PlatEMO

Evolutionary Multi-Objective Optimization Platform

User Manual 3.1

BIMK Group

March 20, 2021

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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.

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 provides a variety of algorithms for solving optimization problems in a black-box manner. To this end, users should define the optimization problem, select an algorithm, and set the parameter values, by means of one of the following ways:

1) Calling the main function with parameters:

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

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:

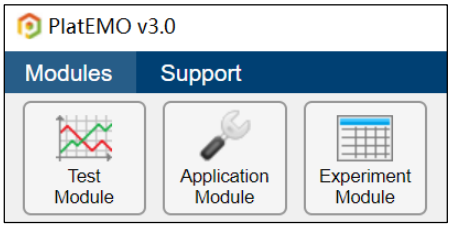
```
f1 = @(x,d)sum(x*d);
f2 = @(x,d)1-sum(x*d);
platemo('objFcn',f1,'conFcn',f2,'algorithm',@GA,…);
```

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 benchmark 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`	Number of evaluations
`'save'`	Integer	`0`	Number of saved populations
`'outputFcn'`	Function handle	`@ALGORITHM.Output`	Function called before each iteration

- `'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.
- `'problem'` denotes the benchmark problem to be solved, 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.
- `'N'` denotes the population size of the algorithm, which usually equals to the number of solutions in the final population.
- `'M'` denotes the number of objectives of the benchmark problem, which is valid for some multi-objective benchmark problems.
- `'D'` denotes the number of decision variables of the benchmark problem, which is valid for some benchmark problems.
- `'maxFE'` denotes the maximum number of available function evaluations, which usually equals to the product of population size and number of generations.
- `'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 zero (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.

For example, the following code runs the genetic algorithm on the sphere function with a population size of 50, where the populations are displayed in a figure:

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

The following code runs NSGA-II on 5-objective 40-variable DTLZ2 for 20000 function evaluations, where the populations are saved to a file:

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

The following code runs MOEA/D with Tchebycheff approach on ZDT1 for ten times, where the populations obtained in each time are saved to a file:

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

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
`'encoding'`	char	`'real'`	Encoding scheme
`'objFcn'`	Function handle or cell	`@(x,d)sum(x)`	Objective functions
`'conFcn'`	Function handle or cell	`@(x,d)0`	Constraint functions
`'lower'`	Row vector	`0`	Lower bounds of variables
`'upper'`	Row vector	`1`	Upper bounds of variables
`'initFcn'`	Function handle	`[]`	Function for initializing a population
`'decFcn'`	Function handle	`[]`	Function for repairing invalid solution
`'parameter'`	Cell	`{}`	Dataset

- `'encoding'` denotes the encoding scheme of the problem, whose value can be `'real'` (variables are real or integer numbers), `'binary'` (variables are binary numbers), or `'permutation'` (variables constitute a permutation). Algorithms

may use different reproduction operators for different encoding schemes.

- `'objFcn'` denotes the objective functions of the problem, whose value can be a function handle (a single objective) or cell (multiple objectives). An objective function has two inputs and an output, where the first input is a decision vector, the second input is the dataset specified by `'parameter'`, and the output is the objective value. All the objectives are to be minimized.
- `'conFcn'` denotes the constraint functions of the problem, whose value can be a function handle (a single constraint) or cell (multiple constraints). A constraint function has two inputs and an output, where the first input is a decision vector, the second input is the dataset specified by `'parameter'`, and the output is the constraint violation. A constraint is satisfied if and only if the constraint violation is not positive.
- `'lower'` denotes the lower bounds of variables, which is valid when the value of `'encoding'` is `'real'`.
- `'upper'` denotes the upper bounds of variables, which is valid when the value of `'encoding'` is `'real'`.
- `'initFcn'` denotes the function for initializing a population, whose value should be a function handle having two inputs and an output, where the first input is the number of solutions in the population, the second input is the dataset specified by `'parameter'`, and the output is a matrix consisting of the decision vectors in the initial population. This function is called at the beginning of most algorithms.
- `'decFcn'` denotes the function for repairing invalid solution, whose value should be a function handle having two inputs and an output, where the first input is a decision vector, the second input is the dataset specified by `'parameter'`, and the output is the repaired decision vector. This function is called before the objective calculation of each solution.
- `'parameter'` denotes the dataset of the problem, which is used as the second input of the functions specified by `'objFcn'`, `'conFcn'`, `'initFcn'`, and `'decFcn'`.

