PlatEMO

进化多目标优化平台

用户手册 4.12

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之一：

[1] 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.

[2] Ye Tian, Weijian Zhu, Xingyi Zhang, and Yaochu Jin, “A practical tutorial on solving optimization problems via PlatEMO,” Neurocomputing, 2023, 518: 190-205.

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 是一个用于求解优化问题的开源平台，它的输入是一个优化问题，输出是在该优化问题上得到的最优解。一个优化问题满足以下定义：

$$\begin{aligned}\min_{\mathbf{x}} \quad & \mathbf{f}(\mathbf{x}) = \left(f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_M(\mathbf{x})\right) \\ \text{s.t.} \quad & \mathbf{x} = (x_1, x_2, \ldots x_D) \in \Omega \\ & g_1(\mathbf{x}), g_2(\mathbf{x}), \ldots, g_K(\mathbf{x}) \leq 0\end{aligned}$$

其中 $\mathbf{x}$ 表示该问题的一个解或决策向量，它由 D 个决策变量 x_i 组成，其中每个决策变量可能被限制为实数、整数或二进制数等。Ω 表示该问题的搜索空间，它由下界 $l_1, l_2, \ldots l_D$ 和上界 $u_1, u_2, \ldots u_D$ 构成，即任意决策变量始终满足 $l_i \leq x_i \leq u_i$。$f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_M(\mathbf{x})$ 表示该解的 M 个目标函数值，$g_1(\mathbf{x}), g_2(\mathbf{x}), \ldots, g_K(\mathbf{x})$ 表示该解的 K 个约束违反值。

为了定义一个优化问题，用户至少需要输入以下内容：

- 每个决策变量的编码方式（实数、整数或二进制数等）；
- 决策变量的下界 $l_1, l_2, \ldots l_D$ 和上界 $u_1, u_2, \ldots u_D$；
- 至少一个目标函数 $f_1(\mathbf{x})$。

为了更精准地定义问题，用户还能输入以下内容：

- 多个目标函数 $f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_M(\mathbf{x})$；
- 多个约束函数 $g_1(\mathbf{x}), g_2(\mathbf{x}), \ldots, g_K(\mathbf{x})$；
- 解的初始化函数；
- 无效解的修复函数；
- 解的评价函数；
- 目标和约束的梯度函数；

- 各函数计算中使用到的数据（一个任意类型的常量）。

以上函数均指的是代码函数而非数学函数，即它需要有符合规定的输入和输出，但不需要有显式的数学表达式。此外，用户还能定义与优化算法相关的内容，通过选择合适的算法和参数设置以提升优化效果。

在 MATLAB 中，用户可以用以下三种方式运行主函数文件 `platemo.m`：

1) 带参数调用主函数：

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

可以利用指定的算法来求解指定的测试问题并设置参数，优化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：

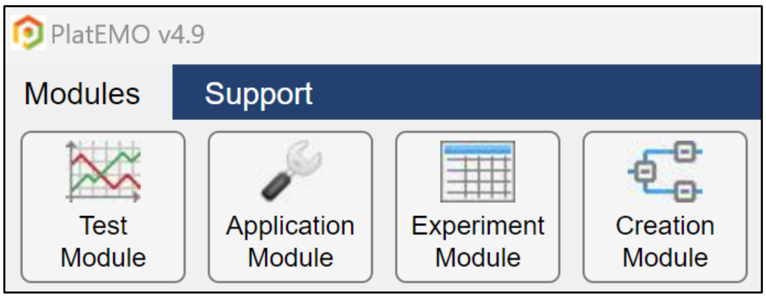
```
f1 = @(x)sum(x);
g1 = @(x)1-sum(x);
platemo('objFcn',f1,'conFcn',g1,'algorithm',@GA);
```

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();
```

可以弹出一个带有四个模块的图形界面，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），创造模块用于零代码构建全新的算法（参阅创造模块章节）。



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	要运行的算法类
'problem'	函数句柄或单元数组	不定	要求解的问题类
'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
'maxRuntime'	正数	inf	最大运行时间
'save'	整数	-10	保存的种群数
'run'	正整数	[]	当前运行的编号
'metName'	字符串或单元数组	{}	要计算的指标名称
'outputFcn'	函数句柄	@DefaultOutput	每代开始前调用的函数 输入一: ALGORITHM 对象 输入二: PROBLEM 对象 输出: 无

- '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。例如以下代码用算法@GA 求解默认问题，并设置了该算法中的参数值:

```
platemo('algorithm',{@GA,1,30,1,30});
```

- '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,…` 指定了该问题中的参数值。例如以下代码用默认算法求解问题`@WFG1`，并设置了该问题中的参数值：

```
platemo('problem',{@WFG1,20});
```

- `'N'`表示算法使用的种群的大小，它通常等于最终输出的解的个数。例如以下代码用算法`@GA` 求解问题`@SOP_F1`，并设置种群大小为 50：

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

- `'M'`表示问题的目标个数，它仅对一些多目标测试问题生效。例如以下代码用算法`@NSGAII` 求解具有 5 个目标的`@DTLZ2` 问题：

```
platemo('algorithm',@NSGAII,'problem',@DTLZ2,'M',5);
```

- `'D'`表示问题的变量个数，它仅对一些测试问题生效。例如以下代码用算法`@GA` 求解具有 100 个变量的`@SOP_F1` 问题：

```
platemo('algorithm',@GA,'problem',@SOP_F1,'D',100);
```

- `'maxFE'`表示算法可用的最大评价次数，它通常等于种群大小乘以迭代次数。例如以下代码设置算法`@GA` 的最大评价次数为 20000：

```
platemo('algorithm',@GA,'problem',@SOP_F1,'maxFE',20000);
```

- `'maxRuntime'`表示算法可用的最大运行时间，单位为秒。当`'maxRuntime'`等于默认值 `inf` 时，算法将在`'maxFE'`次评价次数后停止；否则，算法将在`'maxRuntime'`秒后停止。例如以下代码设置算法`@GA` 的最大运行时间为 10 秒：

```
platemo('algorithm',@GA,'problem',@SOP_F1,'maxRuntime',10);
```

- `'save'`表示保存的种群数，该值大于零时优化结果将被保存在文件中，该值小于零时优化结果将被显示在窗口中（参阅获取运行结果章节）。
- `'run'`表示当前运行的编号，它附加在保存文件名的末尾，使相同算法在相同问题上的多次运行结果对应的文件名不同（参阅获取运行结果章节）。
- `'metName'`表示要计算的指标名称，它可以是一个字符串（单个指标）或一个单元数组（多个指标）。保存的种群会被计算指定的指标值，并保存在文件或显示在窗口中（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。默认的'outputFcn'会根据'save'的值来保存或显示优化结果。

注意以上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
'objFcn'	函数句柄、矩阵或单元数组	{}	问题的目标函数；所有目标函数均被最小化 输入：一个决策向量 输出：目标值（标量）
'encoding'	标量或行向量	1	每个变量的编码方式
'lower'	标量或行向量	0	每个变量的下界
'upper'	标量或行向量	1	每个变量的上界
'conFcn'	函数句柄、矩阵或单元数组	{}	问题的约束函数；当且仅当约束违反值小于等于零时，该约束被满足 输入：一个决策向量 输出：约束违反值（标量）
'decFcn'	函数句柄	{}	无效解修复函数 输入：一个决策向量 输出：修复后的决策向量
'evalFcn'	函数句柄	{}	解的评价函数 输入：一个决策向量 输出一：修复后的决策向量 输出二：所有目标值（向量） 输出三：所有约束违反值（向量）
'initFcn'	函数句柄	{}	种群初始化函数 输入：种群大小 输出：种群的决策向量构成的矩阵
'gradFcn'	函数句柄	{}	目标和约束的梯度函数 输入：一个决策向量 输出一：目标雅可比矩阵 输出二：约束雅可比矩阵
'data'	任意	{}	问题的数据
'once'	逻辑	0	是否支持同时评价多个解

- '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）、矩阵（自动拟合出函数）或一个单元数组（多目标）。每个目标函数必须有一个输入和一个输出，其中输入是一个决策向量、输出是目标值。所有目标函数均被最小化。例如以下代码利用默认算法求解一个含有六个实数变量的双目标优化问题：

```
f1 = @(x)x(1)+sum(x(2:end));
f2 = @(x)sqrt(1-x(1)^2)+sum(x(2:end));
platemo('objFcn',{f1,f2},'D',6);
```

  其中第一个目标为 $x_1+\sum_{i=2}^{D}x_i$ 、第二个目标为 $\sqrt{1-x_1^2}+\sum_{i=2}^{D}x_i$ 。若一个目标函数是矩阵，则高斯过程回归会利用该矩阵自动拟合出一个函数，其中矩阵的每行表示一个样本、每列表示一个变量（除最后一列）或函数值（最后一列）。例如以下代码求解相同的问题，但目标函数是根据矩阵自动拟合出来的：

```
x = rand(50,6);
y1 = x(:,1)+sum(x(:,2:end),2);
y2 = sqrt(1-x(:,1).^2)+sum(x(:,2:end),2);
platemo('objFcn',{[x,y1],[x,y2]},'D',6);
```

- 'encoding'表示每个变量的编码方式，它的值可以是一个标量或行向量，且每维的值可以为 1（实数）、2（整数）、3（标签）、4（二进制数）或 5（序列编号）。算法针对不同的编码方式可能使用不同的算子来产生解。例如以下代码指定三个实数变量、两个整数变量以及一个二进制变量：

```
f1 = @(x)x(1)+sum(x(2:end));
f2 = @(x)sqrt(1-x(1)^2)+sum(x(2:end));
platemo('objFcn',{f1,f2},'encoding',[1,1,1,2,2,4]);
```

  问题的变量数 D 将根据'encoding'的长度自动确定。

- 'lower'和'upper'分别表示每个变量的下界和上界，它们的值可以是标量或行向量，且每维的值必须为实数。'lower'和'upper'的长度必须与'encoding'相同。例如以下代码指定搜索空间为 $[0,1]\times[0,9]^5$：

```
f1 = @(x)x(1)+sum(x(2:end));
f2 = @(x)sqrt(1-x(1)^2)+sum(x(2:end));
platemo('objFcn',{f1,f2},'encoding',[1,1,1,2,2,4],...
'lower',0,'upper',[1,9,9,9,9,9]);
```

- 'conFcn'表示问题的约束函数，它的值可以是一个函数句柄（单约束）、矩阵（自动拟合出函数）或一个单元数组（多约束）。每个约束函数必须有一个输入和一个输出，其中输入是一个决策向量、输出是约束违反值。当且仅当约束违反值小于等于零时，该约束被满足。例如以下代码利用默认算法求解一个双目标优化问题：

```
f1 = @(x)x(1)+sum(x(2:end));
f2 = @(x)sqrt(1-x(1)^2)+sum(x(2:end));
g1 = @(x)1-sum(x(2:end));
platemo('objFcn',{f1,f2},'encoding',[1,1,1,2,2,4],...
'conFcn',g1,'lower',0,'upper',[1,9,9,9,9,9]);
```

  并添加约束函数 $\sum_{i=2}^{6} x_i \geq 1$。注意，等式约束必须转换为不等式约束来处理，详细方法可参阅该论文的 3.2 节。若一个约束函数是矩阵，则高斯过程回归会利用该矩阵自动拟合出一个函数，其中矩阵的每行表示一个样本、每列表示一个变量（除最后一列）或函数值（最后一列）。例如以下代码求解相同的问题，但约束函数是根据矩阵自动拟合出来的：

```
f1 = @(x)x(1)+sum(x(2:end));
f2 = @(x)sqrt(1-x(1)^2)+sum(x(2:end));
x = rand(50,6);
y = 1-sum(x(:,2:end),2);
platemo('objFcn',{f1,f2},'encoding',[1,1,1,2,2,4],...
'conFcn',[x,y],'lower',0,'upper',[1,9,9,9,9,9]);
```

- 'decFcn'表示问题的无效解修复函数，它的值必须是一个函数句柄。该函数必须有一个输入和一个输出，其中输入是一个决策向量、输出是修复后的决策向量。默认的'decFcn'将所有解的范围限定在'lower'和'upper'之间，而以下代码定义了一个新的'decFcn'限制 x_1 为 0.1 的倍数：

```
f1 = @(x)x(1)+sum(x(2:end));
f2 = @(x)sqrt(1-x(1)^2)+sum(x(2:end));
g1 = @(x)1-sum(x(2:end));
h = @(x)[round(x(1)/0.1)*0.1,x(2:end)];
platemo('objFcn',{f1,f2},'encoding',[1,1,1,2,2,4],...
'conFcn',g1,'decFcn',h,'lower',0,'upper',[1,9,9,9,9,9]);
```

- 'evalFcn'表示解的评价函数，它的值必须是一个函数句柄。该函数必须有一个输入和三个输出，其中输入是一个决策向量、第一个输出是修复后的决策向量、第二个输出是目标值向量、第三个输出是约束违反值向量。默认

的'evalFcn'通过依次调用'decFcn'、'objFcn'和'conFcn'来评价解，而以下代码定义了一个新的'evalFcn'来同时进行解的修复、目标计算和约束计算：

```
function [x,f,g] = Eval(x)
    x = [round(x(1)/0.1)*0.1,x(2:end)];
    x = max(0,min([1,9,9,9,9,9],x));
    f(1)  = x(1)+sum(x(2:end));
    f(2)  = sqrt(1-x(1)^2)+sum(x(2:end));
    g = 1-sum(x(2:end));
end
```

接着，以下代码通过仅指定评价函数定义了相同的问题：

```
platemo('evalFcn',@Eval,'encoding',[1,1,1,2,2,4],...
'lower',0,'upper',[1,9,9,9,9,9]);
```

- 'initFcn'表示种群初始化函数，它的值必须是一个函数句柄。该函数必须有一个输入和一个输出，其中输入是种群大小、输出是种群的决策向量构成的矩阵。默认的'initFcn'在整个搜索空间内随机产生初始解，而以下代码定义了一个新的'initFcn'以加速收敛：

```
q = @(N)rand(N,6);
platemo('evalFcn',@Eval,'encoding',[1,1,1,2,2,4],...
'initFcn',q,'lower',0,'upper',[1,9,9,9,9,9]);
```

- 'gradFcn'表示目标和约束的梯度函数，它的值必须是一个函数句柄。该函数必须有一个输入和两个输出，其中输入是一个决策向量、第一个输出是目标雅可比矩阵、第二个输出是约束雅可比矩阵。默认的梯度函数通过有限差分来估计梯度，而以下代码定义了一个新的'gradFcn'以加速收敛：

```
function [oGrad,cGrad] = Grad(x)
    oGrad = [0,x(2:end);0,x(2:end)];
    cGrad = [0,x(2:end)-1/5];
end
```

接着，以下代码通过指定梯度函数来更好地求解问题：

```
platemo('evalFcn',@Eval,'encoding',[1,1,1,2,2,4],...
'gradFcn',@Grad,'lower',0,'upper',[1,9,9,9,9,9]);
```

注意仅有少量算法会使用梯度函数。

- 'data'表示问题的数据，它可以是任意类型的常量。当指定'data'后，以

上所有函数必须增加一个输入参数来接收'data'。例如以下代码求解一个旋转的单目标优化问题：

```
d = rand(RandStream('mlfg6331_64','Seed',28),10)*2-1;
[d,~] = qr(d);
f1 = @(x,d)sum((x*d-0.5).^2);
platemo('objFcn',f1,'encoding',ones(1,10),'data',d);
```

- 'once'表示是否可以同时评价多个解，它是默认值为零的逻辑变量。当指定'once'的值为 1 后，'evalFcn'、'decFcn'、'objFcn'和'conFcn'的输入可以为多个决策向量，即同时评价多个解。在函数中使用矩阵运算或并行计算来支持同时评价多个解，可以显著提升求解效率。例如以下代码将目标函数改写为矩阵运算：

