PlatEMO

进化多目标优化平台

用户手册 3.2

生物智能与知识发现（BIMK）研究所

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非常感谢使用由安徽大学生物智能与知识发现（BIMK）研究所开发的进化多目标优化平台 PlatEMO。本平台是一个开源免费的代码库，仅供教学与科研使用，不得用于商业用途。本平台中的代码基于作者对论文的理解编写而成，作者不对用户因使用代码产生的任何后果负责。包含利用本平台产生的数据的论文应在正文中声明对 PlatEMO 的使用，并引用以下参考文献：

Ye Tian, Ran Cheng, Xingyi Zhang, and Yaochu Jin, “PlatEMO: A MATLAB platform for evolutionary multi-objective optimization [educational forum],” IEEE Computational Intelligence Magazine, 2017, 12(4): 73-87.

如有任何意见或建议，欢迎联系 field910921@gmail.com（田野）。如想将您的代码添加进 PlatEMO 中并公开，也欢迎联系 field910921@gmail.com。您可以在 GitHub 上获取 PlatEMO 的最新版本。

目　录

一 快速入门

软件要求：MATLAB R2018a 或以上（不使用 PlatEMO 图形界面）或
MATLAB R2020b 或以上（使用 PlatEMO 图形界面）及
并行计算工具箱 和
统计与机器学习工具箱

PlatEMO 提供一系列的元启发式算法用于求解各类优化问题。为此，用户需要定义优化问题、选择求解算法并设置参数。PlatEMO 提供以下三种调用方式：

1) 带参数调用主函数：

```
platemo('problem',@SOP_F1,'algorithm',@GA,'Name',Value,…);
```

可以利用指定的算法来求解指定的测试问题并设置参数，求解结果可以被显示在窗口中、保存在文件中或作为函数返回值（参阅*求解测试问题*章节）。

2) 带参数调用主函数：

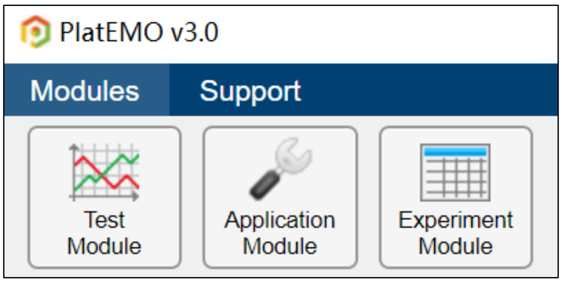
```
f1 = @(x,d)sum(x*d);
f2 = @(x,d)1-sum(x*d);
platemo('objFcn',f1,'conFcn',f2,'algorithm',@GA,…);
```

可以利用指定的算法来求解自定义的问题（参阅*求解自定义问题*章节）。

3) 不带参数调用主函数：

```
platemo();
```

可以弹出一个带有三个模块的图形界面，其中测试模块用于可视化地研究单个算法在单个问题上的性能（参阅*测试模块*章节），应用模块用于求解自定义问题（参阅*应用模块*章节），实验模块用于统计分析多个算法在多个问题上的性能（参阅*实验模块*章节）。



二　通过命令行使用 PlatEMO

1. 求解测试问题

用户可以以如下形式带参数调用主函数 platemo()来求解测试问题：

```
platemo('Name1',Value1,'Name2',Value2,'Name3',Value3,…);
```

其中所有可接受的参数列举如下：

参数名	数据类型	默认值	描述
'algorithm'	函数句柄或单元数组	不定	算法类
'problem'	函数句柄或单元数组	不定	问题类
'N'	正整数	100	种群大小
'M'	正整数	不定	问题的目标数
'D'	正整数	不定	问题的变量数
'maxFE'	正整数	10000	最大评价次数
'save'	整数	0	保存的种群数
'outputFcn'	函数句柄	@ALGORITHM.Output	每代开始前调用的函数

- 'algorithm'表示待运行的算法，它的值可以是一个算法类的句柄，例如@GA。它的值还可以是形如{@GA,p1,p2,…}的单元数组，其中 p1,p2,… 指定了该算法中的参数值。
- 'problem'表示待求解的测试问题，它的值可以是一个问题类的句柄，例如@SOP_F1。它的值还可以是形如{@SOP_F1,p1,p2,…}的单元数组，其中 p1,p2,… 指定了该算法中的参数值。
- 'N'表示算法的种群大小，它通常等于最终种群中解的个数。
- 'M'表示问题的目标数，它仅对一些多目标测试问题生效。
- 'D'表示问题的变量数，它仅对一些测试问题生效。
- 'maxFE'表示算法可使用的最大评价次数，它通常等于种群大小乘以迭代次数。
- 'save'表示保存的种群数，该值大于零时结果将被保存在文件中，该值等

于零时结果将被显示在窗口中（参阅获取运行结果章节）。

- 'outputFcn'表示算法每代开始前调用的函数。该函数必须有两个输入和零个输出，其中第一个输入是当前的 ALGORITHM 对象、第二个输入是当前的 PROBLEM 对象。

例如，以下代码利用遗传算法求球面函数的最小值，其中种群大小为 50 且最终种群会被显示在窗口中：

```
platemo('algorithm',@GA,'problem',@SOP_F1,'N',50);
```

以下代码利用 NSGA-II 来求解 5 目标、40 变量的 DTLZ2 问题，其中最大评价次数为 20000 且最终种群会被保存在文件中：

```
platemo('algorithm',@NSGAII,'problem',@DTLZ2,'M',5,'D',40,'
maxFE',20000,'save',10);
```

以下代码利用基于 Tchebycheff 方法的 MOEA/D 求解 ZDT1 问题十次，其中每次的结果会被保存在独立的文件中：

```
for i = 1 : 10
    platemo('algorithm',{@MOEAD,2},'problem',@ZDT1,'save',5);
end
```

注意每个参数均有一个默认值，用户可以在调用时省略任意参数。

2. 求解自定义问题

当不指定参数'problem'时，用户可以通过指定以下参数来自定义问题：

参数名	数据类型	默认值	描述
'encoding'	字符串	'real'	问题的编码方式
'objFcn'	函数句柄或单元数组	@(x,d)sum(x)	问题的目标函数
'conFcn'	函数句柄或单元数组	@(x,d)0	问题的约束
'lower'	行向量	0	变量的下界
'upper'	行向量	1	变量的上界
'initFcn'	函数句柄	[]	种群初始化函数
'decFcn'	函数句柄	[]	无效解修复函数
'parameter'	单元数组	{}	问题的数据集

- 'encoding'表示问题的编码方式，它的值可以是'real'（实数或整数变量）、'binary'（二进制变量）或'permutation'（序列变量）。算法针对不同的编码方式可能使用不同的算子来产生子代。
- 'objFcn'表示问题的目标函数，它的值可以是一个函数句柄（单目标）或一个单元数组（多目标）。每个目标函数必须有两个输入和一个输出，其中第一个输入是一个决策向量、第二个输入是由'parameter'指定的数据集、输出是目标值。所有目标函数均为最小化问题。
- 'conFcn'表示问题的约束，它的值可以是一个函数句柄（单约束）或一个单元数组（多约束）。每个约束函数必须有两个输入和一个输出，其中第一个输入是一个决策向量、第二个输入是由'parameter'指定的数据集、输出是约束违反值。当且仅当约束违反值小于等于零时，约束被满足。
- 'lower'表示决策变量的下界，它仅在'encoding'的值为'real'时生效。
- 'upper'表示决策变量的上界，它仅在'encoding'的值为'real'时生效。
- 'initFcn'表示种群初始化函数，它的值必须是一个函数句柄。该函数必须有两个输入和一个输出，其中第一个输入是种群大小、第二个输入是由'parameter'指定的数据集、输出是种群的决策向量构成的矩阵。该函数通常在算法开始时被调用。
- 'decFcn'表示无效解修复函数，它的值必须是一个函数句柄。该函数必须有两个输入和一个输出，其中第一个输入是一个决策向量、第二个输入是由'parameter'指定的数据集、输出是修复后的决策向量。该函数会在计算目标函数前被调用。
- 'parameter'表示问题的数据集，它作为函数'objFcn'、'conFcn'、'initFcn'和'decFcn'的第二个输入参数。

例如，以下代码利用差分进化算法求一个 10 变量的单峰函数的最小值：

```
platemo('objFcn',@(x,d)sum(x.^2),'lower',zeros(1,10)-10,
'upper',zeros(1,10)+10,'algorithm',@DE);
```

以下代码利用默认的算法求一个带旋转的 10 变量单峰函数的最小值：

```
platemo('objFcn',@(x,d)sum((x*d).^2),'lower',zeros(1,10)-
10,'upper',zeros(1,10)+10,'parameter',rand(10));
```

以下代码利用 NSGA-II 求一个带约束的 2 目标、20 变量的优化问题的最小值，其中种群大小为 50：

```
f1 = @(x,d)x(1)*sum(x(2:end));
f2 = @(x,d)sqrt(1-x(1)^2)*sum(x(2:end));
g1 = @(x,d)1-sum(x(2:end));
platemo('objFcn',{f1,f2},'conFcn',g1,'lower',zeros(1,20),'upper',ones(1,20),'algorithm',@NSGAII,'N',50);
```

3. 获取运行结果

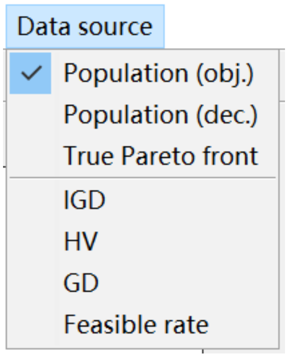
算法运行结束后得到的种群可以被显示在窗口中、保存在文件中或作为函数返回值。若按以下方式调用主函数：

```
[Dec,Obj,Con] = platemo(…);
```

则最终种群会被返回，其中 Dec 表示种群的决策向量构成的矩阵、Obj 表示种群的目标值构成的矩阵、Con 表示种群的约束违反值构成的矩阵。若按以下方式调用主函数：

```
platemo('save',Value,…);
```

则当 Value 的值为零时（默认情况），得到的种群会被显示在窗口中，用户可以利用窗口中的 Data source 菜单来选择要显示的内容。



当 Value 的值大于零时，得到的种群会被保存在命名为 PlatEMO\Data\alg\alg_pro_M_D_run.mat 的 MAT 文件中，其中 alg 表示算法名、pro 表示问题名、M 表示目标数、D 表示变量数、run 是一个自动确定的正整数以保证不和已有文件重名。每个文件存储一个单元数组 result 和一个结构体 metric。算法的整个优化过程被等分为 Value 块，其中 result 的第一列存储每块最后一代时所消耗的评价次数、result 的第二列存储每块最后一代时的种群、metric 存储所有种群的指标值。以上操作均由默认的输出函数@ALGORITHM.Output 实现，用户可以通过指定'outputFcn'的值为其它函数来实现自定义的结果展示或保存方式。

```
result =
  6×2 cell array
    {[ 1650]}     {1×50 SOLUTION}
    {[ 3300]}     {1×50 SOLUTION}
    {[ 5000]}     {1×50 SOLUTION}
    {[ 6650]}     {1×50 SOLUTION}
    {[ 8300]}     {1×50 SOLUTION}
    {[10000]}     {1×50 SOLUTION}
```

```
metric =
  struct with fields:

    runtime: 0.3317
        IGD: [6×1 double]
```

