
        $list_n = list_n + rule$;
      end while
      if $Quality(list_n) > Quality(list_{ib})$ **then**
        $list_{ib} = list_n$;
      end if
    end for
    UpdatePheromones($list_{ib}$);
    if $Quality(list_{ib}) > Quality(list_{gb})$ **then**
      $list_{gb} = list_{ib}$;
    end if
    $m = m + 1$;
  end while
  return $list_{gb}$;

The input of the algorithm is the training data set, and the output is the best rule list. Initially, all terms are initialized with the same amount of pheromone, and the list of the best-discovered rules is empty. The algorithm has user-defined parameters, such as the maximum number of iterations m, number of ants *colony-size*, the maximum number of uncovered instances *MaximumUncovered*, and other related parameters. An ant in the colony starts with an empty list of rules and adds one rule at a time to that list, whereas the number of uncovered training examples is greater than the *MaximumUncovered*. The construction method of rules is as follows: an ant selects a term as an attribute of the rules from the first attribute values according to probability function (3) and then repeats the process to select the second attribute until all the attributes found in the training set have been searched and a rule has been constructed. To simplify the rules, redundant rules are pruned. After a rule is created and pruned, the training examples covered by rule are removed and the rule is added to the current list$_n$ of rules. The heuristic information is recalculated at each iteration of the list of creation process (inner while loop) to reflect the potential changes in the predictive power of the terms owing to the removal of training examples covered by previous rules. When an ant finishes the list creation process, the iteration-best $list_{ib}$ is updated if the quality of the newly created $list_n$ is better than the quality of the iteration-best $list_{ib}$. After all ants have created a candidate $list_{ib}$ of rules, the pheromone values are updated using the iteration-best $list_{ib}$ of rules according to formulas (11)–(13), and the quality of the iteration-best $list_{ib}$ is calculated according to (10). The global-best $list_{gb}$ of rules is updated if the quality of the iteration-best $list_{ib}$ is better than the quality of the global-best $list_{gb}$.

Table 1 Data sets used in the experiments

Data set	Size	Attributes	Classes
Anneal	898	38	6
Balance-scale	625	4	3
Breast-cancer	286	9	2
Credit-a	690	14	2
Credit-g	1000	20	2
Dermatology	366	34	6
Glass	214	9	7
Heart-c	303	13	5
Heart-h	294	13	5
Ionosphere	351	34	2
Liver-disorders	345	6	2
Pima	768	8	2

4 Experiment and result analysis

4.1 Data sets and preprocessing

To evaluate the proposed Ant-Miner$_{PAE}$ algorithm, we conducted experiments using 12 publicly available data sets from the Asuncion and Newman (2007) machine learning repository. The UCI database was proposed by the University of California, Irvine (University of California Irvine) for machine learning database, which currently has a total of 187 common standard test data sets.

The 12 publicly available data sets in this study are Anneal, Balance-scale, Breast-cancer, Credit-a, Credit-g, Dermatology, Glass, Heart-c, Heart-h, Liver-disorders, Pima and Ionosphere, which are specialized for classification problem algorithm test data sets of UCI, they involve binary (two class values) and multiclass (more than two class values) classification problems, with both nominal and continuous predictor attributes, and these data sets have been used in the test of related classification algorithms (Otero et al. (2013)). Table 1 presents a summary of the data sets used in the experiments. The first column provides the data set names, and the other columns, respectively, indicate the number of cases, the number of attributes, and the number of classes of the data sets. For example, Breast-cancer data sets have ten attributes, namely, age, menopause, tumor size, inv-nodes, node-caps, deg-malig, breast, breast-quad, irradiat, and class. The classes have two categories, namely, recurrence-events and non-recurrence-events.

This algorithm discovers rules that refer only to categorical attributes. Therefore, continuous attributes have to be discretized in a preprocessing step. The discretization is performed by the C4.5-Disc discretization method (Kohavi and Sahami 1996), which simply uses the well-known C4.5 algorithm (Quinlan 2014) to discretize continuous attributes. The reduced data set contains only two attributes: the attribute to be discretized and the goal (class) attribute. For a comparison with the results obtained by Ant-Miner$_{\mathrm{PAE}}$, we selected several common classification mining algorithms, such as: (1) CN2 (Clark and Niblett 1989; Clark and Boswell 1991), a well-known classification rule mining algorithm based on sequential covering strategy, which uses an iterative method to produce a rule list; (2) C4.5 algorithm (Quinlan 2014), a rule induction algorithm that extracts a set of classification rules from an unpruned decision tree created by the well-known C4.5 algorithm; (3) PSO/ACO2 (Holden and Freitas 2008), a hybrid particle swarm optimization/ant colony optimization (PSO/ACO) algorithm for the discovery of classification rules, which follows a sequential covering strategy and directly deals with both continuous and nominal attribute; (4) Ant-Miner (Parpinelli et al. 2002a, b), which was proposed by Parpinelli et al. in 2002 and aims discover a list of classification rules by applying a sequential covering strategy, which creates one-rule-at-a-time until the number of uncovered training cases is less than or equal to a user-specified threshold; (5) cAnt-Miner$_{\mathrm{PB}}$ (Otero et al. 2013), which proposes a new sequential covering strategy and considers the interaction between rules. In each iteration of the sequential covering of cAnt-Miner$_{\mathrm{PB}}$, the ants create a complete list of rules and the search is guided by the quality of the list of rule. Finally, the optimal rule list is constructed.

4.2 Ant-Miner$_{\mathrm{PAE}}$'s parameter setting

Ant-Miner$_{\mathrm{PAE}}$ has the following six user-defined parameters: maximum number of iterations m, *colony-size*, evaporation factor ρ, minimum number of cases per rule *min_cases_per_rule*, maximum number of uncovered cases in the training set *MaximumUncovered*, and number of rules used to test convergence of the ants *no_rules_converge*. These parameters are set as follows: $m = 100$, *colony-size* $= 5$, $\rho = 0.9$, *min_cases_per_rule* $= 5$, *MaximumUncovered* $= 10$, *no_rules_converge* $= 10$.

We have made no serious attempt to optimize the setting of these parameters; hence, setting the parameters can be a future work. Even the above setting of non-optimized parameters has produced good results. Other algorithms use default values proposed by their corresponding authors; these values typically represent robust values that work well across different data sets.

4.3 Comparing Ant-Miner$_{\mathrm{PAE}}$ with other algorithms

We evaluated the performance of Ant-Miner$_{\mathrm{PAE}}$ by comparing it with the common rule induction classification algorithms, such as CN2,C4.5 rules, PSO/ACO2, Ant-Miner, and cAnt-Miner$_{\mathrm{PB}}$. All the comparison results are obtained on 12 sets of public data sets. We use an Intel(R) Core(TM) i5-4460 CPU with a clock rate of 3.20 GHZ and 4 GB main memory. Ant-Miner$_{\mathrm{PAE}}$ is developed in Java.

We performed a tenfold cross-validation procedure (Demšar 2006) to test the accuracy of the algorithm. The procedure consists of dividing the data set into ten partitions and maintaining a similar number of examples and class distribution across all partitions. For each partition, the classification algorithm is run by using the remaining nine partitions as the training set, and its performance is evaluated by using the unseen (hold-out) partition, which also typically requires multiple tenfold cross-validation (for example, ten times tenfold cross-validation), and then the average is determined as the accuracy of the estimation algorithm. The data format of this algorithm is based on WEKA program, and the format of WEKA is ARFF (File Format Attribute-Relation), which is a type of ASCII text file.

The comparison is performed based on two criteria.

(1) The predictive accuracy of the discovered rule lists, namely, the correct classification rate of test data samples after the classification experiment by the algorithm, assuming that training set is a training sample set that consists of n data samples, and test set is a test sample set that consists of m data samples: The algorithm is run for training. Each time, the training set is used as the training set and test set is used as the test set. The predictive accuracies (on the test set) of the ten runs are then averaged and reported as the predictive accuracy of the discovered rule list. Accurate classification of the data means better classification performance of this algorithm.
(2) The simplicity of the discovered rule list, measured by the number of discovered rules and the average number of terms (conditions) per rule: the number of rules refers to the number of rules found in the module, which is a cross-validation. The number of conditions in the rule is the number of conditions (antecedent) for the condition of the discovery of a module, which is in a cross-validation. In this experiment, the two values are compared with the average value of the ten cross-validations.

The comparison results between the predictive accuracies of Ant-Miner$_{\mathrm{PAE}}$ and other classification algorithms are reported in Table 2. The numbers that appear after the "±" symbol are the standard deviations of the corresponding predictive accuracies rates. As shown in the

Table 2 Average predictive accuracy (average ± standard error) in % after the tenfold cross-validation procedure

Data set	CN2	C4.5 rules	PSO/ACO2	Ant-Miner	*c*Ant-Miner$_{PB}$	Ant-Miner$_{PAE}$
Anneal	94.99 ± 0.62	94.22 ± 0.62	97.25 ± 0.08	92.88 ± 1.16	**97.60 ± 0.10**	97.44 ± 0.55
Balance-scale	**88.47 ± 1.81**	74.87 ± 1.16	79.16 ± 0.19	73.90 ± 2.08	76.83 ± 0.24	84.47 ± 1.48
Breast-cancer	66.77 ± 1.69	68.56 ± 1.93	71.29 ± 0.31	75.95 ± 3.14	72.32 ± 0.31	**85.06 ± 1.88**
Credit-a	81.31 ± 1.36	85.53 ± 1.53	84.66 ± 0.24	85.51 ± 1.65	85.68 ± 0.15	**90.29 ± 1.56**
Credit-g	69.50 ± 1.33	71.60 ± 0.92	69.99 ± 0.23	69.70 ± 1.04	73.63 ± 0.23	**77.80 ± 1.02**
Dermatology	91.79 ± 1.37	93.45 ± 1.22	91.80 ± 0.22	86.95 ± 2.56	92.46 ± 0.31	**94.73 ± 1.03**
Glass	68.14 ± 2.39	68.63 ± 1.70	70.24 ± 0.51	52.08 ± 2.77	**73.94 ± 0.49**	68.74 ± 1.81
Heart-c	48.85 ± 3.14	53.12 ± 1.92	55.20 ± 0.51	79.11 ± 3.32	55.50 ± 0.37	**90.78 ± 1.24**
Heart-h	52.81 ± 3.38	63.31 ± 1.40	63.18 ± 0.45	81.37 ± 3.07	64.75 ± 0.27	**91.50 ± 1.04**
Ionosphere	88.03 ± 2.68	90.85 ± 2.59	86.55 ± 0.43	81.70 ± 2.23	89.65 ± 0.31	**92.37 ± 1.53**
Liver-disorders	62.27 ± 2.84	64.90 ± 3.21	**68.78 ± 0.44**	64.66 ± 2.87	66.72 ± 0.40	67.03 ± 1.52
Pima	72.37 ± 1.26	74.32 ± 1.73	73.10 ± 0.33	69.39 ± 2.05	74.81 ± 0.18	**78.52 ± 1.44**

The best results from different algorithms are shown in bold

Table 3 Average number of terms (rule conditions) in the discovered list (average ± standard error) measured by tenfold cross-validation

Data set	CN2	C4.5 rules	PSO/ACO2	Ant-Miner	*c*Ant-Miner$_{PB}$	Ant-Miner$_{PAE}$
Anneal	52.10 ± 2.72	43.00 ± 3.05	28.60 ± 0.91	14.40 ± 0.56	22.11 ± 0.33	**12.00 ± 0.45**
Balance-scale	90.20 ± 3.51	72.60 ± 3.27	39.87 ± 0.53	12.50 ± 0.17	12.64 ± 0.03	**12.30 ± 0.26**
Breast-cancer	141.60 ± 1.98	16.50 ± 2.60	23.20 ± 1.80	8.50 ± 0.34	19.15 ± 0.40	**6.70 ± 0.58**
Credit-a	96.30 ± 2.57	37.10 ± 3.06	80.27 ± 2.10	9.70 ± 1.10	17.54 ± 0.32	**9.40 ± 1.14**
Credit-g	222.50 ± 2.19	76.90 ± 4.99	227.73 ± 3.51	**11.30 ± 0.47**	64.75 ± 1.50	12.10 ± 0.64
Dermatology	48.60 ± 0.93	45.00 ± 1.89	30.80 ± 0.31	**19.20 ± 0.83**	44.47 ± 0.63	20.20 ± 1.47
Glass	43.90 ± 1.08	48.30 ± 2.05	60.87 ± 1.12	11.50 ± 1.16	10.73 ± 0.14	**9.20 ± 1.10**
Heart-c	110.10 ± 2.48	50.80 ± 4.61	62.20 ± 1.16	7.20 ± 0.53	27.65 ± 0.58	**5.90 ± 0.35**
Heart-h	108.30 ± 2.00	47.80 ± 2.80	48.67 ± 2.43	8.70 ± 0.86	21.49 ± 0.41	**6.70 ± 0.40**
Ionosphere	23.30 ± 0.87	19.50 ± 1.74	11.73 ± 1.34	**8.20 ± 0.73**	11.04 ± 0.17	10.80 ± 0.81
Liver-disorders	76.50 ± 1.37	33.50 ± 3.42	10.33 ± 0.45	**9.20 ± 0.57**	11.78 ± 0.08	11.76 ± 2.34
Pima	135.50 ± 2.05	36.60 ± 4.09	126.93 ± 2.56	**8.20 ± 0.42**	15.93 ± 0.14	10.20 ± 0.51

The best results from different algorithms are shown in bold

table, Ant-Miner$_{PAE}$ discovers rules with a better predictive accuracy than other classification algorithms in eight data sets, namely, Breast-cancer, Credit-a, Credit-g, dermatology, Heart-c, Heart-h, Ionosphere, and Pima. In the Anneal data set, the difference in predictive accuracy between Ant-Miner$_{PAE}$ and other classification algorithms is relatively small. In the Breast-cancer, Credit-a, Heart-c, and Heart-h data sets, Ant-Miner$_{PAE}$ is significantly more accurate than other classification algorithms. In these data sets, the difference is large. By contrast, CN2 discovers rules with a better predictive accuracy than Ant-Miner$_{PAE}$ and other classification algorithms in the Balance-scale data set, with a predictive accuracy of 88.47 ± 1.81. In the Glass data set, *c*Ant-Miner$_{PB}$ is significantly more accurate than other classification algorithms with a predictive accuracy of 73.94±0.49. Experiments show that Ant-Miner$_{PAE}$ obtained better results than other classification algorithms in eight of the 12 data sets.

The results on the simplicity of the discovered rule list as measured by the average number of terms per rule and the number of discovered rules are discussed in this section. The comparison results of the simplicity of the rule lists discovered by Ant-Miner$_{PAE}$ and other classification algorithms are reported in Tables 3 and 4. In the Anneal data set, Ant-Miner$_{PAE}$ discovered a compact rule list with 8.6 ± 0.37 rules and 12.00 ± 0.45 terms per rule, whereas the other classification algorithms discovered a larger rule list. In the Balance-scale data sets, the rule list discovered by Ant-Miner$_{PAE}$ was simpler, that is, it had fewer rules with 13.20 ± 0.20 and the terms with 12.30 ± 0.26 per rule than the rule list discovered by the other classification algorithms. However, the difference in the simplicity of the discovered rule list by Ant-Miner$_{PAE}$ and Ant-Miner and *c*Ant-Miner$_{PB}$ was small. In the Breast-cancer data set, Ant-Miner$_{PAE}$ discovered a compact rule list with 6.10 ± 0.28 rules and 6.70 ± 0.58 terms per rule, similar to that of

Table 4 Average number of rules (average ± standard error) measured by tenfold cross-validation

Data set	CN2	C4.5 rules	PSO/ACO2	Ant-Miner	*c*Ant-Miner$_{PB}$	Ant-Miner$_{PAE}$
Anneal	19.80 ± 0.47	20.03 ± 0.89	15.51 ± 0.09	9.00 ± 0.30	16.12 ± 0.13	**8.6 ± 0.37**
Balance-scale	50.80 ± 1.57	35.70 ± 1.43	25.23 ± 0.16	13.50 ± 0.17	13.64 ± 0.03	**13.20 ± 0.20**
Breast-cancer	60.20 ± 0.77	8.60 ± 1.08	12.97 ± 0.13	6.30 ± 0.21	10.36 ± 0.11	**6.10 ± 0.28**
Credit-a	35.50 ± 0.70	14.00 ± 0.98	25.30 ± 0.11	**7.00 ± 0.49**	12.31 ± 0.10	7.70 ± 0.58
Credit-g	74.40 ± 0.93	27.50 ± 1.27	54.15 ± 0.12	**8.40 ± 0.27**	28.57 ± 0.27	9.30 ± 0.30
Dermatology	18.80 ± 0.44	19.60 ± 0.34	10.29 ± 0.08	8.10 ± 0.35	19.17 ± 0.11	**7.90 ± 0.53**
Glass	16.70 ± 0.26	14.90 ± 0.50	20.34 ± 0.08	7.40 ± 0.45	9.41 ± 0.08	**7.30 ± 0.62**
Heart-c	34.40 ± 0.40	14.90 ± 1.08	15.87 ± 0.05	6.70 ± 0.33	12.85 ± 0.14	**5.50 ± 0.22**
Heart-h	35.10 ± 0.75	12.90 ± 0.59	14.75 ± 0.08	**5.30 ± 0.15**	10.96 ± 0.12	7.00 ± 0.37
Ionosphere	10.40 ± 0.31	10.00 ± 0.36	**3.36 ± 0.07**	8.40 ± 0.64	9.18 ± 0.09	11.10 ± 0.80
Liver-disorders	29.10 ± 0.46	12.20 ± 0.93	21.53 ± 0.07	9.20 ± 0.44	10.39 ± 0.07	**9.00 ± 1.43**
Pima	49.50 ± 0.48	12.50 ± 0.92	33.55 ± 0.13	**9.00 ± 0.37**	14.89 ± 0.09	10.90 ± 0.41

The best results from different algorithms are shown in bold

Table 5 Test results according to nonparametric Friedman test with Holms post hoc test

Data set	CN2	C4.5 rules	PSO/ACO2	Ant-Miner	*c*Ant-Miner$_{PB}$	Ant-Miner$_{PAE}$
Predictive accuracy	4.92	3.75	3.67	4.67	2.50	1.42
Model size	5.75	4.42	4.50	1.67	3.17	1.50
Number of rules	5.58	4.17	4.33	1.67	3.50	1.75

Ant-Miner. In the Credit-a data set, Ant-Miner discovered a compact rule list with 7.00 ± 0.49 rules and Ant-Miner$_{PAE}$ discovered the simplicity of the average number of terms with 9.40 ± 1.14 terms per rule. In the Credit-g data set, Ant-Miner discovered a compact rule list with 8.40 ± 0.27 rules and 11.30 ± 0.47 terms per rule, and in the Dermatology data set, Ant-Miner$_{PAE}$ discovered a compact rule list with 7.90 ± 0.53 rules, and Ant-Miner discovered the simplicity of the average number of terms with 19.20 ± 0.83 terms per rule. In the other two data sets, namely, Glass and Heart-c, Ant-Miner$_{PAE}$ discovered rule lists that were simpler than those discovered by other classification algorithms. In the Ionosphere data set, PSO/ACO2 discovered a compact rule list with3.36 ± 0.07 rules and Ant-Miner discovered the simplicity of the average number of terms with 8.20 ± 0.73 terms per rule. In the Liver-disorders data set, Ant-Miner$_{PAE}$ discovered a compact rule list with9.00 ± 1.43 rules, and Ant-Miner discovered the simplicity of the average number of terms with 9.20 ± 0.57 terms per rule. In the Pima data set, Ant-Miner discovered the optimal average rule number and the average number of terms per rule, which were 9.00 ± 0.37 and 8.20 ± 0.42, respectively.

Experimental results show that Ant-Miner$_{PAE}$ can obtain the shortest condition number in seven groups of data sets among the 12 publicly available data sets. Simultaneously, Ant-Miner$_{PAE}$ can obtain the shortest number of rules in seven groups of data sets; however, they are not completely consistent.

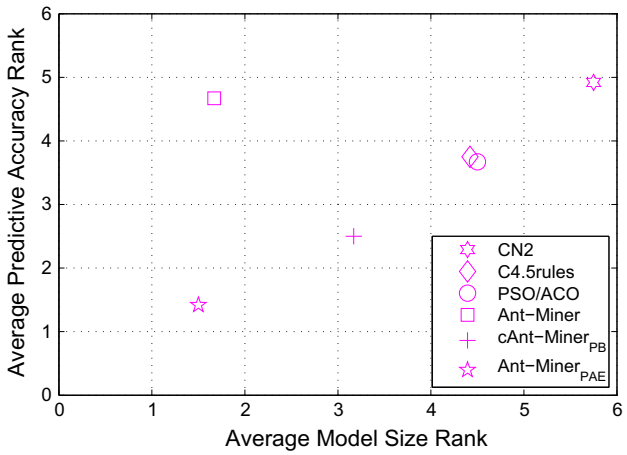


Fig. 2 Average predictive accuracy rank versus average model size rank of the algorithms

Table 5 presents the results of the statistical tests for predictive accuracy, size of the classification model, and total number of discovered rules according to the nonparametric Friedman test with Holm's post hoc test (Demšar 2006), where a lower rank means better algorithm performance.

Figures 2 and 3 illustrate the average predictive accuracy rank versus the average model size rank and average predictive accuracy rank versus the average number of rules rank of the algorithms used in our experiments. A lower average rank means better algorithm performance.

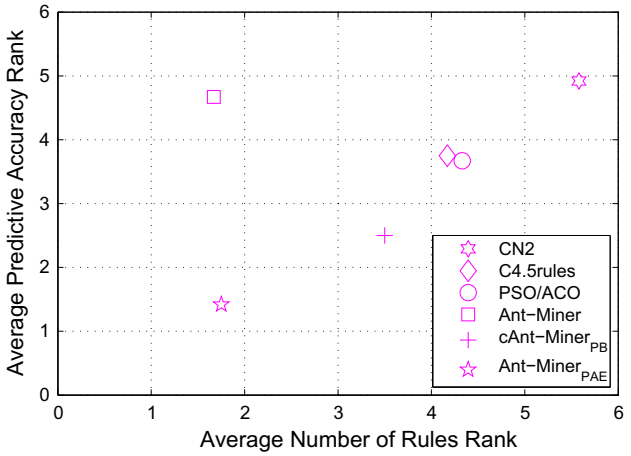


Fig. 3 Average predictive accuracy rank versus the average number of rules rank of the algorithms

4.4 Analysis of Ant-Miner$_{PAE}$ computational complexity

In this section, we discuss the computational complexity of the proposed Ant-Miner$_{PAE}$ algorithm. The analysis is divided into three parts: (1) initialization pheromone; (2) inner while-loop presented in algorithm Ant-Miner$_{PAE}$ and corresponds to the procedure for creating a complete candidate list of rules, and (3) outer while-loop presented in algorithm Ant-Miner$_{PAE}$, which corresponds to an entire execution of Ant-Miner$_{PAE}$. n is the number of training examples, α is the number of attributes representing the choices available to create a rule, m is the number of ants (colony size), and t is the number of iterations. We define the computational complexity of each aforementioned part as follows.

(1) *Initialization pheromone* Each iteration starts by initializing the pheromone, that is, specifying the values of all $\tau_{ij}(t) = 0$, which takes $O(\alpha \cdot v)$, where α is the number of attributes, and v is the number of values per attribute.

(2) *Computational complexity of creating a list of rules* A list of rules is created by an iterative sequential covering procedure that builds a single rule. To create a rule, the heuristic information η_{ij} for every term is computed in a single scan of the training set. Thus, the time complexity of this step is $O(n \cdot \alpha)$, where n is the number of cases, and α is the number of attributes. The inner while-loop is the procedure in which a rule is discovered by an ant and is placed in a rule list. Eventually, a rule list is constructed. The major steps performed by each ant are (a) rule construction, (b) rule evaluation, and (c) rule pruning. The computational complexities of these steps are as follows.

(a) *Rule construction* The choice of a condition to be added to the current rule requires that an ant considers all possible conditions. The values of η_{ij} and $\tau_{ij}(t)$ for all conditions have been computed. The pheromone was initialized before the internal loop starts; therefore, this step takes $O(n \cdot \alpha)$. To construct a rule, an ant will choose k conditions. k is a highly variable number that depends on the data set and on previous rules constructed by other ants. In addition, $k \leq \alpha$; hence, rule construction takes $O(k \cdot \alpha \cdot n)$.

(b) *Rule evaluation* This step measures the quality of a rule as given by (10) and requires matching a rule with k conditions with a training set with n cases, which takes $O(k \cdot n)$.

(c) *Rule pruning* The first pruning iteration requires the evaluation of k new candidate rules. Each rule is obtained by removing one of the conditions from the unpruned rule. Each of these rule evaluations takes $(n \cdot (k-1))$ operations. Thus, the first pruning iteration takes $O(n \cdot (k-1) \cdot k)$ operations, that is, $O(n \cdot k^2)$. The second pruning iteration takes $O(n \cdot (k-2) \cdot (k-1))$ operations. The entire rule pruning process is repeated at most k times. Thus, rule pruning takes at most $n \cdot (k-1) \cdot k + n \cdot (k-2) \cdot (k-1) + n \cdot (k-3) \cdot (k-2) + \cdots + n \cdot (1) \cdot (2)$, which is $O(k^3 \cdot n)$.

In summary, the internal loop takes $O(k \cdot \alpha \cdot n) + O(k \cdot n) + O(k^3 \cdot n)$, which collapses to $O(k \cdot \alpha \cdot n + k^3 \cdot n)$. The process of creating a rule is repeated n times in the worst case of the sequential covering, assuming that the algorithm creates a rule for each training example. Therefore, the upper-bound estimation of time complexity of the creation of a list of rules is $O(k \cdot \alpha \cdot n + k^3 \cdot n) \cdot n$, which collapses to $O(k \cdot \alpha \cdot n^2 + k^3 \cdot n^2)$.

(3) Computational time complexity of an entire execution: An entire execution of the algorithm involves t iterations of a procedure, where a colony of m ants creates a candidate list of rules, and the best candidate list is used to update the pheromone values. The pheromone update consists of increasing or decreasing pheromone values of terms in the candidate list. Therefore, an entire execution takes $O(t \cdot m \cdot (k \cdot \alpha \cdot n^2 + k^3 \cdot n^2)) + O(t \cdot \alpha \cdot n)$, where $O(t \cdot m \cdot (k \cdot \alpha \cdot n^2 + k^3 \cdot n^2))$ represents the upper-bound estimation of time complexity.

The above analysis corresponds to the worst-case estimation and does not account for the number of training examples that decreases at each iteration of the sequential covering used to create a list of rules. Moreover, the algorithm is able to converge before reaching the maximum number of iterations t.

4.5 Complexity of computational time

We calculate the time of classification algorithms that run tenfold cross-validations to be used to measure the efficiency of different algorithms. Table 6 presents the average computational time (in seconds) to complete the tenfold

Table 6 Average computational time in seconds (average ± standard error) taken by PSO/ACO2, Ant-Miner, cAnt-Miner$_{PB}$, Ant-Miner$_{PAE}$ to complete tenfold of the cross-validation

Data set	PSO/ACO2	Ant-Miner	cAnt-Miner$_{PB}$	Ant-Miner$_{PAE}$
Anneal	17.16 ± 0.44	0.31 ± 0.08	1236.60 ± 94.4	12.06 ± 0.151
Balance-scale	21.65 ± 1.15	0.012 ± 0.009	2.90 ± 0.13	0.77 ± 0.024
Breast-cancer	3.21 ± 0.12	0.009 ± 0.007	3.40 ± 0.27	0.65 ± 0.013
Credit-a	15.87 ± 0.30	0.03 ± 0.009	27.20 ± 1.12	2.71 ± 0.036
Credit-g	51.24 ± 0.69	0.065 ± 0.011	1330.50 ± 66.7	6.31 ± 0.052
Dermatology	5.27 ± 0.05	0.095 ± 0.048	57.70 ± 2.59	8.35 ± 0.858
Glass	4.28 ± 0.03	0.01 ± 0.01	16.51 ± 0.78	2.59 ± 0.458
Heart-c	6.19 ± 0.03	0.01 ± 0.009	17.32 ± 1.35	1.577 ± 0.039
Heart-h	5.47 ± 0.03	0.014 ± 0.008	24.33 ± 1.44	1.209 ± 0.123
Ionosphere	4.33 ± 0.06	0.212 ± 0.057	104.07 ± 4.87	38.03 ± 1.836
Liver-disorders	6.25 ± 0.03	0.011 ± 0.034	18.13 ± 0.74	39.01 ± 2.56
Pima	21.35 ± 0.08	0.018 ± 0.006	75.40 ± 4.27	2.87 ± 0.041

cross-validation for PSO/ACO2, Ant-Miner, cAnt-Miner$_{PB}$, and Ant-Miner$_{PAE}$ algorithms over ten runs. In general, the computational time of Ant-Miner$_{PAE}$ is slower than that of Ant-Miner but faster than that of PSO/ACO2 and cAnt-Miner$_{PB}$. We adjust the structure of the algorithm and increase the calculation method of the pheromone of attraction and exclusion on the basis of the basic ant colony classification-mining algorithm; hence, the Ant-Miner$_{PAE}$ running time of the algorithm is slightly longer. In many data mining applications, the computational time taken by the algorithm to induce a classification model has a minor importance. Instead, better prediction accuracy and rules that are more concise are needed. In addition, Ant-Miner$_{PAE}$ algorithms can be easily parallelized because each ant builds and evaluates a candidate solution independently from all the other ants, thereby also possibly increasing the speed of the algorithm.

5 Conclusion and future work

5.1 Conclusion

In this study, which is based on the study of Ant-Miner and cAnt-Miner$_{PB}$, we proposed a new improved ant colony classification mining algorithm called Ant-Miner$_{PAE}$, which is based on the principle of attraction and exclusion of pheromone. In Ant-Miner$_{PAE}$, the basic algorithm structure was modified, the order of the iteration was adjusted, and the problem of rule interaction was mitigated. The new pheromone calculation method was designed, and the search was guided by the new probability transfer formula. The pheromones of the search rule process by ants contained attractive parts and exclusive sections, which make the ants in the search rule process explore initially and develop later in the period. The method could effectively improve the quality and accuracy of the search for a rule list. Our experiments, which used 12 publicly available data sets, showed that the predictive accuracy obtained by the Ant-Miner$_{PAE}$ algorithm with the proposed pheromone attraction and exclusion strategy was statistically significantly higher than the predictive accuracy of other rule induction classification algorithms, such as CN2, C4.5 rules, PSO/ACO2, Ant-Miner, and cAnt-Miner$_{PB}$. Moreover, the rule lists discovered by the Ant-Miner$_{PAE}$ algorithm were considerably simpler.

5.2 Future research

Future research can focus on several interesting directions. First, prediction accuracy, simplicity of rules, and time from different data sets by the same algorithm for classification rules mining have significant differences. Studying the correlation between these aspects would be interesting. Second, the prediction accuracy of different data sets could be improved further. Finally, determining a means of obtaining a significant speedup by running a parallel version of Ant-Miner$_{PAE}$ would be an interesting topic.

Acknowledgments This work was partially supported by Science and Technology Project of Guangdong Province of China (Grant Nos. 2015A020209119 and 2014A020208087), National Natural Science Foundation of China (Grant No. 61573157), and Fund of Natural Science Foundation of Guangdong Province of China (Grant No. S2013040015755). The authors also gratefully acknowledge the reviewers for their helpful comments and suggestions that helped to improve the presentation.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

References

Asuncion A, Newman DJ (2007) UCI machine learning repository. School of Information and Computer Science, University of California, Irvine. http://www.ics.uci.edu/~mlearn/mlrepository.html

Chan A, Freitas AA (2006) A new ant colony algorithm for multi-label classification with applications in bioinfomatics. Proceedings of the 8th annual conference on genetic and evolutionary computation. ACM, New York, pp 27–34

Chan A, Freitas AA (2006) A new classification-rule pruning procedure for an ant colony algorithm. Artificial evolution. Springer, New York, pp 25–36

Clark P, Boswell R (1991) Rule induction with CN2: some recent improvements. Machine learning EWSL-91. Springer, New York, pp 151–163

Clark P, Niblett T (1989) The CN2 induction algorithm. Mach Learn 3(4):261–283

De López R, Mántaras M (1991) A distance-based attribute selection measure for decision tree induction. Mach Learn 6(1):81–92

Demšar J (2006) Statistical comparisons of classifiers over multiple data sets. J Mach Learn Res 7:1–30

Dhar V, Chou D, Provost F (2000) Discovering interesting patterns for investment decision making with glowera genetic learner overlaid with entropy reduction. Data Min Knowl Discov 4(4):251–280

Dorigo M (1994) Learning by probabilistic boolean networks. IEEE world congress on computational intelligence, IEEE international conference on neural networks, vol 2. IEEE, New York, pp 887–891

Dorigo M, Stützle T (2004) Ant colony optimization for NP-hard problems. Ant Colony Optimization. MIT press, pp 153–222

Dorigo M, Maniezzo V, Colorni A (1996) Ant system: optimization by a colony of cooperating agents. IEEE Trans Syst Man Cybern Part B Cybern 26(1):29–41

Freitas AA, Wieser DC, Apweiler R (2010) On the importance of comprehensible classification models for protein function prediction. IEEE/ACM Trans Comput Biol Bioinform (TCBB) 7(1):172–182

Han J, Kamber M (2001) Data mining: concepts and technologies. Data Mining Concepts Models Methods & Algorithms, 2nd edn, 5(4): 1–18

Holden N, Freitas AA (2008) A hybrid PSO/ACO algorithm for discovering classification rules in data mining. J Artif Evol Appl 2008. doi:10.1122/2008/316145

Jin P, Zhu Y, Hu K, Li S (2006) Classification rule mining based on ant colony optimization algorithm. Intelligent control and automation. Springer, New York, pp 654–663

Kaltenbacher B (2001) On the regularizing properties of a full multigrid method for ill-posed problems. Inverse Probl 17(4):767–788

Kaltenbacher B, Schicho J (2002) A multi-grid method with a priori and a posteriori level choice for the regularization of nonlinear ill-posed problems. Numer Math 93(1):77–107

Keung YL, Zou J (2000) An efficient linear solver for nonlinear parameter identification problems. Siam J Sci Compt 22(5):1511–1526

Kohavi R, Sahami M (1996) Error-based and entropy-based discretization of continuous features. In: KDD, pp 114–119

Li J, Zou J (2007) A multilevel model correction method for parameter identification. Inverse Probl 23(5):1759–1786

Liu B, Pan J (2007) Research of classification algorithm based on ant colony optimization. Comput Appl Softw 24(4):50–53

Liu B, Abbass HA, McKay B (2002) Density-based heuristic for rule discovery with ant-miner. In: The 6th Australia-Japan joint workshop on intelligent and evolutionary system, vol 184, Citeseer

Liu B, Abbass HA, McKay B (2003) Classification rule discovery with ant colony optimization. In: Null. IEEE, New York, p 83

Martens D, De Backer M, Haesen R, Vanthienen J, Snoeck M, Baesens B (2007) Classification with ant colony optimization. IEEE Trans Evol Comput 11(5):651–665

Meyer F, Parpinelli RS (2012) ACO: public software. http://www.aco-metaheuristic.org/aco-code/public-software.html

Otero FEB, Freitas AA, Johnson CG (2008) Cant-miner: an ant colony classification algorithm to cope with continuous attributes. Ant colony optimization and swarm intelligence. Springer, New York, pp 48–59

Otero FEB, Freitas A, Johnson CG et al (2009) Handling continuous attributes in ant colony classification algorithms. IEEE symposium on computational intelligence and data mining, CIDM'09. IEEE, New York, pp 225–231

Otero FEB, Freitas A, Johnson Colin G et al (2013) A new sequential covering strategy for inducing classification rules with ant colony algorithms. IEEE Trans Evol Comput 17(1):64–76

Parpinelli RS, Lopes HS, Freitas AA (2001) An ant colony based system for data mining: applications to medical data. In: Proceedings of the genetic and evolutionary computation conference (GECCO-2001), pp 791–797, Citeseer

Parpinelli Rafael S, Lopes Heitor S, Freitas A et al (2002a) Data mining with an ant colony optimization algorithm. IEEE Trans Evol Comput 6(4):321–332

Parpinelli RS, Lopes HS, Freitas AA (2002) An ant colony algorithm for classification rule discovery. In: Data mining: a heuristic approach, pp 191–208

Quinlan JR (2014) C4.5: programs for machine learning. Elsevier, New York

Smaldon J, Freitas AA (2006) A new version of the ant-miner algorithm discovering unordered rule sets. Proceedings of the 8th annual conference on genetic and evolutionary computation. ACM, New York, pp 43–50

Wang Z, Feng B (2005) Classification rule mining with an improved ant colony algorithm. AI 2004: advances in artificial intelligence. Springer, New York, pp 357–367

Applied Soft Computing Journal 166 (2024) 112161

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

An enhanced diversity indicator-based many-objective evolutionary algorithm with shape-conforming convergence metric

Jiale Cao [a], Lei Yang [a,*], Kangshun Li [a], Yuanye Zhang [a], Jinglin Tian [a], Dongya Wang [b]

[a] College of Mathematics and Informatics, South China Agricultural University, Guangzhou, 510642, Guangdong, China
[b] College of Engineering, Mathematics and Physical Sciences, University of Exeter, Exeter, EX4 4QF, Devon, UK

ARTICLE INFO

Keywords:
Many-objective evolutionary algorithm
Enhanced diversity I_{ϵ^+} indicator
Shape-conforming convergence metric
Mating strategy

ABSTRACT

As the number of objectives increases, many-objective optimization problems (MaOPs) become increasingly complex. Traditional indicator-based many-objective evolutionary algorithms can often ensure the convergence of the population but tend to struggle with maintaining its diversity. In this paper, an enhanced diversity indicator-based many-objective evolutionary algorithm with shape-conforming convergence metric, namely, MaOEA-DISC, is presented to relieve this weakness. In MaOEA-DISC, firstly, we focus on the inter-individual spacing relationships within the population based on I_{ϵ^+} Indicator, proposing a novel enhanced diversity I_{ϵ^+} Indicator to ensure the enhancement of population diversity while converging. Secondly, we propose a new metric of individual convergence, which calculates the convergence of individuals based on the shape of Pareto front, reducing the errors caused by the shape of the Pareto front when measuring individual convergence, thereby assessing individual convergence more accurately. Finally, to further improve the convergence speed of the population, different mating strategies are employed for mating in the parental generation. MaOEA-DISC is compared with other algorithms on various benchmark MaOPs ranging from 3 to 10 objectives, as well as a real-world MaOPs. Experimental results demonstrate that when dealing with MaOPs, MaOEA-DISC not only achieves excellent population convergence and diversity but also effectively maintains a balance between them, showing promising practical value.

1. Introduction

Many-objective optimization problems (MaOPs) are a class of optimization problems that involve simultaneously considering three or more conflicting objective functions during the solution process. In such problems, improving the performance of one objective typically leads to a degradation in the performance of other objectives. Therefore, finding a solution that optimizes all objectives is usually infeasible, and instead, one aims to find a set of optimal solutions as much as possible. Minimizing MaOPs can be define as (1) [1]:

$$\begin{aligned} &\text{Minimize } F(x) = \left(f_1(x), f_2(x), \ldots, f_M(x)\right)^T \\ &\text{Subject to } x \in \Omega \end{aligned} \tag{1}$$

Where x is an n-dimensional decision vector in the decision space Ω, $F(x)$ is an m-dimensional objective vector ($m \geq 3$), and $f_i(x)$ represents the objective function of the ith objective. For two solutions x_i and x_j in Ω, if for any objective k, it holds $f_k(x_i) \geq f_k(x_j)$, and there exists an objective t such that $f_t(x_i) > f_t(x_j)$, then x_i Pareto dominates x_j. If x_i is not Pareto dominated by any other solution, it is termed as a non-dominated solution. A set of non-dominated solutions forms the Pareto optimal solution set (PS) [2]. The mapping of the Pareto optimal solution set in the objective space is referred to as the Pareto front (PF) [3].

In real-world scenarios, many fields involve many-objective optimization, making it a perennially hot research topic. For instance, in synchronous motor design, considerations encompass objectives such as high specific power and efficiency [4]. Similarly, when predicting the popularity of online content, objectives like accuracy and latency are paramount [5]. Enhancing public transportation services while reducing carbon emissions requires balancing objectives such as economic costs and energy consumption [6]. To address MaOPs, researchers have explored various methodologies, such as lightweight surrogate models [7], immune algorithms [8], and artificial bee colony algorithms [9]. Despite this variety, evolutionary algorithms remain predominant in the realm of many-objective optimization. Evolutionary algorithms, as heuristic optimization methods, mimic natural evolution processes and effectively address diverse optimization challenges [10–12]. However, as the number of objectives increases, achieving a high-quality population with both convergence and diversity in handling

* Corresponding author.
E-mail address: yanglei_s@scau.edu.cn (L. Yang).

https://doi.org/10.1016/j.asoc.2024.112161
Received 11 December 2023; Received in revised form 24 May 2024; Accepted 20 August 2024
Available online 30 August 2024
1568-4946/© 2024 Elsevier B.V. All rights are reserved, including those for text and data mining, AI training, and similar technologies.

MaOPs becomes increasingly challenging [13]. To effectively address this issue, numerous researchers have conducted extensive studies and proposed many outstanding many-objective evolutionary algorithms (MaOEAs). Currently, these MaOEAs can be roughly categorized into the following three categories:

Pareto dominance-based MaOEAs belongs to the first category of MaOEAs. As the number of objectives increases, the Pareto dominance region becomes progressively smaller, making it challenging to select effective non-dominating solutions [14,15]. Consequently, the relaxation of Pareto dominance relationships has emerged as a popular approach to address this issue. This method is typically achieved by expanding the dominance range through the relaxation of Pareto dominance relationships to identify non-dominated solutions with elite information. For instance, in DRS dominance [16], dominance relationships are dynamically adjusted by measuring the proximity between offspring and parents, with the dominance range expanding when offspring are close to their parents. In DD-dominance [17], the size of a niche is calculated based on the number of objectives and evolutionary status, and then the convergence size within that niche is used as the criterion for comparing dominance relationships. However, methods that relax Pareto dominance relationships are highly dependent on parameters, resulting in poor generality of such algorithms. Additionally, using secondary selection criteria related to diversity on the basis of Pareto dominance can also help in selecting non-dominated solutions with elite information. Li et al. [18] divided the population into several regions evenly based on Euclidean distance after non-dominated sorting to maintain population diversity, while Dai et al. [19] consider the components of each dimension in crowded distance calculation to search for solutions with good diversity in high-dimensional space when Pareto dominance fails. Although these algorithms can effectively maintain population diversity, they tend to overlook population convergence.

The second category of MaOEAs refers to decomposition-based MaOEAs. The core idea of these algorithms is to decompose a MaOP into multiple single-objective subproblems, which are then simultaneously addressed. The most representative algorithm in this category is MOEA/D [20], which primarily employs aggregation functions and reference vectors for the decomposition of MaOPs, thereby maintaining the convergence and diversity of the population. However, when the shape of PF in MaOPs is irregular, predefined uniformly distributed reference vectors may fail to conform to the shape of PF, leading to a deterioration in the diversity of the population [21–23]. Therefore, adjusting the reference vectors to match the shape of PF has become a hot research topic for these algorithms. For instance, in RVEA-DWC [24], the adjustment of reference vectors is achieved by periodically removing invalid ones and introducing new ones with both local and global diversity. In SPARVEA [25], reference vectors are updated by evaluating the potential of solutions, generating new reference vectors in high-potential directions, and removing ineffective vectors. In MOEA/D-ND [26], a normal distribution is used to generate reference vectors, which enables a better alignment with the complex shape of PF. However, these algorithms cannot generate an arbitrary number of reference vectors, and multiple adjustments to the reference vectors can lead to a decrease in population convergence.

The algorithms in the third category, indicator-based MaOEAs, employ performance evaluation indicators as individuals' fitness functions and use them as selection criteria, thereby transforming MaOPs into single-objective problems. Among these, $I_{\epsilon+}$ [27], HV [28], IGD [29], and R2 [30] are four of the most common performance evaluation indicators that effectively assess the overall performance of a population, making them widely utilized in MaOEAs. IBEA [27] was the first algorithm to adopt indicators in MaOEAs. It utilizes the $I_{\epsilon+}$ indicator to compute the fitness values of each individual, enabling diverse adaptability to preferences and optimization scenarios without the need for any diversity-preserving techniques. Subsequently, indicator-based MaOEAs have experienced rapid development. For instance, In MaOEA-LAMG [31], updating the elite archive based on the $I_{\epsilon+}$ indicator aims to retain individuals with excellent convergence and diversity from past iterations. In TosHVT [32], which is based on the HV indicator, a coarse-grained selection of the population is rapidly accomplished by computing the total HV contribution of each individual. In AR-MOEA [33], the IGD with noncontributing solution detection, is employed to adjust reference points. In R2 indicator-based R2HCA-EMOA [34], a utility tensor structure is introduced to compute variants of the R2 indicator, approximating hypervolume values based on these R2 indicator variants. Besides using common single indicators to select individuals, some algorithms employ multiple novel indicators for individual selection. For instance, in Mo4Ma-DE [35], shift-based density estimation is utilized as a diversity indicator, and the sum of all objective values is used as a convergence indicator, then elite individuals are selected based on these two indicators. Similarly, NSPI-EMO [36] uses the angle between individuals and their nearest neighbour as a diversity indicator, while the distance from individuals to the ideal point and the worst point serves as a convergence indicator, thus selecting high-quality individuals. Additionally, algorithms like onebyoneEA [37], SRA [38], etc., also treat diversity and convergence as two independent indicators for individual selection.

Although these indicator-based MaOEAs provide an effective solution for dealing with MaOPs, their performance deteriorates as the dimensionality increases. Specifically, for MaOEAs employing a single indicator, even though they can achieve good convergence of individuals, they exhibit poor population diversity maintenance. Furthermore, some performance evaluation indicators they use have high computational complexity and require information such as reference points and reference vectors, which reduces their generality. Although employing multi-indicator MaOEAs can partially alleviate the problems associated with single-indicator MaOEAs, most multi-indicator MaOEAs separate diversity and convergence into two independent indicators and then use additional methods to balance them. However, balancing the two objectives of diversity and convergence is also a multi-objective optimization problem, making multi-indicator MaOEAs more complex and difficult to balance convergence and diversity. Additionally, multi-indicator MaOEAs often focus on balancing diversity and convergence, overlooking their performance on irregular PFs. Therefore, utilizing indicator-based MaOEAs to handle MaOPs still presents challenges.

$I_{\epsilon+}$ Indicator has found widespread application in many-objective optimization due to its simplicity and versatility. Inspired by $I_{\epsilon+}$ Indicator, this paper proposes an enhanced diversity indicator-based many-objective evolutionary algorithm with shape-conforming convergence metric, named MaOEA-DISC, which seeks to enhance diversity and maintain convergence in indicator-based many-objective optimization. In contrast to traditional MaOEAs, which employ multiple indicators to separately enhance the convergence and diversity of the population, MaOEA-DISC utilizes two indicators that simultaneously consider both convergence and diversity. This eliminates the need for additional methods to balance the two, effectively maintaining their equilibrium. Furthermore, these two indicators remain unaffected by the shape of the PF, facilitating the preservation of population diversity on irregular PF. Additionally, the simplicity of MaOEA-DISC's indicator calculation, which does not require reference points or similar information, endows it with strong generality. Specifically, in MaOEA-DISC, the shape of PF is estimated first. Then, based on the shape of PF, individuals are mapped onto surfaces similar to PF shape. The convergence of individuals is represented by the distance between individuals and their mapped counterparts. After computing the convergence of each individual, the convergence status of the current population is assessed, and in the case of non-convergence, a selection of individuals with superior convergence properties is chosen for mating. Finally, an enhanced diversity indicator is employed for environmental selection, choosing individuals with both good convergence and diversity. This indicator builds on $I_{\epsilon+}$ indicator, which maintains population diversity by calculating the cosine similarity between individuals of a population and their nearest neighbours, as well as the cosine similarity between individuals and all other individuals. The main contributions of this paper are as follows:

- This paper presents an enhanced diversity $I_{\epsilon+}$ Indicator called $I_{\epsilon+D}$, which measures the diversity of a population by multiplying the cosine similarity between individuals and their nearest neighbours by the sum of cosine similarities between individuals and all other individuals, ensuring that individuals are able to uniformly dispersion across the entire PF. Additionally, it evaluates individual convergence using fitness values computed by the $I_{\epsilon+}$ Indicator. Ultimately, by assessing the product of diversity and convergence, it effectively enhances the quality of environmental selection, selecting individuals that balance both convergence and diversity.
- To avoid the influence of PF shape when assessing the convergence of population individuals. A shape-conforming convergence metric is introduced to calculate the individual convergence. This method estimates the shape of the current problem's PF based on the Lp-norm and computes the convergence of individuals accordingly. Thus, it accurately measures the convergence of individuals even under different PF shapes.
- In order to expedite the convergence rate of the population while maintaining its diversity, this paper proposes different mating strategies based on the population's convergence status. When the population has not converged, the method selects individuals with higher convergence as parents to ensure offspring inherit superior convergence, thus expediting convergence speed. As the population approaches convergence, parents are randomly selected to preserve diversity.

The remainder of the paper is organized as follows. We will introduce related work in Section 2. After that, we will describe our algorithm and its principles in Section 3. In Section 4, we will provide our experimental design and conduct experimental comparisons and related analysis of the proposed algorithm. Finally, Section 5 presents the conclusion of this paper and possible future work.

2. Related work

2.1. $I_{\epsilon+}$ Indicator

The $I_{\epsilon+}$ Indicator is characterized by its relatively low computational time complexity and the absence of requirements for reference points, reference vectors, or information about the true PF. Consequently, it has found widespread application in assessing the performance of individuals within a population. The selection of individuals using the $I_{\epsilon+}$ Indicator primarily involves two steps:

The first step entails the computation of the $I_{\epsilon+}$ Indicator value, which is derived by calculating the minimum distance required to shift one solution x, among two non-dominated solutions, across all objectives relative to the other solution y. This is expressed as shown in Eqs. (2):

$$I_{\epsilon+}(x,y) = \min_{\epsilon}(f_i(x) - \epsilon \le f_i(y)), i \in \{1,\dots,m\} \tag{2}$$

The second step involves deriving the fitness values for each individual by summarizing their $I_{\epsilon+}$ Indicator values in relation to the rest of the population, as detailed in Eqs. (3):

$$F(x) = \sum_{x \in P \setminus \{y\}} -e^{-I_{\epsilon+}(x,y)/0.05} \tag{3}$$

While computing fitness values for individuals using (2) and (3) is effective in selecting individuals with good convergence properties, it can lead to issues such as nonuniform population distribution and low distribution coverage, as depicted in Fig. 1. Consequently, this paper proposes a novel approach for calculating $I_{\epsilon+}$ Indicator fitness values, aiming to enhance the diversity within the population.

2.2. Convergence metric

In MaOEAs, the convergence of a solution is typically assessed through convergence metrics. Different convergence metrics can lead to significant differences in the assessment of a solution's convergence. In order to assess the convergence of a solution as accurately as possible, several convergence metrics have been proposed [37]:

The first method involves calculating the sum of each objective value for a given solution (SUMC for short), as shown in Eqs. (4).

$$c(x) = \sum_{i=1}^{m} f_i(x) \tag{4}$$

The second method calculates the Chebyshev distance from a solution to the ideal point z_i^* (CBSC for short), as depicted in Eqs. (5).

$$c(x) = \max\left|f_i(x) - z_i^*\right|, i \in \{1,\dots,m\} \tag{5}$$

The third method computes the Euclidean distance from a solution to the ideal point z_i^* (EIC for short), as indicated in Eqs. (6).

$$c(x) = \sqrt{\sum_{i=1}^{m}(f_i(x) - z_i^*)^2}, i \in \{1,\dots,m\} \tag{6}$$

The fourth method calculates the Euclidean distance from a solution to the Nadir point z_i^{nad} (ENC for short), as shown in Eqs. (7).

$$c(x) = \frac{1}{\sqrt{\sum_{i=1}^{m}(f_i(x) - z_i^{nad})^2}}, i \in \{1,\dots,m\} \tag{7}$$

Fig. 2 presents the convergence contour plots of these four methods in a bi-objective space. From Fig. 2(a), it can be observed that the first method's convergence contour is a straight line, making it suitable for measuring the convergence of solutions in MaOPs with a linear PF. However, it is not suitable for measuring the convergence of solutions in MaOPs with a concave PF. Conversely, the second method is effective for measuring the convergence of solutions in MaOPs with a concave PF, its contour consists of two lines forming a square with the coordinate axes. Although its performance in continuous problems is lacking, it is effective for discrete problems. The third method is similar to the second method and is suitable for measuring the convergence of solutions in MaOPs with a concave PF. Its contour forms a 1/4 circle, making it particularly suitable for measuring the convergence of solutions in MaOPs where the PF is part of a spherical shape. However, its accuracy in measuring the convergence of solutions in MaOPs with convex PF is limited. The fourth method is essentially a reflection of the third method, and its contour is the opposite of the third method's, making it suitable for measuring the convergence of solutions in MaOPs with convex PF.

