PlatEMO

Evolutionary Multi-Objective Optimization Platform

User Manual 4.1

BIMK Group

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[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.

If you have any comment or suggestion to PlatEMO, please send it to *field910921@gmail.com* (*Dr. Ye Tian*). If you want to add your code to PlatEMO, please send the ready-to-use code and the relevant literature to *field910921@gmail.com* as well. You can obtain the newest version of PlatEMO from GitHub.

Contents

I. Quick Start

Requirement: MATLAB R2018a or higher (PlatEMO without GUI) or
MATLAB R2020b or higher (PlatEMO with GUI) with
Parallel Computing Toolbox and
Statistics and Machine Learning Toolbox

PlatEMO is an open-source platform for solving optimization problems, whose input is an optimization problem and output is the found optimal solutions. An optimization problem is defined as

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

where $\mathbf{x}$ denotes a **solution** or **decision vector** for the problem, which consists of D **decision variables** x_i, and each decision variable can be a real number, integer, binary number, or others. Ω denotes the **search space** of the problems, which consists of the **lower bound** $l_1, l_2, \dots l_D$ and the **upper bound** $u_1, u_2, \dots u_D$, i.e., each decision variable should always satisfy that $l_i \leq x_i \leq u_i$. $f_1(\mathbf{x}), f_2(\mathbf{x}), \dots, f_M(\mathbf{x})$ denote the M **objective values** of the solution, and $g_1(\mathbf{x}), g_2(\mathbf{x}), \dots, g_K(\mathbf{x})$ denote the K **constraint violations** of the solution.

To define an optimization problem, users should input at least the following contents:

- The encoding scheme of each decision variable (real, integer, binary, etc.);
- The lower bound $l_1, l_2, \dots l_D$ and the upper bound $u_1, u_2, \dots u_D$;
- At least one objective function $f_1(\mathbf{x})$.

To define an optimization problem more precisely, users can also input the following contents:

- Multiple objective functions $f_1(\mathbf{x}), f_2(\mathbf{x}), \dots, f_M(\mathbf{x})$;
- Multiple constraint functions $g_1(\mathbf{x}), g_2(\mathbf{x}), \dots, g_K(\mathbf{x})$;
- Function for initializing solutions;
- Function for repairing invalid solutions;
- Function for evaluating solutions;
- Gradient functions of objectives $f_1'(\mathbf{x}), f_2'(\mathbf{x}), \dots, f_M'(\mathbf{x})$;
- Gradient functions of constraints $g_1'(\mathbf{x}), g_2'(\mathbf{x}), \dots, g_K'(\mathbf{x})$;
- Data used in the calculation of all functions (an arbitrary constant).

The above functions are MATLAB functions rather than mathematical functions, which should have specified inputs and outputs but need not have explicit mathematical expressions. Moreover, users can define the settings of optimization algorithms, to achieve the improvement of optimization performance via selecting suitable algorithms and parameter settings.

In MATLAB, users can call the main file `platemo.m` in the following three ways:

1) Calling the main function with parameters:

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

Then the specified benchmark problem will be solved by the specified algorithm with specified parameter settings, where the result can be displayed, saved, or returned (see *Solving Benchmark Problems* for details).

2) Calling the main function with parameters:

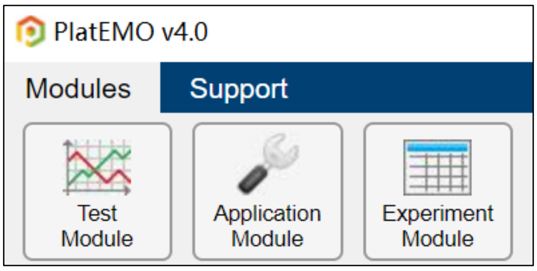
```
f1 = @(x)sum(x);
f2 = @(x)1-sum(x);
platemo('objFcn',f1,'conFcn',f2,'algorithm',@GA);
```

Then the user-defined problem will be solved by the specified algorithm with specified parameter settings (see *Solving User-Defined Problems* for details).

3) Calling the main function without parameter:

```
platemo();
```

Then a GUI with three modules will be displayed, where the test module is used to visually investigate the performance of an algorithm on a benchmark problem (see *Functions of Test Module* for details), the application module is used to solve user-defined problems (see *Functions of Application Module* for details), and the experiment module is used to statistically analyze the performance of multiple algorithms on multiple benchmark problems (see *Functions of Experiment Module* for details).



II. Using PlatEMO without GUI

A. *Solving Benchmark Problems*

Users can use PlatEMO without GUI by calling the main function `platemo()` with parameters like

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

where all the acceptable names and values are

Name	Data type	Default value	Description
`'algorithm'`	Function handle or cell	`dependent`	Class of algorithm
`'problem'`	Function handle or cell	`dependent`	Class of problem
`'N'`	Positive integer	`100`	Population size
`'M'`	Positive integer	`dependent`	Number of objectives
`'D'`	Positive integer	`dependent`	Number of variables
`'maxFE'`	Positive integer	`10000`	Maximum number of function evaluations
`'maxRuntime'`	Positive number	`inf`	Maximum runtime
`'save'`	Integer	`-10`	Number of saved populations
`'outputFcn'`	Function handle	`@DefaultOutput`	Function called before each iteration Input 1: Class of algorithm Input 2: Class of problem Output: None

- `'algorithm'` denotes the algorithm to be run, whose value should be the function handle of an algorithm, such as `@GA`. The value can also be a cell like `{@GA,p1,p2,…}`, where `p1,p2,…` specify the parameter values of the algorithm. For example, the following code solves the default problem via the algorithm `@GA` with specified parameters:

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

- `'problem'` denotes the benchmark problem to solve, whose value should be the function handle of a benchmark problem, such as `@SOP_F1`. The value can also be a cell like `{@SOP_F1,p1,p2,…}`, where `p1,p2,…` specify the parameter values of the benchmark problem. For example, the following code solves the problem

`@WFG1` with specified parameters via the default algorithm:

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

- `'N'` denotes the population size of the algorithm, which usually equals the number of solutions in the final population. For example, the following code solves the problem `@SOP_F1` via the algorithm `@GA` with a population size of 50:

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

- `'M'` denotes the number of objectives of the benchmark problem, which is valid for some multi-objective benchmark problems. For example, the following code solves the problem `@SOP_F1` via the algorithm `@GA` with a population size of 50:

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

- `'D'` denotes the number of decision variables of the benchmark problem, which is valid for some benchmark problems. For example, the following code solves the problem `@SOP_F1` with 100 variables via the algorithm `@GA`:

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

- `'maxFE'` denotes the maximum number of available function evaluations, which usually equals the product of population size and number of generations. For example, the following code sets the maximum number of function evaluations to 20000 for the algorithm:

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

- `'maxRuntime'` denotes the maximum runtime (in second). When `'maxRuntime'` equals its default value `inf`, the algorithm will terminate after `'maxFE'` function evaluations; otherwise, the algorithm will terminate after `'maxRuntime'` seconds. For example, the following code sets the maximum runtime to 10 seconds for the algorithm:

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

- `'save'` denotes the number of saved populations, where the populations are saved to a file if the value is positive and displayed in a figure if the value is negative (see *Collecting the Results* for details).
- `'outputFcn'` denotes the function called before each iteration of the algorithm. An output function has two inputs and no output, where the first input is the current `ALGORITHM` object and the second input is the current `PROBLEM` object. The default `'outputFcn'` saves or displays the populations according the value of `'save'`.

Note that users need not specify all the parameters as each of them has a default value.

B. Solving User-Defined Problems

When the parameter `'problem'` is not specified, users can define their own problem by specifying the following parameters:

Name	Data type	Default value	Description
`'objFcn'`	Function handle, matrix, or cell	{}	Objective functions; all the objectives are to be minimized Input: A decision vector Output: Objective value (scalar)
`'encoding'`	Scalar or row vector	1	Encoding scheme of each variable
`'lower'`	Scalar or row vector	0	Lower bound of each variable
`'upper'`	Scalar or row vector	1	Upper bound of each variable
`'conFcn'`	Function handle, matrix, or cell	{}	Constraint functions; a constraint is satisfied if and only if the constraint violation is not positive Input: A decision vector Output: Constraint violation (scalar)
`'decFcn'`	Function handle	{}	Function for repairing an invalid solution Input: A decision vector Output: Repaired decision vector
`'evalFcn'`	Function handle	{}	Function for evaluating a solution Input: A decision vector Output 1: Repaired decision vector Output 2: All objective values (vector) Output 3: All constraint violations (vector)
`'initFcn'`	Function handle	{}	Function for initializing a population Input: Population size Output: A matrix consisting of the decision vectors of all solutions
`'objGradFcn'`	Function handle or cell	{}	Gradient functions of objectives Input: A decision vector Output: Gradient (vector)
`'conGradFcn'`	Function handle or cell	{}	Gradient functions of constraints Input: A decision vector Output: Gradient (vector)
`'data'`	Any	{}	Data of the problem

- `'objFcn'` denotes the objective functions of the problem, whose value can be a function handle (a single objective), a matrix (a function is automatically fitted), or cell (multiple objectives). An objective function has one input and one output, where the input is a decision vector and the output is the objective value. All the objectives are to be minimized. For example, the following code solves a bi-objective optimization problem with six real variables via the default algorithm:

```
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);
```

where the first objective is $x_1 + \sum_{i=2}^{D} x_i$ and the second objective is $\sqrt{1-x_1^2} + \sum_{i=2}^{D} x_i$. If an objective function is a matrix, a function will be automatically fitted via Gaussian process regression, where each row of the matrix is a sample and each column of the matrix is a variable (except for the last column) or a function value (the last column). For example, the following code solves the same problem, while the objective functions are automatically fitted:

```
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'` denotes the encoding scheme of each variable, whose value can be a scalar or row vector, and the value of each dimension can be `1` (real number), `2` (integer), `3` (label), `4` (binary number), or `5` (permutation number). The algorithms may generate solutions via different strategies for different encoding schemes. For example, the following code specifies three real variables, two integer variables, and one binary variable:

```
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]);
```

the number of variables *D* is automatically set to the length of `'encoding'`.

- `'lower'` and `'upper'` denote the lower and upper bound of each variable, respectively, whose values can be scalars or row vectors, and the value of each dimension should be real. `'lower'` and `'upper'` should have the same length as `'encoding'`. For example, the following code specifies a search space $[0,1] \times [0,9]^5$:

```
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'` denotes the constraint functions of the problem, whose value can be a function handle (a single constraint), a matrix (a function is automatically fitted), or cell (multiple constraints). A constraint function has one input and one output, where the input is a decision vector and the output is the constraint violation. A constraint is satisfied if and only if the constraint violation is not positive. For example, the following code solves a bi-objective optimization problem via the default algorithm:

```
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]);
```

  and adds a constraint $\sum_{i=2}^{6} x_i \geq 1$. Note that equality constraints should be converted into inequality constraints, the details of which can be found in Section 3.2 of *this paper*. If a constraint function is a matrix, a function will be automatically fitted via Gaussian process regression, where each row of the matrix is a sample and each column of the matrix is a variable (except for the last column) or a function value (the last column). For example, the following code solves the same problem, while the constraint function is automatically fitted:

```
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'` denotes the function for repairing an invalid solution, whose value should be a function handle having one input and one output, where the input is a decision vector and the output is the repaired decision vector. For example, the following code makes x_1 always be a multiple of 0.1:

```
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'` denotes the function for evaluating a solution, whose value should be a function handle having one input and three output, where the input is a decision vector, the first output is the repaired decision vector, the second output is the vector of objective values, and the third vector is the vector of constraint violations. The default 'evalFcn' calls 'decFcn', 'objFcn', and 'conFcn' in sequence to evaluate a solution, while the following code defines a new 'evalFcn' to achieve solution repair, objective calculation, and constraint calculation simultaneously:

```
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
```

Then, the following codes solve the same problem by specifying only the evaluation function:

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

- 'initFcn' denotes the function for initializing a population, whose value should be a function handle having one input and one output, where the input is the number of solutions in the population and the output is a matrix consisting of the decision vectors in the population. The default 'initFcn' randomly generates solutions in the whole search space, while the following code defines a new 'initFcn' to accelerate the convergence:

```
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]);
```

- 'objGradFcn' and 'conGradFcn' denote the gradient functions of objectives and constraints, respectively, whose values can be function handles or cells. Each gradient function should have one input and one output, where the input is a decision vector and the output is the gradient. The default gradient function estimates the gradient via finite difference, while the following code defines a new 'objGradFcn' to accelerate the convergence and ensure the population diversity:

```
fg = @(x)[0,x(2:end)];
platemo('evalFcn',@Eval,'encoding',[1,1,1,2,2,4],...
'objGradFcn',fg,'lower',0,'upper',[1,9,9,9,9,9]);
```

Note that only a few algorithms will use gradient information.

