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EVALUATION OF THE PERFORMANCES OF ARTIFICIAL BEE COLONY AND INVASIVE WEED OPTIMIZATION ALGORITHMS ON THE MODIFIED BENCHMARK FUNCTIONS

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ABSTRACT

In this paper, the performances of the Artificial Bee Colony (ABC) Algorithm and Invasive Weed Optimization (IWO) Algorithm are compared on the basis of modified versions of five well known benchmark functions. The modifications are performed on these functions in order to get rid of the symmetrical properties of the selected functions. Further a solution space is shifted so that the optimal function values are not equal to zero. The experimental results have shown that the ABC algorithm outperforms the IWO algorithm on the modified versions of the benchmark functions.

Keywords: swarm intelligence, optimization algorithm, Artificial Bee Colony Algorithm, Invasive Weed Optimization Algorithm

INTRODUCTION

In the past decades many different metaheuristic optimization algorithms have been developed. All of the proposed algorithms and their modified versions present good results for specific types of problems. On the other hand, classical benchmark problems are well known by the optimization community and are used to examine the performance of a proposed algorithm or a proposed modification on the existing algorithms (Yao et al., 1999). But, it is also recognized that some heuristic operators of the algorithms may exploit some special properties of these benchmark functions (Ahrari et al., 2010).

In this work, five of the classical benchmark problems are modified in order to get rid of some special properties that can be exploited by some heuristic operators. These modifications are aimed to satisfy the following requirements (Liang et al. 2005) : (1) Global optimum point is not at the origin; (2) Optimum parameter value is different for each variable; and (3) Optimum parameter value is not lying in the center of the search range.

Artificial Bee Colony Algorithm is one of the recently introduced swarm-based algorithms which is proposed by Karaboga (Karaboga &Akay, 2009). The algorithm simulates the behaviour of a honey bee swarm. In the literature, the algorithm is applied to the optimization of many unimodal and multimodal numerical functions (Yao et al., 1999). The algorithm is also compared with the other well known algorithms in the literature (Karaboga &Akay, 2009), (Karaboga & Basturk, 2007).

Invasive Weed Optimization is an optimization algorithm which is inspired from colonizing weeds. It is known that weeds are very robust to environmental changes and also they can easily adapt themselves to environmental changes. This algorithm is designed in order to mimic the robustness, adaptation and randomness of colonizing weeds. The experimental results obtained in the literature through the use of this algorithm have shown that the algorithm is a powerful algorithm (Mehrabian & Lucas, 2006).

In this study, these two algorithms are compared on the basis of five modified benchmark functions. The results that are tabulated in the experimental results section, clearly demonstrate that the ABC algorithm performs better than IWO algorithm for many of these functions.

ARTIFICIAL BEE COLONY ALGORITHM

ABC is developed based on the observation of the behaviour of honeybees on their finding of nectar and sharing this information to the other honeybees in the hive. In this algorithm, three groups of bees have been defined for finding food source. These are called as employed bees, onlooker bees and scout bees (Karaboga &Akay, 2009). The algorithm consists of three steps which are sending the employed bees onto their food sources and evaluating their nectar amounts; after sharing the nectar information of food sources, the selection of food source regions by the onlooker bees and evaluating the nectar amount of the food sources; determining the scout bees and then sending them randomly onto possible new food sources (Karaboga&Akay, 2009). In this algorithm, the position of a food source represents a possible solution to the optimization problem and the nectar amount of a food source corresponds to the fitness of the associated solution (Karaboga&Akay, 2009). The number of the employed bees or the onlooker bees is equal to the number of solutions in the population (Karaboga&Akay, 2009).