此外，图形界面的实验模块可以自动计算种群的指标值并存储到 metric 中。若需要手动计算指标值，用户需获取问题的最优值并调用指标函数，例如

```
pro = DTLZ2();
IGD(result{end},pro.optimum);
```

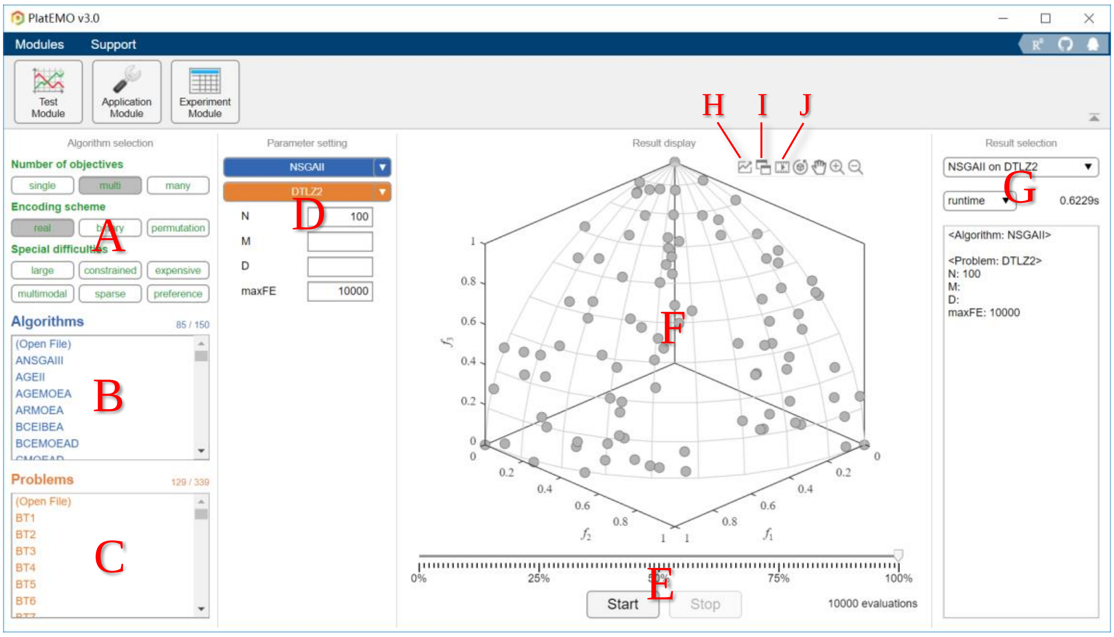
三　通过图形界面使用 PlatEMO

1. 测试模块

用户可以通过无参数调用主函数 `platemo()` 来使用 PlatEMO 的图形界面：

```
platemo();
```

图形界面的测试模块会被首先显示，它用于可视化地研究单个算法在单个问题上的性能。

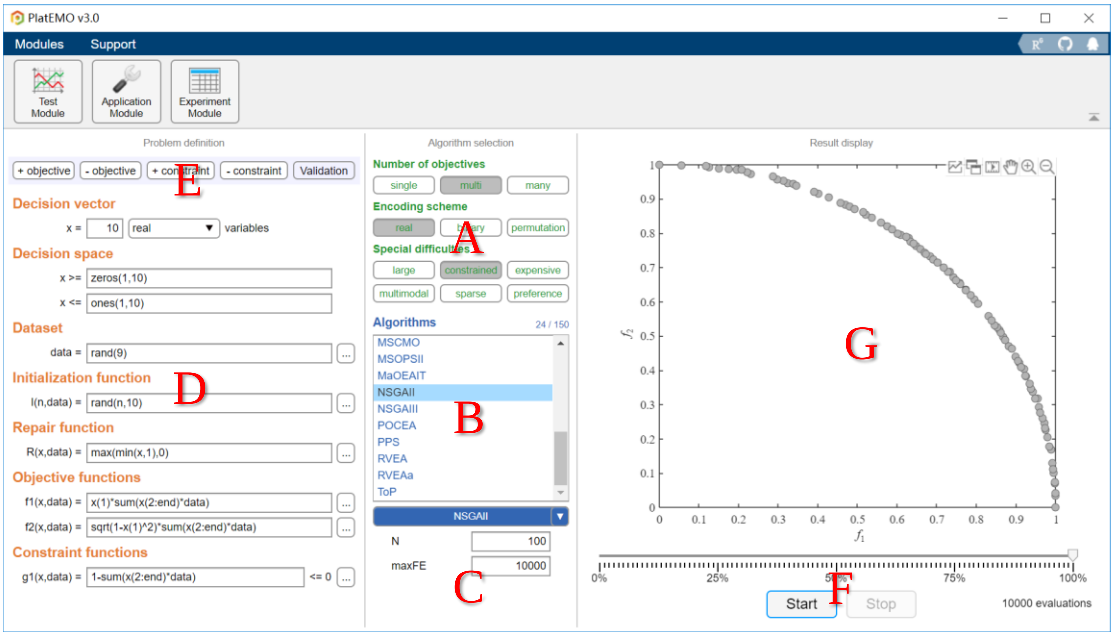


在该模块中，用户首先需要在区域 A 中选择问题类型（参阅算法和问题的标签章节），在区域 B 中选择一个算法，在区域 C 中选择一个测试问题，并在区域 D 中设定相关参数。之后，用户可以在区域 E 中控制算法的运行，在区域 F 中观察算法运行的实时结果，并在区域 G 中调取历史运行结果。

按钮 H 用于选择要显示的内容，按钮 I 用于将当前显示内容显示在一个新窗口中并存储至工作空间，按钮 J 用于将算法运行的动态过程保存为一个 20 帧的 GIF 图像。

2. 应用模块

用户可以通过图形界面中的菜单切换至应用模块，它用于求解自定义问题。



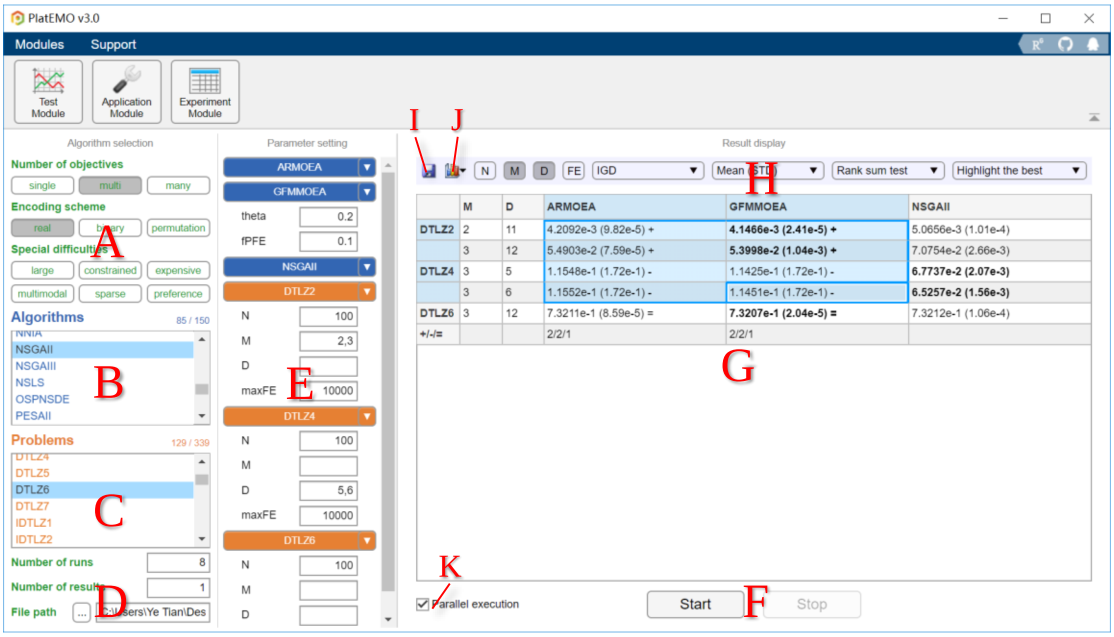
在该模块中，用户首先需要在区域 D 中定义问题，定义方式与求解自定义问题相同，其中

- Decision vector　　对应　'encoding'
- Decision space　　对应　'lower' 和 'upper'
- Dataset　　对应　'parameter'
- Initialization function　对应　'initFcn'
- Repair function　　对应　'decFcn'
- Objective functions　对应　'objFcn'
- Constraint functions　对应　'conFcn'

在简单情况下，用户可以仅定义 Decision vector、Decision space、Objective functions 和 Constraint functions。同时，用户可以在区域 E 中更改目标数量、约束数量和验证问题定义的合法性。之后，区域 A 中的问题类型可以被自动确定，用户需要在区域 B 中选择一个算法并在区域 C 中设定相关参数。最后，用户可以在区域 F 中控制算法的运行，并在区域 G 中观察算法运行的实时结果。

3. 实验模块

用户可以通过图形界面中的菜单切换至实验模块，它用于统计分析多个算法在多个问题上的性能。



在该模块中，用户首先需要在区域 A 中选择问题类型（参阅算法和问题的标签章节），在区域 B 中选择一个或多个算法，在区域 C 中选择一个或多个测试问题，在区域 D 中设定实验参数，并在区域 E 中设定相关参数；这里的目标数 M 和变量数 D 可以是向量。之后，用户可以在区域 F 中控制实验的运行，并在区域 G 中观察实验运行的实时结果。

需要在表格中显示的统计信息可以在区域 H 中选择。按钮 I 用于将当前表格保存为 Excel、TeX、TXT 或 MAT 文件，按钮 J 用于将所选单元格中的结果显示在一个新窗口中，按钮 K 用于选择实验在单处理器上运行（串行）或多处理器上运行（并行）。

所有结果将会被以 MAT 文件的形式保存在区域 D 中指定的文件夹中。如果存在同名的结果文件，该文件将会被读取以代替算法运行。

4. 算法和问题的标签

每个算法或测试问题需要被添加上标签，这些标签以注释的形式添加在主函数代码的第二行。例如在 PSO.m 代码的开头部分：

```
classdef PSO < ALGORITHM
% <single> <real> <large/none> <constrained/none>
```