```
d = rand(RandStream('mlfg6331_64','Seed',28),10)*2-1;
[d,~] = qr(d);
f1 = @(x,d)sum((x*d-0.5).^2,2);
platemo('objFcn',f1,'encoding',ones(1,10),'data',d,'once',1);
```

除以上定义问题的方式之外，用户还能创建一个自定义问题对象并创建算法对象予以求解。例如以下代码利用算法@GA 和算法@DE 求解相同的问题：

```
d = rand(RandStream('mlfg6331_64','Seed',28),10)*2-1;
[d,~] = qr(d);
f1 = @(x,d)sum((x*d-0.5).^2);
PRO = UserProblem('objFcn',f1,'encoding',ones(1,10),'data',d);
ALG1 = GA();
ALG2 = DE();
ALG1.Solve(PRO);
ALG2.Solve(PRO);
```

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 的值为负整数时（默认情况），得到的种群会被显示在窗口中，用户可以在窗口中的 Data source 菜单选择要显示的内容。当 Value 的值为正整数时，得到的种群会被保存在名为 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。同时，可按以下方式主动指定 run 的值：

```
parfor i = 1 : 100
    platemo('save',Value,'run',i,…);
end
```

则 run 的值会被指定为 1 到 100。在并行多次运行时，主动指定 run 的值可以避免文件编号混乱或缺失。

每个保存的数据文件存储一个单元数组 result 和一个结构体 metric，其中 result 保存得到的种群、metric 保存指标值。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。

```
result =
  6×2 cell array
    {[ 1600]}    {1×100 SOLUTION}
    {[ 3300]}    {1×100 SOLUTION}
    {[ 5000]}    {1×100 SOLUTION}
    {[ 6600]}    {1×100 SOLUTION}
    {[ 8300]}    {1×100 SOLUTION}
    {[10000]}    {1×100 SOLUTION}
```

```
metric =
  struct with fields:

    runtime: 0.2267
        IGD: [6×1 double]
         HV: [6×1 double]
```

可以通过参数'metName'来指定要计算的指标，例如以下代码用算法@NSGAII 求解@DTLZ2 问题，并计算 IGD 和 HV 指标值保存在文件中：

```
platemo('algorithm',@NSGAII,'problem',@DTLZ2,...
'save',6,'metName',{'IGD','HV'});
```

其中'IGD'和'HV'为要计算的指标名（参阅指标函数章节）。特别地，IGD 和 HV 是多目标优化中最常用的性能指标，它们的适用范围和参考点定义方法参阅该论文的 5.3 节。以上操作均由默认的输出函数@DefaultOutput 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。此外，可按以下方式计算单个种群的指标值：

```
% 在执行以下代码之前需先载入 result
pro = DTLZ2();
pro.CalMetric('IGD',result{end});
```

同时，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文件中。

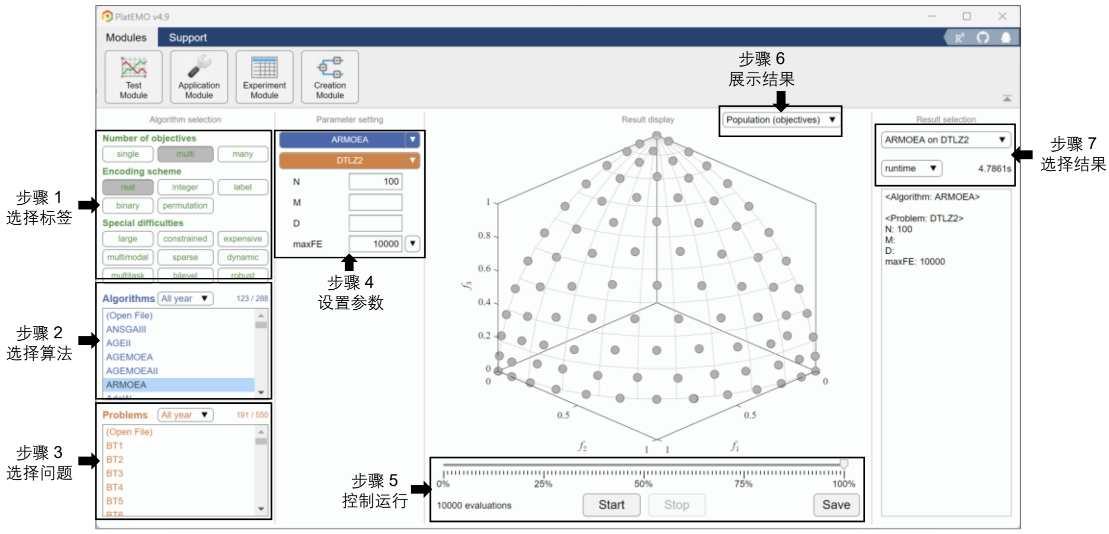
三　通过图形界面使用 PlatEMO

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。

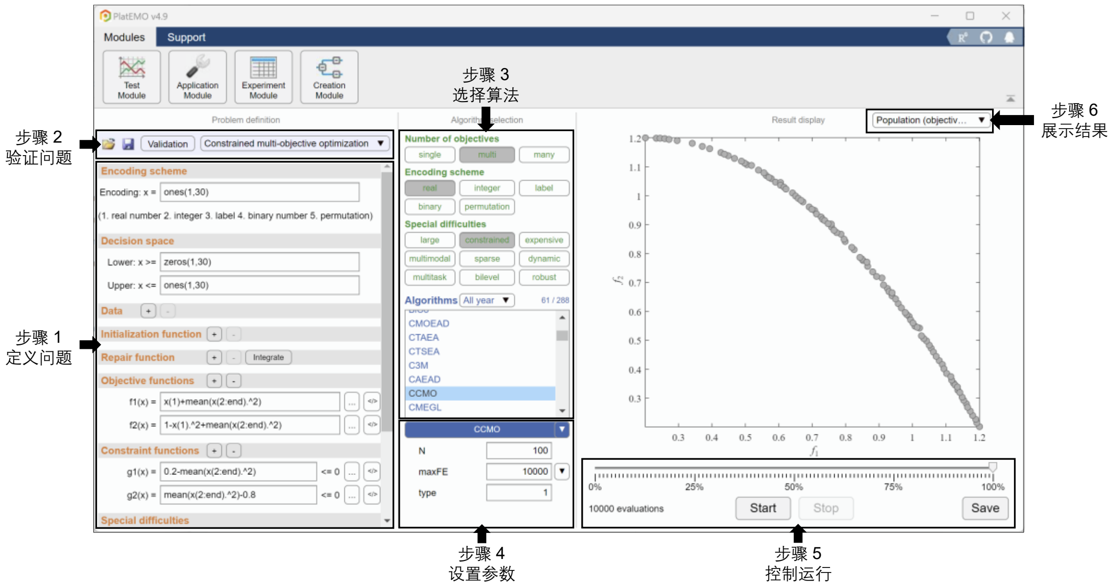


在该模块中，用户能用以下步骤研究单个算法在单个问题上的性能：

- 步骤 1：选择多个标签确定问题类型（参阅算法、问题和指标的标签章节）。
- 步骤 2：在列表中选择一个算法。
- 步骤 3：在列表中选择一个问题。
- 步骤 4：设置算法和问题的参数。不同算法和问题可能有不同的参数，在参数上悬停可查看具体说明。
- 步骤 5：开始、暂停、停止或回退算法的运行；保存当前结果到文件。当前结果可被保存为一个 N 行 $D+M+K$ 列的矩阵，N 表示解的个数，D 表示决策变量个数，M 表示目标个数，K 表示约束个数。
- 步骤 6：选择要显示的数据，例如当前种群的目标值、变量值和各指标值。
- 步骤 7：选择要显示的历史运行结果。

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。

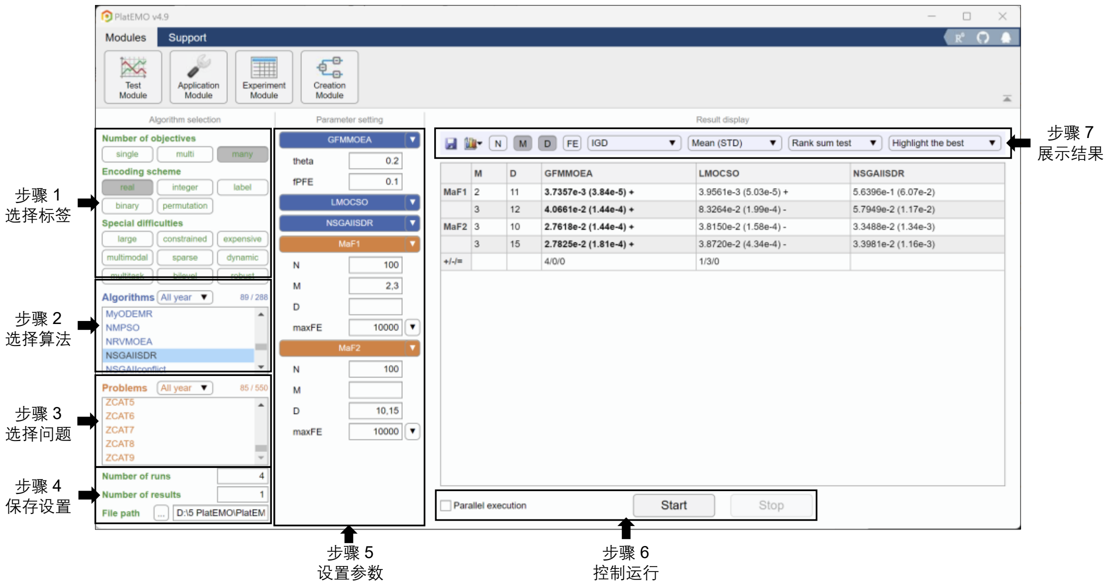


在该模块中，用户能用以下步骤求解自定义问题：

- 步骤 1：定义一个问题，定义的内容与求解自定义问题相同，其中 Encoding scheme 对应'encoding'，Decision space 对应'lower'和'upper'，Data 对应'data'，Initialization function 对应'initFcn'，Repair function 对应'decFcn'，Objective functions 对应'objFcn'，Constraint functions 对应'conFcn'，Evaluation function 对应'evalFcn'。
- 步骤 2：保存或载入问题；检测问题定义的合法性；选择一个问题模板。保存的问题可在其它模块中打开并求解。
- 步骤 3：在列表中选择一个算法。标签会根据问题定义自动确定（参阅算法、问题和指标的标签章节）。
- 步骤 4：设置算法的参数。不同算法可能有不同的参数，在参数上悬停可查看具体说明。
- 步骤 5：开始、暂停、停止或回退算法的运行；保存当前结果到文件。当前结果可被保存为一个 N 行 $D+M+K$ 列的矩阵，N 表示解的个数，D 表示决策变量个数，M 表示目标个数，K 表示约束个数。
- 步骤 6：选择要显示的数据，例如种群的目标值、变量值和各指标值。

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。该模块中所有优化结果将被保存至 MAT 文件（参见获取运行结果章节），如文件存在则会直接读取而不运行算法。

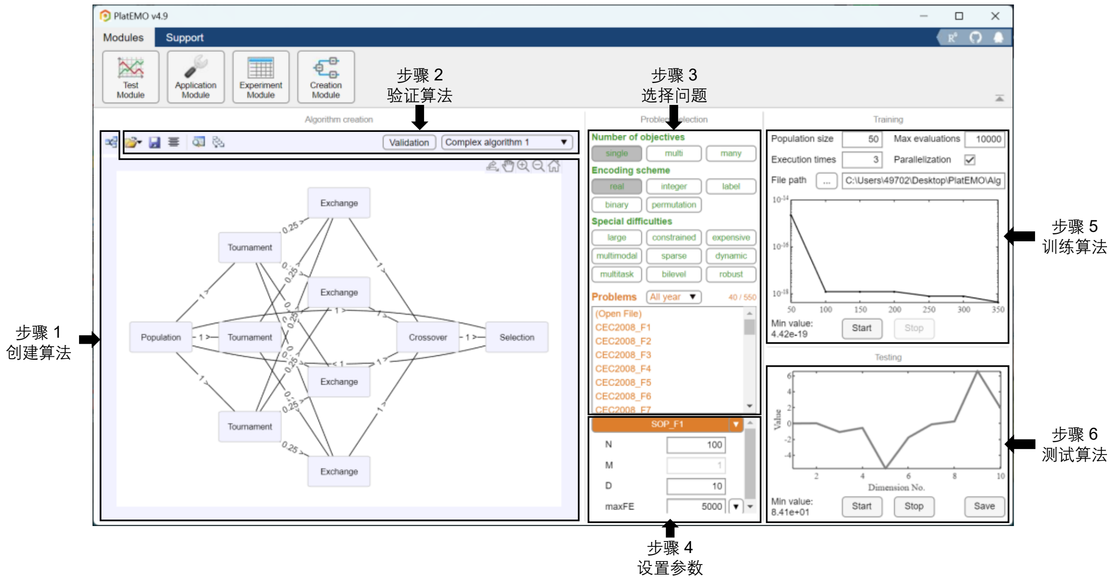


在该模块中，用户能用以下步骤比较多个算法在多个问题上的性能：

- 步骤 1：选择多个标签确定问题类型（参阅算法、问题和指标的标签章节）。
- 步骤 2：在列表中选择多个算法。
- 步骤 3：在列表中选择多个问题。
- 步骤 4：设置实验重复次数、每次保存的种群个数及保存的文件路径（参阅获取运行结果章节）。
- 步骤 5：设置算法和问题的参数。不同算法和问题可能有不同的参数，在参数上悬停可查看具体说明。此处问题的参数可以设置为向量，这使得同一个问题可以产生多个不同的测试实例。
- 步骤 6：开始或停止实验的运行；选择串行（单 CPU）或并行（多 CPU）运行实验。
- 步骤 7：选择要显示的指标值；选择要执行的统计分析；保存表格到文件；将选中的多个单元格的数据显示在图窗中。

4. 创造模块

用户可以通过图形界面中的菜单切换至创造模块，它用于创造全新的算法，并在指定问题上训练它。



在该模块中，用户能用以下步骤创造并训练算法：

- 步骤 1：通过点击按钮来添加模块，通过点击两个模块来添加连接，通过拖动模块和连接来改变布局。模块包含种群模块、算子模块和选择模块，每个模块有一些预设的超参数和一些待训练的参数；连接表示模块间解的传递方向和比例。一个算法视为一个以模块为节点、以连接为边的有权有向循环图，其中第一个节点必须为种群模块、算法至少包含一个算子模块节点、所有节点必须有前驱和后继节点、所有节点必须互相可达、所有环中必须包含至少一个种群模块节点。
- 步骤 2：保存或载入算法或模块；生成算法代码；改变显示样式；自动排列模块；检测算法的合法性；选择一个算法模板。算法训练完成后，可生成算法代码并在其它模块使用。
- 步骤 3：选择多个标签确定问题类型（参阅算法、问题和指标的标签章节）；在列表中选择一个问题。
- 步骤 4：设置问题的参数。不同问题可能有不同的参数，在参数上悬停可查看具体说明。
- 步骤 5：在选择的问题上训练算法中所有模块的参数。这个过程可能较慢，较大的模块数目、问题变量数目、种群大小和评价次数可能耗费数天。
- 步骤 6：在选择的问题上测试训练后的算法的性能。

5. 算法、问题和指标的标签

每个算法、测试问题和指标需要被添加上标签，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
% <1995> <single> <real/integer> <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
<integer>	整数优化：决策变量为整数
<label>	标签优化：决策变量为标签
<binary>	二进制优化：决策变量为二进制数
<permutation>	序列优化：决策变量构成一个全排列
<large>	大规模优化：问题含有 100 或更多的决策变量
<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
<dynamic>	动态优化：目标函数和约束函数随时间变化
<multitask>	多任务优化：同时优化多个问题，每个问题可能含有多个目标函数和约束函数
<bilevel>	双层优化：旨在寻找上层问题的可行且最优的解，一个解对于上层问题是可行的当且仅当它是下层问题的最优解
<robust>	鲁棒优化：目标函数和约束函数受噪声影响，旨在寻找受噪声影响尽可能小且尽可能优的解
<none>	空标签
<min>	（仅用于指标）该指标值越小表示性能越好
<max>	（仅用于指标）该指标值越大表示性能越好

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问题；若标签集合为<single> <real> <constrained>，表示该算法只能求解有约束问题；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、测试问题和指标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。当用户在图形界面中选择多个标签后，仅有符合该标签组合的算法、测试问题和指标才会被显示供选择。标签过滤的具体原理可参阅这里。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。

除此之外，每个算法和测试问题可以被添加一个年份标签如<2024>，这使得图形界面的列表中的算法和测试问题可以按年份选择。

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
run	用户	当前运行的编号
metName	用户	要计算的指标名称
outputFcn	用户	在 NotTerminated() 中调用用的函数
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
starttime	NotTerminated()	用于记录当前运行用时
方法	是否可重定义	描述
ALGORITHM	不可	设定由用户指定的属性值 输入：形如 'Name',Value,… 的参数设置 输出：ALGORITHM 对象
Solve	不可	利用算法求解一个问题 输入：PROBLEM 对象 输出：无
main	必须	算法的主体部分 输入：PROBLEM 对象 输出：无
NotTerminated	不可	main() 中每次迭代前调用的函数 输入：SOLUTION 对象数组，即种群 输出：是否达到终止条件（逻辑变量）
ParameterSet	不可	根据 parameter 设定算法参数 输入：默认的参数设置 输出：用户指定的参数设置

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
% <1992><single><real/integer/label/binary/permutation><large/none><constrained/none>
% Genetic algorithm
```

```
4  % proC ---  1 --- Probability of crossover
5  % disC --- 20 --- Distribution index of crossover
6  % proM ---  1 --- Expectation of the number of mutated variables
7  % disM --- 20 --- Distribution index of mutation
8
9  %------------------------ Reference -----------------------
10 % J. H. Holland, Adaptation in Natural and Artificial
11 % Systems, MIT Press, 1992.
12 %-----------------------------------------------------------
13
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                 Q = TournamentSelection(2,Pro.N,FitnessSingle(P));
20                 O = OperatorGA(P(Q),{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
27 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、问题和指标的标签章节）；

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是否达到终止条件；若达到终止条件则通过抛出错误强行终止算法；

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	算法每代前调用的函数，用于保存当前种群及判断是否终止
ALGORITHM. ParameterSet	根据用户的输入设定算法参数
PROBLEM. Initialization	初始化一个种群
PROBLEM. Evaluation	评价一个种群并产生 SOLUTION 对象数组
CrowdingDistance	计算解的拥挤距离（仅用于多目标优化）
FitnessSingle	计算解的适应度（仅用于单目标优化）
NDSort	非支配排序（仅用于多目标优化）
OperatorDE	差分进化算子
OperatorFEP	进化规划算子
OperatorGA	遗传算子
OperatorGAhalf	遗传算子（仅返回前一半的子代）
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	Evaluation()	当前运行中已消耗的评价次数
maxRuntime	用户	求解该问题可使用的最大运行时间（秒）
encoding	Setting()	每个变量的编码方式
lower	Setting()	每个变量的下界
upper	Setting()	每个变量的上界
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 输入：形如 'Name',Value,… 的参数设置 输出：PROBLEM 对象
Setting	必须	设定默认的属性值 输入：无 输出：无
Initialization	可以	初始化一个种群 输入：种群大小 输出：SOLUTION 对象数组，即种群
Evaluation	可以	评价一个种群并产生解对象 输入：种群的决策向量构成的矩阵 输出：SOLUTION 对象数组，即种群
CalDec	可以	修复一个种群中的无效解 输入：种群的决策向量构成的矩阵 输出：修复后的决策向量构成的矩阵
CalObj	必须	计算一个种群中解的目标值；所有目标函数均被最小化 输入：种群的决策向量构成的矩阵 输出：种群的目标值构成的矩阵
CalCon	可以	计算一个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 输入：种群的决策向量构成的矩阵 输出：种群的约束违反值构成的矩阵
CalGrad	可以	计算一个解在所有目标和约束上的梯度 输入：一个决策向量 输出一：目标雅可比矩阵 输出二：约束雅可比矩阵
GetOptimum	可以	产生问题的最优值并保存在 optimum 中 输入：最优值的个数 输出：最优值集合（矩阵）
GetPF	可以	产生问题的前沿面并保存在 PF 中 输入：无 输出：用于绘制前沿面的数据（矩阵或单元数组）
CalMetric	可以	计算种群的指标值 输入一：指标名 输入二：SOLUTION 对象数组，即种群 输出：指标值（标量）
DrawDec	可以	显示一个种群的决策向量 输入：SOLUTION 对象数组，即种群 输出：无
DrawObj	可以	显示一个种群的目标向量 输入：SOLUTION 对象数组，即种群 输出：无
ParameterSet	不可	根据 parameter 设定问题参数 输入：默认的参数设置 输出：用户指定的参数设置

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
% <1999><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)
```

```
13             obj.M = 1;
14             if isempty(obj.D); obj.D = 30; end
15             obj.lower = zeros(1,obj.D) - 100;
16             obj.upper = zeros(1,obj.D) + 100;
17             obj.encoding = ones(1,obj.D);
18         end
19         function PopObj = CalObj(obj,PopDec)
20             PopObj = sum(PopDec.^2,2);
21         end
22     end
23 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、问题和指标的标签章节）；

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：　设置决策变量的编码方式；

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 = obj.Evaluation(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，使得该问题无需添加约束函数：