Although these convergence metric methods can measure the convergence of solutions, their applicability is limited. When dealing with PF that do not conform to the shape of their convergence contours, these metrics become inaccurate. Hence, convergence metric methods that align with the shape of the PF provide the most accurate results, as shown in Fig. 2(e) and Fig. 2(f). Ideally, regardless of the shape of the PF, the convergence contours of an ideal convergence metric method should align with the PF. To enhance the accuracy of measuring a solution's convergence, this paper introduces a convergence metric method based on the shape of the PF.

3. Proposed algorithm

3.1. General framework

The overall framework of the proposed MaOEA-DISC is presented in Algorithm 1. In MaOEA-DISC, an initial population P of size N with M objectives is randomly generated. Subsequently, the population undergoes iterative evolution. In each iteration, the shape of PF is

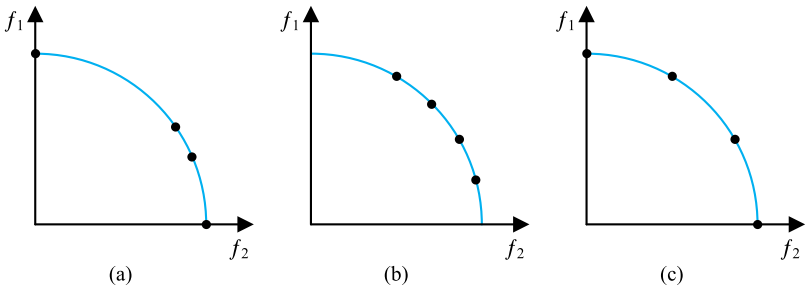


Fig. 1. Different population distributions. The blue curve represents PF, while the black dots represent individual members of the population. (a) Nonuniform population distribution. (b) Population distribution with poor coverage. (c) Ideal population distribution.

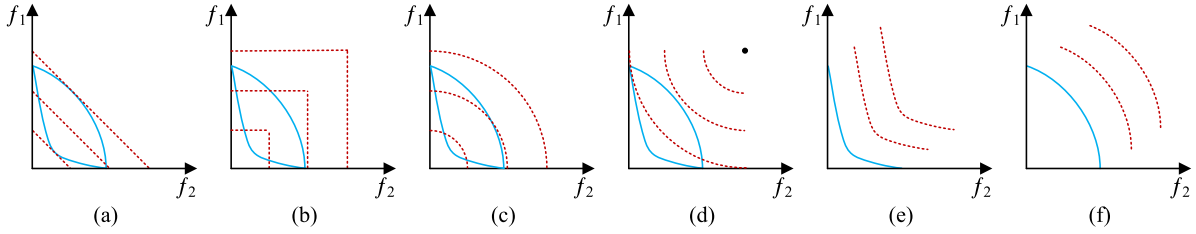


Fig. 2. Contour plots of convergence under different convergence metrics. The red dashed lines represent the contour lines. (a) SUMC. (b) CBSC. (c) EIC. (d) ENC. (e)(f) Ideal Method.

estimated, and based on the shape information of PF represented by "p", the convergence of individuals in the population is calculated. Once the convergence values C for the population individuals are determined, a new offspring F of size N is generated through crossover and mutation based on the convergence of population individuals. Finally, environmental selection is applied to P and F to select N outstanding individuals. This evolutionary process is repeated until the termination criteria are satisfied. A detailed description of the key components of MaOEA-DISC will be provided in the following sections.

Algorithm 1 Framework of the Proposed MaOEA-DISC.

Input: N (Population size), M (Number of objective)
Output: P (Population)
1: $P \leftarrow$ Initialize Population(N, M)
2: **while** termination criterion not fulfilled **do**
3: $p \leftarrow$ ShapeEstimate(P, N);
4: $C \leftarrow$ ConvergenceCount(P, N, M, p)
5: $F \leftarrow$ MatingandReproduction(P, N, C)
6: $P \leftarrow$ EnvironmentalSelection(P, N, M, F)
7: **end while**

3.2. Shape-conforming convergence metric

After the initialization of the population, the convergence of each individual in the population was then calculated, facilitating the selection of elite individuals for reproduction. Nevertheless, as mentioned in Section 2.2, various convergence metric methods often yield convergence contours that do not conform well to the shapes of diverse PF, making it challenging to accurately measure the convergence of a solution. To address this issue, drawing inspiration from the diversity of populations in 2REA [39] through PF estimation, we propose a shape-conforming convergence metric (SCCM). When employing SCCM to measure the convergence of individuals, it is imperative to estimate the shape of the PF first, determining the curvature of the PF. Therefor, in this paper, we adopt a similar approach as 2REA to estimate the shape of the PF, as outlined in Algorithm 2.

It is first necessary to limit the curvature of the PF to a suitable range of values, and then sample based on certain intervals within that range to obtain the set Cp of all curvatures, and then calculate the Lp-norm distance $ALp_i = \{Lp(x_1|p_i), Lp(x_2|p_i), \ldots, Lp(x_N|p_i)\}$ for all individuals

Algorithm 2 ShapeEstimate.

Input: P (Population),N (Population size)
Output: p (Curvature of PF)
1: Cp =[0.1,0.2,0.3,0.4...,10]
2: $Vp \leftarrow \emptyset$
3: **for** $i = 1 \rightarrow$length(Cp) **do**
4: $ALp_i \leftarrow \emptyset$
5: **for** $j = 1 \rightarrow N$ **do**
6: Calculate the Lp−norm distance Lp_j of each individual in the population under the value of Cp_i using Eqs. (8).
7: $ALp_i \leftarrow Lp_j \cup ALp_i$
8: **end for**
9: Remove outliers from ALp_i using the quartile method
10: Calculate the standard deviation Vp_i of ALp_i.
11: $Vp \leftarrow Vp_i \cup Vp$
12: **end for**
13: index = argmin(Vp)
14: $p = p$(index)

in the population at the current value of Cp_i (Steps 1–8 of Algorithm 2), where the Lp-norm distance is defined as follows:

$$L(x|p) = \left(\sum_{i=1}^{m} (f_i(x))^p\right)^{\frac{1}{p}}, p > 0 \tag{8}$$

Where $p > 0$ is the curvature of PF.

After obtaining ALp_i, it is necessary to remove outliers from ALp_i using the quartile method, and finally calculate the standard deviation Vp_i of ALp_i (Steps 9–12 of Algorithm 2). Repeat all of the above steps until the Vp values of all curvatures in the set Cp have been calculated. Finally, select the value of p that corresponds to the minimum Vp as the curvature for the estimated PF. (Steps 13–14 of Algorithm 2), because a smaller Vp indicates that the surface constructed by the chosen p values is closer to PF.

After obtaining the curvature p of the estimated PF, it is necessary to map the individuals of the population onto the surface formed by this curvature. Finally, the distance between each individual and its corresponding mapped individual is considered as its convergence

Algorithm 3 ConvergenceCount.

Input: P (Population),N (Population size), M (Number of objective), p (Curvature of PF)
Output: C (The set containing the convergence values of each individual in the population)

```
for i = 1 → N do
    for j = 1 → M do
        Normalize the j-th objective of the i-th individual in the population using Eqs. (9).
    end for
end for
for i = 1 → N do
    for j = 1 → M do
        Using Eqs. (10) to map the j-th objective of the i-th individual in the population.
    end for
end for
for i = 1 → N do
    Calculate the convergence C_i of the i-th population individual using Eqs. (11).
    C ← C_i ∪ C
end for
```

metric. Algorithm 3 outlines the procedure for evaluating the convergence of population individuals after determining the curvature p of the estimated PF. Firstly, the individuals of the population are normalized using Eq. (9) (Steps 1–5 of Algorithm 3). The normalization formula is as follows:

$$f_i'(x) = \frac{f_i(x) - z_i^*}{z_i^{nad} - z_i^*}, i \in \{1, \dots, m\} \tag{9}$$

Where z^* represents the ideal point, which in this paper consists of the minimum of each objective value in the population. Where z^{nad} represents the nadir point, which in this paper consists of the maximum value of each objective value in the population.

After completing population normalization, the population individuals are mapped onto a surface constructed by the curvature p (Steps 6–10 of Algorithm 3). The mapping formula is as follows [39]:

$$f_i''(x) = \frac{f_i'(x)}{(\sum_{j=1}^{M} f_j'(x)^p)^{\frac{1}{p}}}, i \in \{1, \dots, m\} \tag{10}$$

Finally, calculate the Manhattan distance between the non-normalized population individuals and their respective mapped individuals as a measure of their convergence (Steps 11–13 of Algorithm 3). The reason for using the Manhattan distance as the distance metric here is that in high-dimensional spaces, Manhattan distance is more effective than Euclidean distance [40]. The calculation of SCCM is as follows:

$$d_{SCCM}(x) = \sum_{i=1}^{M} |f_i(x) - f_i''(x)|, x \in P \tag{11}$$

The process of assessing convergence through SCCM for four individuals A, B, C, and D in a bi-objective optimization problem is illustrated in Fig. 3. As shown in the figure, for different shapes of PF, the distances of individuals A, B, C, and D to their corresponding mapping points A′, B′, C′, and D′ (brown line segments) are equal. Through SCCM calculations, it can be determined that their convergence is consistent, meaning they lie on the same contour line. It can be observed from the figure that this contour line closely approximates the shape of the PF. Therefore, SCCM is capable of accurately measuring an individual's convergence, enabling MaOEA-DISC to more precisely assess the convergence quality among individuals when handling MaOPs.

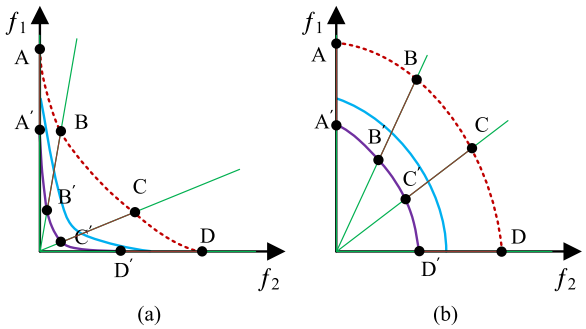


Fig. 3. A schematic diagram illustrating population convergence calculated by SCCM under different PF shapes. The purple curve represents the unit curve constructed by curvature p, while the brown line segment corresponds to SCCM. (a) Convex PF. (b) Concave PF.

3.3. Mating and reproduction

After obtaining convergence for each individual, promising individuals are selected for mating and reproduction operations in MaOEA-DISC. The specific mating and reproduction operation in MaOEA-DISC is outlined in Algorithm 4.

Algorithm 4 MatingandReproduction.

Input: P (Population), N (Population size), C (Convergence of individual population)
Output: F (Offspring)

```
flag ← 0
C_max=max(C)
if C_max remains constant within a certain algebraic range. then
    flag ← 1
end if
for i = 1 → N do
    r_1 ← Random(N)
    r_2 ← Random(N)
    if C_{r_1} ≤ C_{r_2} then
        pool ← pool ∪ P_{r_1}
    else
        pool ← pool ∪ P_{r_2}
    end if
end for
for i = 1 → N do
    r_1 ← Random(N)
    if flag = 0 then
        F_i ← CrossoverAndMutation(P_i, pool_{r_1})
    else
        F_i ← CrossoverAndMutation(P_i, P_{r_1})
    end if
end for
```

Differing from traditional mating and reproduction procedures, the mating and reproduction operation in MaOEA-DISC first assesses the convergence status of the population. In this paper, when the convergence of the worst-converging individuals in the population remains unchanged for a certain number of generations, we consider the population to be approaching or having already achieved convergence (Algorithm 4, Steps 1–5). The stability in convergence of the worst-converging individual implies its proximity to convergence or its attainment of convergence. Consequently, other individuals with better convergence than this worst-converging individual should also be approaching or have already achieved convergence. After determining the convergence status of the population, we randomly select two individuals and compare their convergence. We then retain the individual with better convergence in the candidate mating pool until the pool contains N individuals (Algorithm 4, Steps 6–14).

Subsequently, the mating and reproduction operation begins. If the population has not converged, one individual from the parent population is chosen to mate with an individual from the candidate mating pool, resulting in one offspring, until N offspring are produced from all parent individuals. If the population is approaching or has already achieved convergence, for each individual in the parent population, a random parent individual is selected for mating and reproduction (Algorithm 4, Steps 15–22). There are two specific reasons for this approach. Firstly, selecting some moderately converging individuals as parents when the population has not yet converged can to some extent improve the convergence speed of the population. Secondly, when the population is approaching or has already achieved convergence, continuing to select individuals with better convergence as parents would deteriorate the diversity of the offspring they generate. This mating strategy considers both convergence speed and population diversity, enabling MaOEA-DISC to rapidly converge while ensuring population diversity when handling MaOPs.

3.4. Environmental selection based on $I_{\epsilon+D}$ indicator

After completing the mating and reproduction operations within the population, yielding a total of $2N$ individuals comprising parents and offspring, the need arises to perform environmental selection to choose N individuals with superior performance. To address this, we propose an enhanced diversity $I_{\epsilon+}$ indicator($I_{\epsilon+D}$ Indicator) as the criterion for environmental selection, aiming to select individuals that exhibit both convergence and diversity. The inspiration for $I_{\epsilon+D}$ Indicator is derived from $I_{\epsilon+}$ Indicator. However, $I_{\epsilon+}$ Indicator heavily relies on the dominance relationships among individuals to evaluate their quality, leading to an emphasis on convergence while neglecting the importance of diversity. In order to address this limitation, the proposed $I_{\epsilon+D}$ Indicator takes into account not only dominance relationships but also individual diversity. The calculation of $I_{\epsilon+D}$ Indicator primarily consists of three components, with the first part involving the calculation of individual diversity as described in Eqs (12), (13), and (14):

$$DIV_c = CloseDis_c \times AllDis_c \tag{12}$$

$$CloseDis_c = \min_{i,i\neq c}(1-\cos(x_c, x_i)) \tag{13}$$

$$AllDis_c = \sum_{i=1,i\neq c}^{N}(1-\cos(x_c, x_i)) \tag{14}$$

Where c is the individual whose $I_{\epsilon+D}$ Indicator value is currently being calculated, and i represents the ith in the population.

In the calculation of individual diversity based on $I_{\epsilon+D}$ Indicator, inspired by the maximum outreach distance in MaOES [41], we define the product DIV_c of cosine similarity $CloseDis_c$ between x_c and its nearest individual and the sum of cosine similarities $AllDis_c$ between x_c and all individuals as the individual's diversity. A larger DIV_c value indicates better individual diversity. A larger $CloseDis_c$ implies a greater distance between x_c and its nearest neighbour, avoiding the phenomenon of crowded distances among some individuals as shown in Fig. 1(a). Similarly, a larger $AllDis_c$ implies a greater distance between x_c and all individuals, preventing the occurrence of individuals being unable to spread throughout the entire PF as depicted in Fig. 1(b). Thus, a larger product of $CloseDis_c$ and $AllDis_c$ indicates better individual diversity. Additionally, cosine distance is utilized as the distance metric because it reduces the likelihood of selecting dominance resistance solutions, thereby maximizing the convergence of individuals.

In the second part, individual convergence is calculated as shown in Eqs. (2) and (3). The final section involves assigning fitness values to individuals, as demonstrated in Eqs. (15).

$$F(x_c) = DIV_c \times \frac{1}{|\sum_{x_c\in P\setminus\{x_i\}} -e^{-I_{\epsilon+}(x_c,x_i)/0.05}|} \tag{15}$$

It is essential to note that DIV_c is a positive value, and the larger it is, the better the diversity of individuals. On the other hand, the results calculated through Eqs. (2) and (3) are negative values, and the larger these values are, the better the convergence of individuals. In order to ensure consistency in the sign of diversity and convergence while preserving the principle that a larger value in Eqs. (2) and (3) reflects better individual convergence, the convergence calculation part of Eqs. (15) takes the reciprocal of the absolute value of the result from Eqs. (3) as the measure of individual convergence. Consequently, larger values obtained from Eqs. (15) indicate superior individual convergence and diversity. As shown in Fig. 4(a), there are two individuals A and B. The $I_{\epsilon+}$ Indicator exhibits a greater inclination toward selecting individual A, which is positioned closer to PF centre, while the $I_{\epsilon+D}$ Indicator exhibits a stronger preference for selecting individual B, which is situated farther from other individuals. Fig. 4(b) reveals that, after the $I_{\epsilon+}$ Indicator selects individual A, the central region of the entire population becomes relatively crowded. Conversely, as illustrated in Fig. 4(c), when the $I_{\epsilon+D}$ Indicator selects individual B, the crowding level in the central region of the population decreases, resulting in a more uniform distribution of the population. Consequently, the $I_{\epsilon+D}$ Indicator proves to be superior to the $I_{\epsilon+D}$ Indicator in terms of promoting diversity.

Algorithm 5 EnvironmentalSelection.

Input: P (Population), N (Population size), M (Number of objective), F (Offspring)
Output: P (Population)

for $i \leftarrow 1$ to N **do**
  if $F_i \prec P_i$ **then**
    $P_i \leftarrow F_i$
  else if $P_i \prec F_i$ **then**
    continue
  else
    $PBeDom \leftarrow$ the number of individuals in P that dominate P_i
    $FBeDom \leftarrow$ the number of individuals in P that dominate F_i
    if $PBeDom = FBeDom$ **then**
      Calculate the $I_{\epsilon+D}$ Indicator values $P_i^{I_{\epsilon+D}}$ and $F_i^{I_{\epsilon+D}}$ for P_i and F_i using Eqs (2), (3), (12), (13), (14), and (15), respectively.
      if $P_i^{I_{\epsilon+D}} < F_i^{I_{\epsilon+D}}$ **then**
        $P_i \leftarrow F_i$
      end if
    else if $PBeDom > FBeDom$ **then**
      $P_i \leftarrow F_i$
    else
      continue
    end if
  end if
end for

The pseudocode for environment selection based on $I_{\epsilon+D}$ Indicator in MaOEA-DISC is as shown in Algorithm 5. First, compare the dominance relationship between the ith parent individual P_i and its corresponding ith offspring individual F_i. If the offspring F_i dominates the parent P_i, replace P_i with F_i. If P_i dominates F_i, keep P_i. If P_i and F_i do not dominate each other, calculate the number $PBeDom$ of P_i dominated by all parent individuals and calculate the number $FBeDom$ of F_i dominated by all parent individuals. If $PBeDom$ is greater than $FBeDom$, replace P_i with the offspring P_i. If $PBeDom$ is less than $FBeDom$, keep P_i. If $PBeDom$ is equal to $FBeDom$, calculate the $I_{\epsilon+D}$ Indicator value between F_i and the population P' with P_i removed, as well as $I_{\epsilon+D}$ Indicator between P_i and P'. If the $I_{\epsilon+D}$ Indicator value of F_i is greater, replace P_i with F_i; otherwise, retain P_i. As previously mentioned, the $I_{\epsilon+D}$ Indicator can simultaneously measure convergence and diversity. Therefore, employing the $I_{\epsilon+D}$ Indicator to select individuals that cannot be distinguished by the Pareto dominance relationship allows MaOEA-DISC to obtain populations with both excellent convergence and diversity when handling MaOPs.

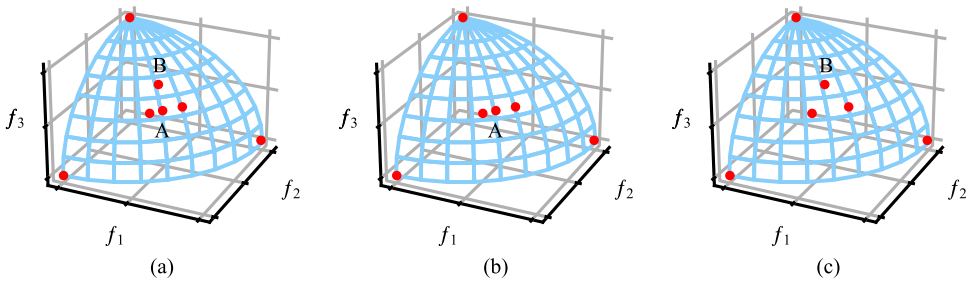


Fig. 4. Individuals selected under different indicators.(a) Not selected. (b) I_{ϵ^+} Indicator. (c) I_{ϵ^+D} Indicator.

3.5. Computational complexity analysis

The MaOEA-DISC consists of three components: individual convergence assessment, mating and reproduction, and environmental selection. When calculating the convergence of each individual in the population, the time complexity required for estimating the shape part of the PF is $O(N)$, while normalizing, mapping, and computing population convergence for the population requires a time complexity of $O(NM)$. Therefore, the total time complexity for this part is $O(NM)$. In the mating and reproduction phase, the time complexity for populating the mating pool is $O(N)$, while the time complexity for performing crossover and mutation on the population is O(ND), where D represents the number of decision variables. Therefore, the time complexity for this part is $O(ND)$. When calculating I_{ϵ^+D} Indicator in the environmental selection phase, the time complexity is $O(N^2M)$. Consequently, selecting the N best individuals based on I_{ϵ^+D} Indicator in the environmental selection phase requires a time complexity of $O(N^3M)$. Overall, the time complexity of MaOEA-DISC is $O(N^3M)$.

4. Experimental study

4.1. Experimental design

4.1.1. Test problems

In this paper, we employ three benchmark test suites: DTLZ [42], WFG [43] and MAF [44], to evaluate the performance of our proposed MaOEA-DISC. The DTLZ and WFG suites encompass a variety of MaOPs, including those characterized by difficulties in convergence, concavity, convexity, linearity, degeneracy, and non-continuous PF. They are the most widely used benchmark test suites in the field of many-objective optimization. Meanwhile, the MAF test suites, which are more aligned with real-world problems, have been recently introduced. However, it is noteworthy that MAF14 and MAF15 belong to the category of large-scale MaOPs, and as such, this paper excludes them from consideration. The parameters associated with DTLZ, WFG, and MAF are configured based on the respective papers that introduced them.

4.1.2. Comparison algorithm

In this paper, to demonstrate the competitive advantage of MaOEA-DISC in comparison to other MaOEAs, experiments were conducted to compare MaOEA-DISC against six state-of-the-art algorithms in the Evolutionary Many-Objective Optimization Platform (PlatEMO) [45]. These six algorithms encompass various types of MaOEAs, Their specific descriptions are detailed as follows:

- PRVNSGAII [46]: It is an algorithm utilizing a Pareto dominance relation based on reference vectors(PRV). Its core lies in enhancing the convergence of the population through a ranking method based on the objective function values, while simultaneously maintaining the diversity of the population by considering the density of different subregions.
- HEA [47]: it quantifies the convergence of each solution through hyper-dominance and utilizes a tolerance adjustment strategy to control the selection pressure during optimization. It also employs an improved weighted vector-based diversity preservation strategy to maintain population diversity.
- TSNSGAII [48]: In this algorithm, the evolution process is divided into two stages. The first stage employs subregion dominance and modified mating methods to enhance the convergence of the population, while in the second stage, level Pareto dominance and traditional Pareto dominance are used to maintain population diversity.
- VMEF [49]: It employs a strategy of adaptively allocating the total number of votes, distributing votes based on the contributions of different solution sorting methods, rewarding significant contributors, penalizing poor contributors, to select the optimal solution obtained from the solution sorting method most suitable for the current problem as the final solution.
- FDEAII [50]: This algorithm proposes a method of fractional dominance to strengthen the convergence of the population. Additionally, it improves the objective space decomposition strategy to maintain population diversity.
- MultiGPO [51]: it is an algorithm based on generalized Pareto dominance(GPO). It enhances both population convergence and diversity simultaneously by expanding the dominance region of M (M is the objective number) -1 objectives while keeping the dominance region of the remaining objective unchanged.

4.1.3. Performance indicators

This paper primarily employs Inverted Generational Distance (IGD) [29], Hypervolume (HV) [28], and Averaged Hausdorff Distance (Δp) [52] indicators to assess the overall performance of the solution sets obtained by experimental algorithms. Additionally, the Generational Distance plus (GD+) [53] and Diversity metrics (DM) [54] indicators are used to evaluate the performance of the solution sets obtained by the algorithms in terms of convergence and diversity, respectively. The specific introductions of these indicators are as follows:

- IGD: IGD measures the average Euclidean distance from each reference point uniformly sampled from the true PF to the nearest point on the known PF. A smaller IGD value indicates a better convergence and diversity of the population. Its definition is as follows:

$$\mathrm{IGD} = \frac{\sum_{p\in P^*} \min_{q\in P} \|p-q\|}{|P^*|} \tag{16}$$

  Where P^* represents a set of reference points uniformly sampled from the true PF, P is the set of all points known on PF, p is a point in P^*, and q is a point in P. While calculating IGD has low time complexity, enabling quick assessment of an algorithm's performance in handling problems with a large number of objectives, it is impractical to use IGD to evaluate algorithm performance in real-world scenarios. This is because calculating IGD requires using points from the true PF, which are often unavailable in practical problems.

Table 1
Population size and the maximum number of evaluations under different numbers of objectives.

Numbers of objectives (m)	Population size (N)	the maximum number of evaluations
3	120	156 000
5	126	214 000
8	120	264 000
10	110	330 000

Table 2
Algorithm parameter settings.

Algorithm	Parameter values
PRVNSGAII	$p_c = 1,\ p_m = 1/n,\ \eta_c = 20,\ \eta_m = 20$
HEA	$p_c = 1,\ p_m = 1/n,\ \eta_c = 20,\ \eta_m = 20,\ MaxT = 0.05$
TSNSGAII	$p_c = 1,\ p_m = 1/n,\ \eta_c = 20,\ \eta_m = 20$
VMEF	$p_c = 1,\ p_m = 1/n,\ \eta_c = 20,\ \eta_m = 20$
FDEAII	$p_c = 1,\ p_m = 1/n,\ \eta_c = 20,\ \eta_m = 20,\ a = 0.1,\ b = 0.4$
MultiGPO	$p_c = 1,\ p_m = 1/n,\ \eta_c = 20,\ \eta_m = 20,\ \varphi = 20$
MaOEADISC	$p_c = 1,\ p_m = 1/n,\ \eta_c = 20,\ \eta_m = 20$

- HV: HV evaluates the performance of a MaOEA by computing the hypervolume of the space bounded by the non-dominated solution set and reference points. A larger value indicates better convergence and diversity of the solution set obtained by a MaOEA. Its calculation formula is as follows:

$$\mathrm{HV} = \lambda\left(\bigcup_{i=1}^{|S|} v_i\right) \tag{17}$$

  Where λ represents Lebesgue measure, v_i represents the hypervolume composed of the reference point and the ith non-dominated solution, S represents the set of non-dominated solutions. HV differs from IGD in that it does not require points on the true PF and can evaluate algorithm performance in practical problems. However, the computation time complexity of the HV is high, making comprehensive performance evaluation more challenging as the number of objectives increases. Additionally, HV is sensitive to reference point selection, leading to significant differences in HV values with different reference points. Lastly, in non-convex problems, HV can easily yield errors. Therefore, HV often needs to be complemented with other indicators to consistently evaluate algorithm performance.
- Δp: Δp is similar to IGD, with the computation method detailed in [52]. The difference lies in that Δp measures the average Hausdorff distance from reference points on the true PF to the nearest points in the solution set obtained by a MaOEA. A smaller value indicates better convergence and diversity of the solution set obtained by a MaOEA. Similarly, Δp also suffers from the drawbacks of IGD, but it can evaluate algorithm performance from different distance metric perspectives. In high-dimensional spaces, results from different distance metrics may vary, thus using both Δp and IGD simultaneously can provide a fairer evaluation of algorithm performance.
- GD+ : The computation of GD+ is opposite to that of IGD, as detailed in [53]. GD+ measures the Euclidean distance from the solution set obtained by a MaOEA to the nearest reference point on the true PF. Additionally, GD+ also considers the dominance relationships between solutions during computation. A smaller value indicates better convergence of the solution set obtained by the algorithm.
- DM: The principle of DM is to project the approximate solution onto an $(m-1)$-dimensional hyperplane and divide it into multiple hypercubes, then consider each hypercube and give the evaluation value according to the distribution of the solutions in it and their neighbouring solutions. When the hypercube containing the reference solution also contains approximate solutions, its then the higher the index value, but also represents the better diversity of the solution set obtained by the algorithm, and its specific calculation process can be referred to [54].

4.1.4. Parameter settings

(i) Population Size, Termination Conditions, and Number of Runs: Since decomposition-based MaOEAs require the population size to be the same as the number of reference points [55], the population size of other algorithms is set to the same value for fair comparison. Additionally, for each algorithm under different objectives, the termination condition is set to reach the corresponding the maximum number of evaluations. The specific numbers of objectives, population size, and maximum evaluation counts are shown in Table 1. To ensure the reliability of experimental results, each experimental algorithm is independently executed 30 times for each test problem under every objective. The average and variance of the results are then computed from these 30 runs.

(ii) Algorithm parameter settings: All experimental algorithms employed simulated binary crossover (SBX) [56] and polynomial mutation (PM) [57] to generate offspring. Here, p_c and p_m denote the probabilities of crossover and mutation, respectively, while η_c and η_m represent the distribution indices for SBX and PM. In HEA, $MaxT$ stands for tolerance magnitude, used to adjust the selection pressure within the population. In FDEAII, a and b respectively denote the number of weight update generations and the weight update count. In MultiGPO, φ represents the widening angle in the generalized Pareto dominance relation. The specific values of these parameters are shown in Table 2.

(iii) Significance test: In order to visually depict the differences between experimental results, a significance level of 0.05 was employed for the Wilcoxon rank-sum test [58] to assess whether one algorithm is significantly better than that of another algorithm. In the resulting table, the best results will be highlighted. The symbols "+ ", "−", and "≈" respectively signify that the results of MaOEA-DISC is worse than, better than, or equal to the comparative algorithm.

4.2. Performance on DTLZ, WFG, and MaF problems

To validate the effectiveness of MaOEA-DISC in addressing MaOPs, this section conducted experimental comparisons between MaOEA-DISC and six other state-of-the-art algorithms using multiple evaluation indicators. Table 3 and Table 4 display the mean and standard deviation of IGD obtained by different algorithms across all test problems, while Fig. 8 illustrates the average ranking of IGD values obtained by different algorithms across all test problems. From these tables and figures, it can be observed that MaOEA-DISC is capable of obtaining populations with superior diversity and convergence in most test problems, making it more effective than other algorithms. Specific details are elaborated as follows:

Linear Problem: DTLZ1 is a MaOP with a linear PF and challenging convergence characteristics. As shown in Table 3, when dealing with DTLZ1, MaOEA-DISC achieves suboptimal results in objectives 3 to 8, and the third-best result in objective 10, mainly because the diversity of the $I_{\epsilon+D}$ indicator is calculated using cosine similarity, which is not as accurate in measuring distances between individuals on a linear PF as Euclidean distance. HEA adopts weight vectors that are distributed evenly on the linear PF, hence outperforming MaOEA-DISC in objectives 3 and 10. MultiGPO, utilizing GPO dominance, effectively enhances diversity and convergence in problems with linear PFs, thus outperforming MaOEA-DISC in objectives 5 to 10. Nevertheless, compared to other algorithms such as PRVNSGAII, TSNSGAII, VMEF, and FDEAII, MaOEA-DISC demonstrates significantly better performance in

Table 3
The average and standard deviation of IGD obtained by all algorithms in DTLZ and WFG benchmark test suites.

Problem	M	PRVNSGAII	HEA	TSNSGAII	VMEF	FDEAII	MultiGPO	MaOEADISC
DTLZ1	3	2.5574e−2 (9.64e−4) −	1.7623e−2 (3.56e−6) +	1.9361e−2 (1.14e−3) −	2.3160e−2 (1.25e−3) −	3.9590e−2 (1.31e−2) −	1.8675e−2 (1.86e−4) −	1.8064e−2 (9.10e−5)
	5	7.8806e−2 (2.60e−3) −	6.3356e−2 (4.45e−5) −	6.6480e−2 (4.55e−3) −	7.3526e−2 (5.29e−3) −	9.1964e−2 (8.36e−3) −	6.1556e−2 (3.06e−4) +	6.3023e−2 (2.96e−4)
	8	1.5785e−1 (1.01e−2) −	1.2274e−1 (1.14e−4) −	1.5003e−1 (3.21e−2) −	1.3341e−1 (1.31e−2) −	1.6563e−1 (9.73e−3) −	1.0992e−1 (8.75e−4) +	1.1594e−1 (2.12e−3)
	10	1.8948e−1 (1.11e−2) −	1.1342e−1 (9.81e−5) +	1.6566e−1 (3.22e−2) −	1.6808e−1 (2.14e−2) −	2.0913e−1 (1.13e−2) −	1.3098e−1 (7.67e−4) +	1.3801e−1 (3.38e−3)
DTLZ2	3	5.7432e−2 (2.26e−3) −	4.8116e−2 (5.02e−4) ≈	4.6828e−2 (3.83e−5) +	6.0300e−2 (1.66e−3) −	5.6705e−2 (7.67e−4) −	5.6518e−2 (1.76e−3) −	4.7949e−2 (2.51e−4)
	5	2.1154e−1 (2.52e−3) −	1.9489e−1 (2.19e−5) −	1.9487e−1 (9.87e−5) −	2.1015e−1 (3.00e−3) −	2.3075e−1 (3.22e−3) −	1.9962e−1 (1.14e−3) −	1.9167e−1 (8.23e−4)
	8	3.7397e−1 (2.09e−3) −	3.6914e−1 (1.53e−5) −	3.6982e−1 (5.92e−4) −	3.8576e−1 (4.72e−3) −	3.9775e−1 (3.00e−3) −	3.7377e−1 (1.98e−3) −	3.6877e−1 (5.13e−4)
	10	4.9665e−1 (5.50e−3) −	4.3758e−1 (1.25e−3) +	4.4059e−1 (2.62e−3) +	4.8363e−1 (1.65e−2) −	5.2219e−1 (5.91e−3) −	4.7495e−1 (1.35e−3) −	4.4511e−1 (3.21e−3)
DTLZ3	3	7.0469e−2 (3.44e−3) −	4.8043e−2 (4.82e−4) ≈	5.0815e−2 (6.39e−3) −	7.0501e−2 (2.28e−2) −	9.9215e−2 (2.17e−2) −	5.8652e−2 (2.14e−3) −	4.8042e−2 (3.96e−4)
	5	2.5073e−1 (8.34e−3) −	1.9503e−1 (1.29e−4) −	2.6341e−1 (2.89e−2) −	4.5502e−1 (3.28e−2) −	2.8967e−1 (2.48e−2) −	1.9973e−1 (1.43e−3) −	1.9285e−1 (2.93e−3)
	8	4.8281e−1 (1.10e−2) −	3.6963e−1 (1.46e−4) ≈	5.4881e−1 (2.83e−2) −	3.1618e+0 (1.59e+0) −	5.0511e−1 (1.44e−2) −	3.7348e−1 (1.65e−3) −	3.6948e−1 (3.57e−3)
	10	6.7110e−1 (2.24e−1) −	4.3745e−1 (7.93e−4) +	8.4835e−1 (1.49e−1) −	1.0556e+1 (5.81e+0) −	7.1556e−1 (2.64e−1) −	4.7785e−1 (1.53e−2) −	4.6754e−1 (7.34e−3)
DTLZ4	3	5.7324e−2 (1.63e−3) +	3.1898e−1 (3.16e−1) −	4.6901e−2 (1.04e−4) +	6.0227e−2 (1.89e−3) +	5.6399e−2 (6.79e−4) +	5.7934e−2 (1.68e−3) +	9.7491e−2 (1.50e−1)
	5	2.0951e−1 (1.56e−3) −	3.0742e−1 (2.02e−1) −	1.9542e−1 (1.97e−4) −	2.1013e−1 (2.50e−3) −	2.2638e−1 (2.88e−3) −	2.0165e−1 (1.93e−3) −	1.9317e−1 (8.75e−4)
	8	3.7185e−1 (1.27e−3) −	3.9804e−1 (6.92e−2) −	3.7220e−1 (9.22e−4) −	3.9208e−1 (2.70e−2) −	4.0588e−1 (3.09e−2) −	3.7272e−1 (1.47e−3) −	3.7044e−1 (1.07e−3)
	10	4.9283e−1 (3.49e−3) −	4.4095e−1 (1.46e−2) +	4.4141e−1 (2.22e−3) +	4.8884e−1 (1.67e−2) −	5.3578e−1 (2.44e−2) −	4.7468e−1 (1.17e−3) −	4.6895e−1 (2.65e−3)
DTLZ5	3	2.7911e−2 (5.69e−3) −	2.7516e−2 (2.07e−3) −	1.5868e−2 (5.72e−3) −	1.5922e−2 (2.14e−3) −	2.8754e−2 (1.27e−2) −	4.1910e−3 (2.51e−4) −	3.3209e−3 (1.79e−5)
	5	1.1155e−1 (3.36e−2) −	8.8328e−2 (2.53e−2) ≈	1.5663e−1 (4.14e−2) −	1.1808e−1 (2.77e−2) −	2.4070e−1 (1.22e−1) −	4.4843e−2 (1.53e−2) +	8.6145e−2 (3.24e−2)
	8	3.6969e−1 (8.65e−2) −	2.0104e−1 (1.90e−2) −	5.2204e−1 (2.80e−2) −	3.5883e−1 (1.01e−1) −	9.1839e−1 (2.58e−1) −	1.8345e−1 (2.27e−2) ≈	1.6461e−1 (4.59e−2)
	10	7.8016e−1 (1.02e−1) −	2.1025e−1 (3.89e−2) ≈	6.0541e−1 (1.29e−1) −	4.0421e−1 (1.45e−1) −	2.3346e+0 (3.89e−1) −	2.2776e−1 (4.42e−2) ≈	2.0745e−1 (5.32e−2)
DTLZ6	3	3.2072e−2 (1.05e−2) −	3.3217e−2 (6.00e−4) −	2.8528e−2 (3.09e−3) −	1.1060e−2 (1.75e−3) −	3.1806e−2 (6.05e−3) −	4.1937e−3 (2.11e−4) −	3.3349e−3 (2.32e−5)
	5	1.8163e−1 (6.86e−2) ≈	1.2415e−1 (2.59e−2) +	2.5255e−1 (6.98e−2) −	2.1251e−1 (6.67e−2) −	2.1967e−1 (7.28e−2) −	6.3809e−2 (1.69e−2) +	1.7898e−1 (5.93e−2)
	8	3.2600e−1 (1.62e−1) ≈	3.2994e−1 (1.13e−1) ≈	9.0411e−1 (1.09e+0) −	6.9917e−1 (9.09e−2) −	1.0584e+0 (3.48e−1) −	3.2606e−1 (4.09e−2) ≈	3.2579e−1 (1.14e−1)
	10	1.2755e+0 (5.80e−1) −	4.7573e−1 (1.16e−1) −	5.2272e−1 (2.09e−1) −	7.1315e−1 (2.18e−1) −	5.8312e+0 (1.69e+0) −	2.7759e−1 (2.52e−2) ≈	2.3419e−1 (1.09e−1)
DTLZ7	3	7.8696e−2 (4.69e−3) −	2.5791e−1 (3.41e−1) −	8.9275e−2 (6.87e−2) −	7.0150e−2 (3.69e−3) −	8.9011e−2 (1.11e−2) −	9.7918e−2 (6.87e−2) −	5.3237e−2 (9.21e−4)
	5	3.6390e−1 (1.56e−2) −	7.1163e−1 (5.10e−1) −	3.2158e−1 (5.48e−3) −	3.6023e−1 (1.15e−2) −	5.0565e−1 (7.25e−2) −	4.4707e−1 (1.97e−1) −	2.8069e−1 (5.28e−3)
	8	9.6056e−1 (7.65e−2) −	9.3870e−1 (2.43e−2) −	9.8190e−1 (9.72e−3) −	9.7695e−1 (6.39e−2) −	1.6103e+0 (2.88e−1) −	6.5198e−1 (1.04e−2) +	7.9289e−1 (4.69e−2)
	10	1.5389e+0 (1.05e−1) −	1.5115e+0 (9.77e−2) −	1.6061e+0 (2.41e−2) −	2.0689e+0 (1.52e−1) −	1.8356e+0 (3.05e−1) −	1.0646e+0 (2.29e−2) −	9.5831e−1 (3.45e−2)
WFG1	3	1.5320e−1 (6.14e−3) +	1.3074e−1 (2.24e−3) +	1.4296e−1 (7.91e−3) +	1.6244e−1 (5.24e−3) +	1.4651e−1 (4.57e−3) +	2.0275e−1 (1.64e−2) −	1.8898e−1 (1.81e−2)
	5	4.8967e−1 (9.41e−2) +	4.4850e−1 (2.47e−2) +	4.4795e−1 (1.20e−2) +	5.0120e−1 (1.37e−2) ≈	4.4237e−1 (1.02e−2) +	7.4612e−1 (3.18e−1) ≈	5.0829e−1 (1.52e−2)
	8	1.4754e+0 (1.56e−1) −	1.1475e+0 (1.32e−1) −	1.0131e+0 (4.56e−2) ≈	9.9356e−1 (2.53e−2) +	1.2698e+0 (4.89e−2) −	1.3247e+0 (2.24e−1) −	1.0174e+0 (1.16e−2)
	10	2.0614e+0 (2.44e−1) −	1.7542e+0 (1.77e−1) −	1.3977e+0 (6.68e−2) −	1.5109e+0 (7.62e−2) −	1.7488e+0 (8.97e−2) −	1.3338e+0 (1.81e−1) ≈	1.2352e+0 (1.47e−2)
WFG2	3	1.6100e−1 (5.24e−3) −	1.3632e−1 (1.72e−3) +	1.4988e−1 (3.52e−3) −	1.6980e−1 (6.26e−3) −	1.7580e−1 (4.46e−3) −	2.9372e−1 (1.34e−2) −	1.4610e−1 (3.11e−3)
	5	4.8397e−1 (5.67e−3) −	4.6411e−1 (5.10e−3) +	4.8726e−1 (1.70e−2) −	5.1587e−1 (1.48e−2) −	5.4668e−1 (1.10e−2) −	9.4261e−1 (1.95e−1) −	4.7734e−1 (5.06e−3)
	8	1.2113e+0 (3.54e−2) −	1.0967e+0 (1.29e−2) −	1.1399e+0 (3.56e−2) −	1.0879e+0 (5.39e−2) ≈	1.2182e+0 (3.84e−2) −	1.7129e+0 (1.73e−1) −	1.0783e+0 (1.51e−2)
	10	1.6534e+0 (5.82e−2) −	1.5991e+0 (2.95e−1) −	1.4761e+0 (7.99e−2) −	1.4421e+0 (9.24e−2) −	1.7305e+0 (5.48e−2) −	1.8538e+0 (1.21e−1) −	1.2950e+0 (2.56e−2)
WFG3	3	1.0131e−1 (1.09e−2) −	6.1378e−2 (5.13e−3) +	1.1136e−1 (1.21e−2) −	8.5121e−2 (9.39e−3) −	1.1254e−1 (1.73e−2) −	3.4538e−2 (4.40e−3) +	7.7535e−2 (4.30e−3)
	5	4.8805e−1 (5.86e−2) +	4.0425e−1 (1.58e−2) +	6.0903e−1 (7.44e−2) −	4.2945e−1 (4.05e−2) +	7.5662e−1 (3.46e−1) −	6.4224e−1 (1.22e−1) −	5.1023e−1 (2.81e−2)
	8	1.5422e+0 (1.20e−1) −	1.3929e+0 (4.82e−2) +	1.7164e+0 (1.90e−1) −	1.2254e+0 (2.03e−1) +	3.4570e+0 (1.40e+0) −	2.7937e+0 (3.38e−1) −	1.4655e+0 (1.00e−1)
	10	2.5396e+0 (2.60e−1) ≈	2.4911e+0 (1.25e−1) ≈	3.3865e+0 (3.42e−1) −	2.2194e+0 (3.51e−1) +	1.3568e+0 (2.45e−1) +	3.4100e+0 (6.13e−1) −	2.5620e+0 (2.55e−1)
WFG4	3	2.1705e−1 (3.54e−3) −	1.9352e−1 (1.64e−3) −	1.8987e−1 (1.67e−4) +	2.2004e−1 (4.97e−3) −	2.2801e−1 (3.41e−3) −	2.9990e−1 (1.65e−2) −	1.9202e−1 (1.17e−3)
	5	1.2242e+0 (1.44e−2) −	1.1785e+0 (2.21e−4) −	1.1759e+0 (1.18e−3) −	1.1878e+0 (1.79e−2) −	1.2854e+0 (1.48e−2) −	1.3800e+0 (4.60e−2) −	1.0875e+0 (4.82e−3)
	8	3.4082e+0 (5.19e−2) −	3.4855e+0 (2.32e−4) −	3.4607e+0 (5.28e−3) −	3.4357e+0 (4.82e−2) −	3.4514e+0 (5.80e−2) −	3.7419e+0 (1.50e−1) −	3.0657e+0 (1.33e−2)
	10	5.4359e+0 (2.16e−1) −	5.0879e+0 (2.00e−2) −	5.0696e+0 (2.21e−2) −	5.2903e+0 (6.97e−2) −	5.5632e+0 (1.86e−1) −	5.3111e+0 (2.19e−1) −	4.7113e+0 (3.40e−2)
WFG5	3	2.2920e−1 (4.06e−3) −	2.0388e−1 (1.61e−3) −	2.0146e−1 (1.54e−4) −	2.4274e−1 (5.76e−3) −	2.3571e−1 (2.48e−3) −	3.0144e−1 (1.38e−2) −	2.0029e−1 (7.95e−4)
	5	1.2347e+0 (1.45e−2) −	1.1653e+0 (1.29e−4) −	1.1604e+0 (8.90e−4) −	1.1755e+0 (1.29e−2) −	1.2935e+0 (1.24e−2) −	1.3345e+0 (4.70e−2) −	1.0693e+0 (3.66e−3)
	8	3.5391e+0 (5.22e−2) −	3.4460e+0 (1.46e−4) −	3.4123e+0 (5.52e−3) −	3.4173e+0 (3.10e−2) −	3.5000e+0 (3.44e−2) −	3.2968e+0 (4.42e−2) −	3.0471e+0 (1.65e−2)
	10	5.4411e+0 (1.22e−1) −	5.0550e+0 (1.53e−2) −	5.0686e+0 (1.22e−2) −	5.2133e+0 (5.83e−2) −	5.5113e+0 (6.80e−2) −	4.9970e+0 (7.78e−2) −	4.6896e+0 (2.84e−2)

(*continued on next page*)

Table 3 (*continued*).

WFG6	3	2.4818e−1 (1.14e−2) −	2.1540e−1 (1.32e−2) ≈	2.1575e−1 (1.06e−2) ≈	2.4979e−1 (8.85e−3) −	2.4797e−1 (9.44e−3) −	3.1937e−1 (1.69e−2) −	2.1537e−1 (6.18e−3)
	5	1.2233e+0 (1.90e−2) −	1.1631e+0 (2.18e−3) −	1.1587e+0 (1.70e−3) −	1.2098e+0 (1.54e−2) −	1.2690e+0 (1.44e−2) −	1.5357e+0 (6.68e−2) −	1.0827e+0 (4.71e−3)
	8	3.5969e+0 (8.32e−2) −	3.4342e+0 (1.37e−2) −	3.3907e+0 (1.07e−2) −	3.4452e+0 (2.72e−2) −	3.4261e+0 (4.45e−2) −	3.7493e+0 (2.74e−1) −	3.0711e+0 (1.47e−2)
	10	5.3610e+0 (1.80e−1) −	5.0749e+0 (1.67e−2) −	5.0705e+0 (3.31e−2) −	5.3913e+0 (8.97e−2) −	5.5362e+0 (1.83e−1) −	5.5080e+0 (4.56e−1) −	4.7452e+0 (2.88e−2)
WFG7	3	2.2115e−1 (3.10e−3) −	1.9444e−1 (1.80e−3) −	1.9054e−1 (3.45e−4) +	2.5104e−1 (8.78e−3) −	2.2647e−1 (3.98e−3) −	3.0707e−1 (2.18e−2) −	1.9268e−1 (1.37e−3)
	5	1.2358e+0 (1.49e−2) −	1.1783e+0 (3.04e−4) −	1.1716e+0 (1.00e−3) −	1.2044e+0 (1.74e−2) −	1.2869e+0 (1.37e−2) −	1.5134e+0 (4.16e−2) −	1.0921e+0 (5.22e−3)
	8	3.4356e+0 (6.41e−2) −	3.4803e+0 (1.40e−3) −	3.4552e+0 (4.26e−3) −	3.4364e+0 (4.76e−2) −	3.4256e+0 (3.47e−2) −	3.6732e+0 (1.55e−1) −	3.0764e+0 (1.57e−2)
	10	5.2023e+0 (6.97e−2) −	5.0839e+0 (2.57e−2) −	5.0435e+0 (3.80e−2) −	5.2140e+0 (6.44e−2) −	5.3241e+0 (6.16e−2) −	5.3932e+0 (2.53e−1) −	4.7392e+0 (2.44e−2)
WFG8	3	3.1027e−1 (5.91e−3) −	2.6039e−1 (4.38e−3) −	2.7443e−1 (3.58e−3) −	3.1942e−1 (6.81e−3) −	3.1154e−1 (9.77e−3) −	3.3044e−1 (7.79e−3) −	2.4526e−1 (2.45e−3)
	5	1.2459e+0 (1.33e−2) −	1.1640e+0 (1.09e−3) −	1.1642e+0 (1.99e−3) −	1.2178e+0 (1.17e−2) −	1.2869e+0 (1.42e−2) −	1.2316e+0 (2.13e−2) −	1.1012e+0 (5.11e−3)
	8	3.5090e+0 (3.77e−2) −	3.3191e+0 (1.31e−2) −	3.3156e+0 (1.17e−2) −	3.6789e+0 (2.77e−1) −	3.5116e+0 (5.02e−2) −	3.3084e+0 (2.09e−2) −	3.1329e+0 (2.13e−2)
	10	5.7408e+0 (1.79e−1) −	5.2930e+0 (3.68e−2) −	5.2119e+0 (3.05e−2) −	5.5767e+0 (7.75e−2) −	5.6333e+0 (1.39e−1) −	5.0190e+0 (7.12e−2) −	4.7331e+0 (3.63e−2)
WFG9	3	2.3129e−1 (6.55e−3) −	1.9719e−1 (2.40e−2) +	1.9312e−1 (2.03e−3) +	2.2999e−1 (5.70e−3) −	2.2800e−1 (4.76e−3) −	2.8406e−1 (2.99e−2) −	1.9881e−1 (6.96e−3)
	5	1.2166e+0 (1.34e−2) −	1.1493e+0 (3.15e−3) −	1.1327e+0 (6.98e−3) −	1.1595e+0 (1.54e−2) −	1.3281e+0 (2.21e−2) −	1.3663e+0 (5.09e−2) −	1.0586e+0 (4.67e−3)
	8	3.4532e+0 (4.98e−2) −	3.3760e+0 (1.37e−2) −	3.2788e+0 (2.56e−2) −	3.3176e+0 (4.94e−2) −	3.4865e+0 (3.57e−2) −	3.3216e+0 (5.69e−2) −	3.0378e+0 (1.31e−2)
	10	5.3509e+0 (1.13e−1) −	5.1010e+0 (1.42e−2) −	5.1192e+0 (4.39e−2) −	5.2488e+0 (8.56e−2) −	5.4620e+0 (8.69e−2) −	4.9990e+0 (6.20e−2) −	4.5657e+0 (3.37e−2)
+/−/≈		4/57/3	14/42/8	9/53/2	6/56/2	4/60/0	8/50/6	

Table 4
The average and standard deviation of IGD obtained by all algorithms in MAF benchmark test suites.