- 'data' denotes the data of the problem, which can be a constant of any type. If 'data' is specified, all the above functions should have an additional input to receive 'data'. For example, the following code solves a rotated single-objective optimization problem:

```
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);
```

In addition to the above way for defining a problem, a problem object can be created and solved by specified algorithm objects. For example, the following code solves the problem via the algorithm @GA and the algorithm @DE.

```
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);
```

C. Collecting the Results

The generated populations can be displayed, saved, or returned after the algorithm terminates. If the main function is called like

```
[Dec,Obj,Con] = platemo(…);
```

Then the final population will be returned, where Dec is a matrix consisting of the decision vectors in the final population, Obj is a matrix consisting of the objective values in the final population, and Con is a matrix consisting of the constraint violations in the final population. If the main function is called like

```
platemo('save',Value,…);
```

Then the generated populations will be displayed in a figure if Value is negative (default), where various plots can be displayed by switching the Data source menu on the figure. While if Value is positive, the generated populations will be saved to a MAT file named as PlatEMO\Data\alg\alg_pro_M_D_run.mat, where alg is the algorithm name, pro is the problem name, M is the number of objectives, D is the number of variables, and run automatically increases from 1 until the file name does not exist. A file saves a cell result consisting of the generated populations and a struct metric consisting of the metric values. The whole optimization process of the algorithm is divided into `Value` equal intervals, where the first column of `result` stores the number of consumed function evaluations at the last iteration of each interval, the second column of `result` stores the population at the last iteration of each interval, and `metric` stores the metric values of the stored populations. The above are achieved by the default output function `@DefaultOutput`, while users can collect the results in their own ways by specifying the value of `'outputFcn'` to the handle of a user-defined output function.

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

```
metric =
  struct with fields:

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

Besides, the metric values can be automatically calculated and saved in the experiment module of the GUI. To calculate the metric values manually, users should load a population, construct a `PROBLEM` object, and call its method `CalMetric`, for example,

```
% Load result before performing the following code
pro = DTLZ2();
pro.CalMetric('IGD',result{end});
```

where `'IGD'` is the name of the calculated metric (see *Metric Function* for details). In particular, IGD and HV are the most popular metrics for multi-objective optimization, whose application scopes and methods for defining reference points can be found in Section 5.3 of *this paper*.

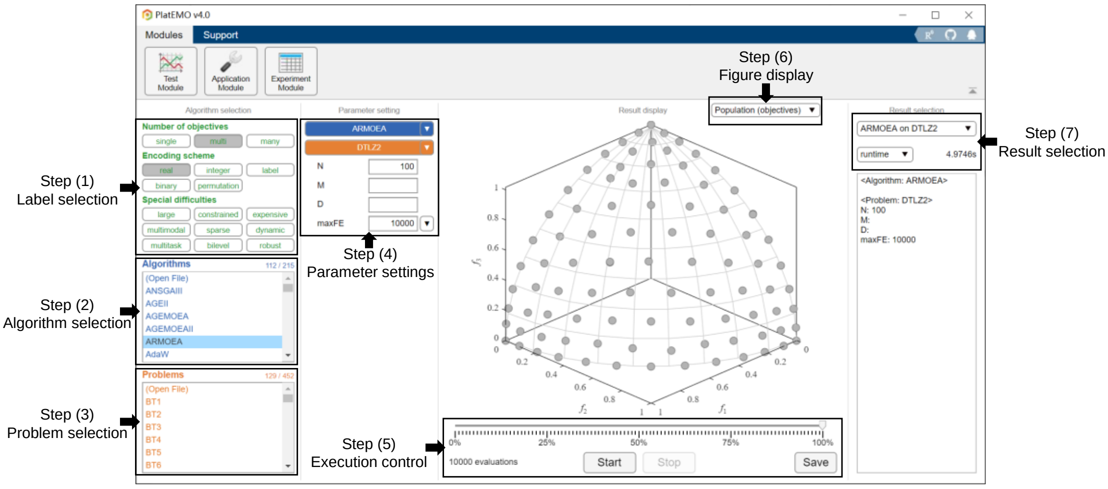
III. Using PlatEMO with GUI

A. Functions of Test Module

Users can use PlatEMO with GUI by calling the main function `platemo()` without parameter like

```
platemo();
```

Then the test module of the GUI will be displayed, which is used to visually investigate the performance of an algorithm on a benchmark problem.

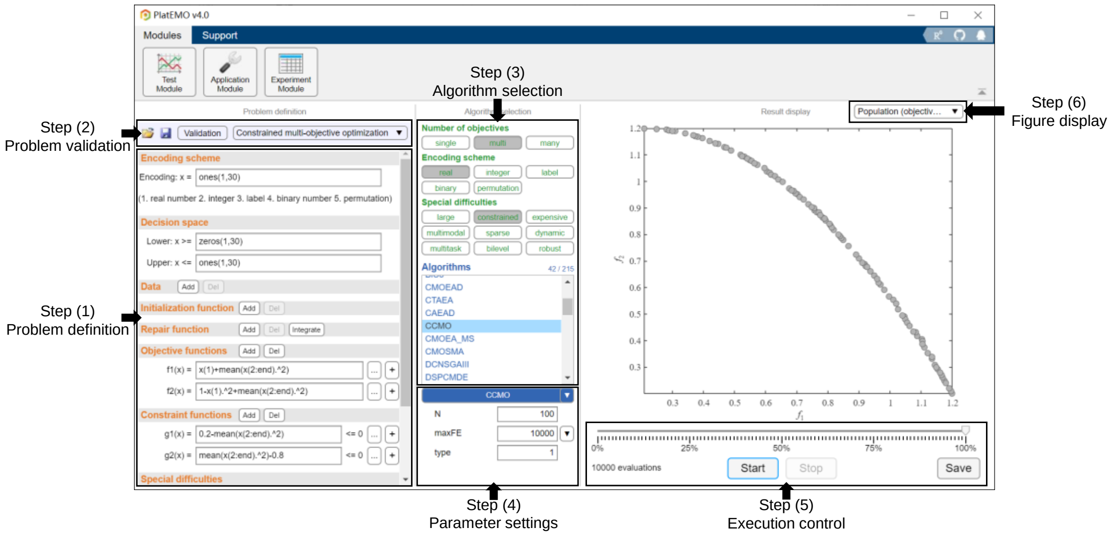


In this module, the performance investigation can be achieved by the following steps:

- Step (1) Select multiple labels to determine the type of problems (see *Labels of Algorithms, Problems, and Metrics* for details).
- Step (2) Select an algorithm from the list.
- Step (3) Select a benchmark problem from the list.
- Step (4) Set the parameters of the algorithm and benchmark problem. Different algorithms and benchmark problems may have different parameters, the details of which can be obtained by hovering over each parameter.
- Step (5) Start, pause, stop, or back off the current execution; save the current result to a file. The current result can be saved as a matrix with N rows and $D + M + K$ columns, where N denotes the number of solutions, D denotes the number of variables, M denotes the number of objectives, and K denotes the number of constraints.
- Step (6) Select a data to display, such as the objective values, variables, and metric values of the current population.
- Step (7) Select a historical result to display.

B. Functions of Application Module

Users can press the menu button to switch to the application module, which is used to solve user-defined problems.

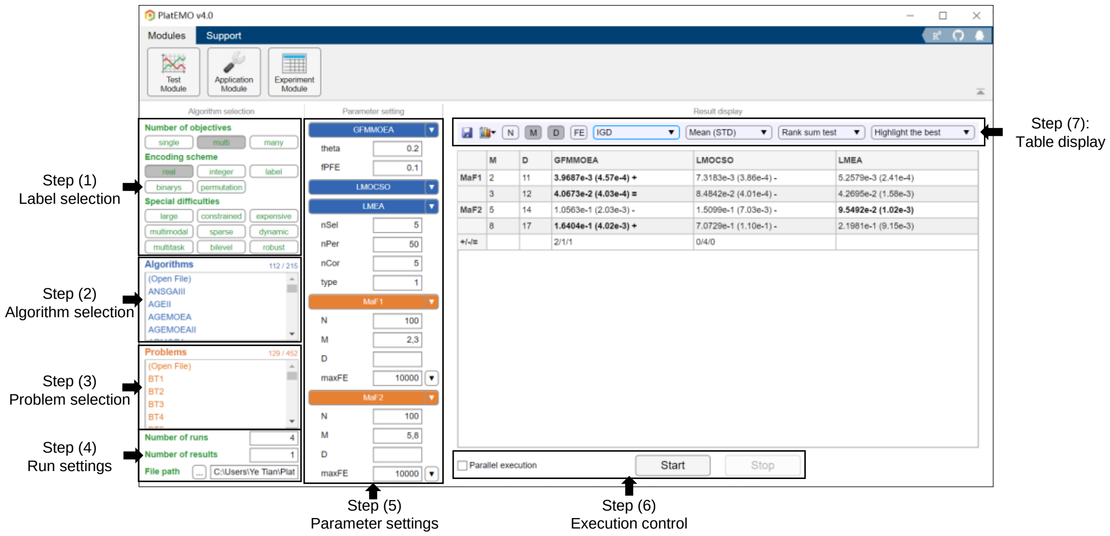


In this module, the solving of problems can be achieved by the following steps:

- Step (1) Define a problem, the contents of which are the same as those in *Solving User-Defined Problems*, where Encoding scheme corresponds to `'encoding'`, Decision space corresponds to `'lower'` and `'upper'`, Data corresponds to `'data'`, Initialization function corresponds to `'initFcn'`, Repair function corresponds to `'decFcn'`, Objective functions corresponds to `'objFcn'`, Constraint functions corresponds to `'conFcn'`, and Evaluation function corresponds to `'evalFcn'`.
- Step (2) Save or load a problem; check the validity of the problem; select a problem template. The saved problem can be opened and solved in other modules.
- Step (3) Select an algorithm from the list. The labels are automatically determined according to the problem definition (see *Labels of Algorithms, Problems, and Metrics* for details).
- Step (4) Set the parameters of the algorithm. Different algorithms may have different parameters, the details of which can be obtained by hovering over each parameter.
- Step (5) Start, pause, stop, or back off the current execution; save the current result to a file. The current result can be saved as a matrix with N rows and $D + M + K$ columns, where N denotes the number of solutions, D denotes the number of variables, M denotes the number of objectives, and K denotes the number of constraints.
- Step (6) Select a data to display, such as the objective values, variables, and metric values of the current population.

C. *Functions of Experiment Module*

Users can press the menu button to switch to the experiment module, which is used to statistically analyze the performance of multiple algorithms on multiple problems.



In this module, comparative experiments can be achieved by the following steps:

- Step (1) Select multiple labels to determine the type of problems (see *Labels of Algorithms, Problems, and Metrics* for details).
- Step (2) Select multiple algorithms from the list.
- Step (3) Select multiple benchmark problems from the list.
- Step (4) Set the number of repeated runs, number of saved populations in each run, and path for saving results (see *Collecting the Results* for details).
- Step (5) Set the parameters of the algorithms and benchmark problems. Different algorithms and benchmark problems may have different parameters, the details of which can be obtained by hovering over each parameter.
- Step (6) Start or stop the experiment; perform multiple runs in sequence (on a single CPU) or in parallel (on all CPUs).
- Step (7) Select a metric; select a statistical method; save the table to a file; display the results of the selected cells in a figure.

D. *Labels of Algorithms, Problems, and Metrics*

Each algorithm, benchmark problem, and metric should be tagged with labels by the comment in the second line of its main function. For example, in the code of `PSO.m`:

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

which indicates the types of problems the algorithm can solve. All the labels are

Label	Description
<single>	Single-objective optimization: The problem has a single objective
<multi>	Multi-objective optimization: The problem has two or three objectives
<many>	Many-objective optimization: The problem has four or more objectives
<real>	Continuous optimization: The decision variables are real numbers
<integer>	Integer optimization: The decision variables are integers
<label>	Label optimization: The decision variables are labels
<binary>	Binary optimization: The decision variables are binary numbers
<permutation>	Permutation optimization: All decision variables constitute a permutation
<large>	Large-scale optimization: The problem has 100 or more variables
<constrained>	Constrained optimization: The problem has at least one constraint
<expensive>	Expensive optimization: The objectives are computationally expensive, only a limited number of function evaluations are available
<multimodal>	Multimodal optimization: There exist multiple optimal solutions with similar objective values but considerably different decision vectors, all of which should be found
<sparse>	Sparse optimization: Most variables of the optimal solutions are zero
<dynamic>	Dynamic optimization: The objectives and constraints vary over time
<multitask>	Multitasking optimization: Optimize multiple problems simultaneously, each problem may have multiple objectives and constraints
<bilevel>	Bilevel optimization: Find the feasible and optimal solution for the upper-level problem, where a solution is feasible for the upper-level problem if and only if it is optimal for the lower-level problem
<robust>	Robust optimization: The objectives and constraints are affected by noise, the robust and optimal solutions should be found
<none>	Empty label
<min>	(for metrics only) The metric value is the smaller the better
<max>	(for metrics only) The metric value is the larger the better

An algorithm may have multiple sets of labels, where the Cartesian product between all the label sets constitutes all the types of problems that can be solved by the algorithm. If the label sets of an algorithm are `<single> <real> <constrained/none>`, it will be able to solve single-objective continuous optimization problems with or without constraints. On the other hand, the label sets `<single> <real>` mean that the algorithm can only solve unconstrained problems, the label sets `<single> <real> <constrained>` mean that the algorithm can only solve constrained problems, and the label sets `<single> <real/binary>` mean that the algorithm can solve problems with either real variables or binary variables.

Each algorithm, benchmark problem, and metric should be tagged with at least one label, otherwise it will not be appeared in the lists in the GUI. After selecting multiple labels in the GUI, only the algorithms, benchmark problems, and metrics containing the same labels will be appeared. Details of the label based filter strategy can be found *here*. The labels of all the algorithms and benchmark problems in PlatEMO are referred to *List of Algorithms* and *List of Problems*, respectively.

IV. Extending PlatEMO

A. ALGORITHM Class

An algorithm should be written as a subclass of `ALGORITHM` and put in the folder `PlatEMO\Algorithms`, which contains the following properties and methods:

Property	Specified by	Description
`parameter`	Users	Parameters of the algorithm
`save`	Users	Number of populations saved in an execution
`outputFcn`	Users	Function called in `NotTerminated()`
`pro`	`Solve()`	Problem solved in current execution
`result`	`NotTerminated()`	Populations saved in current execution
`metric`	`NotTerminated()`	Metric values of saved populations
Method	**Be redefined**	**Description**
`ALGORITHM`	Cannot	Set the properties specified by users Input: Parameter settings like `'Name',Value,`… Output: `ALGORITHM` object
`Solve`	Cannot	Solve a problem via the algorithm Input: `PROBLEM` object Output: None
`main`	Must	Main procedure of the algorithm Input: `PROBLEM` object Output: None
`NotTerminated`	Cannot	Function called before each iteration in `main()` Input: An array of `SOLUTION` objects, i.e., a population Output: Whether the algorithm terminates (logical)
`ParameterSet`	Cannot	Set the parameter values according to `parameter` Input: Default parameter settings Output: User-specified parameter settings

Each algorithm should inherit `ALGORITHM` and redefine the method `main()`. For example, the code of `GA.m` is

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