通过多个标签指定了该算法可求解的问题类型。所有的标签列举如下：

标签	描述
<single>	单目标优化：问题含有一个目标函数
<multi>	多目标优化：问题含有两或三个目标函数
<many>	超多目标优化：问题含有三个以上目标函数
<real>	连续优化：决策变量为实数或整数
<binary>	二进制优化：决策变量为二进制数
<permutation>	序列优化：决策变量构成一个序列
<large>	大规模优化：问题含有 100 个以上的决策变量
<constrained>	约束优化：问题含有至少一个约束
<expensive>	昂贵优化：目标函数的计算非常耗时，即最大评价次数非常小
<multimodal>	多模优化：存在多个目标值接近但决策向量差异很大的最优解，它们都需要被找到
<sparse>	稀疏优化：最优解中大部分的决策变量均为零
<preference>	偏好优化：仅需寻找前沿面上指定区域的最优解
<none>	空标签

每个算法可能含有多个标签集合，这些集合的笛卡尔积构成该算法可求解的所有的问题类型。例如当标签集合为<single><real><constrained/none>时，表示该算法可求解带或不带约束的单目标连续优化问题；若标签集合为<single><real>，表示该算法只能求解无约束的问题；若标签集合为<single><real><constrained>，表示该算法只能求解带约束的问题；若标签集合为<single><real/binary>，表示该算法可以求解连续或二进制优化问题。

每个算法和测试问题都需要被添加至少一个标签，否则它将不会在图形界面的列表中出现。当用户在图形界面的区域 A 中选择问题类型后，所有可求解该类型问题的算法将会出现在图形界面的区域 B 中，且所有符合该类型的测试问题将会出现在图形界面的区域 C 中。PlatEMO 中所有算法和测试问题的标签分别参阅*算法列表*和*问题列表*章节。

四 扩展 PlatEMO

1. 算法类

每个算法需要被定义为 ALGORITHM 类的子类并保存在 PlatEMO\Algorithms 文件夹中。算法类包含的属性与方法如下：

属性	赋值方式	描述
parameter	用户	算法的参数
save	用户	每次运行中保存的种群数
outputFcn	用户	在 NotTerminated() 中调用的函数
pro	Solve()	当前运行中求解的问题对象
result	NotTerminated()	当前运行中保存的种群
metric	NotTerminated()	当前保存的种群的指标值
方法	是否可重定义	描述
ALGORITHM	不可	设定由用户指定的属性值
Solve	不可	通过调用 alg.Solve(pro) 来利用算法 alg 求解问题 pro
main	必须	算法的主体部分
NotTerminated	不可	main() 中每次迭代前调用的函数
ParameterSet	不可	根据 parameter 设定算法参数

每个算法需要继承 ALGORITHM 类并重定义方法 main()。例如 GA.m 的代码为：

```
classdef GA < ALGORITHM
% <single><real/binary/permutation><large/none><constrained/none>
% Genetic algorithm
% proC --- 1 --- Probability of crossover
% disC --- 20 --- Distribution index of crossover
% proM --- 1 --- Expectation of the number of mutated variables
% disM --- 20 --- Distribution index of mutation

%--------------------------- Reference --------------------------
% J. H. Holland, Adaptation in Natural and Artificial Systems,
% MIT Press, 1992.
%----------------------------------------------------------------

```

```
14      methods
15          function main(Alg,Pro)
16              [proC,disC,proM,disM] = Alg.ParameterSet(1,20,1,20);
17              P = Pro.Initialization();
18              while Alg.NotTerminated(P)
19                  P1 = TournamentSelection(2,Pro.N,FitnessSingle(P));
20                  O = OperatorGA(P(P1),{proC,disC,proM,disM});
21                  P = [P,O];
22                  [~,rank] = sort(FitnessSingle(P));
23                  P = P(rank(1:Pro.N));
24              end
25          end
26      end
```

各行代码的功能如下：

第 1 行： 继承 ALGORITHM 类；

第 2 行： 为算法添加标签（参阅算法和问题的标签章节）；

第 3 行： 算法的全称；

第 4-7 行： 参数名 --- 默认值 --- 参数描述，将会显示在图形界面的参数设置列表中；

第 9-12 行：算法的参考文献；

第 15 行： 重定义算法主体流程的方法；

第 16 行： 获取用户指定的参数设置，其中 1,20,1,20 分别表示参数 proC, disC,proM,disM 的默认值。

第 17 行： 调用 PROBLEM 类的方法获得一个初始种群；

第 18 行： 保存当前种群并检查评价次数是否超过最大值；若超过则终止算法；

第 19 行： 调用公共函数实现基于二元联赛的交配池选择；

第 20 行： 调用公共函数产生子代种群；

第 21 行： 将父子代种群合并；

第 22 行： 调用公共函数计算种群中解的适应度，并依此对解进行排序；

第 23 行： 保留适应度较好的一半解进入下一代。

在以上代码中，函数 ParameterSet() 和 NotTerminated() 是 ALGORITHM 类的方法，函数 Initialization() 是 PROBLEM 类的方法，而函数 TournamentSelection()、FitnessSingle() 和 OperatorGA() 是在 PlatEMO\Algorithms\Utility functions 文件夹中的公共函数。所

有可被算法调用的方法及公共函数列举如下，详细的调用方式参阅代码中的注释；此外，函数中用于提升算法效率的技术参阅这里。

函数名	描述
ALGORITHM. NotTerminated	算法每次迭代前调用的函数
ALGORITHM. ParameterSet	根据用户的输入设定算法参数
PROBLEM. Initialization	初始化一个种群
CrowdingDistance	计算解的拥挤距离（用于多目标优化）
FitnessSingle	计算解的适应度（用于单目标优化）
NDSort	非支配排序
OperatorDE	差分进化算子
OperatorFEP	进化规划算子
OperatorGA	遗传算子
OperatorGAhalf	遗传算子（仅产生前一半的子代）
OperatorPSO	粒子群优化算子
RouletteWheel Selection	轮盘赌选择
Tournament Selection	联赛选择
UniformPoint	产生均匀分布的参考点

2. 问题类

每个问题需要被定义为 PROBLEM 类的子类并保存在 PlatEMO\Problems 文件夹中。问题类包含的属性与方法如下：

属性	赋值方式	描述
N	用户	求解该问题的算法的种群大小
M	用户和 Setting()	问题的目标数
D	用户和 Setting()	问题的变量数
maxFE	用户	求解该问题可使用的最大评价次数
FE	SOLUTION()	当前运行中已消耗的评价次数
encoding	Setting()	问题的编码方式
lower	Setting()	决策变量的下界
upper	Setting()	决策变量的上界
optimum	GetOptimum()	问题的最优值，例如目标函数的最小值（单目标优化）和前沿面上一组均匀参考点（多目标优化）

PF	GetPF()	问题的前沿面，例如 1 维曲线（双目标优化）、2 维曲面（三目标优化）和可行区域（约束优化）
parameter	用户	问题的参数
方法	是否可重定义	描述
PROBLEM	不可	设定由用户指定的属性值
Setting	必须	设定默认的属性值
Initialization	可以	初始化一个种群
CalDec	可以	修复种群中的无效解
CalObj	必须	计算种群中解的目标值；所有目标函数均为最小化问题
CalCon	可以	计算种群中解的约束违反值；当且仅当约束违反值小于等于零时，约束被满足
GetOptimum	可以	产生问题的最优值并保存在 optimum 中
GetPF	可以	产生问题的前沿面并保存在 PF 中
DrawDec	可以	显示一个种群的决策向量
DrawObj	可以	显示一个种群的目标向量
Current	不可	用来设定或获取当前 PROBLEM 对象的静态方法
ParameterSet	不可	根据 parameter 设定问题参数

每个算法需要继承 PROBLEM 类并重定义方法 Setting()和 CalObj()。例如 SOP_F1.m 的代码为：

```
classdef SOP_F1 < PROBLEM
% <single><real><expensive/none>
% Sphere function

%------------------------------- Reference --------------------------------
% X. Yao, Y. Liu, and G. Lin, Evolutionary programming made
% faster, IEEE Transactions on Evolutionary Computation, 1999, 3
% (2): 82-102.
%--------------------------------------------------------------------------

    methods
        function Setting(obj)
            obj.M = 1;
            if isempty(obj.D); obj.D = 30; end
            obj.lower = zeros(1,obj.D) - 100;
            obj.upper = zeros(1,obj.D) + 100;
            obj.encoding = 'real';
        end
```

```
19          function PopObj = CalObj(obj,PopDec)
20              PopObj = sum(PopDec.^2,2);
21          end
22      end
```

各行代码的功能如下：

第 1 行：　继承 PROBLEM 类；

第 2 行：　为问题添加标签（参阅算法和问题的标签章节）；

第 3 行：　问题的全称；

第 5-9 行：问题的参考文献；

第 12 行：　重定义设定默认属性值的方法；

第 13 行：　设置问题的目标数；

第 14 行：　设置问题的变量数（若未被用户指定）；

第15-16行：设置决策变量的上下界；

第 17 行：　设置问题的编码方式；

第 19 行：　重定义计算目标函数的方法；

第 20 行：　计算种群中解的目标值。

除以上代码外，默认的方法 Initialization()用于随机初始化一个种群，用户可以重定义该方法来指定特殊的种群初始化策略。例如 Sparse_NN.m 将初始化的种群中随机一半的决策变量置零：

```
function Population = Initialization(obj,N)
    if nargin < 2; N = obj.N; end
    PopDec = (rand(N,obj.D)-0.5)*2.*randi([0 1],N,obj.D);
    Population = SOLUTION(PopDec);
end
```

默认的方法 CalDec()将大于上界的决策变量设为上界值、将小于下界的决策变量设为下界值，用户可以重定义该方法来指定特殊的解修复策略。例如 MOKP.m 修复了超过背包容量限制的解：

```
function PopDec = CalDec(obj,PopDec)
    C = sum(obj.W,2)/2;
    [~,rank] = sort(max(obj.P./obj.W));
    for i = 1 : size(PopDec,1)
        while any(obj.W*PopDec(i,:)'>C)
            k = find(PopDec(i,rank),1);
            PopDec(i,rank(k)) = 0;
```

```
        end
    end
end
```

默认的方法 CalCon()返回零作为解的约束违反值（即解都是满足约束的），用户可以重定义该方法来指定问题的约束。例如 MW1.m 添加了一个约束：

```
function PopCon = CalCon(obj,X)
    PopObj = obj.CalObj(X);
    l = sqrt(2)*PopObj(:,2) - sqrt(2)*PopObj(:,1);
    PopCon = sum(PopObj,2) - 1 - 0.5*sin(2*pi*l).^8;
end
```

用户可以重定义方法 GetOptimum()来指定问题的最优值。例如 SOP_F8.m 指定了目标函数的最小值：

```
function R = GetOptimum(obj,N)
    R = -418.9829*obj.D;
end
```