For example, the following code solves a unimodal problem with 10 variables by differential evolution:

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

The following code solves a rotated unimodal problem with 10 variables by the default algorithm:

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

The following code solves a constrained bi-objective problem with 20 variables by NSGA-II with a population size of 50:

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

C. Collecting the Results

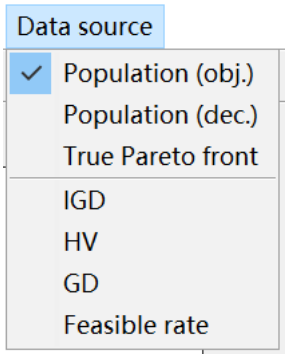
The generated populations can be displayed, saved, or returned after the algorithm terminates. If the main function is called like

```
[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 zero (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. Note that the above are achieved by the default output function `@ALGORITHM.Output`, 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 obtain the optimums of the problem and then call the metric functions, for example,

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

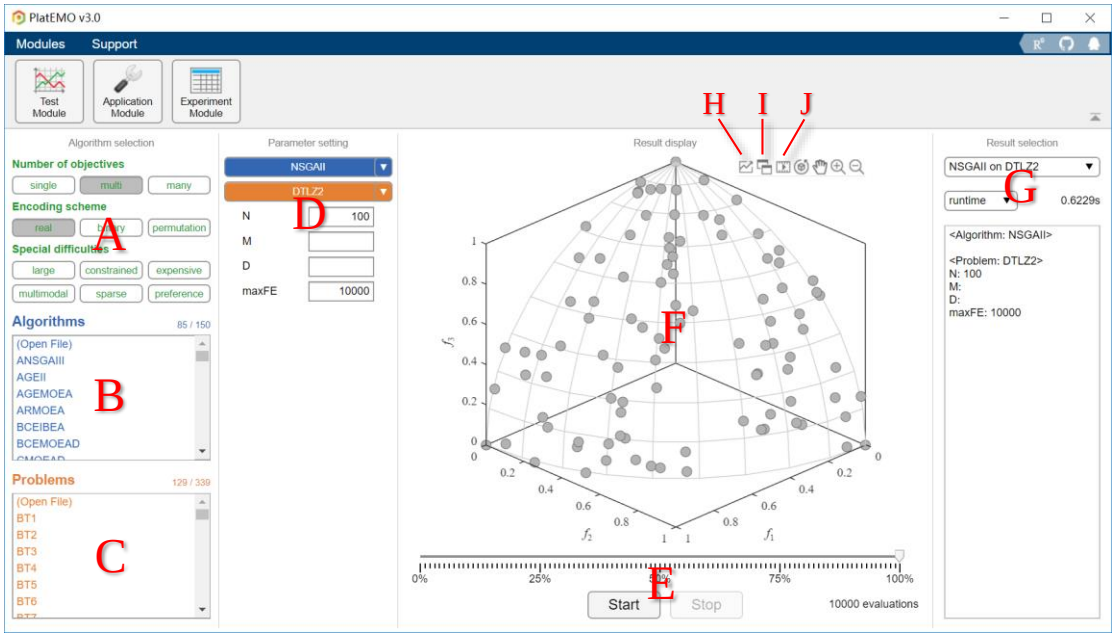
III. Using PlatEMO with GUI

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.

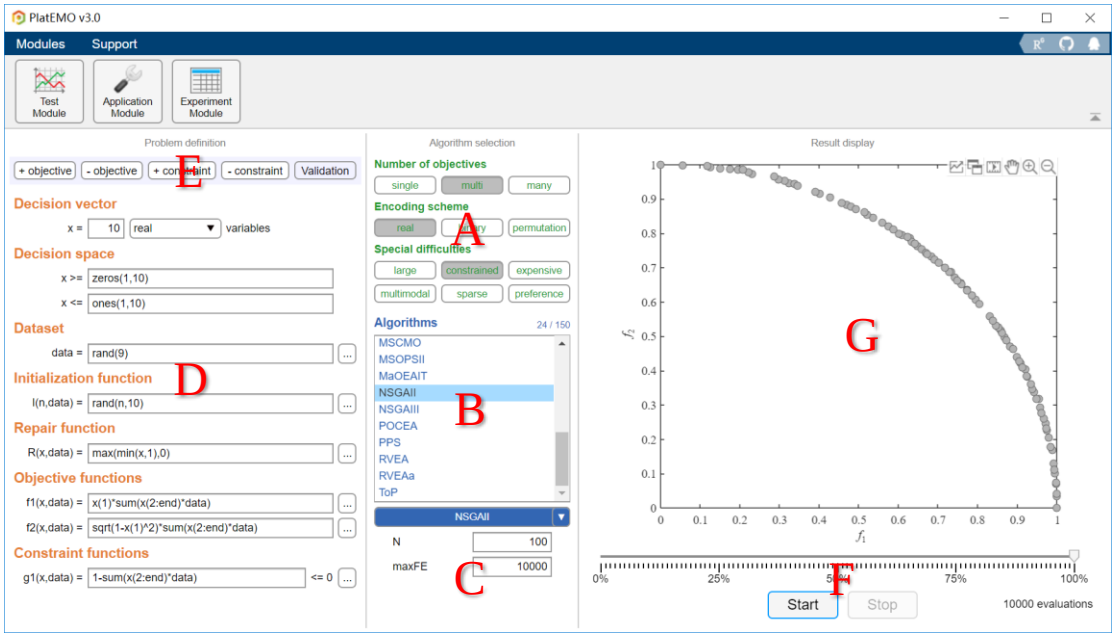


Users should first determine the type of problems in Region A (see *Labels of Algorithms and Problems* for details), select an algorithm in Region B, select a benchmark problem in Region C, and set the parameter values in Region D. Then, the optimization process can be started and controlled in Region E, where the real-time result is displayed in Region F and the historical results can be reviewed in Region G.

Pressing Button H can choose the plot to be displayed, pressing Button I can display the plot in a new figure and save the data in the plot to workspace, and pressing Button J can save the whole optimization process to a GIF file with 20 frames.

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.



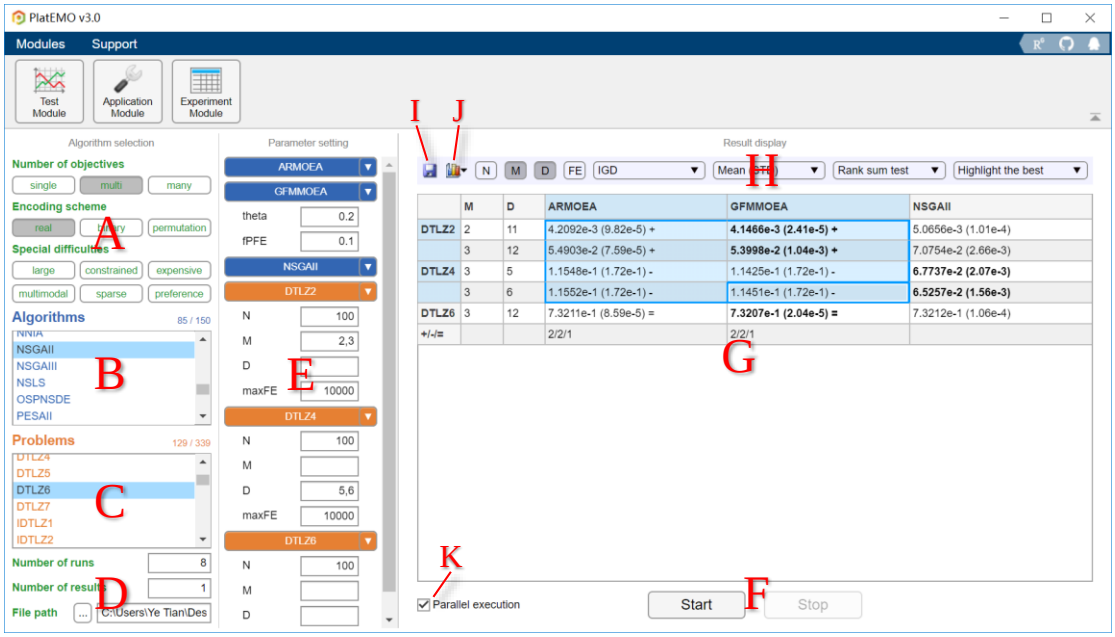
Users should first define the problem in Region D, whose details are the same to those in *Solving User-Defined Problems*, where