Problem	M	PRVNSGAII	HEA	TSNSGAII	VMEF	FDEAII	MultiGPO	MaOEADISC
MaF1	3	5.6731e−2 (2.44e−3) −	6.1626e−2 (1.82e−4) −	6.2086e−2 (6.22e−4) −	5.4149e−2 (1.78e−3) −	6.6003e−2 (7.47e−3) −	3.6945e−2 (2.14e−4) −	3.6273e−2 (2.15e−4)
	5	1.8383e−1 (1.18e−2) −	2.0106e−1 (8.06e−4) −	1.8538e−1 (1.88e−3) −	2.1898e−1 (1.17e−2) −	2.2659e−1 (2.26e−2) −	1.2602e−1 (1.20e−3) +	1.2909e−1 (6.76e−4)
	8	3.0048e−1 (7.02e−3) −	3.0879e−1 (2.91e−3) −	3.0680e−1 (2.20e−3) −	2.3033e−1 (3.92e−3) ≈	3.6393e−1 (1.95e−2) −	2.2563e−1 (1.76e−3) +	2.3046e−1 (1.69e−3)
	10	3.4065e−1 (1.91e−2) −	3.3641e−1 (7.44e−3) −	4.0165e−1 (3.18e−2) −	2.9077e−1 (3.83e−3) −	4.6318e−1 (3.66e−2) −	2.8250e−1 (3.86e−3) −	2.6608e−1 (2.80e−3)
MaF2	3	3.7154e−2 (1.27e−3) −	3.1461e−2 (6.69e−5) −	3.7155e−2 (1.06e−3) −	3.5820e−2 (1.15e−3) −	3.8750e−2 (1.21e−3) −	2.6817e−2 (4.89e−4) −	2.5207e−2 (1.22e−4)
	5	1.5835e−1 (5.25e−3) −	1.2577e−1 (1.50e−3) −	1.3599e−1 (1.15e−3) −	1.2203e−1 (2.99e−3) −	1.6358e−1 (6.21e−3) −	1.1199e−1 (2.19e−3) −	1.0243e−1 (1.24e−3)
	8	2.0809e−1 (6.33e−3) −	1.6509e−1 (1.28e−3) ≈	1.6750e−1 (9.93e−4) −	1.9667e−1 (1.81e−2) −	3.9981e−1 (1.25e−1) −	1.7278e−1 (6.00e−3) −	1.6366e−1 (2.82e−3)
	10	2.5166e−1 (3.35e−3) −	1.8728e−1 (1.83e−3) +	1.8971e−1 (8.39e−4) +	2.0667e−1 (8.57e−3) ≈	7.3884e−1 (1.36e−2) −	2.1225e−1 (9.40e−3) −	2.0625e−1 (8.85e−3)
MaF3	3	1.9610e−1 (8.01e−3) −	3.5478e−2 (6.76e−4) +	1.2797e−1 (7.64e−2) −	7.3681e−2 (3.72e−2) −	2.7162e−1 (9.00e−2) −	6.0987e−2 (6.31e−3) −	4.3001e−2 (1.72e−3)
	5	3.7594e−1 (1.98e−1) −	6.9768e−2 (1.70e−3) +	2.4362e−1 (6.52e−2) −	3.9437e−1 (1.07e−1) −	3.3636e−1 (1.51e−1) −	1.1418e−1 (1.43e−2) −	8.9068e−2 (2.56e−3)
	8	7.6631e−1 (1.78e−2) −	8.9709e−2 (1.60e−3) +	4.9492e+0 (1.31e+1) −	1.7975e+5 (1.76e+5) −	4.3182e−1 (6.72e−1) +	1.5728e−1 (1.23e−2) +	6.8423e−1 (1.49e+0)
	10	8.1239e−1 (3.01e−2) +	1.3938e−1 (1.40e−2) +	4.5270e+3 (2.41e+4) ≈	3.5610e+6 (1.70e+7) −	8.5630e−1 (1.79e+0) +	1.4027e−1 (7.99e−3) +	9.1816e+0 (1.11e+1)
MaF4	3	4.6504e−1 (5.00e−2) −	3.0444e−1 (5.41e−3) −	3.6207e−1 (3.92e−2) −	4.1704e−1 (2.53e−1) −	6.0952e−1 (1.15e−1) −	3.9959e−1 (2.92e−2) −	2.8507e−1 (1.14e−2)
	5	3.6317e+0 (1.80e−1) −	2.7745e+0 (3.58e−2) −	3.1976e+0 (2.32e−1) −	2.7872e+0 (4.66e−1) −	4.0212e+0 (4.66e−1) −	2.7405e+0 (1.98e−1) −	2.1759e+0 (5.95e−2)
	8	3.2375e+1 (2.71e+0) −	2.9725e+1 (1.70e+0) −	3.5610e+1 (9.18e−1) −	2.8217e+1 (3.47e+0) −	3.7892e+1 (4.69e+0) −	2.1525e+1 (2.13e+0) −	1.7454e+1 (1.15e+0)
	10	1.2083e+2 (1.28e+1) −	1.1232e+2 (8.69e+0) −	1.4352e+2 (4.64e+0) −	1.1491e+2 (1.52e+1) −	1.5847e+2 (2.11e+1) −	8.0033e+1 (9.58e+0) −	6.6965e+1 (4.77e+0)
MaF5	3	2.6242e−1 (8.78e−3) +	6.8282e−1 (1.23e+0) −	2.2365e−1 (6.07e−4) +	2.6941e−1 (8.11e−3) −	2.5876e−1 (2.98e−3) +	8.3757e−1 (3.32e−1) −	2.6833e−1 (2.31e−1)
	5	2.2580e+0 (3.72e−2) −	3.0009e+0 (1.31e+0) −	2.4077e+0 (1.20e−2) −	2.2751e+0 (5.04e−2) −	2.7193e+0 (8.36e−2) −	6.4199e+0 (8.42e−1) −	2.1714e+0 (2.91e−2)
	8	2.0880e+1 (1.24e+0) −	2.8822e+1 (3.26e+0) −	2.8372e+1 (4.99e−1) −	1.9980e+1 (1.57e+0) ≈	2.4020e+1 (5.41e+0) −	5.4763e+1 (6.50e+0) −	1.9953e+1 (6.18e−1)
	10	7.1309e+1 (3.60e+0) +	1.1258e+2 (5.61e+0) −	1.1014e+2 (4.04e+0) −	7.0175e+1 (3.32e+0) +	1.1379e+2 (2.02e+1) −	2.1752e+2 (9.85e+0) −	8.3847e+1 (4.47e+0)
MaF6	3	3.6648e−2 (1.23e−2) −	3.2462e−2 (1.71e−3) −	2.6107e−2 (3.53e−3) −	1.2743e−2 (1.36e−3) −	9.7241e−2 (1.31e−1) −	4.4431e−3 (2.71e−4) −	3.3268e−3 (1.88e−5)
	5	8.7622e−2 (2.61e−2) −	1.2690e−1 (5.76e−3) −	1.1347e−1 (1.40e−2) −	1.0220e−1 (2.18e−2) −	5.4067e−1 (1.49e−1) −	5.4011e−3 (4.52e−4) −	3.1685e−3 (1.80e−5)
	8	1.5605e−1 (4.45e−2) −	1.5517e−1 (9.31e−2) −	2.1975e−1 (2.82e−2) −	1.6834e−1 (1.13e−1) −	6.3701e−1 (1.58e−1) −	7.2725e−3 (1.49e−3) −	3.3250e−3 (2.26e−5)
	10	3.5740e−1 (1.50e−1) −	1.6439e−1 (6.79e−2) −	2.0385e−1 (8.89e−2) −	2.5816e−1 (4.36e−2) −	6.0039e−1 (1.03e−1) −	2.0778e−2 (1.42e−2) −	3.6406e−3 (6.19e−5)
MaF7	3	8.9075e−2 (5.11e−2) −	1.9938e−1 (1.89e−1) −	8.0956e−2 (4.93e−2) −	7.1276e−2 (5.56e−3) −	8.5822e−2 (1.19e−2) −	1.4358e−1 (1.17e−1) −	5.3233e−2 (8.94e−4)
	5	3.5780e−1 (1.56e−2) −	5.2326e−1 (3.71e−1) −	3.1999e−1 (5.63e−3) −	3.5702e−1 (1.54e−2) −	4.8321e−1 (5.03e−2) −	4.0018e−1 (1.72e−1) −	2.8227e−1 (4.63e−3)
	8	9.5782e−1 (7.07e−2) −	9.3529e−1 (4.48e−3) −	9.8281e−1 (1.08e−2) −	9.9308e−1 (8.42e−2) −	1.6659e+0 (2.68e−1) −	6.5627e−1 (1.16e−2) +	7.9673e−1 (3.97e−2)
	10	1.6103e+0 (1.92e−1) −	1.5012e+0 (3.55e−2) −	1.6078e+0 (2.65e−2) −	2.0251e+0 (2.70e−1) −	1.8454e+0 (2.88e−1) −	1.0841e+0 (4.23e−2) −	9.7918e−1 (5.88e−2)
MaF8	3	1.1477e−1 (1.45e−2) −	2.0621e−1 (3.39e−1) −	1.2852e−1 (7.46e−3) −	7.5181e−1 (1.48e−1) −	1.2657e−1 (1.32e−2) −	5.6806e−2 (8.25e−4) ≈	5.6663e−2 (5.05e−4)
	5	2.8826e−1 (2.97e−2) −	2.3801e−1 (2.32e−2) −	1.9429e−1 (1.05e−2) −	3.7156e−1 (2.78e−2) −	4.3681e−1 (8.49e−2) −	9.9618e−2 (2.91e−3) ≈	9.9522e−2 (1.10e−3)
	8	5.0549e−1 (5.65e−2) −	3.8322e−1 (2.03e−2) −	3.3638e−1 (1.94e−2) −	5.9071e−1 (7.61e−2) −	6.8431e−1 (1.07e−1) −	1.4156e−1 (3.86e−3) ≈	1.4114e−1 (2.07e−3)
	10	6.1133e−1 (9.46e−2) −	2.2421e−1 (3.76e−3) −	2.4879e−1 (1.09e−2) −	5.7983e−1 (5.70e−2) −	7.8789e−1 (1.38e−1) −	1.6230e−1 (3.02e−3) +	1.6754e−1 (2.61e−3)
MaF9	3	9.1147e−2 (9.26e−3) −	8.9555e−2 (1.39e−1) −	3.6930e−1 (9.63e−2) −	1.0560e+0 (2.42e−1) −	1.4436e−1 (3.84e−2) −	5.7048e−2 (5.45e−4) ≈	5.6928e−2 (1.27e−3)
	5	2.6783e−1 (5.09e−2) −	1.2955e+0 (6.44e+0) −	3.9346e−1 (1.91e−1) −	8.2808e−1 (1.92e−1) −	3.1585e−1 (5.08e−2) −	9.3759e−2 (9.62e−4) +	1.0848e−1 (2.55e−3)
	8	5.1727e−1 (8.32e−2) −	2.3768e−1 (3.05e−3) −	1.3475e+0 (5.75e−1) −	1.9853e+2 (1.35e+2) −	4.7165e−1 (6.66e−2) −	1.3008e−1 (1.25e−3) +	2.2432e−1 (8.39e−3)
	10	5.2695e−1 (1.03e−1) −	2.9161e−1 (1.49e−2) −	2.0987e+0 (2.68e+0) −	1.1968e+0 (3.48e−1) −	6.6315e−1 (1.15e−1) −	1.5664e−1 (1.89e−3) +	2.1719e−1 (5.60e−3)
MaF10	3	1.5380e−1 (5.40e−3) +	1.3086e−1 (2.53e−3) +	1.4324e−1 (8.78e−3) +	1.6159e−1 (4.77e−3) +	1.4627e−1 (4.87e−3) +	1.9892e−1 (1.55e−2) ≈	1.9707e−1 (1.85e−2)
	5	4.8096e−1 (8.26e−2) +	4.4419e−1 (3.30e−3) +	4.5020e−1 (1.43e−2) +	5.0354e−1 (1.28e−2) ≈	4.4451e−1 (8.77e−3) +	8.4941e−1 (3.26e−1) −	5.0502e−1 (1.78e−2)
	8	1.3815e+0 (1.17e−1) −	1.1198e+0 (9.03e−2) −	1.0179e+0 (4.09e−2) ≈	9.9209e−1 (3.52e−2) +	1.2771e+0 (8.69e−2) −	1.2477e+0 (2.48e−1) ≈	1.0188e+0 (1.11e−2)
	10	2.1251e+0 (1.98e−1) −	1.7452e+0 (2.04e−1) −	1.4044e+0 (7.71e−2) −	1.5183e+0 (7.40e−2) −	1.7648e+0 (1.05e−1) −	1.2705e+0 (1.57e−1) ≈	1.2358e+0 (1.23e−2)
MaF11	3	1.6042e−1 (3.33e−3) −	1.3647e−1 (1.22e−3) +	1.5075e−1 (4.22e−3) −	1.7052e−1 (4.33e−3) −	1.7566e−1 (5.30e−3) −	2.9066e−1 (1.27e−2) −	1.4597e−1 (2.29e−3)
	5	4.8247e−1 (7.00e−3) −	4.6288e−1 (5.50e−3) +	4.8791e−1 (1.59e−2) −	5.1275e−1 (1.43e−2) −	5.5041e−1 (8.07e−3) −	9.7180e−1 (1.58e−1) −	4.7948e−1 (4.86e−3)
	8	1.1975e+0 (3.53e−2) −	1.0951e+0 (1.30e−2) −	1.1299e+0 (3.41e−2) −	1.1013e+0 (4.31e−2) −	1.2120e+0 (4.43e−2) −	1.7674e+0 (1.55e−1) −	1.0716e+0 (1.44e−2)
	10	1.6621e+0 (8.29e−2) −	1.6680e+0 (2.87e−1) −	1.4731e+0 (6.80e−2) −	1.4479e+0 (8.63e−2) −	1.7550e+0 (8.34e−2) −	1.8457e+0 (1.13e−1) −	1.2931e+0 (2.34e−2)
MaF12	3	2.3470e−1 (2.07e−2) −	1.9261e−1 (2.27e−3) +	1.9317e−1 (1.58e−3) ≈	2.3094e−1 (7.53e−3) −	2.2808e−1 (5.04e−3) −	2.7801e−1 (2.08e−2) −	1.9647e−1 (6.30e−3)
	5	1.2167e+0 (1.62e−2) −	1.1498e+0 (2.90e−3) −	1.1322e+0 (7.56e−3) −	1.1599e+0 (1.40e−2) −	1.3290e+0 (2.30e−2) −	1.3552e+0 (6.28e−2) −	1.0592e+0 (4.36e−3)
	8	3.4524e+0 (5.45e−2) −	3.3734e+0 (1.77e−2) −	3.2801e+0 (2.03e−2) −	3.3010e+0 (3.04e−2) −	3.4921e+0 (4.81e−2) −	3.3173e+0 (7.15e−2) −	3.0390e+0 (1.58e−2)
	10	5.3321e+0 (7.99e−2) −	5.0992e+0 (1.13e−2) −	5.1273e+0 (3.78e−2) −	5.2247e+0 (7.68e−2) −	5.4682e+0 (7.08e−2) −	5.0226e+0 (8.55e−2) −	4.5666e+0 (3.71e−2)
MaF13	3	1.2703e−1 (1.56e−2) −	8.5656e−2 (2.00e−2) −	1.1323e−1 (1.39e−2) −	1.0841e−1 (1.57e−2) −	1.3519e−1 (1.28e−2) −	1.0278e−1 (2.07e−2) −	5.7357e−2 (2.87e−3)
	5	2.6019e−1 (3.58e−2) −	2.0527e−1 (1.93e−2) −	2.6024e−1 (1.31e−1) −	3.5725e−1 (4.05e−2) −	5.4281e−1 (1.15e−1) −	1.7371e−1 (4.39e−2) −	8.8091e−2 (4.56e−3)
	8	3.7693e−1 (6.14e−2) −	3.6007e−1 (3.53e−2) −	6.5298e−1 (3.09e−1) −	4.1675e−1 (7.97e−2) −	6.7319e−1 (1.30e−1) −	2.7071e−1 (3.94e−2) −	1.0351e−1 (4.65e−3)
	10	5.0236e−1 (1.07e−1) −	4.9576e−1 (4.79e−2) −	7.9400e−1 (3.74e−1) −	4.8612e−1 (7.76e−2) −	7.8862e−1 (2.34e−1) −	3.5857e−1 (3.58e−2) −	1.1400e−1 (3.97e−3)
+/−/≈		5/47/0	10/41/1	4/45/3	3/45/4	5/47/0	9/36/7	

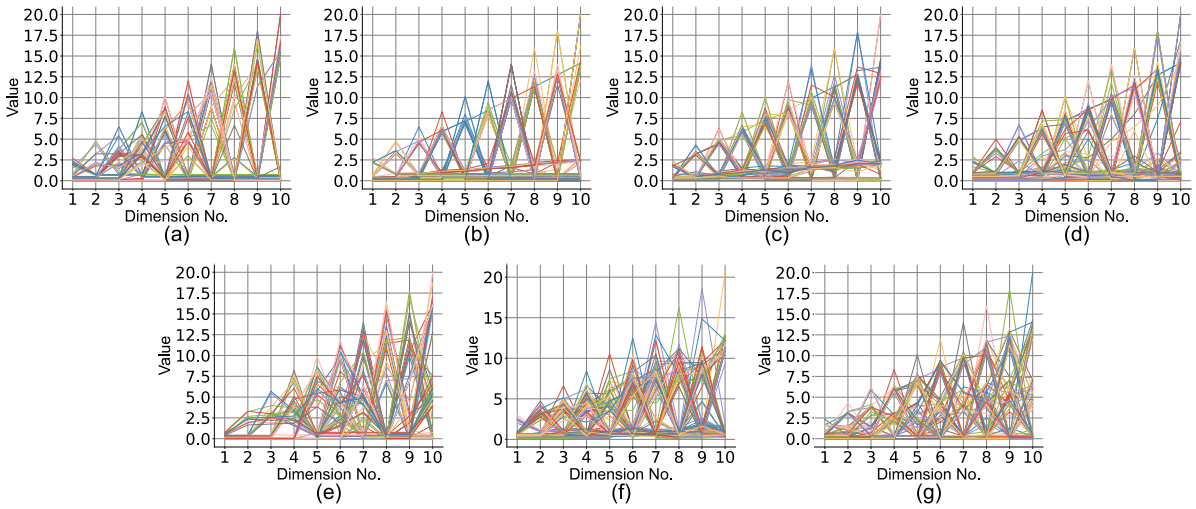


Fig. 5. Distribution of the final population obtained by all experimental algorithms on the 10-dimensional WFG8 problem. (a) PRVNSGAII. (b) HEA. (c) TSNSGAII. (d) VMEF. (e) FDEAII. (f) MultiGPO. (g) MaOEADISC.

handling linear PF problems. This suggests that the method of maintaining population diversity in MaOEA-DISC by continuously selecting individuals farther away from others, thus keeping individuals evenly distributed, still holds significant advantages in linear PF problems. It also indicates that MaOEA-DISC's mating strategy promotes population convergence.

Concave problems: on DTLZ2-4,WFG4-9,MAF2,MAF5, MAF12, and MAF13, which are problems with concave PFs, as shown in Table 3 and Table 4, MaOEA-DISC outperforms other algorithms in general. Particularly, as depicted in Fig. 8, MaOEA-DISC obtains the best average ranking of IGD, on problems like WFG4-9 which exhibit multimodality, large basin sizes, and deceptive features in the search space. Its score significantly outperforms other algorithms. To visually demonstrate this result, Fig. 5 shows the population distribution obtained by different algorithms on the 10-dimensional WFG8 problem. It can be observed from the figure that MaOEA-DISC achieves the best population diversity, benefiting from the comprehensive consideration of inter-individual spacing by the $I_{\epsilon+D}$ indicator. Although MultiGPO also achieves good population diversity due to its relaxation of dominance relationships, its population coverage in the range of objectives 9 and 10, with objective values from 10 to 20, is lower than that of MaOEA-DISC. HEA, TSNSGAII, and VMEF, due to their diversity maintenance strategies failing to ensure population coverage in the central region of the PF, exhibit mostly blank areas in the middle region of the PF in Fig. 5(b), (c), and (d). While PRVNSGAII and FDEAII have better coverage in the middle region of the PF compared to the aforementioned three algorithms, they still lag behind MaOEA-DISC.

Degenerate problems: DTLZ5, DTLZ6, WFG3, MAF6, MAF8, and MAF9 are MaOPs with degenerate PF. As shown in Fig. 8, MaOEA-DISC achieves the top average ranking in terms of IGD for problems with degenerate PF, across all problems except WFG3. Particularly noteworthy is its performance on the MAF6 problem, which not only exhibits a degenerate PF but also reflects more realistic characteristics, where MaOEA-DISC achieves optimal IGD values across the board. As depicted in Fig. 6 for the 10-dimensional MAF6 problem, the population obtained by MaOEA-DISC not only converges effectively to the PF but also uniformly covers the entire PF. In contrast, HEA, when confronted with degenerate problems, exhibits a weight vector distribution range far exceeding that of the degenerate PF. Consequently, the majority of its obtained population is concentrated along the PF boundaries. MultiGPO, by relaxing dominance relations for m-1 objectives, facilitates population convergence to the PF but lacks in ensuring sufficient diversity, thus resulting in a less uniform distribution compared to MaOEA-DISC. Unlike MultiGPO, although both PRVNSGAII and TSNSGAII improve dominance relations handling, they still fail to provide adequate selection pressure in high-dimensional spaces, leading to populations that do not converge well to the PF. Similarly, VMEF, lacking a suitable solution sorting method for MAF6, results in populations that also fail to converge to the PF.

Discontinuous problems: In DTLZ7, WFG2, and MAF7, the shape of the PF is discontinuously disconnected. As shown in Table 3 and Table 4, in problems with discontinuous PFs, MaOEA-DISC achieves approximately 66.7% of the optimal IGD values, with its average IGD ranking being the highest. This is attributed to the $I_{\epsilon+D}$ indicator's ability to dynamically adjust the spacing between individuals based on their angles, ensuring their uniform spread across the entire PF. Fig. 7 presents the final population distributions obtained by all algorithms for the 3-dimensional DTLZ7 problem with discontinuous PFs. It is evident that, besides the populations obtained by MaOEA-DISC, which are distributed more uniformly across each PF, populations obtained by other algorithms either only cover a few PFs or fail to spread evenly across all PFs. This indicates that MaOEA-DISC significantly outperforms other algorithms in handling problems with PFs that are discontinuous and consist of multiple segments.

Convex problems: WFG1, MAF3, MAF10, and MAF11 exhibit convex PF. From Fig. 8, it can be inferred that MaOEA-DISC ranks first on average in terms of IGD only in MAF11. In MAF10, because the cosine similarity cannot accurately measure the spacing between individuals in problems with large differences between individual objectives, MaOEA-DISC's results in 3 to 5 dimensions of WFG1 and MAF10 are inferior to most algorithms. However, as shown in Table 3 and 4, in 8 to 10 dimensions of WFG1 and MAF10, MaOEA-DISC's results gradually surpass the majority of algorithms. This is because in high-dimensional spaces, cosine similarity facilitates the measurement of distances between individuals, making it difficult to select dominance resistance solutions, thereby improving the convergence of the population. Thus, MaOEA-DISC is more suitable for handling such higher-dimensional problems. It is worth noting that MaOEA-DISC performs better in low-dimensional spaces when dealing with the MAF3 problem, which is characterized by difficult convergence. This indicates that MaOEA-DISC's mating strategy and SCCM can enhance the convergence speed of the population. However, as dimensions increase, the effectiveness decreases, resulting in a larger standard deviation of IGD in high-dimensional spaces.

Inverted problem: MAF1 is an inversion of DTLZ1, while MAF4 is an inversion of DTLZ3. As shown in Table 4, in the Inverted problem, MaOEA-DISC achieved 75% of the optimal IGD results, primarily concentrated on MAF4 with significant scaling features. This is because

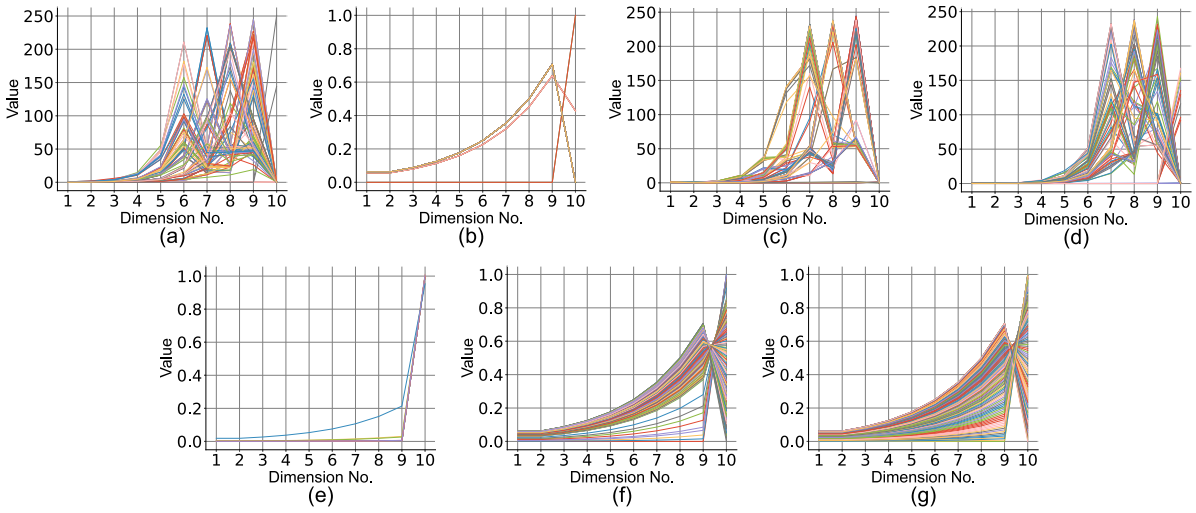


Fig. 6. Distribution of the final population obtained by all experimental algorithms on the 10-dimensional MAF6 problem. (a) PRVNSGAII. (b) HEA. (c) TSNSGAII. (d) VMEF. (e) FDEAII. (f) MultiGPO. (g) MaOEADISC.

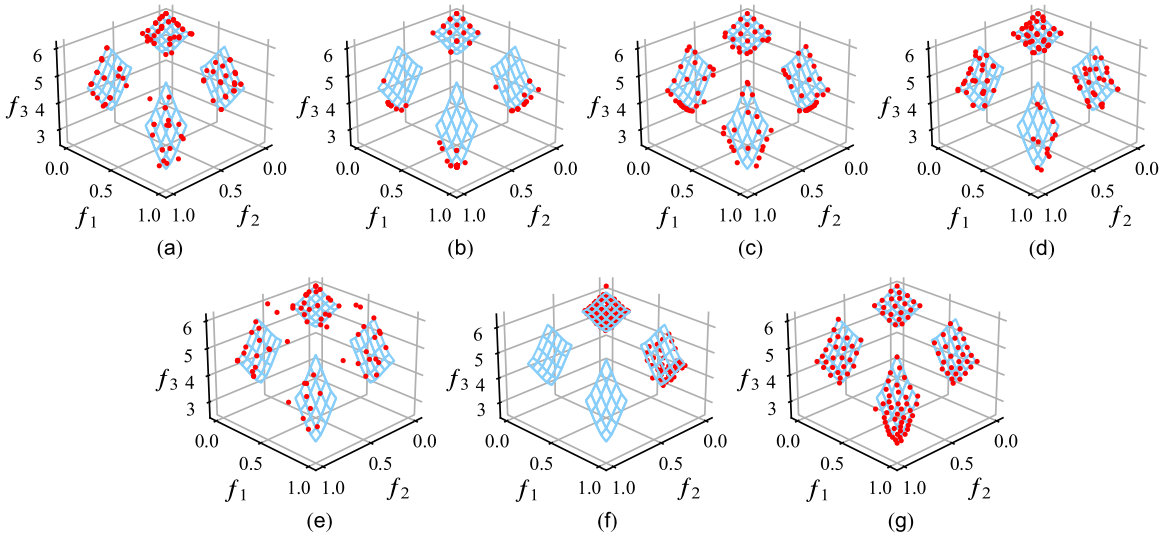


Fig. 7. Distribution of the final population obtained by all experimental algorithms on the 3-dimensional DTLZ7 problem. (a) PRVNSGAII. (b) HEA. (c) TSNSGAII. (d) VMEF. (e) FDEAII. (f) MultiGPO. (g) MaOEADISC.

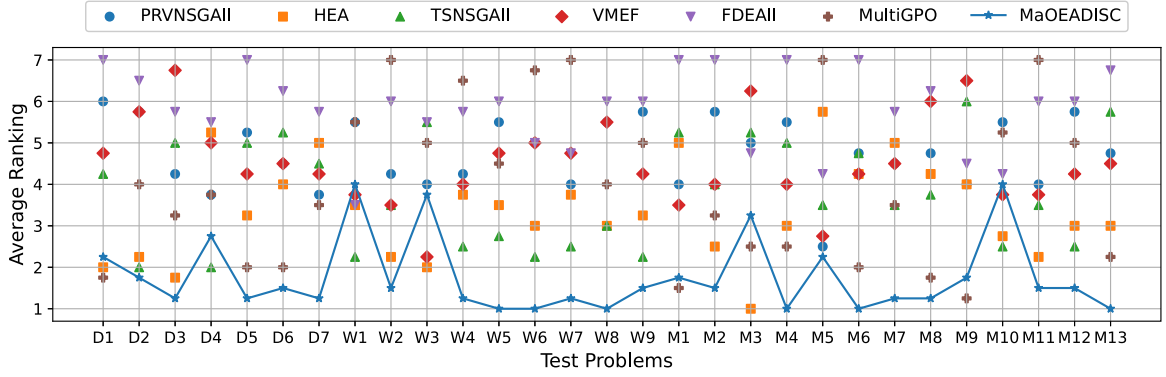


Fig. 8. Average ranking of IGD values obtained by different algorithms for each test problem. Lower rankings indicate better convergence and diversity of populations generated by the algorithms.

SCCM calculations are based on the current PF shape, so individual convergence of SCCM calculations is not affected even when the PF is severely scaled, which can improve population convergence. Moreover, the I_{ϵ^+D} indicator is not affected by PF shape, enhancing population diversity. Therefore, MaOEA-DISC is more effective in dealing with reverse problems compared to other algorithms.

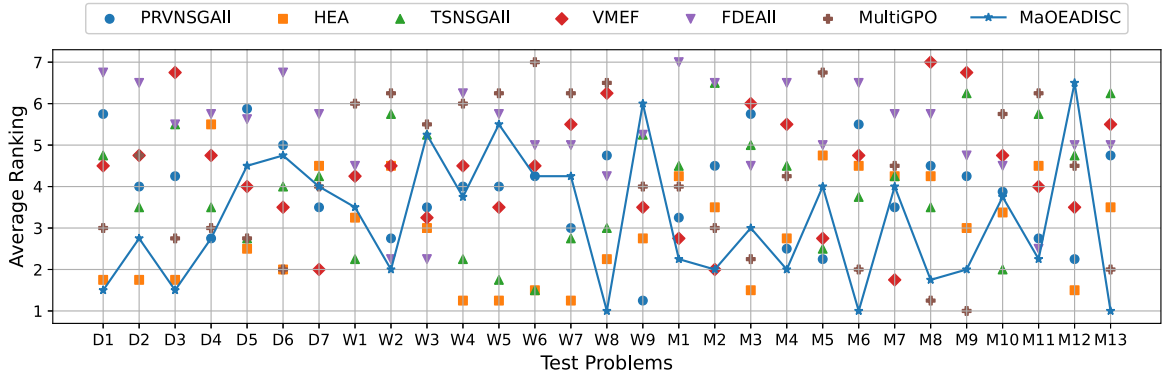


Fig. 9. Average ranking of HV values obtained by different algorithms for each test problem. Lower rankings indicate better convergence and diversity of populations generated by the algorithms.

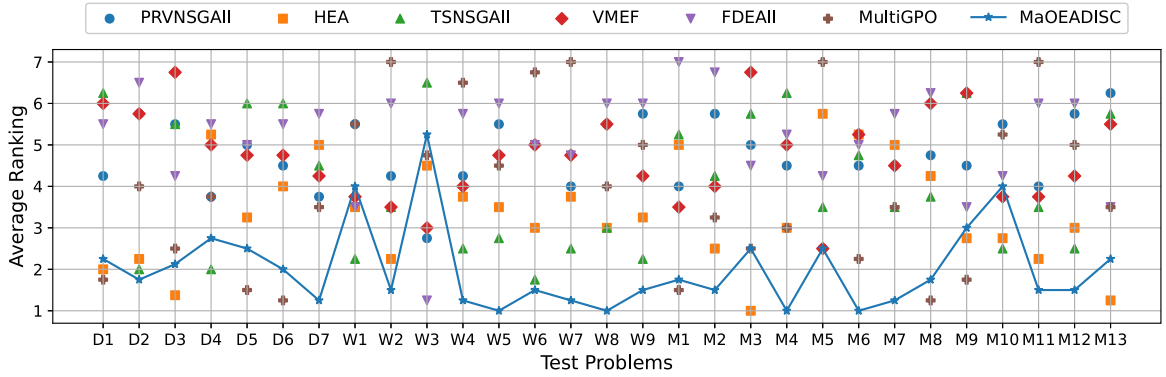


Fig. 10. Average ranking of Δp values obtained by different algorithms for each test problem. Lower rankings indicate better convergence and diversity of populations generated by the algorithms.

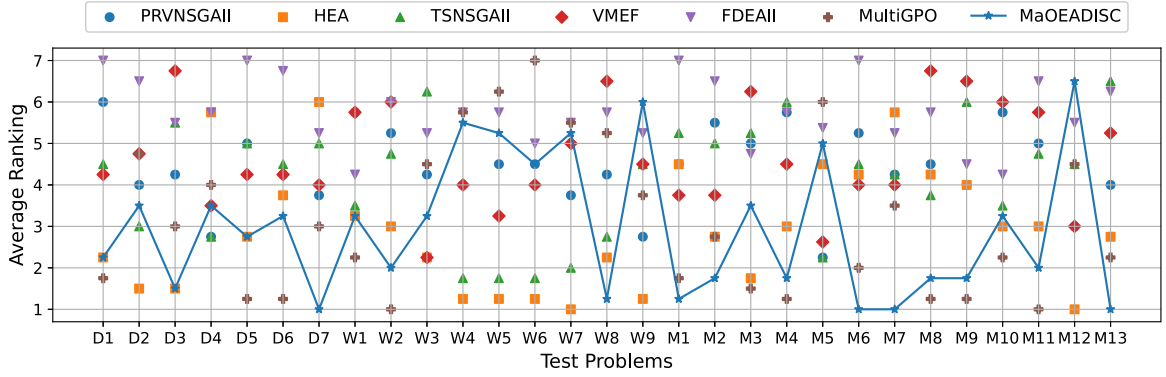


Fig. 11. Average ranking of GD+ values obtained by different algorithms for each test problem. Lower rankings indicate better convergence of populations generated by the algorithms.

Table 5
A summary of the performance comparison between six state-of-the-art algorithms and MaOEADISC across all test problems.

Comparison			Summary(+ /−/≈)				
			IGD	HV	Δp	GD+	DM
PRVNSGAII	VS	MaOEADISC	9/104/3	45/64/7	11/104/1	33/79/4	10/98/8
HEA	VS	MaOEADISC	24/83/9	50/57/9	29/80/7	46/63/7	8/106/2
TSNSGAII	VS	MaOEADISC	13/98/5	41/67/8	13/99/4	33/78/5	4/103/9
VMEF	VS	MaOEADISC	9/101/6	42/68/6	10/100/6	30/80/6	16/89/11
FDEAII	VS	MaOEADISC	9/107/0	23/80/13	14/99/3	21/88/7	15/97/4
MultiGPO	VS	MaOEADISC	17/86/13	33/77/6	26/80/10	47/54/15	25/69/22

Fig. 9, 10, 11, and Fig. 12 give the average rankings of HV, Δp, GD+, and DM obtained by the different algorithms in the test set of 3 to 10 objectives, while Table 5 gives the statistics of the comparative results of HV, Δp, GD+, and DM values obtained by these algorithms, and

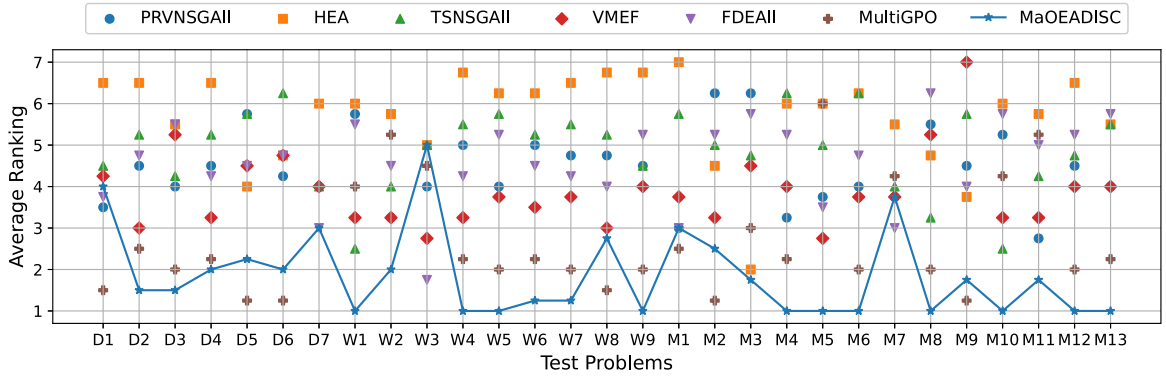


Fig. 12. Average ranking of DM values obtained by different algorithms for each test problem. Lower rankings indicate better diversity of populations generated by the algorithms.

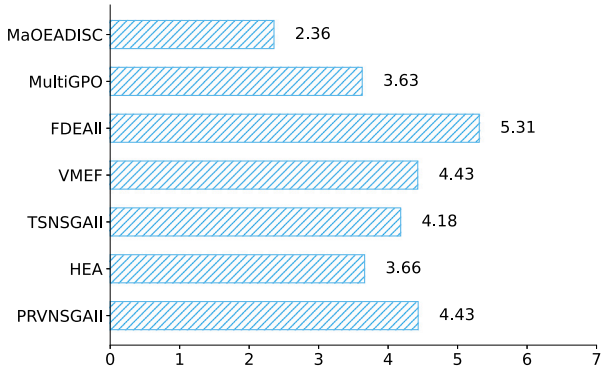


Fig. 13. The average ranking of different algorithms across all test problems based on all performance Indicators.

due to space constraints, the detailed experimental results are placed in the Supplementary file. As can be seen from Table 5, the HV, Δp, GD+ and DM values obtained by MaOEA-DISC are superior to the other algorithms in all the test sets, which suggests that even if different indicators are used to evaluate the effectiveness of MaOEA-DISC in dealing with MaOPs in different aspects, MaOEA-DISC still outperforms the comparison algorithms. The specific analysis is as follows:

According to Fig. 10, the average ranking of Δp obtained by MaOEA-DISC in each test problem is essentially identical to its IGD average rankings in each test problem. This suggests that even when Hausdorff distance is utilized to assess MaOEA-DISC's performance across various MaOPs from the perspective of distinct distance metrics, MaOEA-DISC significantly outperforms other algorithms. This superiority can be attributed to MaOEA-DISC's utilization of cosine similarity, which is notably more efficacious in high-dimensional spaces, for calculating the spacing between individuals, thereby facilitating the maintenance of population diversity. From Fig. 9, it is evident that MaOEA-DISC does not achieve as high average rankings in HV across all test sets compared to IGD and Δp average rankings. However, Table 5 reveals that MaOEA-DISC obtains HV values that are significantly superior to other algorithms across all test sets with different objectives, except for being slightly better than HEA. On partially convex PF problems within the DTLZ-WFG suites, the average HV rankings obtained by MaOEA-DISC show a considerable discrepancy compared to IGD and Δp average rankings. There are two main reasons for this. Firstly, as mentioned in Section 4.1.3, there exists an inherent error in evaluating algorithm performance in convex PF problems using the HV indicator. Secondly, although HV can assess both convergence and diversity of populations, it may place more emphasis on convergence, whereas IGD and Δp indicators may prioritize diversity. As depicted in Fig. 11 and Fig. 12, the average GD+ rankings obtained by MaOEA-DISC in problems with convex PF are similar to its average HV rankings, placing it at a moderate level, whereas its average DM rankings are closer to its average IGD and Δp rankings, significantly outperforming other algorithms. In conclusion, due to the significant influence of convex PF shape and convergence on HV indicator evaluation, MaOEA-DISC does not exhibit particularly outstanding average rankings on convex PF problems. Conversely, using IGD and Δp indicators to evaluate algorithm performance in handling convex PF problems yields opposite results, indicating that MaOEA-DISC significantly enhances population diversity when dealing with MaOPs with convex PF, thus validating the effectiveness of our method for enhancing diversity in the I_{ϵ^+} indicators. When handling MAF suites problems with more realistic features, MaOEA-DISC achieves relatively small differences in IGD, HV, Δp, GD+, and DM average rankings, except for MAF7 and MAF12, and its average rankings surpass those of the vast majority of algorithms, indicating that MaOEA-DISC is more suitable for handling real-world problems.

In summary, Fig. 13 provides the average rankings obtained by different algorithms across all test suites with different objectives based on all indicators. It can be observed from the figure that the rankings of MaOEA-DISC are higher than those of other algorithms. So far, we have verified that MaOEA-DISC demonstrates superior performance in handling the majority of MaOPs compared to other algorithms.

4.3. Effectiveness of shape-conforming convergence metric

In order to demonstrate the superiority of SCCM, the selection of individuals in the MaOEA-DISC environment is no longer based on the use of I_{ϵ^+D} indicators. Instead, individuals are selected solely through convergence metrics. In this context, we conducted experiments comparing SCCM with four convergence metrics mentioned in Section 2. The experimental results are shown in Fig. 14 and Fig. 15. Fig. 14 illustrates the population distributions obtained using different convergence metrics in the 10-dimensional DLTZ2 problem with concave PF, while Fig. 15 shows the population distributions obtained with different convergence metrics in the 10-dimensional WFG2 problem with convex PF.

Since SUMC is primarily suitable for addressing MaOPs with linear PF, irrespective of whether the PF is concave or convex, the populations obtained using SUMC are concentrated at a single point in the PF. Although CBSC performs better than SUMC in handling MaOPs with concave PF, its populations are still mostly concentrated at one or two points in the PF. Notably, when dealing with convex PF, the populations obtained by CBSC are not concentrated at a single point but rather spread across a small region of the PF, specifically in the range of PF objective values from 0 to 0.35. Consequently, both SUMC and CBCS exhibit imprecise population convergence, regardless of whether the PF is concave or convex. In contrast, for EIC, ENC, and SCCM, the populations obtained are more similar to the true PF. However, in the

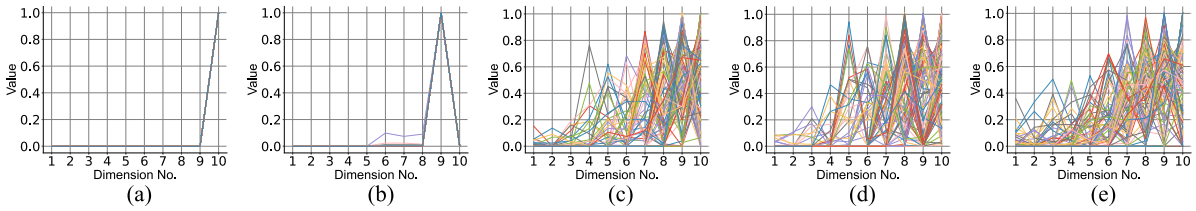


Fig. 14. Distribution of the final population obtained by all convergence metrics on the 10-dimensional DTLZ2 problem. (a) SUMC. (b) CBSC. (c) EIC. (d) ENC. (e) SCCM.

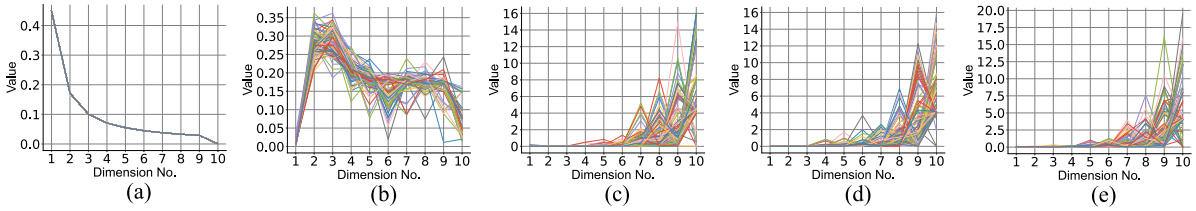


Fig. 15. Distribution of the final population obtained by all convergence metrics on the 10-dimensional WFG2 problem. (a) SUMC. (b) CBSC. (c) EIC. (d) ENC. (e) SCCM.

case of the concave PF shown in Fig. 14, SCCM outperforms the other two methods because SCCM's calculations are based on an estimation of the PF shape, resulting in a broader population distribution within the range of objectives 1 to 3. For EIC and ENC, some regions of the convergence contour align with the PF shape, making EIC better in the 4th objective and ENC superior for the 5th objective. Nevertheless, overall, SCCM's calculations prove to be more accurate. As the PF becomes increasingly complex, the probability of EIC and ENC convergence contours aligning with the PF shape diminishes, whereas SCCM, due to its estimation of the PF shape, provides convergence contours that better match the PF's shape. Similarly, in the case of the convex PF in Fig. 15, SCCM produces a more extensive distribution of populations, while EIC and ENC, though still providing good population distribution, fall short compared to SCCM, especially in the 10th objective, where the range of objective values is limited to 0 to 16, unlike SCCM's broader range from 0 to 20.

It is evident that SCCM, whether dealing with concave or convex PF, produces populations closer to the PF compared to other convergence metrics. Consequently, SCCM possesses a competitive advantage over other convergence metrics.

4.4. Effectiveness of $I_{\epsilon+D}$ indicator

In order to validate the effectiveness of $I_{\epsilon+D}$ Indicator, we conducted a comparative analysis between MaOEA-DISC and its variant, MaOEA-ISC. The MaOEA-ISC variant was generated by replacing $I_{\epsilon+D}$ Indicator with $I_{\epsilon+}$ Indicator. Fig. 16 and Fig. 17 illustrate the differences between the final populations obtained by MaOEA-DISC and MaOEA-ISC. From the figures, it is evident that under various shapes of PF, MaOEA-DISC not only focuses on the convergence of the population but also emphasizes the spacing between individuals within the population. Consequently, the populations obtained are not only close to PF but also uniformly distributed across the entire PF. In contrast, the populations obtained by MaOEA-ISC, while close to PF, are densely concentrated around the centre of PF and sparse around its periphery. Therefore, it can be inferred that MaOEA-DISC excels in diversity compared to MaOEA-ISC, implying that $I_{\epsilon+D}$ Indicator is effective in maintaining both the convergence and diversity of the population.

4.5. Performance on real-world problem

In order to validate the performance of MaOEA-DISC in real-world optimization problems, this section conducts experimental comparisons

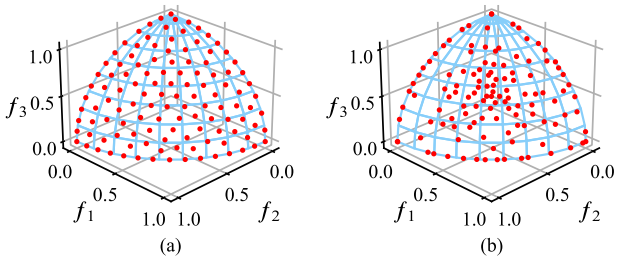


Fig. 16. Distribution of the final population obtained by all experimental algorithms on the 3-dimensional DTLZ4 problem. (a) MaOEADISC. (b) MaOEAISC.

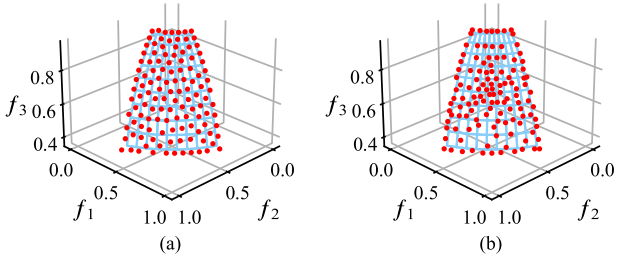


Fig. 17. Distribution of the final population obtained by all experimental algorithms on the 3-dimensional MAF2 problem. (a) MaOEADISC. (b) MaOEAISC.

between MaOEA-DISC and six state-of-the-art algorithms on the optimization problem of crash safety design of vehicles (CSDV) [59]. This problem has three primary objectives: firstly, to reduce the weight of the car to achieve lightweighting goals; secondly, to decrease the integral of the car's acceleration, thereby reducing the impact force experienced by the driver and passengers; and finally, to minimize the intrusion of the footboard to reduce the risk of severe mechanical damages suffered by the driver and passengers in collisions. These three objectives conflict with each other and need to be minimized simultaneously, satisfying the definition of a MaOEA. Therefore, this problem can be represented by the following mathematical model:

$$\begin{aligned} &\text{Minimize } F(x) = \left(f_1(x), f_2(x), f_3(x)\right)^T \\ &\text{Subject to } 1 \text{ mm} \le x \le 3 \text{ mm} \\ &\text{Where } x = (x_1, x_2, x_3, x_4, x_5)^T \end{aligned} \tag{18}$$

$$\begin{aligned} f_1(x) = {} & 1640.2823 + 2.3573285x_1 + 2.3220035x_2 + 4.5688768x_3 \\ & + 7.7213633x_4 + 4.4559504x_5 \end{aligned} \tag{19}$$

Table 6
The average HV obtained by different algorithms in the application of vehicle crash safety design.

Algorithm	PRVNSGAII	HEA	TSNSGAII	VMEF	FDEAII	MultiGPO	MaOEADISC
HV	0.0375367	0.0363174	0.0377613	0.0383228	0.0352509	0.0367291	0.0385082
Rank	4	6	3	2	7	5	1

$$\begin{aligned} f_2(x) = {} & 6.5856 + 1.15x_1 - 1.0427x_2 + 0.9738x_3 + 0.8364x_4 - 0.3695x_1x_4 \\ & + 0.0861x_1x_5 + 0.3628x_2x_4 \\ & - 0.1106x_1^2 - 0.3437x_3^2 + 0.1764x_4^2 \end{aligned} \tag{20}$$

$$\begin{aligned} f_3(x) = {} & -0.0551 + 0.0181x_1 + 0.1024x_2 + 0.0421x_3 - 0.0073x_1x_2 \\ & + 0.024x_2x_3 - 0.0118x_2x_4 \\ & - 0.0204x_3x_4 - 0.008x_3x_5 - 0.0241x_2^2 + 0.0109{x_4}^2 \end{aligned} \tag{21}$$

Where $x = (x_1, x_2, x_3, x_4, x_5)^T$ is a 5-dimensional decision variable, representing the thickness of five reinforced members around the frontal structure. $f_1(x)$, $f_2(x)$, and $f_3(x)$ represent the objective functions of the three objectives: car mass, acceleration integral, and footboard intrusion, respectively.

It should be noted that since the optimization problem of CSDV is a real-world problem, it is not feasible to evaluate the performance of algorithms using indicators related to the true PF. Therefore, this paper employs HV to assess the overall performance of different algorithms in this problem. Additionally, since the optimization problem of CSDV involves three objectives, the experimental settings in this section are consistent with those of the three-objective test problem mentioned in Section 4.1.