The code of the ABC algorithm can be given as follows:

1: Initialize the population of solutions $x_i, i = 1, \ldots, SN$

2: Evaluate the population

3: cycle = 1

4: repeat

5: Produce new solutions v_i for the employed bees using the evaluation $v_{ij} = \phi_{ij}(x_{ij} - x_{kj})$ and evaluate them

6: Apply the greedy selection process for the employed bees

7: Calculate the probability values P_i for the solutions x_i using the evaluation $P_i = \frac{fit_i}{\sum_{n-1}^{SN} fit_n}$

8: Produce the new solutions v_i for the onlookers from the solutions x_i selected depending on P_i and evaluate them

9: Apply the greedy selection process for the onlookers

10: Determine the abandoned solution for the scout, if exists, and replace it with a new randomly produced solution x_i using the evaluation $x_i^j = x_{\min}^j + rand[0,1](x_{\max}^j - x_{\min}^j)$

11: Memorize the best solution achieved so far

12: cycle = cycle + 1

13: until cycle = MCN

INVASIVE WEED OPTIMIZATION ALGORITHM

This algorithm is mainly simulating the behaviour of colonizing weeds. The algorithm has mainly four steps which can be explained briefly as follows:

Initialization

A generation of a population of initial solutions randomly in the region of interest.

Reproduction

Based on the fitness of the plant (initial solution), the new seeds (new solutions) will be reproduced. The number of seeds generated for each plant is proportional to the fitness of it.

Spatial Dispersal

The new generated seeds for each plant are randomly distributed near to their parent plant. The closeness of the seeds to their parent plant is changing as the numbers of iterations are changing.

Competitive Exclusion

It is the mechanism of eliminating the plants with lower fitness in the generation after the number of plants (solutions) reaches the maximum number of plants in the colony. It is the ranking of the generated seeds together with their parent's according to their fitness values and selecting the ones with higher fitness values. Figure. 1 shows the flowchart of the IWO.

