Evaluation of Performance of Adaptive and Hybrid ABC (aABC) Algorithm in Solution of Numerical Optimization Problems

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***Abstract*—Artificial bee colony (ABC) algorithm is a heuristic optimization algorithm that models food search behavior of the honey bees. It is used to solve many real-world problems and has been successful. In the literature, it is seen that different modifications of ABC algorithm are proposed to obtain more effective results. In this study, adaptive and hybrid ABC (aABC) algorithm which is one of the modifications of ABC algorithm is used. Its performance is evaluated in solving numerical test functions. Unlike standard ABC algorithm, aABC algorithm uses arithmetic crossover and adaptive neighborhood radius in the solution generation mechanism. The applications are performed on 6 numerical test functions. The results are evaluated in terms of solution quality and convergence speed. In addition, Wilcoxon signed-rank test is used to examine the significance of the results. The results show that aABC algorithm is more effective than ABC algorithm in solving numerical optimization problems.**

Keywords—artificial bee colony, aABC algorithm, numerical optimization problems, optimization

I. INTRODUCTION

When the literature is examined, it appears that many heuristic optimization algorithms have been proposed recently. ABC [1], HS [2], FA [3] and CS [4] are some of these.

ABC algorithm is one of the most popular optimization algorithm based on swarm intelligence. It has achieved successful results in solving many real-world problems in different fields [5].

Many modifications have been proposed to achieve more effective results with ABC algorithm. Although global convergence speed of ABC algorithm is good, these modifications aim to increase the local convergence speed and improve the quality of the solution. Tsai ve ark. [6] introduced the concept of universal gravitation taking into account the relation between the employed and the onlooker bees for ABC algorithm. Zhu and Kwong [7] proposed gbest-guided ABC (GABC) algorithm influenced by PSO. In solution generating mechanism of GABC, global best solution was utilized in order to improve local search ability. Gao and Liu [8] proposed two solution generating mechanisms called "ABC / best / 1" and "ABC / rand / 1" inspired by differential evolution (DE) algorithm. Alam and Islam [9] used a solution generating mechanism that step size of the bees are adjusted according to mutation dynamically. Akay and Karaboga [10] presented an variant of ABC algorithm that uses modification rate and scaling factor.

aABC algorithm is one of the modifications of ABC algorithm [11]. Unlike standard ABC algorithm, it has arithmetic crossover and adaptive neighborhood radius. It was first proposed for ANFIS training. In this study, it is used to solve numerical optimization problems first time.

II. ARTIFICIAL BEE COLONY (ABC) ALGORITHM

A. *Standard ABC Algorithm*

ABC algorithm models the food searching behavior of the honey bees [1]. Artificial bee colony includes three different foraging bee groups; employed, onlooker and scout. Half of the colony is composed of onlooker bees and the other half is also employed bees. Optimization process is realized in 3 stages in ABC algorithm. The basic steps showing these stages are given below:

- Initialization
- **REPEAT**
    - Employed bee stage
    - Onlooker bee stage
    - Scout bee stage
- **UNTIL** (requirements are met)

In the first stage, ABC algorithm starts with a randomly created solution. It determines by using (1). Here, x_i shows i[th] solution. SN is population size and i can take a value between [1, SN]. Each solution is composed of a vector with D element. D refers to the number of parameters to be optimized. $x_j^{\min}$ shows the lowest value of j parameter and $x_j^{\max}$ is also the highest value.

$$X_{ij} = X_j^{\min} + rand(0,\ 1)\left(X_j^{\max} - X_j^{\min}\right) \tag{1}$$

Employed bees determine new sources in the neighborhood of their food source. They evaluate the quality of the source they identified. If the quality of the new source is better than the previous one, they delete the information of the previous