Table 6 presents the average HV values and rankings obtained by MaOEA-DISC and six state-of-the-art algorithms on the optimization problem of CSDV. The results indicate that MaOEA-DISC achieves the best HV value, suggesting that compared to other algorithms, MaOEA-DISC can provide better vehicle crash safety performance. This can be attributed to the $I_{\epsilon+D}$ indicator used by MaOEA-DISC, which is independent of PF shape and can find solutions that match the shape of the real-world PF. Furthermore, MaOEA-DISC's SCCM and mating mechanisms enhance its search capability when dealing with complex real-world problems, enabling it to rapidly select solutions with superior convergence. Although VMEF's HV value is close to MaOEA-DISC, as the number of objectives increases, the difference between them may widen due to VMEF's use of multiple older solution sorting methods, which are significantly influenced by the number of objectives, while the $I_{\epsilon+D}$ indicator in MaOEA-DISC is less affected by the number of objectives. TSNSGAII and PRVNSGAII rank third and fourth, respectively, because they are both improvements on NSGAII, resulting in similar HV values. Despite MultiGPO ranking fifth in performance, its use of GPO dominance is highly influenced by parameters, leading to potential performance variations when faced with different real-world problems. Since HEA maintains population diversity using weight vectors, it tends not to match the PF shape when dealing with more complex real-world problems, hence ranking second to last, whereas MaOEA-DISC's $I_{\epsilon+D}$ indicator is unaffected by PF shape, resulting in significantly higher HV values compared to HEA, thus validating the effectiveness of the $I_{\epsilon+D}$ indicator in maintaining diversity. As for FDEAII, its obtained HV value is the smallest and significantly lower compared to other algorithms, indicating its unsuitability for handling such problems. In summary, MaOEA-DISC demonstrates superior feasibility and robustness in addressing practical engineering problems, making it a powerful tool for solving real-world engineering applications. Its outstanding performance in addressing practical problems further proves its effectiveness in handling MaOPs.

5. Conclusion

In this paper, we propose an enhanced diversity indicator-based many-objective evolutionary algorithm with shape-conforming convergence metric (MaOEA-DISC) to address many-objective optimization problems. In MaOEA-DISC, in order to select a population with good convergence and diversity, we first design a method to calculate the convergence of population individuals based on the estimated PF shape. This method dynamically adjusts the convergence computation according to different shapes of the Pareto front, enabling a more accurate assessment of individual convergence. Subsequently, individuals' convergence is computed using this method, and individuals with better convergence are selected as parents for mating. This approach ensures that the generated offspring exhibit superior convergence, thereby accelerating population convergence. Finally, we introduce an enhanced diversity $I_{\epsilon+}$ indicator for environmental selection. This indicator considers the distance between individuals and their neighbouring individuals when evaluating individual diversity, ensuring population uniformity. Moreover, it also takes into account the distance between individuals and other individuals in the population, thus ensuring population coverage breadth. As these methods are designed to address both convergence and diversity simultaneously, MaOEA-DISC effectively handles various types of MaOPs.

Evaluating the performance of MaOEA-DISC with six other different types of MaOEAs in 3 to 10 dimensional DTLZ, WFG, and MAF test suites by multiple indicators. It is observed that MaOEA-DISC is able to improve the diversity and convergence of the populations and maintain the balance between them when dealing with different types of MaOPs. Additionally, comparisons are made under different convergence metrics and using the modified and unmodified $I_{\epsilon+}$ indicators to obtain populations. Experimental results demonstrate that our proposed shape-conforming convergence metric can more accurately measure the convergence of individuals, while the introduced $I_{\epsilon+D}$ indicator significantly improves the diversity of the population. Finally, we apply MaOEA-DISC to the optimization problem of CSDV, validating its practicality.

In general, MaOEA-DISC exhibits superior performance on the majority of test suites. However, when handling many-objective optimization problems with convex PFs, MaOEA-DISC exhibits a relatively poor population diversity due to the inability of cosine similarity to accurately measure the inter-individual distances within convex PF with trailing tails. Additionally, although MaOEA-DISC performs well in the optimization problem of CSDV, it focuses on fewer objectives. However, real-world MaOPs typically involve more objectives. Therefore, the performance of MaOEA-DISC in handling scenarios with a greater number of objectives requires further investigation. In future work, we will seek more effective strategies to enhance population diversity specifically on convex PF with trailing tails. Simultaneously, we intend to apply MaOEA-DISC to real-world optimization problems with a higher number of objectives.

CRediT authorship contribution statement

Jiale Cao: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Data curation, Conceptualization. **Lei Yang:** Writing – review & editing, Validation, Supervision, Project administration, Investigation, Funding acquisition. **Kangshun Li:** Validation, Project administration, Investigation, Funding acquisition. **Yuanye Zhang:** Writing – review & editing, Visualization, Investigation, Formal analysis, Data curation. **Jinglin Tian:** Writing –

review & editing, Visualization, Methodology, Investigation. **Dongya Wang:** Writing – review & editing, Validation, Project administration, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

This work was partially supported by Natural Science Foundation of Guangdong Province of China (Grant No. 2020A1515010691), Science and Technology Innovation Special Project of Guangdong Province (Grant No. SDZX2023032), Agricultural Science and Technology Commissioner Project of Guangzhou City (Grant No. 20212100036), National Key R&D Program Projects (Grant Nos. 2023YFF1105101 and 2023YFF1104201), and National Natural Science Foundation of China (Grant Nos.61573157 and 61703170). The authors also gratefully acknowledge the reviewers for their helpful comments and suggestions that helped to improve the presentation.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.asoc.2024.112161.

References

[1] M. Elarbi, S. Bechikh, A. Gupta, L. Ben Said, Y.-S. Ong, A new decomposition-based NSGA-II for many-objective optimization, IEEE Trans. Syst. Man Cybern. 48 (7) (2018) 1191–1210, http://dx.doi.org/10.1109/TSMC.2017.2654301.

[2] Q. Lin, J. Li, Z. Du, J. Chen, Z. Ming, A novel multi-objective particle swarm optimization with multiple search strategies, European J. Oper. Res. 247 (3) (2015) 732–744, http://dx.doi.org/10.1016/j.ejor.2015.06.071.

[3] X. Ma, Q. Zhang, G. Tian, J. Yang, Z. Zhu, On tchebycheff decomposition approaches for multiobjective evolutionary optimization, IEEE Trans. Evol. Comput. 22 (2) (2018) 226–244, http://dx.doi.org/10.1109/TEVC.2017.2704118.

[4] S.-W. Jung, J. Yoon, H.-W. Kim, S. Hahn, S.-Y. Jung, Optimal design study of metal-as-insulation HTS synchronous motor with multiple operating points for EVs based on many-objective optimization, IEEE Trans. Appl. Supercond. 34 (5) (2024) 1–5, http://dx.doi.org/10.1109/TASC.2024.3381104.

[5] Z. Hu, C. Fang, Z. Wang, S.-M. Tseng, M. Dong, Many-objective optimization-based content popularity prediction for cache-assisted cloud–edge–end collaborative IoT networks, IEEE Internet Things J. 11 (1) (2024) 1190–1200, http://dx.doi.org/10.1109/JIOT.2023.3290793.

[6] C. Zhao, J. Tang, W. Gao, Y. Zeng, Z. Li, Many-objective optimization of multimode public transportation under carbon emission reduction, Energy 286 (2024) 129627, http://dx.doi.org/10.1016/j.energy.2023.129627.

[7] S. Liu, H. Wang, W. Yao, W. Peng, Surrogate-assisted environmental selection for fast hypervolume-based many-objective optimization, IEEE Trans. Evol. Comput. 28 (1) (2024) 132–146, http://dx.doi.org/10.1109/TEVC.2023.3243632.

[8] H. Zhang, J. Gan, J. Zhou, W. Gao, Rank-based multimodal immune algorithm for many-objective optimization problems, Eng. Appl. Artif. Intell. 133 (2024) 108153, http://dx.doi.org/10.1016/j.engappai.2024.108153.

[9] T. Ye, H. Wang, T. Zeng, M.G. Omran, F. Wang, Z. Cui, J. Zhao, An improved two-archive artificial bee colony algorithm for many-objective optimization, Expert Syst. Appl. 236 (2024) 121281, http://dx.doi.org/10.1016/j.eswa.2023.121281.

[10] W. Zhang, J. Liu, Y. Liu, J. Liu, S. Tan, A many-objective evolutionary algorithm under diversity-first selection based framework, Expert Syst. Appl. 250 (2024) 123949, http://dx.doi.org/10.1016/j.eswa.2024.123949.

[11] G. Liu, Z. Pei, N. Liu, Y. Tian, Subspace segmentation based co-evolutionary algorithm for balancing convergence and diversity in many-objective optimization, Swarm Evol. Comput. (2023) 101410, http://dx.doi.org/10.1016/j.swevo.2023.101410.

[12] X. Wang, Z. Xie, X. Zhou, X. Gu, A two-stage adaptive reference direction guided evolutionary algorithm with modified dominance relation for many-objective optimization, Swarm Evol. Comput. 78 (2023) 101272, http://dx.doi.org/10.1016/j.swevo.2023.101272.

[13] B. Li, J. Li, K. Tang, X. Yao, Many-objective evolutionary algorithms: A survey, ACM Comput. Surv. 48 (1) (2015) 1–35, http://dx.doi.org/10.1145/2792984.

[14] Y. Tian, R. Cheng, X. Zhang, Y. Su, Y. Jin, A strengthened dominance relation considering convergence and diversity for evolutionary many-objective optimization, IEEE Trans. Evol. Comput. 23 (2) (2019) 331–345, http://dx.doi.org/10.1109/TEVC.2018.2866854.

[15] Y. Tian, H. Wang, X. Zhang, Y. Jin, Effectiveness and efficiency of non-dominated sorting for evolutionary multi-and many-objective optimization, Complex Intell. Syst. 3 (2017) 247–263, http://dx.doi.org/10.1007/s40747-017-0057-5.

[16] S. Zhou, Y. Dai, Z. Chen, Dominance relation selection and angle-based distribution evaluation for many-objective evolutionary algorithm, Swarm Evol. Comput. 86 (2024) 101515, http://dx.doi.org/10.1016/j.swevo.2024.101515.

[17] W. Zhang, J. Liu, J. Liu, Y. Liu, S. Tan, A dual distance dominance based evolutionary algorithm with selection-replacement operator for many-objective optimization, Expert Syst. Appl. 237 (2024) 121244, http://dx.doi.org/10.1016/j.eswa.2023.121244.

[18] W. Li, H. Chen, G. Wang, L. Song, Y. Xia, Z. Wang, K. Jia, Many-objective optimization evolutionary algorithm based on dynamic region partitioning, in: 2024 4th International Conference on Consumer Electronics and Computer Engineering, ICCECE, 2024, pp. 59–63, http://dx.doi.org/10.1109/ICCECE61317.2024.10504213.

[19] C. Dai, C. Peng, X. Lei, A point crowding-degree based evolutionary algorithm for many-objective optimization, Memet. Comput. 15 (2023) 391–403, http://dx.doi.org/10.1007/s12293-023-00398-9.

[20] Q. Zhang, H. Li, MOEA/D: a multiobjective evolutionary algorithm based on decomposition, IEEE Trans. Evol. Comput. 11 (6) (2007) 712–731, http://dx.doi.org/10.1109/TEVC.2007.892759.

[21] M. Li, X. Yao, What weights work for you? Adapting weights for any Pareto front shape in decomposition-based evolutionary multiobjective optimisation, Evol. Comput. 28 (2) (2020) 227–253, http://dx.doi.org/10.1162/evco_a_00269.

[22] H.-L. Liu, L. Chen, Q. Zhang, K. Deb, Adaptively allocating search effort in challenging many-objective optimization problems, IEEE Trans. Evol. Comput. 22 (3) (2018) 433–448, http://dx.doi.org/10.1109/TEVC.2017.2725902.

[23] Y. Zhou, Y. Xiang, Z. Chen, J. He, J. Wang, A scalar projection and angle-based evolutionary algorithm for many-objective optimization problems, IEEE Trans. Cybern. 49 (6) (2019) 2073–2084, http://dx.doi.org/10.1109/TCYB.2018.2819360.

[24] J. Chen, X. Yan, C. Hu, W. Gong, Deep and wide search assisted evolutionary algorithm with reference vector guidance for many-objective optimization, Swarm Evol. Comput. 88 (2024) 101585, http://dx.doi.org/10.1016/j.swevo.2024.101585.

[25] W. Li, Y. Chen, Y. Dong, Y. Huang, A solution potential-based adaptation reference vector evolutionary algorithm for many-objective optimization, Swarm Evol. Comput. 84 (2024) 101451, http://dx.doi.org/10.1016/j.swevo.2023.101451.

[26] J. Zheng, Z. Du, J. Zou, S. Yang, A weight vector generation method based on normal distribution for preference-based multi-objective optimization, Swarm Evol. Comput. 77 (2023) 101250, http://dx.doi.org/10.1016/j.swevo.2023.101250.

[27] E. Zitzler, S. Künzli, Indicator-based selection in multiobjective search, in: Parallel Problem Solving from Nature - PPSN VIII, Springer Berlin Heidelberg, 2004, pp. 832–842, http://dx.doi.org/10.1007/978-3-540-30217-9_84.

[28] L. While, P. Hingston, L. Barone, S. Huband, A faster algorithm for calculating hypervolume, IEEE Trans. Evol. Comput. 10 (1) (2006) 29–38, http://dx.doi.org/10.1109/TEVC.2005.851275.

[29] Q. Zhang, A. Zhou, Y. Jin, RM-MEDA: A regularity model-based multiobjective estimation of distribution algorithm, IEEE Trans. Evol. Comput. 12 (1) (2008) 41–63, http://dx.doi.org/10.1109/TEVC.2007.894202.

[30] D. Brockhoff, T. Wagner, H. Trautmann, On the properties of the R2 indicator, in: Proceedings of the 14th Annual Conference on Genetic and Evolutionary Computation, ACM, 2012, pp. 465–472, http://dx.doi.org/10.1145/2330163.2330230.

[31] J. Xiong, G. Liu, Z. Gao, C. Zhou, P. Hu, Q. Bao, A many-objective evolutionary algorithm based on learning assessment and mapping guidance of historical superior information, J. Comput. Des. Eng. 11 (2) (2024) 194–229, http://dx.doi.org/10.1093/jcde/qwae022.

[32] C. Wen, H. Ma, A two-stage hypervolume-based evolutionary algorithm for many-objective optimization, Mathematics 11 (20) (2023) 4247, http://dx.doi.org/10.3390/math11204247.

[33] Y. Tian, R. Cheng, X. Zhang, F. Cheng, Y. Jin, An indicator-based multiobjective evolutionary algorithm with reference point adaptation for better versatility, IEEE Trans. Evol. Comput. 22 (4) (2018) 609–622, http://dx.doi.org/10.1109/TEVC.2017.2749619.

[34] K. Shang, H. Ishibuchi, A new hypervolume-based evolutionary algorithm for many-objective optimization, IEEE Trans. Evol. Comput. 24 (5) (2020) 839–852, http://dx.doi.org/10.1109/TEVC.2020.2964705.

[35] S.-C. Liu, Z.-H. Zhan, K.C. Tan, J. Zhang, A multiobjective framework for many-objective optimization, IEEE Trans. Cybern. 52 (12) (2022) 13654–13668, http://dx.doi.org/10.1109/TCYB.2021.3082200.

[36] H. Wang, C. Sun, G. Zhang, J.E. Fieldsend, Y. Jin, Non-dominated sorting on performance indicators for evolutionary many-objective optimization, Inform. Sci. 551 (2021) 23–38, http://dx.doi.org/10.1016/j.ins.2020.11.008.

[37] Y. Liu, D. Gong, J. Sun, Y. Jin, A many-objective evolutionary algorithm using a one-by-one selection strategy, IEEE Trans. Cybern. 47 (9) (2017) 2689–2702, http://dx.doi.org/10.1109/TCYB.2016.2638902.

[38] B. Li, K. Tang, J. Li, X. Yao, Stochastic ranking algorithm for many-objective optimization based on multiple indicators, IEEE Trans. Evol. Comput. 20 (6) (2016) 924–938, http://dx.doi.org/10.1109/TEVC.2016.2549267.

[39] Z. Liang, K. Hu, X. Ma, Z. Zhu, A many-objective evolutionary algorithm based on a two-round selection strategy, IEEE Trans. Cybern. 51 (3) (2021) 1417–1429, http://dx.doi.org/10.1109/TCYB.2019.2918087.

[40] C.C. Aggarwal, A. Hinneburg, D.A. Keim, On the surprising behavior of distance metrics in high dimensional space, in: Database Theory—ICDT 2001: 8th International Conference London, UK, January 4–6, 2001 Proceedings 8, Springer, 2001, pp. 420–434, http://dx.doi.org/10.1007/3-540-44503-X_27.

[41] K. Zhang, Z. Xu, S. Xie, G.G. Yen, Evolution strategy-based many-objective evolutionary algorithm through vector equilibrium, IEEE Trans. Cybern. 51 (11) (2021) 5455–5467, http://dx.doi.org/10.1109/TCYB.2019.2960039.

[42] K. Deb, L. Thiele, M. Laumanns, E. Zitzler, Scalable test problems for evolutionary multiobjective optimization, in: Evolutionary Multiobjective Optimization: Theoretical Advances and Applications, Springer London, 2005, pp. 105–145, http://dx.doi.org/10.1007/1-84628-137-7_6.

[43] S. Huband, P. Hingston, L. Barone, L. While, A review of multiobjective test problems and a scalable test problem toolkit, IEEE Trans. Evol. Comput. 10 (5) (2006) 477–506, http://dx.doi.org/10.1109/TEVC.2005.861417.

[44] R. Cheng, M. Li, Y. Tian, X. Zhang, S. Yang, Y. Jin, X. Yao, A benchmark test suite for evolutionary many-objective optimization, Complex Intell. Syst. 3 (1) (2017) 67–81, http://dx.doi.org/10.1007/s40747-017-0039-7.

[45] Y. Tian, R. Cheng, X. Zhang, Y. Jin, Platemo: A MATLAB platform for evolutionary multi-objective optimization [educational forum], IEEE Comput. Intell. Mag. 12 (4) (2017) 73–87, http://dx.doi.org/10.1109/MCI.2017.2742868.

[46] S. Wang, H. Wang, Z. Wei, F. Wang, Q. Zhu, J. Zhao, Z. Cui, A Pareto dominance relation based on reference vectors for evolutionary many-objective optimization, Appl. Soft Comput. 157 (2024) 111505, http://dx.doi.org/10.1016/j.asoc.2024.111505.

[47] Z. Liu, F. Han, Q. Ling, H. Han, J. Jiang, A many-objective optimization evolutionary algorithm based on hyper-dominance degree, Swarm Evol. Comput. 83 (2023) 101411, http://dx.doi.org/10.1016/j.swevo.2023.101411.

[48] F. Ming, W. Gong, L. Wang, A two-stage evolutionary algorithm with balanced convergence and diversity for many-objective optimization, IEEE Trans. Syst. Man Cybern. 52 (10) (2022) 6222–6234, http://dx.doi.org/10.1109/TSMC.2022.3143657.

[49] W. Qiu, J. Zhu, G. Wu, H. Chen, W. Pedrycz, P.N. Suganthan, Ensemble many-objective optimization algorithm based on voting mechanism, IEEE Trans. Syst. Man Cybern. 52 (3) (2022) 1716–1730, http://dx.doi.org/10.1109/TSMC.2020.3034180.

[50] W. Qiu, J. Zhu, G. Wu, M. Fan, P.N. Suganthan, Evolutionary many-objective algorithm based on fractional dominance relation and improved objective space decomposition strategy, Swarm Evol. Comput. 60 (2021) 100776, http://dx.doi.org/10.1016/j.swevo.2020.100776.

[51] S. Zhu, L. Xu, E.D. Goodman, Z. Lu, A new many-objective evolutionary algorithm based on generalized Pareto dominance, IEEE Trans. Cybern. 52 (8) (2022) 7776–7790, http://dx.doi.org/10.1109/TCYB.2021.3051078.

[52] O. Schutze, X. Esquivel, A. Lara, C.A.C. Coello, Using the averaged hausdorff distance as a performance measure in evolutionary multiobjective optimization, IEEE Trans. Evol. Comput. 16 (4) (2012) 504–522, http://dx.doi.org/10.1109/TEVC.2011.2161872.

[53] H. Ishibuchi, H. Masuda, Y. Tanigaki, Y. Nojima, Modified distance calculation in generational distance and inverted generational distance, in: Evolutionary Multi-Criterion Optimization, Springer International Publishing, Cham, 2015, pp. 110–125, http://dx.doi.org/10.1007/978-3-319-15892-1_8.

[54] K. Deb, S. Jain, Running performance metrics for evolutionary multi-objective optimizations, in: Proceedings of the Fourth Asia-Pacific Conference on Simulated Evolution and Learning, SEAL'02, 2002, pp. 13–20.

[55] J. Blank, K. Deb, Y. Dhebar, S. Bandaru, H. Seada, Generating well-spaced points on a unit simplex for evolutionary many-objective optimization, IEEE Trans. Evol. Comput. 25 (1) (2021) 48–60, http://dx.doi.org/10.1109/TEVC.2020.2992387.

[56] K. Deb, Multi-objective optimisation using evolutionary algorithms: An introduction, in: Multi-Objective Evolutionary Optimisation for Product Design and Manufacturing, Springer London, 2011, pp. 3–34, http://dx.doi.org/10.1007/978-0-85729-652-8_1.

[57] K. Deb, Geneas: A robust optimal design technique for mechanical component design, in: Evolutionary Algorithms in Engineering Applications, Springer Berlin Heidelberg, 1997, pp. 497–514, http://dx.doi.org/10.1007/978-3-662-03423-1_27.

[58] J. Derrac, S. García, D. Molina, F. Herrera, A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms, Swarm Evol. Comput. 1 (1) (2011) 3–18, http://dx.doi.org/10.1016/j.swevo.2011.02.002.

[59] X. Liao, Q. Li, X. Yang, W. Zhang, W. Li, Multiobjective optimization for crash safety design of vehicles using stepwise regression model, Struct. Multidiscip. Optim. 35 (6) (2008) 561–569, http://dx.doi.org/10.1007/s00158-007-0163-x.

◎理论与研发◎

面向高维多目标优化的双阶段双种群进化算法

曹嘉乐,杨 磊,田井林,李华德,李康顺
华南农业大学 数学与信息学院,广州 510642

摘 要:随着目标维度的上升,高维多目标优化问题的帕累托前沿越来越复杂,传统的基于分解的高维多目标进化算法难以挑选出多样性和收敛性良好的种群。针对以上问题提出了一种面向高维多目标优化的双阶段双种群进化算法。该算法将进化过程划分为两个阶段,在第一阶段判断帕累托前沿的形状是否规则,而在第二阶段则根据帕累前沿的形状选择是否对权重向量进行调整,以保证种群在规则及不规则帕累托前沿上都能获得良好的多样性。为了对权重向量进行调整且不影响算法的收敛性,该算法使用了两个种群进行进化,一个主种群正常进化,另一个辅种群作为权重向量。为了在不规则的帕累托前沿上获得一组适应种群分布的权重向量,引入了自然界中能量平衡的概念收集了多样性良好的辅种群作为权重向量。将提出的算法与其他算法在3-10目标的测试问题上进行比较。实验结果表明,提出的算法在大多数测试问题上性能优于比较的算法。

关键词:高维多目标优化;进化算法;双阶段;双种群;权重向量;能量平衡
文献标志码:A **中图分类号:**TP301 doi:10.3778/j.issn.1002-8331.2307-0381

Dual-Stage Dual-Population Evolutionary Algorithm for Many-Objective Optimization

CAO Jiale, YANG Lei, TIAN Jinglin, LI Huade, LI Kangshun
College of Mathematics and Informatics, South China Agricultural University, Guangzhou 510642, China

Abstract: As the number of objectives increases, the Pareto front of many-objective optimization problem becomes increasingly complex. Traditional decomposition-based many-objective evolutionary algorithms struggle to select populations with both good diversity and convergence characteristics. To address this issue, a novel dual-stage dual-population evolutionary algorithm for many-objective optimization is proposed. In this algorithm, the evolutionary process is divided into two stages. In the first stage, it determines whether the shape of the Pareto front is regular. In the second stage, it adjusts the weight vectors based on the shape of the Pareto front, ensuring that the population can achieve good diversity on both regular and irregular Pareto fronts. To perform weight vector adjustments without affecting the convergence of the algorithm, two populations are used for evolution: one main population evolves normally, and the other auxiliary population serves as the weight vectors. Finally, to obtain a set of weight vectors that adapt well to populations distributed on irregular Pareto fronts, the concept of energy balance in nature is introduced to collect a well-diverse auxiliary population as weight vectors. The proposed algorithm is compared with other algorithms on test problems with 3-10 objectives. Experimental results demonstrate that the proposed algorithm outperforms the compared algorithms on the majority of the test problems.
Key words: many-objective optimization; evolutionary algorithm; dual-stage; dual-population; weight vector; energy balance

高维多目标优化问题在现实世界中广泛存在,如楼宇负荷优化调度[1]、汽车碰撞安全设计[2]和配送中心拣货系统作业[3]等。这类问题通常涉及三个或三个以上相互冲突的目标,提升其中一个目标的性能往往会导致其他目标的性能下降,因此需尽可能地优化这些冲突的目标使得总目标达到最优。近年来,进化算法作为一种启

基金项目:国家自然科学基金(61573157);广东省自然科学基金(2020A1515010691);广州市农业科技特派员项目(20212100036)。
作者简介:曹嘉乐(1999—),男,硕士研究生,CCF学生会员,研究方向为智能计算、多目标优化;杨磊(1978—),通信作者,男,博士,讲师,研究方向为数据挖掘、智能计算,E-mail:yanglei_s@scau.edu.cn;田井林(1998—),男,硕士研究生,研究方向为智能计算、多目标优化;李华德(1999—),男,硕士研究生,研究方向为数据挖掘、时间序列预测;李康顺(1962—),男,博士,教授,研究方向为机器学习、人工智能。
收稿日期:2023-07-26 **修回日期:**2023-09-12 **文章编号:**1002-8331(2024)09-0159-13

(C)1994-2024 China Academic Journal Electronic Publishing House. All rights reserved. http://www.cnki.net

发式优化算法,因其能够模拟自然进化过程来解决各种复杂的优化问题而在多目标优化领域中得到了广泛应用。如今的高维多目标进化算法大致分为如下四类:

第一类为基于帕累托支配关系的高维多目标优化算法。这类算法一般基于两种策略来选择个体:第一种策略是通过改进帕累托支配关系来选择个体,该策略通常通过放宽帕累托支配关系,使得不可比较的解能够进行比较,从而增强环境选择压力。如CSDR-Dominance[4]、GPO-Dominance[5]等。这些算法虽然能提高高维多目标优化算法的选择压力,但是对参数依赖性很强,往往很难找到合适的参数。第二种策略则是通过新型的多样性选择标准来选择个体,如Zhou等人[6]采用一种基于全局和局部多样性的多样性维护机制来管理种群的多样性,Chen等人[7]通过多样性排序的方法来提高种群在不同类型帕累托前沿上的多样性。这些算法虽然在增加选择压力方面有效,但在平衡多样性和收敛性方面稍有不足。

基于指标的高维多目标进化算法属于第二类,如HyPE[8]、MaOEA-IGD[9]等。这些算法使用超体积(hypervolume,HV)[10]、反向世代距离(inverted generational distance,IGD)[11]等准确指标或估计的指标值来进行环境选择。然而,这些算法的计算成本是非常昂贵的,并且生成的解很难保证分布的均匀性。

第三类是采用新型自定义进化框架的高维多目标优化算法。如基于决策变量分类的DVC-MOEA[12]采用一种新型的决策变量分类方法来生成有前景的解,但是决策变量贡献的变化可能会导致错误的分类,从而影响算法效能。基于两阶段代理辅助进化算法TS-SAEA[13]通过将进化过程划分为收敛性阶段和多样性阶段,以分别提高种群的收敛性和多样性,但是对收敛性和多样性分别进行处理,可能无法保持收敛性与多样性的平衡。而Two_Arch2[14]则使用收敛性种群档案及多样性种群档案来指导种群的进化,该方法能够有效地维持收敛性和多样性的平衡,其缺点是在高维空间多样性档案难以更新,会导致解集的多样性变差。

第四类则为基于分解的高维多目标进化算法,该类算法通常采用均匀分布的权重向量将一个高维多目标优化问题分解成多个单目标子问题,然后同时对它们进行优化。其中,MOEA/D[15]、RVEA[16]是这类算法中的一些代表性算法。相较于其他三种类型的算法,该类算法具有计算复杂度低、能够提供良好的选择压力和维持多样性简单等优点。然而,当处理具有不规则形状的帕累托前沿时(例如断开、退化、反向、约束、严重缩放和复杂的帕累托前沿),使用预定义均匀分布的权重向量的算法性能会受到影响[17],无法挑选出分布均匀的解,同时还会导致权重向量的浪费。

为了有效地处理具有不规则帕累托前沿的高维多目标优化问题,一种有效的方法是在进化过程中自适应地调整权重向量。例如,Liu等人[18]通过改进的 k-均值聚类方法从种群中提取符合帕累托前沿形状的权重向量。Zhao等人[19]采用双重调整策略对权重向量进行调整。Zhang等人[20]周期性地将权重向量分组为多个子集,并将每个子集中的权重向量数量与边界个体形成的范围成比例,从而挑选出覆盖范围良好的解。

即使上述权重向量调整方法能够一定程度上处理具有不规则帕累托前沿的高维多目标优化问题,但是这些方法大多都只能处理具有不规则帕累托前沿的高维多目标优化问题,在具有规则帕累托前沿的高维多目标优化问题上表现较差。此外,在高维多目标优化问题中,保持种群的收敛性是相当具有挑战性的。而这些方法大多都是在预定义的权重向量的基础上进行权重向量的调整,需要多次对权重向量进行调整,虽然能够提高种群的多样性,但也会导致种群的收敛性变差。最后,这些方法在对权重向量调整时所需的参数较多,在不同的问题上使用固定的参数可能难以处理具有极端不规则帕累托前沿的高维多目标优化问题。

综上所述,在高维多目标优化问题上获得具有良好收敛性与多样性的种群是一项充满挑战性的任务,虽然基于分解的高维多目标优化算法在该问题上表现出色,但是其所生成的权重向量往往会与一些帕累托前沿的形状不匹配,从而无法有效兼顾处理具有规则和不规则帕累托前沿的高维多目标优化问题,最终导致算法的性能下降,甚至失效。

为了有效地处理具有规则和不规则帕累托前沿的高维多目标优化问题。本文提出了一种面向高维多目标优化的双阶段双种群进化算法(dual-stage dual-population evolutionary algorithm for many-objective optimization,MaOEA-DD)。与以往采用双阶段或双种群挑选个体以分别提高种群的收敛性和多样性的算法有所不同,MaOEA-DD算法主要是通过双阶段双种群策略对权重向量进行调整,以同时提高种群的收敛性和多样性。具体而言,该算法将进化过程划分为两个阶段并且使用两个种群进行进化。在第一阶段,两个种群同时进化,其中一个种群作为辅种群,根据能量平衡的关系收集多样性较好的个体,另一个种群作为主种群,采用基于分解的方法进行进化,当主种群达到一定稳定状态后,根据权重向量与其对应的主种群个体之间的夹角,判断帕累托前沿是否规则。在第二阶段,根据第一阶段得到的帕累托前沿的形状,选择是否对权重向量进行调整,若帕累托前沿规则,则不进行调整,否则将辅种群作为主种群的权重向量指导主种群进化。其主要贡献有如下三点:

(1)提出了一种双阶段的进化过程。在第一阶段,通过权重向量与种群个体之间的角度关系判断帕累托

(C)1994-2024 China Academic Journal Electronic Publishing House. All rights reserved. http://www.cnki.net

前沿形状是否规则。在第二阶段,根据帕累托前沿的形状,选择是否对权重向量进行调整,以兼顾处理具有规则和不规则帕累托前沿的高维多目标优化问题。

(2)设计了一种双种群权重向量调整方法。其中一个主种群由预定义权重向量指导进化,另一个辅种群则负责收集多样性良好的个体。当需要调整权重向量时,将辅种群作为权重向量指导另一个种群的进化。该方法不依赖预定义的权重向量,仅调整一次权重向量,能够提高种群的多样性,同时保持种群的收敛性。

(3)本文根据自然界中多体和相互作用的物理系统趋向于均匀有序状态的特性,提出了一种收集均匀分布的种群作为权重向量的方法。该挑选过程无需额外参数,挑选的权重向量能够有效处理具有不规则帕累托前沿的多目标优化问题。

1　相关背景

定义1(高维多目标优化问题)以最小化高维多目标优化问题为例,其数学模型使用如下公式描述:

$$\begin{cases}\min F(\boldsymbol{x})=(f_1(x),f_2(x),\cdots,f_m(x))^{\mathrm{T}}\\ \text{s.t. } \boldsymbol{x}\in\Omega\end{cases}\tag{1}$$

其中 $\boldsymbol{x}=(x_1,x_2,\cdots,x_n)^{\mathrm{T}}$ 是决策空间 Ω 中一个 n 维的决策向量,$m\geqslant 3$ 是目标数量,$F(\boldsymbol{x})$ 是 m 维的目标向量。

定义2(帕累托支配关系)给定两个决策向量 $\boldsymbol{x}_a$ 和 $\boldsymbol{x}_b$,如果 $\boldsymbol{x}_a$ 帕累托支配 $\boldsymbol{x}_b$($\boldsymbol{x}_a\prec\boldsymbol{x}_b$),则其对应的目标值必有:$f(\boldsymbol{x}_a)_i\leqslant f(\boldsymbol{x}_b)_i,\forall i\in\{1,2,\cdots,m\}$,且 $f(\boldsymbol{x}_a)_i<f(\boldsymbol{x}_b)_i,\exists i\in\{1,2,\cdots,m\}$。

定义3(帕累托最优解)当一个解不被任何一个解支配时,则称这个解为非支配解或帕累托最优解。

定义4(帕累托最优集Pareto optimal set,PS)指的是一个包含所有非支配解或帕累托最优解的集合。

定义5(帕累托最优前沿Pareto optimal front,PF)指的是在目标空间中由PS映射而成的图形。

定义6(权重向量)一组用于衡量不同目标之间重要性的向量,通常预定义权重向量由如下公式产生:

$$n=\mathrm{C}_{m-1+p}^{m-1},\lambda=\left\{\frac{0}{p},\frac{1}{p},\cdots,\frac{p}{p}\right\}\tag{2}$$

其中,n 是权重向量个数,m 是目标数,C是组合数,p 是每一个坐标轴的分区数,λ 是权重向量的集合。

2　MaOEA-DD算法

2.1　双阶段进化过程

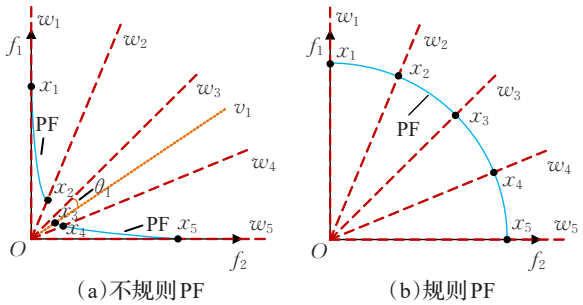
采用一组预定义均匀分布权重向量的基于分解的高维多目标进化算法可以有效地处理具有规则PF的高维多目标优化问题,而无法处理具有不规则PF的问题。采用动态调整权重向量的基于分解的高维多目标进化算法则相反。为兼顾两者,本文将进化过程分为两阶段:

第一阶段确定PF形状:在初始状态下,种群呈现混乱无序的特征,无法准确判断PF的形状,因此本文首先采用预定义均匀分布的权重向量指导种群进化,直至种群处于稳定有序的状态。而在本文中判断种群是否达到稳定有序状态的计算公式如下:

$$\begin{cases}MD=(\sum_{i=1}^{n}\sum_{k=1}^{m}|f(x_i)_k|)\\ \Delta=MD_{\text{current}}-MD_{\text{before}}\end{cases},x\in P\tag{3}$$

其中,$f(x_i)_k$ 是种群中第 i 个体的第 k 个目标值,MD 代表种群中所有个体到坐标原点的曼哈顿距离。在最小化问题中,较小的 MD 值意味着个体离坐标原点越近,即个体越接近PF,收敛性越好[21]。因此,MD 值能够一定程度上代表种群的状态。在本文中,如果相邻几代种群的 MD 值变化小于 10^{-6} 即 $\Delta<10^{-6}$,则认为该种群的收敛性已经不再变化,即达到种群达到稳定状态。

在确定种群达到稳定状态后,本文通过判断预定义权重向量与其指导的个体之间是否存在夹角来确定当前PF的形状。由于在不规则的PF上,预定义的权重向量没有考虑到PF的形状,只考虑了两两权重向量之间的等距离关系。因此,由这些权重向量指导进化的个体无法完全分布在这些权重向量上,只能尽可能靠近它们,并与它们成一定角度。图1(a)展示了这种情况,在图中,权重向量 $\boldsymbol{w}_3$ 与断开的PF并没有交点,这使得由其指导进化的个体 x_3 无法与由边界附近权重向量 $\boldsymbol{w}_4$ 指导的个体 x_4 保持均匀的间隙,只能分布在尽可能接近 $\boldsymbol{w}_3$ 的PF边界上,即 x_3 与 $\boldsymbol{w}_3$ 会存在一定的角度。而在规则的PF上,每个个体都能均匀分布在指导其进化的权重向量上。如图1(b)所示,每个权重向量与PF都有交点,与其指导的个体之间不存在夹角,每个个体都分布在对应的权重向量上,即均匀地分布在PF上。因此,在本文中,将权重向量与其指导的个体存在角度的PF判定为不规则PF,否则为规则PF。



(a)不规则PF　　(b)规则PF

图1　在不同形状的PF上个体与权重向量的关系

Fig.1　Relationship between individuals and weight vector on PF of different shapes

需要注意的是,在本文中是通过计算权重向量与其夹角最小的个体来粗略确定当前权重向量指导的个体,因为通常情况下,由当前权重向量指导的个体是与该权重向量距离最近的个体。然而,在进化过程中,即使在

(C)1994-2024 China Academic Journal Electronic Publishing House. All rights reserved.　http://www.cnki.net

规则PF上,个体与权重向量之间的角度也可能不为零度,而是存在微小角度。因此,本文以10^{-6}作为边界值,当两者角度差小于10^{-6}时,说明两者无夹角,否则存在夹角。此外,文中权重向量指导的个体与该权重向量之间的夹角指的是被指导个体和坐标原点构成的向量与对应权重向量之间的角度,如x_3与坐标原点构成的向量v_1与w_3的角度θ_1。

第二阶段调整权重向量:在第一阶段确定PF形状后,在第二阶段则根据PF的形状进行权重向量的调整。如果PF是不规则的,则进行权重向量调整,以确保种群在不规则PF上均匀分布。而如果PF是规则的,则不调整权重向量,以保持预定义权重向量在规则PF上的优势。

具体而言,MaOEA-DD双阶段进化过程的主要目的是通过第一阶段判断PF的形状,然后在第二阶段选择是否对权重向量进行调整,以综合应对处理具有规则PF和不规则PF的高维多目标优化问题,与以往的双阶段多目标进化算法在不同阶段分别侧重于收集收敛性与多样性良好的个体的目的有所不同。同时在MaOEA-DD中阶段转换是依据种群收敛性的稳定性和权重向量与种群之间的关系这两个条件进行的,并不是依据种群的收敛性与多样性之间的关系进行的。此外,在MaOEA-DD的第一阶段中提出了一种根据权重向量指导的个体与PF的夹角判断PF形状的方法,在第二阶段对具有规则PF的问题和具有不规则PF的问题进行了不同的处理。

2.2　双种群权重向量调整

目前已有的权重向量调整方法大多数是权重向量的调整与种群进化同时进行,每次调整权重向量后,种群需根据新的权重向量重新进化。虽然提高了种群的分布但也严重降低了种群收敛速度,使得种群的收敛性变差。为解决此问题,本研究提出了一种使用双种群调整权重向量的方法。其中,一个种群称为主种群,使用预定义权重向量指导进化;另一个种群称为辅种群,其在进化过程中收集多样性良好的个体。这两个种群相互独立且无关。辅种群主要收集的是多样性良好的种群个体,并不受PF形状的影响,而主种群是通过权重向量指导进化的,多样性受PF形状影响,但是能够保持良好的收敛性,因此其收敛性优于辅种群但多样性差于辅种群。当种群收敛性稳定后将辅种群作为主种群的权重向量,此后便不再调整权重向量,这不仅提升了主种群在不规则PF上的多样性而且也能够保持主种群的收敛性。将辅种群转化为权重向量的具体公式如下:

$$\lambda_i=\left(\frac{f(x_i)_1}{\max(f(x_i))},\frac{f(x_i)_2}{\max(f(x_i))},\cdots,\frac{f(x_i)_m}{\max(f(x_i))}\right) \tag{4}$$

其中,λ_i表示第i个参考向量,$f(x_i)_m$是种群中第i个体的第m个目标值,$\max(f(x_i))$表示第i个体的最大目标值。通过该公式能够将辅种群的目标值范围限定在0到1,以符合权重向量的规范。

总而言之,MaOEA-DD双种群策略的目的是收集一个多样性良好的辅种群作为权重向量,以提高主种群的多样性。而大多数已有的双种群多目标进化算法的目的是使用一个种群收集收敛性良好的个体,另一个种群收集多样性良好的个体,然后综合挑选收敛性与多样性良好的个体。此外,MaOEA-DD的两个种群采用了不同的进化框架进行进化,结合了不同进化框架的优点,主种群采用了基于分解的进化框架,而辅种群采用基于帕累托支配的进化框架进行,接下来的章节将会对此进行详细介绍。最后,通常权重向量是通过公式(2)计算获得的,而在MaOEA-DD中则是通过公式(4)将辅种群转化成权重向量获得的。

2.3　多样性良好的辅种群获取

高维多目标优化问题中的PF是一个高维超曲面,这使得收集均匀分布的种群成为了一项艰巨的任务。为此本文使用了一种称为Riesz s-Energy[22]的势能在不规则PF上收集多样性良好的种群。其原理是自然界中多体和相互作用的物理系统最终会趋向于最小总势能的均匀有序状态。由于物体间势能与距离成反比,因此系统总势能较大时,系统中的物体会迅速扩散以降低势能。当系统中的物体间距离相等时,系统总势能达到最小值,此时系统中的物体停止运动。具体地,Riesz s-energy数学定义如下:

$$E=\sum_{i=1}^{n}\sum_{j=1}^{n}\frac{1}{\left\|y_i-y_j\right\|^{m-1}},y\in R \tag{5}$$

其中,E代表所有点的能量总和,这里的能量用两点之间的欧式距离表示,距离越大,能量越小则点越均匀。$\|\cdot\|$表示欧式距离,n是点的数量,y_i和y_j分别代表点集R的第i、j个点,m是目标数。

由于欧式距离在高维空间中不适用[23],所以文中两个个体之间的距离是通过计算它们对应的目标值之间的曼哈顿距离获得的。因此,在本文中的Riesz s-energy被定义为如下所示:

$$E=\sum_{i=1}^{n}\sum_{j=1}^{n}\frac{1}{\left(\sum_{k=1}^{m}\left|f_i(\boldsymbol{x}_k)-f_j(\boldsymbol{x}_k)\right|\right)^{m-1}} \tag{6}$$

其中,$\boldsymbol{x}_k$表示第k个个体的决策向量,$f_i(\boldsymbol{x}_k)$表示第k个个体的第i目标值,$|\cdot|$表示两者之间的绝对值。

尽管Riesz s-energy在保持点集均匀性方面表现良好,但在多目标优化中,种群分布需要同时满足均匀性和符合PF形状(帕累托支配关系)。因此,本文在帕累托支配关系下使用Riesz s-energy。具体挑选过程如下:假设辅种群大小为N,在每次进化过程中,使用辅种群生成N个子代。从该子代和辅种群组成的$2N$个体集合中,选择符合帕累托支配关系且具有最小Riesz s-energy的N个个体作为下一代辅种群。然而,从$2N$个个体中挑选N个符合要求的个体的时间复杂度很高。因此,在文中首先对子代和辅种群共$2N$个个体进

(C)1994-2024 China Academic Journal Electronic Publishing House. All rights reserved.　http://www.cnki.net

行非支配排序。然后,从排名前 N 的个体中选取 N 个个体。如果有多个个体排名相同且导致前 N 名个体数量超过 N ,则从这些个体中选择与当前已选个体构成的种群的Riesz s-energy最小的个体,直到选择的个体数达到 N 为止。这种选择方法类似于贪心算法,但可能不够准确。为了提高选择结果的准确性,完成上述选择后,逐一使用排名前 N 且未被选择的个体替换与其排名相同且已被选择的个体。如果种群的Riesz s-energy变小,则同意替换。重复此步骤,直到所有排名相同且未被选择的个体都被操作。此外,计算Riesz s-energy需重复计算两点距离。为降低计算时间复杂度,本文使用矩阵记录已计算的距离。

以上方法挑选的种群符合PF形状且均匀分布。虽然该种群的收敛性可能不佳,但将其用作主种群的权重向量指导主种群在不规则PF上的进化方向,能够提升主种群的多样性。

2.4 算法主流程

MaOEA-DD算法处理高维多目标优化问题的主要流程与基于分解的高维多目标进化算法类似。然而MaOEA-DD将进化过程划分为了两个阶段,并采用了两个种群进行进化,同时还对权重向量进行了调整。其算法流程图如图2所示,具体步骤如下:

输入:

步骤1 一个高维多目标优化问题,种群规模 N ,最大迭代次数 $t_{\max}$ 。

初始化:

步骤2 生成大小为 N 的主种群和辅种群,并创建 N 个预定义的权重向量。

第一阶段:

步骤3 对主种群进行交叉变异,产生 N 个子代。

步骤4 对辅种群进行交叉变异,产生 N 个子代。

步骤5 由权重向量的指导下从主种群及其子代中挑选 N 个个体作为下一代主种群。

步骤6 对辅种群及其子代共 $2N$ 个个体进行非支配排序,挑选排名靠前且具有最小Riesz s-energy的 N 个个体作为下一代辅种群。

步骤7 判断是否达到最大迭代次数 $t_{\max}$,是则执行步骤12,否则继续进行下一步。

步骤8 判断当前是否处于第一阶段,是则进行下一步,否则依次执行步骤3、5、7。

步骤9 判断主种群是否达到稳定状态,如果未达到稳定状态,则返回步骤3。否则,通过权重向量与其指导的个体之间的夹角来判断PF的形状。

第二阶段:

步骤10 如果第一阶段判断的PF形状是规则的,则不对权重向量进行调整,否则使用辅种群作为主种群的权重向量。

步骤11 依次执行步骤3、5、7。

输出:

步骤12 输出大小为 N 的主种群。

2.5 算法时间复杂度

针对具有 m 个目标的高维多目标优化问题,主种群采用了基于分解的高维多目标进化框架进行进化。其时间复杂度为 $O(mNT)$,其中 N 是种群大小, T 是相邻权重向量的数量,且 $T<N$ 。对于辅种群,比较父代与子代的支配关系以及Riesz s-energy大小的时间复杂度为 $O(N^3m)$,而计算Riesz s-energy的时间复杂度为 $O(N^2m)$ 。因此,辅种群每一代进化所需时间复杂度为 $O(N^3m)$ 。综上,MaOEA-DD的总体时间复杂度为 $O(mNT+N^3m)=O(N^3m)$ 。

3 实验验证

3.1 实验设置

3.1.1 测试问题及对比算法

为了验证本文所提出的算法在处理不同目标下的高维多目标优化问题时的性能,本文选择了在3、5、10目标下的DTLZ2、DTLZ3、DTLZ5、DTLZ6、DTLZ7、W-FG4、WFG5、MAF1、MAF2、MAF3、MAF6、MAF7、

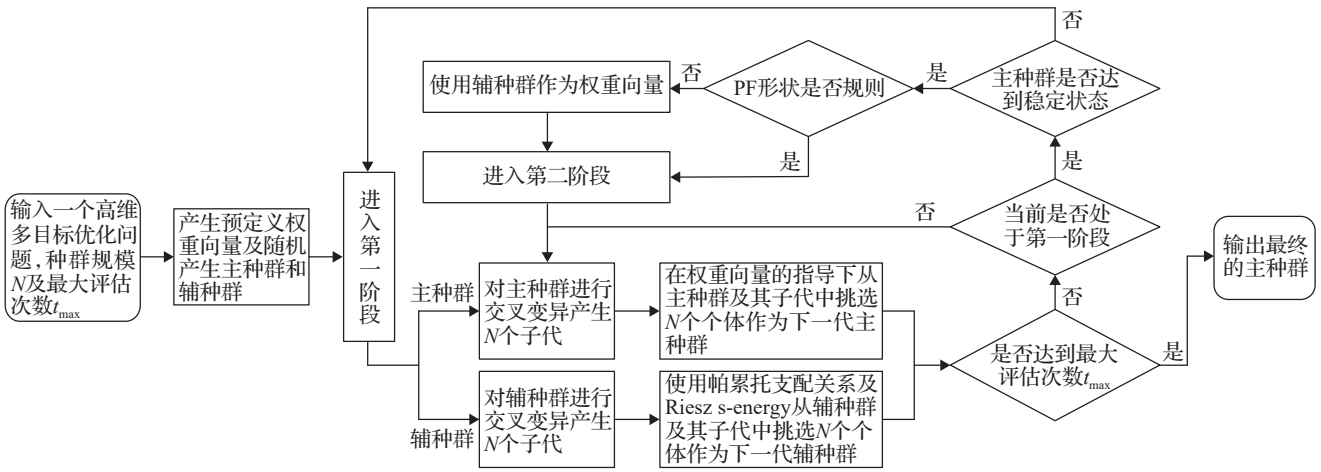


图2 MaOEA-DD算法主流程

Fig.2 Main process of MaOEA-DD algorithm

(C)1994-2024 China Academic Journal Electronic Publishing House. All rights reserved. http://www.cnki.net

IDTLZ1、IDTLZ2[24-27]共14个测试问题来进行了实验。这组测试问题覆盖了多种高维多目标优化问题类型,包括但不限于多模态、欺骗性、难以收敛、凹形、凸形、线性、退化、不连续以及具有严重扩展PF的问题。这些测试问题的具体介绍如表1所示。同时,本文选取来自3种不同类型的4个算法作为对比算法,这些算法分别为基于帕累托支配关系的KnEA[28],基于指标的MaOEA-IGD[9],基于分解且采用预定义权重向量的M-OEA/D[15],基于分解且采用了权重向量调整的VaEA[29]。

表1　测试问题

Table 1　Test problems

问题	特征
DTLZ2	PF凹型、规则、难维持多样性
DTLZ3	PF凹型、规则、多模态、难收敛
DTLZ5	PF退化、不规则
DTLZ6	PF退化、不规则、难收敛
DTLZ7	PF断开、不规则
WFG4	PF凹型、不规则、多模态
WFG5	PF凹型、不规则、欺骗性
MAF1	PF倒三角、不规则
MAF2	PF凹型、不规则、难收敛
MAF3	PF凸型、规则、难收敛
MAF6	PF退化、不规则
MAF7	PF断开、不规则
IDTLZ1	PF倒三角、不规则
IDTLZ2	PF凹型、不规则、难维持多样性

3.1.2　参数设置

交叉和变异算子:实验中的所有算法使用的交叉算子和变异算子分别为模拟二元交叉(simulated binary crossover,SBX)[30]和多项式变异(polynomial mutation,PM)[31]。其中SBX的交叉概率设置为1,分布指数设置为20。PM的突变变量数量的期望值设置为1,分布指数设置为20。

种群大小、停机条件及运行次数:为了确保公平比较,在不同目标下种群的大小需要同参考点数量相同,表2展示了本文在不同目标下的种群大小。此外,在不同目标下每个算法运行的停机条件是达到对应的最大迭代次数,如表2所示。为了确保实验结果的可靠性,每个实验算法在每个目标下的每个测试问题上都独立运行30次后取其结果的平均值及方差。

