

Problem Definitions and Evaluation Criteria for Computational Expensive Optimization

B. Liu¹, Q. Chen² and Q. Zhang³, J. J. Liang⁴, P. N. Suganthan⁵, B. Y. Qu⁶

¹ Department of Computing, Glyndwr University, UK

² Facility Design and Instrument Institute, China Aerodynamic Research and Development Center, China

³ Department of Computer Science, City University of Hong Kong, Hong Kong & School of Computer Science and Electronic Engineering, University of Essex, UK.

⁴ School of Electrical Engineering, Zhengzhou University, Zhengzhou, China

⁵ School of EEE, Nanyang Technological University, Singapore

⁶ School of Electric and Information Engineering, Zhongyuan University of Technology, Zhengzhou, China

b.liu@glyndwr.ac.uk, qingfu.zhang@cityu.edu.hk, chenqin1980@gmail.com
liangjing@zzu.edu.cn, epnsugan@ntu.edu.sg, qby1984@hotmail.com

Many real-world optimization problems require computationally expensive computer or physical simulations for evaluating their candidate solutions. Often, canonical evolutionary algorithms (EA) cannot directly solve them since a large number of function evaluations are unaffordable. In recent years, various kinds of novel methods for computationally expensive optimization problems have been proposed and surrogate model assisted evolutionary algorithm (SAEA) is attracting more and more attention.

To promote research on expensive optimization, we propose to organize a competition focusing on small- to medium-scale (from 10 decision variables to 30 decision variables) real parameter bound constrained single-objective computationally expensive optimization. We encourage all participants to test their algorithms on the CEC 14 expensive optimization test suite which includes 24 black-box benchmark functions (8 popular test problems with 10, 20 and 30 dimensions). The participants are required to send the final results in the format given in the technical report to the organizers. The organizers will conduct an overall analysis and comparison. Special attention will be paid to which algorithm has advantages on which kind of problems.

The C and Matlab codes for CEC'14 test suite can be downloaded from the website given below:

http://www.ntu.edu.sg/home/EPNSugan/index_files/CEC2014

1. Introduction to the 24 CEC'14 expensive optimization test problems

1.1 Summary of CEC'14 expensive optimization test problems

Eight popular test functions are used. The test suites include unimodal / multi-modal, continuous / discrete and separable / non-separable functions. All test functions are scalable and 10 decision variables, 20 decision variables and 30 decision variables are used.

Most functions are shifted and / or rotated. For a problem with D dimensions, the global optimum is shifted by $o_i = [o_{i1}, o_{i2}, \dots, o_{iD}]$, and o_i is randomly distributed in $[-10, 10]^D$. The shifted data are

defined in “shift_data_x.txt”. The rotation matrixes M are defined in “M_x_D.txt”, where x is the number of basic functions.

The test problems are summarized in Table I.

Table I. Summary of the CEC’ 14 expensive optimization test problems

No.	Functions	Dimensionality	Search ranges	$f_i^* = f_i(x^*)$
1-3	Shifted Sphere function	10, 20, 30	[-20,20]	0
4-6	Shifted Ellipsoid function	10, 20, 30	[-20,20]	0
7-9	Shifted and Rotated Ellipsoid function	10, 20, 30	[-20,20]	0
10-12	Shifted Step function	10, 20, 30	[-20,20]	0
13-15	Shifted Ackley’s function	10, 20, 30	[-32,32]	0
16-18	Shifted Griewank’s function	10, 20, 30	[-600,600]	0
19-21	Shifted Rotated Rosenbrock’s function	10, 20, 30	[-20,20]	0
22-24	Shifted Rotated Rastrigin’s function	10, 20, 30	[-20,20]	0

Please notice: These problems should be treated as black-box optimization problems and without any prior knowledge. Neither the analytical equations nor the problem landscape characters extracted from analytical equations are allowed to be used, except the continuous / integer decision variables. However, the dimensionality and the number of available function evaluations can be considered as known values and can be used.