- Decision vector is the same to `'encoding'`
- Decision space is the same to `'lower'` and `'upper'`
- Dataset is the same to `'parameter'`
- Initialization function is the same to `'initFcn'`
- Repair function is the same to `'decFcn'`
- Objective functions is the same to `'objFcn'`
- Constraint functions is the same to `'conFcn'`

For simplicity, users can only specify Decision vector, Decision space, Objective functions, and Constraint functions. Meanwhile, users can increase or decrease the numbers of objectives and constraints, and check the validity of the problem in Region E. Then, the type of problems can be automatically determined in Region A, while users should select an algorithm in Region B and set the parameter values in Region C. The optimization process can be started and controlled in Region F, and the real-time result is displayed in Region G.

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.



Users should first determine the type of problems in Region A (see *Labels of Algorithms and Problems* for details), select multiple algorithms in Region B, select multiple benchmark problems in Region C, configure the experimental settings in Region D, and set the parameter values in Region E, where the number of objectives `M` and the number of variables `D` can be vectors. Then, the optimization process can be started and controlled in Region F, where the statistical results are listed in Region G.

The statistical results to be listed can be customized in Region H. Pressing Button I can save the table to an Excel, TeX, TXT, or MAT file, and pressing Button J can display the results in the selected cells of the table in a new figure. Button K determines whether the experiment is performed on a single CPU (in sequence) or all the CPUs (in parallel).

All the results are saved to MAT files in the folder specified in Region D. If a result file already exists, the file will be loaded and the algorithm will not be run.

D. Labels of Algorithms and Problems

Each algorithm or benchmark problem is 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> <large/none> <constrained/none>
```