表2　不同目标数下的种群大小与最大迭代次数

Table 2　Population size and maximum number of iterations for different target numbers

目标数 m	种群大小 N	最大迭代次数 t_{max}
3	91	2 200
5	105	2 500
10	65	4 000

显著性检验:本文采用Wilcoxon秩和检验[32],显著性水平为0.05,对实验结果进行统计和分析。信号“+”“-”和“=”分别表示比较算法的结果显著优于、显著低于或没有显著差异于MaOEA-DD的结果。

MaOEA-DD参数设置:MaOEA-DD采用了基于分解的进化框架,需要在分解时对相邻的权重向量数 T 进行设置,T 会对算法的收敛速度产生影响,由于本文在分解中采用的方法与MOEA/D一致,因此按照MOEA/D的相关说明将 T 设为10。此外,MaOEA-DD在种群稳定性判断中,是通过判断相邻 n 代个体之间 MD 值不变来确定种群稳定性的,这里的 n 文中设置为2。通常情况 MD 值一代未变,则能够说明种群处于稳定状态,但是在一些具有欺骗性的问题上将 n 设置为1可能会出现局部最优的情况,从而错误判断种群的稳定性,在实验中发现设置为2有助于避免这种情况的发生,且该值不宜设置过大,因为这会使得算法一直判断种群处于不稳定状态。

3.1.3　评价指标

本文采用IGD[11]作为评估不同算法综合性能的指标。该指标是通过计算真实PF上每个参考点到由高维多目标进化算法得出的近似PF上距离最近解的平均距离来近似评估最终解的收敛性和多样性。IGD的值越小,则说明算法的综合性能越好,即收敛性与多样性越好。IGD数学表达式如下:

$$IGD=\frac{\sum_{p\in P_{\text{true}}}\min_{q\in P_{\text{know}}}\|p-q\|}{|P_{\text{true}}|} \tag{7}$$

其中,P_{true} 代表从真实PF中获取的参考点,P_{know} 代表通过多目标进化算法得到的最终解集,p 表示来自 P_{true} 的解,q 表示来自 P_{know} 的解。$\|p-q\|$ 表示 p 和 q 之间的欧氏距离,$|P_{\text{true}}|$ 表示真实PF参考点的数量。

此外,由于种群的多样性包含种群的分布广泛性及分布均匀性,因此,本文还采用了广泛性(spread)[33]和间距(spacing)[33]来对这两方面进行评估,从而评估不同算法获得的种群的多样性。具体说明如下:

Spread是通过判断极端解与非支配边界解及非支配连续解之间的关系来评估种群分布的广泛程度。其数学定义如下:

$$Spread=\frac{\sum_{i=1}^{n-1}|d_i-\bar{d}|+\sum_{k=1}^{m}d_k^e}{(n-1)\bar{d}+\sum_{k=1}^{m}d_k^e} \tag{8}$$

其中,n 表示种群大小,m 表示目标个数,d_i 表示所获得的非支配解中相邻解的距离,$\bar{d}$ 是 d_i 的平均值,d_k^e 是极端解与第 k 个边界解之间的距离。

Spacing是通过计算解之间的最小距离的标准差来确定种群的分布均匀性,该值越小种群分布越均匀。其数学定义如下:

$$Spacing=\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(\bar{d}-d_i)^2} \tag{9}$$

其中,n 表示种群大小,d_i 表示第 i 个解到种群中其他解的最小距离,$\bar{d}$ 指的是所有 d_i 的均值。

(C)1994-2024 China Academic Journal Electronic Publishing House. All rights reserved.　http://www.cnki.net

由于在现实问题中,无法提前得知真实PF,从而无法使用与真实PF相关的指标来评估算法的性能,因此,本文采用HV[10]来评估不同算法在现实应用中的综合性能。HV是通过计算非支配解集和参考点包围的空间的超体积值来评估多目标优化算法的性能。其值越大则表示算法性能越好。其计算公式如下:

$$HV=\lambda\left(\bigcup_{i=1}^{|S|}v_i\right) \tag{10}$$

其中,λ表示勒贝格测度,v_i代表由参考点与第i个非支配解构成的超体积,S代表非支配解集。

3.2 实验结果与分析

3.2.1 MaOEA-DD的总体性能

为了验证MaOEA-DD在处理高维多目标优化问题时的有效性,本小节采用IGD作为评价指标,将MaOEA-DD与一些著名的算法进行了实验对比,实验结果如表3所示。由表3中给出的所有实验算法在不同

表3 所有实验算法在不同测试问题上的IGD值

Table 3 IGD values of all experimental algorithms on different test problems

问题	m	KnEA	MaOEA-IGD	MOEA/D	VaEA	MaOEA-DD
DTLZ2	3	7.153 1E−2(3.68E−3)−	1.711 7E−1(3.92E−4)−	5.446 4E−2(9.03E−8)=	5.784 9E−2(7.08E−4)−	5.446 4E−2(5.56E−8)
	5	2.290 7E−1(6.53E−3)−	2.119 3E−1(3.04E−3)−	1.956 3E−1(8.20E−7)=	2.034 4E−1(1.21E−3)−	1.956 1E−1(1.17E−3)
	10	5.722 5E−1(1.23E−2)−	8.692 3E−1(6.80E−2)−	5.000 5E−1(1.70E−4)=	5.240 3E−1(1.78E−3)−	5.020 0E−1(7.03E−3)
DTLZ3	3	1.067 8E−1(2.56E−2)−	1.399 0E+1(5.70E+0)−	5.449 9E−2(3.72E−5)=	6.005 7E−2(5.58E−3)−	5.448 9E−2(3.44E−5)
	5	4.550 1E−1(1.38E−1)−	1.539 9E+1(6.54E+0)−	1.957 1E−1(7.74E−5)=	4.296 8E−1(7.76E−2)−	1.977 1E−1(1.08E−2)
	10	2.145 2E+2(7.43E+1)−	1.316 1E+1(6.18E+0)−	5.666 2E−1(1.97E−1)−	6.737 8E−1(3.57E−2)−	**5.113 6E−1(1.13E−2)**
DTLZ5	3	1.076 3E−2(1.08E−3)−	6.165 9E−1(1.77E−1)−	3.392 1E−2(3.50E−6)−	5.389 4E−3(1.82E−4)−	**4.662 8E−3(7.56E−5)**
	5	1.736 6E−1(4.69E−2)−	5.647 6E−1(1.64E−1)−	**2.976 9E−2(3.37E−4)+**	1.399 7E−1(3.21E−2)−	4.776 5E−2(1.11E−2)
	10	3.806 2E−1(1.24E−1)−	6.524 2E−1(1.34E−1)−	7.373 0E−2(1.90E−6)−	4.404 3E−1(1.45E−1)−	**3.710 0E−2(1.38E−2)**
DTLZ6	3	1.864 5E−2(1.40E−2)−	6.653 7E−1(1.64E−1)−	3.392 8E−2(1.11E−6)−	5.118 0E−3(1.78E−4)−	**4.605 8E−3(7.49E−5)**
	5	3.452 8E−1(5.18E−2)−	7.527 0E−1(2.98E−1)−	2.965 1E−2(8.46E−4)=	2.873 3E−1(6.42E−2)−	3.607 4E−2(1.30E−2)
	10	7.104 3E−1(1.90E−1)−	1.037 1E+0(6.43E−1)−	7.417 6E−2(6.42E−4)−	4.282 3E−1(1.64E−1)−	**3.476 4E−2(1.03E−2)**
DLTZ7	3	8.027 3E−2(5.25E−2)−	1.020 6E+0(5.67E−1)−	2.179 9E−1(1.98E−1)−	6.473 1E−2(1.56E−3)−	**6.298 5E−2(1.95E−3)**
	5	3.278 9E−1(1.17E−2)−	2.092 7E+0(1.13E+0)−	1.091 1E+0(4.54E−2)−	3.557 3E−1(9.39E−3)−	**3.153 3E−1(6.30E−2)**
	10	1.243 6E+0(6.86E−2)=	6.532 5E+0(8.85E−2)−	1.957 7E+0(3.02E−1)−	1.251 3E+0(2.90E−2)=	1.313 6E+0(2.73E−1)
WFG4	3	2.703 0E−1(1.05E−2)−	3.721 1E+0(5.41E−1)−	2.494 7E−1(2.84E−3)−	2.312 4E−1(4.27E−3)−	**2.269 2E−1(1.40E−2)**
	5	1.301 9E+0(2.41E−2)=	6.386 1E+0(6.46E−1)−	1.505 6E+0(5.58E−2)−	1.168 9E+0(1.17E−2)=	1.308 4E+0(2.11E−1)
	10	6.071 1E+0(1.25E−1)−	1.345 2E+1(2.72E+0)−	9.475 1E+0(2.93E−1)−	5.448 0E+0(4.10E−2)−	**5.259 2E+0(4.75E−2)**
WFG5	3	2.759 6E−1(8.60E−3)−	1.889 2E+0(1.38E+0)−	2.467 3E−1(2.26E−3)−	2.414 6E−1(3.72E−3)−	**2.258 1E−1(3.32E−3)**
	5	1.297 7E+0(2.53E−2)−	6.659 0E+0(1.42E+0)−	1.424 3E+0(3.22E−2)−	1.164 0E+0(7.38E−3)−	**1.099 7E+0(4.63E−3)**
	10	6.022 6E+0(1.36E−1)−	1.476 6E+1(3.63E+0)−	9.217 0E+0(1.92E−1)−	5.441 7E+0(2.64E−2)−	**5.247 1E+0(5.42E−2)**
MAF1	3	4.982 1E−2(4.03E−3)−	1.618 1E−1(4.64E−4)−	7.047 5E−2(2.96E−7)−	4.412 5E−2(4.81E−4)−	**4.377 2E−2(2.84E−4)**
	5	**1.310 1E−1(3.25E−3)+**	2.885 6E−1(1.24E−2)−	2.257 2E−1(2.08E−5)−	1.348 3E−1(1.02E−3)+	1.367 8E−1(1.18E−3)
	10	3.233 8E−1(3.86E−2)=	3.834 9E−1(2.35E−2)−	5.347 5E−1(5.12E−4)−	**2.960 7E−1(4.67E−3)+**	3.078 1E−1(5.23E−3)
MAF2	3	3.546 1E−2(1.55E−3)−	3.188 3E−1(1.77E−1)−	3.838 1E−2(3.23E−4)−	**3.104 5E−2(4.34E−4)+**	3.232 8E−2(5.46E−4)
	5	1.357 5E−1(4.06E−3)−	1.917 4E−1(9.54E−2)−	1.247 9E−1(6.33E−4)−	**1.130 2E−1(1.78E−3)+**	1.142 8E−1(1.23E−3)
	10	2.471 3E−1(2.64E−3)−	4.158 0E−1(1.28E−2)−	3.673 1E−1(4.53E−4)−	2.376 3E−1(3.61E−3)−	**2.146 5E−1(6.93E−3)**
MAF3	3	1.561 4E−1(5.29E−2)−	2.776 1E+2(3.99E+2)−	5.428 9E−2(4.31E−4)=	8.682 8E−2(4.20E−2)−	5.422 0E−2(5.24E−4)
	5	1.554 4E−1(6.80E−2)=	3.734 3E+1(4.36E+1)−	1.234 1E−1(7.83E−4)=	1.517 8E−1(3.32E−2)−	1.230 9E−1(8.25E−4)
	10	1.077 9E+8(1.15E+8)−	1.449 8E+2(1.52E+2)−	**1.404 8E−1(3.16E−4)+**	2.914 1E−1(7.70E−2)−	1.910 9E−1(3.76E−2)
MAF6	3	2.891 6E−2(1.82E−2)−	6.973 1E−1(3.47E−2)−	3.393 1E−2(3.55E−7)−	5.206 6E−3(1.73E−4)−	**4.639 3E−3(1.12E−4)**
	5	8.298 2E−3(2.96E−3)−	6.859 9E−1(4.04E−2)−	1.177 5E−1(1.76E−1)−	5.276 9E−3(3.27E−4)−	**4.162 9E−3(9.55E−5)**
	10	2.969 7E+0(5.08E+0)−	7.146 9E−1(2.13E−2)−	2.420 2E−1(2.63E−1)−	2.380 7E−1(8.26E−2)−	**8.033 1E−2(7.84E−2)**
MAF7	3	1.273 8E−1(1.16E−1)−	8.920 1E−1(4.92E−1)−	1.535 9E−1(1.28E−3)−	6.416 1E−2(1.48E−3)−	**6.278 9E−2(2.06E−3)**
	5	3.273 6E−1(9.98E−3)−	2.532 3E+0(9.13E−1)−	1.077 9E+0(7.63E−2)−	3.596 1E−1(9.23E−3)−	**3.106 1E−1(5.82E−2)**
	10	1.248 6E+0(7.31E−2)=	6.364 0E+0(8.66E−1)−	2.051 6E+0(3.41E−1)−	1.246 5E+0(3.05E−2)=	1.269 8E+0(1.22E−1)
IDTLZ1	3	6.037 4E−2(4.21E−2)−	1.663 3E−1(7.63E−2)−	3.523 8E−2(1.84E−6)−	2.981 5E−2(1.22E−2)−	**2.251 5E−2(3.46E−3)**
	5	7.006 6E−2(4.70E−3)=	1.390 1E−1(7.52E−2)−	1.127 9E−1(2.88E−3)−	6.887 5E−2(4.05E−3)−	6.876 2E−2(5.58E−4)
	10	1.607 8E−1(1.81E−2)=	4.470 6E−1(1.05E−1)−	2.689 3E−1(4.17E−3)−	**1.448 1E−1(5.93E−3)+**	1.573 9E−1(1.58E−2)
IDTLZ2	3	7.666 3E−2(7.91E−3)−	3.311 3E−1(1.91E−2)−	6.960 5E−2(1.14E−4)−	7.415 9E−2(2.22E−3)−	**5.594 6E−2(5.12E−4)**
	5	2.225 1E−1(1.30E−2)−	5.003 0E−1(1.73E−2)−	2.417 9E−1(4.62E−4)−	2.165 0E−1(1.87E−3)−	**1.997 0E−1(1.30E−3)**
	10	5.615 8E−1(2.22E−2)−	7.766 8E−1(9.60E−4)−	7.460 8E−1(4.30E−3)−	5.386 4E−1(4.65E−3)−	**4.961 2E−1(3.72E−3)**
+/−/=		1/34/7	0/42/0	2/32/8	5/34/3	

注:实验结果中最优的结果用粗体表示,同等最优的结果用下划线表示。

(C)1994-2024 China Academic Journal Electronic Publishing House. All rights reserved. http://www.cnki.net

测试问题上的IGD平均值及标准差可知,在绝大多数测试问题中,MaOEA-DD获得了最佳IGD值,相比其他竞争算法具有明显的优势。具体介绍如下:

在处理DTLZ2、IDTLZ2、MAF1等难以维持种群多样性的问题上,由于MaOEA-DD在面对具有规则形状及不规则形状的PF问题上分别采用了均匀分布的权重向量及辅种群作为的权重向量,因此其IGD值取得了总体最优的结果的,即使其IGD在MAF1的5维、10维稍逊于或等于KnEA和VaEA,但明显优于其他算法。

为了更直观地展示这一结果,图3和图4分别展示了各个算法在3维DTLZ2和IDTLZ2上获得的最终种群的分布情况。

在图3具有规则PF的DTLZ2问题上,KnEA和MaOEA-IGD获得的种群分布在PF四周,中间位置分布稀疏,甚至没有。由于MOEA/D也是采用预定均匀分布的权重向量指导种群的进化,因此它与MaOEA-DD在DTLZ2问题上分布一致,都分布得非常均匀。VaEA在规则的PF上对权重向量进行了调整,因此其获得的种群在PF顶端分布的较为密集,均匀性略差于MaOEA-DD与MOEA/D。

而在图4具有不规则PF的IDTLZ2上,MaOEA-DD获得的种群分布在PF上的各个位置,并且间隔较为均匀,而其他算法获得的种群分布较为密集。

对于DTLZ3、MAF2、MAF3、IDTLZ1等难以收敛的问题,MaOEA-DD表现最佳。这归因于MaOEA-DD采用了基于分解的进化策略,并且避免了选择压力的存在,从而能够有效地收敛到PF。因此,同样采用基于分解的进化策略的MOEA/D和VaEA也能够有效地收敛到PF。然而,由于MOEA/D和VaEA的权重向量在不同层面上并不如MaOEA-DD的均匀,它们的IGD值差于MaOEA-DD。另一方面,对于基于帕累托支配策略的KnEA,其IGD较差的原因是在高维空间中选择压力不足,因此难以收敛到PF。而对于基于指标的MaOEA-IGD虽然其能够有效地收敛到PF,但是它也存在着基于指标的多目标进化算法的通病,即难以维持多样性,因此其IGD值也较差。

在DTLZ5、DTLZ6、DTLZ7、MAF6、MAF7等具有复杂PF的高维多目标优化问题上,MaOEA-DD同样展现出了最佳性能,这是因为MaOEA-DD引入了自然界中能量平衡的概念,以此收集了多样性良好的种群作为权重向量,从而能够有效地维持种群的多样性。

从图5可以直观观察到在10维MAF6问题上,所有实验算法得到的最终种群的分布情况。MaOEA-DD能够有效地收敛到PF,同时种群个体分布均匀且符合PF形状。相比之下,KnEA和VaEA无法收敛到PF,原因可

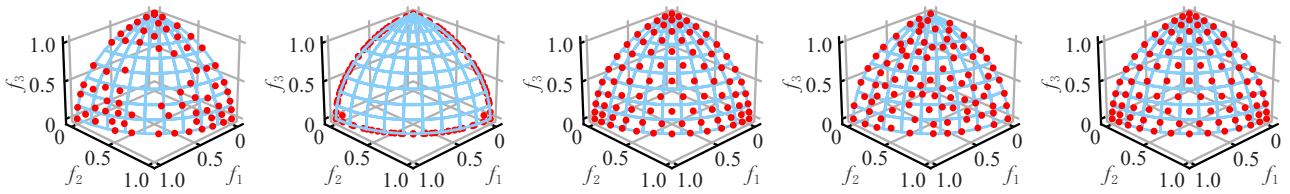


图3　所有实验算法在3维DTLZ2上获得的最终种群的分布

Fig.3　Distribution of final population obtained by all experimental algorithms on 3-dimensional DTLZ2 problem

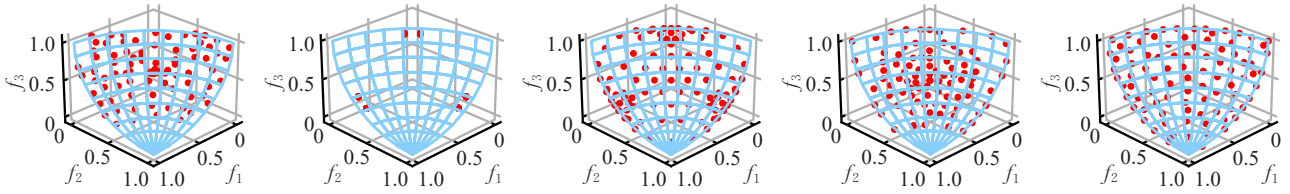


图4　所有实验算法在3维IDTLZ2上获得的最终种群的分布

Fig.4　Distribution of final population obtained by all experimental algorithms on 3-dimensional IDTLZ2 problem

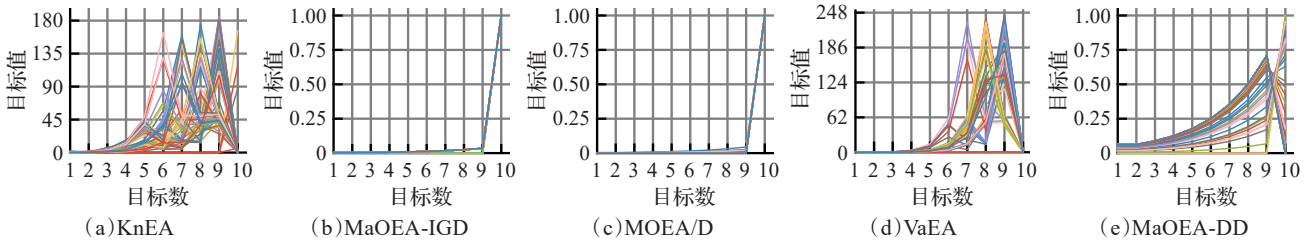


图5　所有实验算法在10维MAF6上获得的最终种群的分布

Fig.5　Distribution of final population obtained by all experimental algorithms on 10-dimensional MAF6 problem

(C)1994-2024 China Academic Journal Electronic Publishing House. All rights reserved.　http://www.cnki.net

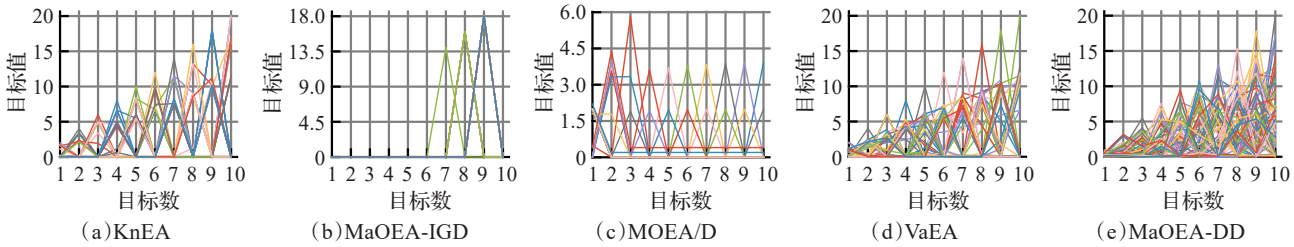


图6　所有实验算法在10维WFG4上获得的最终种群的分布

Fig.6　Distribution of final population obtained by all experimental algorithms on 10-dimensional WFG4 problem

能是KnEA在高维空间失去了选择压力，而VaEA则是因为过度调整权重向量，降低了算法的收敛性。而对于MaOEA-IGD和MOEA/D虽然能够收敛到PF，但是由PF过于复杂无法维持种群的多样性。

最后，在具有多模态特性的WFG4和具有欺骗性特征的WFG5上，MaOEA-DD取得了最佳的IGD值。如图6所示，MaOEA-DD获得了良好的种群多样性，而KnEA和VaEA获得的种群只是在分布的广泛程度上表现较好，种群个体之间的间隔并不均匀，存在许多空白区域。相比之下，MaOEA-IGD与MOEA/D则是因为没有有效处理具有多模态特性的问题方法，因此它们获得的种群分布密集，容易汇聚到一点上。

至此，这些结果已经证实了MaOEA-DD对多种高维多目标优化问题上的有效性。

3.2.2　权重向量调整方法的有效性验证

为了评估本文提出的权重向量调整方法在规则和不规则PF上是否能够获得分布性良好的解，本小节采用Spacing以及Spread作为评价指标，将MaOEA-DD与同样采用权重向量调整方法的VaEA进行了实验比较，实验结果见表4。

根据表4中给出的所有实验算法在不同测试问题上获得的Spacing和Spread的平均值及标准差，可得出MaOEA-DD在Spacing以及Spread指标上均表现出最佳结果。具体说明如下：

规则PF：在DTLZ2、DTLZ3、MAF3等具有规则PF的测试问题中，MaOEA-DD的Spacing和Spread值几乎全优于VaEA，这意味着MaOEA-DD获得的种群在分布的均匀性与广泛性几乎全优于VaEA，即MaOEA-DD获得的种群多样性更优。这归因于MaOEA-DD的双阶段进化过程，使其在第一阶段中准确地判断了PF的形状是规则的，因此其并未对权重向量进行调整，从而保持了预定均匀分布的权重向量能够在处理具有规则PF的问题上获得良好多样性的优点。而VaEA在规则的PF上对权重向量进行了调整，因此导致了其在规则PF上的获得的解的多样性要差于MaOEA-D。

不规则PF：在DTLZ6、DTLZ7、WFG4、WFG5、MA-F3、MAF2、MAF6、MAF7、IDTLZ1、IDTLZ2等具有不规则PF的问题上，MaOEA-DD的Spacing和Spread值分别取得25个和18个最优结果，而VaEA的Spacing和Spread值仅分别取得4个和12个最优结果。可知MaOEA-DD的Spacing最优结果个数远多于VaEA，即MaOEA-DD获得的种群在分布均匀性上优于VaEA获得的种群。这是因为MaOEA-DD采用Riesz　s-Energy收集的种群作为的权重向量，可以获得分布更均匀的效果。而VaEA采用的是最大向量角原则收集的权重向量，该原则在凸问题等复杂问题中，存在着两两个体之间角度均匀并不代表它们之间的距离也均匀的问题，因此VaEA获得的种群均匀性会较差。对于MaOEA-DD的Spread最优结果个数仅比VaEA的Spread最优结果个数多6个，这是因为种群分布的广泛程度会受种群收敛性的影响。如在图5的10维MAF6问题上，VaEA获得的种群并未收敛，因此其分布广泛程度必然会远优于MaOEA-DD，但这并不能说明在收敛的情况下MaOEA-DD的广泛程度不如VaEA。类似的情况也出现在DTLZ5和DTLZ6上。即便不考虑这些情况，MaOEA-DD获得的种群的分布广泛程度仍优于VaEA。综上所述，MaOEA-DD获得的种群分布的均匀性及广泛程度均优于VaEA，即MaOEA-DD获得的种群多样性优于VaEA。

MaOEA-DD获得的种群不仅在具有规则PF的高维多目标优化问题上多样性优于VaEA，并且在具有不规则PF的高维多目标优化问题上多样性也优于VaEA，这说明了本文所提出的权重向量调整方法比VaEA所采用的权重向量调整方法更有效，能够同时处理具有规则PF和不规则PF的高维多目标优化问题。

3.2.3　收敛速度分析

为探究MaOEA-DD与其他对比算法在收敛速度方面的差异，本小节记录了不同算法在不同测试问题下随着迭代次数增加，其IGD值的变化情况。

具体变化见图7，说明如下：

规则PF：如图7(a)所示，在较易收敛且具有规则PF的DTLZ2问题上MaOEA-DD与MOEA/D均在迭代3 000次左右收敛，这是因为MaOEA-DD在双阶段进化过程中将DTLZ2问题识别为具有规则PF的问题，采用了预定义的权重向量进化，因此MaOEA-DD与MOEA/D

(C)1994-2024 China Academic Journal Electronic Publishing House. All rights reserved.　http://www.cnki.net

表4　所有实验算法在不同测试问题上的Spacing和Spread值

Table 4　Spacing and Spread values of all experimental algorithms on different test problems

问题	m	Spacing		Spread	
		VaEA	MaOEA-DD	VaEA	MaOEA-DD
DTLZ2	3	**3.728 7E−2(6.90E−3)+**	5.719 8E−2(2.04E−6)	1.570 4E−1(2.57E−2)=	1.704 6E−1(1.45E−5)
	5	1.308 3E−1(1.50E−2)−	**1.110 9E−1(2.36E−3)**	1.190 8E−1(1.56E−2)−	**6.157 6E−2(2.17E−2)**
	10	5.254 6E−1(2.83E−2)−	**2.251 5E−1(7.59E−2)**	3.465 0E−1(3.43E−2)−	**2.157 0E−1(4.61E−2)**
DTLZ3	3	1.815 5E−1(6.99E−1)−	**5.721 5E−2(3.42E−5)**	2.551 7E−1(2.86E−1)=	1.705 6E−1(1.24E−4)
	5	1.896 9E+1(1.67E+1)−	**1.153 8E−1(2.55E−2)**	1.712 4E+0(4.69E−1)−	**8.706 5E−2(1.61E−1)**
	10	7.521 1E+1(4.38E+1)−	**2.384 5E−1(6.43E−2)**	1.808 9E+0(1.96E−1)−	**2.639 3E−1(6.54E−2)**
DTLZ5	3	9.096 1E−3(9.66E−4)−	**4.342 5E−3(8.25E−4)**	3.285 8E−1(3.87E−2)−	**1.586 7E−1(2.52E−2)**
	5	**2.373 6E−1(2.51E−2)+**	2.784 3E−1(2.41E−2)	**4.125 6E−1(3.27E−2)+**	7.661 9E−1(7.90E−2)
	10	1.033 4E+0(7.31E−2)−	**2.974 2E−1(4.56E−2)**	**4.747 0E−1(3.33E−2)+**	1.177 4E+0(7.63E−2)
DTLZ6	3	1.078 0E−2(9.35E−4)−	**2.873 2E−3(8.31E−4)**	3.614 2E−1(5.24E−2)−	**1.303 8E−1(2.45E−2)**
	5	**5.019 0E−1(8.86E−2)+**	6.051 7E−1(1.76E−1)	**5.442 4E−1(5.46E−2)+**	1.355 7E+0(9.17E−2)
	10	3.893 3E+0(3.64E−1)−	**5.249 3E−1(1.95E−1)**	**5.672 5E−1(1.12E−1)+**	1.428 6E+0(9.41E−2)
DLTZ7	3	7.230 2E−2(5.70E−3)−	**6.330 8E−2(7.05E−3)**	3.571 7E−1(2.66E−2)−	**3.150 2E−1(4.63E−2)**
	5	2.907 3E−1(1.85E−2)−	**2.111 4E−1(2.35E−2)**	**2.938 9E−1(2.11E−2)+**	3.764 5E−1(1.17E−1)
	10	1.164 5E+0(5.51E−2)−	**9.142 1E−1(3.09E−1)**	**6.700 5E−1(3.68E−2)+**	7.605 7E−1(1.08E−1)
WFG4	3	1.627 7E−1(1.48E−2)−	**1.477 6E−1(6.31E−2)**	2.338 2E−1(2.17E−2)−	**1.735 5E−1(6.12E−2)**
	5	7.579 5E−1(8.29E−2)=	7.969 7E−1(3.73E−1)	2.212 9E−1(2.44E−2)=	2.822 7E−1(2.59E−1)
	10	4.957 9E+0(2.51E−1)−	**1.511 2E+0(3.02E−1)**	4.437 3E−1(4.80E−2)−	**1.904 5E−1(1.46E−2)**
WFG5	3	1.635 3E−1(1.73E−2)−	**1.308 0E−1(3.87E−2)**	2.394 6E−1(2.31E−2)−	**1.575 7E−1(4.79E−2)**
	5	8.197 5E−1(3.98E−2)−	**4.180 1E−1(9.15E−2)**	2.446 9E−1(1.82E−2)−	**1.246 0E−1(1.60E−2)**
	10	5.078 7E+0(2.01E−1)−	**1.339 8E+0(1.89E−1)**	4.757 5E−1(3.22E−2)−	**1.913 2E−1(1.25E−2)**
MAF1	3	2.821 2E−2(3.86E−3)=	2.907 5E−2(3.12E−3)	1.627 2E−1(1.72E−2)=	1.613 9E−1(2.13E−2)
	5	**6.716 5E−2(1.25E−2)+**	8.113 8E−2(9.12E−3)	**1.290 5E−1(1.89E−2)+**	2.210 9E−1(3.20E−2)
	10	3.129 8E−1(3.90E−2)−	**2.042 1E−1(3.37E−2)**	4.628 3E−1(8.53E−2)−	**4.118 6E−1(7.96E−2)**
MAF2	3	**2.296 9E−2(1.53E−3)+**	3.170 4E−2(2.89E−3)	**1.754 9E−1(1.81E−2)+**	3.067 5E−1(3.94E−2)
	5	7.957 7E−2(2.39E−3)−	**5.169 7E−2(9.75E−3)**	1.974 1E−1(1.30E−2)−	**1.687 9E−1(2.16E−2)**
	10	2.762 8E−1(8.15E−3)−	**5.796 4E−2(7.59E−3)**	4.428 6E−1(1.14E−2)−	**1.632 9E−1(1.31E−2)**
MAF3	3	5.381 5E+6(2.53E+7)−	**1.172 9E−2(2.28E−4)**	9.825 5E−1(6.71E−1)−	**2.263 1E−1(1.90E−3)**
	5	4.241 3E+7(9.89E+7)−	**3.864 2E−2(1.42E−3)**	1.853 4E+0(4.64E−1)−	**4.842 5E−1(5.81E−3)**
	10	1.207 4E+11(9.86E+10)−	**1.763 6E+7(8.30E+7)**	1.622 9E+0(1.47E−1)−	**1.030 5E+0(5.75E−1)**
MAF6	3	9.213 6E−3(9.14E−4)−	**2.981 7E−3(7.13E−4)**	3.346 8E−1(4.10E−2)−	**1.370 7E−1(1.96E−2)**
	5	1.286 8E−2(1.28E−3)−	**3.930 4E−3(5.58E−4)**	5.274 3E−1(4.33E−2)−	**1.982 8E−1(2.48E−2)**
	10	2.282 0E+1(1.07E+1)−	**7.929 3E−2(9.82E−2)**	**9.979 8E−1(9.67E−2)+**	1.568 1E+0(5.44E−1)
MAF7	3	6.982 4E−2(4.69E−3)−	**6.486 4E−2(8.00E−3)**	3.477 3E−1(2.58E−2)−	**3.213 6E−1(5.36E−2)**
	5	2.868 1E−1(2.05E−2)−	**2.051 9E−1(2.21E−2)**	**3.021 7E−1(1.78E−2)+**	3.649 9E−1(1.13E−1)
	10	1.154 0E+0(7.01E−2)=	1.004 1E+0(2.77E−1)	**6.624 7E−1(2.79E−2)+**	7.959 6E−1(1.47E−1)
IDTLZ1	3	4.455 6E+0(7.90E+0)−	**1.531 3E−2(9.91E−3)**	7.973 6E−1(7.61E−1)−	**1.848 4E−1(1.69E−1)**
	5	6.629 3E+0(1.40E+1)=	4.069 9E−2(4.47E−3)	6.784 4E−1(7.45E−1)=	2.231 9E−1(2.89E−2)
	10	9.898 1E+0(2.52E+1)−	**1.072 0E−1(2.07E−2)**	7.905 2E−1(6.15E−1)−	**4.731 4E−1(2.54E−1)**
IDTLZ2	3	5.682 7E−2(4.31E−3)−	**3.759 3E−2(5.64E−3)**	3.275 8E−1(1.85E−2)−	**1.714 1E−1(2.37E−2)**
	5	1.415 5E−1(6.65E−3)−	**1.142 2E−1(1.16E−2)**	**1.726 3E−1(1.21E−2)+**	2.054 8E−1(2.67E−2)
	10	5.167 6E−1(3.66E−2)−	**2.542 8E−1(3.02E−2)**	5.503 4E−1(3.18E−2)−	**2.675 3E−1(4.39E−2)**
+/−/=		5/33/4		12/25/5	

注:实验结果中最优的结果用粗体表示,同等最优的结果用下划线表示。

的收敛速度相同,同理在图7(b)较难收敛且具有规则PF的DTLZ3问题上MaOEA-DD与MOEA/D的收敛速度也相同,在迭代1 000次左右收敛。而KnEA虽然在DTLZ3中IGD变化幅度较大,但其收敛速度在DTLZ2和DTLZ3都是最快的。对于MaOEA-IGD其收敛速度仅次于KnEA,无论在DTLZ2还是DTLZ3均在迭代500次左右收敛。由于VaEA在进化过程中频繁调整权重向量因此其收敛速度最慢。因此在规则PF上所有算法的收敛速度排名为KnEA>MaOEA-IGD>MaOEA-DD=MOEA/D>VaEA。

(C)1994-2024 China Academic Journal Electronic Publishing House. All rights reserved.　http://www.cnki.net

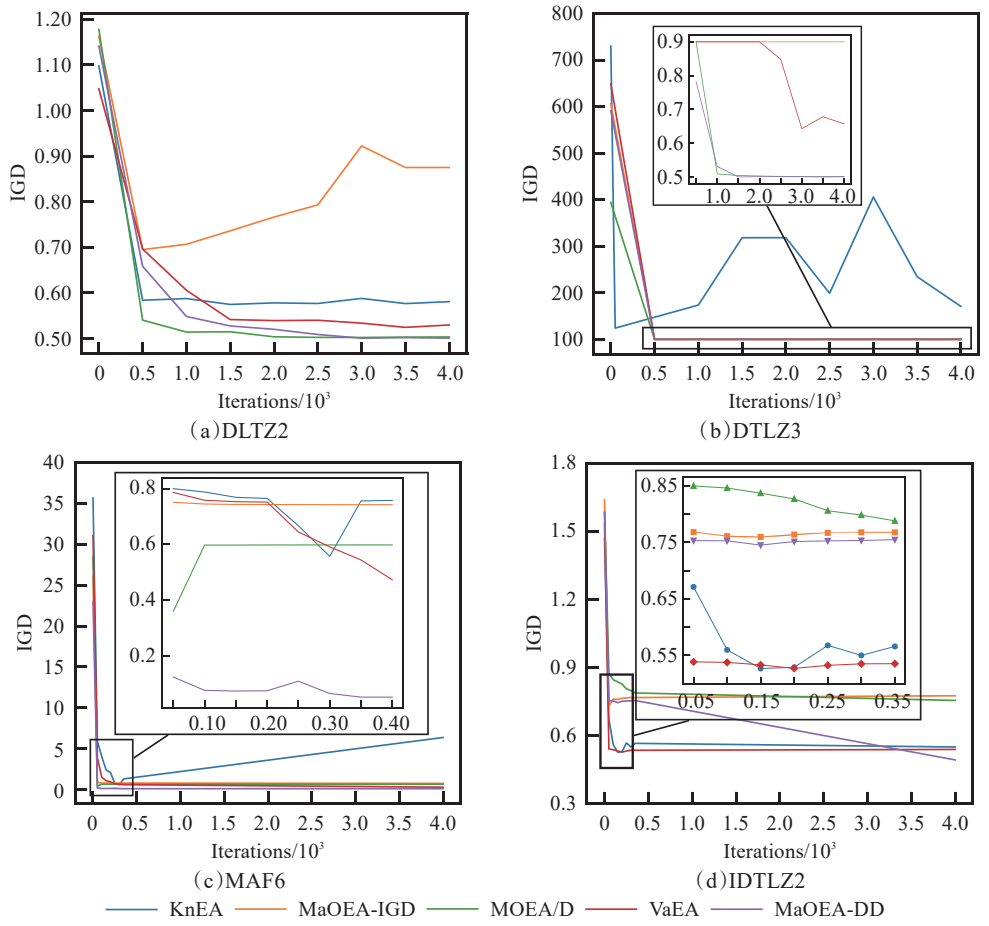


图7　5种算法在10维DTLZ2、DTLZ3、MAF6和IDTLZ2上IGD值的变化

Fig.7　Variation of IGD values of 5 algorithms on 10-dimensional DTLZ2，DTLZ3，MAF6，and IDTLZ2

不规则PF：如图7所示不论是在难收敛且具有不规则PF的MAF6问题上还是在较易收敛且具有不规则PF的IDTLZ2问题上MaOEA-IGD的收敛速度都是最快的。如图7(c)所示，MOEA/D收敛速度仅次于MaOEA-IGD，而KnEA虽然IGD变化幅度较大，但是其值在迭代200次左右在固定的范围摆动，其收敛速度快于MaOEA-DD。MaOEA-DD在迭代350次左右收敛，速度优于VaEA，但是因为MaOEA-DD对权重向量进行了调整因此收敛速度慢于MOEA/D。对于VaEA，其收敛速度最慢，在迭代4 000次时才取得最小值。而在图7(d)较易收敛且具有不规则PF的IDTLZ2问题上VaEA收敛速度仅次于MaOEA-IGD。虽然KnEA在迭代100次后IGD值在浮动，但是其浮动幅度较小，因此KnEA收敛速度在IDTLZ2上排名第三。即便MOEA/D与MaOEA-DD都在迭代4 000次后取得最小IGD值，但是MOEA/D的IGD值变化幅度较小，所以其收敛速度快于MaOEA-DD。因此，在不规则PF上算法收敛速度排名为MaOEA-IGD>MOEA/D=KnEA>VaEA>MaOEA-DD。

综上所述，所有实验算法在具有规则及不规则PF的问题上综合收敛速度排名为MaOEA-IGD≥KnEA>MOEA/D>VaEA≥MaOEA-DD。需要注意的是，这只是对所有实验算法的收敛速度粗略的排名，具体每个算法的收敛速度需要根据实际问题进行判断。虽然MaOEA-DD的收敛速度较慢，但其收敛性最优。因此其在解决高维多目标优化问题中仍有着竞争优势。

3.2.4　汽车碰撞安全设计优化

为了验证MaOEA-DD在现实世界优化问题中的实用性，本小节将MaOEA-DD与其他对比算法分别应用在汽车碰撞安全设计优化问题[34]上。该问题的主要目的是通过对汽车结构进行优化，以满足碰撞安全性标准。为确保汽车满足碰撞安全性标准，需要对汽车结构的重量、加速度特性和脚板侵入这三个目标进行优化，其中这三个目标相互冲突并且需要同时最小化，是一个高维多目标优化问题。在对该问题应用实验算法进行优化时，种群大小统一设置为91，迭代次数设置为1 500，并且每个算法在该问题上独立运行30次取平均HV值作为实验结果。实验结果如表5所示。在汽车碰撞安全设计优化中，MaOEA-DD获得了最优的HV值，虽然VaEA获得的HV值与MaOEA-DD相近，但是随着目标数的增加，PF越来越复杂，MaOEA-DD与VaEA的差距可能会逐渐增大。KnEA的性能虽然不如MaOEA-DD和VaEA，但优于其他算法。对于MOEA/D，由于其采用

(C)1994-2024 China Academic Journal Electronic Publishing House. All rights reserved.　http://www.cnki.net

了固定的权重向量进行进化,因此其性能远不如MaOEA-DD,这也验证了本文权重向量调整方法的有效性。由于MaOEA-IGD难以保持种群的多样性,其性能最差。由此可得,MaOEA-DD在现实优化问题中具有一定的实用性。

表5 所有算法在汽车碰撞安全设计优化中获得的HV值

Table 5 HV values obtained from all algorithms in optimization of crash safety design for vehicles

算法	HV
KnEA	0.036 394 65
MaOEA-IGD	0.025 806 05
MOEA/D	0.032 358 53
VaEA	0.037 618 48
MaOEA-DD	0.037 726 08

4 结束语

为了在具有规则和不规则帕累托前沿的高维多目标优化问题中获得收敛性和多样性良好的种群,本文提出了一种面向高维多目标优化的双阶段双种群进化算法。该算法将进化过程划分为两个阶段,以同时考虑种群在具有规则和不规则帕累托前沿的问题上的多样性。在处理具有不规则帕累托前沿的问题时,该算法使用了一个辅种群收集多样性良好的个体作为权重向量,一个主种群正常进化,避免了在权重向量调整时主种群的收敛性下降。此外,该算法还借鉴自然界中能量平衡的概念来选择多样性良好的辅种群作为权重向量。为了验证该算法的性能,将该算法与其他4个著名的算法进行了实验对比,实验结果表明,本文算法能够有效地处理不同类型的高维多目标优化问题。此外,本文提出的权重向量调整方法在与其他权重向量调整方法进行的实验对比中也被证实是有效的。然而,本文算法获得的种群在不连续的帕累托前沿上的分布广泛性并没有达到最优。针对该问题,下一步将设计一种保护边界解的方法以提高种群的分布广泛性。

参考文献:

[1] 易灵芝, 林佳豪, 刘建康, 等. 改进自适应MOEA/D算法的楼宇负荷优化调度[J]. 计算机工程与应用, 2022, 58(2): 295-302.
YI L Z, LIN J H, LIU J K, et al. Improved adaptive MOEA/D algorithm for building load optimization scheduling[J]. Computer Engineering and Applications, 2022, 58(2): 295-302.

[2] 顾清华, 骆家乐, 李学现. 基于小生境的多目标进化算法[J]. 计算机工程与应用, 2023, 59(1): 126-139.
GU Q H, LUO J L, LI X X. Evolutionary algorithm based on niche for multi-objective optimization[J]. Computer Engineering and Applications, 2023, 59(1): 126-139.

[3] 安宇欣, 王转. 配送中心多区并行拣货系统投产顺序优化研究[J]. 计算机工程与应用, 2023, 59(7): 328-336.
AN Y X, WANG Z. Research on optimization of production sequence of multi-district parallel picking system in distribution center[J]. Computer Engineering and Applications, 2023, 59(7): 328-336.

[4] SHEN J, WANG P, WANG X. A controlled strengthened dominance relation for evolutionary many-objective optimization[J]. IEEE Transactions on Cybernetics, 2020, 52(5): 3645-3657.

[5] ZHU S, XU L, GOODMAN E D, et al. A new many-objective evolutionary algorithm based on generalized Pareto dominance[J]. IEEE Transactions on Cybernetics, 2021, 52(8): 7776-7790.

[6] ZHOU Y, LI S, PEDRYCZ W, et al. ACDB-EA: adaptive convergence-diversity balanced evolutionary algorithm for many-objective optimization[J]. Swarm and Evolutionary Computation, 2022, 75: 101145.

[7] CHEN G, LI J. A diversity ranking based evolutionary algorithm for multi-objective and many-objective optimization[J]. Swarm and Evolutionary Computation, 2019, 48: 274-287.

[8] BADER J, ZITZLER E. HypE: an algorithm for fast hypervolume-based many-objective optimization[J]. Evolutionary Computation, 2011, 19(1): 45-76.

[9] SUN Y, YEN G G, YI Z. IGD indicator-based evolutionary algorithm for many-objective optimization problems[J]. IEEE Transactions on Evolutionary Computation, 2018, 23(2): 173-187.

[10] ZITZLER E, THIELE L. Multiobjective optimization using evolutionary algorithms—a comparative case study[C]//International Conference on Parallel Problem Solving from Nature. Berlin, Heidelberg: Springer, 1998: 292-301.

[11] COELLO COELLO C A, REYES SIERRA M. A study of the parallelization of a convolutionary multi-objective evolutionary algorithm[C]//Proceedings of the Third Mexican International Conference on Artificial Intelligence, Mexico City, Mexico, April 26-30, 2004. Berlin, Heidelberg: Springer, 2004: 688-697.

[12] LIU Q, ZOU J, YANG S, et al. A multiobjective evolutionary algorithm based on decision variable classification for many-objective optimization[J]. Swarm and Evolutionary Computation, 2022, 73: 101108.

[13] LI J, WANG P, DONG H, et al. A two-stage surrogate-assisted evolutionary algorithm (TS-SAEA) for expensive multi/many-objective optimization[J]. Swarm and Evolutionary Computation, 2022, 73: 101107.

[14] WANG H, JIAO L, YAO X. Two_Arch2: an improved two-archive algorithm for many-objective optimization[J]. IEEE Transactions on Evolutionary Computation, 2014, 19(4): 524-541.

[15] ZHANG Q, LI H. MOEA/D: a multiobjective evolutionary algorithm based on decomposition[J]. IEEE Transactions on

(C)1994-2024 China Academic Journal Electronic Publishing House. All rights reserved. http://www.cnki.net

Evolutionary Computation, 2007, 11(6): 712-731.

[16] CHENG R, JIN Y, OLHOFER M, et al. A reference vector guided evolutionary algorithm for many-objective optimization[J]. IEEE Transactions on Evolutionary Computation, 2016, 20(5): 773-791.

[17] SAXENA D K, DEB K. Non-linear dimensionality reduction procedures for certain large-dimensional multi-objective optimization problems: employing correntropy and a novel maximum variance unfolding[C]//International Conference on Evolutionary Multi-Criterion Optimization. Berlin, Heidelberg: Springer, 2007: 772-787.

[18] LIU S, LIN Q, WONG K C, et al. A self-guided reference vector strategy for many-objective optimization[J]. IEEE Transactions on Cybernetics, 2020, 52(2): 1164-1178.

[19] ZHAO C, ZHOU Y, HAO Y. Decomposition-based evolutionary algorithm with dual adjustments for many-objective optimization problems[J]. Swarm and Evolutionary Computation, 2022, 75: 101168.

[20] ZHANG C, TAN K C, LEE L H, et al. Adjust weight vectors in MOEA/D for bi-objective optimization problems with discontinuous Pareto fronts[J]. Soft Computing, 2018, 22: 3997-4012.

[21] LIU Y, GONG D, SUN J, et al. A many-objective evolutionary algorithm using a one-by-one selection strategy[J]. IEEE Transactions on Cybernetics, 2017, 47(9): 2689-2702.

[22] HARDIN D P, SAFF E B. Minimal Riesz energy point configurations for rectifiable d-dimensional manifolds[J]. Advances in Mathematics, 2005, 193(1): 174-204.

[23] AGGARWAL C C, HINNEBURG A, KEIM D A. On the surprising behavior of distance metrics in high dimensional space[C]//Proceedings of the 8th International Conference on Database Theory, London, UK, January 4-6, 2001. Berlin, Heidelberg: Springer, 2001: 420-434.

[24] DEB K, THIELE L, LAUMANNS M, et al. Scalable test problems for evolutionary multiobjective optimization[M]// Evolutionary multiobjective optimization: theoretical advances and applications. London: Springer, 2005: 105-145.

[25] HUBAND S, HINGSTON P, BARONE L, et al. A review of multiobjective test problems and a scalable test problem toolkit[J]. IEEE Transactions on Evolutionary Computation, 2006, 10(5): 477-506.

[26] CHENG R, LI M, TIAN Y, et al. A benchmark test suite for evolutionary many-objective optimization[J]. Complex & Intelligent Systems, 2017, 3: 67-81.

[27] JAIN H, DEB K. An evolutionary many-objective optimization algorithm using reference-point based nondominated sorting approach, part II: handling constraints and extending to an adaptive approach[J]. IEEE Transactions on Evolutionary Computation, 2013, 18(4): 602-622.

[28] ZHANG X, TIAN Y, JIN Y. A knee point-driven evolutionary algorithm for many-objective optimization[J]. IEEE Transactions on Evolutionary Computation, 2014, 19(6): 761-776.

[29] XIANG Y, ZHOU Y, LI M, et al. A vector angle-based evolutionary algorithm for unconstrained many-objective optimization[J]. IEEE Transactions on Evolutionary Computation, 2016, 21(1): 131-152.

[30] DEB K, SINDHYA K, OKABE T. Self-adaptive simulated binary crossover for real-parameter optimization[C]//Proceedings of the 9th Annual Conference on Genetic and Evolutionary Computation, 2007: 1187-1194.

[31] DEB K, GOYAL M. A combined genetic adaptive search (GeneAS) for engineering design[J]. Computer Science and Informatics, 1996, 26: 30-45.

[32] DERRAC J, GARCÍA S, MOLINA D, et al. A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms[J]. Swarm and Evolutionary Computation, 2011, 1(1): 3-18.

[33] MAO Z, LIU M. A local search-based many-objective five-element cycle optimization algorithm[J]. Swarm and Evolutionary Computation, 2022, 68: 101009.

[34] LIAO X, LI Q, YANG X, et al. Multiobjective optimization for crash safety design of vehicles using stepwise regression model[J]. Structural and Multidisciplinary Optimization, 2008, 35: 561-569.