```
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 CF4.m 添加了一个约束：

```
function PopCon = CalCon(obj,X)
    t = X(:,2)-sin(6*pi*X(:,1)+2*pi/size(X,2))-0.5*X(:,1)+0.25;
    PopCon = -t./(1+exp(4*abs(t)));
end
```

利用 all(PopCon<=0,2)可确定每个解是否满足所有约束。注意等式约束必须转换为不等式约束来处理，详细方法可参阅该论文的 3.2 节。默认的方法 Evaluation()通过依次调用 CalDec()、CalObj()和 CalCon()来实例化 SOLUTION 对象，同时增加已消耗的评价次数 FE 的值。用户可以重定义该方法在一个函数内完成种群的修复、目标计算和约束计算工作，此时 CalDec()、CalObj()和 CalCon()将不会被调用。例如 MW2.m 同时计算了种群的目标值与约束违反值：

```
function Population = Evaluation(obj,varargin)
    X = varargin{1};
    X=max(min(X,repmat(obj.upper,size(X,1),1)),repmat(obj.lower,size(X,1),1));
    z=1-exp(-10*(X(:,obj.M:end)-(repmat(obj.M:obj.D,size(X,1),1)-1)/obj.D).^2);
    g = 1+sum((1.5+(0.1/obj.D)*z.^2-1.5*cos(2*pi*z)),2);
    PopObj(:,1) = X(:,1);
    PopObj(:,2) = g.*(1-PopObj(:,1)./g);
    L = sqrt(2)*PopObj(:,2)-sqrt(2)*PopObj(:,1);
    PopCon = sum(PopObj,2)-1-0.5*sin(3*pi*l).^8;
    Population = SOLUTION(X,PopObj,PopCon,varargin{2:end});
    obj.FE = obj.FE+length(Population);
end
```

默认的方法 CalGrad()通过有限差分来估计目标函数和约束函数的梯度，用户可以重定义该方法以更准确地计算梯度。用户可以重定义方法 GetOptimum()

来指定问题的最优值，最优值被用于指标值的计算。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，它们被用于 DrawObj()的可视化中。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 CalMetric()将一个种群与问题的最优值 optimum 传入指标函数中进行计算，用户可以重定义该方法来将不同的变量传入指标函数中。例如 SMMOP1.m 在计算 IGDX 指标时传入问题的最优解集而非前沿面上的参考点：

```
function score = CalMetric(obj,metName,Population)
```

```
    switch metName
        case 'IGDX'
            score = feval(metName,Population,obj.POS);
        otherwise
            score = feval(metName,Population,obj.optimum);
    end
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。

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	PROBLEM.Evaluation()	解的决策向量
obj	PROBLEM.Evaluation()	解的目标值
con	PROBLEM.Evaluation()	解的约束违反值
add	PROBLEM.Evaluation()	解的额外属性值（例如速度）
方法	描述	
SOLUTION	生成 SOLUTION 对象数组	

	输入一：多个解的决策向量构成的矩阵 输入二：多个解的目标值构成的矩阵 输入三：多个解的约束违反值构成的矩阵 输入四：多个解的额外属性值构成的矩阵 输出：SOLUTION 对象数组
decs	获取多个解的决策向量 输入：无 输出：多个解的决策向量构成的矩阵
objs	获取多个解的目标值 输入：无 输出：多个解的目标值构成的矩阵
cons	获取多个解的约束违反值 输入：无 输出：多个解的约束违反值构成的矩阵
adds	设置并获取多个解的额外属性值 输入：默认的额外属性值 输出：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） 输入：无 输出：种群中可行且最好的 SOLUTION 对象子数组

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),rand(10,1),zeros(10,1));
BestObjs   = Population.best.objs
```