1.2 Definitions of CEC’14 expensive optimization test problems

1) Shifted Sphere function

$$f_1(\mathbf{x}) = \sum_{i=1}^D x_i^2$$

$$F_1(\mathbf{x}) = f_1(x - o_{1,10d}) : D = 10$$

$$F_2(\mathbf{x}) = f_1(x - o_{1,20d}) : D = 20$$

$$F_3(\mathbf{x}) = f_1(x - o_{1,30d}) : D = 30$$

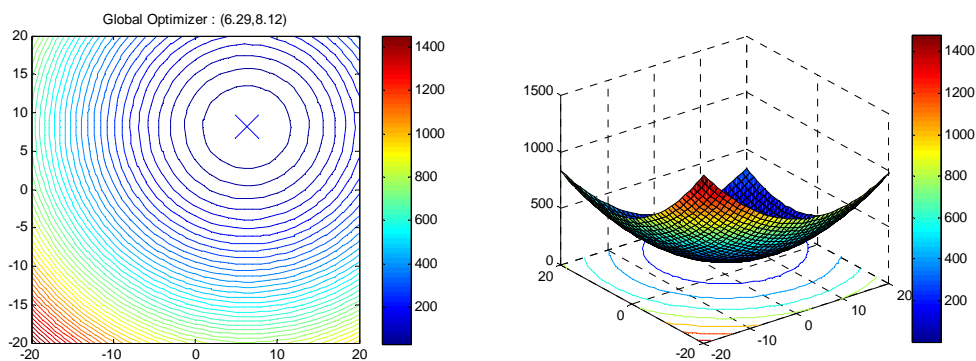


Figure 1. 3-D map for 2-D Shifted Sphere function

Properties:

- Unimodal

2) Shifted Ellipsoid function

$$f_2(\mathbf{x}) = \sum_{i=1}^D ix_i^2$$

$$F_4(\mathbf{x}) = f_2(x - o_{2,10d}) : D = 10$$

$$F_5(\mathbf{x}) = f_2(x - o_{2,20d}) : D = 20$$

$$F_6(\mathbf{x}) = f_2(x - o_{2,30d}) : D = 30$$

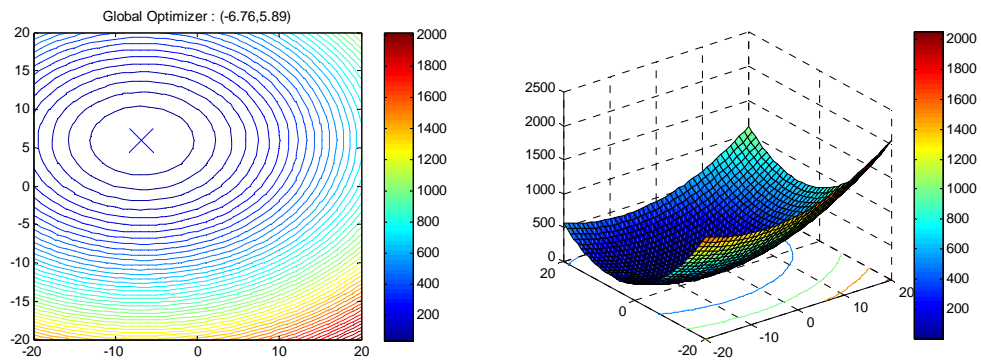


Figure 2. 3-D map for 2-D Shifted Ellipsoid function

Properties:

- Unimodal

3) Shifted and Rotated Ellipsoid function

$$F_7(\mathbf{x}) = f_2(\mathbf{M}_{1,10d}(x - o_{3,10d})) : D = 10$$

$$F_8(\mathbf{x}) = f_2(\mathbf{M}_{1,20d}(x - o_{3,20d})) : D = 20$$

$$F_9(\mathbf{x}) = f_2(\mathbf{M}_{1,30d}(x - o_{3,30d})) : D = 30$$

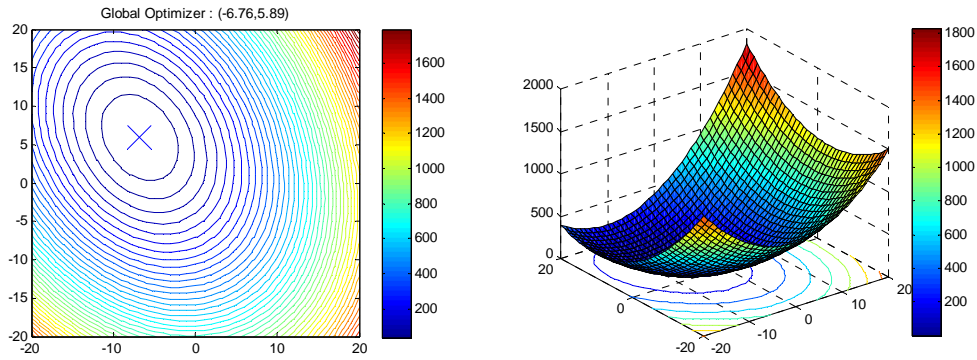


Figure 3. 3-D map for 2-D Shifted and Rotated Ellipsoid function

Properties:

- Unimodal

4) Shifted Step function

$$f_3(\mathbf{x}) = \sum_{i=1}^D (\lfloor x_i + 0.5 \rfloor)^2$$

$$F_{10}(\mathbf{x}) = f_3(\mathbf{x} - o_{4,10d}) : D = 10$$

$$F_{11}(\mathbf{x}) = f_3(\mathbf{x} - o_{4,20d}) : D = 20$$

$$F_{12}(\mathbf{x}) = f_3(\mathbf{x} - o_{4,30d}) : D = 30$$

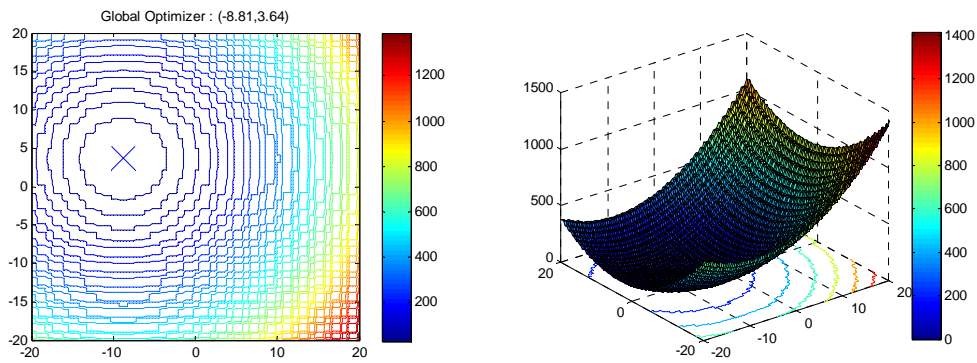


Figure 4. 3-D map for 2-D Shifted Step function

Properties:

- Unimodal
- Discontinuous

5) Shifted Ackley's function

$$f_4(\mathbf{x}) = -20 \exp(-0.2 \sqrt{\frac{1}{D} \sum_{i=1}^D x_i^2}) - \exp(\frac{1}{D} \sum_{i=1}^D \cos(2\pi x_i)) + 20 + e$$