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

Label	Description
<single>	The problem has a single objective
<multi>	The problem has two or three objectives
<many>	The problem has four or more objectives
<real>	The decision variables are real or integer numbers
<binary>	The decision variables are binary numbers
<permutation>	The decision variables constitute a permutation
<large>	The problem has more than 100 decision variables
<constrained>	The problem has at least one constraint
<expensive>	The objectives are computationally expensive, i.e., only a very limited number of function evaluations are available
<multimodal>	There exist multiple optimal solutions with similar objective values but considerably different decision vectors, all of which should be found
<sparse>	Most decision variables of the optimal solutions are zero
<preference>	Only the optimal solutions in the predefined regions of the Pareto front are expected to be found
<none>	Empty label

An algorithm may have multiple sets of labels, where the Cartesian product between all the label sets include 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 or benchmark problem should be tagged with labels, otherwise it will not be appeared in the lists in the GUI. When determining the type of problems in Region A, the algorithms that can solve such type of problems will be appeared in the list in Region B, and the benchmark problems belonging to this type will be appeared in the list in Region C. 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 current populations
Method	**Be redefined**	**Description**
`ALGORITHM`	Cannot	Set the properties specified by users
`Solve`	Cannot	Call `alg.Solve(pro)` to solve problem `pro` by algorithm `alg`
`main`	Must	Main procedure of the algorithm
`NotTerminated`	Cannot	Function called before each iteration in `main()`
`ParameterSet`	Cannot	Set the parameter values according to `parameter`

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

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

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

    methods
        function main(Alg,Pro)
```

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

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 and Problems* 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 last population and checking whether the number of function evaluations exceeds; if so, the algorithm will terminate immediately;

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

Line 20: Using the mating pool to generate offsprings by calling a public function;

Line 21: Combing the current population with the offsprings;

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

Line 23: Retaining the solutions with better fitness for 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`, which provides a number of operations commonly used in algorithms. 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
ALGORITHM.ParameterSet	Set the parameter values specified by users
PROBLEM.Initialization	Initialize a population for the problem
CrowdingDistance	Crowding distance calculation for multi-objective optimization
FitnessSingle	Fitness calculation for single-objective optimization
NDSort	Non-dominated sorting
OperatorDE	The reproduction operator of differential evolution
OperatorFEP	The reproduction operator of fast evolutionary programming
OperatorGA	The reproduction operators of genetic algorithm
OperatorGAhalf	The reproduction operators of genetic algorithm, where only the first half of offsprings are generated
OperatorPSO	The reproduction operator of particle swarm optimization
RouletteWheelSelection	Roulette-wheel selection
TournamentSelection	Tournament selection
UniformPoint	Generate a set of uniformly distributed points

B. PROBLEM Class

A benchmark 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	SOLUTION()	Number of function evaluations consumed in current execution
encoding	Setting()	Encoding scheme of the problem
lower	Setting()	Lower bounds of the decision variables
upper	Setting()	Upper bounds of the decision variables
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
Setting	Must	Default settings of the problem
Initialization	Can	Initialize a population for the problem
CalDec	Can	Repair invalid solutions in a population
CalObj	Must	Calculate the objective values of solutions in a population. All objectives are to be minimized
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
GetOptimum	Can	Generate the optimal values and store in optimum
GetPF	Can	Generate the Pareto front and store in PF
DrawDec	Can	Display the decision variables of a population
DrawObj	Can	Display the objective values of a population
Current	Cannot	Static method for getting or setting the current PROBLEM object
ParameterSet	Cannot	Set the parameter values according to parameter

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