```
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
```

The functions of each line are as follows:

Line 1: Inheriting the `ALGORITHM` class;

Line 2: Tagging the algorithm with labels (see *Labels of Algorithms, Problems, and Metrics* for details);

Line 3: Full name of the algorithm;

Lines 4-7: Parameter name --- default value --- description, which are shown in the parameter setting list in the GUI;

Lines 9-12: Reference of the algorithm;

Line 15: Redefining the method of main procedure;

Line 16: Obtaining the parameter values specified by users, where `1,20,1,20` are default values of the four parameters `proC,disC,proM,disM`;

Line 17: Obtaining an initial population by calling a method of the problem;

Line 18: Storing the population and checking whether the algorithm terminates; if so, the algorithm will immediately terminate by throwing an error;

Line 19: Binary tournament based mating selection achieved by a public function;

Line 20: Offspring generation achieved by a public function;

Line 21: Combing the current population with the offspring population;

Line 22: Sorting the solutions based on their fitness calculated by a public function;

Line 23: Retaining half the solutions with better fitness for the next iteration.

In the above codes, the functions `ParameterSet()` and `NotTerminated()` are provided by the `ALGORITHM` class, and the function `Initialization()` is provided by the `PROBLEM` class. Besides, the functions `TournamentSelection()`, `FitnessSingle()`, and `OperatorGA()` are public functions in the folder `PlatEMO\Algorithms\Utility functions`. The following table lists the functions that can be used in algorithms, where the details of them are referred to the comments in their codes. Besides, their techniques for efficiency improvement can be found *here*.

Function Name	Description
`ALGORITHM.NotTerminated`	Function called before each iteration of the algorithm, which stores the current population and check whether the algorithm terminates
`ALGORITHM.ParameterSet`	Set the parameter values specified by users
`PROBLEM.Initialization`	Initialize a population for the problem
`PROBLEM.Evaluation`	Evaluate a population and generate an array of `SOLUTION` object
`CrowdingDistance`	Crowding distance calculation for multi-objective optimization
`FitnessSingle`	Fitness calculation for single-objective optimization
`NDSort`	Non-dominated sorting for multi-objective optimization
`OperatorDE`	The variation operator of differential evolution
`OperatorFEP`	The variation operator of fast evolutionary programming
`OperatorGA`	The variation operators of genetic algorithm
`OperatorGAhalf`	The variation operators of genetic algorithm, where only the first half of offspring solutions are returned
`OperatorPSO`	The variation operator of particle swarm optimization
`RouletteWheelSelection`	Roulette-wheel selection
`TournamentSelection`	Tournament selection
`UniformPoint`	Generate a set of uniformly distributed points

B. PROBLEM Class

A problem should be written as a subclass of `PROBLEM` and put in the folder `PlatEMO\Problems`, which contains the following properties and methods:

Property	Specified by	Description
`N`	Users	Population size of algorithms
`M`	Users and `Setting()`	Number of objectives of the problem
`D`	Users and `Setting()`	Number of decision variables of the problem

`maxFE`	Users	Maximum number of function evaluations
`FE`	`Evaluation()`	Number of function evaluations consumed in current execution
`maxRuntime`	Users	Maximum runtime
`encoding`	`Setting()`	Encoding scheme of each variable
`lower`	`Setting()`	Lower bound of each variable
`upper`	`Setting()`	Upper bound of each variable
`optimum`	`GetOptimum()`	Optimal values of the problem, such as the minimum objective value of single-objective optimization problems and a set of points on the Pareto front of multi-objective optimization problems
`PF`	`GetPF()`	Pareto front of the problem, such as a 1-D curve of bi-objective optimization problems, a 2-D surface of tri-objective optimization problems, and feasible regions of constrained optimization problems
`parameter`	Users	Parameters of the problem
Method	**Be redefined**	**Description**
`PROBLEM`	Cannot	Set the properties specified by users Input: Parameter settings like `'Name',Value,`... Output: `ALGORITHM` object
`Setting`	Must	Default settings of the problem Input: None Output: None
`Initialization`	Can	Initialize a population Input: Population size Output: An array of `SOLUTION` objects, i.e., a population
`Evaluation`	Can	Evaluate a population and generate solution objects Input: A matrix consisting of decision vectors Output: An array of `SOLUTION` objects, i.e., a population
`CalDec`	Can	Repair invalid solutions in a population Input: A matrix consisting of decision vectors Output: A matrix consisting of repaired decision vectors
`CalObj`	Must	Calculate the objective values of solutions in a population. All objectives are to be minimized Input: A matrix consisting of decision vectors Output: A matrix consisting of objective values
`CalCon`	Can	Calculate the constraint violations of solutions in a population. A constraint is satisfied if and only if the constraint violation is not positive Input: A matrix consisting of decision vectors Output: A matrix consisting of constraint violations
`CalObjGrad`	Can	Calculate the gradients of a solution on objectives

		Input: A decision vector Output: A Jacobian matrix
CalConGrad	Can	Calculate the gradients of a solution on constraints Input: A decision vector Output: A Jacobian matrix
GetOptimum	Can	Generate the optimal values and store in optimum Input: The number of optimal values Output: Optimal values (a matrix)
GetPF	Can	Generate the Pareto front and store in PF Input: None Output: Data for plotting the Pareto front (a matrix or cell)
CalMetric	Can	Calculate the metric value of a population Input 1: Metric name Input 2: An array of SOLUTION objects, i.e., a population Output: Metric value (scalar)
DrawDec	Can	Display the decision variables of a population Input: An array of SOLUTION objects, i.e., a population Output: None
DrawObj	Can	Display the objective values of a population Input: An array of SOLUTION objects, i.e., a population Output: None
ParameterSet	Cannot	Set the parameter values according to parameter Input: Default parameter settings Output: User-specified parameter settings

Each benchmark problem should inherit PROBLEM and redefine the methods Setting() and CalObj(). For example, the code of SOP_F1.m is

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

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

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

```
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
```

The functions of each line are as follows:

Line 1: Inheriting the `PROBLEM` class;

Line 2: Tagging the problem with labels (see *Labels of Algorithms, Problems, and Metrics* for details);

Line 3: Full name of the problem;

Lines 5-9: Reference of the problem;

Line 12: Redefining the method of default parameter settings;

Line 13: Setting the number of objectives;

Line 14: Setting the number of decision variables if it is not specified by users;

Lines 15-16: Setting the lower bounds and upper bounds of decision variables;

Line 17: Setting the encoding schemes of decision variables;

Line 19: Redefining the method of calculating objective values;

Line 20: Calculating the objective values of solutions in a population.

The default method `Initialization()` randomly initializes a population. This method can be redefined to specify a novel initialization strategy. For example, `Sparse_NN.m` initializes a population in which half the decision variables are zero:

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

The default method `CalDec()` repairs invalid solutions in a population, where each decision variable will be set to the boundary values if it is larger than the upper bound or smaller than the lower bound. This method can be redefined to specify a novel repair strategy. For example, `MOKP.m` repairs solutions that exceed the capacity, so that no constraint needs to be defined in this problem:

```
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
```

The default method `CalCon()` returns zero as the constraint violation of the solutions in a population, i.e., all the solutions are feasible. This method can be redefined to specify constraint functions for the problem. For example, `CF4.m` calculates a constraint for each solution:

```
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
```

Use `all(PopCon<=0,2)` to determine whether each solution is feasible or not. Note that equality constraints should be converted into inequality constraints, the details of which can be found in Section 3.2 of *this paper*. The default method `Evaluation()` calls `CalDec()`, `CalObj()`, and `CalCon()` in sequence to instantiate `SOLUTION` objects, and also adds the number of consumed function evaluations `FE`. This method can be redefined to perform solution repair, objective calculation, and constraint calculation in a single function, where `CalDec()`, `CalObj()`, and `CalCon()` will not be called anymore. For example, `MW2.m` calculates objective values and constraint violations in a single function:

```
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
```

The default method `CalObjGrad()` estimates the gradients of objectives via finite difference, while this method can be redefined to calculate gradients more accurately. Similarly, the default method `CalConGrad()` estimates the gradients of constraints via finite difference, while this method can be redefined to calculate gradients more accurately. The method `GetOptimum()` can be redefined to specify the optimal values of the problem, which are used for metric calculation. For example, `SOP_F8.m` returns the optimal value of the objective function:

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

and `DTLZ2.m` returns a set of uniformly distributed points on the Pareto front:

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

The strategies for sampling points on different Pareto fronts can be found *here*. The method `GetPF()` can be redefined to specify the Pareto front or feasible regions of multi-objective optimization problems for the visualization achieved in `DrawObj()`. For example, `DTLZ2.m` returns the data for plotting the 2-D and 3-D Pareto fronts:

```
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
```

and `MW1.m` returns the data for plotting the feasible regions:

```
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
```

The default method `CalMetric()` feeds a population and the optimal values `optimum` to a metric function to calculate the metric value. This method can be redefined to feed different variables to metric functions. For example, `SMMOP1.m` feeds the Pareto optimal set rather than the points on the Pareto front when calculating the metric value of IGDX:

```
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
```

The method `DrawDec()` displays the decision variables of a population, which is used for the visualization of results in the GUI. This method can be redefined to specify a novel visualization method. For example, `TSP.m` displays the route of the best solution:

```
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
```

The method `DrawObj()` displays the objective values of a population, which is used for the visualization of results in the GUI. This method can be redefined to specify a novel visualization method. For example, `Sparse_CD.m` adds labels to the axes:

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

where `Draw()` is a function in the folder `PlatEMO\GUI` for displaying data.

C. SOLUTION Class

A `SOLUTION` object denotes an individual, and an array of `SOLUTION` objects denote a population. The `SOLUTION` class contains the following properties and methods:

Property	**Specified by**	**Description**
`dec`	Users	Decision variables of the solution
`obj`	`SOLUTION()`	Objective values of the solution
`con`	`SOLUTION()`	Constraint violations of the solution
`add`	`adds()`	Additional properties (e.g., velocity) of the solution
Method	**Description**	
`SOLUTION`	Generate `SOLUTION` objects Input 1: A matrix consisting of decision vectors Input 2: A matrix consisting of objective values	

	Input 3: A matrix consisting of constraint violations Input 4: A matrix consisting of additional properties Output: An array of `SOLUTION` objects
`decs`	Get the decision variables of multiple solutions Input: None Output: A matrix consisting of decision vectors
`objs`	Get the objective values of multiple solutions Input: None Output: A matrix consisting of objective values
`cons`	Get the constraint violations of multiple solutions Input: None Output: A matrix consisting of constraint violations
`adds`	Set and get the additional properties of multiple solutions Input: Default additional properties Output: A matrix consisting of additional properties
`best`	Get the feasible and best solution for single-objective optimization, or the feasible and non-dominated solutions for multi-objective optimization Input: None Output: A subarray of best `SOLUTION` objects in the population

For example, the following code generates a population with ten solutions, then gets the objective matrix of the best solutions in the population:

```
Population = SOLUTION(rand(10,5),rand(10,1),zeros(10,1));
BestObjs   = Population.best.objs
```

Note that `SOLUTION()` should be called only in the method `Evaluation()` of `PROBLEM` class.

D. Whole Procedure of One Run

The following code uses the genetic algorithm to solve the sphere function:

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

where the functions called in the execution of `Alg.Solve(Pro)` are as follows.

E. Metric Function

A metric should be written as a function and put in the folder `PlatEMO\Metrics`. For example, the code of `IGD.m` is