DTLZ2.m 生成了一组前沿面上均匀分布的参考点：

```
function R = GetOptimum(obj,N)
    R = UniformPoint(N,obj.M);
    R = R./repmat(sqrt(sum(R.^2,2)),1,obj.M);
end
```

在不同形状前沿面上的采点方法参阅这里。用户可以重定义方法 GetPF()来指定多目标优化问题的前沿面或可行区域。例如 DTLZ2.m 生成了 2 维和 3 维的前沿面数据：

```
function R = GetPF(obj)
    if obj.M == 2
        R = obj.GetOptimum(100);
    elseif obj.M == 3
        a = linspace(0,pi/2,10)';
        R = {sin(a)*cos(a'),sin(a)*sin(a'),cos(a)*ones(size(a'))};
    else
        R = [];
    end
end
```

MW1.m 生成了可行区域的数据：

```
function R = GetPF(obj)
    [x,y] = meshgrid(linspace(0,1,400),linspace(0,1.5,400));
    z = nan(size(x));
    fes = x+y-1-0.5*sin(2*pi*(sqrt(2)*y-sqrt(2)*x)).^8 <= 0;
    z(fes&0.85*x+y>=1) = 0;
    R = {x,y,z};
end
```

默认的方法 DrawDec()显示种群的决策向量（用于图形界面中），用户可以重定义该方法来指定特殊的显示方式。例如 TSP.m 显示了种群中最优解的路径：

```
function DrawDec(obj,P)
    [~,best] = min(P.objs);
    Draw(obj.R(P(best).dec([1:end,1]),:),'-k','LineWidth',1.5);
    Draw(obj.R);
end
```

默认的方法 DrawObj()显示种群的目标向量（用于图形界面中），用户可以重定义该方法来指定特殊的显示方式。例如 Sparse_CD.m 添加了坐标轴的标签：

```
function DrawObj(obj,P)
    Draw(P.objs,{'Kernel k-means','Ratio cut',[]});
end
```

其中 Draw()用于显示数据，它位于 PlatEMO\GUI 文件夹中。以上方法的详细调用方式参阅代码中的注释。

3. 个体类

一个 SOLUTION 类的对象表示一个个体（即一个解），一组 SOLUTION 类的对象表示一个种群。个体类包含的属性与方法如下：

属性	赋值方式	描述
dec	用户	解的决策向量
obj	SOLUTION()	解的目标值
con	SOLUTION()	解的约束违反值
add	adds()	解的额外属性值（例如速度）
方法	描述	
SOLUTION	接受一个或多个解的决策向量并计算相应的目标值与约束违反值；PROBLEM.FE 的值会自动加上生成的 SOLUTION 对象数目	
decs	获取多个解的决策向量构成的矩阵	

objs	获取多个解的目标值构成的矩阵
cons	获取多个解的约束违反值构成的矩阵
adds	获取多个解的额外属性值构成的矩阵
best	获取种群中可行且最好的解（单目标优化）或可行且非支配的解（多目标优化）

例如，以下代码产生一个具有十个解的种群，并获取其中最好的解的目标值矩阵：

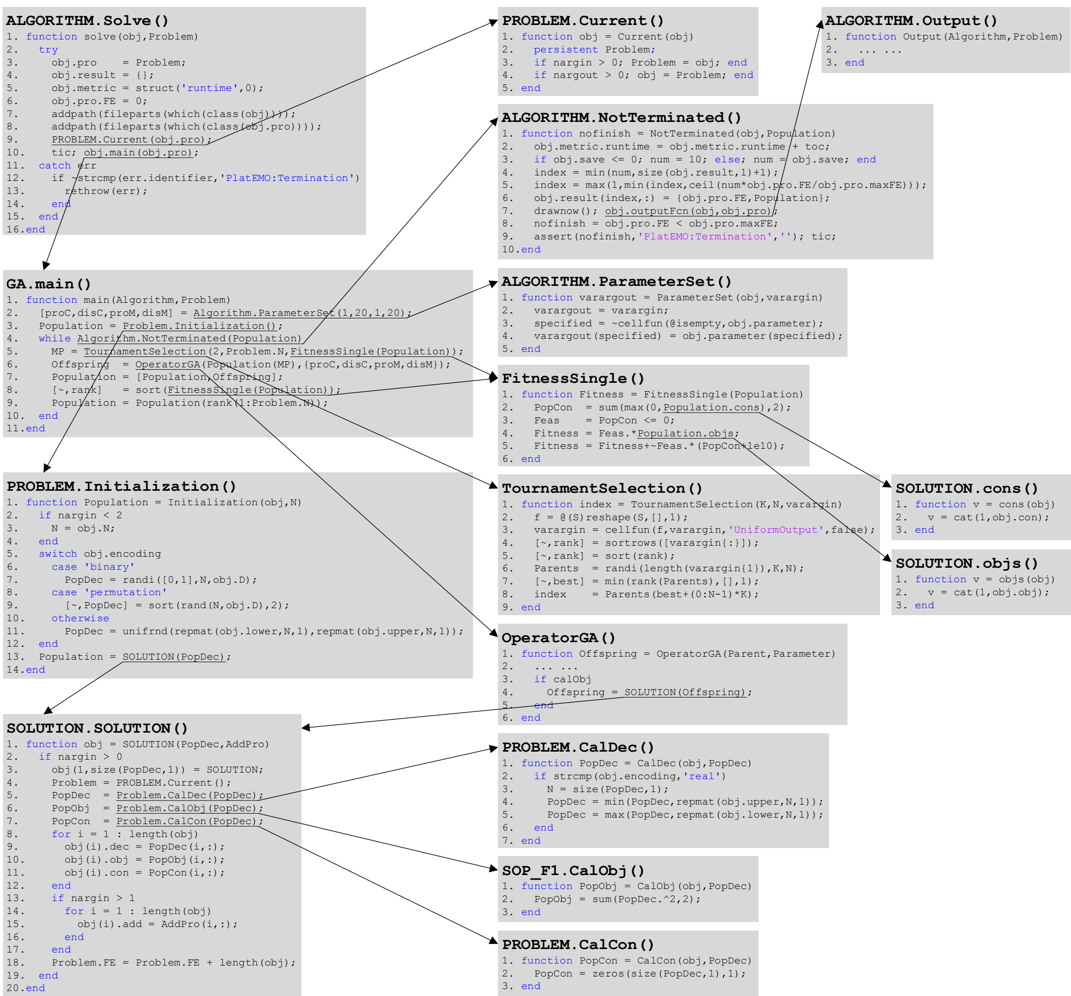
```
Population = SOLUTION(rand(10,5));
BestObjs = Population.best.objs
```

4. 一次完整的运行过程

以下代码利用遗传算法求球面函数的最小值：

```
Alg = GA();
Pro = SOP_F1();
Alg.Solve(Pro);
```

其中代码 `Alg.Solve(Pro)` 执行时所涉及的函数调用过程如下图所示。



5. 指标函数

每个性能指标需要被定义为一个函数并保存在 `PlatEMO\Metrics` 文件夹中。例如 `IGD.m` 的代码为：

```
1  function score = IGD(Population,optimum)
2  % <min>
3  % Inverted generational distance
4  
5  %------------------------------- Reference --------------------------------
6  % C. A. Coello Coello and N. C. Cortes, Solving multiobjective
7  % optimization problem using an artificial immune system, Genetic
8  % Programming and Evolvable Machines, 2005, 6(2): 163-190.
9  %--------------------------------------------------------------------------
10 
11     PopObj = Population.best.objs;
12     if size(PopObj,2) ~= size(optimum,2)
13       score = nan;
14     else
15       score = mean(min(pdist2(optimum,PopObj),[],2));
16     end
17 end
```

各行代码的功能如下：

第 1 行：　函数声明，其中第一个输入为一个种群（即一个 `SOLUTION` 对象数组）、第二个输入为问题的最优值（即问题的 `optimum` 属性）、输出为种群的指标值；

第 2 行：　为指标添加标签，其中`<min>`表示指标值越小越好、`<max>`表示指标值越大越好；

第 3 行：　指标的全称；

第 5-9 行：　指标的参考文献；

第 11 行：　获取种群中最好的解（可行且非支配的解）的目标值矩阵；

第12-13行：若种群不存在可行解则返回 `nan`；

第14-15行：否则返回可行且非支配的解的指标值。

五　算法列表

	算法缩写	算法全称	single	multi	many	real	binary	permutation	large	constrained	expensive	multimodal	sparse	preference
1	ABC	Artificial bee colony algorithm	√			√			√	√				
2	AB-SAEA	Adaptive Bayesian based surrogate-assisted evolutionary algorithm		√	√	√					√			
3	ACO	Ant colony optimization	√					√	√					
4	AGE-II	Approximation-guided evolutionary multi-objective algorithm II		√		√	√	√						
5	AGE-MOEA	Adaptive geometry estimation-based many-objective evolutionary algorithm		√	√	√	√	√		√				
6	A-NSGA-III	Adaptive NSGA-III		√	√	√	√	√		√				
7	AR-MOEA	Adaptive reference points based multi-objective evolutionary algorithm		√	√	√	√	√		√				
8	BCE-IBEA	Bi-criterion evolution based IBEA		√	√	√	√	√						
9	BCE-MOEA/D	Bi-criterion evolution based MOEA/D		√	√	√	√	√						
10	BFGS	A quasi-Newton method proposed by Broyden, Fletcher, Goldfarb, and Shanno	√			√			√					
11	BiGE	Bi-goal evolution			√	√	√	√						
12	BSPGA	Binary space partition tree based genetic algorithm	√				√		√	√				
13	CA-MOEA	Clustering based adaptive multi-objective evolutionary algorithm		√		√	√	√						
14	CCGDE3	Cooperative coevolution GDE3		√		√			√					
15	CCMO	Coevolutionary constrained multi-objective optimization framework		√		√	√	√		√				
16	c-DPEA	Constrained dual-population evolutionary algorithm		√		√	√	√		√				
17	CMA-ES	Covariance matrix adaptation evolution strategy	√			√			√	√				
18	C-MOEA/D	Constraint-MOEA/D		√	√	√	√	√		√				
19	CMOEA-MS	Constrained multiobjective evolutionary algorithm with multiple stages		√		√	√	√		√				
20	CMOPSO	Competitive mechanism based multi-objective particle swarm optimizer		√		√								
21	CPS-MOEA	Classification and Pareto domination based multi-objective evolutionary		√		√					√			
22	CSEA	Classification based surrogate-assisted evolutionary algorithm		√	√	√					√			
23	CSO	Competitive swarm optimizer	√			√			√	√				
24	C-TAEA	Two-archive evolutionary algorithm for constrained MOPs		√	√	√	√	√		√				
25	DAEA	Duplication analysis based evolutionary algorithm		√			√							
26	DCNSGA-III	Dynamic constrained NSGA-III		√	√	√	√	√		√				
27	DE	Differential evolution	√			√			√	√				
28	DGEA	Direction guided evolutionary algorithm		√	√	√			√					

