

# Performance Measures of Metaheuristic Algorithms

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**Abstract** Generally speaking, it is not fully understood why and how metaheuristic algorithms work very well under what conditions. It is the intention of this paper to clarify the performance characteristics of some of popular algorithms depending on the fitness landscape of specific problems. This study shows the performance of each considered algorithm on the fitness landscapes with different problem characteristics. The conclusions made in this study can be served as guidance on selecting algorithms to the problem of interest.

**Keywords** Fitness landscape · Metaheuristic algorithms · Nature-Inspired algorithms · Optimization · Performance measures

## 1 Introduction

Numerous optimization algorithms have been proposed to tackle a number of problems that cannot be solved analytically. Generally, a newly developed algorithm is compared with a set of existing algorithms with respect to their performances on a set of well-known benchmark functions. The development is considered as a success if the new algorithm outperforms the existing algorithms considered. However, conventional benchmark test problems have a limited range of fitness landscape structure (e.g., the number and height of big valley), which makes it difficult to investigate the performance of newly developed algorithm on

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the landscape with specific geometric property [1-2]. Therefore, previous studies provided little guidance for practitioners on selecting the best-suitable algorithm to the problem of interest [3-4].

Recently, a fitness landscape generator proposed by Gallagher and Yuan [5] has drawn attention in the study of various nature-inspired algorithms. The proposed landscape generator is used to generate optimization solution surfaces for continuous, boundary-constrained optimization problems and parameterized by a small number of parameters each of which controls a particular geometric feature of the generating landscapes. Therefore, by using the generator, a number of fitness landscapes of various geometric features can be generated and used for the full investigation of relative strengths and weaknesses of algorithms. General guidance on the algorithm selection can be extracted from the results of the investigations.

This paper compared the performances of eight optimization algorithms using fitness landscapes generated by a modified Gaussian fitness landscape generator originally proposed in Gallagher and Yuan [5]. Eight algorithms are compared with respect to their expected performance and the performance variation (performance reliability). Radar plots of several algorithms were drawn and compared to indicate the level of the two performance measures.

## 2 Methodology

The following sections describe the selected eight algorithms, methodologies for test problem generation, and performance measures and its visualizations.

### 2.1 Algorithm Selection

In this study, total of eight optimization algorithms are compared with respect to their performances on generated fitness landscapes. Eight algorithms are listed as follows: random search (RS) as a comparison target, simulated annealing (SA) [6], particle swarm optimization (PSO) [7], water cycle algorithm (WCA) [8], genetic algorithms (GAs) [9], differential evolution (DE) [10], harmony search (HS) [11, 12], and cuckoo search (CS) [13]. Most algorithms were inspired by nature phenomena or animal behavior and their fundamental optimization mechanisms are based on generating new solutions while adopting different strategies for the task.

RS keeps randomly generating new solutions within the allowable range until stopping criteria are met. SA, inspired by annealing process in metallurgy, moves the current state (solution) of a material to some neighboring state with a probability that depends on two energy states and a temperature parameter. PSO simulates social behavior of organisms in a bird flock or fish school in which particles in a swarm (solutions in a population) are guided by their own best position as well as the entire swarm's best known position. WCA mimics the river network generation process where streams are considered as candidate solutions. GAs has gained

inspiration from natural adaptive behaviors, i.e., "the survival of the fittest". In DE, a new solution is generated by combining three existing randomly selected solutions from the population. HS was inspired by the musical ensemble and contains a solution storage function called harmony memory. CS was inspired by the obligate brood parasitism of some cuckoo species and their various strategies for choosing the nest to lay their eggs.

For more details on the algorithm, please refer to the references supplied above.

## 2.2 Test Problem Generation

To test and compare a newly developed metaheuristic algorithm, several well-known benchmark problems (e.g., Ackley and Rosenbrock functions) have been used [14-17]. In this study, however, a set of fitness landscapes was generated using a Gaussian fitness landscape generator proposed in Gallagher and Yuan [5] and used for testing the reported algorithms. In the generator, a set of  $n$ -dimensional Gaussian functions are combined to generate a  $n$ -dimensional fitness landscape where "the value of a point is given by the maximum value of any of the Gaussian components at that point" [5].

There are several advantages of using such fitness landscape generators compared to using classical benchmark problems [3]. First, the structure of test problems can be easily tunable by a user by altering a small number of parameters. Therefore, general conclusions on the performance of an algorithm can be made by relating its performance to the fitness landscapes in the specific structures. Finally, a large number of fitness landscapes in similar structure can be generated and used to increase the reliability of comparison results. The generated landscape provides a platform for consistent comparison of the eight algorithms listed in Section 2.1.