注意应只在 PROBLEM 类的 Evaluation()方法内调用 SOLUTION()。

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：

```
function score = IGD(Population,optimum)
% <min> <multi/many> <real/integer/label/binary/permutation> <large/none> <constrained/none> <expensive/none> <multimodal/none> <sparse/none> <dynamic/none> <robust/none>
% Inverted generational distance

%------------------------------- Reference --------------------------------
% C. A. Coello Coello and N. C. Cortes, Solving
% multiobjective optimization problem using an artificial
% immune system, Genetic Programming and Evolvable
```

```
9 % Machines, 2005, 6(2): 163-190.
10 %------------------------------------------------------------
11
12     PopObj = Population.best.objs;
13     if size(PopObj,2) ~= size(optimum,2)
14         score = nan;
15     else
16         score = mean(min(pdist2(optimum,PopObj),[],2));
17     end
18 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（参阅算法、问题和指标的标签章节）；注意标签 <min>或<max>必须为第一个标签；

第 3 行：　指标的全称；

第 5-10 行：指标的参考文献；

第 12 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13-14行：若种群不存在可行解则返回 nan；

第15-16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	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
1	ABC	Artificial bee colony algorithm	√			√	√				√	√							
2	AB-SAEA	Adaptive Bayesian based surrogate-assisted evolutionary algorithm		√	√	√	√						√						
3	AC-MMEA	Adaptive merging and coordinated offspring generation based multi-modal multi-objective evolutionary algorithm		√		√	√				√			√	√				
4	ACO	Ant colony optimization	√							√	√								
5	Adam	Adaptive moment estimation	√			√					√								
6	AdaW	Evolutionary algorithm with adaptive weights		√	√	√	√	√	√	√									
7	ADSAPSO	Adaptive dropout based surrogate-assisted particle swarm optimization		√	√	√	√						√						
8	AESSPSO	Adaptive exploration state-space particle swarm optimization	√			√	√				√	√							
9	AFSEA	Adjoint feature-selection-based evolutionary algorithm		√		√	√		√		√	√			√				
10	AGE-II	Approximation-guided evolutionary multi-objective algorithm II		√		√	√	√	√	√									
11	AGE-MOEA	Adaptive geometry estimation-based many-objective evolutionary algorithm		√	√	√	√	√	√	√		√							
12	AGE-MOEA-II	Adaptive geometry estimation-based many-objective evolutionary algorithm II		√	√	√	√	√	√	√		√							
13	AGSEA	Automated guiding vector selection-based evolutionary algorithm		√		√	√		√		√	√			√				
14	A-NSGA-III	Adaptive NSGA-III		√	√	√	√	√	√	√		√							
15	APSEA	Adaptive population sizing based evolutionary algorithm		√		√	√	√	√	√		√							
16	AR-MOEA	Adaptive reference points based multi-objective evolutionary algorithm		√	√	√	√	√	√	√		√							
17	AutoV	Automated design of variation operators	√	√		√	√				√	√							
18	AVG-SAEA	Adaptive variable grouping based surrogate-assisted evolutionary algorithm		√		√	√				√		√						
19	BCE-IBEA	Bi-criterion evolution based IBEA		√	√	√	√	√	√	√									
20	BCE-MOEA/D	Bi-criterion evolution based MOEA/D		√	√	√	√	√	√	√									
21	BFGS	A quasi-Newton method proposed by Broyden, Fletcher, Goldfarb, and Shanno	√			√					√								
22	BiCo	Bidirectional coevolution constrained multiobjective evolutionary algorithm		√		√	√	√	√	√		√							
23	BiGE	Bi-goal evolution			√	√	√	√	√	√									
24	BLEAQII	Bilevel evolutionary algorithm based on quadratic approximations II		√		√						√						√	

	算法缩写	算法全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
25	BL-SAEA	Bi-level surrogate modelling based evolutionary algorithm		√		√						√						√	
26	BSPGA	Binary space partition tree based genetic algorithm	√						√		√	√							
27	C3M	Constraint, multiobjective, multi-stage, multi-constraint evolutionary algorithm		√		√	√	√	√	√		√							
28	CAEAD	Dual-population evolutionary algorithm based on alternative evolution and degeneration		√		√	√	√	√	√		√							
29	CA-MOEA	Clustering based adaptive multi-objective evolutionary algorithm		√		√	√	√	√	√									
30	CCGDE3	Cooperative coevolution GDE3		√		√	√				√								
31	CCMO	Coevolutionary constrained multi-objective optimization framework		√		√	√	√	√	√		√							
32	c-DPEA	Constrained dual-population evolutionary algorithm		√		√	√	√	√	√		√							
33	CLIA	Evolutionary algorithm with cascade clustering and reference point incremental learning		√	√	√	√	√	√	√									
34	CMaDPPs	Constrained many-objective optimization with determinantal point processes		√	√	√	√	√	√	√		√							
35	CMA-ES	Covariance matrix adaptation evolution strategy	√			√	√				√	√							
36	CMDEIPCM	Constrained multiobjective differential evolution algorithm with an infeasible proportion control mechanism		√		√	√				√	√							
37	CMEGL	Constrained evolutionary multitasking with global and local auxiliary tasks		√		√	√	√	√	√		√							
38	CMME	Constrained many-objective evolutionary algorithm with enhanced mating and environmental selections		√		√	√	√	√	√		√							
39	CMMO	Coevolutionary multi-modal multi-objective optimization framework		√		√	√	√	√	√				√					
40	CMOCSO	Competitive and cooperative swarm optimization constrained multi-objective optimization algorithm		√		√					√	√							
41	CMODE-FTR	Constrained multiobjective differential evolution based on the fusion of two rankings		√		√	√					√							
42	CMOEA-CD	Constraint-Pareto dominance and diversity enhancement strategy based CMOEA		√	√	√	√	√	√	√		√							
43	C-MOEA/D	Constraint-MOEA/D		√	√	√	√	√	√	√		√							
44	CMOEA-MS	Constrained multiobjective evolutionary algorithm with multiple stages		√		√	√	√	√	√		√							
45	CMOEA-MSG	Multi-stage constrained multi-objective evolutionary algorithm		√		√	√					√							
46	CMOEMT	Constrained multi-objective optimization based on evolutionary multitasking optimization		√		√						√							
47	CMOES	Constrained multi-objective optimization based on even search		√		√	√	√	√	√		√							
48	CMOPSO	Competitive mechanism based multi-objective particle swarm optimizer		√		√	√												
49	CMOQLMT	Constrained multi-objective optimization based on Q-learning and multitasking		√		√						√							
50	CMOSMA	Constrained multi-objective evolutionary algorithm with self-organizing map		√	√	√	√					√							

	算法缩写	算法全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
51	CNSDE/DVC	Constrained nondominated sorting differential evolution based on decision variable classification		√		√	√												√
52	CoMMEA	Coevolutionary multimodal multi-objective evolutionary algorithm		√		√	√	√	√	√				√					
53	CPS-MOEA	Classification and Pareto domination based multi-objective evolutionary		√		√	√						√						
54	CSEA	Classification based surrogate-assisted evolutionary algorithm		√	√	√							√						
55	CSEMT	Constraints separation based evolutionary multitasking		√		√	√	√	√	√		√							
56	CSO	Competitive swarm optimizer	√			√	√				√	√							
57	C-TAEA	Two-archive evolutionary algorithm for constrained MOPs		√	√	√	√	√	√	√		√							
58	C-TSEA	Constrained two-stage evolutionary algorithm		√	√	√	√	√	√	√		√							
59	DAEA	Duplication analysis based evolutionary algorithm		√					√										
60	DBEMTO	Double-balanced evolutionary multi-task optimization		√		√	√	√	√	√		√							
61	DCNSGA-III	Dynamic constrained NSGA-III		√	√	√	√	√	√	√		√							
62	DE	Differential evolution	√			√	√				√	√							
63	DEA-GNG	Decomposition based evolutionary algorithm guided by growing neural gas		√	√	√	√	√	√	√									
64	DGEA	Direction guided evolutionary algorithm		√	√	√	√				√								
65	DirHV-EI	Expected direction-based hypervolume improvement		√	√	√	√						√						
66	DISK	Distribution-based Kriging-assisted evolutionary algorithm		√	√	√	√						√						
67	DISKplus	Distribution-based Kriging-assisted constrained evolutionary algorithm		√	√	√	√					√	√						
68	DKCA	Dynamic knowledge-guided coevolutionary algorithm		√		√			√		√	√			√				
69	DMOEA-eC	Decomposition-based multi-objective evolutionary algorithm with the e-constraint framework		√		√	√	√	√	√									
70	dMOPSO	MOPSO based on decomposition		√		√	√												
71	DN-NSGA-II	Decision space based niching NSGA-II		√		√	√							√					
72	DNSGA-II	Dynamic NSGA-II		√		√	√	√	√	√						√			
73	DOA	Dandelion optimization algorithm	√			√	√				√	√							
74	DPCPRA	Dual-population with dynamic constraint processing and resource allocating		√		√	√	√	√	√		√							
75	DP-PPS	Tri-population based push and pull search		√		√						√							
76	DPVAPS	Dual-population with variable auxiliary population size		√		√	√				√	√							
77	DRLOS-EMCMO	EMCMO with deep reinforcement learning-assisted operator selection		√		√	√	√	√	√		√							
78	DRL-SAEA	Deep reinforcement learning-based expensive constrained evolutionary algorithm		√		√						√	√						
79	DSPCMDE	Dynamic selection preference-assisted constrained multiobjective differential evolution		√		√	√					√							

	算法缩写	算法全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
80	DSSEA	Dynamic subspace search-based evolutionary algorithm		√	√	√	√				√	√							
81	DVCEA	Decision variables classification-based evolutionary algorithm		√	√	√	√				√	√							
82	DWU	Dominance-weighted uniformity multi-objective evolutionary algorithm		√		√	√	√	√	√									
83	EAG-MOEA/D	External archive guided MOEA/D		√		√	√	√	√	√									
84	ECPO	Electric charged particles optimization	√			√	√				√	√							
85	EDN-ARMOEA	Efficient dropout neural network based AR-MOEA		√	√	√	√						√						
86	EFR-RR	Ensemble fitness ranking with a ranking restriction scheme		√	√	√	√	√	√	√									
87	EGO	Efficient global optimization	√			√	√						√						
88	EIM-EGO	Expected improvement matrix based efficient global optimization		√		√	√						√						
89	EMCMMS	Evolutionary multitasking with a cooperative multistep mutation strategy		√		√	√	√	√	√		√							
90	EMCMO	Evolutionary multitasking-based constrained multiobjective optimization		√		√	√	√	√	√		√							
91	EMMOEA	Expensive multi-/many-objective evolutionary algorithm		√		√	√						√						
92	e-MOEA	Epsilon multi-objective evolutionary algorithm		√	√	√	√	√	√	√									
93	EMOSKT	Evolutionary multi-objective optimization with sparsity knowledge transfer		√		√			√		√	√			√		√		
94	EMyO/C	Evolutionary many-objective optimization algorithm with clustering-based		√	√	√	√												
95	ENS-MOEA/D	Ensemble of different neighborhood sizes based MOEA/D		√	√	√	√												
96	ESBCEO	Bayesian co-evolutionary optimization based entropy search		√		√							√						
97	FDV	Fuzzy decision variable framework with various internal optimizers		√	√	√	√				√								
98	FEP	Fast evolutionary programming	√			√	√				√	√							
99	FLEA	Fast sampling based evolutionary algorithm		√	√	√					√								
100	FRCG	Fletcher-Reeves conjugate gradient	√			√					√								
101	FRCGM	Fletcher-Reeves conjugate gradient (for multi-objective optimization)		√	√	√					√	√							
102	FROFI	Feasibility rule with the incorporation of objective function information	√			√	√				√	√							
103	GA	Genetic algorithm	√			√	√	√	√	√	√	√							
104	GCNMOEA	Graph convolutional network based multi-objective evolutionary algorithm		√		√	√												
105	GDE3	Generalized differential evolution 3		√		√	√					√							
106	GFM-MOEA	Generic front modeling based multi-objective evolutionary algorithm		√	√	√	√	√	√	√									
107	GLMO	Grouped and linked mutation operator algorithm		√		√	√				√								

	算法缩写	算法全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
108	g-NSGA-II	g-dominance based NSGA-II		√		√	√	√	√	√									
109	GPSO	Gradient based particle swarm optimization algorithm	√			√					√	√							
110	GPSOM	Gradient based particle swarm optimization algorithm (for multi-objective optimization)		√	√	√					√	√							
111	GrEA	Grid-based evolutionary algorithm			√	√	√	√	√	√									
112	GWASF-GA	Global weighting achievement scalarizing function genetic algorithm		√		√	√	√	√	√									
113	GWO	Grey wolf optimizer	√			√	√				√	√							
114	HEA	Hyper-dominance based evolutionary algorithm		√	√	√			√	√									
115	HeE-MOEA	Multiobjective evolutionary algorithm with heterogeneous ensemble based infill criterion		√		√	√						√						
116	HHC-MMEA	Hybrid hierarchical clustering based multi-modal multi-objective evolutionary algorithm		√		√					√			√	√				
117	hpaEA	Hyperplane assisted evolutionary algorithm		√	√	√	√	√	√	√									
118	HREA	Hierarchy ranking based evolutionary algorithm		√		√	√							√					
119	HypE	Hypervolume estimation algorithm		√	√	√	√	√	√	√									
120	IBEA	Indicator-based evolutionary algorithm		√	√	√	√	√	√	√									
121	ICMA	Indicator based constrained multi-objective algorithm		√		√	√					√							
122	I-DBEA	Improved decomposition-based evolutionary algorithm		√	√	√	√	√	√	√		√							
123	IM-C-MOEA/D	Inverse modeling constrained MOEA/D		√		√	√				√	√							
124	IM-MOEA	Inverse modeling based multiobjective evolutionary algorithm		√		√	√				√								
125	IM-MOEA/D	Inverse modeling MOEA/D		√		√	√				√								
126	IMODE	Improved multi-operator differential evolution	√			√	√				√	√							
127	IMTCMO	Improved evolutionary multitasking-based CMOEA		√		√	√	√	√	√		√							
128	IMTCMO_BS	Improved evolutionary multitasking-based CMOEA with bidirectional sampling		√	√	√	√	√	√	√		√							
129	I-SIBEA	Interactive simple indicator-based evolutionary algorithm		√		√	√	√	√	√									
130	Izui	An aggregative gradient based multi-objective optimizer proposed by Izui et al.		√	√	√					√	√							
131	KMA	Komodo mlipir algorithm	√			√	√				√	√							
132	KnEA	Knee point driven evolutionary algorithm			√	√	√	√	√	√		√							
133	K-RVEA	Surrogate-assisted RVEA		√	√	√	√						√						
134	KTA2	Kriging-assisted Two_Arch2		√	√	√	√						√						
135	KTS	Kriging-assisted evolutionary algorithm with two search modes		√	√		√					√	√						
136	L2SMEA	Linear subspace surrogate modeling assisted evolutionary algorithm	√			√							√						
137	LCMEA	Large-scale constrained multi-objective evolutionary algorithm		√		√					√	√							

	算法缩写	算法全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
138	LCSA	Linear combination-based search algorithm		√	√	√	√				√								
139	LDS-AF	Low-dimensional surrogate aggregation function		√		√	√				√		√						
140	LERD	Large-scale evolutionary algorithm with reformulated decision variable analysis		√	√	√					√								
141	LMEA	Evolutionary algorithm for large-scale many-objective optimization		√	√	√	√				√								
142	LMOCSO	Large-scale multi-objective competitive swarm optimization algorithm		√	√	√	√				√	√							
143	LMOEA-DS	Large-scale evolutionary multi-objective optimization assisted by directed sampling		√		√	√				√								
144	LMPFE	Evolutionary algorithm with local model based Pareto front estimation		√	√	√	√	√	√	√									
145	LRMOEA	Large-scale robust multi-objective evolutionary algorithm		√		√			√		√	√			√				√
146	LSMOF	Large-scale multi-objective optimization framework with NSGA-II		√		√	√				√								
147	MaOEA-CSS	Many-objective evolutionary algorithms based on coordinated selection		√	√	√	√	√	√	√									
148	MaOEA-DDFC	Many-objective evolutionary algorithm based on directional diversity and favorable convergence		√	√	√	√	√	√	√									
149	MaOEA/IGD	IGD based many-objective evolutionary algorithm			√	√	√	√	√	√									
150	MaOEA/IT	Many-objective evolutionary algorithms based on an independent two-stage		√	√	√	√					√							
151	MaOEA-R&D	Many-objective evolutionary algorithm based on objective space reduction			√	√	√	√	√	√									
152	MCCMO	Multi-population coevolutionary constrained multi-objective optimization		√		√	√	√	√	√		√							