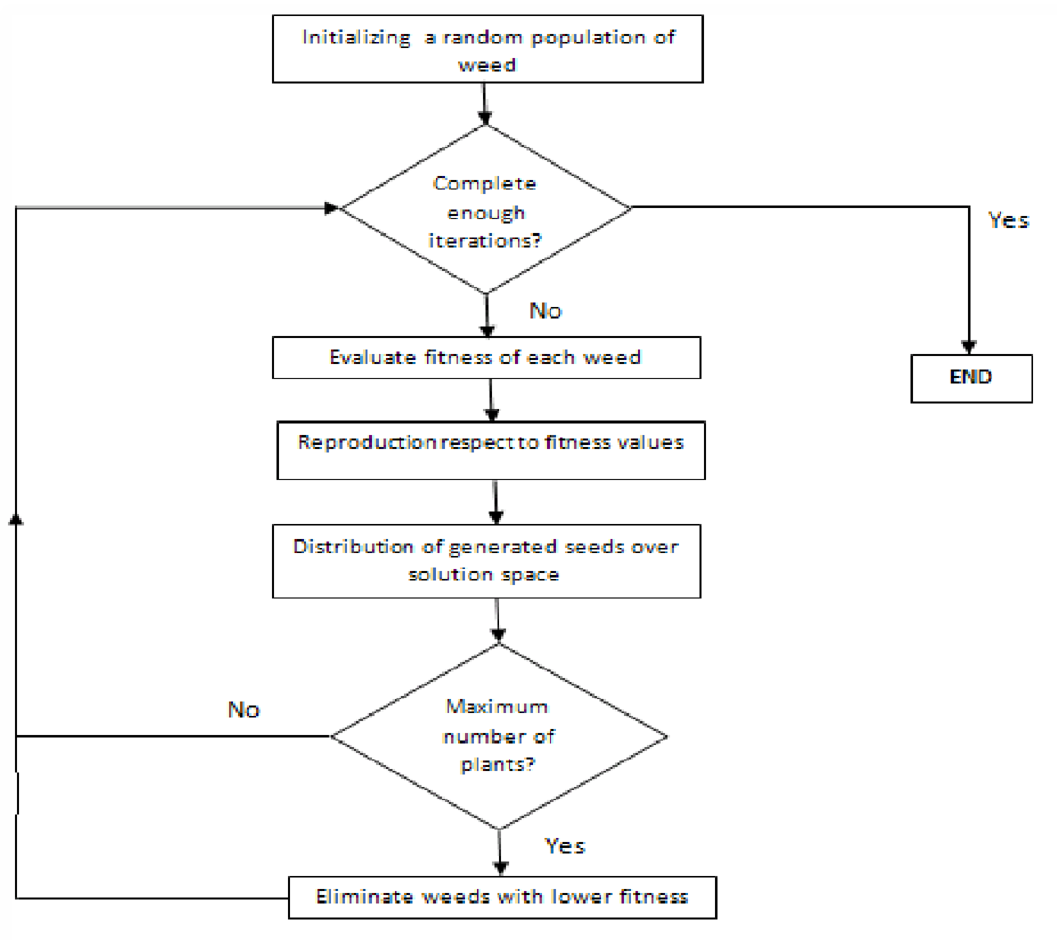

Figure 1.Flow chart depicting the IWO algorithm

EXPERIMENTAL RESULTS

In this paper, our aim is to compare the performances of the ABC algorithm and the IWO algorithm on some well-known benchmark functions. Five of them are selected in such a way that some of them are unimodal and the others are multimodal. The experiments that we performed have shown us that each of the two algorithms outperforms the other one on different classical benchmark functions. In order to test the effect of some special properties of the classical benchmark functions on these results we modified the selected functions. The modifications are done in such a way that the solution spaces are shifted and also symmetrical properties of them are changed which are the main concerns in literature for the modification of the benchmark functions (Liang et al. 2005), (Ahrari et al., 2010).These five benchmark functions are modified in this study and are presented in Table 1.

Table 1.Modified Benchmark Functions

	Function	*Range*	$f_{\min}$
Modified Sphere Function	$\sum_{i=1}^{N}\left(\left(x_i+(-1)^i ik\right)^2-(-1)^i\frac{N}{i}\right)$ k=3.125	[-100,100]	20.3027
Modified Rosenbrock Function	$\sum_{i=1}^{N-1}\left(400\left(\left(x_{i+1}-\frac{i+1}{2}(-1)^{i+1}\right)-\left(x_i-\frac{i}{2}(-1)^i\right)^2\right)^2+\left(x_i-\frac{i}{2}(-1)^i\right)^2+i\right)$	[-30,30]	435
Modified Quartic Function	$\sum_{i=1}^{N}\left(i\left(x_i-(-1)^i ki\right)^4\right)+\left(\frac{1}{(2i)}\right)+random\ [0,1)$ k=0.02	[-1.28,1.28]	1.99749
Modified Schwefel Function	$\sum_{i=1}^{N}-\left(x_i-(-1)^i\frac{i^2}{40}\right)\sin\left(\sqrt{\left\lvert x_i-(-1)^i\frac{i^2}{40}\right\rvert}\right)+\frac{1}{(2i)}$	[-500,500]	-12571.4841
Modified Griewank Function	$\sum_{i=1}^{N}\left(x_i+(-1)^i\frac{(i)^2}{2}k\right)^2-4000*\prod_{i=1}^{N}\cos\left[\frac{\left(x_i+(-1)^i\frac{(i)^2}{2}k\right)}{\sqrt{i}}\right]+i$ k=0.6	[-600,600]	-3535

In all the following experimental results the dimension of each function is fixed to 30. Because of random initialization for both of the algorithms, the programs run for 30 times and the best, the worst and the average of these 30 runs are presented. Table 2 and Table 3 shows the results obtained for the modified sphere function using the IWO algorithm and the ABC algorithm respectively with respect to function evaluations. These values are obtained by changing the value of the control parameters of each algorithm and selecting the most suitable control parameters in their defined range.

Table 2.The average, worst and best results of the ABC algorithm using Modified Sphere function

Function evaluation (x100)	*500*	*1000*	*2000*	*3000*	*5000*
Average	20.9926	20.30278	20.30275	20.30275	20.3027
Worst	21.7086	20.30280	20.30275	20.30275	20.3027
Best	20.6401	20.30276	20.30275	20.30275	20.3027

Table 3.The average, worst and best results of IWO algorithm using Modified Sphere function

Function evaluation(x100)	*500*	*1000*	*2000*	*3000*	*5000*
Average	207.748581	39.242928	21.084526	21.001790	21.000887
Worst	236.971338	42.365160	21.097156	21.002199	21.001015
Best	161.451039	33.910898	21.057873	21.001587	21.000618

In Figure 2, we plotted the average function value obtained for both of the methods with respect to the number of function evaluations. This step is performed for all 5 modified benchmark functions and the results obtained after 5000(x100) function evaluations are given in Table 4 for both of the algorithms.