	算法缩写	算法全称	single	multi	many	real	binary	permutation	large	constrained	expensive	multimodal	sparse	preference
29	DMOEA-eC	Decomposition-based multi-objective evolutionary algorithm with the e-constraint framework		√		√	√	√						
30	dMOPSO	MOPSO based on decomposition		√		√								
31	DN-NSGA-II	Decision space based niching NSGA-II		√		√						√		
32	DWU	Dominance-weighted uniformity multi-objective evolutionary algorithm		√		√	√	√						
33	EAG-MOEA/D	External archive guided MOEA/D		√		√	√	√						
34	EDN-ARMOEA	Efficient dropout neural network based AR-MOEA		√	√	√					√			
35	EFR-RR	Ensemble fitness ranking with a ranking restriction scheme		√	√	√	√	√						
36	EGO	Efficient global optimization	√			√					√			
37	EIM-EGO	Expected improvement matrix based efficient global optimization		√		√					√			
38	e-MOEA	Epsilon multi-objective evolutionary algorithm		√	√	√	√	√						
39	EMyO/C	Evolutionary many-objective optimization algorithm with clustering-based		√	√	√								
40	ENS-MOEA/D	Ensemble of different neighborhood sizes based MOEA/D		√	√	√								
41	FEP	Fast evolutionary programming	√			√			√	√				
42	FRCG	Fletcher-Reeves conjugate gradient	√			√			√					
43	FROFI	Feasibility rule with the incorporation of objective function information	√			√			√	√				
44	GA	Genetic algorithm	√			√	√	√	√	√				
45	GDE3	Generalized differential evolution 3		√		√				√				
46	GFM-MOEA	Generic front modeling based multi-objective evolutionary algorithm		√	√	√	√	√						
47	GLMO	Grouped and linked mutation operator algorithm		√		√			√					
48	g-NSGA-II	g-dominance based NSGA-II		√		√	√	√						√
49	GrEA	Grid-based evolutionary algorithm			√	√	√	√						
50	HeE-MOEA	Multiobjective evolutionary algorithm with heterogeneous ensemble based infill criterion		√		√					√			
51	hpaEA	Hyperplane assisted evolutionary algorithm		√	√	√	√	√						
52	HypE	Hypervolume estimation algorithm		√	√	√	√	√						
53	IBEA	Indicator-based evolutionary algorithm		√	√	√	√	√						
54	I-DBEA	Improved decomposition-based evolutionary algorithm		√	√	√	√	√		√				
55	IM-MOEA	Inverse modeling based multiobjective evolutionary algorithm		√		√			√					
56	IMODE	Improved multi-operator differential evolution	√			√			√	√				
57	I-SIBEA	Interactive simple indicator-based evolutionary algorithm		√		√	√	√						√
58	KnEA	Knee point driven evolutionary algorithm			√	√	√	√		√				
59	K-RVEA	Surrogate-assisted RVEA		√	√	√					√			
60	KTA2	Kriging-assisted Two_Arch2		√	√	√					√			
61	LCSA	Linear combination-based search algorithm		√	√	√			√					
62	LMEA	Evolutionary algorithm for large-scale many-objective optimization		√	√	√			√					

	算法缩写	算法全称	single	multi	many	real	binary	permutation	large	constrained	expensive	multimodal	sparse	preference
63	LMOCSO	Large-scale multi-objective competitive swarm optimization algorithm		√	√	√			√	√				
64	LSMOF	Large-scale multi-objective optimization framework with NSGA-II		√		√			√					
65	MaOEA-CSS	Many-objective evolutionary algorithms based on coordinated selection		√	√	√	√	√						
66	MaOEA-DDFC	Many-objective evolutionary algorithm based on directional diversity and favorable convergence		√	√	√	√	√						
67	MaOEA/IGD	IGD based many-objective evolutionary algorithm			√	√	√	√						
68	MaOEA/IT	Many-objective evolutionary algorithms based on an independent two-stage		√	√	√				√				
69	MaOEA-R&D	Many-objective evolutionary algorithm based on objective space reduction			√	√	√	√						
70	MMOPSO	MOPSO with multiple search strategies		√		√								
71	MO_Ring_ PSO_SCD	Multiobjective PSO using ring topology and special crowding distance		√		√						√		
72	MOCell	Cellular genetic algorithm		√		√	√	√		√				
73	MO-CMA	Multi-objective covariance matrix adaptation evolution strategy		√		√								
74	MOEA/D	Multiobjective evolutionary algorithm based on decomposition		√	√	√	√	√						
75	MOEA/D-AWA	MOEA/D with covariance matrix adaptation evolution strategy		√	√	√								
76	MOEA/D-CMA	MOEA/D with covariance matrix adaptation evolution strategy		√	√	√								
77	MOEA/DD	Many-objective evolutionary algorithm based on dominance and decomposition		√	√	√	√	√		√				
78	MOEA/D-DAE	MOEA/D with detect-and-escape strategy		√		√	√	√		√				
79	MOEA/D-DE	MOEA/D based on differential evolution		√	√	√								
80	MOEA/D-DRA	MOEA/D with dynamical resource allocation		√	√	√								
81	MOEA/D-DU	MOEA/D with a distance based updating strategy		√	√	√	√	√						
82	MOEA/D-EGO	MOEA/D with efficient global optimization		√		√					√			
83	MOEA/D-FRRMAB	MOEA/D with fitness-rate-rank-based multiarmed bandit		√	√	√								
84	MOEA/D-M2M	MOEA/D based on MOP to MOP		√		√								
85	MOEA/D-MRDL	MOEA/D with maximum relative diversity loss		√		√								
86	MOEA/D-PaS	MOEA/D with Pareto adaptive scalarizing approximation		√	√	√								
87	MOEA/D-STM	MOEA/D with stable matching		√	√	√								
88	MOEA/D-URAW	MOEA/D with uniform randomly adaptive weights		√	√	√	√	√						
89	MOEA/DVA	Multi-objective evolutionary algorithm based on decision variable		√		√			√					
90	MOEA/IGD-NS	Multi-objective evolutionary algorithm based on an enhanced IGD		√		√	√	√						
91	MOEA-PC	Multiobjective evolutionary algorithm based on polar coordinates		√		√								

	算法缩写	算法全称	single	multi	many	real	binary	permutation	large	constrained	expensive	multimodal	sparse	preference
92	MOEA/PSL	Multi-objective evolutionary algorithm based on Pareto optimal subspace		√		√	√		√	√			√	
93	MOMBI-II	Many objective metaheuristic based on the R2 indicator II		√	√	√	√	√						
94	MOPSO	Multi-objective particle swarm optimization		√		√								
95	MOPSO-CD	MOPSO with crowding distance		√		√								
96	M-PAES	Memetic algorithm with Pareto archived evolution strategy		√		√								
97	MP-MMEA	Multi-population multi-modal multi-objective evolutionary algorithm		√		√			√			√	√	
98	MPSO/D	Multi-objective particle swarm optimization algorithm based on decomposition		√	√	√								
99	MSCMO	Multi-stage constrained multi-objective evolutionary algorithm		√		√	√	√		√				
100	MSEA	Multi-stage multi-objective evolutionary algorithm		√		√	√	√						
101	MSOPS-II	Multiple single objective Pareto sampling II		√	√	√				√				
102	MTS	Multiple trajectory search		√		√								
103	MultiObjective EGO	Multi-objective efficient global optimization		√		√				√	√			
104	MyO-DEMR	Many-objective differential evolution with mutation restriction		√	√	√								
105	NMPSO	Novel multi-objective particle swarm optimization		√	√	√								
106	NNIA	Nondominated neighbor immune algorithm		√		√	√	√						
107	NSGA-II	Nondominated sorting genetic algorithm II		√		√	√	√		√				
108	NSGA-II+ARSBX	NSGA-II with adaptive rotation based simulated binary crossover		√		√				√				
109	NSGA-II-conflict	NSGA-II with conflict-based partitioning strategy			√	√	√	√						
110	NSGA-III	Nondominated sorting genetic algorithm III		√	√	√	√	√		√				
111	NSGA-II/SDR	NSGA-II with strengthened dominance relation			√	√	√	√						
112	NSLS	Multiobjective optimization framework based on nondominated sorting and local search		√		√								
113	OFA	Optimal foraging algorithm	√			√			√	√				
114	one-by-one EA	Many-objective evolutionary algorithm using a one-by-one selection		√	√	√	√	√						
115	OSP-NSDE	Non-dominated sorting differential evolution with prediction in the objective space		√		√								
116	ParEGO	Efficient global optimization for Pareto optimization		√		√					√			
117	PESA-II	Pareto envelope-based selection algorithm II		√		√	√	√						
118	PICEA-g	Preference-inspired coevolutionary algorithm with goals		√	√	√	√	√						
119	PM-MOEA	Pattern mining based multi-objective evolutionary algorithm		√		√			√	√				
120	POCEA	Paired offspring generation based constrained evolutionary algorithm		√		√			√	√				
121	PPS	Push and pull search algorithm		√	√	√				√				
122	PREA	Promising-region based EMO algorithm		√	√	√	√	√						
123	PSO	Particle swarm optimization	√			√			√	√				
124	RM-MEDA	Regularity model-based multiobjective estimation of distribution		√		√								