(C)1994-2024 China Academic Journal Electronic Publishing House. All rights reserved. http://www.cnki.net

Journal of Computer Applications
计算机应用,2024,44(6):1824－1831
ISSN 1001-9081
CODEN JYIIDU
2024-06-10
http://www.joca.cn

文章编号:1001-9081(2024)06-1824-08
DOI:10.11772/j.issn.1001-9081.2023060799

较短的长序列时间序列预测模型

徐泽鑫,杨　磊*,李康顺
(华南农业大学 数学与信息学院,广州 510642)
(*通信作者电子邮箱 yanglei_s@scau.edu.cn)

摘　要:针对现有的研究大多将短序列时间序列预测和长序列时间序列预测分开研究而导致模型在较短的长序列时序预测时精度较低的问题,提出一种较短的长序列时间序列预测模型(SLTSFM)。首先,利用卷积神经网络(CNN)和PBUSM(Probsparse Based on Uniform Selection Mechanism)自注意力机制搭建一个序列到序列(Seq2Seq)结构,用于提取长序列输入的特征;其次,设计"远轻近重"策略将多个短序列输入特征提取能力较强的长短时记忆(LSTM)模块提取的各时段数据特征进行重分配;最后,用重分配的特征增强提取的长序列输入特征,提高预测精度并实现时序预测。利用4个公开的时间序列数据集验证模型的有效性。实验结果表明,与综合表现次优的对比模型循环门单元(GRU)相比,SLTSFM的平均绝对误差(MAE)指标在4个数据集上的单变量时序预测分别减小了61.54%、13.48%、0.92%和19.58%,多变量时序预测分别减小了17.01%、18.13%、3.24%和6.73%。由此可见SLTSFM在提升较短的长序列时序预测精度方面的有效性。

关键词:较短的长序列时间序列预测;序列到序列;长短期记忆;自注意力机制;特征重分配
中图分类号:TP183　　**文献标志码**:A

Shorter long-sequence time series forecasting model

XU Zexin, YANG Lei*, LI Kangshun
(*College of Mathematics and Informatics, South China Agricultural University, Guangzhou Guangdong* 510642, *China*)

Abstract: Aiming at the problem that most of the existing researches study short-sequence time series forecasting and long-sequence time series forecasting separately, which leads to the poor forecasting accuracy of the model in the shorter long-sequence time series, a Shorter Long-sequence Time Series Forecasting Model (SLTSFM) was proposed. Firstly, a Sequence-to-Sequence (Seq2Seq) structure was constructed using Convolutional Neural Network (CNN) and PBUSM (Probsparse Based on Uniform Selection Mechanism) self-attention mechanism, which was used to extract the features of the long-sequence input. Secondly, "far light, near heavy" strategy was designed to apply to reallocate the features of each time period extracted from multiple Long Short-Term Memory (LSTM) modules, which were more capable of short-sequence input feature extraction. Finally, the reallocated features were used to enhance the extracted long-sequence input features to improve the forecasting accuracy and realize the time series forecasting. Four publicly available time series datasets were utilized to verify the effectiveness of the proposed model. The experimental results demonstrate that, compared with the suboptimal comprehensive performing model Gated Recurrent Unit (GRU), the Mean Absolute Error (MAE) metrics of SLTSFM were reduced by 61.54%, 13.48%, 0.92% and 19.58% for univariate time series forecasting, and were reduced by 17.01%, 18.13%, 3.24% and 6.73% for multivariate time series forecasting on the four datasets. It's verified that SLTSFM is effective in improving the accuracy of shorter long-sequence time series forecasting.

Key words: shorter long-sequence time series forecasting; Sequence-to-Sequence (Seq2Seq); Long Short-Term Memory (LSTM); self-attention mechanism; feature reallocation

0　引言

时间序列预测旨在利用大量过去行为的数据,通过一定的数据分析和合适的模型建模预测未来。时间序列预测是大数据分析的一个重要分支,也是当下深度学习的一个热门研究领域。由于时间序列中包含可观的因果信息,能在许多复杂的问题中得到应用,因此,时间序列预测涵盖了多个领域,如经济金融领域[1]、电力负荷需求[2]和交通流量预测[3-4]等。

随着现实问题要求的提升,短序列预测越发难以满足问题的需要;在长序列预测中,预测结果的靠前一段受的关注度较高,人们需要根据最近的结果作出及时反应。当前研究中,大多数模型都把长序列时间序列预测和短序列时间序列预测分开研究。在短序列时间序列预测中,常用的深度学习

收稿日期:2023-06-25;**修回日期**:2023-08-10;**录用日期**:2023-08-14。
基金项目:广东省自然科学基金资助项目(2020A1515010691);广州市农业科技特派员项目(20212100036)。
作者简介:徐泽鑫(1998—),男,广东饶平人,硕士研究生,主要研究方向:数据挖掘、深度学习;　杨磊(1978—),男,河南南阳人,讲师,博士,主要研究方向:数据挖掘、智能计算;　李康顺(1962—),男,江西兴国人,教授,博士,主要研究方向:机器学习、人工智能。

(C)1994-2024 China Academic Journal Electronic Publishing House. All rights reserved.　http://www.cnki.net

模型有长短时记忆(Long Short-Term Memory, LSTM)[5]和循环门单元(Gate Recurrent Unit, GRU)[6]等,或整合移动平均自回归模型[7]和支持向量回归模型[8]等回归模型。这些模型在短序列时间预测中通常都能取得不错的结果,但在长序列预测中随着预测长度的增加,预测精度通常都会大幅下降。在长序列预测中,常用的有卷积神经网络(Convolutional Neural Network, CNN)[9]和注意力机制等。受关注度最高的这段预测结果,处于短序列预测和长序列预测的过渡阶段,本文称为较短的长序列时间序列预测。由于它的特殊性,可以利用短序列预测模型提高预测精度,但较少学者研究该问题。

本文将预测的长度范围(步长)设定在24~168,该范围对短序列时间序列预测较长,同时又属于长序列时间序列预测中较短的部分,本文结合短序列预测和长序列预测提高这部分的预测精度。对此,针对较短的长序列时间序列预测,本文提出一个较短的长序列时间序列预测模型(Shorter Long-sequence Time Series Forecasting Model,SLTSFM)。该模型能更合理地利用短序列预测模型的特征提取能力,加强长序列输入的特征,提高该部分预测的精度。

本文的主要工作内容如下:

1)设计一个面向较短的长序列时间序列预测模型(SLTSFM)。该模型用CNN和多头自注意力机制搭建了一个序列到序列(Sequence-to-Sequence, Seq2Seq)[10]结构,以提取长序列输入特征;并设计特征增强模块对提取的长序列输入特征进行特征增强,提高预测精度。

2)设计一个"远轻近重"的策略重分配多个LSTM模块提取的特征,以缓解长序列输入给LSTM带来的性能衰减。

3)提出一个PBUSM(Probsparse Based on Uniform Selection Mechanism)自注意力机制。针对Probsparse自注意力机制存在的一些问题进行改进,缓解了Probsparse自注意力机制在时间序列特征提取时过于依赖单个得分的问题。

1　相关工作

在时间序列预测研究中,Seq2Seq结构能自动建模时间序列的相关性,捕捉它的随机过程的潜在状态,更好地反映序列数据的演化趋势。相较于传统的统计方法,Seq2Seq结构更适合长期预测需求,因为它可以捕捉更全面的时间序列规律,估计和预测未来的趋势。同时Seq2Seq结构具有较强的可扩展性,可以根据研究需要进行修改和扩展,例如使用注意力机制、半监督学习等先进技术。这一优点不仅使得自定义Seq2Seq结构变为可能,也为构建适合个人研究需求的模型提供了广阔的发挥空间。

Bahdanau等[11]将注意力机制应用于自然语言处理,给时间序列预测领域带来了一定程度的启发。Vaswani等[12]提出的Transformer网络架构中,一个高效的自注意力机制被提出,即Scaled Dot-Product注意力机制。该机制的输入包含多个$\boldsymbol{q}$(query)、$\boldsymbol{k}$(key)、$\boldsymbol{v}$(value),并将它们打包为对应的$\boldsymbol{Q}$、$\boldsymbol{K}$、$\boldsymbol{V}$矩阵。输出如式(1)~(2)所示。同时为了增加可学习的参数量,在该自注意力机制的基础上,提出多头自注意力机制。由于注意力机制的应用可以让模型更好地捕捉序列中的上下文关系,因此经常被用于长序列预测任务。

$$\text{Attention}(\boldsymbol{Q},\boldsymbol{K},\boldsymbol{V})=\text{Softmax}\left(\boldsymbol{Q}\boldsymbol{K}^{\mathrm{T}}/\sqrt{d_k}\right)\boldsymbol{V} \tag{1}$$

$$\text{Attention}(\boldsymbol{q}_i,\boldsymbol{K},\boldsymbol{V})=\sum_{j=1}^{J}\frac{\boldsymbol{q}_i\boldsymbol{k}_j^{\mathrm{T}}/\sqrt{d_k}}{\sum_{n=1}^{N}\left(\boldsymbol{q}_i\boldsymbol{k}_n^{\mathrm{T}}/\sqrt{d_k}\right)}\boldsymbol{v}_j \tag{2}$$

其中:d_k为$\boldsymbol{k}$的输入维度,J为$\boldsymbol{v}$的个数,N为$\boldsymbol{k}$的个数。

循环神经网络(Recurrent Neural Network, RNN)是一种由Hopfiled网络[13]启发变种的人工神经网络。由于RNN存在难以学习长期依赖的问题,使RNN的训练困难,应用也受限。为了缓解这一问题,LSTM使用各种门结构控制信息的输入、删除和输出。图1展示了单个LSTM的神经元结构。

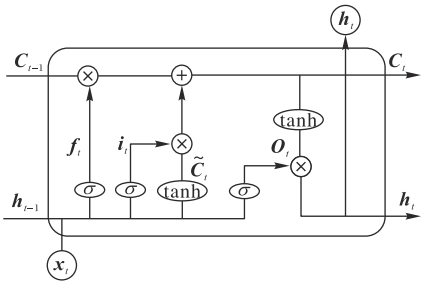


图1　LSTM的神经元结构

Fig. 1　Neuronal structure of LSTM

LSTM中的门结构计算过程如式(3)所示:

$$\begin{cases}\boldsymbol{f}_t=\sigma(\boldsymbol{\omega}_f\cdot[\boldsymbol{h}_{t-1},\boldsymbol{x}_t]+\boldsymbol{b}_f)\\ \boldsymbol{i}_t=\sigma(\boldsymbol{\omega}_i\cdot[\boldsymbol{h}_{t-1},\boldsymbol{x}_t]+\boldsymbol{b}_i)\\ \tilde{\boldsymbol{C}}_t=\tanh(\boldsymbol{\omega}_C\cdot[\boldsymbol{h}_{t-1},\boldsymbol{x}_t]+\boldsymbol{b}_C)\\ \boldsymbol{C}_t=\boldsymbol{f}_t\cdot\boldsymbol{C}_{t-1}+\boldsymbol{i}_t\cdot\tilde{\boldsymbol{C}}_t\\ \boldsymbol{O}_t=\sigma(\boldsymbol{\omega}_O\cdot[\boldsymbol{h}_{t-1},\boldsymbol{x}_t]+\boldsymbol{b}_O)\\ \boldsymbol{h}_t=\boldsymbol{O}_t\cdot\tanh(\boldsymbol{C}_t)\end{cases} \tag{3}$$

其中:σ为Sigmod函数,$\boldsymbol{\omega}$为对应结构的权重矩阵,$\boldsymbol{b}$为对应部分的偏置值矩阵。

当序列变长时,LSTM模型依然容易遗忘起始时间步之前的信息,因此LSTM常用于短序列预测任务。

相较于上述工作,本文致力于结合短序列时序预测和长序列时序预测,以提高较短的长序列时间序列的预测精度。

2　本文模型

2.1　整体模型

图2展示了本文提出的SLTSFM的整体框架。

SLTSFM可以分为2个部分:第1部分是对长序列输入的特征提取模块,采用了Seq2Seq结构。在编码器模块中,采用本文提出的自注意力机制。该机制可以一次性获取输入数据的特征,适合用于提取长时间序列输入特征。第2部分是对提取的长序列输入特征的增强模块,由多个LSTM模块组成。该模块将长输入分割给这些LSTM模块提取特征,然后根据本文设定的"远轻近重"策略进行特征重分配。该模块的主要目的是希望通过多个RNN结构提取长序列的特征。采用多个RNN结构旨在缓解输入过长给RNN带来的梯度消失和梯度爆炸问题。这部分的输出会与第1部分的长时间序列输入特征结合,加强提取的长序列输入的整体特征。这两部分的具体实现在2.2节和2.3节介绍。这两个模块会各自输出一个结果。如式(4)所示,最后根据预测需要处理这2个结果,得到最后的输出结果。

(C)1994-2024 China Academic Journal Electronic Publishing House. All rights reserved.　http://www.cnki.net

$$\boldsymbol{O}_f = (\boldsymbol{\omega} \cdot (\boldsymbol{O}_l \cdot \boldsymbol{O}_s) + \boldsymbol{b})[\mathrm{L}:] \tag{4}$$

其中：$\boldsymbol{O}_f$表示最终的输出，$\boldsymbol{\omega}$表示该层的权重矩阵，$\boldsymbol{b}$表示该层的偏置值矩阵，$\boldsymbol{O}_l$表示模块①的输出，$\boldsymbol{O}_s$表示模块②的输出，[L:]表示保留从标签长度开始到最后的结果。

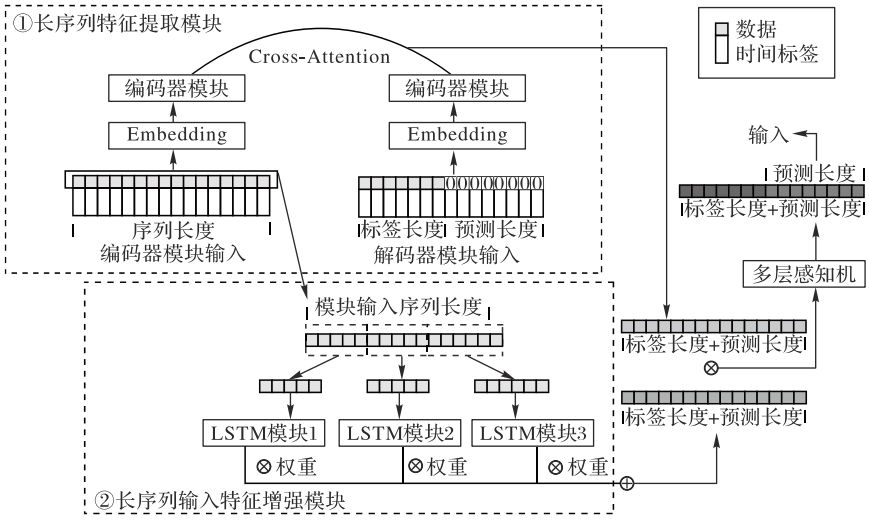


图2 SLTSFM的整体框架

Fig. 2 Overall framework of SLTSFM

2.2 长序列输入特征提取模块

2.2.1 PBUSM自注意力机制

由第1章可见Scaled Dot-Product注意力机制的计算需要用到$O(L_Q L_K)$的存储空间(L_K是$\boldsymbol{K}$矩阵的长度，L_Q是$\boldsymbol{Q}$矩阵的长度)，随着输入序列的增长，存储空间的消耗将呈指数型增长。这也是该机制应用在长时间序列预测特征提取的主要缺点，过量消耗了硬件资源，这在时间序列预测中是不划算的。针对这一缺点，Zhou等[14]提出Probsparse自注意力机制，该机制通过挑选区分“lazy”的$\boldsymbol{q}$把Scaled Dot-Product注意力机制的计算时间复杂性和空间复杂性从$O(L^2)$降低到了$O(L \log L)$，L表示输入长度。

Probsparse自注意力机制的具体步骤如下：

1)对$\boldsymbol{K}$进行采样，随机选n个$\boldsymbol{k}$，n的计算如式(5)所示：

$$n = c \ln L_{\boldsymbol{K}} \tag{5}$$

其中：c是一个自定义的整数，$L_{\boldsymbol{K}}$是$\boldsymbol{K}$矩阵的长度。

2)计算每一个$\boldsymbol{q}$的均匀分布，计算方法如式(6)所示：

$$Ud_i = \frac{1}{L_{\boldsymbol{K}}} \sum_{j=1}^{L_{\boldsymbol{K}}} \frac{\boldsymbol{q}_i \boldsymbol{k}_j^{\mathrm{T}}}{\sqrt{d}} \tag{6}$$

其中：$\boldsymbol{q}_i$表示第i个$\boldsymbol{q}$，d是输入维度，Ud_i表示第i个$\boldsymbol{q}$的均匀分布分数。

3)计算每个$\boldsymbol{q}$的最大均值差得分，计算过程如式(7)所示：

$$\bar{M}(\boldsymbol{q}_i, \tilde{\boldsymbol{K}}) = \max\left\{\boldsymbol{q}_i \boldsymbol{k}_j^{\mathrm{T}} / \sqrt{d}\right\} - Ud_i \tag{7}$$

其中：$\bar{M}(\boldsymbol{q}_i, \tilde{\boldsymbol{K}})$代表第$i$个$\boldsymbol{q}$的最大均值差得分，$\tilde{\boldsymbol{K}}$为随机选出的$\boldsymbol{k}$组成的矩阵。

4)根据计算的最大均值差得分，选出得分最高的u个$\boldsymbol{q}$，u的计算如式(8)所示：

$$u = c \ln L_Q \tag{8}$$

5)这u个位置的$\boldsymbol{q}$的输出采用常规的计算，如式(9)所示；其余的用所有$\boldsymbol{v}$的均值替代，如式(10)所示：

$$\mathrm{Attention}(\bar{\boldsymbol{Q}}, \boldsymbol{K}, \boldsymbol{V}) = \mathrm{Softmax}\left(\bar{\boldsymbol{Q}}\boldsymbol{K}^{\mathrm{T}} / \sqrt{d}\right)\boldsymbol{V} \tag{9}$$

$$\mathrm{Attention}(\tilde{\boldsymbol{Q}}, \boldsymbol{K}, \boldsymbol{V}) = \frac{1}{L_V} \sum_{i=1}^{L_V} \boldsymbol{v}_i \tag{10}$$

其中：$\bar{\boldsymbol{Q}}$为选出的u个$\boldsymbol{q}$组成的矩阵，$\tilde{\boldsymbol{Q}}$表示其余的$\boldsymbol{q}$的组成的矩阵，L_V指$\boldsymbol{V}$矩阵的长度。

从上述步骤1)中可见，Probsparse自注意力机制靠随机数挑选n个$\boldsymbol{k}$，该挑选机制会导致一些特别的情况。

第1种情况如图3(a)的第2行所示，随机挑选的$\boldsymbol{k}$过于集中。由于时间序列数据的特性，邻近的数据相关度较高，这种密集的采样，会让被选择的$\boldsymbol{q}$没有普遍性，即这些$\boldsymbol{q}$可能只对这部分数据较活跃，而无法适应整体数据。第2种情况如图3(a)的第3行所示，本来挑选的$\boldsymbol{k}$已经减少了，但有些挑选的$\boldsymbol{k}$是重复的，这进一步降低了所选$\boldsymbol{k}$的代表性。

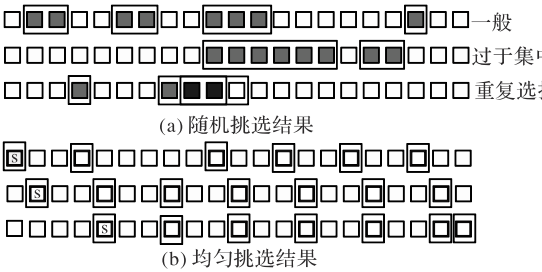


图3 $\boldsymbol{k}$的挑选机制

Fig. 3 Selection mechanisms of $\boldsymbol{k}$

对此，本文提出另外一种新的挑选$\boldsymbol{k}$的机制。希望在挑选$\boldsymbol{k}$的时候能够尽量均匀地分布在$\boldsymbol{K}$矩阵中。这样挑选的$\boldsymbol{k}$更能代表$\boldsymbol{K}$矩阵的整体水平，在判断$\boldsymbol{q}$是否“lazy”的时候才更合理。可以看到，第1个选出的$\boldsymbol{k}$是随机的，后面选出的$\boldsymbol{k}$根据滑动窗口添加，这样选出的$\boldsymbol{k}$会均匀地分布在$\boldsymbol{K}$矩阵中。最后将这些挑选的$\boldsymbol{k}$组成$\bar{\boldsymbol{K}}$矩阵。选取结果如图3(b)所示。

为了挑选活跃的$\boldsymbol{q}$，在式(6)~(7)中，分别展示了均匀分布的计算和$\boldsymbol{q}$的得分计算。对于活跃的$\boldsymbol{q}$，希望它的得分情况能够在均匀分布分数线起伏波动；“lazy”的$\boldsymbol{q}$则相反，分布情况较平稳。但从式(7)可见，第i个活跃的$\boldsymbol{q}$挑选的依据是按该$\boldsymbol{q}$与被挑选的$\boldsymbol{k}$中的最高得分决定，这会导致一个特殊的情况，如图4所示。这种情况下，一些看来“lazy”的$\boldsymbol{q}$被选择，而一些看来活跃的$\boldsymbol{q}$反而不被选择。对此，更希望活跃

(C)1994-2024 China Academic Journal Electronic Publishing House. All rights reserved. http://www.cnki.net

的$\boldsymbol{q}$有机会被选到。因此,对式(7)进行改进,修改完的得分公式如式(11)所示:

$$\bar{M}(\boldsymbol{q}_i,\bar{\boldsymbol{K}})=\sum_{j=1}^{L_K}\left|\left(\boldsymbol{q}_i\boldsymbol{k}_j^{\mathrm{T}}/\sqrt{d}\right)-\frac{1}{L_{\bar{K}}}\sum_{j=1}^{L_K}\left(\boldsymbol{q}_i\boldsymbol{k}_j^{\mathrm{T}}/\sqrt{d}\right)\right| \tag{11}$$

其中$L_{\bar{K}}$是$\bar{\boldsymbol{K}}$的长度。

式(11)使挑选$\boldsymbol{q}$时不是仅依赖最高得分,而是综合考虑所有得分,且时间复杂度都为$O(n)$,不会增加计算的时间复杂度。该自注意力机制的多头实现和其他注意力机制的多头实现一致。

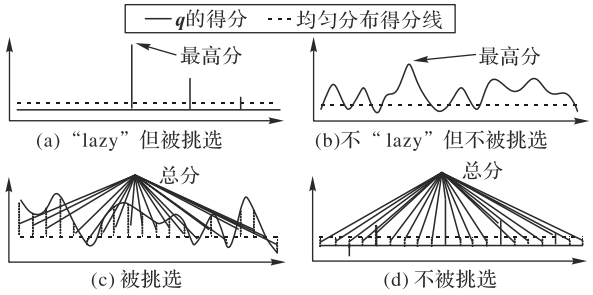


图4　改进挑选$\boldsymbol{q}$时的得分公式

Fig. 4　Score formula when improving selection of $\boldsymbol{q}$

2.2.2　编码器模块

图5展示了本文编码器模块的结构。输入在经过PBUSM多头自注意力机制后会继续经过2层卷积层加大参数的学习量。在编码器的最后一层无虚线方框内的卷积池化操作,其余的编码器层都有。经过卷积和池化操作后,特征的长度会减半,以提高运算速度。

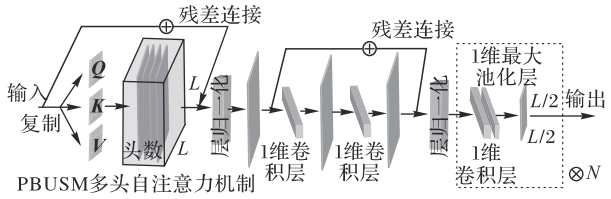


图5　编码器模块结构

Fig. 5　Structure of encoder module

编码器模块的计算过程如式(12)所示:

$$\begin{cases}\boldsymbol{x}=\mathrm{Input_e}\\(\boldsymbol{Q},\boldsymbol{K},\boldsymbol{V})=(\boldsymbol{x},\boldsymbol{x},\boldsymbol{x})\\\boldsymbol{a}_{\mathrm{out}}=\boldsymbol{x}+\mathrm{PBUSM}(\boldsymbol{Q},\boldsymbol{K},\boldsymbol{V})\\\boldsymbol{m}_{\mathrm{out}}=\mathrm{Lay}(\boldsymbol{a}_{\mathrm{out}})+\mathrm{C1d}(\mathrm{R}(\mathrm{C1d}_2(\mathrm{Lay}(\boldsymbol{a}_{\mathrm{out}}))))\\\boldsymbol{el}_{\mathrm{out}}=\mathrm{Lay}(\mathrm{M1d}(\mathrm{E}(\mathrm{Bat}(\mathrm{C1d}_3(\boldsymbol{m}_{\mathrm{out}})))))\\\boldsymbol{e}_{\mathrm{out}}=\{\mathrm{EncoderLayer}(\boldsymbol{x})\}\otimes N\end{cases} \tag{12}$$

其中:$\mathrm{Input_e}$表示编码器的输入,Lay代表层归一化操作,Bat代表批归一化操作,R代表ReLU(Rectified Linear Unit)函数,E代表ELU(Exponential Linear Unit)函数,C1d代表一维卷积操作,M1d代表一维最大池化操作,⊗代表需要重复多次且该次输出作为下次输入,N为重复次数。

2.2.3　解码器模块

图6展示了解码器模块的结构。与编码器模块相比,解码器模块采用Scaled Dot-Product注意力机制,因为本文解码器的输入比编码器的输入短,所以本文对解码器模块使用的自注意力机制并没有采取特别的操作。同时由于解码器层数比编码器层少,也没有了后面卷积池化加速操作。输入在进入解码器层后会经过2次Scaled Dot-Product注意力机制:第1个是带掩码的,即当前的特征提取只会受到之前和当前输入的影响,不会受到后面(未来)的影响;第2个的$\boldsymbol{Q}$、$\boldsymbol{K}$、$\boldsymbol{V}$由两部分组成($\boldsymbol{K}$、$\boldsymbol{V}$为编码器模块的输出,$\boldsymbol{Q}$为当前输出),再经过两次卷积操作后得到解码器层的输出,重复N次得到解码器模块的输出。

计算过程如式(13)所示:

$$\begin{cases}\boldsymbol{x}=\mathrm{Input_d}\\(\boldsymbol{Q}_1,\boldsymbol{K}_1,\boldsymbol{V}_1)=(\boldsymbol{x},\boldsymbol{x},\boldsymbol{x})\\\boldsymbol{a}_{\mathrm{out1}}=\boldsymbol{x}+\mathrm{MaskAttention}(\boldsymbol{Q}_1,\boldsymbol{K}_1,\boldsymbol{V}_1)\\(\boldsymbol{Q}_2,\boldsymbol{K}_2,\boldsymbol{V}_2)=(\mathrm{Lay}(\boldsymbol{a}_{\mathrm{out1}}),\boldsymbol{e}_{\mathrm{out}},\boldsymbol{e}_{\mathrm{out}})\\\boldsymbol{a}_{\mathrm{out2}}=\mathrm{Lay}(\boldsymbol{a}_{\mathrm{out1}})+\mathrm{CrossAttention}(\boldsymbol{Q}_2,\boldsymbol{K}_2,\boldsymbol{V}_2)\\\boldsymbol{dl}_{\mathrm{out}}=\mathrm{Lay}(\boldsymbol{a}_{\mathrm{out2}})+\mathrm{C1d}_2(\mathrm{R}(\mathrm{C1d}_1(\mathrm{Lay}(\boldsymbol{a}_{\mathrm{out2}}))))\\\boldsymbol{d}_{\mathrm{out}}=\{\mathrm{DecoderLayer}(\boldsymbol{x})\}\otimes N\end{cases} \tag{13}$$

其中:$\mathrm{Input_d}$表示解码器的输入,MaskAttention()表示带掩码的Scaled Dot-Product多头自注意力机制,CrossAttention()表示Scaled Dot-Product多头注意力机制。

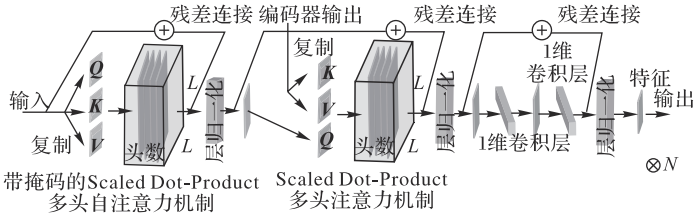


图6　解码器模块结构

Fig. 6　Structure of decoder module

2.3　长序列输入特征增强模块

长序列输入特征增强模块旨在利用多个适合短序列输入特征提取的结构,如RNN,对提取的长序列输入特征进行特征增强。

2.3.1　长短期记忆模块

循环网络结构的长期依赖问题,使它难以将长时间以前的系统状态信息为己所用。为了降低训练难度,让它应用于不同长度的数据,循环网络结构是共享权值的,即使这些权值只发生了一些变化,在经过多次循环以后,也会使它趋于消失或爆炸。

LSTM在一定程度上能缓解循环网络结构的长期依赖问题,但局限于输入序列在一定的范围。图7展示了本文的LSTM模块实现细节。该模块中,包含了两层LSTM和一层全连接层。该模块的输出如式(14)所示:

$$\boldsymbol{L}_{\mathrm{out}}=\mathrm{r}(\mathrm{R}(\boldsymbol{\omega}_{\mathrm{L}}\cdot\mathrm{LSTM}_2(\mathrm{LSTM}_1(\boldsymbol{x}))+\boldsymbol{b}_{\mathrm{L}})) \tag{14}$$

其中:r代表reshape操作,$\boldsymbol{\omega}_{\mathrm{L}}$代表全连接层的权重矩阵,$\boldsymbol{b}_{\mathrm{L}}$代表全连接层的偏置值。

(C)1994-2024 China Academic Journal Electronic Publishing House. All rights reserved.　http://www.cnki.net

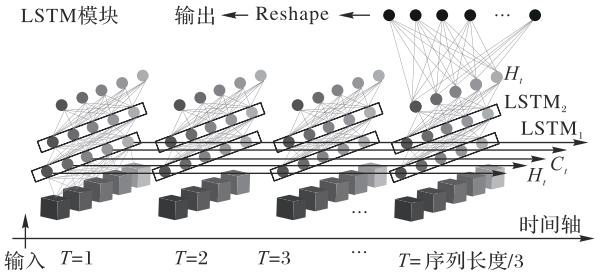


图7 LSTM模块实现

Fig. 7 Implementation of LSTM module

2.3.2 数据分割和“远轻近重”策略

考虑长序列输入会给LSTM带来瓶颈，本文通过多个LSTM模块缓解该问题。本文采用3个LSTM模块分割输入，输入的数据按式(15)分配给LSTM模型：

$$\boldsymbol{IL}_1, \boldsymbol{IL}_2, \boldsymbol{IL}_3 = \boldsymbol{x}[:k], \boldsymbol{x}[k:2\times k], \boldsymbol{x}[2\times k:] \tag{15}$$

其中：$\boldsymbol{x}$代表该模块的输入，k为整数(大小为$\boldsymbol{x}$的长度除以3且向下取整)，$\boldsymbol{IL}_i$代表第i个LSTM模块的输入。

根据时间序列数据的一般特性，离预测数据越近的数据影响预测数据的程度越大，所以本文采用“远轻近重”策略对每个LSTM模块进行权重分配。即处理离预测数据近的LSTM模块的输出结果在汇总时会获得更大的权重。第二部分的输出如式(16)所示：

$$\boldsymbol{S}_O = \boldsymbol{\omega}_1\boldsymbol{L}_{O1} + \boldsymbol{\omega}_2\boldsymbol{L}_{O2} + \boldsymbol{\omega}_3\boldsymbol{L}_{O3} \tag{16}$$

其中：$\boldsymbol{\omega}_i$为对应模块输出的权重矩阵，$\boldsymbol{L}_{Oi}$代表第i个LSTM模块的输出。

3 实验与结果分析

3.1 数据集介绍

为了验证SLTSFM的性能，本文选取了4个公开数据集进行性能测试，分别为：ETT(Electricity Transformer Temperature)[14]、WTH(Weather)[14]、PM2.5A(Particulate Matter 2.5(A))[15]和PM2.5B(Particulate Matter 2.5(B))[16]。ETT数据集以小时为单位收集了中国某县2年的电力变压器温度数据，数据集的维度为8，共有17 420条数据。PM2.5A数据集以小时为单位收集了2010年至2015年的中国北京市的气象数据，数据集的维度为9，共有34 824条数据。PM2.5B数据集以小时为单位收集了2014年至2015年的中国北京市的气象数据，数据集的维度为7，共有7 552条数据。PM2.5A和PM2.5B收集的采样具体地点和数据内容均不一致。WTH数据集以小时为单位收集了2010年至2013年美国某地的气候数据，数据集的维度为13，共有35 064条数据。以上4个数据集均可以在相应的参考文献中获得获取方式。

实验中数据集分为训练集、验证集和测试集。划分规则为数据集前70%的数据作为训练集，中间20%的数据作为验证集，最后10%的数据作为测试集。

3.2 性能评价指标

本文选取了时间序列预测中常用到两种性能评估指标，分别为平均绝对误差(Mean Absolute Error, MAE)和均方误差(Mean Squared Error, MSE)。MAE和MSE的值越小，表示预测值越接近真实值，模型的性能越好。计算方法如式(17)~(18)所示：

$$V_{\mathrm{MAE}} = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{17}$$

$$V_{\mathrm{MSE}} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{18}$$

其中：n为样本数，y_i代表真实值，$\hat{y}_i$代表预测值。

本文还使用了Friedman统计量χ^2进行整体评估，Friedman统计量是常用于评估一组算法在不同数据集上性能差异的统计方法。通过查表可以计算自由度为$g-1$和$(g-1)(h-1)$的F分布的临界值，该值用于和F_f比较，评估算法的表现。计算定义如式(19)~(21)所示：

$$R_j = \frac{1}{h}\sum_{i=1}^{h} r_i^j \tag{19}$$

$$\chi^2 = \frac{12h}{g(g+1)}\sum_{j=1}^{g}R_j^2 - 3h(g+1) \tag{20}$$

$$F_f = \frac{(h-1)\chi^2}{h(g-1)-\chi^2} \tag{21}$$

其中：r_i^j为第j个算法在第i个数据集上的排名，g为算法数，h为数据集数。

3.3 实验设置和对比模型

所有数据集都先经过数据预处理，进行标准化，公式如式(22)所示，然后进行训练建模和性能评价。

$$y = \frac{x-\mu}{\sqrt{\dfrac{1}{T-1}\sum_{i=1}^{T}(x_i-\mu)^2}} \tag{22}$$

其中：μ是数据集的均值，T为数据集的长度。

实验共分为2个部分：第1部分为单变量预测，即输入多变量数据预测目标变量数据；第2部分为多变量预测，即输入多变量数据，同时预测相同变量的数据。

其次在这两部分实验中，分别进行24、48、72、96和168这5个步长的多步预测。表1展示了这5个不同长度对应的数据集制作参数，时间戳频率均是小时。

表1 不同预测步长的多步预测的数据集制作参数

Tab. 1 Dataset production parameters for multi-step forecasting with different forecasting steps

预测步长	输入长度	标签长度
24	96	48
48	128	64
72	152	86
96	176	110
168	256	192

在本文中，SLSTSM的编码器层数为3，解码器层数为2。对比的基准模型如下：

1)SLTSFM-。与SLTSFM的结构和参数一致，但减掉特征增强模块且编码器的层中采用Probsparse自注意力机制。

2)LSTM+。与SLTSFM特征增强模块的结构和参数保持一致，采用两层LSTM循环单元，隐层维度均为30，同时也采用“远轻近重”策略对提取特征重分配。

3)GRU。GRU是一种基于LSTM进行改进的RNN。相较于LSTM，GRU减少了一些网络参数，简化了门控机制，因此在训练的速度上更高。本文使用两层GRU循环单元，隐层维度分别为128和64。

4)时间卷积网络(Temporal Convolutional Network, TCN)[17]。TCN通过引入因果卷积和膨胀卷积结构，从而加强时间序列特征的提取。为了解决长序列输入带来的过深

(C)1994-2024 China Academic Journal Electronic Publishing House. All rights reserved. http://www.cnki.net

的网络层数问题,TCN还引入了残差连接[18],进一步提高了网络的学习能力。本文对TCN的残差块数设置随输入长度变化而变化,保证在最后一个残差块中的输出会包含之前所有输入的信息。

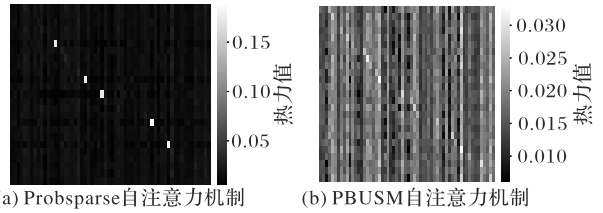
5)SeriesNet[19]。SeriesNet包含了2个部分:LSTM用于学习时间序列数据的整体特征,因果扩张卷积网络用于学习不同区间长度的时间序列数据的特征。本文实验对比中使用$SeriesNet_{50}$结构。

6)基于自注意机制的LSTM-CNN模型(LSTM-CNN based on Self-attention mechanism, LCS)[20]。LCS先用LSTM提取时间序列数据的长期行为特征,然后用CNN提取非平稳性特征,最后用自注意力机制强调关键信息。

3.4　PBUSM自注意力机制

在验证PBUSM自注意力机制时,首先随机生成60个$\boldsymbol{q}$,其次将设置的"lazy"的$\boldsymbol{q}$随机替换这60个里面的10个。从图8可以看到,在Probsparse自注意力机制中,设置的"lazy"的$\boldsymbol{q}$有5个被成功选中。若在挑选$\boldsymbol{k}$时,有更多复制的"lazy"$\boldsymbol{q}$的$\boldsymbol{k}$被随机选中,那将有更多的"lazy"的$\boldsymbol{q}$被选中。而在PBSUM自注意力机制中,打印均匀挑选机制选中的$\boldsymbol{k}$,发现即使挑选的$\boldsymbol{k}$有多个是复制了"lazy"的$\boldsymbol{q}$的情况下,"lazy"的$\boldsymbol{q}$也没有一个被成功选中。

这些"lazy"的$\boldsymbol{q}$对时间序列特征提取主要有2个影响:1)这些$\boldsymbol{q}$只与某个或少数的其他几个$\boldsymbol{q}$有较大联系,而时间序列数据特征提取更希望得到的是当前时间点与其他各个时间点之间的联系,"lazy"的$\boldsymbol{q}$明显无法做到;2)"lazy"的$\boldsymbol{q}$会被Probsparse自注意力机制选中是由于某些得分较高,如图8(a)中白点所示,这也意味着这个$\boldsymbol{q}$中有某个维度明显大于正常水平,这导致模型学习时这些点的梯度会过大或过小,影响建模。



(a) Probsparse自注意力机制　　(b) PBUSM自注意力机制

图8　2个自注意力机制的热力图对比

Fig. 8　Heat map comparison of two self-attention mechanisms

本文提出的PBUSM自注意力机制很大程度上避免了这些"lazy"的$\boldsymbol{q}$被选中,使时间序列数据特征的提取更合理。

3.5　实验结果与分析

在本文中,每个模型在每个数据集上的5个不同预测步长(24、48、72、96、168)都进行了5次或5次以上的实验,然后取平均值,结果如图9所示。表2展示了将模型对这5个不同预测步长实验结果进行平均后的数值。图9和表2中的指标结果均为测试集的结果。

表2　各模型在4个数据集上的5个不同预测步长平均指标

Tab. 2　Average metrics of various models for five different forecasting steps on four datasets

数据集	类型	SLTSFM		SLTSFM−		LSTM+		GRU		TCN		SeriesNet		LCS	
		MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETT	U	**0.107**	**0.255**	0.181	0.351	0.584	0.663	0.584	0.663	0.591	0.668	0.586	0.664	0.583	0.663
	M	**0.586**	**0.556**	1.006	0.760	0.861	0.676	0.855	0.670	0.972	0.739	0.846	0.667	0.957	0.742
PM2.5A	U	**0.817**	**0.629**	1.058	0.765	0.914	0.730	0.906	0.727	1.025	0.754	0.964	0.738	0.935	0.727
	M	**0.587**	**0.429**	1.376	0.746	0.709	0.528	0.699	0.524	0.822	0.697	0.748	0.538	0.811	0.568
PM2.5B	U	0.696	**0.647**	0.888	0.790	0.701	0.661	**0.687**	0.653	0.752	0.675	0.719	0.663	0.748	0.671
	M	1.048	**0.716**	1.581	1.007	1.007	0.747	**0.993**	0.740	1.182	0.816	1.026	0.743	1.124	0.797
WTH	U	**0.306**	**0.423**	0.907	0.786	0.491	0.521	0.499	0.526	0.807	0.722	0.657	0.626	0.767	0.694
	M	**0.535**	**0.513**	0.935	0.749	0.598	0.551	0.608	0.550	0.820	0.697	0.671	0.599	0.732	0.643

注:U表示单变量实验,M表示多变量实验,粗体表示最优结果。

从图9可见,在单变量的时间序列预测实验中,SLTSFM在4个数据集上的5个不同预测步长的测试集MSE和MAE表现上,取得了19次最佳表现。MSE另外的1次最优表现由LSTM+取得,MAE另外的1次最优表现由GRU取得。在多变量的时间序列预测中,SLTSFM在测试集的MSE和MAE表现上,分别取得了16次和18次最佳表现。LSTM+各取得了2次最佳表现。GRU取得了2次最佳的测试集MSE表现。即在80组实验结果中,SLTSFM共取得了72次最佳表现。从图9还可见,在较短的长序列时间序列预测中,相较于基于卷积结构的网络模型,基于循环结构的网络模型更占优势;但随着预测步数的增加,该优势也渐渐变小。同时,可以看到GRU模型在大多数数据集上一开始的表现都比LSTM+模型好,但随着预测步数的增加,LSTM+模型的表现逐渐超过了GRU。这可以看出,随着预测长度的增加,梯度消失或爆炸将给循环结构的网络带来一定程度的性能打击,而应用了多循环结构和"远轻近重"特征重分配策略的LSTM+一定程度上缓解了该问题。

由于各个模型在不同预测步长的性能表现都有所差异,即各模型取得较好的实验结果对应的步长不一致。如果统一一个预测步长作为实验结果,对某个模型可能有利,但对其他模型可能有失公平。为了公平地评价各模型并说明模型的普适性,本文将各模型在不同步长的实验结果进行平均,且作为评价模型的最终指标。在表2中可以看到,在整体平均结果上,SLTSFM在大多数情况下都取得了最优性能指标。在将单变量和多变量预测结果进行平均后,和综合表现次优的模型GRU相比,SLTSFM的MAE指标在4个数据集上的单变量时序预测分别减小61.54%、13.48%、0.92%和19.58%,多变量时序预测分别减小了17.01%、18.13%、3.24%和6.73%。最后,从SLTSFM和LSTM+与SLTSFM−的表现对比可以看到,SLTSFM合理地将时间序列数据特征交由两个模块提取,改进Probsparse自注意力机制给模型性能带来较大提升。

为了进一步对各个模型在这些数据集上的性能表现进

(C)1994-2024 China Academic Journal Electronic Publishing House. All rights reserved.　http://www.cnki.net

行对比，使用Friedman统计量评估。将各个模型在各个数据集上不同步数的预测性能结果进行平均后进行排序得到表3。由表3可知数据集共有8个(多变量和单变量各4个)，即 n=8，模型数为7，即 k=7。将平均排名、n 和 k 代入式(20)~(21)后计算 Friedman 统计量的 χ^2=35.903 1，则 F_f=20.096 9。所以 F_f 服从自由度为 7 − 1 = 6 和 (8 − 1)(7 − 1) = 42 的 F 分布。查表可得，$F(6,42)$ 的临界值为 2.324，在高显著水平下拒绝原假设，即模型算法性能在这些数据集上有显著差异。因此，在这些数据集上，模型性能表现的排序为：SLTSFM，GRU，LSTM+，SeriesNet，LCS，TCN，SLTSFM−。

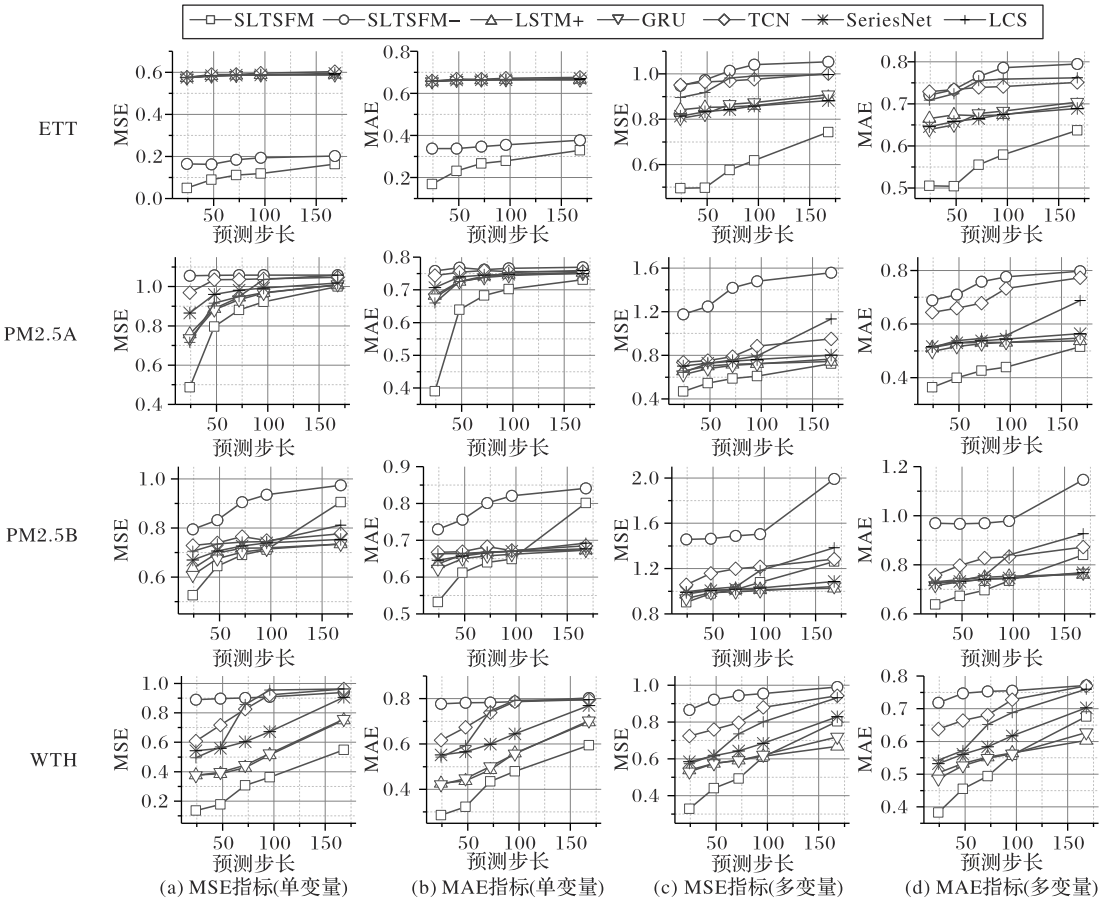


图9 各模型在不同数据集上不同的预测步长的实验结果

Fig. 9 Experimental results of various models with different forecasting steps on different datasets

表3 各模型在测试集上的实验结果排名

Tab. 3 Experimental result ranking of various models on test set

模型	ETT				PM2.5A				PM2.5B				WTH				平均排名
	单变量		多变量		单变量		多变量		单变量		多变量		单变量		多变量		
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	
SLTSFM	1	1	1	1	1	1	1	1	2	1	4	1	1	1	1	1	**1.25**
SLTSFM−	2	2	7	7	7	7	7	7	7	7	7	7	7	7	7	7	6.38
LSTM+	5	5	4	4	3	4	3	3	3	3	2	4	2	2	2	3	3.25
GRU	4	4	3	3	2	2	2	2	1	2	1	2	3	3	3	2	2.44
TCN	7	7	6	5	6	6	6	6	6	6	6	6	6	6	6	6	6.06
SeriesNet	6	6	2	2	5	5	4	4	4	4	3	3	4	4	4	4	4.00
LCS	3	3	5	6	4	3	5	5	5	5	5	5	5	5	5	5	4.63

4 结语

本文提出了一种面向较短的长序列时间序列预测的模型，SLTSFM 充分利用循环结构网络在短序列时间序列预测中的特征提取能力，对长序列输入特征进行增强。针对 Probsparse 自注意力机制中存在的问题，包括 k 的挑选方法和 q 的得分公式，本文提出了 PBUSM 自注意力机制，以避免“lazy”的 q 被选中，使得时间序列特征的提取更合理。在长序列特征的增强模块中，为了缓解长序列输入对循环结构网络性能的影响，本文将输入分配给多个循环结构网络，并根据“远轻近重”策略重分配它们提取的特征，以提高长序列特征的增强效果。为了验证 SLTSFM 的性能，本文在多个公开数据集上进行不同预测步数的实验，包括单变量和多变量的实验。实验结果表明，SLTSFM 在这些数据集上表现了更强的特征提取能力和更高的预测精度。

在 SLTSFM 的长序列特征增强模块，循环结构网络数和“远轻近重”策略的权重赋值都是经验值。在未来的工作中，

(C)1994-2024 China Academic Journal Electronic Publishing House. All rights reserved. http://www.cnki.net

将致力于利用其他模型寻找最优的个数和权重数值,进一步提高SLTSFM的特征提取能力。

参考文献(References)

[1] 徐晓芳,管瑞. 基于神经网络集成学习算法的金融时间序列预测[J]. 计算机系统应用, 2022, 31(6): 29-37. (XU X F, GUAN R. Financial time series forecasting based on neural network ensemble learning algorithms [J]. Computer Systems & Applications, 2022, 31(6): 29-37.)

[2] 李毅,彭晋卿,廖维,等. 一种基于时间序列的集成电力负荷预测方法研究[J]. 建筑科学, 2022, 38(10): 190-197. (LI Y, PENG J Q, LIAO W, et al. Research on an integrated model for electrical load forecasting based on time series [J]. Building Science, 2022, 38(10): 190-197.)

[3] 夏进,王正群,朱世明. 基于时间序列分解的交通流量预测模型[J]. 计算机应用, 2023, 43(4): 1129-1135. (XIA J, WANG Z Q, ZHU S M. Traffic flow prediction model based on time series decomposition [J]. Journal of Computer Applications, 2023, 43(4): 1129-1135.)

[4] 王海起,王志海,李留珂,等. 基于网格划分的城市短时交通流量时空预测模型[J]. 计算机应用, 2022, 42(7): 2274-2280. (WANG H Q, WANG Z H, LI L K, et al. Spatial-temporal prediction model of urban short-term traffic flow based on grid division [J]. Journal of Computer Applications, 2022, 42(7): 2274-2280.)

[5] HOCHREITER S, SCHMIDHUBER J. Long short-term memory [J]. Neural Computation, 1997, 9(8): 1735-1780.

[6] CHO K, VAN MERRIËNBOER B, BAHDANAU D, et al. On the properties of neural machine translation: encoder-decoder approaches [EB/OL]. (2014-10-07) [2023-06-20]. https://arxiv.org/pdf/1409.1259.pdf.

[7] BOX G E P, JENKINS G M, REINSEL G C, et al. Time Series Analysis: Forecasting and Control [M]. 5th ed. Hoboken: John Wiley & Sons, 2015: 88-94.

[8] DRUCKER H, BURGES C J C, KAUFMAN L, et al. Support vector regression machines [C]// Proceedings of the 9th International Conference on Neural Information Processing Systems. Cambridge: MIT Press, 1997: 155-161.

[9] LeCUN Y, BOSER B, DENKER J S, et al. Backpropagation applied to handwritten zip code recognition [J]. Neural Computation, 1989, 1(4): 541-551.

[10] SUTSKEVER I, VINYALS O, LE Q V. Sequence to sequence learning with neural networks [C]// Proceedings of the 27th International Conference on Neural Information Processing Systems. Cambridge: MIT Press, 2014: 3104-3112.

[11] BAHDANAU D, CHO K, BENGIO Y. Neural machine translation by jointly learning to align and translate [EB/OL]. (2016-05-19) [2023-06-20]. https://arxiv.org/pdf/1409.0473.pdf.

[12] VASWANI A, SHAZEER N, PARMAR N, et al. Attention is all you need [C]// Proceedings of the 31st International Conference on Neural Information Processing Systems. Red Hook: Curran Associates, 2017: 6000-6010.

[13] HOPFIELD J J. Neural networks and physical systems with emergent collective computational abilities [J]. Proceedings of the National Academy of Sciences of the United States of America, 1982, 79(8): 2554-2558.

[14] ZHOU H, ZHANG S, PENG J, et al. Informer: beyond efficient Transformer for long sequence time-series forecasting [C]// Proceedings of the 35th AAAI Conference on Artificial Intelligence. Menlo Park: AAAI Press, 2021: 11106-11115.

[15] LIANG X, ZOU T, GUO B, et al. Assessing Beijing's $PM_{2.5}$ pollution: severity, weather impact, APEC and winter heating [J]. Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences, 2015, 471: 20150257.

[16] ZHENG Y, YI X, LI M, et al. Forecasting fine-grained air quality based on big data [C]// Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. New York: ACM, 2015: 2267-2276.