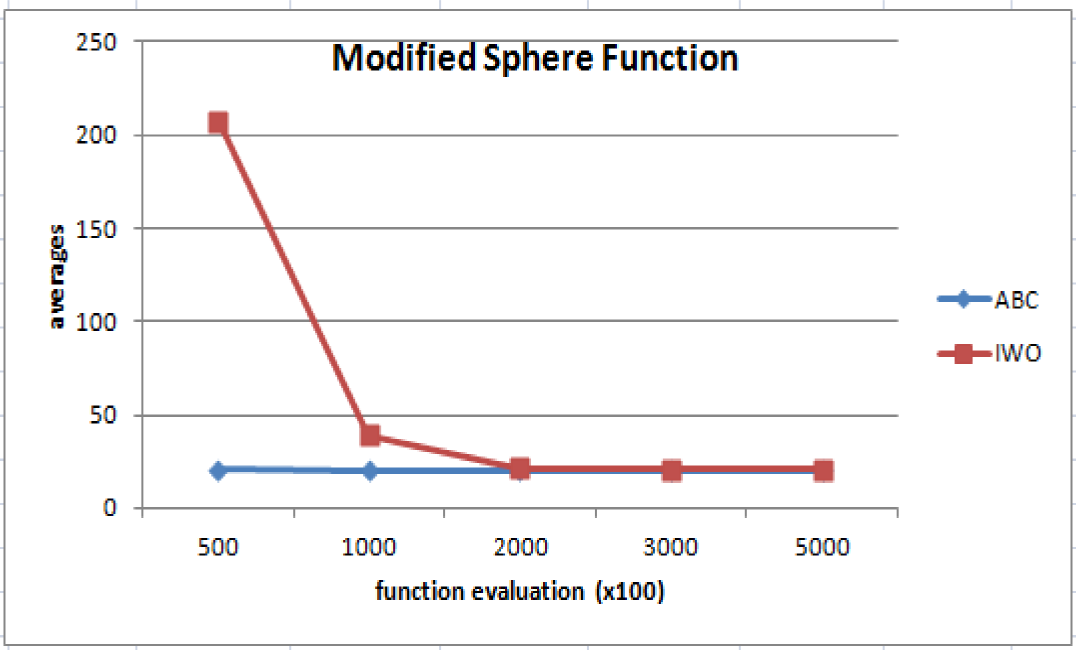

Figure 2.Modified Sphere function for ABC and IWO algorithms

DISCUSSION AND CONCLUSION

It is observed that the convergence speed of the ABC algorithm is better than the convergence speed of the IWO algorithm for the modified sphere function as can be seen from Table 2 and Table 3. This observation is also supported by results obtained for the other modified functions. Table 4 shows the best function values obtained by a fixed number of function evaluations. These results also show that the ABC algorithm has better performance than the IWO algorithm. The values that are obtained by the ABC algorithm are the exact global solutions for the modified sphere and modified Griewank functions while the IWO algorithm could not reach to optimal values. For other three functions the ABC algorithm reaches values that are closer to the global optimums than the values by the IWO algorithm.

Hence, from our experimental results, we deduced that the ABC algorithm performs better than the IWO algorithm for these modified functions. We are aware of the fact that, these results may change for some other modified functions or even for the same functions with different modifications.

Table 4.Performance of ABC and IWO algorithms on modified functions

		Modified Sphere Func.	Modified RosenbrockFunc.	Modified Quartic Func.	Modified SchwefelFunc.	Modified GriewankFunc.
Minimum function values		20.3027	435	1.99749	-12571.4841	-3535
ABC	average	20.3027	435.0758708	1.998014	-12496.611	-3535.00
	worst	20.3027	436.51740	1.998309	-12310.020	-3535.00
	best	20.3027	435.0000	1.997820	-12567.490	-3535.00
IWO	average	21.000887	503.5538325	2.0009531	-11165.9	-3422.4417
	worst	21.001015	800.001568	2.002943	-9823.54	-3339.8924
	best	21.000618	435.003865	1.9994688	-12370.0	-3466.3209

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