153	MCEA/D	Multiple classifiers-assisted evolutionary algorithm based on decomposition		√	√	√	√						√						
154	MFEA	Multifactorial evolutionary algorithm	√			√	√	√	√	√	√						√		
155	MFEA-II	Multifactorial evolutionary algorithm II	√			√	√	√	√	√	√						√		
156	MFFS	Multiform feature selection		√					√										
157	MFO-SPEA2	Multiform optimization framework based on SPEA2		√		√	√	√	√	√		√							
158	MGCEA	Multi-granularity clustering based evolutionary algorithm		√		√			√		√	√			√				
159	MGO	Mountain gazelle optimizer	√			√	√				√	√							
160	MGSAEA	Multigranularity surrogate-assisted constrained evolutionary algorithm		√		√						√	√						
161	MMEAPSL	Multimodal multi-objective evolutionary algorithm assisted by Pareto set learning		√		√	√	√	√	√				√					
162	MMEA-WI	Weighted indicator-based evolutionary algorithm for multimodal multi-objective optimization		√		√	√							√					
163	MMOPSO	MOPSO with multiple search strategies		√		√	√												
164	MO_Ring_PSO_SCD	Multiobjective PSO using ring topology and special crowding distance		√		√	√							√					
165	MOBCA	Multi-objective besiege and conquer algorithm		√		√	√												

	算法缩写	算法全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
166	MOCell	Cellular genetic algorithm		√		√	√	√	√	√		√							
167	MOCGDE	Multi-objective conjugate gradient and differential evolution algorithm		√	√	√					√	√							
168	MO-CMA	Multi-objective covariance matrix adaptation evolution strategy		√		√	√												
169	MOEA/CKF	Multi-objective evolutionary algorithm based on cross-scale knowledge fusion		√		√			√		√	√			√				
170	MOEA/D	Multiobjective evolutionary algorithm based on decomposition		√	√	√	√	√	√	√									
171	MOEA/D-2WA	MOEA/D with two-type weight vector adjustments		√	√	√	√	√	√	√		√							
172	MOEA/D-AWA	MOEA/D with adaptive weight adjustment		√	√	√	√	√	√	√									
173	MOEA/D-CMA	MOEA/D with covariance matrix adaptation evolution strategy		√	√	√	√												
174	MOEA/D-CMT	MOEA/D with competitive multitasking		√		√						√							
175	MOEA/DD	Many-objective evolutionary algorithm based on dominance and decomposition		√	√	√	√	√	√	√		√							
176	MOEA/D-DAE	MOEA/D with detect-and-escape strategy		√		√	√	√	√	√		√							
177	MOEA/D-DCWV	MOEA/D with distribution control of weight vector set		√	√	√	√	√	√	√									
178	MOEA/D-DE	MOEA/D based on differential evolution		√	√	√	√												
179	MOEA/D-DQN	MOEA/D based on deep Q-network		√	√	√	√												
180	MOEA/D-DRA	MOEA/D with dynamical resource allocation		√	√	√	√												
181	MOEA/D-DU	MOEA/D with a distance based updating strategy		√	√	√	√	√	√	√									
182	MOEA/D-DYTS	MOEA/D with dynamic Thompson sampling		√	√	√	√												
183	MOEA/D-EGO	MOEA/D with efficient global optimization		√		√	√						√						
184	MOEA/D-FRRMAB	MOEA/D with fitness-rate-rank-based multiarmed bandit		√	√	√	√												
185	MOEA/D-M2M	MOEA/D based on MOP to MOP		√		√	√												
186	MOEA/D-MRDL	MOEA/D with maximum relative diversity loss		√		√	√												
187	MOEA/D-PaS	MOEA/D with Pareto adaptive scalarizing approximation		√	√	√	√												
188	MOEA/D-PFE	MOEA/D with Pareto front estimation		√	√	√	√	√	√	√									
189	MOEA/D-STM	MOEA/D with stable matching		√	√	√	√												
190	MOEA/D-UR	MOEA/D with update when required		√	√	√	√	√	√	√									
191	MOEA/D-URAW	MOEA/D with uniform randomly adaptive weights		√	√	√	√	√	√	√									
192	MOEA/DVA	Multi-objective evolutionary algorithm based on decision variable		√		√	√				√								
193	MOEA/D-VOV	MOEA/D with virtual objective vectors		√	√	√	√	√	√	√									
194	MOEA/IGD-NS	Multi-objective evolutionary algorithm based on an enhanced IGD		√		√	√	√	√	√									

	算法缩写	算法全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
195	MOEA-NZD	Multi-objective evolutionary algorithm with nonzero detection		√	√	√					√	√			√				
196	MOEA-PC	Multiobjective evolutionary algorithm based on polar coordinates		√		√	√												
197	MOEA/PSL	Multi-objective evolutionary algorithm based on Pareto optimal subspace		√		√	√		√		√	√			√				
198	MOEA-RE	Multi-objective evolutionary algorithm with robustness enhancement		√		√	√	√	√	√									√
199	MO-EGS	Multi-objective evolutionary gradient search		√		√					√								
200	MO-L2SMEA	Multi-objective linear subspace surrogate modeling assisted evolutionary algorithm		√		√					√		√						
201	MOMBI-II	Many objective metaheuristic based on the R2 indicator II		√	√	√	√	√	√	√									
202	MO-MFEA	Multi-objective multifactorial evolutionary algorithm		√		√	√	√	√	√		√					√		
203	MO-MFEA-II	Multi-objective multifactorial evolutionary algorithm II		√		√	√	√	√	√		√					√		
204	MOMFEA-SADE	Multi-objective multifactorial evolutionary algorithm with subspace alignment and adaptive differential evolution		√		√	√	√	√	√		√					√		
205	MOPSO	Multi-objective particle swarm optimization		√		√	√												
206	MOPSO-CD	MOPSO with crowding distance		√		√	√												
207	MOSD	Multiobjective steepest descent		√		√					√	√							
208	M-PAES	Memetic algorithm with Pareto archived evolution strategy		√		√	√												
209	MP-MMEA	Multi-population multi-modal multi-objective evolutionary algorithm		√		√	√				√			√	√				
210	MPSO/D	Multi-objective particle swarm optimization algorithm based on decomposition		√	√	√	√												
211	MSCEA	Multi-stage constrained multi-objective evolutionary algorithm		√		√	√	√	√	√		√							
212	MSCMO	Multi-stage constrained multi-objective evolutionary algorithm		√		√	√	√	√	√		√							
213	MSEA	Multi-stage multi-objective evolutionary algorithm		√		√	√	√	√	√									
214	MSKEA	Multi-stage knowledge-guided evolutionary algorithm		√		√	√		√		√	√			√				
215	MSOPS-II	Multiple single objective Pareto sampling II		√	√	√	√					√							
216	MTCMO	Multitasking constrained multi-objective optimization		√		√	√	√	√	√		√							
217	MTDE-MKTA	Multitasking differential evolution with multiple knowledge types and transfer adaptation		√		√	√	√	√	√		√					√		
218	MTEA/D-DN	Multiobjective multitask evolutionary algorithm based on decomposition with dual neighborhoods		√		√	√	√	√	√		√					√		
219	MTS	Multiple trajectory search		√		√	√												
220	MultiObjective EGO	Multi-objective efficient global optimization		√		√	√					√	√						
221	MVPA	Most valuable player algorithm	√			√	√				√	√							

	算法缩写	算法全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
222	MyO-DEMR	Many-objective differential evolution with mutation restriction		√	√	√	√												
223	NBLEA	Nested bilevel evolutionary algorithm		√		√						√						√	
224	NelderMead	The Nelder-Mead algorithm	√			√													
225	NMPSO	Novel multi-objective particle swarm optimization		√	√	√	√												
226	NNDREA-MO	Evolutionary algorithm with neural network-based dimensionality reduction (multi-objective)		√					√		√	√			√				
227	NNDREA-SO	Evolutionary algorithm with neural network-based dimensionality reduction (single-objective)	√						√		√	√			√				
228	NNIA	Nondominated neighbor immune algorithm		√		√	√	√	√	√									
229	NRV-MOEA	Adaptive normal reference vector-based multi- and many-objective evolutionary algorithm		√	√	√	√	√	√	√									
230	NSBiDiCo	Non-dominated sorting bidirectional differential coevolution algorithm		√		√	√	√	√	√		√							
231	NSGA-II	Nondominated sorting genetic algorithm II		√		√	√	√	√	√		√							
232	NSGA-II+ARSBX	NSGA-II with adaptive rotation based simulated binary crossover		√		√	√					√							
233	NSGA-II-conflict	NSGA-II with conflict-based partitioning strategy			√	√	√	√	√	√									
234	NSGA-II-DTI	NSGA-II of Deb's type I robust version		√		√	√	√	√	√		√							√
235	NSGA-III	Nondominated sorting genetic algorithm III		√	√	√	√	√	√	√		√							
236	NSGAIII-EHVI	NSGA-III with expected hypervolume improvement		√	√	√							√						
237	NSGA-II/SDR	NSGA-II with strengthened dominance relation			√	√	√	√	√	√									
238	NSLS	Multiobjective optimization framework based on nondominated sorting and local search		√		√	√												
239	NUCEA	Non-uniform clustering based evolutionary algorithm		√		√			√		√	√			√				
240	OFA	Optimal foraging algorithm	√			√	√				√	√							
241	one-by-one EA	Many-objective evolutionary algorithm using a one-by-one selection		√	√	√	√	√	√	√									
242	OSP-NSDE	Non-dominated sorting differential evolution with prediction in the objective space		√		√	√												
243	ParEGO	Efficient global optimization for Pareto optimization		√		√	√						√						
244	PB-NSGA-III	NSGA-III based on Pareto based bi-indicator infill sampling criterion		√	√	√	√						√						
245	PB-RVEA	RVEA based on Pareto based bi-indicator infill sampling criterion		√	√	√	√						√						
246	PC-SAEA	Pairwise comparison based surrogate-assisted evolutionary algorithm		√	√								√						
247	PeEA	Pareto front shape estimation based evolutionary algorithm		√	√	√	√	√	√	√									
248	PESA-II	Pareto envelope-based selection algorithm II		√		√	√	√	√	√									
249	PICEA-g	Preference-inspired coevolutionary algorithm with goals		√	√	√	√	√	√	√									
250	PIEA	Performance indicator-based evolutionary algorithm		√	√	√							√						
251	PIMD	Probability and mapping crowding distance		√	√	√							√						

	算法缩写	算法全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
252	PM-MOEA	Pattern mining based multi-objective evolutionary algorithm		√		√	√		√		√	√			√				
253	POCEA	Paired offspring generation based constrained evolutionary algorithm		√		√	√				√	√							
254	PPS	Push and pull search algorithm		√	√	√	√					√							
255	PRDH	Problem reformulation and duplication handling		√					√										
256	PREA	Promising-region based EMO algorithm		√	√	√	√	√	√	√									
257	PSO	Particle swarm optimization	√			√	√				√	√							
258	REMO	Expensive multiobjective optimization by relation learning and prediction		√	√	√							√						
259	RGA-M1-2	Real-coded genetic algorithm with framework M1-2		√		√						√	√						
260	RGA-M2-2	Real-coded genetic algorithm with framework M2-2		√		√						√	√						
261	RM-MEDA	Regularity model-based multiobjective estimation of distribution		√		√	√												
262	RMOEA/DVA	Robust multi-objective evolutionary algorithm with decision variable assortment		√		√	√												√
263	RMSProp	Root mean square propagation	√			√					√								
264	r-NSGA-II	r-dominance based NSGA-II		√		√	√	√	√	√									
265	RPD-NSGA-II	Reference point dominance-based NSGA-II		√	√	√	√	√	√	√									
266	RPEA	Reference points-based evolutionary algorithm			√	√	√	√	√	√									
267	RSEA	Radial space division based evolutionary algorithm		√	√	√	√	√	√	√									
268	RVEA	Reference vector guided evolutionary algorithm		√	√	√	√	√	√	√		√							
269	RVEAa	RVEA embedded with the reference vector regeneration strategy			√	√	√	√	√	√									
270	RVEA-iGNG	RVEA based on improved growing neural gas		√	√	√	√	√	√	√									
271	S3-CMA-ES	Scalable small subpopulations based covariance matrix adaptation		√	√	√	√				√								
272	SA	Simulated annealing	√			√	√				√	√							
273	SACC-EAM-II	Surrogate-assisted cooperative co-evolutionary algorithm of Minamo	√			√	√						√						
274	SACOSO	Surrogate-assisted cooperative swarm optimization	√			√	√				√		√						
275	SADE-AMSS	Surrogate-assisted differential evolution with adaptive multi-subspace search	√			√	√						√						
276	SADE-ATDSC	Surrogate-assisted differential evolution with adaptation of training data selection criterion	√			√	√						√						
277	SADE-Sammon	Sammon mapping assisted differential evolution	√			√	√						√						
278	SAMSO	Multiswarm-assisted expensive optimization	√			√	√				√		√						
279	SAPO	Surrogate-assisted partial optimization	√			√	√					√	√						
280	S-CDAS	Self-controlling dominance area of solutions			√	√	√	√	√	√									
281	SCEA	Sparsity clustering basec evolutionary algorithm		√		√			√		√	√			√				
282	SD	Steepest descent	√			√					√								

	算法缩写	算法全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
283	S-ECSO	Enhanced competitive swarm optimizer for sparse optimization		√		√					√				√				
284	SFADE	Scalarization function approximation based differential evolution algorithm		√	√	√	√						√						
285	SGEA	Steady-state and generational evolutionary algorithm		√		√	√	√	√	√		√				√			
286	SGECF	Sparsity-guided elitism co-evolutionary framework		√		√			√		√	√			√				
287	SHADE	Success-history based adaptive differential evolution	√			√	√				√	√							
288	SIBEA	Simple indicator-based evolutionary algorithm		√		√	√	√	√	√									
289	SIBEA-kEMOSS	SIBEA with minimum objective subset of size k with minimum error			√	√	√	√	√	√									
290	SLMEA	Super-large-scale multi-objective evolutionary algorithm		√		√	√		√		√	√			√				
291	SMEA	Self-organizing multiobjective evolutionary algorithm		√		√	√												
292	SMOA	Supervised multi-objective optimization algorithm		√		√							√						
293	SMPSO	Speed-constrained multi-objective particle swarm optimization		√		√	√												
294	SMS-EGO	S metric selection based efficient global optimization		√		√	√						√						
295	SMS-EMOA	S metric selection based evolutionary multiobjective optimization		√		√	√	√	√	√									
296	S-NSGA-II	Sparse NSGA-II		√		√					√	√			√				
297	SparseEA	Evolutionary algorithm for sparse multi-objective optimization problems		√		√	√		√		√	√			√				
298	SparseEA2	Improved SparseEA		√		√	√		√		√	√			√				
299	SPEA2	Strength Pareto evolutionary algorithm 2		√		√	√	√	√	√									
300	SPEA2+SDE	SPEA2 with shift-based density estimation			√	√	√	√	√	√									
301	SPEA/R	Strength Pareto evolutionary algorithm based on reference direction		√	√	√	√	√	√	√									
302	SQP	Sequential quadratic programming	√			√					√	√							
303	SRA	Stochastic ranking algorithm			√	√	√	√	√	√									
304	SSCEA	Subspace segmentation based co-evolutionary algorithm		√	√	√	√												
305	SSDE	Self-organized surrogate-assisted differential evolution		√	√	√	√					√	√						
306	t-DEA	theta-dominance based evolutionary algorithm		√	√	√	√	√	√	√									
307	tDEA-CPBI	Theta-dominance based evolutionary algorithm with CPBI		√	√	√	√	√	√	√		√							
308	TELSO	Two-layer encoding learning swarm optimizer		√		√			√		√	√			√				
309	TiGE-2	Tri-Goal Evolution Framework for CMaOPs			√	√	√	√	√	√		√							
310	ToP	Two-phase framework with NSGA-II		√		√	√					√							
311	TPCMaO	Three-population based constrained many-objective co-evolutionary algorithm			√	√	√	√	√	√		√							
312	TriMOEA-	Multi-modal MOEA using two-archive and		√		√	√							√					

	算法缩写	算法全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
	TA&R	recombination strategies																	
313	TS-NSGA-II	Two-stage NSGA-II		√	√	√	√	√	√	√									
314	TS-SparseEA	Two-stage SparseEA		√		√			√		√	√			√				
315	TSTI	Two-stage evolutionary algorithm with three indicators		√		√	√	√	√	√		√							
316	Two_Arch2	Two-archive algorithm 2		√	√	√	√	√	√	√									
317	URCMO	Utilizing the relationship between constrained and unconstrained Pareto fronts for constrained multi-objective optimization		√		√	√					√							
318	VaEA	Vector angle based evolutionary algorithm		√	√	√	√	√	√	√									
319	WASF-GA	Weighting achievement scalarizing function genetic algorithm		√		√	√	√	√	√									
320	WOA	Whale optimization algorithm	√			√	√				√	√							
321	WOF	Weighted optimization framework		√		√	√				√								
322	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	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