[17] BAI S, KOLTER J Z, KOLTUN V. An empirical evaluation of generic convolutional and recurrent networks for sequence modeling [EB/OL]. (2018-04-19) [2023-06-20]. https://arxiv.org/pdf/1803.01271.pdf.

[18] HE K, ZHANG X, REN S, et al. Deep residual learning for image recognition [C]// Proceedings of the 2016 IEEE Conference on Computer Vision and Pattern Recognition. Piscataway: IEEE, 2016:770-778.

[19] SHEN Z, ZHANG Y, LU J, et al. A novel time series forecasting model with deep learning [J]. Neurocomputing, 2020, 396: 302-313.

[20] YI S, LIU H, CHEN T, et al. A deep LSTM-CNN based on self-attention mechanism with input data reduction for short-term load forecasting [J]. IET Generation, Transmission & Distribution, 2023, 17(7): 1538-1552.

This work is partially supported by Natural Science Foundation of Guangdong Province (2020A1515010691); Agricultural Science and Technology Commissioner Project of Guangzhou (20212100036).

XU Zexin, born in 1998, M. S. candidate. His research interests include data mining, deep learning.

YANG Lei, born in 1978, Ph. D., lecturer. His research interests include data mining, intelligent computing.

LI Kangshun, born in 1962, Ph. D., professor. His research interests include machine learning, artificial intelligence.

(C)1994-2024 China Academic Journal Electronic Publishing House. All rights reserved.　http://www.cnki.net

Journal of Computer Applications
计算机应用,2025,45(8):2656 - 2665
ISSN 1001-9081
CODEN JYIIDU
2025-08-10
http://www.joca.cn

文章编号:1001-9081(2025)08-2656-10
DOI:10.11772/j.issn.1001-9081.2024081130

面向复杂约束多目标优化问题的双种群双阶段进化算法

袁志超,杨　磊*,田井林,魏晓威,李康顺
(华南农业大学 数学与信息学院,广州 510642)
(*通信作者电子邮箱 yanglei_s@scau.edu.cn)

摘　要:针对包含复杂约束条件的约束多目标优化问题(CMOP),在确保算法满足严格约束的同时,有效平衡算法的收敛性与多样性是重大挑战。因此,提出一种双种群双阶段的进化算法(DPDSEA)。该算法引入2个独立进化种群:主种群和副种群,并分别利用可行性规则和改进的epsilon约束处理方法进行更新。在第一阶段,主种群和副种群分别探索约束Pareto前沿(CPF)与无约束Pareto前沿(UPF),从而获取UPF和CPF的位置信息;在第二阶段,设计一种分类方法,根据UPF与CPF的位置对CMOP进行分类,从而对不同类型的CMOP执行特定的进化策略;此外,提出一种随机扰动策略,在副种群进化到CPF附近时,对它进行随机扰动以产生一些位于CPF上的个体,从而促进主种群在CPF上的收敛与分布。把所提算法与6个具有代表性的算法:CMOES(Constrained Multi-objective Optimization based on Even Search)、dp-ACS(dual-population evolutionary algorithm based on Adaptive Constraint Strength)、c-DPEA(Dual-Population based Evolutionary Algorithm for constrained multi-objective optimization)、CAEAD(Constrained Evolutionary Algorithm based on Alternative Evolution and Degeneration)、BiCo(evolutionary algorithm with Bidirectional Coevolution)和DDCMOEA(Dual-stage Dual-population Evolutionary Algorithm for Constrained Multiobjective Optimization)在LIRCMOP和DASCMOP两个测试集上进行实验比较。实验结果表明,DPDSEA在23个问题中取得了15个最优反转世代距离(IGD)值和12个最优超体积(HV)值,展现了DPDSEA在处理复杂CMOP时显著的性能优势。

关键词:约束多目标优化;双种群;双阶段;进化算法;约束处理方法;分类方法;随机扰动

中图分类号:TP301.6　　**文献标志码**:A

Dual-population dual-stage evolutionary algorithm for complex constrained multi-objective optimization problems

YUAN Zhichao, YANG Lei*, TIAN Jinglin, WEI Xiaowei, LI Kangshun
(*College of Mathematics and Informatics, South China Agricultural University, Guangzhou Guangdong* 510642, *China*)

Abstract: For Constrained Multi-Objective Optimization Problem (CMOP) with complex constraints, balancing the algorithm's convergence and diversity effectively while ensuring strict constraint satisfaction is a significant challenge. Therefore, a Dual-Population Dual-Stage Evolutionary Algorithm (DPDSEA) was proposed. In this algorithm, two independently evolving populations were introduced: the main and secondary populations, and the feasibility rules and an improved epsilon constraint handling method were used for updating, respectively. In the first stage, the main and secondary populations were employed to explore the Constrained Pareto Front (CPF) and the Unconstrained Pareto Front (UPF), respectively, to obtain positional information about the UPF and the CPF. In the second stage, a classification method was designed to classify CMOPs based on positions of the UPF and the CPF, thereby executing specific evolutionary strategies for different types of CMOPs. Additionally, a random perturbation strategy was proposed to perturb the secondary population evolved near the CPF randomly to generate some individuals on the CPF, thereby promoting convergence and distribution of the main population on the CPF. Finally, experiments were conducted on LIRCMOP and DASCMOP test sets to compare the proposed algorithm with six representative algorithms: CMOES (Constrained Multi-Objective Optimization based on Even Search), dp-ACS (dual-population evolutionary algorithm based on Adaptive Constraint Strength), c-DPEA (Dual-population based Evolutionary Algorithm for constrained multi-objective optimization), CAEAD (Constrained Evolutionary Algorithm based on Alternative Evolution and Degeneration), BiCo (evolutionary algorithm with Bidirectional Coevolution), and DDCMOEA (Dual-stage Dual-Population Evolutionary Algorithm for Constrained Multiobjective Optimization). The results show that DPDSEA achieves 15 best Inverted Generational Distance (IGD) values and 12 best Hyper Volume (HV)

收稿日期:2024-08-12;**修回日期**:2024-11-10;**录用日期**:2024-11-12。
基金项目:国家重点研发计划项目(2023YFF1105101,2023YFF1104201);广东省科技创新专项资金资助项目(SDZX2023032)。
作者简介:袁志超(2000—),男,广东东莞人,硕士研究生,CCF会员,主要研究方向:多目标优化、进化计算;　杨磊(1978—),男,河南南阳人,讲师,博士,主要研究方向:数据挖掘、进化计算;　田井林(1998—),男,四川凉山人,硕士研究生,主要研究方向:多目标优化、进化计算;魏晓威(1998—),男,河南信阳人,硕士研究生,主要研究方向:多目标优化、进化计算;　李康顺(1962—),男,江西兴国人,教授,博士,主要研究方向:机器学习、人工智能。

中国知网　https://www.cnki.net

values in 23 problems, demonstrating DPDSEA's performance advantages in handling complex CMOPs significantly.

Key words: constrained multi-objective optimization; dual-population; dual-stage; evolutionary algorithm; constraint handling method; classification method; random perturbation

0　引言

在真实世界的众多应用场景中,如无人机轨迹规划[1]、电力系统调度[2]和自动驾驶决策[3]等,由于这类问题包含多个需要同时优化的目标和约束条件,因此被称为约束多目标优化问题(Constrained Multi-objective Optimization Problem, CMOP)[4]。鉴于目标间的内在冲突及约束条件的严格限制,寻求一个能够同时最优地满足所有目标的单一解变得不切实际。因此,求解CMOP的最终目标是获得一组能够保持良好的收敛性和多样性且逼近Pareto前沿(Pareto Front, PF)的可行解。

在解决多目标优化问题(Multi-objective Optimization Problem, MOP)时,进化算法作为一类强大的启发式搜索技术,已展现出卓越的适应性和效率。然而,当问题进一步拓展至CMOP范畴时,单纯依赖传统的进化算法显得力不从心。为了解决这一难题,研究者们将焦点转向了结合多目标进化算法(Multi-Objective Evolutionary Algorithm, MOEA)与约束处理技术(Constraint Handling Techniques, CHT),从而形成约束多目标进化算法(Constrained Multi-Objective Evolutionary Algorithm, CMOEA)[5]。

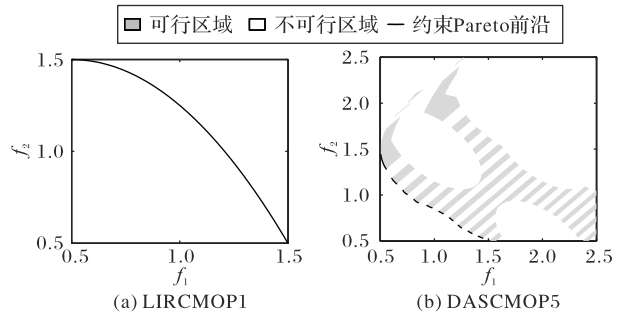
根据CHT的不同,CMOEA可以分为4种类型[6]。第一类是基于惩罚函数法的CMOEA[7]。这种方法通过将不可行解转化为可行解来提高算法的有效性,核心在于对违反约束的解施加惩罚,从而降低这些解的选择概率,使搜索偏向可行区域。第二类是基于约束与目标分离法的CMOEA[8]。通过将约束条件和目标函数分开处理,从而更有效应对CMOP,主要包括3个方法:约束支配原则(Constraint Dominance Principle, CDP)[9]、epsilon约束法[10]和随机排序法(Stochastic Ranking, SR)[11]。第三类是基于多目标优化法的CMOEA[12]。在这种方法中,通常将一个或多个约束条件视为优化问题的一部分,与目标函数一同优化,从而将CMOP转换为对应的MOP。这样就能够借助现有的MOEA求解转换后的MOP。第四类是基于混合法的CMOEA[13]。面对复杂多变的CMOP时,单一的CHT通常难以奏效。因此,研究者们将多种不同的CHT相结合,旨在发挥各种CHT的独特优势求解CMOP。

随着CMOP的复杂性和多样性的增加,研究者们还提出了基于多种群[14]和基于分阶段的方法[15]。Liu等[16]提出了一种双向协同进化的算法BiCo(evolutionary algorithm with Bidirectional Coevolution),利用主种群和档案种群,从约束边界的两侧来同时探索约束Pareto前沿(Constrained Pareto Front, CPF)。Ming等[17]提出一种双种群的进化算法c-DPEA(Dual-Population based Evolutionary Algorithm for constrained multi-objective optimization),设计了2个互补的种群分别保留可行解与不可行解,利用不可行解中的潜在信息辅助可行解的搜索。

Sun等[18]提出一种多阶段搜索的方法,根据种群的非支配水平划分约束处理优先级,并对约束之间的关系进行分析,删除一些不必要的约束,简化问题的复杂程度,随后按照设定的约束处理优先级逐个处理约束。Ming等[19]提出了一种双阶段的进化算法CMOES(Constrained Multi-objective Optimization based on Even Search),第一阶段旨在寻找接近CPF的可行解,第二阶段在可行区域内均匀搜索。

受到上述2种方法的启发,相关学者还提出了一些结合双种群和双阶段的CMOEA。例如,Yang等[20]提出了一种基于自适应约束强度的双种群算法dp-ACS(dual-population evolutionary algorithm based on Adaptive Constraint Strength),2个种群分别探索原始的CMOP及其对应的无约束版本。在dp-ACS的早期阶段,设置较小的约束强度,使种群在目标空间中广泛分布,维持良好的多样性;在后期阶段,逐渐加强约束强度,压缩可行解空间,使得种群跨越不可行区域以探索真实PF。Zou等[21]提出了一种名为CAEAD(Constrained Evolutionary Algorithm based on Alternative Evolution and Degeneration)的双种群双阶段算法,将搜索阶段分为进化和退化阶段,根据主种群与辅助种群的状态,交替选择搜索阶段,实现对搜索空间的充分探索。

虽然目前已提出了多种CMOEA求解CMOP,但是这些CMOEA在处理具有复杂约束的CMOP时,难以兼顾算法的收敛性和多样性。在这类问题中,包含多个约束条件和决策变量[22],每个决策变量都有不同的取值范围,变量之间存在的组合关系形成了等式约束或不等式约束,要求多个变量一起满足特定条件,这些不同的约束使得可行区域分布情况变得复杂。以图1中的LIRCMOP1(CMOPs with Large Infeasible Regions)和DASCMOP5(Difficulty-Adjustable and Scalable CMOPs)为例,由于多个约束条件的共同限制,可行区域可能是狭窄或离散的,并且被大面积的不可行区域包围。这使得许多算法在早期找到某个可行区域的解后,通常在该解附近反复迭代,导致错失其他潜在更优解。



(a) LIRCMOP1　　(b) DASCMOP5

图1　复杂CMOP示意图

Fig. 1　Schematic diagrams of complex CMOPs

更具体地分析,基于惩罚函数法的CMOEA,难以设置合理的惩罚系数来有效处理复杂约束;基于约束与目标分离法的CMOEA,难以在约束和目标之间找到合适的平衡,导致优化效果不理想;基于多目标优化法的CMOEA,在复杂约束条件下容易陷入局部最优;基于混合法的CMOEA,虽然融合多种策略,但对复杂约束的适应性不足;基于多种群的CMOEA,在种群之间的协同进化上可能存在信息交互不充分的问题;基于分阶段的CMOEA,在处理不同阶段的策略衔

中国知网　https://www.cnki.net

接上，处理复杂约束的效率有限。

为了有效处理具有复杂约束的CMOP，本文提出了一种面向复杂约束多目标优化问题的双种群双阶段进化算法（Dual-Population Dual-Stage Evolutionary Algorithm for complex constrained multi-objective optimization problems，DPDSEA）。与现有双种群或双阶段的CMOEA相比，DPDSEA具有更灵活的种群分工和阶段性目标设计，充分考虑了复杂约束在进化过程中的特殊性。通过双种群机制分别处理可行解与不可行解，利用不可行解信息减少复杂约束对算法收敛的限制。算法在第一阶段侧重收敛性，快速定位可行解空间；第二阶段更注重多样性，使种群在真实PF上分布更均匀。主副种群分别侧重不同方向，避免搜索局限于特定区域，以有效应对复杂约束CMOP。本文主要工作如下：

1）提出一种双种群双阶段的进化机制。主种群在可行区域内进行局部搜索以找到可行解，副种群在全局范围内搜索并保留优秀的不可行解以辅助主种群进化。第一阶段注重算法的收敛性，主种群考虑约束进化，副种群不受约束限制，帮助主种群跨越复杂约束所构成的障碍。第二阶段，主种群与副种群分别从可行区域和不可行区域两侧向真实PF靠拢。

2）设计一种CMOP的分类方法，根据主种群与副种群的分布情况，对CMOP分类，选择合适的进化策略对问题进行处理。

3）提出一种改进的epsilon约束方法，利用该方法实现副种群的无约束进化，将副种群从不可行区域一端向真实PF牵引。

4）设计一种随机扰动策略，当副种群进化到真实PF附近时，利用该策略对副种群进行小范围的扰动，生成一个临时的子代种群，并将该临时子代种群加入主种群的环境选择。

与现有的6个CMOEA在LIRCMOP和DASCMOP基准测试集上进行对比实验。实验结果表明，DPDSEA在处理包含复杂约束的CMOP时具有较强的竞争力。

1 理论基础

以最小化问题的CMOP为例，它的数学模型可以用以下公式表示：

$$\min \boldsymbol{F}(\boldsymbol{x}) = \left(f_1(\boldsymbol{x}), f_2(\boldsymbol{x}), \cdots, f_m(\boldsymbol{x})\right)^{\mathrm{T}} \tag{1}$$

$$\text{s. t.} \begin{cases} g_i(\boldsymbol{x}) \leqslant 0, & i = 1, 2, \cdots, l \\ h_j(\boldsymbol{x}) = 0, & j = l+1, l+2, \cdots, k \\ \boldsymbol{x} = (x_1, x_2, \cdots, x_{\mathrm{D}})^{\mathrm{T}} \in \mathbb{S} \end{cases}$$

其中：$\boldsymbol{F}(\boldsymbol{x})$是目标函数，由$m$个需要优化的目标组成；$g_i(\boldsymbol{x})$表示第$i$个不等式约束，$h_j(\boldsymbol{x})$是第$j$个等式约束，它们的数量分别为$l$和$(k-l)$；$\boldsymbol{x}$是决策空间$\mathbb{S}$中的决策变量，具有$D$个维度。

对于决策变量$\boldsymbol{x}$，它在第j个约束下的违反程度可以用式（2）计算：

$$cv_j(\boldsymbol{x}) = \begin{cases} \max(0, g_j(\boldsymbol{x})), & j = 1, 2, \cdots, l \\ \max(0, h_j(\boldsymbol{x}) - \delta), & j = l+1, l+2, \cdots, k \end{cases} \tag{2}$$

其中δ表示一个非常小的正值，用于放松等式约束。此外，将每个约束下的违反程度相加，可以得到解$\boldsymbol{x}$的总体约束违反程度。

$$CV(\boldsymbol{x}) = \sum_{j=1}^{k} cv_j(\boldsymbol{x}) \tag{3}$$

定义1 可行解。对于一个解$\boldsymbol{x}$，当且仅当$CV(\boldsymbol{x}) = 0$时，解$\boldsymbol{x}$被称为可行解，否则为不可行解。

定义2 Pareto支配。对于任意的2个解$\boldsymbol{x}$和$\boldsymbol{y}$，如果$\boldsymbol{x}$Pareto支配$\boldsymbol{y}(\boldsymbol{x} \prec \boldsymbol{y})$，需要满足：$\forall i \in \{1, 2, \cdots, m\}$，且$f_i(\boldsymbol{x}) \leqslant f_i(\boldsymbol{y})$，同时$\exists f_j(\boldsymbol{x}) < f_j(\boldsymbol{y}), j \in \{1, 2, \cdots, m\}$。

定义3 Pareto最优解。如果一个解$\boldsymbol{x}$不被其他任何解支配，那么这个解为Pareto最优解。

定义4 Pareto最优解集。是指由所有Pareto最优解构成的集合。

定义5 Pareto前沿。是指Pareto最优解集映射在目标空间中形成的图像。

2 DPDSEA

2.1 算法框架

图2展示了DPDSEA的总体框架。首先，初始化生成主种群和副种群2个种群，进入算法的第一阶段。主种群与副种群分别独立进化，从2个种群中各自挑选父代产生子代1和子代2，合并2个子代进行种群的环境选择。主种群利用可行性规则进行更新，副种群利用改进的epsilon约束方法更新。当副种群进化到无约束Pareto前沿（Unconstrained Pareto Front，UPF）时，算法进入第二阶段。然后根据目前主种群与副种群的个体分布情况，对当前处理的CMOP进行分类，根据CMOP的类型选择是否采取随机扰动策略，生成子代3加入主种群的更新过程。循环上述过程，直至达到算法的终止条件，最后以主种群作为最终的结果输出。

算法1描述了DPDSEA的实现过程。首先对种群初始化，种群大小都设置为N（第1）行），设置当前为第一阶段和初始的*epislon*值（第2）、3）行）；其次进入算法主体循环，进行繁殖操作（第5）、6）行）；再次进行阶段转换的判断（第7）~9）行）和对CMOP的分类（第10）行），根据分类的结果选择合适的进化策略（第12）~18）行）。最后，对主种群和副种群进行环境选择（第19）、20）行）。

算法1 DPDSEA。

输入 种群大小N，最大代数$T_{\max}$，阶段转换参数λ；

输出 主种群***Pop***1。

1） 初始化种群大小为N的主种群***Pop***1和副种群***Pop***2
2） 设置当前搜索阶段*stage* = 1
3） 设置初始*epsilon* = +∞
4） while $t \leqslant T_{\max}$ do
5） 对***Pop***1进行繁殖操作产生$N/2$个子代***Off***1
6） 对***Pop***2进行繁殖操作产生$N/2$个子代***Off***2
7） 计算***Pop***2连续两代目标值差的绝对值*gap*
8） if *gap* ≤ λ then
9） *stage* = 2
10） 执行算法2对CMOP进行分类
11） end if
12） if *stage* = 2 and (*type* = 3 or 4) then
13） 利用式（4）更新*epislon*值
14） 判断***Pop***2是否进化到CPF附近，使用式（5）进行随机扰动，生成临时子代***Off***3
15） ***CP***1 = ***Off***1 ∪ ***Off***2 ∪ ***Off***3

中国知网 https://www.cnki.net

16)　else
17)　　$CP2 = Off1 \cup Off2$
18)　end if
19)　利用可行性规则对 $Pop1$ 进行环境选择
20)　利用改进的 epsilon 约束方法对 $Pop2$ 进行环境选择
21)　end while

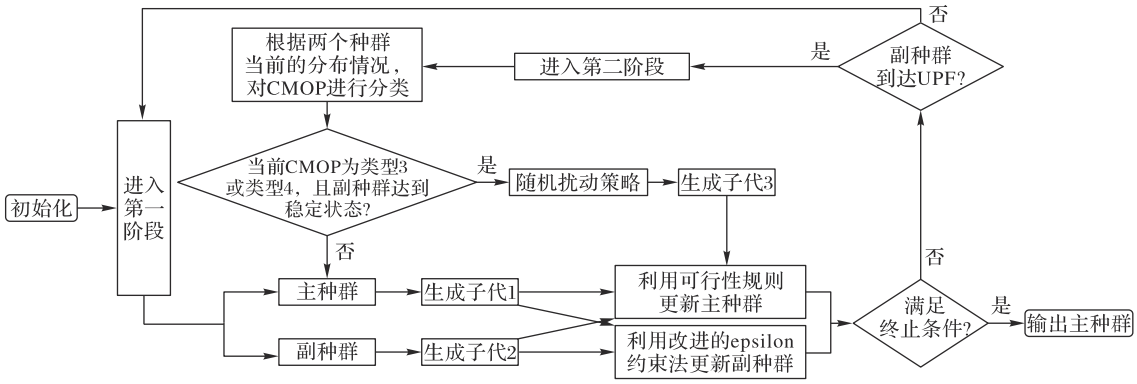


图 2　DPDSEA 的总体框架

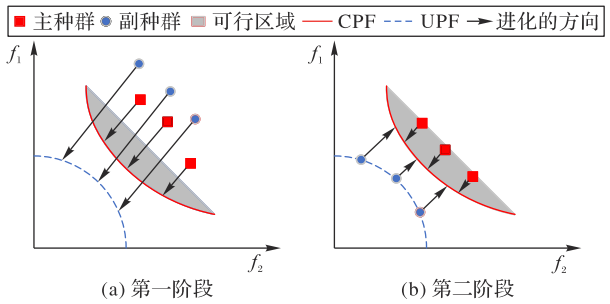
Fig. 2　Overall framework of DPDSEA

2.2　双种群双阶段进化机制

DPDSEA 设计了 2 个协同进化的种群,分别为主种群和副种群。虽然它们各自拥有不同的进化规则和目标,但两者可以通过子代信息共享实现协同合作。副种群在早期探索 UPF 时,能快速穿越不可行区域,并利用副种群中的解帮助主种群摆脱局部最优可行区域;而主种群找到的优秀可行解能提供 CPF 的位置信息,指引副种群后期向 CPF 进化。当副种群进化至 CPF 附近时,副种群个体在 CPF 附近呈均匀分布,具有较低的 CV(Constrained Violation)值和良好的目标值,帮助主种群在 CPF 上进一步收敛并提高解的多样性。

2 个种群在繁殖阶段只使用各自的种群信息,通过差分进化算子产生子代,子代个体携带了 2 个种群中的优秀信息,最后在环境选择阶段才合并 2 个种群的子代进行信息共享。因此,2 个种群的合作互补使算法能充分搜索空间,有助于算法更好地收敛至真正的 PF。

算法将搜索过程分为 2 个阶段,如图 3 所示,展示了 2 个种群在算法不同阶段的搜索方向。



(a) 第一阶段　　(b) 第二阶段

图 3　主种群与副种群在不同阶段的搜索方向

Fig. 3　Search directions of main population and secondary population at different stages

在第一阶段,算法注重全局搜索,主种群考虑约束条件,将种群快速收敛至可行区域内,在可行区域中搜索可行解;副种群不考虑约束条件,对目标空间进行全局搜索,帮助主种群跨越不可行障碍,直到种群收敛至 UPF。在第二阶段,计算副种群的可行率大小,根据 UPF 与 CPF 的位置关系,对当前处理的 CMOP 进行分类。主种群利用可行性规则,继续在可行区域内探索 CPF;副种群根据 CMOP 的类型执行改进的 epsilon 约束方法和随机扰动策略,将副种群从 UPF 向 CPF 牵引,保留位于 CPF 附近高质量的不可行解,利用这些解辅助主种群的进化,提高主种群在 CPF 上收敛性和多样性。

2.3　CMOP 的分类方法

由于不同类型 CMOP 的真实 PF 存在显著差异,本文提出基于 CPF 和 UPF 关系的分类方法,旨在帮助算法更好地识别问题特性,从而降低问题的复杂性。通过选择适合的约束处理方法,避免不必要的计算开销和搜索误差。

在第一阶段结束时,根据主种群和副种群的位置情况,对当前所处理的 CMOP 进行分类。根据 CPF 和 UPF 的关系[23],CMOP 可以分为 4 种类型。类型 1:CPF 与 UPF 完全相同;类型 2:CPF 是 UPF 的一部分;类型 3:CPF 与 UPF 部分重合;类型 4:CPF 与 UPF 完全分离。

因此,针对类型 1 和类型 2 的 CMOP,保持原有的搜索策略,不额外调整现有的约束处理方式。而对于类型 3 和类型 4 的 CMOP,选择改进的 epsilon 约束方法与随机扰动策略。通过这种分类和策略选择,算法能够在不同类型的 CMOP 上展现更强的适应性与更高的求解性能。

算法 2 描述了 CMOP 的分类方法。为了获取 CPF 与 UPF 的关系,在第一阶段要将主种群和副种群进化到 CPF 与 UPF,以主种群、副种群和当前搜索阶段作为算法的输入。首先,计算副种群的可行率大小(第 1)行),以此对 CMOP 类型进行初步区分。如果副种群的可行率为 1 或 0,表明 UPF 上的所有解都为可行解或不可行解,因此当前处理的 CMOP 可以视为类型 1 和 4(第 2)~5)行)。而对于类型 2 和 3 的问题,UPF 中既有可行解,也有不可行解。因此,需要同时利用主种群与副种群的信息进行判断。具体地,先将主种群与副种群合并,然后执行非支配排序,计算主种群中处于第一层非支配等级个体数占主种群个数的比例 $ratio$(第 7)~9)行)。当 $ratio \geqslant \alpha$ 时,则当前 CMOP 为类型 2,否则为类型 3(第 10)~14)行)。

算法 2　分类方法。

输入　主种群 $Pop1$,副种群 $Pop2$,当前阶段 $stage$;

输出　当前处理的 CMOP 类型 $type$。

1)　计算 $Pop2$ 的可行率 $Feasible_rate$
2)　if $Feasible_rate = 1$ then
3)　　$type = 1$
4)　else if $Feasible_rate = 0$ then

中国知网　https://www.cnki.net

5) $type = 4$
6) else
7) $\boldsymbol{Q} = \boldsymbol{Pop}1 \cup \boldsymbol{Pop}2$
8) 对联合种群 $\boldsymbol{Q}$ 进行非支配排序，得到每个个体的非支配等级
9) 计算联合种群 $\boldsymbol{Q}$ 中 $\boldsymbol{Pop}1$ 第一层的个体数在 $\boldsymbol{Pop}1$ 的占比 $ratio$
10) if $ratio \geqslant \alpha$ then
11) $type = 2$
12) else
13) $type = 3$
14) end if
15) end if

2.4 改进的 epsilon 约束方法

在算法的第一阶段，主要强调算法的收敛性，副种群只考虑目标值进化，最终收敛至 UPF。对于类型 1 和类型 2 的 CMOP，该方法非常有效，通过 2 个种群的协同进化，能帮助主种群快速通过目标空间中的不可行区域，找到真实 PF 所在的可行区域。而对于类型 3 和类型 4 这样的问题，它们的 CPF 与 UPF 交集较小甚至无交集，主种群与副种群之间相距较远，信息交互难以充分发挥作用。在这种情况下，副种群始终停留在远离可行区域的 UPF 上，不可行解无法为主种群提供有价值的指导，降低了算法的效率。

因此，为了有效促进两种群之间的信息传递，设计了一种改进的 epsilon 约束方法。通过逐步引导副种群向 CPF 靠近，使主种群和副种群的分布位置更接近，从而增强子代个体信息交互的有效性，提高算法对复杂约束问题的求解能力。具体的实现公式如下：

$$\varepsilon = \begin{cases} +\infty, & stage = 1 \\ \varepsilon_0\left(1 - \dfrac{t}{T_{\max}}\right)^{cp}, & (type = 3 \text{ or } 4) \text{ and } cp \geqslant 0 \end{cases} \tag{4}$$
$$\varepsilon_0 = CV_{\max}(\boldsymbol{x})$$
$$cp = -\ln(\varepsilon_0 + 6)/\ln(1 - p)$$

其中：ε_0 是指当前种群中的最大 CV 值；cp 是控制 ε 减小速率的参数，初始值为一个大于 0 的数；t 表示当前的进化代数；$T_{\max}$ 表示算法的最大代数；p 设置为 0.5。当算法处于第一阶段时，ε 值设置为 $+\infty$，相当于忽略约束条件搜索。在第二阶段时，根据当前 CMOP 的类型，判断 ε 值是否逐渐减小，实现副种群向 CPF 的牵引。

2.5 随机扰动策略

当 ε 值不再更新，且 $\boldsymbol{Pop}2$ 处于平稳状态时，此时种群将位于 CPF 的下方。可以利用随机扰动策略，使种群在一定的范围内波动，防止主种群的进化停滞，同时帮助主种群更好地接近真实 PF。这个扰动是基于高斯噪声的随机扰动，使用高斯分布生成扰动值。高斯分布的特点是大多数生成的值会集中在均值附近，极端值的出现概率较低。本文提出的随机扰动策略的原理是通过给每个决策变量添加一个小范围的随机噪声，引入一定程度的随机性。它的数学计算公式如下：

$$Offspring_{ij} = Offspring_{ij} + disturbance_{ij};$$
$$disturbance_{ij} = (upper_j - lower_j) \times \beta \times \mathrm{N}(0, 1) \tag{5}$$

其中：$Offspring_{ij}$ 表示第 i 个子代的第 j 个决策变量，$upper_j$ 和 $lower_j$ 分别是第 j 个决策变量的上下界，确定了每个变量的范围；β 是一个缩放因子，用于控制扰动的幅度，本文中设置为 0.01；$\mathrm{N}(0, 1)$ 是一个从标准正态分布中采样的随机变量，均值为 0、标准差为 1。可以用式(6)表示：

$$\mathrm{N}(0, 1) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} \tag{6}$$

通过引入小范围的随机扰动，可以帮助算法更好地探索搜索空间的细节，并且在保持种群主要特征的同时，增加个体的多样性，从而提高找到真实 PF 的概率。

3 实验与结果分析

为了验证 DPDSEA 的性能，将它与 BiCo[16]、c-DPEA[17]、CMOES[19]、dp-ACS[20]、CAEAD[21] 和 DDCMOEA（Dual-stage Dual-population Evolutionary Algorithm for Constrained Multiobjective Optimization）[24] 这 6 个具有代表性的算法进行对比实验。为了简洁明了地展示性能差异，本文采用了 3 种符号进行标注，“+”“-”和“≈”分别表示对比的 CMOEA 的性能优于、差于和接近于 DPDSEA，每个测试问题上最好结果以加粗显示。此外，所有实验均在 PlatEMO[25] 上进行。

3.1 测试函数

本文选择了 LIRCMOP[26] 和 DASCMOP[27] 评估套件检验 DPDSEA 的性能。其中 LIRCMOP 是目前常用的测试套件，包含 14 个测试问题，对现有的 CMOEA 是一个巨大的挑战，因为它的搜索空间较复杂，存在较大的不可行区域限制，可行区域被分割为离散的且互不连通的几块区域，一些问题的真实 PF 甚至为不连续的曲线。DASCMOP 是具有复杂约束条件的测试套件，其中包含 9 个 CMOP，并且每个 CMOP 的约束个数都较多，它具有可扩展性和难度可调性。在 DASCMOP 测试套件中，大多数问题的可行区域彼此分散，且与 UPF 相距甚远。

3.2 性能指标和参数设置

3.2.1 性能指标

为了综合评估不同算法的性能表现，在实验中采用了 2 种广泛认可的性能指标：反转世代距离（Inverted Generational Distance，IGD）[28] 和超体积（Hyper Volume，HV）[29]。

IGD 能够量化算法生成的解集与真实前沿之间的贴近程度。IGD 值越小，算法在多样性和收敛性方面表现越好，它的数学公式如下：

$$IGD(\boldsymbol{P}, \boldsymbol{Q}) = \frac{1}{|\boldsymbol{P}|}\sum_{\boldsymbol{v} \in \boldsymbol{P}} d(\boldsymbol{v}, \boldsymbol{Q}) \tag{7}$$

其中：$\boldsymbol{P}$ 是算法获得的最终解集，$|\boldsymbol{P}|$ 是分布在真实 PF 上的点集的个体数；$\boldsymbol{Q}$ 是分布在 PF 上均匀的参考点集；$d(\boldsymbol{v}, \boldsymbol{Q})$ 是 $\boldsymbol{P}$ 中个体 $\boldsymbol{v}$ 到种群 $\boldsymbol{Q}$ 的最小欧氏距离。

HV 通过评估非支配解集与预设参考点围成的体积反映解集的收敛和分布情况，它的数学公式如下：

$$V_{\mathrm{HV}} = vol\left(\bigcup_{i \in \boldsymbol{P}}\left[f_1(i), r_1\right] \times \left[f_2(i), r_2\right] \times \cdots \times \left[f_m(i), r_m\right]\right) \tag{8}$$

其中 $vol(\cdot)$ 表示 Lebesgue 度量，$\boldsymbol{P}$ 表示获得的近似 PF。与 IGD 类似，HV 也可以衡量 PF 近似的多样性和收敛性。HV 值越大，$\boldsymbol{P}$ 越接近真实 PF。

3.2.2 实验参数设置

为了保证实验的公平性，本文严格遵循了原论文中的参数设定，对所有参与比较的算法采用了统一的配置。每个算

中国知网 https://www.cnki.net

法的种群规模都设置为100,独立运行30次,以最大评价次数作为终止条件,其中LIRCMOP和DASCMOP测试集的最大评价次数都为300 000。对于LIRCMOP测试集,除了LIRCMOP13和LIRCMOP14的目标数为3外,其余测试问题的目标数均为2。对于DASCMOP测试集,DASCMOP1-6的目标数为2,其余测试问题的目标数均为3。

繁殖操作采用了模拟二进制交叉[30]与多项式变异[31]生成后代,以及差分进化[32]与多项式变异生成后代。其中,模拟二进制交叉的概率设置为1。多项式变异的概率设置为1/D。交叉和变异的分布指数都设置为20,交叉率CR = 1,缩放因子F = 0.5。

3.3　在LIRCMOP测试集上的比较结果

表1和表2为DPDSEA与6种CMOEA在LIRCMOP上的IGD和HV结果。其中LIRCMOP5、6和13是属于类型1的CMOP,LIRCMOP9和10属于类型2,LIRCMOP11和12属于类型3,其余问题属于类型4。

如表1所示,在LIRCMOP的14个问题中,DPDSEA在与6个CMOEA的比较结果中取得了8个最佳的IGD值,dp-ACS、CAEAD和DDCMOEA各取得了1个、2个和3个最优结果。如表2所示,DPDSEA取得了6个最佳的HV结果,CMOES、dp-ACS、c-DPEA、DDCMOEA分别在1、1、1、5个测试问题上取得了最优HV结果。

表1　DPDSEA与6种算法在LIRCMOP测试集上的IGD值对比

Tab. 1　Comparison of IGD values of DPDSEA and six algorithms on LIRCMOP test set

测试问题	CMOES		dp-ACS		c-DPEA		CAEAD		BiCo		DDCMOEA		DPDSEA	
	平均值	标准差	平均值	标准差	平均值	标准差	平均值	标准差	平均值	标准差	平均值	标准差	平均值	标准差
LIRCMOP1	1.542 6E−2	4.37E−3	2.859 6E−2	8.40E−3	1.171 8E−1	9.67E−2	1.040 6E−2	2.03E−3	1.072 7E−2	2.97E−3	**7.395 1E−3**	**8.87E−4**	8.767 1E−3	1.46E−3
LIRCMOP2	2.130 0E−2	1.14E−2	5.041 3E−2	4.00E−2	6.571 3E−2	3.17E−2	9.399 3E−3	2.31E−3	8.397 2E−3	3.26E−3	8.244 5E−3	1.32E−3	**6.868 8E−3**	**6.79E−4**
LIRCMOP3	6.598 6E−2	3.39E−2	2.269 6E−2	1.26E−2	9.925 3E−2	6.21E−2	**5.047 4E−3**	**3.20E−3**	1.354 2E−2	8.50E−3	6.184 5E−3	3.75E−3	8.536 4E−3	6.94E−3
LIRCMOP4	5.752 0E−2	2.99E−2	2.607 3E−2	1.49E−2	1.119 3E−1	7.33E−2	**5.066 8E−3**	**3.90E−3**	1.414 9E−2	1.06E−2	5.846 7E−3	4.22E−3	7.745 8E−3	7.41E−3
LIRCMOP5	5.382 5E−3	1.97E−4	5.202 6E−3	1.49E−3	7.115 9E−3	1.48E−3	5.159 4E−3	1.76E−4	5.334 9E−1	5.24E−1	5.854 0E−3	1.43E−3	**5.110 6E−3**	**1.62E−4**
LIRCMOP6	5.417 6E−3	1.87E−4	5.165 0E−3	1.36E−3	6.364 7E−3	2.01E−4	5.246 9E−3	1.22E−4	3.903 7E−1	5.90E−1	5.145 7E−3	1.24E−4	**5.132 5E−3**	**1.22E−4**
LIRCMOP7	7.254 1E−3	2.36E−4	8.383 3E−3	4.61E−4	7.139 8E−3	3.27E−4	7.180 2E−3	1.98E−4	9.596 8E−3	3.21E−3	8.342 4E−3	6.02E−3	**7.045 7E−3**	**1.13E−4**
LIRCMOP8	7.261 4E−3	2.01E−4	8.269 2E−3	5.62E−4	7.128 6E−3	1.92E−4	7.172 1E−3	2.33E−4	8.107 6E−3	2.29E−3	**6.839 2E−3**	**3.70E−4**	7.063 3E−3	1.77E−4
LIRCMOP9	2.674 0E−3	7.27E−5	4.191 7E−3	1.71E−4	4.387 0E−2	3.70E−2	2.811 3E−3	8.24E−5	1.050 3E−1	6.37E−2	3.083 5E−3	9.99E−4	**2.611 5E−3**	**6.27E−5**
LIRCMOP10	4.728 0E−3	1.64E−4	5.606 5E−3	2.09E−4	4.572 2E−3	1.59E−4	4.755 0E−3	1.46E−4	4.553 9E−2	8.62E−2	**4.140 3E−3**	**1.09E−4**	4.518 9E−3	1.44E−4
LIRCMOP11	2.402 0E−3	5.05E−5	2.611 6E−3	1.68E−4	2.371 5E−3	4.01E−5	2.387 4E−3	4.72E−5	3.926 5E−3	5.32E−3	2.362 0E−3	3.77E−5	**2.331 8E−3**	**3.51E−5**
LIRCMOP12	3.078 3E−3	1.87E−4	3.671 7E−3	2.92E−4	3.009 1E−3	5.04E−5	3.015 3E−3	1.81E−4	7.987 4E−3	7.46E−3	2.995 2E−3	7.00E−5	**2.959 2E−3**	**1.56E−4**
LIRCMOP13	1.068 7E−1	1.60E−3	**9.341 5E−2**	**1.11E−4**	9.384 4E−2	7.74E−4	1.069 2E−1	1.36E−3	9.374 2E−2	1.10E−3	9.806 9E−2	1.08E−3	9.366 4E−2	1.23E−3
LIRCMOP14	9.996 2E−2	1.13E−3	9.665 2E−2	3.72E−4	9.574 1E−2	8.88E−4	9.992 9E−2	1.17E−3	9.602 2E−2	1.15E−3	1.011 9E−1	1.02E−3	**9.523 7E−2**	**7.43E−4**
+/−/=	0/14/0		0/13/1		0/10/4		2/9/3		0/13/1		4/6/4			

表2　DPDSEA与6种算法在LIRCMOP测试集上的HV值对比

Tab. 2　Comparison of HV values of DPDSEA and six algorithms on LIRCMOP test set

测试问题	CMOES		dp-ACS		c-DPEA		CAEAD		BiCo		DDCMOEA		DPDSEA	
	平均值	标准差	平均值	标准差	平均值	标准差	平均值	标准差	平均值	标准差	平均值	标准差	平均值	标准差
LIRCMOP1	2.328 1E−1	3.24E−3	2.235 5E−1	7.02E−3	1.906 0E−1	2.94E−2	2.355 6E−1	8.87E−4	2.342 6E−1	2.51E−3	**2.371 8E−1**	**3.10E−4**	2.360 7E−1	1.27E−3
LIRCMOP2	3.503 2E−1	6.52E−3	3.290 8E−1	2.41E−2	3.276 8E−1	1.51E−2	3.572 1E−1	1.71E−3	3.580 1E−1	1.70E−3	3.587 8E−1	4.84E−4	**3.588 1E−1**	**5.85E−4**
LIRCMOP3	1.782 6E−1	1.53E−2	1.985 1E−1	5.25E−3	1.691 2E−1	2.10E−2	2.060 7E−1	1.89E−3	2.026 6E−1	3.67E−3	**2.080 7E−1**	**5.48E−4**	2.039 9E−1	4.17E−3
LIRCMOP4	2.899 9E−1	1.39E−2	3.036 9E−1	6.05E−3	2.660 3E−1	3.56E−2	3.148 1E−1	2.30E−3	3.114 6E−1	4.74E−3	**3.160 0E−1**	**1.43E−3**	3.133 9E−1	3.60E−3
LIRCMOP5	2.920 1E−1	9.55E−5	2.919 1E−1	1.13E−3	2.908 9E−1	1.22E−3	2.921 3E−1	8.85E−5	1.514 6E−1	1.27E−1	2.915 7E−1	1.05E−3	**2.921 5E−1**	**8.88E−5**
LIRCMOP6	1.972 1E−1	1.05E−4	1.973 4E−1	7.44E−4	1.967 6E−1	9.99E−5	1.973 2E−1	8.65E−5	1.338 8E−1	8.50E−2	1.973 6E−1	7.07E−5	**1.973 8E−1**	**7.81E−5**
LIRCMOP7	2.945 6E−1	1.19E−4	2.936 5E−1	3.47E−4	2.944 9E−1	4.02E−4	2.946 3E−1	9.09E−5	2.920 1E−1	3.07E−3	2.937 9E−1	3.78E−3	**2.946 6E−1**	**5.65E−5**
LIRCMOP8	2.945 5E−1	1.19E−4	2.936 1E−1	4.42E−4	2.946 4E−1	7.42E−5	2.946 3E−1	1.08E−4	2.936 8E−1	2.27E−3	2.946 4E−1	1.09E−4	**2.946 5E−1**	**9.52E−5**
LIRCMOP9	**5.675 4E−1**	**6.53E−5**	5.662 1E−1	1.94E−4	5.555 0E−1	9.59E−3	5.674 3E−1	6.80E−5	5.377 4E−1	1.77E−2	5.671 6E−1	8.17E−4	5.675 3E−1	5.36E−5
LIRCMOP10	7.076 9E−1	1.09E−4	7.065 6E−1	1.41E−4	7.080 6E−1	9.11E−5	7.076 0E−1	1.03E−4	6.866 8E−1	4.51E−2	**7.082 0E−1**	**7.21E−5**	7.077 5E−1	7.93E−5
LIRCMOP11	6.940 0E−1	1.26E−5	6.936 9E−1	8.83E−5	6.940 4E−1	8.89E−6	6.940 2E−1	8.50E−6	6.929 3E−1	3.87E−3	**6.940 5E−1**	**4.45E−6**	6.940 1E−1	9.22E−6
LIRCMOP12	6.202 9E−1	2.31E−5	6.200 3E−1	1.27E−4	**6.203 6E−1**	**4.98E−6**	6.203 2E−1	1.50E−5	6.180 4E−1	3.26E−3	6.203 1E−1	3.17E−6	6.203 2E−1	1.79E−5
LIRCMOP13	5.292 9E−1	2.37E−3	**5.562 5E−1**	**3.51E−4**	5.546 6E−1	1.45E−3	5.292 1E−1	2.46E−3	5.544 4E−1	1.56E−3	5.518 6E−1	1.70E−3	5.544 9E−1	1.73E−3
LIRCMOP14	5.452 9E−1	1.69E−3	5.547 1E−1	5.55E−4	5.538 0E−1	1.69E−3	5.455 5E−1	1.80E−3	5.544 1E−1	1.56E−3	5.511 4E−1	1.12E−3	**5.547 6E−1**	**1.13E−3**
+/−/=	0/13/1		1/12/1		3/8/3		3/7/4		0/7/7		5/5/4			

CMOES在处理不可行区域较大的问题时,难以定位至CPF所在的可行区域,导致后续的均匀搜索效果变差。dp-ACS和c-DPEA在处理可行区域狭窄的问题时,辅助种群难以从大量的不可行解中获取有用信息,导致算法的多样性表现较差。对于可行区域较多的问题,CAEAD的辅助种群无法对每个可行区域充分探索,难以获得其潜在的有用信息。BiCo利用基于角度的选择机制,能选择靠近约束边界的不可行解,但是对于这些解的利用能力有限。在DDCMOEA中,辅助种群通过权重向量被牵引至CPF附近。虽然这一方法增加了解的多样性,但是对于与CPF不相交的权重向量,

中国知网　https://www.cnki.net

生成的解不仅对算法的性能提升有限，还会消耗较多的计算资源，导致它无法在有限的评价次数内取得较好的结果。

相比之下，DPDSEA 在 LIRCMOP 测试问题中表现更加出色。这得益于其合理的双种群双阶段进化机制，能够同时搜索并有效利用可行解与不可行解。在第一阶段，以收敛性和可行性为主，副种群仅考虑目标值进化，为主种群跨越不可行区域提供助力；在第二阶段，更关注算法的多样性，利用改进的 epsilon 约束方法和随机扰动策略，提高对不可行区域的探索能力，获得接近真实 PF 且目标值良好的不可行解，从而帮助算法在真实 PF 上更好地收敛。因此，DPDSEA 在性能上展现了显著的优势。

为了更直观展示各种算法的性能，图 4 绘制了 7 种算法在 LIRCMOP2 上获得的最终解分布情况。从图 4 可以看到，LIRCMOP2 测试问题中的搜索空间被大面积的不可行区域包围，真实 PF 只是一条非常狭窄的曲线。CMOES、dp-ACS 和 c-DPEA 的最终解仅能分布在真实 PF 的部分区域，CAEAD、BiCo 和 DDCMOEA 虽然覆盖了大部分的 PF，但仍存在明显缝隙。相比之下，DPDSEA 的解能均匀地分布在整个 CPF 上，显著提升了解集的覆盖率与分布均匀性。这一点在 IGD 结果中得到了具体体现：在 6 种对比算法中，IGD 值最接近 DPDSEA 的分别为 8.397 2E−3 和 9.399 3E−3，而 DPDSEA 的 IGD 值为 6.868 8E−3。与其他算法相比，DPDSEA 的 IGD 值至少降低了 18%，这一改进在复杂的约束多目标优化问题中，尤其是在高精度要求的场景下，能带来显著的优化效果。

3.4 在 DASCMOP 测试集上的比较结果

表 3 和表 4 为 DPDSEA 与 6 种 CMOEA 在 DASCMOP 上的 IGD 和 HV 结果。DASCMOP 测试集中所有问题均为类型 4 的 CMOP。

由表 3 可知，DPDSEA 在 DASCMOP 测试集上取得了 7 个最优的 IGD 值。只有 CMOES 和 c-DPEA 各在 1 个测试问题上优于 DPDSEA，其余算法均无法取得优于 DPDSEA 的 IGD 结果。

由表 4 可知，DPDSEA 取得了 6 个最好的 HV 值，CMOES、BiCo 分别在 1、2 个测试问题上取得了最佳结果。DPDSEA 在进化过程中，能够对问题进行分类，针对 CMOP 的类型自适应选择合适的进化策略，使得算法对于不同类型问题的适应能力更强。因此，DPDSEA 在 DASCMOP 测试集上的综合表现更好。

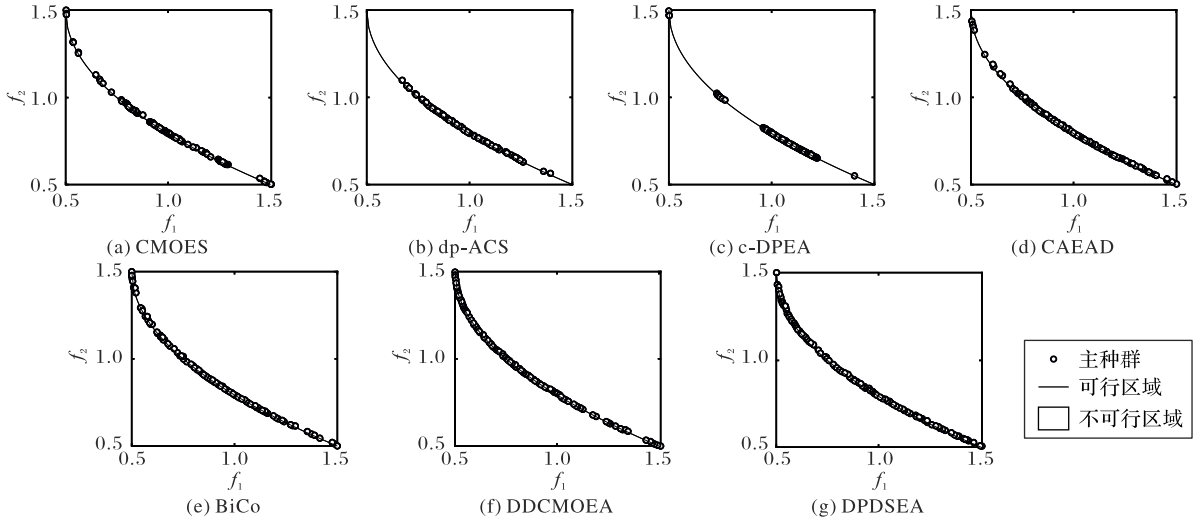


图 4 DPDSEA 与 6 种对比算法在 LIRCMOP2 上获得的最终解

Fig. 4 Final solution obtained by DPDSEA and 6 comparison algorithms on LIRCMOP2

表 3 DPDSEA 与 6 种算法在 DASCMOP 测试集上的 IGD 值对比

Tab. 3 Comparison of IGD values of DPDSEA and six algorithms on DASCMOP test set

测试问题	CMOES		dp-ACS		c-DPEA		CAEAD		BiCo		DDCMOEA		DPDSEA	
	平均值	标准差	平均值	标准差	平均值	标准差	平均值	标准差	平均值	标准差	平均值	标准差	平均值	标准差
DASCMOP1	3.010 7E−3	2.20E−4	4.663 9E−3	1.19E−3	2.144 7E−2	4.62E−2	2.809 5E−3	1.34E−4	1.752 1E−1	2.32E−1	3.035 9E−3	5.53E−4	**2.782 0E−3**	**1.89E−4**
DASCMOP2	7.855 4E−3	1.94E−2	5.561 3E−3	2.35E−4	1.560 3E−2	1.32E−2	5.812 1E−3	8.78E−3	7.917 5E−2	3.38E−2	1.098 6E−2	1.67E−2	**4.209 6E−3**	**7.96E−5**
DASCMOP3	**1.893 5E−2**	**1.77E−3**	1.940 1E−2	2.02E−3	1.134 8E−1	6.77E−2	2.007 3E−2	5.47E−3	1.754 6E−1	8.09E−2	1.374 1E−1	5.68E−2	1.907 6E−2	1.25E−3
DASCMOP4	1.832 0E−3	1.23E−3	1.811 0E−3	7.67E−5	1.293 8E−3	5.37E−4	1.153 6E−3	1.54E−5	1.152 1E−3	3.27E−5	1.146 5E−3	1.21E−5	**1.145 7E−3**	**1.51E−5**
DASCMOP5	3.618 5E−3	4.20E−4	3.774 2E−3	2.36E−4	3.105 2E−3	2.36E−4	3.329 0E−3	2.45E−4	2.779 3E−3	6.55E−5	2.754 9E−3	4.36E−5	**2.748 4E−3**	**8.97E−5**
DASCMOP6	1.945 8E−2	2.26E−4	2.106 1E−2	2.61E−3	1.928 2E−2	1.57E−3	1.942 1E−2	4.51E−3	1.873 0E−2	2.20E−2	1.829 4E−2	2.61E−3	**1.812 4E−2**	**5.74E−3**
DASCMOP7	4.060 1E−2	2.57E−3	3.833 5E−2	6.72E−4	3.126 0E−2	6.11E−4	3.834 8E−2	2.18E−3	3.175 7E−2	7.74E−4	3.246 3E−2	8.00E−4	**3.113 6E−2**	**5.12E−4**
DASCMOP8	4.827 9E−2	4.31E−3	4.744 1E−2	1.13E−3	**4.017 8E−2**	**8.05E−4**	4.644 2E−2	6.22E−3	4.090 6E−2	8.55E−4	4.199 4E−2	8.82E−4	4.075 8E−2	7.70E−4
DASCMOP9	4.122 5E−2	1.03E−3	4.941 0E−2	1.76E−3	4.278 7E−2	2.09E−3	4.113 7E−2	1.03E−3	4.160 0E−2	1.09E−3	4.204 6E−2	8.95E−4	**4.024 6E−2**	**9.93E−4**
+/−/=	1/8/0		0/9/0		1/6/2		0/5/4		0/6/3		0/5/4			