```
1  classdef SOP_F1 < PROBLEM
2  % <single><real><expensive/none>
3  % Sphere function
4
5  %--------------------------- Reference --------------------------
6  % X. Yao, Y. Liu, and G. Lin, Evolutionary programming made
7  % faster, IEEE Transactions on Evolutionary Computation, 1999, 3
8  % (2): 82-102.
9  %----------------------------------------------------------------
10
11     methods
12         function Setting(obj)
13             obj.M = 1;
14             if isempty(obj.D); obj.D = 30; end
15             obj.lower = zeros(1,obj.D) - 100;
16             obj.upper = zeros(1,obj.D) + 100;
17             obj.encoding = 'real';
18         end
19         function PopObj = CalObj(obj,PopDec)
20             PopObj = sum(PopDec.^2,2);
21         end
22     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 and Problems* 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 scheme of the problem;
Line 19: Redefining the method of calculating objective values;
Line 20: Calculating the objective values of solutions in a population.

The method `Initialization()` randomly initializes a population for the problem. 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 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:

```
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 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, `MW1.m` calculates a constraint for each solution:

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

The method `GetOptimum()` can be redefined to specify the optimal values of the problem. 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 the problem for the visualization achieved in `DrawObj()`. For example, `DTLZ2.m` returns the data for plotting the 2-D or 3-D Pareto front:

```
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 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. The details of the above functions are referred to the comments in their codes.

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`	Receive the decision variables and calculate the objective values and constraint violations of one or more solutions. `PROBLEM.FE` will be automatically increased by the number of `SOLUTION` objects returned
`decs`	Get the matrix of decision variables of multiple solutions
`objs`	Get the matrix of objective values of multiple solutions
`cons`	Get the matrix of constraint violations of multiple solutions
`adds`	Get the matrix of additional properties of multiple solutions
`best`	Get the feasible and best solution for single-objective optimization, or the feasible and non-dominated solutions for multi-objective optimization

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

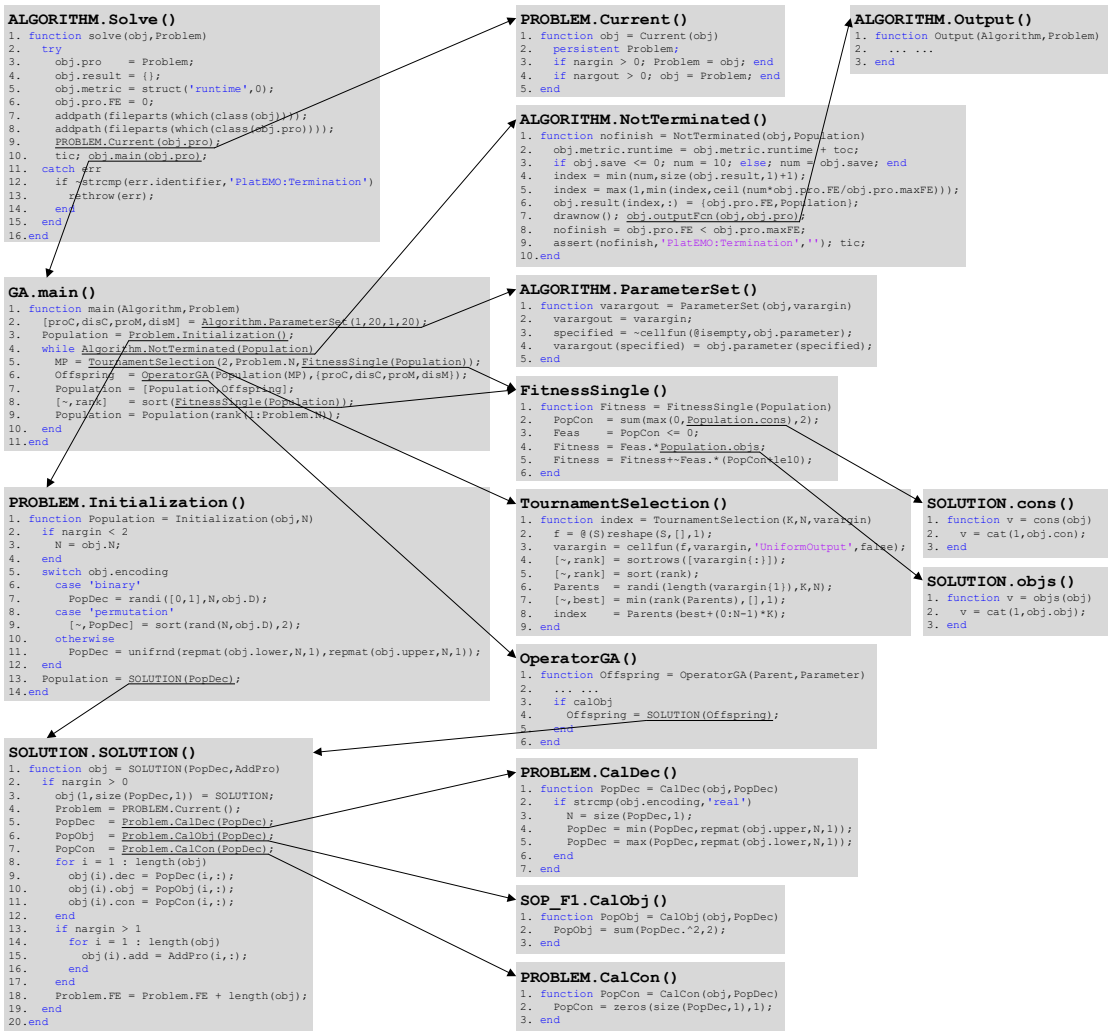
```
Population = SOLUTION(rand(10,5));
BestObjs = Population.best.objs
```