```
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
```

The functions of each line are as follows:

Line 1: Function declaration, where the first input is a population (i.e., an array of `SOLUTION` objects), the second input is the optimums of a problem (i.e., the `optimum` property of the problem), and the output is the metric value;

Line 2: Tagging the metric with labels (see *Labels of Algorithms, Problems, and Metrics* for details); note that `<min>` or `<max>` should be the first label;

Line 3: Full name of the metric;

Lines 5-10: Reference of the metric;

Line 12: Obtaining the feasible and non-dominated solutions in the population;

Lines 13-14: Returns `nan` if there is no feasible solution in the population;

Lines 15-16: Returns the IGD value of the feasible and non-dominated solutions.

V. List of Algorithms

	Abbreviation	Full name	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	ACO	Ant colony optimization	√							√	√								
4	Adam	Adaptive moment estimation	√			√					√								
5	AdaW	Evolutionary algorithm with adaptive weights		√	√	√	√	√	√	√									
6	AGE-II	Approximation-guided evolutionary multi-objective algorithm II		√		√	√	√	√	√									
7	AGE-MOEA	Adaptive geometry estimation-based many-objective evolutionary algorithm		√	√	√	√	√	√	√		√							
8	AGE-MOEA-II	Adaptive geometry estimation-based many-objective evolutionary algorithm II		√	√	√	√	√	√	√		√							
9	A-NSGA-III	Adaptive NSGA-III		√	√	√	√	√	√	√		√							
10	AR-MOEA	Adaptive reference points based multi-objective evolutionary algorithm		√	√	√	√	√	√	√		√							
11	BCE-IBEA	Bi-criterion evolution based IBEA		√	√	√	√	√	√	√									
12	BCE-MOEA/D	Bi-criterion evolution based MOEA/D		√	√	√	√	√	√	√									
13	BFGS	A quasi-Newton method proposed by Broyden, Fletcher, Goldfarb, and Shanno	√			√					√								
14	BiCo	Bidirectional coevolution constrained multiobjective evolutionary algorithm		√		√	√	√	√	√		√							
15	BiGE	Bi-goal evolution			√	√	√	√	√	√									
16	BLEAQII	Bilevel evolutionary algorithm based on quadratic approximations II		√		√						√						√	
17	BSPGA	Binary space partition tree based genetic algorithm	√						√		√	√							
18	C3M	Constraint, multiobjective, multi-stage, multi-constraint evolutionary algorithm		√		√	√	√	√	√		√							
19	CAEAD	Dual-population evolutionary algorithm based on alternative evolution and degeneration		√		√	√	√	√	√		√							
20	CA-MOEA	Clustering based adaptive multi-objective evolutionary algorithm		√		√	√	√	√	√									
21	CCGDE3	Cooperative coevolution GDE3		√		√	√				√								
22	CCMO	Coevolutionary constrained multi-objective optimization framework		√		√	√	√	√	√		√							
23	c-DPEA	Constrained dual-population evolutionary algorithm		√		√	√	√	√	√		√							
24	CLIA	Evolutionary algorithm with cascade clustering and reference point incremental learning		√	√	√	√	√	√	√									
25	CMA-ES	Covariance matrix adaptation evolution strategy	√			√	√				√	√							
26	C-MOEA/D	Constraint-MOEA/D		√	√	√	√	√	√	√		√							

	Abbreviation	Full name	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
27	CMOEA-MS	Constrained multiobjective evolutionary algorithm with multiple stages		√		√	√	√	√	√		√							
28	CMOPSO	Competitive mechanism based multi-objective particle swarm optimizer		√		√	√												
29	CMOSMA	Constrained multi-objective evolutionary algorithm with self-organizing map		√	√	√	√					√							
30	CNSDE/DVC	Constrained nondominated sorting differential evolution based on decision variable classification		√		√	√												√
31	CPS-MOEA	Classification and Pareto domination based multi-objective evolutionary		√		√	√						√						
32	CSEA	Classification based surrogate-assisted evolutionary algorithm		√	√	√							√						
33	CSO	Competitive swarm optimizer	√			√	√				√	√							
34	C-TAEA	Two-archive evolutionary algorithm for constrained MOPs		√	√	√	√	√	√	√		√							
35	DAEA	Duplication analysis based evolutionary algorithm		√					√										
36	DCNSGA-III	Dynamic constrained NSGA-III		√	√	√	√	√	√	√		√							
37	DE	Differential evolution	√			√	√				√	√							
38	DEA-GNG	Decomposition based evolutionary algorithm guided by growing neural gas		√	√	√	√	√	√	√									
39	DGEA	Direction guided evolutionary algorithm		√	√	√	√				√								
40	DMOEA-eC	Decomposition-based multi-objective evolutionary algorithm with the e-constraint framework		√		√	√	√	√	√									
41	dMOPSO	MOPSO based on decomposition		√		√	√												
42	DN-NSGA-II	Decision space based niching NSGA-II		√		√	√							√					
43	DNSGA-II	Dynamic NSGA-II		√		√	√	√	√	√						√			
44	DSPCMDE	Dynamic selection preference-assisted constrained multiobjective differential evolution		√		√	√					√							
45	DWU	Dominance-weighted uniformity multi-objective evolutionary algorithm		√		√	√	√	√	√									
46	EAG-MOEA/D	External archive guided MOEA/D		√		√	√	√	√	√									
47	EDN-ARMOEA	Efficient dropout neural network based AR-MOEA		√	√	√	√						√						
48	EFR-RR	Ensemble fitness ranking with a ranking restriction scheme		√	√	√	√	√	√	√									
49	EGO	Efficient global optimization	√			√	√						√						
50	EIM-EGO	Expected improvement matrix based efficient global optimization		√		√	√						√						
51	EMCMO	Evolutionary multitasking-based constrained multiobjective optimization		√		√	√	√	√	√		√							
52	e-MOEA	Epsilon multi-objective evolutionary algorithm		√	√	√	√	√	√	√									
53	EMyO/C	Evolutionary many-objective optimization algorithm with clustering-based		√	√	√	√												
54	ENS-MOEA/D	Ensemble of different neighborhood sizes based MOEA/D		√	√	√	√												
55	FDV	Fuzzy decision variable framework with various internal optimizers		√	√	√	√				√								

	Abbreviation	Full name	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
56	FEP	Fast evolutionary programming	√			√	√				√	√							
57	FLEA	Fast sampling based evolutionary algorithm		√	√	√					√								
58	FRCG	Fletcher-Reeves conjugate gradient	√			√					√								
59	FRCGM	Fletcher-Reeves conjugate gradient (for multi-objective optimization)		√	√	√					√	√							
60	FROFI	Feasibility rule with the incorporation of objective function information	√			√	√				√	√							
61	GA	Genetic algorithm	√			√	√	√	√	√	√	√							
62	GDE3	Generalized differential evolution 3		√		√	√					√							
63	GFM-MOEA	Generic front modeling based multi-objective evolutionary algorithm		√	√	√	√	√	√	√									
64	GLMO	Grouped and linked mutation operator algorithm		√		√	√				√								
65	g-NSGA-II	g-dominance based NSGA-II		√		√	√	√	√	√									
66	GPSO	Gradient based particle swarm optimization algorithm	√			√					√	√							
67	GPSOM	Gradient based particle swarm optimization algorithm (for multi-objective optimization)		√	√	√					√	√							
68	GrEA	Grid-based evolutionary algorithm			√	√	√	√	√	√									
69	HeE-MOEA	Multiobjective evolutionary algorithm with heterogeneous ensemble based infill criterion		√		√	√						√						
70	hpaEA	Hyperplane assisted evolutionary algorithm		√	√	√	√	√	√	√									
71	HREA	Hierarchy ranking based evolutionary algorithm		√		√	√							√					
72	HypE	Hypervolume estimation algorithm		√	√	√	√	√	√	√									
73	IBEA	Indicator-based evolutionary algorithm		√	√	√	√	√	√	√									
74	ICMA	Indicator based constrained multi-objective algorithm		√		√	√					√							
75	I-DBEA	Improved decomposition-based evolutionary algorithm		√	√	√	√	√	√	√		√							
76	IM-MOEA	Inverse modeling based multiobjective evolutionary algorithm		√		√	√				√								
77	IM-MOEA/D	Inverse modeling multiobjective evolutionary algorithm based on decomposition		√		√	√				√								
78	IMODE	Improved multi-operator differential evolution	√			√	√				√	√							
79	I-SIBEA	Interactive simple indicator-based evolutionary algorithm		√		√	√	√	√	√									
80	Izui	An aggregative gradient based multi-objective optimizer proposed by Izui et al.		√	√	√					√	√							
81	KnEA	Knee point driven evolutionary algorithm			√	√	√	√	√	√		√							
82	K-RVEA	Surrogate-assisted RVEA		√	√	√	√						√						
83	KTA2	Kriging-assisted Two_Arch2		√	√	√	√						√						
84	LCSA	Linear combination-based search algorithm		√	√	√	√				√								
85	LERD	Large-scale evolutionary algorithm with reformulated decision variable analysis		√	√	√					√								

	Abbreviation	Full name	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
86	LMEA	Evolutionary algorithm for large-scale many-objective optimization		√	√	√	√				√								
87	LMOCSO	Large-scale multi-objective competitive swarm optimization algorithm		√	√	√	√				√	√							
88	LMOEA-DS	Large-scale evolutionary multi-objective optimization assisted by directed sampling		√		√	√				√								
89	LMPFE	Evolutionary algorithm with local model based Pareto front estimation		√	√	√	√	√	√	√									
90	LSMOF	Large-scale multi-objective optimization framework with NSGA-II		√		√	√				√								
91	MaOEA-CSS	Many-objective evolutionary algorithms based on coordinated selection		√	√	√	√	√	√	√									
92	MaOEA-DDFC	Many-objective evolutionary algorithm based on directional diversity and favorable convergence		√	√	√	√	√	√	√									
93	MaOEA/IGD	IGD based many-objective evolutionary algorithm			√	√	√	√	√	√									
94	MaOEA/IT	Many-objective evolutionary algorithms based on an independent two-stage		√	√	√	√					√							
95	MaOEA-R&D	Many-objective evolutionary algorithm based on objective space reduction			√	√	√	√	√	√									
96	MCEA/D	Multiple classifiers-assisted evolutionary algorithm based on decomposition		√	√	√	√						√						
97	MFEA	Multifactorial evolutionary algorithm	√			√	√	√	√	√	√						√		
98	MFEA-II	Multifactorial evolutionary algorithm II	√			√	√	√	√	√	√						√		
99	MMEA-WI	Weighted indicator-based evolutionary algorithm for multimodal multi-objective optimization		√		√	√							√					
100	MMOPSO	MOPSO with multiple search strategies		√		√	√												
101	MO_Ring_ PSO_SCD	Multiobjective PSO using ring topology and special crowding distance		√		√	√							√					
102	MOCell	Cellular genetic algorithm		√		√	√	√	√	√		√							
103	MOCGDE	Multi-objective conjugate gradient and differential evolution algorithm		√	√	√					√	√							
104	MO-CMA	Multi-objective covariance matrix adaptation evolution strategy		√		√	√												
105	MOEA/D	Multiobjective evolutionary algorithm based on decomposition		√	√	√	√	√	√	√									
106	MOEA/D-AWA	MOEA/D with adaptive weight adjustment		√	√	√	√	√	√	√									
107	MOEA/D-CMA	MOEA/D with covariance matrix adaptation evolution strategy		√	√	√	√												
108	MOEA/DD	Many-objective evolutionary algorithm based on dominance and decomposition		√	√	√	√	√	√	√		√							
109	MOEA/D-DAE	MOEA/D with detect-and-escape strategy		√		√	√	√	√	√		√							
110	MOEA/D-DCWV	MOEA/D with distribution control of weight vector set		√	√	√	√	√	√	√									
111	MOEA/D-DE	MOEA/D based on differential evolution		√	√	√	√												
112	MOEA/D-DRA	MOEA/D with dynamical resource allocation		√	√	√	√												
113	MOEA/D-DU	MOEA/D with a distance based updating strategy		√	√	√	√	√	√	√									

	Abbreviation	Full name	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
114	MOEA/D-DYTS	MOEA/D with dynamic Thompson sampling		√	√	√	√												
115	MOEA/D-EGO	MOEA/D with efficient global optimization		√		√	√						√						
116	MOEA/D-FRRMAB	MOEA/D with fitness-rate-rank-based multiarmed bandit		√	√	√	√												
117	MOEA/D-M2M	MOEA/D based on MOP to MOP		√		√	√												
118	MOEA/D-MRDL	MOEA/D with maximum relative diversity loss		√		√	√												
119	MOEA/D-PaS	MOEA/D with Pareto adaptive scalarizing approximation		√	√	√	√												
120	MOEA/D-PFE	MOEA/D with Pareto front estimation		√	√	√	√	√	√	√									
121	MOEA/D-STM	MOEA/D with stable matching		√	√	√	√												
122	MOEA/D-UR	MOEA/D with update when required		√	√	√	√	√	√	√									
123	MOEA/D-URAW	MOEA/D with uniform randomly adaptive weights		√	√	√	√	√	√	√									
124	MOEA/DVA	Multi-objective evolutionary algorithm based on decision variable		√		√	√				√								
125	MOEA/D-VOV	MOEA/D with virtual objective vectors		√	√	√	√	√	√	√									
126	MOEA/IGD-NS	Multi-objective evolutionary algorithm based on an enhanced IGD		√		√	√	√	√	√									
127	MOEA-PC	Multiobjective evolutionary algorithm based on polar coordinates		√		√	√												
128	MOEA/PSL	Multi-objective evolutionary algorithm based on Pareto optimal subspace		√		√	√		√		√	√			√				
129	MOEA-RE	Multi-objective evolutionary algorithm with robustness enhancement		√		√	√	√	√	√									√
130	MO-EGS	Multi-objective evolutionary gradient search		√		√					√								
131	MOMBI-II	Many objective metaheuristic based on the R2 indicator II		√	√	√	√	√	√	√									
132	MO-MFEA	Multi-objective multifactorial evolutionary algorithm		√		√	√	√	√	√		√					√		
133	MO-MFEA-II	Multi-objective multifactorial evolutionary algorithm II		√		√	√	√	√	√		√					√		
134	MOPSO	Multi-objective particle swarm optimization		√		√	√												
135	MOPSO-CD	MOPSO with crowding distance		√		√	√												
136	MOSD	Multiobjective steepest descent		√		√					√	√							
137	M-PAES	Memetic algorithm with Pareto archived evolution strategy		√		√	√												
138	MP-MMEA	Multi-population multi-modal multi-objective evolutionary algorithm		√		√	√				√			√	√				
139	MPSO/D	Multi-objective particle swarm optimization algorithm based on decomposition		√	√	√	√												
140	MSCMO	Multi-stage constrained multi-objective evolutionary algorithm		√		√	√	√	√	√		√							
141	MSEA	Multi-stage multi-objective evolutionary algorithm		√		√	√	√	√	√									

	Abbreviation	Full name	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
142	MSKEA	Multi-stage knowledge-guided evolutionary algorithm		√		√	√		√		√	√			√				
143	MSOPS-II	Multiple single objective Pareto sampling II		√	√	√	√					√							
144	MTCMO	Multitasking constrained multi-objective optimization		√		√	√	√	√	√		√							