图 5 绘制了 7 种算法在 DASCMOP2 上获得的最终种群。从图 5 可以看到，DASCMOP2 的可行区域被不可行区域分成了许多离散且狭小的区域，使问题的求解变得非常困难。其中：c-DPEA、BiCo 只能探索到部分的 CPF，难以保留位于 CPF 两端的个体，性能表现较差；而 CMOES、dp-ACS、CAEAD 和 DDCMOEA 都展现出了较好的性能，都能找到一组收敛良好

中国知网 https://www.cnki.net

且分布均匀的可行解,但是它们在稳定性方面较差,因此在DASCMOP2上的平均表现不如DPDSEA。与6种对比算法相比,DPDSEA的IGD值比其他算法降低了至少24%,显示出更强的算法性能。

表4　DPDSEA与6种算法在DASCMOP测试集上的HV值对比

Tab. 4　Comparison of HV values of DPDSEA and six algorithms on DASCMOP test set

测试问题	CMOES		dp-ACS		c-DPEA		CAEAD		BiCo		DDCMOEA		DPDSEA	
	平均值	标准差	平均值	标准差	平均值	标准差	平均值	标准差	平均值	标准差	平均值	标准差	平均值	标准差
DASCMOP1	2.126 2E−1	2.97E−4	2.004 2E−1	3.58E−3	2.058 9E−1	1.18E−2	2.127 5E−1	3.20E−4	1.658 7E−1	5.36E−2	2.122 7E−1	9.35E−4	**2.129 1E−1**	**1.96E−4**
DASCMOP2	3.537 5E−1	7.80E−3	3.541 9E−1	1.72E−4	3.471 2E−1	7.92E−3	3.544 5E−1	4.53E−3	3.153 3E−1	1.13E−2	3.526 6E−1	6.41E−3	**3.552 7E−1**	**6.36E−5**
DASCMOP3	3.122 0E−1	1.66E−4	3.116 1E−1	4.63E−4	2.829 0E−1	1.66E−2	3.115 9E−1	4.36E−3	2.617 7E−1	1.94E−2	2.661 4E−1	1.61E−2	**3.122 6E−1**	**1.28E−4**
DASCMOP4	2.034 6E−1	1.59E−3	2.039 7E−1	7.83E−5	2.038 3E−1	1.54E−3	2.042 8E−1	7.83E−5	2.043 2E−1	8.74E−5	**2.043 3E−1**	**4.58E−5**	2.043 0E−1	6.43E−5
DASCMOP5	3.504 5E−1	4.07E−4	3.504 6E−1	2.42E−4	3.512 2E−1	2.80E−4	3.506 2E−1	2.75E−4	3.515 3E−1	1.33E−4	3.516 1E−1	1.16E−4	**3.516 3E−1**	**1.47E−4**
DASCMOP6	3.121 0E−1	2.73E−4	3.099 0E−1	2.00E−3	3.114 8E−1	2.26E−3	3.115 6E−1	3.51E−3	3.104 2E−1	8.30E−3	**3.124 3E−1**	**9.01E−5**	3.115 7E−1	3.88E−3
DASCMOP7	2.811 0E−1	1.11E−3	2.830 4E−1	1.44E−3	2.882 8E−1	4.13E−4	2.823 8E−1	1.23E−3	2.873 8E−1	3.08E−4	2.876 7E−1	3.72E−4	**2.883 0E−1**	**3.68E−4**
DASCMOP8	2.013 8E−1	1.46E−3	2.059 7E−1	7.26E−4	2.067 9E−1	6.25E−4	2.015 7E−1	3.81E−3	2.061 9E−1	4.91E−4	2.065 2E−1	4.53E−4	**2.068 6E−1**	**5.33E−4**
DASCMOP9	2.045 4E−1	3.90E−4	2.038 8E−1	5.75E−4	2.060 7E−1	4.19E−4	2.046 4E−1	5.86E−4	**2.063 2E−1**	**4.63E−4**	2.062 6E−1	3.67E−4	2.049 6E−1	4.49E−4
+/−/=	1/7/1		0/9/0		1/6/2		0/4/5		2/6/1		3/5/1			

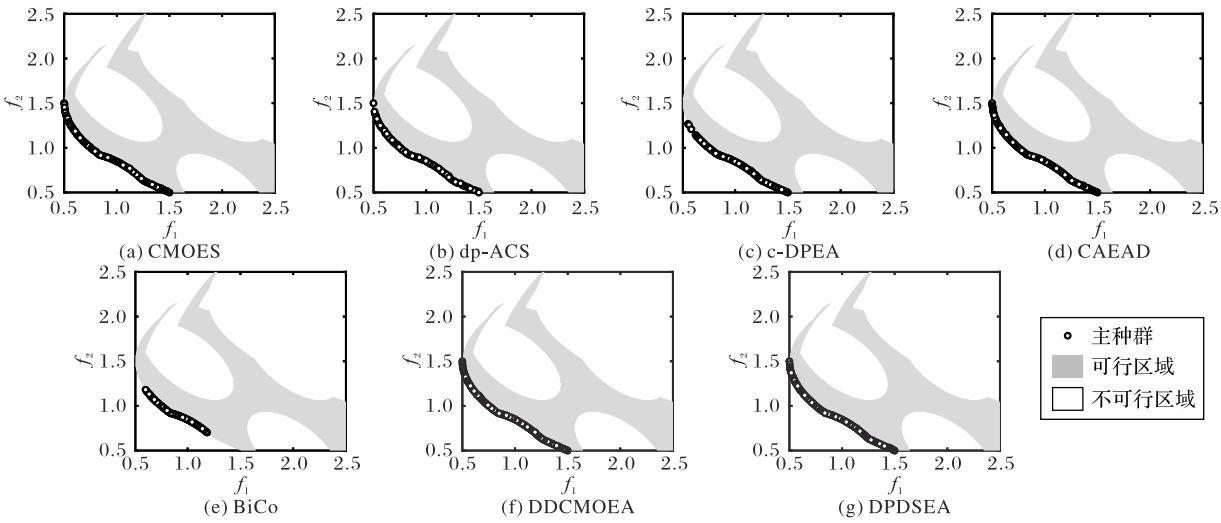


图5　DPDSEA与6种对比算法在DASCMOP2上获得的最终解

Fig. 5　Final solution obtained by DPDSEA and 6 comparison algorithms on DASCMOP2

3.5　策略有效性验证

为了进一步验证所提出的改进的epsilon约束方法和随机扰动策略,设计了DPDSEA的2个变体进行对比实验。其中:DPDSEA1仅使用了随机扰动策略,不使用改进的epsilon约束方法;而DPDSEA2仅使用了改进的epsilon约束方法,不使用随机扰动策略。

从表5和表6可以看出,DPDSEA在DASCMOP测试集上的所有问题都取得了最优的IGD平均值,在HV方面取得7个最优结果,综合下来,DPDSEA的性能表现最好。实验结果表明,所提出的改进的epsilon约束方法和随机扰动策略对算法的收敛性和多样性都有显著的提升,验证了DPDSEA的有效性。

表5　DPDSEA与它的两种变体在DASCMOP测试集上的IGD值对比

Tab. 5　Comparison of IGD values of DPDSEA and its two variants on DASCMOP test set

测试问题	DPDSEA1		DPDSEA2		DPDSEA	
	平均值	标准差	平均值	标准差	平均值	标准差
DASCMOP1	3.087 8E−1	2.87E−1	9.808 1E−2	1.80E−1	**2.782 0E−3**	**1.89E−4**
DASCMOP2	1.095 9E−1	3.51E−2	8.612 7E−2	3.71E−2	**4.209 6E−3**	**7.96E−5**
DASCMOP3	1.766 4E−1	5.32E−2	2.410 3E−1	4.83E−2	**1.907 6E−2**	**1.25E−3**
DASCMOP4	1.625 7E−3	8.06E−4	1.365 7E−3	2.46E−4	**1.145 7E−3**	**1.51E−5**
DASCMOP5	3.625 0E−3	4.33E−4	3.034 9E−3	1.60E−4	**2.748 4E−3**	**8.97E−5**
DASCMOP6	1.965 8E−2	9.00E−4	1.938 5E−2	4.51E−3	**1.812 4E−2**	**5.74E−3**
DASCMOP7	4.499 8E−2	4.74E−3	3.789 4E−2	3.69E−3	**3.113 6E−2**	**5.12E−4**
DASCMOP8	5.065 5E−2	5.48E−3	4.555 2E−2	5.83E−3	**4.075 8E−2**	**7.70E−4**
DASCMOP9	4.134 9E−2	9.26E−4	4.069 3E−2	9.08E−4	**4.024 6E−2**	**9.93E−4**
+/−/=	0/8/1		0/7/2			

中国知网　https://www.cnki.net

表 6 DPDSEA 与它的两种变体在 DASCMOP 测试集上的 HV 值对比

Tab. 6 Comparison of HV values of DPDSEA and its two variants on DASCMOP test set

测试问题	DPDSEA1		DPDSEA2		DPDSEA	
	平均值	标准差	平均值	标准差	平均值	标准差
DASCMOP1	1.360 9E−1	5.97E−2	1.858 7E−1	4.03E−2	**2.129 1E−1**	**1.96E−4**
DASCMOP2	3.062 7E−1	1.16E−2	3.142 7E−1	1.11E−2	**3.552 7E−1**	**6.36E−5**
DASCMOP3	2.635 4E−1	9.71E−3	2.566 7E−1	1.35E−2	**3.122 6E−1**	**1.28E−4**
DASCMOP4	2.037 4E−1	3.69E−4	2.039 0E−1	2.69E−4	**2.043 0E−1**	**6.43E−5**
DASCMOP5	3.503 9E−1	4.21E−4	3.510 9E−1	2.15E−4	**3.516 3E−1**	**1.47E−4**
DASCMOP6	**3.118 2E−1**	**8.79E−4**	3.116 1E−1	3.47E−3	3.115 7E−1	3.88E−3
DASCMOP7	2.789 6E−1	2.08E−3	2.823 5E−1	2.14E−3	**2.883 0E−1**	**3.68E−4**
DASCMOP8	2.005 6E−1	1.78E−3	2.018 6E−1	2.58E−3	**2.068 6E−1**	**5.33E−4**
DASCMOP9	2.043 6E−1	5.04E−4	**2.050 3E−1**	**4.14E−4**	2.049 6E−1	4.49E−4
+/−/=	0/8/1		0/7/2			

3.6 实例验证

为了验证算法在实际优化问题中的有效性，将 DPDSEA 与 6 种对比算法在汽车侧面碰撞问题[33]上测试。该问题需要同时最小化汽车的重量、乘客所承受的力以及负责承受冲击的 V 柱的平均速度，是一个三目标的 CMOP，具有 7 个决策变量和 10 个不等式约束，涉及腹部负荷、耻骨力和 V 柱速度等极限值。

每种算法在该问题上的种群大小设置为 100，最大评价次数为 100 000，并且独立运行 30 次，比较每个算法所获得的 HV 平均值和标准差。实验结果如表 7 所示，在汽车侧面碰撞问题中，DPDSEA 的 HV 平均值和标准差均表现最好。因此，DPDSEA 在处理实际优化问题时也比较有优势。

表 7 DPDSEA 与 6 种算法在汽车侧面碰撞问题上的 HV 值对比

Tab. 7 Comparison of HV values of DPDSEA and six algorithms on car side impact problem

算法	平均值	标准差
CMOES	4.039 6E−3	3.68E−5
dp-ACS	4.046 7E−3	6.61E−5
c-DPEA	4.192 4E−3	4.34E−5
CAEAD	4.199 7E−3	4.83E−5
BiCo	4.154 2E−3	8.87E−5
DDCMOEA	4.118 2E−3	3.96E−5
DPDSEA	**4.221 7E−3**	**3.59E−5**

4 结语

本文针对包含复杂约束条件的 CMOP，提出了一种双种群双阶段的进化算法 DPDSEA。通过双种群机制有效规避了算法陷入局部最优的问题，并设计了两阶段的搜索策略，旨在平衡算法的收敛性和多样性。具体地，在第一阶段主种群与副种群分别向 CPF 与 UPF 进化，以获取它们之间的关系；在第二阶段，根据获得的 CPF 与 UPF 关系，设计了一种 CMOP 的分类方法，针对不同类型的 CMOP 设计相应的进化策略。此外，通过改进的 epsilon 约束方法，使得不可行解种群更接近真实 PF，为主种群提供更有价值的信息。同时，设计了一种随机扰动策略，在副种群无法更接近真实 PF 时对副种群进行扰动，产生对主种群进化有帮助的可行解。为了验证 DPDSEA 的性能，与其他 6 种具有代表性的算法进行对比实验，实验结果表明，所提算法在解决包含复杂约束条件的 CMOP 方面具有显著优势。

此外，DPDSEA 在处理高维 CMOP 时还存在一定的局限性。当目标数增加时，DPDSEA 难以精准定位到 UPF，需要花费大量的时间，进而可能影响后续算法流程的效率。在未来的工作中，希望设计更合理的方法来寻找 UPF，并优化阶段转换机制，进一步提高算法的性能。

参考文献（References）

[1] CHEN G, ZHANG W, QI L, et al. Constrained multi-objective trans-media maneuver trajectory optimization for morphing unmanned aerial-underwater vehicles [J]. Ocean Engineering, 2024, 299: No. 117380.

[2] ZHANG Z, ZHANG H, TIAN Y, et al. Cooperative constrained multi-objective dual-population evolutionary algorithm for optimal dispatching of wind-power integrated power system [J]. Swarm and Evolutionary Computation, 2024, 87: No. 101525.

[3] HE X, LV C. Toward personalized decision making for autonomous vehicles: a constrained multi-objective reinforcement learning technique [J]. Transportation Research Part C: Emerging Technologies, 2023, 156: No. 104352.

[4] 陈少淼，陈瑞，梁伟，等. 面向复杂约束优化问题的进化算法综述[J]. 软件学报，2023，34(2)：565-581.（CHEN S M, CHEN R, LIANG W, et al. Overview of evolutionary algorithms for complex constrained optimization problems [J]. Journal of Software, 2023, 34(2): 565-581.）

[5] 朱亚文，周红标，李杨，等. 约束多目标进化算法研究进展[J]. 计算机应用研究，2022，39(9)：2582-2590，2602.（ZHU Y W, ZHOU H B, LI Y, et al. Research progress of constrained multi-objective evolutionary algorithms [J]. Application Research of Computers, 2022, 39(9): 2582-2590, 2602.）

[6] 李笠，李广鹏，常亮，等. 约束进化算法及其应用研究综述[J]. 计算机科学，2021，48(4)：1-13.（LI L, LI G P, CHANG L, et al. Survey of constrained evolutionary algorithms and their applications[J]. Computer Science, 2021, 48(4): 1-13.）

[7] MA Z, WANG Y. Shift-based penalty for evolutionary constrained multiobjective optimization and its application [J]. IEEE Transactions on Cybernetics, 2023, 53(1): 18-30.

[8] WANG B C, LI H X, LI J P, et al. Composite differential evolution for constrained evolutionary optimization[J]. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 2019, 49(7): 1482-1495.

[9] GU Q, BAI J, LI X, et al. A constrained multi-objective evolutionary algorithm based on decomposition with improved constrained dominance principle [J]. Swarm and Evolutionary Computation, 2022, 75: No. 101162.

[10] SONG S, ZHANG K, ZHANG L, et al. A dual-population algorithm based on self-adaptive epsilon method for constrained

中国知网 https://www.cnki.net

multi-objective optimization [J]. Information Sciences, 2024, 655: No. 119906.
[11] GU Q, WANG Q, XIONG N N, et al. Surrogate-assisted evolutionary algorithm for expensive constrained multi-objective discrete optimization problems [J]. Complex and Intelligent Systems, 2022, 8(4): 2699-2718.
[12] PENG C, LIU H L, GU F. An evolutionary algorithm with directed weights for constrained multi-objective optimization [J]. Applied Soft Computing, 2017, 60: 613-622.
[13] URIBE L, LARA A, SCHÜTZE O. On the efficient computation and use of multi-objective descent directions within constrained MOEAs [J]. Swarm and Evolutionary Computation, 2020, 52: No. 100617.
[14] TIAN Y, ZHANG T, XIAO J, et al. A coevolutionary framework for constrained multiobjective optimization problems [J]. IEEE Transactions on Evolutionary Computation, 2020, 25 (1): 102-116.
[15] FAN Z, LI W, CAI X, et al. Push and pull search for solving constrained multi-objective optimization problems [J]. Swarm and Evolutionary Computation, 2019, 44: 665-679.
[16] LIU Z Z, WANG B C, TANG K. Handling constrained multiobjective optimization problems via bidirectional coevolution [J]. IEEE Transactions on Cybernetics, 2022, 52(10): 10163-10176.
[17] MING M, TRIVEDI A, WANG R, et al. A dual-population-based evolutionary algorithm for constrained multiobjective optimization [J]. IEEE Transactions on Evolutionary Computation, 2021, 25(4): 739-753.
[18] SUN R, ZOU J, LIU Y, et al. A multistage algorithm for solving multiobjective optimization problems with multiconstraints [J]. IEEE Transactions on Evolutionary Computation, 2023, 27(5): 1207-1219.
[19] MING F, GONG W, JIN Y. Even search in a promising region for constrained multi-objective optimization [J]. IEEE/CAA Journal of Automatica Sinica, 2024, 11(2): 474-486.
[20] YANG K, ZHENG J, ZOU J, et al. A dual-population evolutionary algorithm based on adaptive constraint strength for constrained multi-objective optimization [J]. Swarm and Evolutionary Computation, 2023, 77: No. 101247.
[21] ZOU J, SUN R, YANG S, et al. A dual-population algorithm based on alternative evolution and degeneration for solving constrained multi-objective optimization problems [J]. Information Sciences, 2021, 579: 89-102.
[22] MA H, WEI H, TIAN Y, et al. A multi-stage evolutionary algorithm for multi-objective optimization with complex constraints [J]. Information Sciences, 2021, 560: 68-91.
[23] LIANG J, BAN X, YU K, et al. A survey on evolutionary constrained multiobjective optimization [J]. IEEE Transactions on Evolutionary Computation, 2023, 27(2): 201-221.
[24] MING M, WANG R, ISHIBUCHI H, et al. A novel dual-stage dual-population evolutionary algorithm for constrained multiobjective optimization [J]. IEEE Transactions on Evolutionary Computation, 2022, 26(5): 1129-1143.
[25] TIAN Y, CHENG R, ZHANG X, et al. PlatEMO: a Matlab platform for evolutionary multi-objective optimization [educational forum] [J]. IEEE Computational Intelligence Magazine, 2017, 12(4): 73-87.
[26] FAN Z, LI W, CAI X, et al. An improved epsilon constraint-handling method in MOEA/D for CMOPs with large infeasible regions [J]. Soft Computing, 2019, 23(23): 12491-12510.
[27] FAN Z, LI W, CAI X, et al. Difficulty adjustable and scalable constrained multiobjective test problem toolkit [J]. Evolutionary Computation, 2020, 28(3): 339-378.
[28] BOSMAN P A N, THIERENS D. The balance between proximity and diversity in multiobjective evolutionary algorithms [J]. IEEE Transactions on Evolutionary Computation, 2003, 7(2): 174-188.
[29] ZITZLER E, THIELE L. Multiobjective evolutionary algorithms: a comparative case study and the strength Pareto approach [J]. IEEE Transactions on Evolutionary Computation, 1999, 3(4): 257-271.
[30] DEB K, AGRAWAL R B. Simulated binary crossover for continuous search space [J]. Complex Systems, 1995, 9(2): 115-148.
[31] DEB K, GOYAL M. A combined Genetic Adaptive Search (GeneAS) for engineering design [J]. Journal of Computer Science and Informatics, 1996, 26: 30-45.
[32] LI H, ZHANG Q. Multiobjective optimization problems with complicated Pareto sets, MOEA/D and NSGA-Ⅱ [J]. IEEE Transactions on Evolutionary Computation, 2009, 13 (2): 284-302.
[33] JAIN H, DEB K. An evolutionary many-objective optimization algorithm using reference-point based nondominated sorting approach, part Ⅱ: handling constraints and extending to an adaptive approach [J]. IEEE Transactions on Evolutionary Computation, 2014, 18(4): 602-622.

This work is partially supported by National Key Research and Development Program (2023YFF1105101, 2023YFF1104201); Guangdong Province Science and Technology Innovation Special Fund (SDZX2023032).

YUAN Zhichao, born in 2000, M. S. candidate. His research interests include multi-objective optimization, evolutionary computation.

YANG Lei, born in 1978, Ph. D., lecturer. His research interests include data mining, evolutionary computation.

TIAN Jinglin, born in 1998, M. S. candidate. His research interests include multi-objective optimization, evolutionary computation.

WEI Xiaowei, born in 1998, M. S. candidate. His research interests include multi-objective optimization, evolutionary computation.

LI Kangshun, born in 1962, Ph. D., professor. His research interests include machine learning, artificial intelligence.

中国知网 https://www.cnki.net



XINXI JISHU BEIJINGXIA KEJI QINGBAO YANJIU YU
KEJI XINXI YUNFUWU TANSUO

信息技术背景下科技情报研究与科技信息云服务探索

赖志杰　杨　磊　著

東北林業大學出版社
Northeast Forestry University Press

版权所有　侵权必究
举报电话:0451-82113295

图书在版编目(CIP)数据

信息技术背景下的科技情报研究与科技信息云服务探索
/赖志杰，杨磊著. —哈尔滨：东北林业大学出版社，2017.5
ISBN　978-7-5674-1136-4

Ⅰ. ①信…　Ⅱ. ①赖…　②杨…　Ⅲ. ①科技情报
工作－研究　②计算机网络－应用－科技情报－情报服务
Ⅳ. ①G255.51②G252.7

中国版本图书馆 CIP 数据核字(2017)第 146438 号

图书策划:国中频媒
责任编辑:王翠燕
封面设计:赫小平
出版发行:东北林业大学出版社(哈尔滨市香坊区哈平六道街 6 号　邮编:150040)
印　　装:哈尔滨圣铂印刷有限公司
开　　本:787mm × 1092mm　1/16
印　　张:10.25
字　　数:200 千字
版　　次:2017 年 8 月第 1 版
印　　次:2017 年 8 月第 1 次印刷
定　　价:36.00 元

发现印装质量问题,请与出版社联系调换。(电话:0451-82113296　82191620)

赖志
传播学硕
技信息可
管,是广
目评审专
学技术情
息协会和
15 项,参
论文 16 篇

杨
华南农业
挖掘、农业
东省企业
多篇,其中
项。主持

断进步，我国科技情报
发展过程并不是一帆风
问题，笔者进行了相关
技情报研究与科技信息
都包含两个章节。本书
的相关内容展开论述
发展趋势和国家科技情
的主要内容包括中国情
析方法。中篇的主要内
中篇的第一章主要分析
主要介绍了信息技术时
科技信息云服务的相关
了分析总结。下篇的第
篇的第二章探索了我国
为我国科技情报研究行

著者

2017 年 4 月

目 录

上篇 我国情报与科技情报浅谈

第一章 全球科技创新中心战略情报 …… (1)
第一节 全球科技创新发展趋势及国家科技创新战略 …… (1)
第二节 全球企业之间合作的信息安全问题及安全体系的建立 … (25)
第三节 国家科技创新投入与科技创新中心 …… (37)
第二章 中国情报工作与情报学 …… (46)
第一节 我国情报研究发展史 …… (46)
第二节 科技情报服务与科技信息资源检索 …… (59)
第三节 情报分析法 …… (71)
第四节 情报研究比较 …… (82)

中篇 信息技术背景下科技情报研究工作

第一章 科技情报与信息技术 …… (87)
第一节 科技情报工作与信息技术绪论 …… (87)
第二节 信息技术的情报分析方法研究 …… (93)
第三节 基于互联网的情报收集技术解析 …… (96)
第二章 信息技术时代的科技情报工作 …… (102)
第一节 科技情报业务系统相关信息安全技术发展 …… (102)
第二节 信息技术时代科技情报服务的相关思考 …… (105)
第三节 信息技术时代科技情报工作的机遇与变革 …… (111)

下篇 科技信息云服务研究及科技情报信息化发展探索

第一章 科学技术信息以及网络服务 …… (115)
第一节 科学技术信息的探索以及网络服务的关键技术 …… (115)
第二节 基础设施即服务(IAAS) …… (117)
第三节 平台即服务(PAAS) …… (118)
第四节 软件即服务(SAAS) …… (122)
第五节 科学技术信息安全 …… (124)
第二章 我国科技情报信息化发展探索 …… (132)
第一节 科技资源的重组利用 …… (132)
第二节 基于数据、网络的科技工作 …… (140)
第三节 数据条件下的科学技术信息的难题 …… (143)
参考文献 …… (148)

证书号第8301261号

专利公告信息

发明专利证书

发明名称：基于约束多目标进化算法的区域农业种植结构优化方法、装置、设备及介质

专利权人：华南农业大学

地　　址：510640 广东省广州市天河区五山路483号

发 明 人：杨磊;魏晓威;梁早清;田井林;袁志超;徐振林;雷红涛

专　利　号：ZL 2024 1 1808636.9　　授权公告号：CN 119991330 B

专利申请日：2024年12月10日　　授权公告日：2025年09月26日

申请日时申请人：华南农业大学

申请日时发明人：杨磊;魏晓威;梁早清;田井林;袁志超;徐振林;雷红涛

国家知识产权局依照中华人民共和国专利法进行审查，决定授予专利权，并予以公告。

专利权自授权公告之日起生效。专利权有效性及专利权人变更等法律信息以专利登记簿记载为准。

局长
申长雨

国家知识产权局
2025年09月26日

证书号第5764803号

发明专利证书

发 明 名 称：基于向量角粒子群的农田多目标控制排水模型的求解方法

发 明 人：杨磊;胡鑫;黄康

专 利 号：ZL 2020 1 1088524.2

专利申请日：2020年10月13日

专 利 权 人：华南农业大学

地 址：510640 广东省广州市天河区五山路483号

授权公告日：2023年03月03日　　授权公告号：CN 112182948 B

国家知识产权局依照中华人民共和国专利法进行审查，决定授予专利权，颁发发明专利证书并在专利登记簿上予以登记。专利权自授权公告之日起生效。专利权期限为二十年，自申请日起算。

专利证书记载专利权登记时的法律状况。专利权的转移、质押、无效、终止、恢复和专利权人的姓名或名称、国籍、地址变更等事项记载在专利登记簿上。

局长
申长雨

国家知识产权局
2023年03月03日

其他事项参见续页

证书号第5764803号

专利权人应当依照专利法及其实施细则规定缴纳年费。本专利的年费应当在每年10月13日前缴纳。未按照规定缴纳年费的，专利权自应当缴纳年费期满之日起终止。

申请日时本专利记载的申请人、发明人信息如下：

申请人：

华南农业大学

发明人：

杨磊;胡鑫;黄康

中华人民共和国国家版权局
计算机软件著作权登记证书

证书号：软著登字第16267658号

软件名称：基于Pathformer的多数据时序预测小程序V1.0

著作权人：华南农业大学

权利取得方式：原始取得

权利范围：全部权利

登记号：2025SR1611460

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局 计算机软件著作权登记专用章

2025年08月25日

中华人民共和国国家版权局
计算机软件著作权登记证书

证书号：软著登字第15066371号

软件名称：基于区块链技术的稻米溯源云平台后台管理系统
[简称：稻米溯源管理系统]
V1.0

著作权人：华南农业大学;阳江市漠阳香农业发展有限公司;广东新智农信息科技有限公司

权利取得方式：原始取得

权利范围：全部权利

登记号：2025SR0410173

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局
计算机软件著作权登记专用章

2025年03月07日

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号： 软著登字第11552709号

软 件 名 称： 基于数据挖掘的精准施肥决策系统后台管理系统
[简称：精准施肥管理系统]
V1.0

著 作 权 人： 华南农业大学

开发完成日期： 2023年03月01日

首次发表日期： 未发表

权利取得方式： 原始取得

权 利 范 围： 全部权利

登 记 号： 2023SR0965536

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局
计算机软件著作权登记专用章

2023年08月23日

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号： 软著登字第11845329号

软 件 名 称： 基于深度学习的新冠疫情预测系统
[简称：新冠疫情预测系统]
V1.0

著 作 权 人： 华南农业大学

开发完成日期： 2023年05月24日

首次发表日期： 未发表

权利取得方式： 原始取得

权 利 范 围： 全部权利

登 记 号： 2023SR1258156

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局
计算机软件著作权登记专用章

2023年10月18日

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号： 软著登字第9984109号

软 件 名 称： 基于LSTM的预测小程序
V1.0

著 作 权 人： 华南农业大学

开发完成日期： 2022年04月10日

首次发表日期： 未发表

权利取得方式： 原始取得

权 利 范 围： 全部权利

登 记 号： 2022SR1029910

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局
计算机软件著作权
登记专用章

No. 11370702

2022年08月08日

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号： 软著登字第8062811号

软 件 名 称： 基于贝叶斯信念网络的茶树病害智能诊断后台系统
[简称：IDMIS of tea plant diseases]
V1.0

著 作 权 人： 华南农业大学

开发完成日期： 2021年06月20日

首次发表日期： 未发表

权利取得方式： 原始取得

权 利 范 围： 全部权利

登 记 号： 2021SR1340185

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局
计算机软件著作权
登记专用章

No. 08201359

2021年09月08日

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号： 软著登字第6422600号

软 件 名 称： CMA-ES 及变种算法测试系统
V1.0

著 作 权 人： 华南农业大学

开发完成日期： 2020年08月10日

首次发表日期： 未发表

权利取得方式： 原始取得

权 利 范 围： 全部权利

登 记 号： 2020SR1621628

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局
计算机软件著作权
登记专用章

No. 06769035

2020年11月23日

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号： 软著登字第6425138号

软 件 名 称： 基于信息素权值的多目标蚁群优化算法系统 V1.0

著 作 权 人： 华南农业大学

开发完成日期： 2020年08月30日

首次发表日期： 未发表

权利取得方式： 原始取得

权 利 范 围： 全部权利

登 记 号： 2020SR1624166

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局 计算机软件著作权登记专用章

No. 06773962

2020年11月23日

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号： 软著登字第5417971号

软 件 名 称： 函数发现与预测软件
[简称：FDP]
V1.0

著 作 权 人： 华南农业大学

开发完成日期： 2020年03月01日

首次发表日期： 未发表

权利取得方式： 原始取得

权 利 范 围： 全部权利

登 记 号： 2020SR0539275

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局
计算机软件著作权
登记专用章

No. 05768956

2020年05月29日

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号：软著登字第4440603号

软件名称：Geatpy高性能实用型进化算法工具箱平台
[简称：Geatpy EA Toolkit]
V1.0

著作权人：华南农业大学

开发完成日期：2019年06月01日

首次发表日期：2019年07月01日

权利取得方式：原始取得

权利范围：全部权利

登记号：2019SR1019846

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局
计算机软件著作权
登记专用章

No. 04575523

2019年10月09日

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号：软著登字第3086312号

软件名称：基于数据挖掘技术的茶树病害智能诊疗系统
[简称：茶树病害诊疗系统]
V1.0

著作权人：华南农业大学

开发完成日期：2018年07月09日

首次发表日期：2018年07月09日

权利取得方式：原始取得

权利范围：全部权利

登记号：2018SR757217

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局
计算机软件著作权
登记专用章
2018年09月18日

No. 03011716

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号： 软著登字第2136996号

软 件 名 称： 猪病智能诊疗系统
[简称：The Intelligent Diagnosis System of Pig’s Disease]
V1.0

著 作 权 人： 华南农业大学

开发完成日期： 2017年05月17日

首次发表日期： 2017年05月17日

权利取得方式： 原始取得

权 利 范 围： 全部权利

登 记 号： 2017SR551712

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局
计算机软件著作权
登记专用章

2017年09月27日

No. 01998206

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号：软著登字第2136993号

软件名称：基于NFC和二维码的农产品可溯源APP软件
[简称：Traceability APP software based on NFC and QR]
V1.0

著作权人：华南农业大学

开发完成日期：2017年05月17日

首次发表日期：2017年05月17日

权利取得方式：原始取得

权利范围：全部权利

登记号：2017SR551709

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局
计算机软件著作权
登记专用章
2017年09月27日

No. 01998205

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号： 软著登字第1487895号

软 件 名 称： 动植物药品信息监管追溯服务平台
[简称：Drug Regulatory Information Management Platform]
V1.0

著 作 权 人： 华南农业大学

开发完成日期： 2016年03月01日

首次发表日期： 2016年04月01日

权利取得方式： 原始取得

权 利 范 围： 全部权利

登 记 号： 2016SR309278

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局
计算机软件著作权
登记专用章
2016年10月27日

No. 01293532

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号： 软著登字第1487832号

软 件 名 称： 畜禽免疫任务提醒系统
[简称：Livestock Immunization Task Reminder]
V1.0

著 作 权 人： 华南农业大学

开发完成日期： 2016年03月01日

首次发表日期： 2016年04月01日

权利取得方式： 原始取得

权 利 范 围： 全部权利

登 记 号： 2016SR309215

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局
计算机软件著作权
登记专用章
2016年10月27日

No. 01293509

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号：软著登字第1251289号

软件名称：基于改进基因表达式程序设计的短期蔬菜价格智能预测软件
[简称：STVPFT based on IGEP]
V1.0

著作权人：华南农业大学

开发完成日期：2015年09月10日

首次发表日期：2015年10月01日

权利取得方式：原始取得

权利范围：全部权利

登记号：2016SR072672

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局
计算机软件著作权
登记专用章
2016年04月11日

No. 01008011

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号： 软著登字第0940545号

软 件 名 称： 基于RFID和进化加密二维码的智能农产品溯源系统
[简称：IAP traceability system]
V1.0

著 作 权 人： 华南农业大学

开发完成日期： 2014年09月10日

首次发表日期： 2014年12月01日

权利取得方式： 原始取得

权 利 范 围： 全部权利

登 记 号： 2015SR053459

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局
计算机软件著作权
登记专用章

2015年03月25日

No. 00680679

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号：　软著登字第0940475号

软 件 名 称：基于信息素排斥蚁群算法的分类规则挖掘软件
[简称：NEWIMPantminer]
V1.0

著 作 权 人：华南农业大学

开发完成日期：2014年09月10日

首次发表日期：2014年12月01日

权利取得方式：原始取得

权 利 范 围：全部权利

登 记 号：2015SR053389

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局
计算机软件著作权
登记专用章
2015年03月25日

No. 00681836

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号：软著登字第4314940号

软件名称：FMS视频会议系统
[简称：Video Conference System based on FMS]
V1.0

著作权人：华南农业大学

开发完成日期：2019年05月30日

首次发表日期：2019年06月09日

权利取得方式：原始取得

权利范围：全部权利

登记号：2019SR0894183

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局
计算机软件著作权
登记专用章
2019年08月28日

No. 04431185

中华人民共和国国家版权局
计算机软件著作权登记证书

证书号：软著登字第16267653号

软件名称：基于知识图谱的计算机组成原理综合人工智能知识问答系统
V1.0

著作权人：华南农业大学

权利取得方式：原始取得

权利范围：全部权利

登记号：2025SR1611455

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局
计算机软件著作权登记专用章

2025年08月25日

中华人民共和国国家版权局
计算机软件著作权登记证书

证书号：　软著登字第15860392号

软 件 名 称：　《C语言程序设计》课程泛在学习系统V1.0

著 作 权 人：　华南农业大学

权利取得方式：　原始取得

权 利 范 围：　全部权利

登　记　号：　2025SR1204194

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局 计算机软件著作权登记专用章

2025年07月09日

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号： 软著登字第7635558号

软 件 名 称： 基于 SPOC 和翻转课堂的《计算机组成原理》泛在学习APP系统
[简称：ubiquitous learning app]
V1.0

著 作 权 人： 华南农业大学

开发完成日期： 2021年03月25日

首次发表日期： 未发表

权利取得方式： 原始取得

权 利 范 围： 全部权利

登 记 号： 2021SR0912932

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局
计算机软件著作权
登记专用章

No. 08180288

2021年06月18日

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号： 软著登字第7635577号

软 件 名 称： 《计算机组成原理》泛在学习后台管理系统
[简称：ubiquitous learning MS]
V1.0

著 作 权 人： 华南农业大学

开发完成日期： 2021年03月25日

首次发表日期： 未发表

权利取得方式： 原始取得

权 利 范 围： 全部权利

登 记 号： 2021SR0912951

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局
计算机软件著作权
登记专用章

No. 08180307

2021年06月18日

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号： 软著登字第4307596号

软 件 名 称： 教师课程教学环节管理系统
[简称：Teaching Link MIS]
V1.0

著 作 权 人： 华南农业大学

开发完成日期： 2019年05月30日

首次发表日期： 2019年06月09日

权利取得方式： 原始取得

权 利 范 围： 全部权利

登 记 号： 2019SR0886839

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局
计算机软件著作权
登记专用章

2019年08月27日

No. 04410745

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号：软著登字第2130838号

软 件 名 称：基于SPOC的数据库技术学习系统
[简称：Database technology learning system based on SPOC]
V1.0

著 作 权 人：华南农业大学

开发完成日期：2017年05月17日

首次发表日期：2017年05月17日

权利取得方式：原始取得

权 利 范 围：全部权利

登 记 号：2017SR545554

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局
计算机软件著作权
登记专用章

2017年09月26日

No. 02000277

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号：软著登字第1614810号

软件名称：课外学习APP系统
[简称：Extra-Curricular Learning App]
V1.0

著作权人：华南农业大学

开发完成日期：2016年03月01日

首次发表日期：2016年04月01日

权利取得方式：原始取得

权利范围：全部权利

登记号：2017SR029526

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局
计算机软件著作权
登记专用章
2017年02月04日

No. 01424209

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号： 软著登字第5789713号

软 件 名 称： 《计算机组成原理》课外移动学习APP系统 V1.0

著 作 权 人： 华南农业大学

开发完成日期： 2020年06月02日

首次发表日期： 未发表

权利取得方式： 原始取得

权 利 范 围： 全部权利

登 记 号： 2020SR0911017

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

No. 06205410

中华人民共和国国家版权局 计算机软件著作权登记专用章

2020年08月11日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导麦祖文荣获第十六届蓝桥杯全国软件和信息技术专业人才大赛全国总决赛Java软件开发大学B组二等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：1605028503

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2025年6月23日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导谭皓荣获第十六届蓝桥杯全国软件和信息技术专业人才大赛全国总决赛Java软件开发大学B组二等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：1605028568

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2025年6月23日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导江正宏荣获第十六届蓝桥杯全国软件和信息技术专业人才大赛全国总决赛Python程序设计大学B组三等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：1633030558

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2025年6月23日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导彭渝淇荣获第十六届蓝桥杯全国软件和信息技术专业人才大赛全国总决赛Python程序设计大学B组三等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：1633031631

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2025年6月23日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导谢雨杨荣获第十六届蓝桥杯全国软件和信息技术专业人才大赛全国总决赛C/C++程序设计大学B组三等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：1602113240

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2025年6月23日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导谭皓荣获第十五届蓝桥杯全国软件和信息技术专业人才大赛全国总决赛C/C++程序设计大学B组二等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：021563777

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2024年6月2日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导蔡依珂荣获第十五届蓝桥杯全国软件和信息技术专业人才大赛全国总决赛C/C++程序设计大学B组三等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：021564191

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2024年6月2日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导蔡依珂荣获第十四届蓝桥杯全国软件和信息技术专业人才大赛全国总决赛C/C++程序设计大学A组三等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：011417235

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2023年6月16日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导范裕燨荣获第十四届蓝桥杯全国软件和信息技术专业人才大赛全国总决赛C/C++程序设计大学B组优秀奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：021454861

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2023年6月16日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导范裕燨荣获第十三届蓝桥杯全国软件和信息技术专业人才大赛全国总决赛C/C++程序设计大学B组三等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：021359418

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2022年6月27日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导谭皓荣获第十三届蓝桥杯全国软件和信息技术专业人才大赛全国总决赛C/C++程序设计大学B组三等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：021359406

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2022年6月27日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导蔡依珂荣获第十三届蓝桥杯全国软件和信息技术专业人才大赛全国总决赛C/C++程序设计大学A组优秀奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：011314151

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2022年6月27日

2020

Interdisciplinary Contest In Modeling®

Certificate of Achievement

Be It Known That The Team Of

Jianfan Lu
Zexin Xu
Jingyi Lin

With Faculty Advisor

Lei Yang

Of

South China Agricultural University

Was Designated As

Honorable Mention

Amanda Beecher, Contest Director

Administered by

COMAP

Kayla Blyman, Head Judge

With support from

AMS ASA informs MAA siam

CPIPC
中国研究生
创新实践系列大赛

获奖证书

证书编号：243143

《基于深度学习和群体智能算法的区域共享单车需求预测及调度优化项目》

荣获2024年第十届中国研究生智慧城市技术与创意设计大赛

三等奖

参赛单位：华南农业大学
团队成员：王凯欣 赵品杰 袁志超
指导老师：杨磊

中国学位与研究生教育学会

二〇二四年十二月

中国科协青少年科技中心



获 奖 证 书

Certificate of Achievement



颁给/Awarded to

华南农业大学 / South China Agricultural University

何展宁 / He Zhanning, 张俊杰 / Zhang Junjie, 曾庆烨 / Zeng Qingye

杨磊(教练) / Yang Lei(Coach)

银奖/ Silver Medal

2020年中国大学生程序设计竞赛威海站

2020 China Collegiate Programming Contest, Weihai Site

哈尔滨工业大学（威海） 2020年10月/ Harbin Institute of Technology， Weihai, October 2020



G2020WHT034U022S3



中国大学生程序设计竞赛组委会，主席

Committee for CCPC, Chairman

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导麦祖文荣获第十六届蓝桥杯全国软件和信息技术专业人才大赛广东赛区Java软件开发大学B组一等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：1605014585

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2025年5月26日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导谭皓荣获第十六届蓝桥杯全国软件和信息技术专业人才大赛广东赛区Java软件开发大学B组一等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：1605014398

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2025年5月26日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导江正宏荣获第十六届蓝桥杯全国软件和信息技术专业人才大赛广东赛区Python程序设计大学B组一等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：1633015875

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2025年5月26日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导彭渝淇荣获第十六届蓝桥杯全国软件和信息技术专业人才大赛广东赛区Python程序设计大学B组一等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：1633015768

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2025年5月26日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导谢雨杨荣获第十六届蓝桥杯全国软件和信息技术专业人才大赛广东赛区C/C++程序设计大学B组一等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：1602056566

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2025年5月26日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导梁祖宁荣获第十六届蓝桥杯全国软件和信息技术专业人才大赛广东赛区Python程序设计大学B组二等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：1633015866

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2025年5月26日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导陈颖豪荣获第十六届蓝桥杯全国软件和信息技术专业人才大赛广东赛区C/C++程序设计大学B组三等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：1602058349

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2025年5月26日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导杨谨瑄荣获第十六届蓝桥杯全国软件和信息技术专业人才大赛广东赛区C/C++程序设计大学B组三等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：1602058627

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2025年5月26日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导蔡依珂荣获第十五届蓝桥杯全国软件和信息技术专业人才大赛广东赛区C/C++程序设计大学B组一等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：021548170

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2024年4月29日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导谭皓荣获第十五届蓝桥杯全国软件和信息技术专业人才大赛广东赛区C/C++程序设计大学B组一等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：021549647

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2024年4月29日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导蓝逸荣获第十五届蓝桥杯全国软件和信息技术专业人才大赛广东赛区C/C++程序设计大学B组二等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：021548913

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2024年4月29日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导马梓楠荣获第十五届蓝桥杯全国软件和信息技术专业人才大赛广东赛区C/C++程序设计大学B组二等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：021549144

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2024年4月29日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导陈智霖荣获第十五届蓝桥杯全国软件和信息技术专业人才大赛广东赛区Java软件开发大学B组二等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：051512297

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2024年4月29日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导麦祖文荣获第十五届蓝桥杯全国软件和信息技术专业人才大赛广东赛区Java软件开发大学B组二等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：051512392

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2024年4月29日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导范裕燨荣获第十五届蓝桥杯全国软件和信息技术专业人才大赛广东赛区C/C++程序设计大学B组三等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：021548082

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2024年4月29日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导黄日华荣获第十五届蓝桥杯全国软件和信息技术专业人才大赛广东赛区C/C++程序设计大学B组三等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：021548509

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2024年4月29日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导潘丽春荣获第十五届蓝桥杯全国软件和信息技术专业人才大赛广东赛区C/C++程序设计大学B组三等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：021550290

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2024年4月29日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导梁书源荣获第十五届蓝桥杯全国软件和信息技术专业人才大赛广东赛区Java软件开发大学B组三等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：051512401

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2024年4月29日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导蔡依珂荣获第十四届蓝桥杯全国软件和信息技术专业人才大赛广东赛区C/C++程序设计大学A组一等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：011412572

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2023年4月23日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导谭皓荣获第十四届蓝桥杯全国软件和信息技术专业人才大赛广东赛区C/C++程序设计大学B组一等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：021435712

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2023年4月23日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导范裕燨荣获第十四届蓝桥杯全国软件和信息技术专业人才大赛广东赛区C/C++程序设计大学B组一等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：021435717

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2023年4月23日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导梁书源荣获第十四届蓝桥杯全国软件和信息技术专业人才大赛广东赛区C/C++程序设计大学B组二等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：021435783

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2023年4月23日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导麦祖文荣获第十四届蓝桥杯全国软件和信息技术专业人才大赛广东赛区C/C++程序设计大学B组二等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：021435805

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2023年4月23日

蓝桥杯大赛

获奖证书

华南农业大学杨磊：

指导刘启健荣获第十四届蓝桥杯全国软件和信息技术专业人才大赛广东赛区C/C++程序设计大学B组三等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：021435660

证件号码：410711197809240099

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2023年4月23日

中国高校计算机大赛

2021微信小程序应用开发赛

获 | 奖 | 证 | 书

华南赛区二等奖

参赛作品

泛在学习系统

指导老师

杨　磊　　华南农业大学

参赛成员

吴楚升	华南农业大学
何泓锋	华南农业大学
林立民	华南农业大学
林勇威	华南农业大学

大赛组委会主任

主办单位

全国高等学校计算机教育研究会

防伪二维码

微信扫一扫
在线验证

清華大學 Tsinghua University　微信

GDCA

2022泛珠三角+大学生计算机作品赛广东选拔赛暨广东省“品高杯”本科组大学生计算机作品赛

奖励证书

获奖项目： LSTM预测小程序

获奖等级： 三等奖

获 奖 者： 周彬鑫、钟志鹏、张渊才、林枫

指导老师： 杨磊

获奖学校： 华南农业大学

证书编号： BK2022038

（证书查询）

广东省计算机学会

2022年6月

GDCA

2021“华资杯”广东省大学生计算机作品赛
暨泛珠三角+大学生计算机作品赛
广东省赛(本科组)

奖 励 证 书

获奖项目： 基于 SPOC 与翻转课堂的《计算机组成原理》泛在学习微信小程序

获奖等级： 三等奖

获 奖 者： 何泓锋 林立民 吴楚升 林勇威

指导老师： 杨磊

获奖学校： 华南农业大学

证书编号： 2021FZSGDBK007

（证书查询）

广东省计算机学会

2021年10月

GDCA

2021“华资杯”广东省大学生计算机作品赛
暨泛珠三角+大学生计算机作品赛
广东省赛(本科组)

奖 励 证 书

获奖项目： 基于贝叶斯网络的茶树病害智能诊断专家系统

获奖等级： 三等奖

获 奖 者： 冯明月 林泽莉 王凯欣 何惠豪 周泽骏

指导老师： 杨磊

获奖学校： 华南农业大学

证书编号： 2021FZSGDBK017

（证书查询）

广东省计算机学会

2021年10月

GDCA

2020“华资杯”广东省大学生计算机作品赛
暨泛珠三角+大学生计算机作品赛
广东选拔赛(本科组)

奖 励 证 书

获奖项目： 基于分段优化GEP的双模式预测平台

获奖等级： 三等奖

获 奖 者： 徐瑞 汪炜 陆健帆

指导老师： 杨磊

获奖学校： 华南农业大学

证书编号： 2020FZSGDBK31

（证书查询）

广东省计算机学会

2020年9月

荣誉证书

杨 磊 同志：

被评为华南农业大学“教书育人”先进个人，特发此证，以资鼓励。

中共华南农业大学委员会
华南农业大学

二〇二〇年八月

奖状

杨 磊 同志：

在2024年度 教学 工作中成绩突出，授予“十佳工作者”称号。

特发此证，以资鼓励。

华南农业大学数学与信息学院 软件学院

2025年1月

荣誉证书

杨 磊 同志：

在2023年度 教学 工作中成绩突出，授予“十佳工作者”称号。特发此证，以资鼓励。

华南农业大学数学与信息学院 软件学院

2024年1月

荣誉证书

杨磊 同志：

在2020年度 科技 工作中成绩突出，授予“十佳工作者”称号。特发此证，以资鼓励。

华南农业大学数学与信息学院 软件学院

二〇二一年一月

荣誉证书

杨 磊 同志：

在2019年度 教学 工作中成绩突出，授予“十佳工作者”称号。特发此证，以资鼓励。

华南农业大学数学与信息学院 软件学院

二〇二〇年一月

荣誉证书

杨磊 同志：

在 2017 年度 教学 工作中成绩突出，授予“十佳工作者”称号。特发此证，以资鼓励。

华南农业大学数学与信息学院

二〇一八年一月

荣誉证书

杨磊同志：

荣获数学与信息学院2016年度“十佳管理工作者”称号。特颁此证，以资鼓励。

数学与信息学院

二〇一六年十二月

荣誉证书

杨磊 老师：

荣获华南农业大学信息学院 软件学院2012-2013学年就业工作积极分子称号。

特发此证，以资鼓励。

信息学院 软件学院

二〇一四年十二月

教职工业绩成果报表

姓　　名	杨磊	工　　号	30003008	所在单位	数学与信息学院、软件学院		
年　　龄	48	职　　称	讲师	学　　历	博士研究生毕业	学　　位	工学博士学位
岗位类别	专业技术	一级分类	教师	二级分类	教学科研型	岗位级别	专业技术岗位9级
年度考核结果	2015年：优秀； 2016年：合格； 2017年：优秀； 2018年：合格； 2019年：优秀； 2020年：合格； 2021年：合格； 2022年：合格； 2023年：合格； 2024年：优秀； 2025年：优秀						