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

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

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 `<min>` (the smaller metric value the better) or `<max>` (the larger metric value the better);

Line 3: Full name of the metric;

Lines 5-9: Reference of the metric;

Line 11: Obtaining the feasible and non-dominated solutions in the population;

Lines 12-13: Returns `nan` if there is no feasible and non-dominated solution;

Lines 14-15: Returns the IGD value of the feasible and non-dominated solutions.

V. List of Algorithms

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

	Abbreviation	Full name	single	multi	many	real	binary	permutation	large	constrained	expensive	multimodal	sparse	preference
30	DWU	Dominance-weighted uniformity multi-objective evolutionary algorithm		√		√	√	√						
31	EAG-MOEA/D	External archive guided MOEA/D		√		√	√	√						
32	EFR-RR	Ensemble fitness ranking with a ranking restriction scheme		√	√	√	√	√						
33	EGO	Efficient global optimization	√			√					√			
34	EIM-EGO	Expected improvement matrix based efficient global optimization		√		√					√			
35	e-MOEA	Epsilon multi-objective evolutionary algorithm		√	√	√	√	√						
36	EMyO/C	Evolutionary many-objective optimization algorithm with clustering-based		√	√	√								
37	ENS-MOEA/D	Ensemble of different neighborhood sizes based MOEA/D		√	√	√								
38	FEP	Fast evolutionary programming	√			√			√	√				
39	FRCG	Fletcher-Reeves conjugate gradient	√			√			√					
40	FROFI	Feasibility rule with the incorporation of objective function information	√			√			√	√				
41	GA	Genetic algorithm	√			√	√	√	√	√				
42	GDE3	Generalized differential evolution 3		√		√				√				
43	GFM-MOEA	Generic front modeling based multi-objective evolutionary algorithm		√	√	√	√	√						
44	GLMO	Grouped and linked mutation operator algorithm		√		√			√					
45	g-NSGA-II	g-dominance based NSGA-II		√		√	√	√						√
46	GrEA	Grid-based evolutionary algorithm			√	√	√	√						
47	hpaEA	Hyperplane assisted evolutionary algorithm		√	√	√	√	√						
48	HypE	Hypervolume estimation algorithm		√	√	√	√	√						
49	IBEA	Indicator-based evolutionary algorithm		√	√	√	√	√						
50	I-DBEA	Improved decomposition-based evolutionary algorithm		√	√	√	√	√		√				
51	IM-MOEA	Inverse modeling based multiobjective evolutionary algorithm		√		√			√					
52	IMODE	Improved multi-operator differential evolution	√			√			√	√				
53	I-SIBEA	Interactive simple indicator-based evolutionary algorithm		√		√	√	√						√
54	KnEA	Knee point driven evolutionary algorithm			√	√	√	√		√				
55	K-RVEA	Surrogate-assisted RVEA		√	√	√					√			
56	LCSA	Linear combination-based search algorithm		√	√	√			√					
57	LMEA	Evolutionary algorithm for large-scale many-objective optimization		√	√	√			√					
58	LMOCSO	Large-scale multi-objective competitive swarm optimization algorithm		√	√	√			√	√				
59	LSMOF	Large-scale multi-objective optimization framework with NSGA-II		√		√			√					
60	MaOEA-CSS	Many-objective evolutionary algorithms based on coordinated selection		√	√	√	√	√						
61	MaOEA-DDFC	Many-objective evolutionary algorithm based on directional diversity and favorable convergence		√	√	√	√	√						
62	MaOEA/IGD	IGD based many-objective evolutionary algorithm			√	√	√	√						