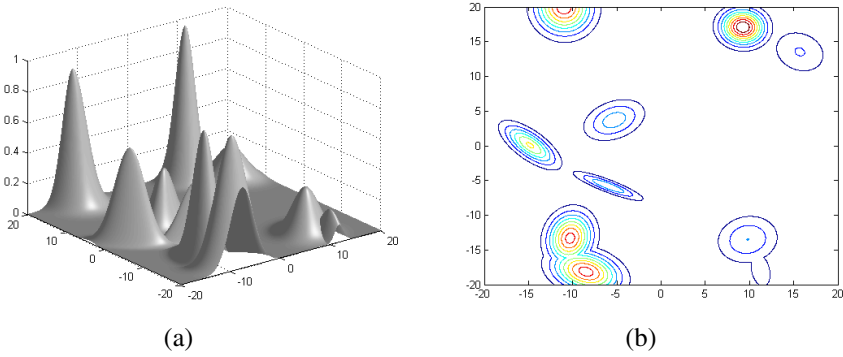
We considered two new parameters in the Gallagher and Yuan's Gaussian landscape generator to additionally manipulate the structure of big valley and the range of optimums. The modified generator has six input parameters:  $n$ ,  $m$ ,  $ul$ ,  $r$ ,  $w$ , and  $d$ .  $n$  indicates the dimensionality of the generated landscape, while  $m$  sets the number of local optimum.  $ul$  defines the rectangular boundary of the solution space.  $r$  indicates the ratio between the fitness values of the best possible local optimum and the global optimum.  $w$  is an identical component in the covariance matrix of the Gaussian functions and controls the orientation and shape of each valley in the landscape. Finally,  $d$  defines the boundary of the centers of Gaussian components.

Total of twenty-four landscapes were generated using the default parameters (bold numbers in Table 1) of four dimensions ( $n = 4$ ), three local optimums ( $m = 3$ ), the Euclidean distance between the upper and lower limits of 20 ( $-10 \leq \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \leq 10$  for the 2-D problem), average ratio of local optimum to global optimum of 0.3,  $w = 0.03$ , and  $d = 0.6$ , with only changing a single parameter's value for each landscape.

**Table 1** Parameters in the modified Gaussian fitness landscape generator

Parameter	Values used
$n$ (dimensionality)	[2, <b>4</b> , 6, 8]
$m$ (number of local optima)	[0, <b>3</b> , 6, 9]
$ul$ (interval span of side constraints)	[10, <b>20</b> , 30, 40]
$r$ (ratio of local optima)	[0.1, <b>0.3</b> , 0.6, 0.9]
$w$ (valley structure coefficient)	[0.01, <b>0.03</b> , 0.06, 0.09]
$d$ (peak density ratio)	[0.4, <b>0.6</b> , 0.8, 1.0]

Fig. 1 shows the 2-D fitness landscape generated using the maximum parameters ( $m = 9$ ,  $ul = 40$ ,  $r = 0.9$ ,  $w = 0.09$ , and  $d = 1.0$ ). Therefore, there exist ten peaks that include nine local optimums and one global optimum. As entered inputs, the heights of nine local optimums were lower than 0.9, while global maximum is 1.0. The range of two decision variables varies from -20 to 20, while the height of peaks is bounded within  $\pm 20$  (i.e.,  $\pm 1.0 \times 20$ ).