$$F_{13}(\mathbf{x}) = f_4(x - o_{5,10d}) : D = 10$$

$$F_{14}(\mathbf{x}) = f_4(x - o_{5,20d}) : D = 20$$

$$F_{15}(\mathbf{x}) = f_4(x - o_{5,30d}) : D = 30$$

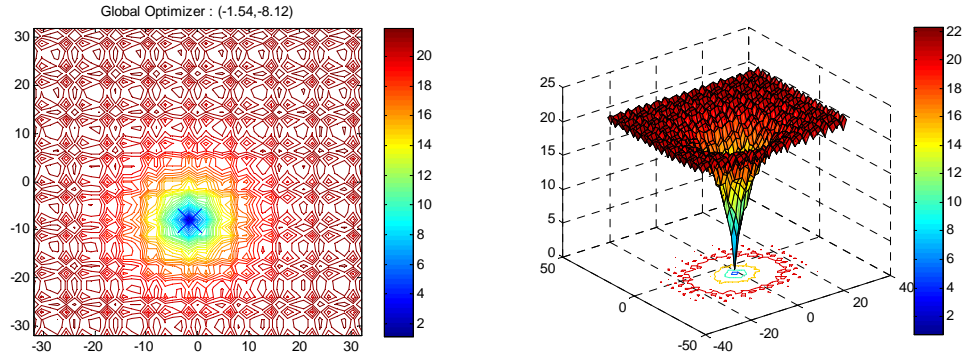


Figure 5. 3-D map for 2-D Shifted Ackley's function

Properties:

- Multi-modal

6) Shifted Griewank's function

$$f_5(\mathbf{x}) = \sum_{i=1}^D \frac{x_i^2}{4000} - \prod_{i=1}^D \cos(\frac{x_i}{\sqrt{i}}) + 1$$

$$F_{16}(\mathbf{x}) = f_5(x - o_{6,10d}) : D = 10$$

$$F_{17}(\mathbf{x}) = f_5(x - o_{6,20d}) : D = 20$$

$$F_{18}(\mathbf{x}) = f_5(x - o_{6,30d}) : D = 30$$

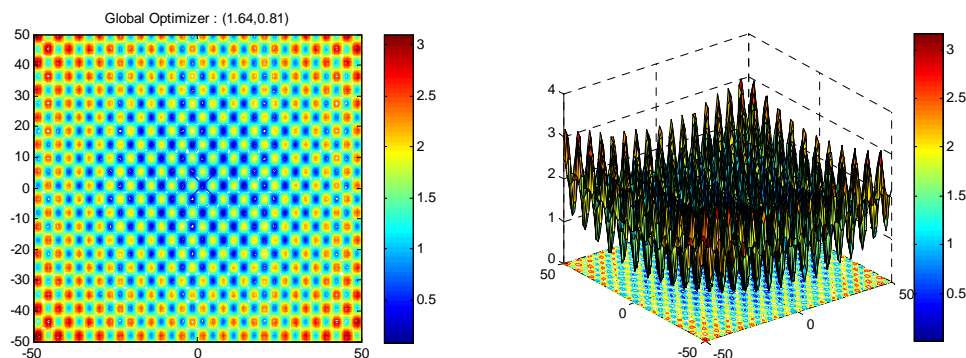


Figure 6. 3-D map for Shifted 2-D Griewank's function

Properties:

➤ Multi-modal

7) Shifted and Rotated Rosenbrock's function

$$f_6(\mathbf{x}) = \sum_{i=1}^{D-1} (100(x_i^2 - x_{i+1})^2 + (x_i - 1)^2)$$

$$F_{19}(\mathbf{x}) = f_6\left(M_{2,10d}\left(\frac{2.048(x - o_{7,10d})}{20}\right) + 1\right) : D = 10$$

$$F_{20}(\mathbf{x}) = f_6\left(M_{2,20d}\left(\frac{2.048(x - o_{7,20d})}{20}\right) + 1\right) : D = 20$$

$$F_{21}(\mathbf{x}) = f_6\left(M_{2,30d}\left(\frac{2.048(x - o_{7,30d})}{20}\right) + 1\right) : D = 30$$