	算法缩写	算法全称	single	multi	many	real	binary	permutation	large	constrained	expensive	multimodal	sparse	preference
125	r-NSGA-II	r-dominance based NSGA-II		√		√	√	√						√
126	RPD-NSGA-II	Reference point dominance-based NSGA-II		√	√	√	√	√						
127	RPEA	Reference points-based evolutionary algorithm			√	√	√	√						
128	RSEA	Radial space division based evolutionary algorithm		√	√	√	√	√						
129	RVEA	Reference vector guided evolutionary algorithm		√	√	√	√	√		√				
130	RVEAa	RVEA embedded with the reference vector regeneration strategy			√	√	√	√						
131	S3-CMA-ES	Scalable small subpopulations based covariance matrix adaptation		√	√	√			√					
132	SA	Simulated annealing	√			√			√	√				
133	SACC-EAM-II	Surrogate-assisted cooperative co-evolutionary algorithm of Minamo	√			√					√			
134	SACOSO	Surrogate-assisted cooperative swarm optimization	√			√			√		√			
135	SADE-Sammon	Sammon mapping assisted differential evolution	√			√					√			
136	SAMSO	Multiswarm-assisted expensive optimization	√			√			√		√			
137	S-CDAS	Self-controlling dominance area of solutions			√	√	√	√						
138	SHADE	Success-history based adaptive differential evolution	√			√			√	√				
139	SIBEA	Simple indicator-based evolutionary algorithm		√		√	√	√						
140	SIBEA-kEMOSS	SIBEA with minimum objective subset of size k with minimum error			√	√	√	√						
141	SMEA	Self-organizing multiobjective evolutionary algorithm		√		√								
142	SMPSO	Speed-constrained multi-objective particle swarm optimization		√		√								
143	SMS-EGO	S metric selection based efficient global optimization		√		√					√			
144	SMS-EMOA	S metric selection based evolutionary multiobjective optimization		√		√	√	√						
145	SparseEA	Evolutionary algorithm for sparse multi-objective optimization problems		√		√	√		√	√			√	
146	SPEA2	Strength Pareto evolutionary algorithm 2		√		√	√	√						
147	SPEA2+SDE	SPEA2 with shift-based density estimation			√	√	√	√						
148	SPEA/R	Strength Pareto evolutionary algorithm based on reference direction		√	√	√	√	√						
149	SQP	Sequential quadratic programming	√			√			√	√				
150	SRA	Stochastic ranking algorithm			√	√	√	√						
151	t-DEA	theta-dominance based evolutionary algorithm		√	√	√	√	√						
152	TiGE-2	Tri-Goal Evolution Framework for CMaOPs			√	√	√	√		√				
153	ToP	Two-phase framework with NSGA-II		√		√				√				
154	TriMOEA-TA&R	Multi-modal MOEA using two-archive and recombination strategies		√		√						√		
155	Two_Arch2	Two-archive algorithm 2		√	√	√	√	√						
156	VaEA	Vector angle based evolutionary algorithm		√	√	√	√	√						
157	WOF	Weighted optimization framework		√		√			√					
158	WV-MOEA-P	Weight vector based multi-objective optimization algorithm with preference		√		√								√

六　问题列表

	问题缩写	问题全称	single	multi	many	real	binary	permutation	large	constrained	expensive	multimodal	sparse	preference
1	BT1	Benchmark MOP with bias feature		√		√			√					
2	BT2	Benchmark MOP with bias feature		√		√			√					
3	BT3	Benchmark MOP with bias feature		√		√			√					
4	BT4	Benchmark MOP with bias feature		√		√			√					
5	BT5	Benchmark MOP with bias feature		√		√			√					
6	BT6	Benchmark MOP with bias feature		√		√			√					
7	BT7	Benchmark MOP with bias feature		√		√			√					
8	BT8	Benchmark MOP with bias feature		√		√			√					
9	BT9	Benchmark MOP with bias feature		√		√			√					
10	CEC2008_F1	Shifted sphere function	√			√			√		√			
11	CEC2008_F2	Shifted Schwefel's function	√			√			√		√			
12	CEC2008_F3	Shifted Rosenbrock's function	√			√			√		√			
13	CEC2008_F4	Shifted Rastrign's function	√			√			√		√			
14	CEC2008_F5	Shifted Griewank's function	√			√			√		√			
15	CEC2008_F6	Shifted Ackley's function	√			√			√		√			
16	CEC2008_F7	FastFractal 'DoubleDip' function	√			√			√		√			
17	CEC2010_F1	CEC'2010 constrained optimization benchmark problem	√			√				√				
18	CEC2010_F2	CEC'2010 constrained optimization benchmark problem	√			√				√				
19	CEC2010_F3	CEC'2010 constrained optimization benchmark problem	√			√				√				
20	CEC2010_F4	CEC'2010 constrained optimization benchmark problem	√			√				√				
21	CEC2010_F5	CEC'2010 constrained optimization benchmark problem	√			√				√				
22	CEC2010_F6	CEC'2010 constrained optimization benchmark problem	√			√				√				
23	CEC2010_F7	CEC'2010 constrained optimization benchmark problem	√			√				√				
24	CEC2010_F8	CEC'2010 constrained optimization benchmark problem	√			√				√				
25	CEC2010_F9	CEC'2010 constrained optimization benchmark problem	√			√				√				
26	CEC2010_F10	CEC'2010 constrained optimization benchmark problem	√			√				√				
27	CEC2010_F11	CEC'2010 constrained optimization benchmark problem	√			√				√				
28	CEC2010_F12	CEC'2010 constrained optimization benchmark problem	√			√				√				
29	CEC2010_F13	CEC'2010 constrained optimization benchmark problem	√			√				√				
30	CEC2010_F14	CEC'2010 constrained optimization benchmark problem	√			√				√				
31	CEC2010_F15	CEC'2010 constrained optimization benchmark problem	√			√				√				
32	CEC2010_F16	CEC'2010 constrained optimization benchmark problem	√			√				√				
33	CEC2010_F17	CEC'2010 constrained optimization benchmark problem	√			√				√				

	问题缩写	问题全称	single	multi	many	real	binary	permutation	large	constrained	expensive	multimodal	sparse	preference
34	CEC2010_F18	CEC'2010 constrained optimization benchmark problem	√			√				√				
35	CEC2013_F1	Shifted elliptic function	√			√			√					
36	CEC2013_F2	Shifted Rastrigin's function	√			√			√					
37	CEC2013_F3	Shifted Ackley's function	√			√			√					
38	CEC2013_F4	7-nonseparable, 1-separable shifted and rotated elliptic function	√			√			√					
39	CEC2013_F5	7-nonseparable, 1-separable shifted and rotated Rastrigin's function	√			√			√					
40	CEC2013_F6	7-nonseparable, 1-separable shifted and rotated Ackley's function	√			√			√					
41	CEC2013_F7	7-nonseparable, 1-separable shifted and rotated Schwefel's function	√			√			√					
42	CEC2013_F8	20-nonseparable shifted and rotated elliptic function	√			√			√					
43	CEC2013_F9	20-nonseparable shifted and rotated Rastrigin's function	√			√			√					
44	CEC2013_F10	20-nonseparable shifted and rotated Rastrigin's function	√			√			√					
45	CEC2013_F11	20-nonseparable shifted and rotated Schwefel's function	√			√			√					
46	CEC2013_F12	Shifted Rosenbrock's function	√			√			√					
47	CEC2013_F13	Shifted Schwefel's function with conforming overlapping subcomponents	√			√			√					
48	CEC2013_F14	Shifted Schwefel's function with conflicting overlapping subcomponents	√			√			√					
49	CEC2013_F15	Shifted Schwefel's function	√			√			√					
50	CEC2017_F1	CEC'2017 constrained optimization benchmark problem	√			√				√				
51	CEC2017_F2	CEC'2017 constrained optimization benchmark problem	√			√				√				
52	CEC2017_F3	CEC'2017 constrained optimization benchmark problem	√			√				√				
53	CEC2017_F4	CEC'2017 constrained optimization benchmark problem	√			√				√				
54	CEC2017_F5	CEC'2017 constrained optimization benchmark problem	√			√				√				
55	CEC2017_F6	CEC'2017 constrained optimization benchmark problem	√			√				√				
56	CEC2017_F7	CEC'2017 constrained optimization benchmark problem	√			√				√				
57	CEC2017_F8	CEC'2017 constrained optimization benchmark problem	√			√				√				
58	CEC2017_F9	CEC'2017 constrained optimization benchmark problem	√			√				√				
59	CEC2017_F10	CEC'2017 constrained optimization benchmark problem	√			√				√				
60	CEC2017_F11	CEC'2017 constrained optimization benchmark problem	√			√				√				
61	CEC2017_F12	CEC'2017 constrained optimization benchmark problem	√			√				√				
62	CEC2017_F13	CEC'2017 constrained optimization benchmark problem	√			√				√				
63	CEC2017_F14	CEC'2017 constrained optimization benchmark problem	√			√				√				
64	CEC2017_F15	CEC'2017 constrained optimization benchmark problem	√			√				√				
65	CEC2017_F16	CEC'2017 constrained optimization benchmark problem	√			√				√				
66	CEC2017_F17	CEC'2017 constrained optimization benchmark problem	√			√				√				
67	CEC2017_F18	CEC'2017 constrained optimization benchmark problem	√			√				√				
68	CEC2017_F19	CEC'2017 constrained optimization benchmark problem	√			√				√				
69	CEC2017_F20	CEC'2017 constrained optimization benchmark problem	√			√				√				

	问题缩写	问题全称	single	multi	many	real	binary	permutation	large	constrained	expensive	multimodal	sparse	preference
70	CEC2017_F21	CEC'2017 constrained optimization benchmark problem	√			√				√				
71	CEC2017_F22	CEC'2017 constrained optimization benchmark problem	√			√				√				
72	CEC2017_F23	CEC'2017 constrained optimization benchmark problem	√			√				√				
73	CEC2017_F24	CEC'2017 constrained optimization benchmark problem	√			√				√				
74	CEC2017_F25	CEC'2017 constrained optimization benchmark problem	√			√				√				
75	CEC2017_F26	CEC'2017 constrained optimization benchmark problem	√			√				√				
76	CEC2017_F27	CEC'2017 constrained optimization benchmark problem	√			√				√				
77	CEC2017_F28	CEC'2017 constrained optimization benchmark problem	√			√				√				
78	CEC2020_F1	Bent cigar function	√			√								
79	CEC2020_F2	Shifted and rotated Schwefel's function	√			√								
80	CEC2020_F3	Shifted and rotated Lunacek bi-Rastrigin function	√			√								
81	CEC2020_F4	Expanded Rosenbrock's plus Griewangk's function	√			√								
82	CEC2020_F5	Hybrid function 1	√			√								
83	CEC2020_F6	Hybrid function 2	√			√								
84	CEC2020_F7	Hybrid function 3	√			√								
85	CEC2020_F8	Composition function 1	√			√								
86	CEC2020_F9	Composition function 2	√			√								
87	CEC2020_F10	Composition function 3	√			√								
88	CF1	Constrained benchmark MOP		√		√			√	√				
89	CF2	Constrained benchmark MOP		√		√			√	√				
90	CF3	Constrained benchmark MOP		√		√			√	√				
91	CF4	Constrained benchmark MOP		√		√			√	√				
92	CF5	Constrained benchmark MOP		√		√			√	√				
93	CF6	Constrained benchmark MOP		√		√			√	√				
94	CF7	Constrained benchmark MOP		√		√			√	√				
95	CF8	Constrained benchmark MOP		√		√			√	√				
96	CF9	Constrained benchmark MOP		√		√			√	√				
97	CF10	Constrained benchmark MOP		√		√			√	√				
98	DAS-CMOP1	Difficulty-adjustable and scalable constrained benchmark MOP		√		√			√	√				
99	DAS-CMOP2	Difficulty-adjustable and scalable constrained benchmark MOP		√		√			√	√				
100	DAS-CMOP3	Difficulty-adjustable and scalable constrained benchmark MOP		√		√			√	√				
101	DAS-CMOP4	Difficulty-adjustable and scalable constrained benchmark MOP		√		√			√	√				
102	DAS-CMOP5	Difficulty-adjustable and scalable constrained benchmark MOP		√		√			√	√				
103	DAS-CMOP6	Difficulty-adjustable and scalable constrained benchmark MOP		√		√			√	√				
104	DAS-CMOP7	Difficulty-adjustable and scalable constrained benchmark MOP		√		√			√	√				
105	DAS-CMOP8	Difficulty-adjustable and scalable constrained benchmark MOP		√		√			√	√				
106	DAS-CMOP9	Difficulty-adjustable and scalable constrained benchmark MOP		√		√			√	√				