145	MTS	Multiple trajectory search		√		√	√												
146	MultiObjective EGO	Multi-objective efficient global optimization		√		√	√					√	√						
147	MyO-DEMR	Many-objective differential evolution with mutation restriction		√	√	√	√												
148	NBLEA	Nested bilevel evolutionary algorithm		√		√						√						√	
149	NelderMead	The Nelder-Mead algorithm	√			√													
150	NMPSO	Novel multi-objective particle swarm optimization		√	√	√	√												
151	NNIA	Nondominated neighbor immune algorithm		√		√	√	√	√	√									
152	NSGA-II	Nondominated sorting genetic algorithm II		√		√	√	√	√	√		√							
153	NSGA-II+ARSBX	NSGA-II with adaptive rotation based simulated binary crossover		√		√	√					√							
154	NSGA-II-conflict	NSGA-II with conflict-based partitioning strategy			√	√	√	√	√	√									
155	NSGA-II-DTI	NSGA-II of Deb's type I robust version		√		√	√	√	√	√		√							√
156	NSGA-III	Nondominated sorting genetic algorithm III		√	√	√	√	√	√	√		√							
157	NSGA-II/SDR	NSGA-II with strengthened dominance relation			√	√	√	√	√	√									
158	NSLS	Multiobjective optimization framework based on nondominated sorting and local search		√		√	√												
159	OFA	Optimal foraging algorithm	√			√	√				√	√							
160	one-by-one EA	Many-objective evolutionary algorithm using a one-by-one selection		√	√	√	√	√	√	√									
161	OSP-NSDE	Non-dominated sorting differential evolution with prediction in the objective space		√		√	√												
162	ParEGO	Efficient global optimization for Pareto optimization		√		√	√						√						
163	PB-NSGA-III	NSGA-III based on Pareto based bi-indicator infill sampling criterion		√	√	√	√						√						
164	PB-RVEA	RVEA based on Pareto based bi-indicator infill sampling criterion		√	√	√	√						√						
165	PeEA	Pareto front shape estimation based evolutionary algorithm		√	√	√	√	√	√	√									
166	PESA-II	Pareto envelope-based selection algorithm II		√		√	√	√	√	√									
167	PICEA-g	Preference-inspired coevolutionary algorithm with goals		√	√	√	√	√	√	√									
168	PM-MOEA	Pattern mining based multi-objective evolutionary algorithm		√		√	√		√		√	√			√				
169	POCEA	Paired offspring generation based constrained evolutionary algorithm		√		√	√				√	√							
170	PPS	Push and pull search algorithm		√	√	√	√					√							
171	PREA	Promising-region based EMO algorithm		√	√	√	√	√	√	√									

	Abbreviation	Full name	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
172	PSO	Particle swarm optimization	√			√	√				√	√							
173	REMO	Expensive multiobjective optimization by relation learning and prediction		√	√	√							√						
174	RM-MEDA	Regularity model-based multiobjective estimation of distribution		√		√	√												
175	RMOEA/DVA	Robust multi-objective evolutionary algorithm with decision variable assortment		√		√	√												√
176	RMSProp	Root mean square propagation	√			√					√								
177	r-NSGA-II	r-dominance based NSGA-II		√		√	√	√	√	√									
178	RPD-NSGA-II	Reference point dominance-based NSGA-II		√	√	√	√	√	√	√									
179	RPEA	Reference points-based evolutionary algorithm			√	√	√	√	√	√									
180	RSEA	Radial space division based evolutionary algorithm		√	√	√	√	√	√	√									
181	RVEA	Reference vector guided evolutionary algorithm		√	√	√	√	√	√	√		√							
182	RVEAa	RVEA embedded with the reference vector regeneration strategy			√	√	√	√	√	√									
183	RVEA-iGNG	RVEA based on improved growing neural gas		√	√	√	√	√	√	√									
184	S3-CMA-ES	Scalable small subpopulations based covariance matrix adaptation		√	√	√	√				√								
185	SA	Simulated annealing	√			√	√				√	√							
186	SACC-EAM-II	Surrogate-assisted cooperative co-evolutionary algorithm of Minamo	√			√	√						√						
187	SACOSO	Surrogate-assisted cooperative swarm optimization	√			√	√				√		√						
188	SADE-Sammon	Sammon mapping assisted differential evolution	√			√	√						√						
189	SAMSO	Multiswarm-assisted expensive optimization	√			√	√				√		√						
190	S-CDAS	Self-controlling dominance area of solutions			√	√	√	√	√	√									
191	SD	Steepest descent	√			√					√								
192	S-ECSO	Enhanced competitive swarm optimizer for sparse optimization		√		√					√				√				
193	SGEA	Steady-state and generational evolutionary algorithm		√		√	√	√	√	√		√				√			
194	SHADE	Success-history based adaptive differential evolution	√			√	√				√	√							
195	SIBEA	Simple indicator-based evolutionary algorithm		√		√	√	√	√	√									
196	SIBEA-kEMOSS	SIBEA with minimum objective subset of size k with minimum error			√	√	√	√	√	√									
197	SLMEA	Super-large-scale multi-objective evolutionary algorithm		√		√	√		√		√	√			√				
198	SMEA	Self-organizing multiobjective evolutionary algorithm		√		√	√												
199	SMOA	Supervised multi-objective optimization algorithm		√		√							√						
200	SMPSO	Speed-constrained multi-objective particle swarm optimization		√		√	√												
201	SMS-EGO	S metric selection based efficient global optimization		√		√	√						√						

	Abbreviation	Full name	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
202	SMS-EMOA	S metric selection based evolutionary multiobjective optimization		√		√	√	√	√	√									
203	SparseEA	Evolutionary algorithm for sparse multi-objective optimization problems		√		√	√		√		√	√			√				
204	SparseEA2	Improved SparseEA		√		√	√		√		√	√			√				
205	SPEA2	Strength Pareto evolutionary algorithm 2		√		√	√	√	√	√									
206	SPEA2+SDE	SPEA2 with shift-based density estimation			√	√	√	√	√	√									
207	SPEA/R	Strength Pareto evolutionary algorithm based on reference direction		√	√	√	√	√	√	√									
208	SQP	Sequential quadratic programming	√			√					√	√							
209	SRA	Stochastic ranking algorithm			√	√	√	√	√	√									
210	t-DEA	theta-dominance based evolutionary algorithm		√	√	√	√	√	√	√									
211	TiGE-2	Tri-Goal Evolution Framework for CMaOPs			√	√	√	√	√	√		√							
212	ToP	Two-phase framework with NSGA-II		√		√	√					√							
213	TriMOEA-TA&R	Multi-modal MOEA using two-archive and recombination strategies		√		√	√							√					
214	TriP	Tri-population based coevolutionary algorithm		√	√	√	√					√							
215	TSTI	Two-stage evolutionary algorithm with three indicators		√		√	√	√	√	√		√							
216	Two_Arch2	Two-archive algorithm 2		√	√	√	√	√	√	√									
217	URCMO	Utilizing the relationship between constrained and unconstrained Pareto fronts for constrained multi-objective optimization		√		√	√					√							
218	VaEA	Vector angle based evolutionary algorithm		√	√	√	√	√	√	√									
219	WOF	Weighted optimization framework		√		√	√				√								
220	WV-MOEA-P	Weight vector based multi-objective optimization algorithm with preference		√		√	√												

VI. List of Problems

	Abbreviation	Full name	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
1	BT1	Benchmark MOP with bias feature		√		√					√								
2	BT2	Benchmark MOP with bias feature		√		√					√								
3	BT3	Benchmark MOP with bias feature		√		√					√								
4	BT4	Benchmark MOP with bias feature		√		√					√								
5	BT5	Benchmark MOP with bias feature		√		√					√								
6	BT6	Benchmark MOP with bias feature		√		√					√								
7	BT7	Benchmark MOP with bias feature		√		√					√								
8	BT8	Benchmark MOP with bias feature		√		√					√								
9	BT9	Benchmark MOP with bias feature		√		√					√								
10	CEC2008_F1	Shifted sphere function	√			√					√		√						
11	CEC2008_F2	Shifted Schwefel's function	√			√					√		√						
12	CEC2008_F3	Shifted Rosenbrock's function	√			√					√		√						
13	CEC2008_F4	Shifted Rastrign's function	√			√					√		√						
14	CEC2008_F5	Shifted Griewank's function	√			√					√		√						
15	CEC2008_F6	Shifted Ackley's function	√			√					√		√						
16	CEC2008_F7	FastFractal 'DoubleDip' function	√			√					√		√						
17	CEC2010_F1	CEC'2010 constrained optimization benchmark problem	√			√						√							
18	CEC2010_F2	CEC'2010 constrained optimization benchmark problem	√			√						√							
19	CEC2010_F3	CEC'2010 constrained optimization benchmark problem	√			√						√							
20	CEC2010_F4	CEC'2010 constrained optimization benchmark problem	√			√						√							
21	CEC2010_F5	CEC'2010 constrained optimization benchmark problem	√			√						√							
22	CEC2010_F6	CEC'2010 constrained optimization benchmark problem	√			√						√							
23	CEC2010_F7	CEC'2010 constrained optimization benchmark problem	√			√						√							
24	CEC2010_F8	CEC'2010 constrained optimization benchmark problem	√			√						√							
25	CEC2010_F9	CEC'2010 constrained optimization benchmark problem	√			√						√							
26	CEC2010_F10	CEC'2010 constrained optimization benchmark problem	√			√						√							
27	CEC2010_F11	CEC'2010 constrained optimization benchmark problem	√			√						√							

	Abbreviation	Full name	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
28	CEC2010_F12	CEC'2010 constrained optimization benchmark problem	√			√						√							
29	CEC2010_F13	CEC'2010 constrained optimization benchmark problem	√			√						√							
30	CEC2010_F14	CEC'2010 constrained optimization benchmark problem	√			√						√							
31	CEC2010_F15	CEC'2010 constrained optimization benchmark problem	√			√						√							
32	CEC2010_F16	CEC'2010 constrained optimization benchmark problem	√			√						√							
33	CEC2010_F17	CEC'2010 constrained optimization benchmark problem	√			√						√							
34	CEC2010_F18	CEC'2010 constrained optimization benchmark problem	√			√						√							
35	CEC2013_F1	Shifted elliptic function	√			√					√								
36	CEC2013_F2	Shifted Rastrigin's function	√			√					√								
37	CEC2013_F3	Shifted Ackley's function	√			√					√								
38	CEC2013_F4	7-nonseparable, 1-separable shifted and rotated elliptic function	√			√					√								
39	CEC2013_F5	7-nonseparable, 1-separable shifted and rotated Rastrigin's function	√			√					√								
40	CEC2013_F6	7-nonseparable, 1-separable shifted and rotated Ackley's function	√			√					√								
41	CEC2013_F7	7-nonseparable, 1-separable shifted and rotated Schwefel's function	√			√					√								
42	CEC2013_F8	20-nonseparable shifted and rotated elliptic function	√			√					√								
43	CEC2013_F9	20-nonseparable shifted and rotated Rastrigin's function	√			√					√								
44	CEC2013_F10	20-nonseparable shifted and rotated Rastrigin's function	√			√					√								
45	CEC2013_F11	20-nonseparable shifted and rotated Schwefel's function	√			√					√								
46	CEC2013_F12	Shifted Rosenbrock's function	√			√					√								
47	CEC2013_F13	Shifted Schwefel's function with conforming overlapping subcomponents	√			√					√								
48	CEC2013_F14	Shifted Schwefel's function with conflicting overlapping subcomponents	√			√					√								
49	CEC2013_F15	Shifted Schwefel's function	√			√					√								
50	CEC2017_F1	CEC'2017 constrained optimization benchmark problem	√			√						√							
51	CEC2017_F2	CEC'2017 constrained optimization benchmark problem	√			√						√							
52	CEC2017_F3	CEC'2017 constrained optimization benchmark problem	√			√						√							
53	CEC2017_F4	CEC'2017 constrained optimization benchmark problem	√			√						√							
54	CEC2017_F5	CEC'2017 constrained optimization benchmark problem	√			√						√							

	Abbreviation	Full name	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
55	CEC2017_F6	CEC'2017 constrained optimization benchmark problem	√			√						√							
56	CEC2017_F7	CEC'2017 constrained optimization benchmark problem	√			√						√							
57	CEC2017_F8	CEC'2017 constrained optimization benchmark problem	√			√						√							
58	CEC2017_F9	CEC'2017 constrained optimization benchmark problem	√			√						√							
59	CEC2017_F10	CEC'2017 constrained optimization benchmark problem	√			√						√							
60	CEC2017_F11	CEC'2017 constrained optimization benchmark problem	√			√						√							
61	CEC2017_F12	CEC'2017 constrained optimization benchmark problem	√			√						√							
62	CEC2017_F13	CEC'2017 constrained optimization benchmark problem	√			√						√							
63	CEC2017_F14	CEC'2017 constrained optimization benchmark problem	√			√						√							
64	CEC2017_F15	CEC'2017 constrained optimization benchmark problem	√			√						√							
65	CEC2017_F16	CEC'2017 constrained optimization benchmark problem	√			√						√							
66	CEC2017_F17	CEC'2017 constrained optimization benchmark problem	√			√						√							
67	CEC2017_F18	CEC'2017 constrained optimization benchmark problem	√			√						√							
68	CEC2017_F19	CEC'2017 constrained optimization benchmark problem	√			√						√							
69	CEC2017_F20	CEC'2017 constrained optimization benchmark problem	√			√						√							
70	CEC2017_F21	CEC'2017 constrained optimization benchmark problem	√			√						√							
71	CEC2017_F22	CEC'2017 constrained optimization benchmark problem	√			√						√							
72	CEC2017_F23	CEC'2017 constrained optimization benchmark problem	√			√						√							
73	CEC2017_F24	CEC'2017 constrained optimization benchmark problem	√			√						√							
74	CEC2017_F25	CEC'2017 constrained optimization benchmark problem	√			√						√							
75	CEC2017_F26	CEC'2017 constrained optimization benchmark problem	√			√						√							
76	CEC2017_F27	CEC'2017 constrained optimization benchmark problem	√			√						√							
77	CEC2017_F28	CEC'2017 constrained optimization benchmark problem	√			√						√							
78	CEC2020_F1	Bent cigar function	√			√													
79	CEC2020_F2	Shifted and rotated Schwefel's function	√			√													

	Abbreviation	Full name	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
80	CEC2020_F3	Shifted and rotated Lunacek bi-Rastrigin function	√			√													
81	CEC2020_F4	Expanded Rosenbrock's plus Griewangk's function	√			√													
82	CEC2020_F5	Hybrid function 1	√			√													
83	CEC2020_F6	Hybrid function 2	√			√													
84	CEC2020_F7	Hybrid function 3	√			√													
85	CEC2020_F8	Composition function 1	√			√													
86	CEC2020_F9	Composition function 2	√			√													
87	CEC2020_F10	Composition function 3	√			√													