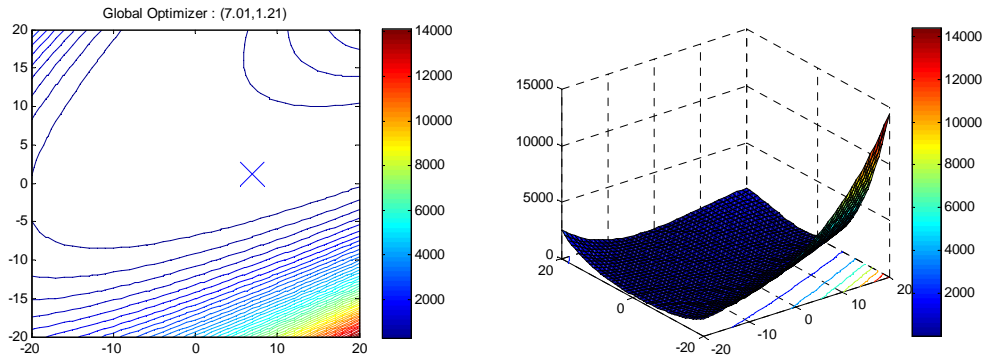


Figure 7. 3-D map for 2-D Shifted and Rotated Rosenbrock's function

Properties:

- Multi-modal
- Non-separable
- Having a very narrow valley from local optimum to global optimum

8) Shifted and Rotated Rastrigin's function

$$f_7(\mathbf{x}) = \sum_{i=1}^D (x_i^2 - 10 \cos(2\pi x_i) + 10)$$

$$F_{22}(\mathbf{x}) = f_7\left(M_{3,10d}\left(\frac{5.12(x - o_{8,10d})}{20}\right)\right) : D = 10$$

$$F_{23}(\mathbf{x}) = f_7\left(M_{3,20d}\left(\frac{5.12(x - o_{8,20d})}{20}\right)\right) : D = 20$$

$$F_{24}(\mathbf{x}) = f_7\left(M_{3,30d}\left(\frac{5.12(x - o_{8,30d})}{20}\right)\right) : D = 30$$

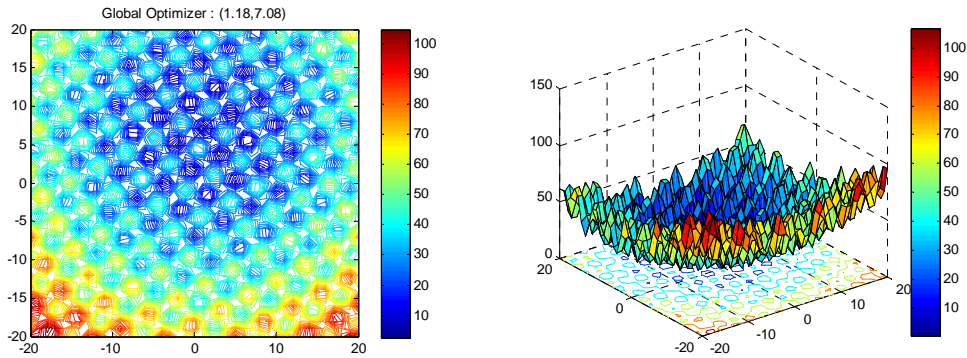


Figure 8. 3-D map for 2-D Shifted and Rotated Rastrigin's function

Properties:

- Multi-modal

2. Evaluation criteria

2.1 Experimental setting:

- Number of independent runs: 20
- Maximum number of exact function evaluations:
 - 10-dimensional problems: 500
 - 20-dimensional problems: 1,000
 - 30-dimensional problems: 1,500
- Initialization: Any problem-independent initialization method is allowed.
- Global optimum: All problems have the global optimum within the given bounds and there is no need to perform search outside of the given bounds for these problems.
- Termination: Terminate when reaching the maximum number of exact function evaluations or the error value ($f_i^* - f_i(x^*)$) is smaller than 10^{-8} .

2.2 Results to record:

(1) Current best function values:

Record current best function values using $0.1 \times \text{MaxFES}$, $0.2 \times \text{MaxFES}$, ..., MaxFES for each run. Sort the obtained best function values after the maximum number of exact function evaluations from the smallest (best) to the largest (worst) and present the best, worst, mean, median and standard deviation values for the 20 runs. Error values smaller than 10^{-8} are taken as zero.