1	BBOB_F1	Sphere function	√			√							√						
2	BBOB_F2	Ellipsoidal function	√			√							√						
3	BBOB_F3	Rastrigin function	√			√							√						
4	BBOB_F4	Buche-Rastrigin function	√			√							√						
5	BBOB_F5	Linear slope	√			√							√						
6	BBOB_F6	Attractive sector function	√			√							√						
7	BBOB_F7	Step ellipsoidal function	√			√							√						
8	BBOB_F8	Rosenbrock function	√			√							√						
9	BBOB_F9	Rotated Rosenbrock function	√			√							√						
10	BBOB_F10	Rotated ellipsoidal function	√			√							√						
11	BBOB_F11	Discus function	√			√							√						
12	BBOB_F12	Bent cigar function	√			√							√						
13	BBOB_F13	Sharp ridge function	√			√							√						
14	BBOB_F14	Different powers function	√			√							√						
15	BBOB_F15	Rastrigin function	√			√							√						
16	BBOB_F16	Weierstrass function	√			√							√						
17	BBOB_F17	Schaffers F7 function	√			√							√						
18	BBOB_F18	Moderately ill-conditioned Schaffers F7 function	√			√							√						
19	BBOB_F19	Composite Griewank-Rosenbrock function F8F2	√			√							√						
20	BBOB_F20	Schwefel function	√			√							√						
21	BBOB_F21	Gallagher's Gaussian 101-me peaks function	√			√							√						
22	BBOB_F22	Gallagher's Gaussian 21-hi peaks function	√			√							√						
23	BBOB_F23	Katsuura function	√			√							√						
24	BBOB_F24	Lunacek bi-Rastrigin function	√			√							√						
25	BT1	Benchmark MOP with bias feature		√		√					√								
26	BT2	Benchmark MOP with bias feature		√		√					√								
27	BT3	Benchmark MOP with bias feature		√		√					√								
28	BT4	Benchmark MOP with bias feature		√		√					√								
29	BT5	Benchmark MOP with bias feature		√		√					√								
30	BT6	Benchmark MOP with bias feature		√		√					√								
31	BT7	Benchmark MOP with bias feature		√		√					√								
32	BT8	Benchmark MOP with bias feature		√		√					√								
33	BT9	Benchmark MOP with bias feature		√		√					√								

	问题缩写	问题全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
34	C10MOP1	Neural architecture search on CIFAR-10		√		√					√								
35	C10MOP2	Neural architecture search on CIFAR-10		√		√					√								
36	C10MOP3	Neural architecture search on CIFAR-10		√		√					√								
37	C10MOP4	Neural architecture search on CIFAR-10		√		√					√								
38	C10MOP5	Neural architecture search on CIFAR-10		√		√					√								
39	C10MOP6	Neural architecture search on CIFAR-10		√		√					√								
40	C10MOP7	Neural architecture search on CIFAR-10		√		√					√								
41	C10MOP8	Neural architecture search on CIFAR-10		√		√					√								
42	C10MOP9	Neural architecture search on CIFAR-10		√		√					√								
43	CEC2008_F1	Shifted sphere function	√			√					√		√						
44	CEC2008_F2	Shifted Schwefel's function	√			√					√		√						
45	CEC2008_F3	Shifted Rosenbrock's function	√			√					√		√						
46	CEC2008_F4	Shifted Rastrign's function	√			√					√		√						
47	CEC2008_F5	Shifted Griewank's function	√			√					√		√						
48	CEC2008_F6	Shifted Ackley's function	√			√					√		√						
49	CEC2008_F7	FastFractal 'DoubleDip' function	√			√					√		√						
50	CEC2010_F1	CEC'2010 constrained optimization benchmark problem	√			√						√							
51	CEC2010_F2	CEC'2010 constrained optimization benchmark problem	√			√						√							
52	CEC2010_F3	CEC'2010 constrained optimization benchmark problem	√			√						√							
53	CEC2010_F4	CEC'2010 constrained optimization benchmark problem	√			√						√							
54	CEC2010_F5	CEC'2010 constrained optimization benchmark problem	√			√						√							
55	CEC2010_F6	CEC'2010 constrained optimization benchmark problem	√			√						√							
56	CEC2010_F7	CEC'2010 constrained optimization benchmark problem	√			√						√							
57	CEC2010_F8	CEC'2010 constrained optimization benchmark problem	√			√						√							
58	CEC2010_F9	CEC'2010 constrained optimization benchmark problem	√			√						√							
59	CEC2010_F10	CEC'2010 constrained optimization benchmark problem	√			√						√							
60	CEC2010_F11	CEC'2010 constrained optimization benchmark problem	√			√						√							
61	CEC2010_F12	CEC'2010 constrained optimization benchmark problem	√			√						√							
62	CEC2010_F13	CEC'2010 constrained optimization benchmark problem	√			√						√							
63	CEC2010_F14	CEC'2010 constrained optimization benchmark problem	√			√						√							

	问题缩写	问题全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
64	CEC2010_F15	CEC'2010 constrained optimization benchmark problem	√			√						√							
65	CEC2010_F16	CEC'2010 constrained optimization benchmark problem	√			√						√							
66	CEC2010_F17	CEC'2010 constrained optimization benchmark problem	√			√						√							
67	CEC2010_F18	CEC'2010 constrained optimization benchmark problem	√			√						√							
68	CEC2013_F1	Shifted elliptic function	√			√					√								
69	CEC2013_F2	Shifted Rastrigin's function	√			√					√								
70	CEC2013_F3	Shifted Ackley's function	√			√					√								
71	CEC2013_F4	7-nonseparable, 1-separable shifted and rotated elliptic function	√			√					√								
72	CEC2013_F5	7-nonseparable, 1-separable shifted and rotated Rastrigin's function	√			√					√								
73	CEC2013_F6	7-nonseparable, 1-separable shifted and rotated Ackley's function	√			√					√								
74	CEC2013_F7	7-nonseparable, 1-separable shifted and rotated Schwefel's function	√			√					√								
75	CEC2013_F8	20-nonseparable shifted and rotated elliptic function	√			√					√								
76	CEC2013_F9	20-nonseparable shifted and rotated Rastrigin's function	√			√					√								
77	CEC2013_F10	20-nonseparable shifted and rotated Rastrigin's function	√			√					√								
78	CEC2013_F11	20-nonseparable shifted and rotated Schwefel's function	√			√					√								
79	CEC2013_F12	Shifted Rosenbrock's function	√			√					√								
80	CEC2013_F13	Shifted Schwefel's function with conforming overlapping subcomponents	√			√					√								
81	CEC2013_F14	Shifted Schwefel's function with conflicting overlapping subcomponents	√			√					√								
82	CEC2013_F15	Shifted Schwefel's function	√			√					√								
83	CEC2017_F1	CEC'2017 constrained optimization benchmark problem	√			√						√							
84	CEC2017_F2	CEC'2017 constrained optimization benchmark problem	√			√						√							
85	CEC2017_F3	CEC'2017 constrained optimization benchmark problem	√			√						√							
86	CEC2017_F4	CEC'2017 constrained optimization benchmark problem	√			√						√							
87	CEC2017_F5	CEC'2017 constrained optimization benchmark problem	√			√						√							
88	CEC2017_F6	CEC'2017 constrained optimization benchmark problem	√			√						√							
89	CEC2017_F7	CEC'2017 constrained optimization benchmark problem	√			√						√							

	问题缩写	问题全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
90	CEC2017_F8	CEC'2017 constrained optimization benchmark problem	√			√						√							
91	CEC2017_F9	CEC'2017 constrained optimization benchmark problem	√			√						√							
92	CEC2017_F10	CEC'2017 constrained optimization benchmark problem	√			√						√							
93	CEC2017_F11	CEC'2017 constrained optimization benchmark problem	√			√						√							
94	CEC2017_F12	CEC'2017 constrained optimization benchmark problem	√			√						√							
95	CEC2017_F13	CEC'2017 constrained optimization benchmark problem	√			√						√							
96	CEC2017_F14	CEC'2017 constrained optimization benchmark problem	√			√						√							
97	CEC2017_F15	CEC'2017 constrained optimization benchmark problem	√			√						√							
98	CEC2017_F16	CEC'2017 constrained optimization benchmark problem	√			√						√							
99	CEC2017_F17	CEC'2017 constrained optimization benchmark problem	√			√						√							
100	CEC2017_F18	CEC'2017 constrained optimization benchmark problem	√			√						√							
101	CEC2017_F19	CEC'2017 constrained optimization benchmark problem	√			√						√							
102	CEC2017_F20	CEC'2017 constrained optimization benchmark problem	√			√						√							
103	CEC2017_F21	CEC'2017 constrained optimization benchmark problem	√			√						√							
104	CEC2017_F22	CEC'2017 constrained optimization benchmark problem	√			√						√							
105	CEC2017_F23	CEC'2017 constrained optimization benchmark problem	√			√						√							
106	CEC2017_F24	CEC'2017 constrained optimization benchmark problem	√			√						√							
107	CEC2017_F25	CEC'2017 constrained optimization benchmark problem	√			√						√							
108	CEC2017_F26	CEC'2017 constrained optimization benchmark problem	√			√						√							
109	CEC2017_F27	CEC'2017 constrained optimization benchmark problem	√			√						√							
110	CEC2017_F28	CEC'2017 constrained optimization benchmark problem	√			√						√							
111	CEC2020_F1	Bent cigar function	√			√													
112	CEC2020_F2	Shifted and rotated Schwefel's function	√			√													
113	CEC2020_F3	Shifted and rotated Lunacek bi-Rastrigin function	√			√													
114	CEC2020_F4	Expanded Rosenbrock's plus Griewangk's function	√			√													

	问题缩写	问题全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
115	CEC2020_F5	Hybrid function 1	√			√													
116	CEC2020_F6	Hybrid function 2	√			√													
117	CEC2020_F7	Hybrid function 3	√			√													
118	CEC2020_F8	Composition function 1	√			√													
119	CEC2020_F9	Composition function 2	√			√													
120	CEC2020_F10	Composition function 3	√			√													
121	CF1	Constrained benchmark MOP		√		√					√	√							
122	CF2	Constrained benchmark MOP		√		√					√	√							
123	CF3	Constrained benchmark MOP		√		√					√	√							
124	CF4	Constrained benchmark MOP		√		√					√	√							
125	CF5	Constrained benchmark MOP		√		√					√	√							
126	CF6	Constrained benchmark MOP		√		√					√	√							
127	CF7	Constrained benchmark MOP		√		√					√	√							
128	CF8	Constrained benchmark MOP		√		√					√	√							
129	CF9	Constrained benchmark MOP		√		√					√	√							
130	CF10	Constrained benchmark MOP		√		√					√	√							
131	CI_HS	Multitasking problem (Griewank function + Rastrigin function)	√			√					√						√		
132	CI_LS	Multitasking problem (Ackley function + Schwefel function)	√			√					√						√		
133	CI_MS	Multitasking problem (Ackley function + Rastrigin function)	√			√					√						√		
134	CitySegMOP1	Neural architecture search on Cityscape segmentation datasets		√		√					√		√						
135	CitySegMOP2	Neural architecture search on Cityscape segmentation datasets		√		√					√		√						
136	CitySegMOP3	Neural architecture search on Cityscape segmentation datasets		√		√					√		√						
137	CitySegMOP4	Neural architecture search on Cityscape segmentation datasets		√		√					√		√						
138	CitySegMOP5	Neural architecture search on Cityscape segmentation datasets		√		√					√		√						
139	CitySegMOP6	Neural architecture search on Cityscape segmentation datasets		√		√					√		√						
140	CitySegMOP7	Neural architecture search on Cityscape segmentation datasets		√		√					√		√						
141	CitySegMOP8	Neural architecture search on Cityscape segmentation datasets		√		√					√		√						
142	CitySegMOP9	Neural architecture search on Cityscape segmentation datasets		√		√					√		√						
143	CitySegMOP10	Neural architecture search on Cityscape segmentation datasets		√		√					√		√						
144	CitySegMOP11	Neural architecture search on Cityscape segmentation datasets		√		√					√		√						

	问题缩写	问题全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
145	CitySegMOP12	Neural architecture search on Cityscape segmentation datasets		√		√					√		√						
146	CitySegMOP13	Neural architecture search on Cityscape segmentation datasets		√		√					√		√						
147	CitySegMOP14	Neural architecture search on Cityscape segmentation datasets		√		√					√		√						
148	CitySegMOP15	Neural architecture search on Cityscape segmentation datasets		√		√					√		√						
149	Community Detection	The community detection problem with label based encoding	√					√			√		√						
150	DAS-CMOP1	Difficulty-adjustable and scalable constrained benchmark MOP		√		√					√	√							
151	DAS-CMOP2	Difficulty-adjustable and scalable constrained benchmark MOP		√		√					√	√							
152	DAS-CMOP3	Difficulty-adjustable and scalable constrained benchmark MOP		√		√					√	√							
153	DAS-CMOP4	Difficulty-adjustable and scalable constrained benchmark MOP		√		√					√	√							
154	DAS-CMOP5	Difficulty-adjustable and scalable constrained benchmark MOP		√		√					√	√							
155	DAS-CMOP6	Difficulty-adjustable and scalable constrained benchmark MOP		√		√					√	√							
156	DAS-CMOP7	Difficulty-adjustable and scalable constrained benchmark MOP		√		√					√	√							
157	DAS-CMOP8	Difficulty-adjustable and scalable constrained benchmark MOP		√		√					√	√							
158	DAS-CMOP9	Difficulty-adjustable and scalable constrained benchmark MOP		√		√					√	√							
159	DOC1	Benchmark MOP with constraints in decision and objective spaces		√		√						√							
160	DOC2	Benchmark MOP with constraints in decision and objective spaces		√		√						√							
161	DOC3	Benchmark MOP with constraints in decision and objective spaces		√		√						√							
162	DOC4	Benchmark MOP with constraints in decision and objective spaces		√		√						√							
163	DOC5	Benchmark MOP with constraints in decision and objective spaces		√		√						√							
164	DOC6	Benchmark MOP with constraints in decision and objective spaces		√		√						√							
165	DOC7	Benchmark MOP with constraints in decision and objective spaces		√		√						√							
166	DOC8	Benchmark MOP with constraints in decision and objective spaces		√		√						√							
167	DOC9	Benchmark MOP with constraints in decision and objective spaces		√		√						√							
168	DTLZ1	Benchmark MOP proposed by Deb, Thiele, Laumanns, and Zitzler		√	√	√					√		√						
169	DTLZ2	Benchmark MOP proposed by Deb, Thiele,		√	√	√					√		√						

	问题缩写	问题全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
		Laumanns, and Zitzler																	
170	DTLZ3	Benchmark MOP proposed by Deb, Thiele, Laumanns, and Zitzler		√	√	√					√		√						
171	DTLZ4	Benchmark MOP proposed by Deb, Thiele, Laumanns, and Zitzler		√	√	√					√		√						
172	DTLZ5	Benchmark MOP proposed by Deb, Thiele, Laumanns, and Zitzler		√	√	√					√		√						
173	DTLZ6	Benchmark MOP proposed by Deb, Thiele, Laumanns, and Zitzler		√	√	√					√		√						
174	DTLZ7	Benchmark MOP proposed by Deb, Thiele, Laumanns, and Zitzler		√	√	√					√		√						
175	DTLZ8	Benchmark MOP proposed by Deb, Thiele, Laumanns, and Zitzler		√	√	√					√	√	√						
176	DTLZ9	Benchmark MOP proposed by Deb, Thiele, Laumanns, and Zitzler		√	√	√					√	√	√						
177	CDTLZ2	Convex DTLZ2		√	√	√					√		√						
178	IDTLZ1	Inverted DTLZ1		√	√	√					√		√						
179	IDTLZ2	Inverted DTLZ2		√	√	√					√		√						
180	SDTLZ1	Scaled DTLZ1		√	√	√					√		√						
181	SDTLZ2	Scaled DTLZ2		√	√	√					√		√						
182	C1-DTLZ1	Constrained DTLZ1		√	√	√					√	√	√						
183	C1-DTLZ3	Constrained DTLZ3		√	√	√					√	√	√						
184	C2-DTLZ2	Constrained DTLZ2		√	√	√					√	√	√						
185	C3-DTLZ4	Constrained DTLZ4		√	√	√					√	√	√						
186	DC1-DTLZ1	DTLZ1 with constrains in decision space		√	√	√					√	√	√						
187	DC1-DTLZ3	DTLZ3 with constrains in decision space		√	√	√					√	√	√						
188	DC2-DTLZ1	DTLZ1 with constrains in decision space		√	√	√					√	√	√						
189	DC2-DTLZ3	DTLZ3 with constrains in decision space		√	√	√					√	√	√						
190	DC3-DTLZ1	DTLZ1 with constrains in decision space		√	√	√					√	√	√						
191	DC3-DTLZ3	DTLZ3 with constrains in decision space		√	√	√					√	√	√						
192	FCP1	Benchmark constrained MOP proposed by Yuan		√		√						√							
193	FCP2	Benchmark constrained MOP proposed by Yuan		√		√						√							