88	CF1	Constrained benchmark MOP		√		√					√	√							
89	CF2	Constrained benchmark MOP		√		√					√	√							
90	CF3	Constrained benchmark MOP		√		√					√	√							
91	CF4	Constrained benchmark MOP		√		√					√	√							
92	CF5	Constrained benchmark MOP		√		√					√	√							
93	CF6	Constrained benchmark MOP		√		√					√	√							
94	CF7	Constrained benchmark MOP		√		√					√	√							
95	CF8	Constrained benchmark MOP		√		√					√	√							
96	CF9	Constrained benchmark MOP		√		√					√	√							
97	CF10	Constrained benchmark MOP		√		√					√	√							
98	CI_HS	Multitasking problem (Griewank function + Rastrigin function)	√			√					√						√		
99	CI_LS	Multitasking problem (Ackley function + Schwefel function)	√			√					√						√		
100	CI_MS	Multitasking problem (Ackley function + Rastrigin function)	√			√					√						√		
101	Community Detection	The community detection problem with label based encoding	√					√			√		√						
102	DAS-CMOP1	Difficulty-adjustable and scalable constrained benchmark MOP		√		√					√	√							
103	DAS-CMOP2	Difficulty-adjustable and scalable constrained benchmark MOP		√		√					√	√							
104	DAS-CMOP3	Difficulty-adjustable and scalable constrained benchmark MOP		√		√					√	√							
105	DAS-CMOP4	Difficulty-adjustable and scalable constrained benchmark MOP		√		√					√	√							
106	DAS-CMOP5	Difficulty-adjustable and scalable constrained benchmark MOP		√		√					√	√							
107	DAS-CMOP6	Difficulty-adjustable and scalable constrained benchmark MOP		√		√					√	√							
108	DAS-CMOP7	Difficulty-adjustable and scalable constrained benchmark MOP		√		√					√	√							
109	DAS-CMOP8	Difficulty-adjustable and scalable constrained benchmark MOP		√		√					√	√							

	Abbreviation	Full name	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
110	DAS-CMOP9	Difficulty-adjustable and scalable constrained benchmark MOP		√		√					√	√							
111	DOC1	Benchmark MOP with constraints in decision and objective spaces		√		√						√							
112	DOC2	Benchmark MOP with constraints in decision and objective spaces		√		√						√							
113	DOC3	Benchmark MOP with constraints in decision and objective spaces		√		√						√							
114	DOC4	Benchmark MOP with constraints in decision and objective spaces		√		√						√							
115	DOC5	Benchmark MOP with constraints in decision and objective spaces		√		√						√							
116	DOC6	Benchmark MOP with constraints in decision and objective spaces		√		√						√							
117	DOC7	Benchmark MOP with constraints in decision and objective spaces		√		√						√							
118	DOC8	Benchmark MOP with constraints in decision and objective spaces		√		√						√							
119	DOC9	Benchmark MOP with constraints in decision and objective spaces		√		√						√							
120	DTLZ1	Benchmark MOP proposed by Deb, Thiele, Laumanns, and Zitzler		√	√	√					√		√						
121	DTLZ2	Benchmark MOP proposed by Deb, Thiele, Laumanns, and Zitzler		√	√	√					√		√						
122	DTLZ3	Benchmark MOP proposed by Deb, Thiele, Laumanns, and Zitzler		√	√	√					√		√						
123	DTLZ4	Benchmark MOP proposed by Deb, Thiele, Laumanns, and Zitzler		√	√	√					√		√						
124	DTLZ5	Benchmark MOP proposed by Deb, Thiele, Laumanns, and Zitzler		√	√	√					√		√						
125	DTLZ6	Benchmark MOP proposed by Deb, Thiele, Laumanns, and Zitzler		√	√	√					√		√						
126	DTLZ7	Benchmark MOP proposed by Deb, Thiele, Laumanns, and Zitzler		√	√	√					√		√						
127	DTLZ8	Benchmark MOP proposed by Deb, Thiele, Laumanns, and Zitzler		√	√	√					√	√	√						
128	DTLZ9	Benchmark MOP proposed by Deb, Thiele, Laumanns, and Zitzler		√	√	√					√	√	√						
129	CDTLZ2	Convex DTLZ2		√	√	√					√		√						
130	IDTLZ1	Inverted DTLZ1		√	√	√					√		√						
131	IDTLZ2	Inverted DTLZ2		√	√	√					√		√						
132	SDTLZ1	Scaled DTLZ1		√	√	√					√		√						
133	SDTLZ2	Scaled DTLZ2		√	√	√					√		√						
134	C1-DTLZ1	Constrained DTLZ1		√	√	√					√	√	√						
135	C1-DTLZ3	Constrained DTLZ3		√	√	√					√	√	√						
136	C2-DTLZ2	Constrained DTLZ2		√	√	√					√	√	√						

	Abbreviation	Full name	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
137	C3-DTLZ4	Constrained DTLZ4		√	√	√					√	√	√						
138	DC1-DTLZ1	DTLZ1 with constrains in decision space		√	√	√					√	√	√						
139	DC1-DTLZ3	DTLZ3 with constrains in decision space		√	√	√					√	√	√						
140	DC2-DTLZ1	DTLZ1 with constrains in decision space		√	√	√					√	√	√						
141	DC2-DTLZ3	DTLZ3 with constrains in decision space		√	√	√					√	√	√						
142	DC3-DTLZ1	DTLZ1 with constrains in decision space		√	√	√					√	√	√						
143	DC3-DTLZ3	DTLZ3 with constrains in decision space		√	√	√					√	√	√						
144	FCP1	Benchmark constrained MOP proposed by Yuan		√		√						√							
145	FCP2	Benchmark constrained MOP proposed by Yuan		√		√						√							
146	FCP3	Benchmark constrained MOP proposed by Yuan		√		√						√							
147	FCP4	Benchmark constrained MOP proposed by Yuan		√		√						√							
148	FCP5	Benchmark constrained MOP proposed by Yuan		√		√						√							
149	FDA1	Benchmark dynamic MOP proposed by Farina, Deb, and Amato		√		√					√					√			
150	FDA2	Benchmark dynamic MOP proposed by Farina, Deb, and Amato		√		√					√					√			
151	FDA3	Benchmark dynamic MOP proposed by Farina, Deb, and Amato		√		√					√					√			
152	FDA4	Benchmark dynamic MOP proposed by Farina, Deb, and Amato		√		√					√					√			
153	FDA5	Benchmark dynamic MOP proposed by Farina, Deb, and Amato		√		√					√					√			
154	IMMOEA_F1	Benchmark MOP for testing IM-MOEA		√		√					√								
155	IMMOEA_F2	Benchmark MOP for testing IM-MOEA		√		√					√								
156	IMMOEA_F3	Benchmark MOP for testing IM-MOEA		√		√					√								
157	IMMOEA_F4	Benchmark MOP for testing IM-MOEA		√		√					√								
158	IMMOEA_F5	Benchmark MOP for testing IM-MOEA		√		√					√								
159	IMMOEA_F6	Benchmark MOP for testing IM-MOEA		√		√					√								
160	IMMOEA_F7	Benchmark MOP for testing IM-MOEA		√		√					√								
161	IMMOEA_F8	Benchmark MOP for testing IM-MOEA		√		√					√								
162	IMMOEA_F9	Benchmark MOP for testing IM-MOEA		√		√					√								
163	IMMOEA_F10	Benchmark MOP for testing IM-MOEA		√		√					√								
164	IMOP1	Benchmark MOP with irregular Pareto front		√		√							√						
165	IMOP2	Benchmark MOP with irregular Pareto front		√		√							√						
166	IMOP3	Benchmark MOP with irregular Pareto front		√		√							√						
167	IMOP4	Benchmark MOP with irregular Pareto front		√		√							√						
168	IMOP5	Benchmark MOP with irregular Pareto front		√		√							√						
169	IMOP6	Benchmark MOP with irregular Pareto front		√		√							√						
170	IMOP7	Benchmark MOP with irregular Pareto front		√		√							√						
171	IMOP8	Benchmark MOP with irregular Pareto front		√		√							√						

	Abbreviation	Full name	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
172	Instance1	Multitasking multi-objective problem (ZDT4-R + ZDT4-G)		√		√					√						√		
173	Instance2	Multitasking multi-objective problem (ZDT4-RC + ZDT4-A)		√		√					√	√					√		
174	KP	The knapsack problem	√						√		√	√							
175	LIR-CMOP1	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
176	LIR-CMOP2	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
177	LIR-CMOP3	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
178	LIR-CMOP4	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
179	LIR-CMOP5	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
180	LIR-CMOP6	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
181	LIR-CMOP7	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
182	LIR-CMOP8	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
183	LIR-CMOP9	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
184	LIR-CMOP10	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
185	LIR-CMOP11	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
186	LIR-CMOP12	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
187	LIR-CMOP13	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
188	LIR-CMOP14	Constrained benchmark MOP with large infeasible regions		√		√					√	√							
189	LSMOP1	Large-scale benchmark MOP		√	√	√					√								
190	LSMOP2	Large-scale benchmark MOP		√	√	√					√								
191	LSMOP3	Large-scale benchmark MOP		√	√	√					√								
192	LSMOP4	Large-scale benchmark MOP		√	√	√					√								
193	LSMOP5	Large-scale benchmark MOP		√	√	√					√								
194	LSMOP6	Large-scale benchmark MOP		√	√	√					√								
195	LSMOP7	Large-scale benchmark MOP		√	√	√					√								
196	LSMOP8	Large-scale benchmark MOP		√	√	√					√								
197	LSMOP9	Large-scale benchmark MOP		√	√	√					√								
198	MaF1	Inverted DTLZ1		√	√	√					√								
199	MaF2	DTLZ2BZ		√	√	√					√								
200	MaF3	Convex DTLZ3		√	√	√					√								

No.	Abbreviation	Full name	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
201	MaF4	Inverted and scaled DTLZ3		√	√	√					√								
202	MaF5	Scaled DTLZ4		√	√	√					√								
203	MaF6	DTLZ5IM		√	√	√					√								
204	MaF7	DTLZ7		√	√	√					√								
205	MaF8	MP-DMP		√	√	√													
206	MaF9	ML-DMP		√	√	√													
207	MaF10	WFG1		√	√	√					√								
208	MaF11	WFG2		√	√	√					√								
209	MaF12	WFG9		√	√	√					√								
210	MaF13	P7		√	√	√					√								
211	MaF14	LSMOP3		√	√	√					√								
212	MaF15	Inverted LSMOP8		√	√	√					√								
213	MaOPP_binary	Many-objective pathfinding problem based on binary encoding			√				√		√		√						
214	MaOPP_real	Many-objective pathfinding problem based on real encoding			√	√					√		√						
215	MLDMP	The multi-line distance minimization problem		√	√	√													
216	MMF1	Multi-modal multi-objective test function		√		√								√					
217	MMF2	Multi-modal multi-objective test function		√		√								√					
218	MMF3	Multi-modal multi-objective test function		√		√								√					
219	MMF4	Multi-modal multi-objective test function		√		√								√					
220	MMF5	Multi-modal multi-objective test function		√		√								√					
221	MMF6	Multi-modal multi-objective test function		√		√								√					
222	MMF7	Multi-modal multi-objective test function		√		√								√					
223	MMF8	Multi-modal multi-objective test function		√		√								√					
224	MMMOP1	Multi-modal multi-objective optimization problem		√	√	√								√					
225	MMMOP2	Multi-modal multi-objective optimization problem		√	√	√								√					
226	MMMOP3	Multi-modal multi-objective optimization problem		√	√	√								√					
227	MMMOP4	Multi-modal multi-objective optimization problem		√	√	√								√					
228	MMMOP5	Multi-modal multi-objective optimization problem		√	√	√								√					
229	MMMOP6	Multi-modal multi-objective optimization problem		√	√	√								√					
230	MOEADDE_F1	Benchmark MOP for testing MOEA/D-DE		√		√					√								
231	MOEADDE_F2	Benchmark MOP for testing MOEA/D-DE		√		√					√								
232	MOEADDE_F3	Benchmark MOP for testing MOEA/D-DE		√		√					√								
233	MOEADDE_F4	Benchmark MOP for testing MOEA/D-DE		√		√					√								
234	MOEADDE_F5	Benchmark MOP for testing MOEA/D-DE		√		√					√								
235	MOEADDE_F6	Benchmark MOP for testing MOEA/D-DE		√		√					√								
236	MOEADDE_F7	Benchmark MOP for testing MOEA/D-DE		√		√					√								

	Abbreviation	Full name	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
237	MOEADDE_F8	Benchmark MOP for testing MOEA/D-DE		√		√					√								
238	MOEADDE_F9	Benchmark MOP for testing MOEA/D-DE		√		√					√								
239	MOEADM2M_F1	Benchmark MOP for testing MOEA/D-M2M		√		√					√								
240	MOEADM2M_F2	Benchmark MOP for testing MOEA/D-M2M		√		√					√								
241	MOEADM2M_F3	Benchmark MOP for testing MOEA/D-M2M		√		√					√								
242	MOEADM2M_F4	Benchmark MOP for testing MOEA/D-M2M		√		√					√								
243	MOEADM2M_F5	Benchmark MOP for testing MOEA/D-M2M		√		√					√								
244	MOEADM2M_F6	Benchmark MOP for testing MOEA/D-M2M		√		√					√								
245	MOEADM2M_F7	Benchmark MOP for testing MOEA/D-M2M		√		√					√								
246	MOKP	The multi-objective knapsack problem		√	√				√		√								
247	MONRP	The multi-objective next release problem		√					√		√								
248	MOTSP	The multi-objective traveling salesman problem		√	√					√	√								
249	MPDMP	The multi-point distance minimization problem		√	√	√													
250	mQAP	The multi-objective quadratic assignment problem		√	√					√	√								
251	MW1	Constrained benchmark MOP proposed by Ma and Wang		√		√					√	√							
252	MW2	Constrained benchmark MOP proposed by Ma and Wang		√		√					√	√							
253	MW3	Constrained benchmark MOP proposed by Ma and Wang		√		√					√	√							
254	MW4	Constrained benchmark MOP proposed by Ma and Wang		√	√	√					√	√							
255	MW5	Constrained benchmark MOP proposed by Ma and Wang		√		√					√	√							
256	MW6	Constrained benchmark MOP proposed by Ma and Wang		√		√					√	√							
257	MW7	Constrained benchmark MOP proposed by Ma and Wang		√		√					√	√							
258	MW8	Constrained benchmark MOP proposed by Ma and Wang		√	√	√					√	√							
259	MW9	Constrained benchmark MOP proposed by Ma and Wang		√		√					√	√							
260	MW10	Constrained benchmark MOP proposed by Ma and Wang		√		√					√	√							
261	MW11	Constrained benchmark MOP proposed by Ma and Wang		√		√					√	√							
262	MW12	Constrained benchmark MOP proposed by Ma and Wang		√		√					√	√							
263	MW13	Constrained benchmark MOP proposed by Ma and Wang		√		√					√	√							
264	MW14	Constrained benchmark MOP proposed by Ma and Wang		√	√	√					√	√							
265	NI_HS	Multitasking problem (Rosenbrock function + Rastrigin function)	√			√					√						√		

	Abbreviation	Full name	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
266	NI_MS	Multitasking problem (Griewank function + Weierstrass function)	√			√					√						√		
267	RMMEDA_F1	Benchmark MOP for testing RM-MEDA		√		√					√								
268	RMMEDA_F2	Benchmark MOP for testing RM-MEDA		√		√					√								
269	RMMEDA_F3	Benchmark MOP for testing RM-MEDA		√		√					√								
270	RMMEDA_F4	Benchmark MOP for testing RM-MEDA		√		√					√								
271	RMMEDA_F5	Benchmark MOP for testing RM-MEDA		√		√					√								