(2) Algorithm complexity:

For expensive optimization, the criterion to judge the efficiency is the obtained best result vs. number of exact function evaluations. But the computational overhead on surrogate modeling and search is also considered as a secondary evaluation criterion. Considering that for different data sets, the computational overhead for a surrogate modeling method can be quite different, the computational overhead of each problem is necessary to be reported. Often, compared to the computational cost on surrogate modeling, the cost on 500, 1000 and 1500 function evaluations can almost be ignored. Hence, the following method is used:

a) Run the test program below:

```
for i=1:1000000
    x= 0.55 + (double) i;
    x=x + x; x=x/2; x=x*x; x=sqrt(x); x=log(x); x=exp(x); x=x/(x+2);
end
Computing time for the above= $T_0$ ;
```

b) The average complete computing time for the algorithm = \hat{T}_1 . The complete computing time refers to the computing time using MaxFEs except that the global optimum is reached with less than MaxFEs evaluations.

The complexity of the algorithm is measured by: \hat{T}_1/T_0 .

(3) Parameters:

Participants are requested not to search for the best distinct set of parameters for each problem/dimension/etc. Please provide details on the following whenever applicable:

- a) All parameters to be adjusted
- b) Corresponding dynamic ranges
- c) Guidelines on how to adjust the parameters
- d) Estimated cost of parameter tuning in terms of number of FEs
- e) Actual parameter values used.

(4) Encoding

If the algorithm requires encoding, then the encoding scheme should be independent of the specific problems and governed by generic factors such as the search ranges, dimensionality of the problems, etc.

(5) Results format

The participants are required to send the final results as the following format to the organizers and the organizers will present an overall analysis and comparison based on these results.

Create one txt document with the name "AlgorithmName_FunctionNo._D_expensive.txt" for each test function and for each dimension. For example, PSO results for test function 5 and $D=30$, the file name should be "PSO_5_30_expensive.txt".

The txt document should contain the mean and median values of current best function values when $0.1 \times \text{MaxFES}$, $0.2 \times \text{MaxFES}$, ..., MaxFES are used of all the 20 runs. The participant can save the results in the matrix shown in Table II and extracts the mean and median values.

Table II Information matrix for function X

	$0.1 \times \text{MaxFES}$	$0.2 \times \text{MaxFES}$...	MaxFES
Run 1				
Run 2				
...				
Run 20				

Notice: All participants are allowed to improve their algorithms further after submitting the initial version of their papers to CEC2014. They are required to submit their results in the introduced format to the organizers after submitting the final version of paper as soon as possible. Considering the surrogate modeling for 30 dimensional functions is often time consuming, especially for MATLAB users, results using 10 runs are requested for initial submission.

2.3 Results template

Language: Matlab 2008a

Algorithm: Surrogate model assisted evolutionary algorithm A

Results

Notice:

Considering the length limit of the paper, only Error Values Achieved with MaxFES are need to be listed.

Table III. Results for 10D

Problem No.	Best	Worst	Median	Mean	Std
F1					
F4					
F7					
F10					
F13					
F16					
F19					
F22					

Table IV. Results for 20D

...

Table V. Results for 30D

Algorithm Complexity

Table VI. Computational Complexity

Problem No.	\hat{T}_1/T_0
F1	
F2	
...	
F23	
F24	

Parameters

- All parameters to be adjusted
- Corresponding dynamic ranges
- Guidelines on how to adjust the parameters
- Estimated cost of parameter tuning in terms of number of FES
- Actual parameter values used

2.4 Sorting method

The mean and median values at the maximum allowed number of evaluations will be used. For each problem, the algorithm with the best result scores 9, the second best scores 6, the third best scores 3 and all the others score 0.

$$\text{Total score} = \sum_{i=1}^{24} \text{score}_i \text{ (using mean value)} + \sum_{i=1}^{24} \text{score}_i \text{ (using median value)}$$

The top three winners will be announced.

Special attention will be paid to which algorithm has advantages on which kind of problems, considering dimensionality and problem characteristics.