	Abbreviation	Full name	single	multi	many	real	binary	permutation	large	constrained	expensive	multimodal	sparse	preference
63	MaOEA/IT	Many-objective evolutionary algorithms based on an independent two-stage		√	√	√				√				
64	MaOEA-R&D	Many-objective evolutionary algorithm based on objective space reduction			√	√	√	√						
65	MMOPSO	MOPSO with multiple search strategies		√		√								
66	MO_Ring_PSO_SCD	Multiobjective PSO using ring topology and special crowding distance		√		√						√		
67	MOCell	Cellular genetic algorithm		√		√	√	√		√				
68	MO-CMA	Multi-objective covariance matrix adaptation evolution strategy		√		√								
69	MOEA/D	Multiobjective evolutionary algorithm based on decomposition		√	√	√	√	√						
70	MOEA/D-AWA	MOEA/D with covariance matrix adaptation evolution strategy		√	√	√								
71	MOEA/D-CMA	MOEA/D with covariance matrix adaptation evolution strategy		√	√	√								
72	MOEA/DD	Many-objective evolutionary algorithm based on dominance and decomposition		√	√	√	√	√		√				
73	MOEA/D-DAE	MOEA/D with detect-and-escape strategy		√		√	√	√		√				
74	MOEA/D-DE	MOEA/D based on differential evolution		√	√	√								
75	MOEA/D-DRA	MOEA/D with dynamical resource allocation		√	√	√								
76	MOEA/D-DU	MOEA/D with a distance based updating strategy		√	√	√	√	√						
77	MOEA/D-EGO	MOEA/D with efficient global optimization		√		√					√			
78	MOEA/D-FRRMAB	MOEA/D with fitness-rate-rank-based multiarmed bandit		√	√	√								
79	MOEA/D-M2M	MOEA/D based on MOP to MOP		√		√								
80	MOEA/D-MRDL	MOEA/D with maximum relative diversity loss		√		√								
81	MOEA/D-PaS	MOEA/D with Pareto adaptive scalarizing approximation		√	√	√								
82	MOEA/D-STM	MOEA/D with stable matching		√	√	√								
83	MOEA/D-URAW	MOEA/D with uniform randomly adaptive weights		√	√	√	√	√						
84	MOEA/DVA	Multi-objective evolutionary algorithm based on decision variable		√		√			√					
85	MOEA/IGD-NS	Multi-objective evolutionary algorithm based on an enhanced IGD		√		√	√	√						
86	MOEA-PC	Multiobjective evolutionary algorithm based on polar coordinates		√		√								
87	MOEA/PSL	Multi-objective evolutionary algorithm based on Pareto optimal subspace		√		√	√		√	√			√	
88	MOMBI-II	Many objective metaheuristic based on the R2 indicator II		√	√	√	√	√						
89	MOPSO	Multi-objective particle swarm optimization		√		√								
90	MOPSO-CD	MOPSO with crowding distance		√		√								
91	M-PAES	Memetic algorithm with Pareto archived evolution strategy		√		√								
92	MP-MMEA	Multi-population multi-modal multi-objective evolutionary algorithm		√		√			√			√	√	