**Fig. 1** A 2-D landscape generated by the Gaussians landscape generator: (a) surface plot, and (b) contour plot

### 2.3 Performance Measures and Their Visualizations

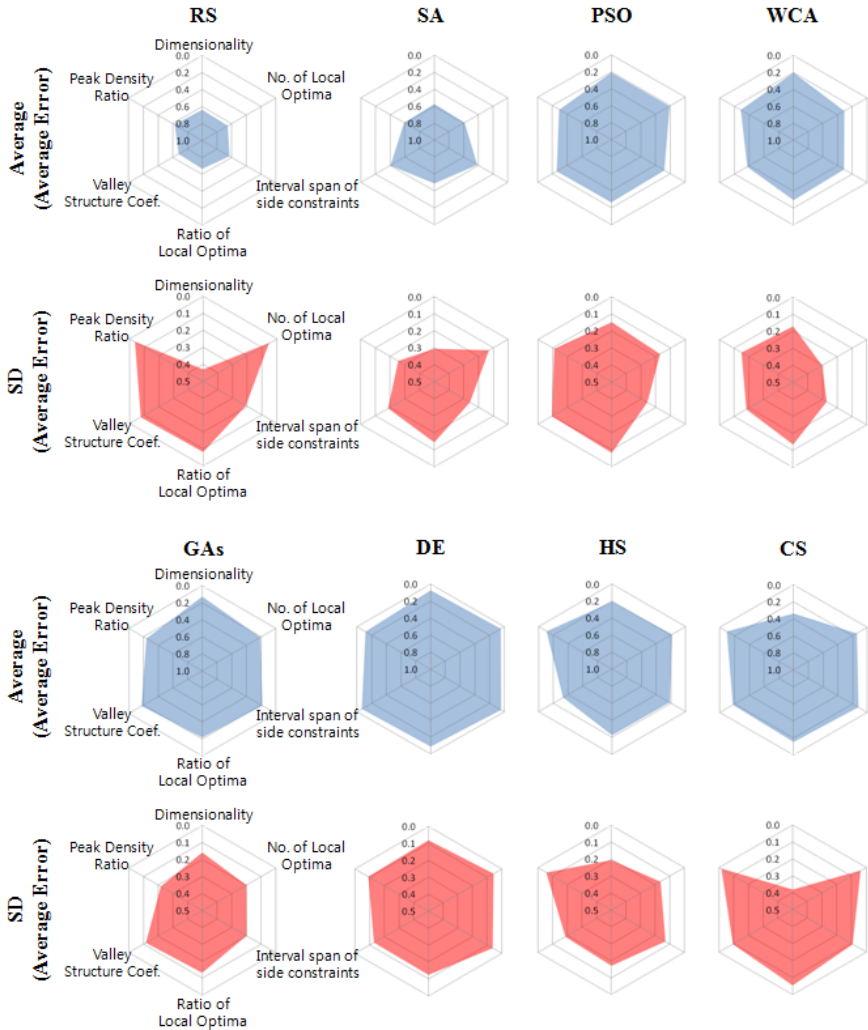
We ran each algorithm for 20 times on each landscape in the twenty-four landscapes each of which represents each particular characteristic structure. Stochastic natures of the algorithms result in the different optimal solution from each optimization. In this study, therefore, we compared the expected performance and reliability of each algorithm to changing landscape structures, in the form of a radar plot as shown in Fig. 2. The former is measured by the averaged fitness distance (error) of final solutions from the known global optimum. On the other hand, the reliability of each algorithm is quantified by the standard deviation (SD) of the average error. Therefore, more robust algorithm results in smaller standard deviations of the error.

A radar plot is in the form of hexagon where six axes connect the center and corners of hexagon. The values of performance measures decrease from the center to the corners of hexagon. Algorithm's performance on a particular characteristic structure is represented by positioning each corner of the colored hexagon. Therefore, an algorithm with larger surface area has better performance.

### 3 Optimization Results

For each of the twenty optimization trials, independent initial population is randomly generated. The maximum number of function evaluations (NFEs) was set as 2,500 and consistently used as a stopping criterion for each reported algorithm.

Fig. 2 shows radar plots indicating average error (blue areas in Fig. 2) and the standard deviation (SD) of the average error (red areas in Fig. 2) for each of eight algorithms with respect to different landscape features. Values close to the corners of the hexagon indicate a smaller value of the average error and the SD in the blue and red areas, respectively. Therefore, a robust algorithm has a large surface area.



**Fig. 2** Radar plots indicating average error (blue surfaces) and the SD of the average error (red surfaces) for each of eight algorithms with respect to different landscape features

The largest surface area was observed from DE. The average errors in DE are very close to zero for all fitness landscapes, also showing robust performances for SD (standard deviations are close to zero). PSO, GAs, and HS have shown overall good performances and outperformed the rest of the algorithms. HS was especially good in the fitness landscape with wide-spreading local optimums. The performance of PSO and WCA were variable in the wide fitness landscapes compared to its performances in other landscapes. CS performed poorly at the high dimensional landscapes (its performance variation was also large). The worst algorithm with the smallest surface area in the blue and red radar plots was RS. Its average errors are around 0.6 regardless of the landscape features. SA with having the largest values of average error and standard deviation has been placed in one before the last ranking after RS.

In this paper, all reported algorithms do not use the derivative information for finding the global solution. Therefore, by altering the ratio of local optima, we should witness no meaningful change in their performances. As can be seen from Fig. 2, for all ratio parameters, RS demonstrates similar performances as it selects new solutions randomly from the entire search space. Algorithms with possessing features of strong global search such as DE and GAs show better performances to avoid being stuck in local optima.

## 4 Conclusions

This paper has compared the performances of eight optimization algorithms using fitness landscapes generated by a modified Gaussian fitness landscape generator. The modified generator can produce a fitness landscape with particular geometric features. The eight algorithms, namely as RS, SA, PSO, WCA, GAs, DE, HS, and CS, are compared with respect to their expected performances and performance variations (performance reliability). A radar plot was drawn to indicate the level of the two performance measures.

This study has several limitations that future research should be addressed. First, this study has compared the original version of the algorithms, while a number of improved versions have been released in the last two decades. Therefore, the most effective improved versions should be selected for each algorithm and compared to investigate the impact of the improvement on the original algorithm performance. Second, in order to provide full guidance for selecting an algorithm, more algorithms including recently developed algorithms need to be included for having comprehensive comparison. Finally, the optimization results presented in this study were obtained under fixed value for number of function evaluations (NFEs). Because the allowed NFEs limits the performance of some algorithms, therefore, the sensitivity analyses on different NFEs (i.e., higher NFEs) will be performed to examine the radar plots and efficiency of the algorithms.

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