	问题缩写	问题全称	single	multi	many	real	binary	permutation	large	constrained	expensive	multimodal	sparse	preference
107	DOC1	Benchmark MOP with constraints in decision and objective spaces		√		√				√				
108	DOC2	Benchmark MOP with constraints in decision and objective spaces		√		√				√				
109	DOC3	Benchmark MOP with constraints in decision and objective spaces		√		√				√				
110	DOC4	Benchmark MOP with constraints in decision and objective spaces		√		√				√				
111	DOC5	Benchmark MOP with constraints in decision and objective spaces		√		√				√				
112	DOC6	Benchmark MOP with constraints in decision and objective spaces		√		√				√				
113	DOC7	Benchmark MOP with constraints in decision and objective spaces		√		√				√				
114	DOC8	Benchmark MOP with constraints in decision and objective spaces		√		√				√				
115	DOC9	Benchmark MOP with constraints in decision and objective spaces		√		√				√				
116	DTLZ1	Benchmark MOP proposed by Deb, Thiele, Laumanns, and Zitzler		√	√	√			√		√			
117	DTLZ2	Benchmark MOP proposed by Deb, Thiele, Laumanns, and Zitzler		√	√	√			√		√			
118	DTLZ3	Benchmark MOP proposed by Deb, Thiele, Laumanns, and Zitzler		√	√	√			√		√			
119	DTLZ4	Benchmark MOP proposed by Deb, Thiele, Laumanns, and Zitzler		√	√	√			√		√			
120	DTLZ5	Benchmark MOP proposed by Deb, Thiele, Laumanns, and Zitzler		√	√	√			√		√			
121	DTLZ6	Benchmark MOP proposed by Deb, Thiele, Laumanns, and Zitzler		√	√	√			√		√			
122	DTLZ7	Benchmark MOP proposed by Deb, Thiele, Laumanns, and Zitzler		√	√	√			√		√			
123	DTLZ8	Benchmark MOP proposed by Deb, Thiele, Laumanns, and Zitzler		√	√	√			√	√	√			
124	DTLZ9	Benchmark MOP proposed by Deb, Thiele, Laumanns, and Zitzler		√	√	√			√	√	√			
125	CDTLZ2	Convex DTLZ2		√	√	√			√		√			
126	IDTLZ1	Inverted DTLZ1		√	√	√			√		√			
127	IDTLZ2	Inverted DTLZ2		√	√	√			√		√			
128	SDTLZ1	Scaled DTLZ1		√	√	√			√		√			
129	SDTLZ2	Scaled DTLZ2		√	√	√			√		√			
130	C1-DTLZ1	Constrained DTLZ1		√	√	√			√	√	√			
131	C1-DTLZ3	Constrained DTLZ3		√	√	√			√	√	√			
132	C2-DTLZ2	Constrained DTLZ2		√	√	√			√	√	√			
133	C3-DTLZ4	Constrained DTLZ4		√	√	√			√	√	√			
134	DC1-DTLZ1	DTLZ1 with constrains in decision space		√	√	√			√	√	√			
135	DC1-DTLZ3	DTLZ3 with constrains in decision space		√	√	√			√	√	√			
136	DC2-DTLZ1	DTLZ1 with constrains in decision space		√	√	√			√	√	√			
137	DC2-DTLZ3	DTLZ3 with constrains in decision space		√	√	√			√	√	√			
138	DC3-DTLZ1	DTLZ1 with constrains in decision space		√	√	√			√	√	√			
139	DC3-DTLZ3	DTLZ3 with constrains in decision space		√	√	√			√	√	√			
140	IMMOEA_F1	Benchmark MOP for testing IM-MOEA		√		√			√					
141	IMMOEA_F2	Benchmark MOP for testing IM-MOEA		√		√			√					
142	IMMOEA_F3	Benchmark MOP for testing IM-MOEA		√		√			√					
143	IMMOEA_F4	Benchmark MOP for testing IM-MOEA		√		√			√					

	问题缩写	问题全称	single	multi	many	real	binary	permutation	large	constrained	expensive	multimodal	sparse	preference
144	IMMOEA_F5	Benchmark MOP for testing IM-MOEA		√		√			√					
145	IMMOEA_F6	Benchmark MOP for testing IM-MOEA		√		√			√					
146	IMMOEA_F7	Benchmark MOP for testing IM-MOEA		√		√			√					
147	IMMOEA_F8	Benchmark MOP for testing IM-MOEA		√		√			√					
148	IMMOEA_F9	Benchmark MOP for testing IM-MOEA		√		√			√					
149	IMMOEA_F10	Benchmark MOP for testing IM-MOEA		√		√			√					
150	IMOP1	Benchmark MOP with irregular Pareto front		√		√					√			
151	IMOP2	Benchmark MOP with irregular Pareto front		√		√					√			
152	IMOP3	Benchmark MOP with irregular Pareto front		√		√					√			
153	IMOP4	Benchmark MOP with irregular Pareto front		√		√					√			
154	IMOP5	Benchmark MOP with irregular Pareto front		√		√					√			
155	IMOP6	Benchmark MOP with irregular Pareto front		√		√					√			
156	IMOP7	Benchmark MOP with irregular Pareto front		√		√					√			
157	IMOP8	Benchmark MOP with irregular Pareto front		√		√					√			
158	KP	The knapsack problem	√				√		√	√				
159	LIR-CMOP1	Constrained benchmark MOP with large infeasible regions		√		√			√	√				
160	LIR-CMOP2	Constrained benchmark MOP with large infeasible regions		√		√			√	√				
161	LIR-CMOP3	Constrained benchmark MOP with large infeasible regions		√		√			√	√				
162	LIR-CMOP4	Constrained benchmark MOP with large infeasible regions		√		√			√	√				
163	LIR-CMOP5	Constrained benchmark MOP with large infeasible regions		√		√			√	√				
164	LIR-CMOP6	Constrained benchmark MOP with large infeasible regions		√		√			√	√				
165	LIR-CMOP7	Constrained benchmark MOP with large infeasible regions		√		√			√	√				
166	LIR-CMOP8	Constrained benchmark MOP with large infeasible regions		√		√			√	√				
167	LIR-CMOP9	Constrained benchmark MOP with large infeasible regions		√		√			√	√				
168	LIR-CMOP10	Constrained benchmark MOP with large infeasible regions		√		√			√	√				
169	LIR-CMOP11	Constrained benchmark MOP with large infeasible regions		√		√			√	√				
170	LIR-CMOP12	Constrained benchmark MOP with large infeasible regions		√		√			√	√				
171	LIR-CMOP13	Constrained benchmark MOP with large infeasible regions		√		√			√	√				
172	LIR-CMOP14	Constrained benchmark MOP with large infeasible regions		√		√			√	√				
173	LSMOP1	Large-scale benchmark MOP		√	√	√			√					
174	LSMOP2	Large-scale benchmark MOP		√	√	√			√					
175	LSMOP3	Large-scale benchmark MOP		√	√	√			√					
176	LSMOP4	Large-scale benchmark MOP		√	√	√			√					
177	LSMOP5	Large-scale benchmark MOP		√	√	√			√					
178	LSMOP6	Large-scale benchmark MOP		√	√	√			√					
179	LSMOP7	Large-scale benchmark MOP		√	√	√			√					
180	LSMOP8	Large-scale benchmark MOP		√	√	√			√					

	问题缩写	问题全称	single	multi	many	real	binary	permutation	large	constrained	expensive	multimodal	sparse	preference
181	LSMOP9	Large-scale benchmark MOP		√	√	√			√					
182	MaF1	Inverted DTLZ1		√	√	√			√					
183	MaF2	DTLZ2BZ		√	√	√			√					
184	MaF3	Convex DTLZ3		√	√	√			√					
185	MaF4	Inverted and scaled DTLZ3		√	√	√			√					
186	MaF5	Scaled DTLZ4		√	√	√			√					
187	MaF6	DTLZ5IM		√	√	√			√					
188	MaF7	DTLZ7		√	√	√			√					
189	MaF8	MP-DMP		√	√	√								
190	MaF9	ML-DMP		√	√	√								
191	MaF10	WFG1		√	√	√			√					
192	MaF11	WFG2		√	√	√			√					
193	MaF12	WFG9		√	√	√			√					
194	MaF13	P7		√	√	√			√					
195	MaF14	LSMOP3		√	√	√			√					
196	MaF15	Inverted LSMOP8		√	√	√			√					
197	MLDMP	The multi-line distance minimization problem		√	√	√								
198	MMF1	Multi-modal multi-objective test function		√		√						√		
199	MMF2	Multi-modal multi-objective test function		√		√						√		
200	MMF3	Multi-modal multi-objective test function		√		√						√		
201	MMF4	Multi-modal multi-objective test function		√		√						√		
202	MMF5	Multi-modal multi-objective test function		√		√						√		
203	MMF6	Multi-modal multi-objective test function		√		√						√		
204	MMF7	Multi-modal multi-objective test function		√		√						√		
205	MMF8	Multi-modal multi-objective test function		√		√						√		
206	MMMOP1	Multi-modal multi-objective optimization problem		√	√	√						√		
207	MMMOP2	Multi-modal multi-objective optimization problem		√	√	√						√		
208	MMMOP3	Multi-modal multi-objective optimization problem		√	√	√						√		
209	MMMOP4	Multi-modal multi-objective optimization problem		√	√	√						√		
210	MMMOP5	Multi-modal multi-objective optimization problem		√	√	√						√		
211	MMMOP6	Multi-modal multi-objective optimization problem		√	√	√						√		
212	MOEADDE_F1	Benchmark MOP for testing MOEA/D-DE		√		√			√					
213	MOEADDE_F2	Benchmark MOP for testing MOEA/D-DE		√		√			√					
214	MOEADDE_F3	Benchmark MOP for testing MOEA/D-DE		√		√			√					
215	MOEADDE_F4	Benchmark MOP for testing MOEA/D-DE		√		√			√					
216	MOEADDE_F5	Benchmark MOP for testing MOEA/D-DE		√		√			√					
217	MOEADDE_F6	Benchmark MOP for testing MOEA/D-DE		√		√			√					