272	RMMEDA_F6	Benchmark MOP for testing RM-MEDA		√		√					√								
273	RMMEDA_F7	Benchmark MOP for testing RM-MEDA		√		√					√								
274	RMMEDA_F8	Benchmark MOP for testing RM-MEDA		√		√					√								
275	RMMEDA_F9	Benchmark MOP for testing RM-MEDA		√		√					√								
276	RMMEDA_F10	Benchmark MOP for testing RM-MEDA		√		√					√								
277	RWMOP1	Pressure vessal problem		√		√						√							
278	RWMOP2	Vibrating platform		√		√						√							
279	RWMOP3	Two bar truss design problem		√		√						√							
280	RWMOP4	Weldan beam design problem		√		√						√							
281	RWMOP5	Disc brake design problem		√		√						√							
282	RWMOP6	Speed reducer design problem		√		√						√							
283	RWMOP7	Gear train design problem		√		√						√							
284	RWMOP8	Car side impact design problem		√		√						√							
285	RWMOP9	Four bar plane truss		√		√						√							
286	RWMOP10	Two bar plane truss		√		√						√							
287	RWMOP11	Water resource management problem		√		√						√							
288	RWMOP12	Simply supported I-beam design		√		√						√							
289	RWMOP13	Gear box design		√		√						√							
290	RWMOP14	Multiple-disk clutch brake design problem		√		√						√							
291	RWMOP15	Spring design problem		√		√						√							
292	RWMOP16	Cantilever beam design problem		√		√						√							
293	RWMOP17	Bulk carriers design problem		√		√						√							
294	RWMOP18	Front rail design problem		√		√						√							
295	RWMOP19	Multi-product batch plant		√		√						√							
296	RWMOP20	Hydro-static thrust bearing design problem		√		√						√							
297	RWMOP21	Crash energy management for high-speed train		√		√						√							
298	RWMOP22	Haverly's pooling problem		√		√						√							
299	RWMOP23	Reactor network design		√		√						√							
300	RWMOP24	Heat exchanger network design		√		√						√							
301	RWMOP25	Process synthesis problem		√		√						√							
302	RWMOP26	Process sythesis and design problem		√		√						√							

	Abbreviation	Full name	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
303	RWMOP27	Process flow sheeting problem		√		√						√							
304	RWMOP28	Two reactor problem		√		√						√							
305	RWMOP29	Process synthesis problem		√		√						√							
306	RWMOP30	Synchronous pptimal pulse-width modulation of 3-level inverters		√		√						√							
307	RWMOP31	Synchronous pptimal pulse-width modulation of 5-level inverters		√		√						√							
308	RWMOP32	Synchronous pptimal pulse-width modulation of 7-level inverters		√		√						√							
309	RWMOP33	Synchronous pptimal pulse-width modulation of 9-level inverters		√		√						√							
310	RWMOP34	Synchronous pptimal pulse-width modulation of 11-level inverters		√		√						√							
311	RWMOP35	Synchronous pptimal pulse-width modulation of 13-level inverters		√		√						√							
312	RWMOP36	Optimal sizing of single phase distributed generation with reactive power support for phase balancing at main transformer/grid and active power loss		√		√						√							
313	RWMOP37	Optimal Sizing of Single Phase Distributed Generation with reactive power support for Phase Balancing at Main Transformer/Grid and reactive Power loss		√		√						√							
314	RWMOP38	Optimal sizing of single phase distributed generation with reactive power support for active and reactive power loss		√		√						√							
315	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		√		√						√							
316	RWMOP40	Optimal power flow for minimizing active and reactive power loss		√		√						√							
317	RWMOP41	Optimal power flow for minimizing voltage deviation, active and reactive power loss		√		√						√							
318	RWMOP42	Optimal power flow for minimizing voltage deviation, and active power loss		√		√						√							
319	RWMOP43	Optimal power flow for minimizing fuel cost, and active power loss		√		√						√							
320	RWMOP44	Optimal power flow for minimizing fuel cost, active and reactive power loss		√		√						√							
321	RWMOP45	Optimal power flow for minimizing fuel cost, voltage deviation, and active power loss		√		√						√							
322	RWMOP46	Optimal power flow for minimizing fuel cost, voltage deviation, active and reactive power loss		√		√						√							
323	RWMOP47	Optimal droop setting for minimizing active and reactive power loss		√		√						√							
324	RWMOP48	Optimal droop setting for minimizing voltage deviation and active power loss		√		√						√							
325	RWMOP49	Optimal droop setting for minimizing voltage deviation, active, and reactive power loss		√		√						√							

	Abbreviation	Full name	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
326	RWMOP50	Power distribution system planning		√		√						√							
327	SMD1	Bilevel optimization problems proposed by Sinha, Malo, and Deb		√		√												√	
328	SMD2	Bilevel optimization problems proposed by Sinha, Malo, and Deb		√		√												√	
329	SMD3	Bilevel optimization problems proposed by Sinha, Malo, and Deb		√		√												√	
330	SMD4	Bilevel optimization problems proposed by Sinha, Malo, and Deb		√		√												√	
331	SMD5	Bilevel optimization problems proposed by Sinha, Malo, and Deb		√		√												√	
332	SMD6	Bilevel optimization problems proposed by Sinha, Malo, and Deb		√		√												√	
333	SMD7	Bilevel optimization problems proposed by Sinha, Malo, and Deb		√		√												√	
334	SMD8	Bilevel optimization problems proposed by Sinha, Malo, and Deb		√		√												√	
335	SMD9	Bilevel optimization problems proposed by Sinha, Malo, and Deb		√		√						√						√	
336	SMD10	Bilevel optimization problems proposed by Sinha, Malo, and Deb		√		√						√						√	
337	SMD11	Bilevel optimization problems proposed by Sinha, Malo, and Deb		√		√						√						√	
338	SMD12	Bilevel optimization problems proposed by Sinha, Malo, and Deb		√		√						√						√	
339	Sparse_CD	The community detection problem		√					√		√		√		√				
340	Sparse_CN	The critical node detection problem		√					√		√		√		√				
341	Sparse_FS	The feature selection problem		√					√		√		√		√				
342	Sparse_IS	The instance selection problem		√					√		√		√		√				
343	Sparse_KP	The sparse multi-objective knapsack problem		√	√				√		√								
344	Sparse_NN	The neural network training problem		√		√					√		√		√				
345	Sparse_PM	The pattern mining problem		√					√		√		√		√				
346	Sparse_PO	The portfolio optimization problem		√		√					√		√		√				
347	Sparse_SR	The sparse signal reconstruction problem		√		√					√		√		√				
348	SMMOP1	Sparse multi-modal multi-objective optimization problem		√	√	√					√			√	√				
349	SMMOP2	Sparse multi-modal multi-objective optimization problem		√	√	√					√			√	√				
350	SMMOP3	Sparse multi-modal multi-objective optimization problem		√	√	√					√			√	√				
351	SMMOP4	Sparse multi-modal multi-objective optimization problem		√	√	√					√			√	√				
352	SMMOP5	Sparse multi-modal multi-objective optimization problem		√	√	√					√			√	√				
353	SMMOP6	Sparse multi-modal multi-objective optimization problem		√	√	√					√			√	√				

	Abbreviation	Full name	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
354	SMMOP7	Sparse multi-modal multi-objective optimization problem		√	√	√					√			√	√				
355	SMMOP8	Sparse multi-modal multi-objective optimization problem		√	√	√					√			√	√				
356	SMOP1	Benchmark MOP with sparse Pareto optimal solutions		√	√	√					√		√		√				
357	SMOP2	Benchmark MOP with sparse Pareto optimal solutions		√	√	√					√		√		√				
358	SMOP3	Benchmark MOP with sparse Pareto optimal solutions		√	√	√					√		√		√				
359	SMOP4	Benchmark MOP with sparse Pareto optimal solutions		√	√	√					√		√		√				
360	SMOP5	Benchmark MOP with sparse Pareto optimal solutions		√	√	√					√		√		√				
361	SMOP6	Benchmark MOP with sparse Pareto optimal solutions		√	√	√					√		√		√				
362	SMOP7	Benchmark MOP with sparse Pareto optimal solutions		√	√	√					√		√		√				
363	SMOP8	Benchmark MOP with sparse Pareto optimal solutions		√	√	√					√		√		√				
364	SOP_F1	Sphere function	√			√							√						
365	SOP_F2	Schwefel's function 2.22	√			√							√						
366	SOP_F3	Schwefel's function 1.2	√			√							√						
367	SOP_F4	Schwefel's function 2.21	√			√							√						
368	SOP_F5	Generalized Rosenbrock's function	√			√							√						
369	SOP_F6	Step function	√			√							√						
370	SOP_F7	Quartic function with noise	√			√							√						
371	SOP_F8	Generalized Schwefel's function 2.26	√			√							√						
372	SOP_F9	Generalized Rastrigin's function	√			√							√						
373	SOP_F10	Ackley's function	√			√							√						
374	SOP_F11	Generalized Griewank's function	√			√							√						
375	SOP_F12	Generalized penalized function	√			√							√						
376	SOP_F13	Generalized penalized function	√			√							√						
377	SOP_F14	Shekel's foxholes function	√			√							√						
378	SOP_F15	Kowalik's function	√			√							√						
379	SOP_F16	Six-hump camel-back function	√			√							√						
380	SOP_F17	Branin function	√			√							√						
381	SOP_F18	Goldstein-price function	√			√							√						
382	SOP_F19	Hartman's family	√			√							√						
383	SOP_F20	Hartman's family	√			√							√						
384	SOP_F21	Shekel's family	√			√							√						
385	SOP_F22	Shekel's family	√			√							√						

	Abbreviation	Full name	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
386	SOP_F23	Shekel's family	√			√							√						
387	TP1	Test problem for robust multi-objective optimization		√		√					√								√
388	TP2	Test problem for robust multi-objective optimization		√		√					√								√
389	TP3	Test problem for robust multi-objective optimization		√		√					√								√
390	TP4	Test problem for robust multi-objective optimization		√		√					√								√
391	TP5	Test problem for robust multi-objective optimization		√		√					√								√
392	TP6	Test problem for robust multi-objective optimization		√		√					√								√
393	TP7	Test problem for robust multi-objective optimization		√		√					√								√
394	TP8	Test problem for robust multi-objective optimization		√		√					√								√
395	TP9	Test problem for robust multi-objective optimization		√		√					√								√
396	TP10	Test problem for robust multi-objective optimization		√		√					√	√							√
397	TREE1	The time-varying ratio error estimation problem		√		√					√	√	√						
398	TREE2	The time-varying ratio error estimation problem		√		√					√	√	√						
399	TREE3	The time-varying ratio error estimation problem		√		√					√	√	√						
400	TREE4	The time-varying ratio error estimation problem		√		√					√	√	√						
401	TREE5	The time-varying ratio error estimation problem		√		√					√	√	√						
402	TREE6	The time-varying ratio error estimation problem		√		√					√	√	√						
403	TSP	The traveling salesman problem	√							√	√								
404	UF1	Unconstrained benchmark MOP		√		√					√								
405	UF2	Unconstrained benchmark MOP		√		√					√								
406	UF3	Unconstrained benchmark MOP		√		√					√								
407	UF4	Unconstrained benchmark MOP		√		√					√								
408	UF5	Unconstrained benchmark MOP		√		√					√								
409	UF6	Unconstrained benchmark MOP		√		√					√								
410	UF7	Unconstrained benchmark MOP		√		√					√								
411	UF8	Unconstrained benchmark MOP		√		√					√								
412	UF9	Unconstrained benchmark MOP		√		√					√								
413	UF10	Unconstrained benchmark MOP		√		√					√								
414	VNT1	Benchmark MOP proposed by Viennet		√		√													
415	VNT2	Benchmark MOP proposed by Viennet		√		√													
416	VNT3	Benchmark MOP proposed by Viennet		√		√													
417	VNT4	Benchmark MOP proposed by Viennet		√		√						√							
418	WFG1	Benchmark MOP proposed by Walking Fish Group		√	√	√					√		√						
419	WFG2	Benchmark MOP proposed by Walking Fish Group		√	√	√					√		√						
420	WFG3	Benchmark MOP proposed by Walking Fish Group		√	√	√					√		√						
421	WFG4	Benchmark MOP proposed by Walking Fish Group		√	√	√					√		√						
422	WFG5	Benchmark MOP proposed by Walking Fish Group		√	√	√					√		√						

	Abbreviation	Full name	single	multi	many	real	integer	label	binary	permutation	large	constrained	expensive	multimodal	sparse	dynamic	multitask	bilevel	robust
423	WFG6	Benchmark MOP proposed by Walking Fish Group		√	√	√					√		√						
424	WFG7	Benchmark MOP proposed by Walking Fish Group		√	√	√					√		√						
425	WFG8	Benchmark MOP proposed by Walking Fish Group		√	√	√					√		√						
426	WFG9	Benchmark MOP proposed by Walking Fish Group		√	√	√					√		√						
427	ZDT1	Benchmark MOP proposed by Zitzler, Deb, and Thiele		√		√					√		√						
428	ZDT2	Benchmark MOP proposed by Zitzler, Deb, and Thiele		√		√					√		√						
429	ZDT3	Benchmark MOP proposed by Zitzler, Deb, and Thiele		√		√					√		√						
430	ZDT4	Benchmark MOP proposed by Zitzler, Deb, and Thiele		√		√					√		√						
431	ZDT5	Benchmark MOP proposed by Zitzler, Deb, and Thiele		√					√		√		√						
432	ZDT6	Benchmark MOP proposed by Zitzler, Deb, and Thiele		√		√					√		√						
433	ZXH_CF1	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
434	ZXH_CF2	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
435	ZXH_CF3	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
436	ZXH_CF4	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
437	ZXH_CF5	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
438	ZXH_CF6	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
439	ZXH_CF7	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
440	ZXH_CF8	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
441	ZXH_CF9	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
442	ZXH_CF10	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
443	ZXH_CF11	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
444	ZXH_CF12	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
445	ZXH_CF13	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
446	ZXH_CF14	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
447	ZXH_CF15	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							
448	ZXH_CF16	Constrained benchmark MOP proposed by Zhou, Xiang, and He		√	√	√					√	√							