194	FCP3	Benchmark constrained MOP proposed by Yuan		√		√						√							
195	FCP4	Benchmark constrained MOP proposed by Yuan		√		√						√							
196	FCP5	Benchmark constrained MOP proposed by Yuan		√		√						√							
197	FDA1	Benchmark dynamic MOP proposed by Farina, Deb, and Amato		√		√					√					√			
198	FDA2	Benchmark dynamic MOP proposed by Farina, Deb, and Amato		√		√					√					√			
199	FDA3	Benchmark dynamic MOP proposed by Farina, Deb, and Amato		√		√					√					√			
200	FDA4	Benchmark dynamic MOP proposed by Farina, Deb, and Amato		√		√					√					√			

	问题缩写	问题全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
201	FDA5	Benchmark dynamic MOP proposed by Farina, Deb, and Amato		√		√					√					√			
202	GLSMOP1	General large-scale benchmark MOP		√	√	√					√		√						
203	GLSMOP2	General large-scale benchmark MOP		√	√	√					√		√						
204	GLSMOP3	General large-scale benchmark MOP		√	√	√					√		√						
205	GLSMOP4	General large-scale benchmark MOP		√	√	√					√		√						
206	GLSMOP5	General large-scale benchmark MOP		√	√	√					√		√						
207	GLSMOP6	General large-scale benchmark MOP		√	√	√					√		√						
208	GLSMOP7	General large-scale benchmark MOP		√	√	√					√		√						
209	GLSMOP8	General large-scale benchmark MOP		√	√	√					√		√						
210	GLSMOP9	General large-scale benchmark MOP		√	√	√					√		√						
211	IMMOEA_F1	Benchmark MOP for testing IM-MOEA		√		√					√								
212	IMMOEA_F2	Benchmark MOP for testing IM-MOEA		√		√					√								
213	IMMOEA_F3	Benchmark MOP for testing IM-MOEA		√		√					√								
214	IMMOEA_F4	Benchmark MOP for testing IM-MOEA		√		√					√								
215	IMMOEA_F5	Benchmark MOP for testing IM-MOEA		√		√					√								
216	IMMOEA_F6	Benchmark MOP for testing IM-MOEA		√		√					√								
217	IMMOEA_F7	Benchmark MOP for testing IM-MOEA		√		√					√								
218	IMMOEA_F8	Benchmark MOP for testing IM-MOEA		√		√					√								
219	IMMOEA_F9	Benchmark MOP for testing IM-MOEA		√		√					√								
220	IMMOEA_F10	Benchmark MOP for testing IM-MOEA		√		√					√								
221	IMOP1	Benchmark MOP with irregular Pareto front		√		√							√						
222	IMOP2	Benchmark MOP with irregular Pareto front		√		√							√						
223	IMOP3	Benchmark MOP with irregular Pareto front		√		√							√						
224	IMOP4	Benchmark MOP with irregular Pareto front		√		√							√						
225	IMOP5	Benchmark MOP with irregular Pareto front		√		√							√						
226	IMOP6	Benchmark MOP with irregular Pareto front		√		√							√						
227	IMOP7	Benchmark MOP with irregular Pareto front		√		√							√						
228	IMOP8	Benchmark MOP with irregular Pareto front		√		√							√						
229	IN1KMOP1	Neural architecture search on ImageNet 1K		√		√					√		√						
230	IN1KMOP2	Neural architecture search on ImageNet 1K		√		√					√		√						
231	IN1KMOP3	Neural architecture search on ImageNet 1K		√		√					√		√						
232	IN1KMOP4	Neural architecture search on ImageNet 1K		√		√					√		√						
233	IN1KMOP5	Neural architecture search on ImageNet 1K		√		√					√		√						
234	IN1KMOP6	Neural architecture search on ImageNet 1K		√		√					√		√						
235	IN1KMOP7	Neural architecture search on ImageNet 1K		√		√					√		√						
236	IN1KMOP8	Neural architecture search on ImageNet 1K		√		√					√		√						
237	IN1KMOP9	Neural architecture search on ImageNet 1K		√		√					√		√						

	问题缩写	问题全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
238	Instance1	Multitasking multi-objective problem (ZDT4-R + ZDT4-G)		√		√					√						√		
239	Instance2	Multitasking multi-objective problem (ZDT4-RC + ZDT4-A)		√		√					√	√					√		
240	KP	The knapsack problem	√						√		√	√							
241	LIR-CMOP1	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
242	LIR-CMOP2	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
243	LIR-CMOP3	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
244	LIR-CMOP4	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
245	LIR-CMOP5	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
246	LIR-CMOP6	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
247	LIR-CMOP7	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
248	LIR-CMOP8	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
249	LIR-CMOP9	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
250	LIR-CMOP10	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
251	LIR-CMOP11	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
252	LIR-CMOP12	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
253	LIR-CMOP13	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
254	LIR-CMOP14	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
255	LRMOP1	Large-scale robust multi-objective benchmark problem		√	√	√					√		√		√				√
256	LRMOP2	Large-scale robust multi-objective benchmark problem		√	√	√					√		√		√				√
257	LRMOP3	Large-scale robust multi-objective benchmark problem		√	√	√					√		√		√				√
258	LRMOP4	Large-scale robust multi-objective benchmark problem		√	√	√					√		√		√				√
259	LRMOP5	Large-scale robust multi-objective benchmark problem		√	√	√					√		√		√				√
260	LRMOP6	Large-scale robust multi-objective benchmark problem		√	√	√					√		√		√				√
261	LSCM1	Large-scale constrained multiobjective benchmark problem		√		√					√	√							
262	LSCM2	Large-scale constrained multiobjective benchmark problem		√		√					√	√							

	问题缩写	问题全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
263	LSCM3	Large-scale constrained multiobjective benchmark problem		√		√					√	√							
264	LSCM4	Large-scale constrained multiobjective benchmark problem		√		√					√	√							
265	LSCM5	Large-scale constrained multiobjective benchmark problem		√		√					√	√							
266	LSCM6	Large-scale constrained multiobjective benchmark problem		√		√					√	√							
267	LSCM7	Large-scale constrained multiobjective benchmark problem		√		√					√	√							
268	LSCM8	Large-scale constrained multiobjective benchmark problem		√		√					√	√							
269	LSCM9	Large-scale constrained multiobjective benchmark problem		√		√					√	√							
270	LSCM10	Large-scale constrained multiobjective benchmark problem		√		√					√	√							
271	LSCM11	Large-scale constrained multiobjective benchmark problem		√		√					√	√							
272	LSCM12	Large-scale constrained multiobjective benchmark problem		√		√					√	√							
273	LSMOP1	Large-scale benchmark MOP		√	√	√					√								
274	LSMOP2	Large-scale benchmark MOP		√	√	√					√								
275	LSMOP3	Large-scale benchmark MOP		√	√	√					√								
276	LSMOP4	Large-scale benchmark MOP		√	√	√					√								
277	LSMOP5	Large-scale benchmark MOP		√	√	√					√								
278	LSMOP6	Large-scale benchmark MOP		√	√	√					√								
279	LSMOP7	Large-scale benchmark MOP		√	√	√					√								
280	LSMOP8	Large-scale benchmark MOP		√	√	√					√								
281	LSMOP9	Large-scale benchmark MOP		√	√	√					√								
282	MaF1	Inverted DTLZ1		√	√	√					√								
283	MaF2	DTLZ2BZ		√	√	√					√								
284	MaF3	Convex DTLZ3		√	√	√					√								
285	MaF4	Inverted and scaled DTLZ3		√	√	√					√								
286	MaF5	Scaled DTLZ4		√	√	√					√								
287	MaF6	DTLZ5IM		√	√	√					√								
288	MaF7	DTLZ7		√	√	√					√								
289	MaF8	MP-DMP		√	√	√													
290	MaF9	ML-DMP		√	√	√													
291	MaF10	WFG1		√	√	√					√								
292	MaF11	WFG2		√	√	√					√								
293	MaF12	WFG9		√	√	√					√								
294	MaF13	P7		√	√	√					√								

	问题缩写	问题全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
295	MaF14	LSMOP3		√	√	√					√								
296	MaF15	Inverted LSMOP8		√	√	√					√								
297	MaOPP_binary	Many-objective pathfinding problem based on binary encoding			√				√		√		√						
298	MaOPP_real	Many-objective pathfinding problem based on real encoding			√	√					√		√						
299	Mario	Play with Mario	√				√	√											
300	MaxCut	The max-cut problem	√						√		√								
301	MLDMP	The multi-line distance minimization problem		√	√	√													
302	MMF1	Multi-modal multi-objective test function		√		√								√					
303	MMF2	Multi-modal multi-objective test function		√		√								√					
304	MMF3	Multi-modal multi-objective test function		√		√								√					
305	MMF4	Multi-modal multi-objective test function		√		√								√					
306	MMF5	Multi-modal multi-objective test function		√		√								√					
307	MMF6	Multi-modal multi-objective test function		√		√								√					
308	MMF7	Multi-modal multi-objective test function		√		√								√					
309	MMF8	Multi-modal multi-objective test function		√		√								√					
310	MMMOP1	Multi-modal multi-objective optimization problem		√	√	√								√					
311	MMMOP2	Multi-modal multi-objective optimization problem		√	√	√								√					
312	MMMOP3	Multi-modal multi-objective optimization problem		√	√	√								√					
313	MMMOP4	Multi-modal multi-objective optimization problem		√	√	√								√					
314	MMMOP5	Multi-modal multi-objective optimization problem		√	√	√								√					
315	MMMOP6	Multi-modal multi-objective optimization problem		√	√	√								√					
316	MMOP_HS1	Large-scale sparse multitasking multi-objective optimization problem		√		√					√				√		√		
317	MMOP_HS2	Large-scale sparse multitasking multi-objective optimization problem		√		√					√				√		√		
318	MMOP_LS1	Large-scale sparse multitasking multi-objective optimization problem		√		√					√				√		√		
319	MMOP_LS2	Large-scale sparse multitasking multi-objective optimization problem		√		√					√				√		√		
320	MMOP_MS1	Large-scale sparse multitasking multi-objective optimization problem		√		√					√				√		√		
321	MMOP_MS2	Large-scale sparse multitasking multi-objective optimization problem		√		√					√				√		√		
322	MMOP_NS1	Large-scale sparse multitasking multi-objective optimization problem		√		√					√				√		√		
323	MMOP_NS2	Large-scale sparse multitasking multi-objective optimization problem		√		√					√				√		√		
324	MOEADDE_F1	Benchmark MOP for testing MOEA/D-DE		√		√					√								
325	MOEADDE_F2	Benchmark MOP for testing MOEA/D-DE		√		√					√								
326	MOEADDE_F3	Benchmark MOP for testing MOEA/D-DE		√		√					√								

	问题缩写	问题全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
327	MOEADDE_F4	Benchmark MOP for testing MOEA/D-DE		√		√					√								
328	MOEADDE_F5	Benchmark MOP for testing MOEA/D-DE		√		√					√								
329	MOEADDE_F6	Benchmark MOP for testing MOEA/D-DE		√		√					√								
330	MOEADDE_F7	Benchmark MOP for testing MOEA/D-DE		√		√					√								
331	MOEADDE_F8	Benchmark MOP for testing MOEA/D-DE		√		√					√								
332	MOEADDE_F9	Benchmark MOP for testing MOEA/D-DE		√		√					√								
333	MOEADM2M_F1	Benchmark MOP for testing MOEA/D-M2M		√		√					√								
334	MOEADM2M_F2	Benchmark MOP for testing MOEA/D-M2M		√		√					√								
335	MOEADM2M_F3	Benchmark MOP for testing MOEA/D-M2M		√		√					√								
336	MOEADM2M_F4	Benchmark MOP for testing MOEA/D-M2M		√		√					√								
337	MOEADM2M_F5	Benchmark MOP for testing MOEA/D-M2M		√		√					√								
338	MOEADM2M_F6	Benchmark MOP for testing MOEA/D-M2M		√		√					√								
339	MOEADM2M_F7	Benchmark MOP for testing MOEA/D-M2M		√		√					√								
340	MOKP	The multi-objective knapsack problem		√	√				√		√	√							
341	MONRP	The multi-objective next release problem		√					√		√								
342	MOTSP	The multi-objective traveling salesman problem		√	√					√	√								
343	MPDMP	The multi-point distance minimization problem		√	√	√													
344	mQAP	The multi-objective quadratic assignment problem		√	√					√	√								
345	MW1	Constrained benchmark MOP proposed by Ma and Wang		√		√					√	√							
346	MW2	Constrained benchmark MOP proposed by Ma and Wang		√		√					√	√							
347	MW3	Constrained benchmark MOP proposed by Ma and Wang		√		√					√	√							
348	MW4	Constrained benchmark MOP proposed by Ma and Wang		√	√	√					√	√							
349	MW5	Constrained benchmark MOP proposed by Ma and Wang		√		√					√	√							
350	MW6	Constrained benchmark MOP proposed by Ma and Wang		√		√					√	√							
351	MW7	Constrained benchmark MOP proposed by Ma and Wang		√		√					√	√							
352	MW8	Constrained benchmark MOP proposed by Ma and Wang		√	√	√					√	√							
353	MW9	Constrained benchmark MOP proposed by Ma and Wang		√		√					√	√							
354	MW10	Constrained benchmark MOP proposed by Ma and Wang		√		√					√	√							
355	MW11	Constrained benchmark MOP proposed by Ma and Wang		√		√					√	√							
356	MW12	Constrained benchmark MOP proposed by Ma and Wang		√		√					√	√							
357	MW13	Constrained benchmark MOP proposed by		√		√					√	√							

	问题缩写	问题全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
		Ma and Wang																	
358	MW14	Constrained benchmark MOP proposed by Ma and Wang		√	√	√					√	√							
359	NI_HS	Multitasking problem (Rosenbrock function + Rastrigin function)	√			√					√						√		
360	NI_MS	Multitasking problem (Griewank function + Weierstrass function)	√			√					√						√		
361	RMMEDA_F1	Benchmark MOP for testing RM-MEDA		√		√					√								
362	RMMEDA_F2	Benchmark MOP for testing RM-MEDA		√		√					√								
363	RMMEDA_F3	Benchmark MOP for testing RM-MEDA		√		√					√								
364	RMMEDA_F4	Benchmark MOP for testing RM-MEDA		√		√					√								
365	RMMEDA_F5	Benchmark MOP for testing RM-MEDA		√		√					√								
366	RMMEDA_F6	Benchmark MOP for testing RM-MEDA		√		√					√								
367	RMMEDA_F7	Benchmark MOP for testing RM-MEDA		√		√					√								
368	RMMEDA_F8	Benchmark MOP for testing RM-MEDA		√		√					√								
369	RMMEDA_F9	Benchmark MOP for testing RM-MEDA		√		√					√								
370	RMMEDA_F10	Benchmark MOP for testing RM-MEDA		√		√					√								
371	RWMOP1	Pressure vessal problem		√		√						√							
372	RWMOP2	Vibrating platform		√		√						√							
373	RWMOP3	Two bar truss design problem		√		√						√							
374	RWMOP4	Weldan beam design problem		√		√						√							
375	RWMOP5	Disc brake design problem		√		√						√							
376	RWMOP6	Speed reducer design problem		√		√						√							
377	RWMOP7	Gear train design problem		√		√						√							
378	RWMOP8	Car side impact design problem		√		√						√							
379	RWMOP9	Four bar plane truss		√		√						√							
380	RWMOP10	Two bar plane truss		√		√						√							
381	RWMOP11	Water resource management problem		√		√						√							
382	RWMOP12	Simply supported I-beam design		√		√						√							
383	RWMOP13	Gear box design		√		√						√							
384	RWMOP14	Multiple-disk clutch brake design problem		√		√						√							
385	RWMOP15	Spring design problem		√		√						√							
386	RWMOP16	Cantilever beam design problem		√		√						√							
387	RWMOP17	Bulk carriers design problem		√		√						√							
388	RWMOP18	Front rail design problem		√		√						√							
389	RWMOP19	Multi-product batch plant		√		√						√							
390	RWMOP20	Hydro-static thrust bearing design problem		√		√						√							
391	RWMOP21	Crash energy management for high-speed train		√		√						√							
392	RWMOP22	Haverly's pooling problem		√		√						√							

	问题缩写	问题全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
393	RWMOP23	Reactor network design		√		√						√							
394	RWMOP24	Heat exchanger network design		√		√						√							
395	RWMOP25	Process synthesis problem		√		√						√							
396	RWMOP26	Process sythesis and design problem		√		√						√							
397	RWMOP27	Process flow sheeting problem		√		√						√							
398	RWMOP28	Two reactor problem		√		√						√							
399	RWMOP29	Process synthesis problem		√		√						√							
400	RWMOP30	Synchronous pptimal pulse-width modulation of 3-level inverters		√		√						√							
401	RWMOP31	Synchronous pptimal pulse-width modulation of 5-level inverters		√		√						√							
402	RWMOP32	Synchronous pptimal pulse-width modulation of 7-level inverters		√		√						√							