	Abbreviation	Full name	single	multi	many	real	binary	permutation	large	constrained	expensive	multimodal	sparse	preference
93	MPSO/D	Multi-objective particle swarm optimization algorithm based on decomposition		√	√	√								
94	MSCMO	Multi-stage constrained multi-objective evolutionary algorithm		√		√	√	√		√				
95	MSEA	Multi-stage multi-objective evolutionary algorithm		√		√	√	√						
96	MSOPS-II	Multiple single objective Pareto sampling II		√	√	√				√				
97	MTS	Multiple trajectory search		√		√								
98	MultiObjective EGO	Multi-objective efficient global optimization		√		√				√	√			
99	MyO-DEMR	Many-objective differential evolution with mutation restriction		√	√	√								
100	NMPSO	Novel multi-objective particle swarm optimization		√	√	√								
101	NNIA	Nondominated neighbor immune algorithm		√		√	√	√						
102	NSGA-II	Nondominated sorting genetic algorithm II		√		√	√	√		√				
103	NSGA-II+ARSBX	NSGA-II with adaptive rotation based simulated binary crossover		√		√				√				
104	NSGA-II-conflict	NSGA-II with conflict-based partitioning strategy			√	√	√	√						
105	NSGA-III	Nondominated sorting genetic algorithm III		√	√	√	√	√		√				
106	NSGA-II/SDR	NSGA-II with strengthened dominance relation			√	√	√	√						
107	NSLS	Multiobjective optimization framework based on nondominated sorting and local search		√		√								
108	OFA	Optimal foraging algorithm	√			√			√	√				
109	one-by-one EA	Many-objective evolutionary algorithm using a one-by-one selection		√	√	√	√	√						
110	OSP-NSDE	Non-dominated sorting differential evolution with prediction in the objective space		√		√								
111	ParEGO	Efficient global optimization for Pareto optimization		√		√					√			
112	PESA-II	Pareto envelope-based selection algorithm II		√		√	√	√						
113	PICEA-g	Preference-inspired coevolutionary algorithm with goals		√	√	√	√	√						
114	PM-MOEA	Pattern mining based multi-objective evolutionary algorithm		√		√			√	√				
115	POCEA	Paired offspring generation based constrained evolutionary algorithm		√		√			√	√				
116	PPS	Push and pull search algorithm		√	√	√				√				
117	PREA	Promising-region based EMO algorithm		√	√	√	√	√						
118	PSO	Particle swarm optimization	√			√			√	√				
119	RM-MEDA	Regularity model-based multiobjective estimation of distribution		√		√								
120	r-NSGA-II	r-dominance based NSGA-II		√		√	√	√						√
121	RPD-NSGA-II	Reference point dominance-based NSGA-II		√	√	√	√	√						
122	RPEA	Reference points-based evolutionary algorithm			√	√	√	√						
123	RSEA	Radial space division based evolutionary algorithm		√	√	√	√	√						
124	RVEA	Reference vector guided evolutionary algorithm		√	√	√	√	√		√				
125	RVEAa	RVEA embedded with the reference vector regeneration strategy			√	√	√	√						
126	S3-CMA-ES	Scalable small subpopulations based covariance matrix adaptation		√	√	√			√					

	Abbreviation	Full name	single	multi	many	real	binary	permutation	large	constrained	expensive	multimodal	sparse	preference
127	SA	Simulated annealing	√			√			√	√				
128	SACC-EAM-II	Surrogate-assisted cooperative co-evolutionary algorithm of Minamo	√			√					√			
129	SACOSO	Surrogate-assisted cooperative swarm optimization	√			√			√		√			
130	SADE-Sammon	Sammon mapping assisted differential evolution	√			√					√			
131	SAMSO	Multiswarm-assisted expensive optimization	√			√			√		√			
132	S-CDAS	Self-controlling dominance area of solutions			√	√	√	√						
133	SHADE	Success-history based adaptive differential evolution	√			√			√	√				
134	SIBEA	Simple indicator-based evolutionary algorithm		√		√	√	√						
135	SIBEA-kEMOSS	SIBEA with minimum objective subset of size k with minimum error			√	√	√	√						
136	SMEA	Self-organizing multiobjective evolutionary algorithm		√		√								
137	SMPSO	Speed-constrained multi-objective particle swarm optimization		√		√								
138	SMS-EGO	S metric selection based efficient global optimization		√		√					√			
139	SMS-EMOA	S metric selection based evolutionary multiobjective optimization		√		√	√	√						
140	SparseEA	Evolutionary algorithm for sparse multi-objective optimization problems		√		√	√		√	√			√	
141	SPEA2	Strength Pareto evolutionary algorithm 2		√		√	√	√						
142	SPEA2+SDE	SPEA2 with shift-based density estimation			√	√	√	√						
143	SPEA/R	Strength Pareto evolutionary algorithm based on reference direction		√	√	√	√	√						
144	SQP	Sequential quadratic programming	√			√			√	√				
145	SRA	Stochastic ranking algorithm			√	√	√	√						
146	t-DEA	theta-dominance based evolutionary algorithm		√	√	√	√	√						
147	TiGE-2	Tri-Goal Evolution Framework for CMaOPs			√	√	√	√		√				
148	ToP	Two-phase framework with NSGA-II		√		√				√				
149	TriMOEA-TA&R	Multi-modal MOEA using two-archive and recombination strategies		√		√						√		
150	Two_Arch2	Two-archive algorithm 2		√	√	√	√	√						
151	VaEA	Vector angle based evolutionary algorithm		√	√	√	√	√						
152	WOF	Weighted optimization framework		√		√			√					
153	WV-MOEA-P	Weight vector based multi-objective optimization algorithm with preference		√		√								√

VI. List of Problems

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

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

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

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

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

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

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

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

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

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