	问题缩写	问题全称	single	multi	many	real	binary	permutation	large	constrained	expensive	multimodal	sparse	preference
218	MOEADDE_F7	Benchmark MOP for testing MOEA/D-DE		√		√			√					
219	MOEADDE_F8	Benchmark MOP for testing MOEA/D-DE		√		√			√					
220	MOEADDE_F9	Benchmark MOP for testing MOEA/D-DE		√		√			√					
221	MOEADM2M_F1	Benchmark MOP for testing MOEA/D-M2M		√		√			√					
222	MOEADM2M_F2	Benchmark MOP for testing MOEA/D-M2M		√		√			√					
223	MOEADM2M_F3	Benchmark MOP for testing MOEA/D-M2M		√		√			√					
224	MOEADM2M_F4	Benchmark MOP for testing MOEA/D-M2M		√		√			√					
225	MOEADM2M_F5	Benchmark MOP for testing MOEA/D-M2M		√		√			√					
226	MOEADM2M_F6	Benchmark MOP for testing MOEA/D-M2M		√		√			√					
227	MOEADM2M_F7	Benchmark MOP for testing MOEA/D-M2M		√		√			√					
228	MOKP	The multi-objective knapsack problem		√	√		√		√					
229	MONRP	The multi-objective next release problem		√			√		√					
230	MOTSP	The multi-objective traveling salesman problem		√	√			√	√					
231	MPDMP	The multi-point distance minimization problem		√	√	√								
232	mQAP	The multi-objective quadratic assignment problem		√	√			√	√					
233	MW1	Constrained benchmark MOP proposed by Ma and Wang		√		√			√	√				
234	MW2	Constrained benchmark MOP proposed by Ma and Wang		√		√			√	√				
235	MW3	Constrained benchmark MOP proposed by Ma and Wang		√		√			√	√				
236	MW4	Constrained benchmark MOP proposed by Ma and Wang		√	√	√			√	√				
237	MW5	Constrained benchmark MOP proposed by Ma and Wang		√		√			√	√				
238	MW6	Constrained benchmark MOP proposed by Ma and Wang		√		√			√	√				
239	MW7	Constrained benchmark MOP proposed by Ma and Wang		√		√			√	√				
240	MW8	Constrained benchmark MOP proposed by Ma and Wang		√	√	√			√	√				
241	MW9	Constrained benchmark MOP proposed by Ma and Wang		√		√			√	√				
242	MW10	Constrained benchmark MOP proposed by Ma and Wang		√		√			√	√				
243	MW11	Constrained benchmark MOP proposed by Ma and Wang		√		√			√	√				
244	MW12	Constrained benchmark MOP proposed by Ma and Wang		√		√			√	√				
245	MW13	Constrained benchmark MOP proposed by Ma and Wang		√		√			√	√				
246	MW14	Constrained benchmark MOP proposed by Ma and Wang		√	√	√			√	√				
247	RMMEDA_F1	Benchmark MOP for testing RM-MEDA		√		√			√					
248	RMMEDA_F2	Benchmark MOP for testing RM-MEDA		√		√			√					
249	RMMEDA_F3	Benchmark MOP for testing RM-MEDA		√		√			√					
250	RMMEDA_F4	Benchmark MOP for testing RM-MEDA		√		√			√					
251	RMMEDA_F5	Benchmark MOP for testing RM-MEDA		√		√			√					
252	RMMEDA_F6	Benchmark MOP for testing RM-MEDA		√		√			√					
253	RMMEDA_F7	Benchmark MOP for testing RM-MEDA		√		√			√					
254	RMMEDA_F8	Benchmark MOP for testing RM-MEDA		√		√			√					

	问题缩写	问题全称	single	multi	many	real	binary	permutation	large	constrained	expensive	multimodal	sparse	preference
255	RMMEDA_F9	Benchmark MOP for testing RM-MEDA		√		√			√					
256	RMMEDA_F10	Benchmark MOP for testing RM-MEDA		√		√			√					
257	Sparse_CD	The community detection problem		√			√		√		√		√	
258	Sparse_CN	The critical node detection problem		√			√		√		√		√	
259	Sparse_FS	The feature selection problem		√			√		√		√		√	
260	Sparse_IS	The instance selection problem		√			√		√		√		√	
261	Sparse_NN	The neural network training problem		√		√			√		√		√	
262	Sparse_PM	The pattern mining problem		√			√		√		√		√	
263	Sparse_PO	The portfolio optimization problem		√		√			√		√		√	
264	Sparse_SR	The sparse signal reconstruction problem		√		√			√		√		√	
265	SMMOP1	Sparse multi-modal multi-objective optimization problem		√	√	√			√			√	√	
266	SMMOP2	Sparse multi-modal multi-objective optimization problem		√	√	√			√			√	√	
267	SMMOP3	Sparse multi-modal multi-objective optimization problem		√	√	√			√			√	√	
268	SMMOP4	Sparse multi-modal multi-objective optimization problem		√	√	√			√			√	√	
269	SMMOP5	Sparse multi-modal multi-objective optimization problem		√	√	√			√			√	√	
270	SMMOP6	Sparse multi-modal multi-objective optimization problem		√	√	√			√			√	√	
271	SMMOP7	Sparse multi-modal multi-objective optimization problem		√	√	√			√			√	√	
272	SMMOP8	Sparse multi-modal multi-objective optimization problem		√	√	√			√			√	√	
273	SMOP1	Benchmark MOP with sparse Pareto optimal solutions		√	√	√			√		√		√	
274	SMOP2	Benchmark MOP with sparse Pareto optimal solutions		√	√	√			√		√		√	
275	SMOP3	Benchmark MOP with sparse Pareto optimal solutions		√	√	√			√		√		√	
276	SMOP4	Benchmark MOP with sparse Pareto optimal solutions		√	√	√			√		√		√	
277	SMOP5	Benchmark MOP with sparse Pareto optimal solutions		√	√	√			√		√		√	
278	SMOP6	Benchmark MOP with sparse Pareto optimal solutions		√	√	√			√		√		√	
279	SMOP7	Benchmark MOP with sparse Pareto optimal solutions		√	√	√			√		√		√	
280	SMOP8	Benchmark MOP with sparse Pareto optimal solutions		√	√	√			√		√		√	
281	SOP_F1	Sphere function	√			√					√			
282	SOP_F2	Schwefel's function 2.22	√			√					√			
283	SOP_F3	Schwefel's function 1.2	√			√					√			
284	SOP_F4	Schwefel's function 2.21	√			√					√			
285	SOP_F5	Generalized Rosenbrock's function	√			√					√			
286	SOP_F6	Step function	√			√					√			
287	SOP_F7	Quartic function with noise	√			√					√			
288	SOP_F8	Generalized Schwefel's function 2.26	√			√					√			
289	SOP_F9	Generalized Rastrigin's function	√			√					√			
290	SOP_F10	Ackley's function	√			√					√			
291	SOP_F11	Generalized Griewank's function	√			√					√			

	问题缩写	问题全称	single	multi	many	real	binary	permutation	large	constrained	expensive	multimodal	sparse	preference
292	SOP_F12	Generalized penalized function	√			√					√			
293	SOP_F13	Generalized penalized function	√			√					√			
294	SOP_F14	Shekel's foxholes function	√			√					√			
295	SOP_F15	Kowalik's function	√			√					√			
296	SOP_F16	Six-hump camel-back function	√			√					√			
297	SOP_F17	Branin function	√			√					√			
298	SOP_F18	Goldstein-price function	√			√					√			
299	SOP_F19	Hartman's family	√			√					√			
300	SOP_F20	Hartman's family	√			√					√			
301	SOP_F21	Shekel's family	√			√					√			
302	SOP_F22	Shekel's family	√			√					√			
303	SOP_F23	Shekel's family	√			√					√			
304	TREE1	The time-varying ratio error estimation problem		√		√			√	√	√			
305	TREE2	The time-varying ratio error estimation problem		√		√			√	√	√			
306	TREE3	The time-varying ratio error estimation problem		√		√			√	√	√			
307	TREE4	The time-varying ratio error estimation problem		√		√			√	√	√			
308	TREE5	The time-varying ratio error estimation problem		√		√			√	√	√			
309	TREE6	The time-varying ratio error estimation problem		√		√			√	√	√			
310	TSP	The traveling salesman problem	√					√	√					
311	UF1	Unconstrained benchmark MOP		√		√			√					
312	UF2	Unconstrained benchmark MOP		√		√			√					
313	UF3	Unconstrained benchmark MOP		√		√			√					
314	UF4	Unconstrained benchmark MOP		√		√			√					
315	UF5	Unconstrained benchmark MOP		√		√			√					
316	UF6	Unconstrained benchmark MOP		√		√			√					
317	UF7	Unconstrained benchmark MOP		√		√			√					
318	UF8	Unconstrained benchmark MOP		√		√			√					
319	UF9	Unconstrained benchmark MOP		√		√			√					
320	UF10	Unconstrained benchmark MOP		√		√			√					
321	VNT1	Benchmark MOP proposed by Viennet		√		√								
322	VNT2	Benchmark MOP proposed by Viennet		√		√								
323	VNT3	Benchmark MOP proposed by Viennet		√		√								
324	VNT4	Benchmark MOP proposed by Viennet		√		√				√				
325	WFG1	Benchmark MOP proposed by Walking Fish Group		√	√	√			√		√			
326	WFG2	Benchmark MOP proposed by Walking Fish Group		√	√	√			√		√			
327	WFG3	Benchmark MOP proposed by Walking Fish Group		√	√	√			√		√			
328	WFG4	Benchmark MOP proposed by Walking Fish Group		√	√	√			√		√			

	问题缩写	问题全称	single	multi	many	real	binary	permutation	large	constrained	expensive	multimodal	sparse	preference
329	WFG5	Benchmark MOP proposed by Walking Fish Group		√	√	√			√		√			
330	WFG6	Benchmark MOP proposed by Walking Fish Group		√	√	√			√		√			
331	WFG7	Benchmark MOP proposed by Walking Fish Group		√	√	√			√		√			
332	WFG8	Benchmark MOP proposed by Walking Fish Group		√	√	√			√		√			
333	WFG9	Benchmark MOP proposed by Walking Fish Group		√	√	√			√		√			
334	ZDT1	Benchmark MOP proposed by Zitzler, Deb, and Thiele		√		√			√		√			
335	ZDT2	Benchmark MOP proposed by Zitzler, Deb, and Thiele		√		√			√		√			
336	ZDT3	Benchmark MOP proposed by Zitzler, Deb, and Thiele		√		√			√		√			
337	ZDT4	Benchmark MOP proposed by Zitzler, Deb, and Thiele		√		√			√		√			
338	ZDT5	Benchmark MOP proposed by Zitzler, Deb, and Thiele		√			√		√		√			
339	ZDT6	Benchmark MOP proposed by Zitzler, Deb, and Thiele		√		√			√		√			