403	RWMOP33	Synchronous pptimal pulse-width modulation of 9-level inverters		√		√						√							
404	RWMOP34	Synchronous pptimal pulse-width modulation of 11-level inverters		√		√						√							
405	RWMOP35	Synchronous pptimal pulse-width modulation of 13-level inverters		√		√						√							
406	RWMOP36	Optimal sizing of single phase distributed generation with reactive power support for phase balancing at main transformer/grid and active power loss		√		√						√							
407	RWMOP37	Optimal Sizing of Single Phase Distributed Generation with reactive power support for Phase Balancing at Main Transformer/Grid and reactive Power loss		√		√						√							
408	RWMOP38	Optimal sizing of single phase distributed generation with reactive power support for active and reactive power loss		√		√						√							
409	RWMOP39	Optimal sizing of single phase distributed generation with reactive power support for phase balancing at main transformer/grid and active and reactive power loss		√		√						√							
410	RWMOP40	Optimal power flow for minimizing active and reactive power loss		√		√						√							
411	RWMOP41	Optimal power flow for minimizing voltage deviation, active and reactive power loss		√		√						√							
412	RWMOP42	Optimal power flow for minimizing voltage deviation, and active power loss		√		√						√							
413	RWMOP43	Optimal power flow for minimizing fuel cost, and active power loss		√		√						√							
414	RWMOP44	Optimal power flow for minimizing fuel cost, active and reactive power loss		√		√						√							
415	RWMOP45	Optimal power flow for minimizing fuel cost, voltage deviation, and active power loss		√		√						√							
416	RWMOP46	Optimal power flow for minimizing fuel cost, voltage deviation, active and reactive power loss		√		√						√							
417	RWMOP47	Optimal droop setting for minimizing active		√		√						√							

	问题缩写	问题全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
		and reactive power loss																	
418	RWMOP48	Optimal droop setting for minimizing voltage deviation and active power loss		√		√						√							
419	RWMOP49	Optimal droop setting for minimizing voltage deviation, active, and reactive power loss		√		√						√							
420	RWMOP50	Power distribution system planning		√		√						√							
421	SDC1	Scalable high-dimensional decicsion constraint benchamrk		√		√						√							
422	SDC2	Scalable high-dimensional decicsion constraint benchamrk		√		√						√							
423	SDC3	Scalable high-dimensional decicsion constraint benchamrk		√		√						√							
424	SDC4	Scalable high-dimensional decicsion constraint benchamrk		√		√						√							
425	SDC5	Scalable high-dimensional decicsion constraint benchamrk		√		√						√							
426	SDC6	Scalable high-dimensional decicsion constraint benchamrk		√		√						√							
427	SDC7	Scalable high-dimensional decicsion constraint benchamrk		√		√						√							
428	SDC8	Scalable high-dimensional decicsion constraint benchamrk		√		√						√							
429	SDC9	Scalable high-dimensional decicsion constraint benchamrk		√		√						√							
430	SDC10	Scalable high-dimensional decicsion constraint benchamrk		√		√						√							
431	SDC11	Scalable high-dimensional decicsion constraint benchamrk		√		√						√							
432	SDC12	Scalable high-dimensional decicsion constraint benchamrk		√		√						√							
433	SDC13	Scalable high-dimensional decicsion constraint benchamrk		√		√						√							
434	SDC14	Scalable high-dimensional decicsion constraint benchamrk		√		√						√							
435	SDC15	Scalable high-dimensional decicsion constraint benchamrk		√		√						√							
436	SMD1	Bilevel optimization problems proposed by Sinha, Malo, and Deb		√		√												√	
437	SMD2	Bilevel optimization problems proposed by Sinha, Malo, and Deb		√		√												√	
438	SMD3	Bilevel optimization problems proposed by Sinha, Malo, and Deb		√		√												√	
439	SMD4	Bilevel optimization problems proposed by Sinha, Malo, and Deb		√		√												√	
440	SMD5	Bilevel optimization problems proposed by Sinha, Malo, and Deb		√		√												√	
441	SMD6	Bilevel optimization problems proposed by Sinha, Malo, and Deb		√		√												√	

	问题缩写	问题全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
442	SMD7	Bilevel optimization problems proposed by Sinha, Malo, and Deb		√		√												√	
443	SMD8	Bilevel optimization problems proposed by Sinha, Malo, and Deb		√		√												√	
444	SMD9	Bilevel optimization problems proposed by Sinha, Malo, and Deb		√		√						√						√	
445	SMD10	Bilevel optimization problems proposed by Sinha, Malo, and Deb		√		√						√						√	
446	SMD11	Bilevel optimization problems proposed by Sinha, Malo, and Deb		√		√						√						√	
447	SMD12	Bilevel optimization problems proposed by Sinha, Malo, and Deb		√		√						√						√	
448	SO_ISCSO_2016	International student competition in structural optimization	√				√				√	√							
449	SO_ISCSO_2017	International student competition in structural optimization	√				√				√	√							
450	SO_ISCSO_2018	International student competition in structural optimization	√				√				√	√							
451	SO_ISCSO_2019	International student competition in structural optimization	√				√				√	√							
452	SO_ISCSO_2021	International student competition in structural optimization	√				√				√	√							
453	SO_ISCSO_2022	International student competition in structural optimization	√				√				√	√							
454	Sparse_CD	The community detection problem		√					√		√		√		√				
455	Sparse_CN	The critical node detection problem		√					√		√		√		√				
456	Sparse_FS	The feature selection problem		√					√		√		√		√				
457	Sparse_IS	The instance selection problem		√					√		√		√		√				
458	Sparse_KP	The sparse multi-objective knapsack problem		√	√				√		√								
459	Sparse_NN	The neural network training problem		√		√					√		√		√				
460	Sparse_PM	The pattern mining problem		√					√		√		√		√				
461	Sparse_PO	The portfolio optimization problem		√		√					√		√		√				
462	Sparse_SR	The sparse signal reconstruction problem		√		√					√		√		√				
463	SMMOP1	Sparse multi-modal multi-objective optimization problem		√	√	√					√			√	√				
464	SMMOP2	Sparse multi-modal multi-objective optimization problem		√	√	√					√			√	√				
465	SMMOP3	Sparse multi-modal multi-objective optimization problem		√	√	√					√			√	√				
466	SMMOP4	Sparse multi-modal multi-objective optimization problem		√	√	√					√			√	√				
467	SMMOP5	Sparse multi-modal multi-objective optimization problem		√	√	√					√			√	√				
468	SMMOP6	Sparse multi-modal multi-objective optimization problem		√	√	√					√			√	√				
469	SMMOP7	Sparse multi-modal multi-objective		√	√	√					√			√	√				

	问题缩写	问题全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
		optimization problem																	
470	SMMOP8	Sparse multi-modal multi-objective optimization problem		√	√	√					√			√	√				
471	SMOP1	Benchmark MOP with sparse Pareto optimal solutions		√	√	√					√		√		√				
472	SMOP2	Benchmark MOP with sparse Pareto optimal solutions		√	√	√					√		√		√				
473	SMOP3	Benchmark MOP with sparse Pareto optimal solutions		√	√	√					√		√		√				
474	SMOP4	Benchmark MOP with sparse Pareto optimal solutions		√	√	√					√		√		√				
475	SMOP5	Benchmark MOP with sparse Pareto optimal solutions		√	√	√					√		√		√				
476	SMOP6	Benchmark MOP with sparse Pareto optimal solutions		√	√	√					√		√		√				
477	SMOP7	Benchmark MOP with sparse Pareto optimal solutions		√	√	√					√		√		√				
478	SMOP8	Benchmark MOP with sparse Pareto optimal solutions		√	√	√					√		√		√				
479	SOP_F1	Sphere function	√			√							√						
480	SOP_F2	Schwefel's function 2.22	√			√							√						
481	SOP_F3	Schwefel's function 1.2	√			√							√						
482	SOP_F4	Schwefel's function 2.21	√			√							√						
483	SOP_F5	Generalized Rosenbrock's function	√			√							√						
484	SOP_F6	Step function	√			√							√						
485	SOP_F7	Quartic function with noise	√			√							√						
486	SOP_F8	Generalized Schwefel's function 2.26	√			√							√						
487	SOP_F9	Generalized Rastrigin's function	√			√							√						
488	SOP_F10	Ackley's function	√			√							√						
489	SOP_F11	Generalized Griewank's function	√			√							√						
490	SOP_F12	Generalized penalized function	√			√							√						
491	SOP_F13	Generalized penalized function	√			√							√						
492	SOP_F14	Shekel's foxholes function	√			√							√						
493	SOP_F15	Kowalik's function	√			√							√						
494	SOP_F16	Six-hump camel-back function	√			√							√						
495	SOP_F17	Branin function	√			√							√						
496	SOP_F18	Goldstein-price function	√			√							√						
497	SOP_F19	Hartman's family	√			√							√						
498	SOP_F20	Hartman's family	√			√							√						
499	SOP_F21	Shekel's family	√			√							√						
500	SOP_F22	Shekel's family	√			√							√						
501	SOP_F23	Shekel's family	√			√							√						

	问题缩写	问题全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
502	TP1	Test problem for robust multi-objective optimization		√		√					√								√
503	TP2	Test problem for robust multi-objective optimization		√		√					√								√
504	TP3	Test problem for robust multi-objective optimization		√		√					√								√
505	TP4	Test problem for robust multi-objective optimization		√		√					√								√
506	TP5	Test problem for robust multi-objective optimization		√		√					√								√
507	TP6	Test problem for robust multi-objective optimization		√		√					√								√
508	TP7	Test problem for robust multi-objective optimization		√		√					√								√
509	TP8	Test problem for robust multi-objective optimization		√		√					√								√
510	TP9	Test problem for robust multi-objective optimization		√		√					√								√
511	TP10	Test problem for robust multi-objective optimization		√		√					√	√							√
512	TREE1	The time-varying ratio error estimation problem		√		√					√	√	√						
513	TREE2	The time-varying ratio error estimation problem		√		√					√	√	√						
514	TREE3	The time-varying ratio error estimation problem		√		√					√	√	√						
515	TREE4	The time-varying ratio error estimation problem		√		√					√	√	√						
516	TREE5	The time-varying ratio error estimation problem		√		√					√	√	√						
517	TREE6	The time-varying ratio error estimation problem		√		√					√	√	√						
518	TSP	The traveling salesman problem	√							√	√								
519	UF1	Unconstrained benchmark MOP		√		√					√								
520	UF2	Unconstrained benchmark MOP		√		√					√								
521	UF3	Unconstrained benchmark MOP		√		√					√								
522	UF4	Unconstrained benchmark MOP		√		√					√								
523	UF5	Unconstrained benchmark MOP		√		√					√								
524	UF6	Unconstrained benchmark MOP		√		√					√								
525	UF7	Unconstrained benchmark MOP		√		√					√								
526	UF8	Unconstrained benchmark MOP		√		√					√								
527	UF9	Unconstrained benchmark MOP		√		√					√								
528	UF10	Unconstrained benchmark MOP		√		√					√								
529	VNT1	Benchmark MOP proposed by Viennet		√		√													
530	VNT2	Benchmark MOP proposed by Viennet		√		√													
531	VNT3	Benchmark MOP proposed by Viennet		√		√													
532	VNT4	Benchmark MOP proposed by Viennet		√		√						√							
533	WFG1	Benchmark MOP proposed by Walking Fish Group		√	√	√					√		√						
534	WFG2	Benchmark MOP proposed by Walking Fish Group		√	√	√					√		√						
535	WFG3	Benchmark MOP proposed by Walking Fish Group		√	√	√					√		√						
536	WFG4	Benchmark MOP proposed by Walking Fish Group		√	√	√					√		√						
537	WFG5	Benchmark MOP proposed by Walking Fish Group		√	√	√					√		√						
538	WFG6	Benchmark MOP proposed by Walking Fish Group		√	√	√					√		√						

	问题缩写	问题全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
539	WFG7	Benchmark MOP proposed by Walking Fish Group		√	√	√					√		√						
540	WFG8	Benchmark MOP proposed by Walking Fish Group		√	√	√					√		√						
541	WFG9	Benchmark MOP proposed by Walking Fish Group		√	√	√					√		√						
542	ZCAT1	Benchmark MOP proposed by Zapotecas, Coello, Aguirre, and Tanaka		√	√	√					√		√						
543	ZCAT2	Benchmark MOP proposed by Zapotecas, Coello, Aguirre, and Tanaka		√	√	√					√		√						
544	ZCA3	Benchmark MOP proposed by Zapotecas, Coello, Aguirre, and Tanaka		√	√	√					√		√						
545	ZCA4	Benchmark MOP proposed by Zapotecas, Coello, Aguirre, and Tanaka		√	√	√					√		√						
546	ZCA5	Benchmark MOP proposed by Zapotecas, Coello, Aguirre, and Tanaka		√	√	√					√		√						
547	ZCAT6	Benchmark MOP proposed by Zapotecas, Coello, Aguirre, and Tanaka		√	√	√					√		√						
548	ZCAT7	Benchmark MOP proposed by Zapotecas, Coello, Aguirre, and Tanaka		√	√	√					√		√						
549	ZCAT8	Benchmark MOP proposed by Zapotecas, Coello, Aguirre, and Tanaka		√	√	√					√		√						
550	ZCAT9	Benchmark MOP proposed by Zapotecas, Coello, Aguirre, and Tanaka		√	√	√					√		√						
551	ZCAT10	Benchmark MOP proposed by Zapotecas, Coello, Aguirre, and Tanaka		√	√	√					√		√						
552	ZCAT11	Benchmark MOP proposed by Zapotecas, Coello, Aguirre, and Tanaka		√	√	√					√		√						
553	ZCAT12	Benchmark MOP proposed by Zapotecas, Coello, Aguirre, and Tanaka		√	√	√					√		√						
554	ZCAT13	Benchmark MOP proposed by Zapotecas, Coello, Aguirre, and Tanaka		√	√	√					√		√						
555	ZCAT14	Benchmark MOP proposed by Zapotecas, Coello, Aguirre, and Tanaka		√	√	√					√		√						
556	ZCAT15	Benchmark MOP proposed by Zapotecas, Coello, Aguirre, and Tanaka		√	√	√					√		√						
557	ZCAT16	Benchmark MOP proposed by Zapotecas, Coello, Aguirre, and Tanaka		√	√	√					√		√						
558	ZCAT17	Benchmark MOP proposed by Zapotecas, Coello, Aguirre, and Tanaka		√	√	√					√		√						
559	ZCAT18	Benchmark MOP proposed by Zapotecas, Coello, Aguirre, and Tanaka		√	√	√					√		√						
560	ZCAT19	Benchmark MOP proposed by Zapotecas, Coello, Aguirre, and Tanaka		√	√	√					√		√						
561	ZCAT20	Benchmark MOP proposed by Zapotecas, Coello, Aguirre, and Tanaka		√	√	√					√		√						
562	ZDT1	Benchmark MOP proposed by Zitzler, Deb, and Thiele		√		√					√		√						
563	ZDT2	Benchmark MOP proposed by Zitzler, Deb, and Thiele		√		√					√		√						
564	ZDT3	Benchmark MOP proposed by Zitzler, Deb,		√		√					√		√						

	问题缩写	问题全称	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
		and Thiele																	
565	ZDT4	Benchmark MOP proposed by Zitzler, Deb, and Thiele		√		√					√		√						
566	ZDT5	Benchmark MOP proposed by Zitzler, Deb, and Thiele		√					√		√		√						
567	ZDT6	Benchmark MOP proposed by Zitzler, Deb, and Thiele		√		√					√		√						
568	ZXH_CF1	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
569	ZXH_CF2	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
570	ZXH_CF3	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
571	ZXH_CF4	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
572	ZXH_CF5	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
573	ZXH_CF6	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
574	ZXH_CF7	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
575	ZXH_CF8	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
576	ZXH_CF9	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
577	ZXH_CF10	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
578	ZXH_CF11	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
579	ZXH_CF12	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
580	ZXH_CF13	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
581	ZXH_CF14	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
582	ZXH_CF15	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
583	ZXH_CF16	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							