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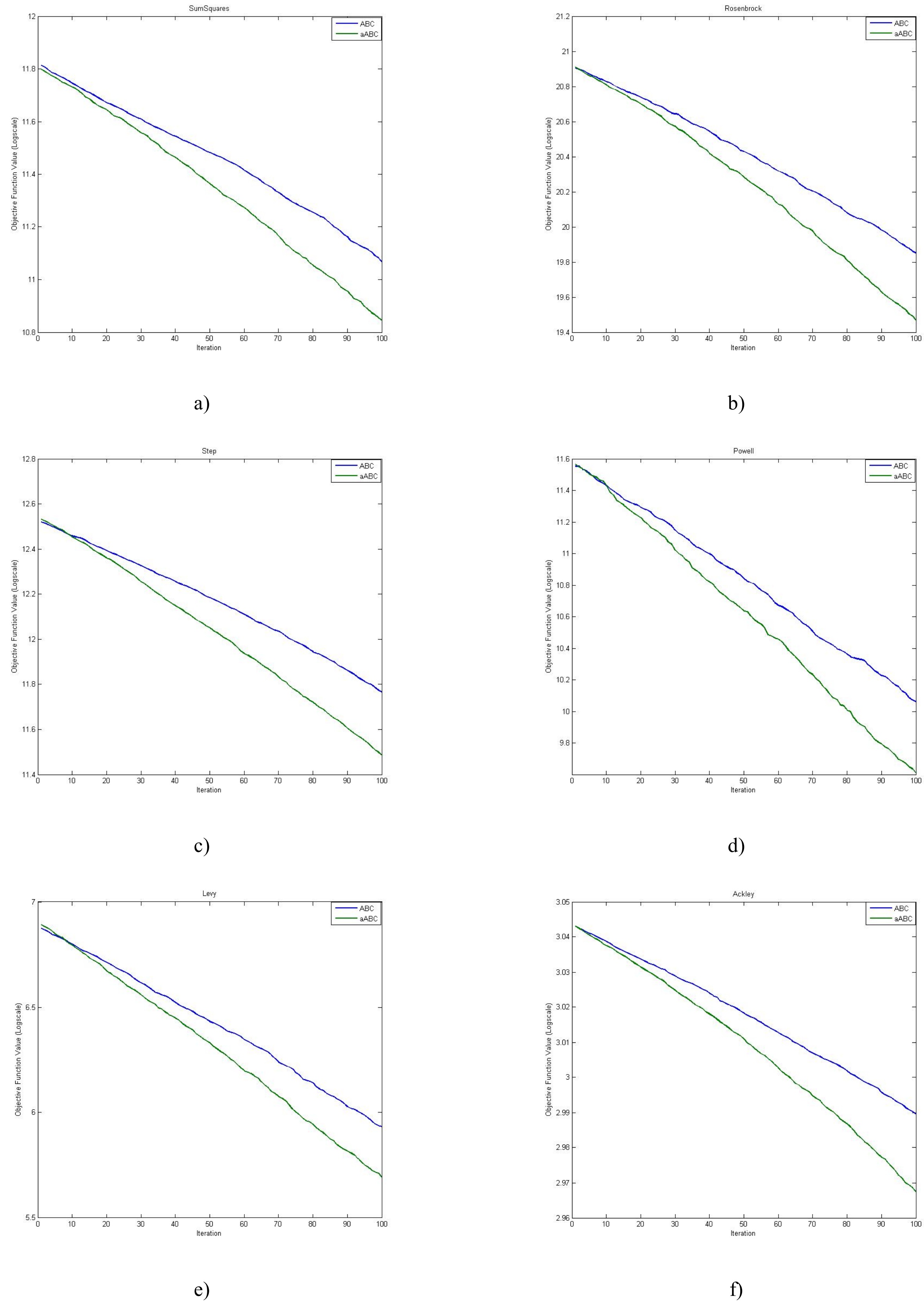

Fig. 1. Comparison of ABC and aABC algorithms' convergence on a) SumSquares b) Rosenbrock c) Step d) Powell e) Levy f) Ackley function.

TABLE I. THE FUNCTIONS USED IN EXPERIMENTS.

Function	Formulation
SumSquares	$f(x)=\sum_{i=1}^{n} i{x_i}^2$
Rosenbrock	$f(x)=\sum_{i=1}^{n-1}\left[100\left(x_{i+1}-{x_i}^2\right)^2+(x_i-1)^2\right]$
Step	$f(x)=\sum_{i=1}^{n}\left(\lfloor x_i+0.5\rfloor\right)^2$
Powell	$f(x)=\sum_{i=1}^{n/4}\left[(x_{4i-3}+10x_{4i-2})^2+5(x_{4i-1}+x_{4i})^2+(x_{4i-2}+2x_{4i-1})^4+10(x_{4i-3}+x_{4i})^4\right]$
Levy	$f(x)=\sin^2(\pi w_1)+\sum_{i=1}^{n-1}(w_i-1)^2\left[1+10\sin^2(\pi w_i+1)\right]+(w_n-1)^2\left[1+\sin^2(2\pi w_n)\right]$ $w_i=1+\frac{x_i-1}{4}$
Ackley	$f(x)=-20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}{x_i}^2}\right)-\exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right)+20+e$

TABLE II. COMPARISON OF THE RESULTS OBTAINED BY USING ABC AND AABC.

Function	ABC		aABC	
	Mean	**Std.**	**Mean**	**Std.**
SumSquares	7.869e-03	3.959e-02	**3.336e-03**	**5.296e-03**
Rosenbrock	209.509	116.33	**110.098**	**89.1986**
Step	2.797e-02	7.904e-02	**2.975e-03**	**5.658e-03**
Powell	6.957e-01	3.372e-01	**2.534e-01**	**1.046e-01**
Levy	4.971e-04	1.258e-03	**1.099e-04**	**2.157e-04**
Ackley	2.462e-01	3.390e-01	**3.166e-02**	**2.880e-02**

TABLE III. WILCOXON SIGNED RANK TEST RESULTS.

Function	p
SumSquares	0.047
Rosenbrock	0.001
Step	0.139
Powell	0.000
Levy	0.221
Ackley	0.000

source from their memory. Instead, they store the information of the new source in their memory. Otherwise, they retain the information of the previous position. At this stage, employed bees use (2) to determine new food source. Here, Φ_{ij} is a random number chosen between [-1, 1].

$$V_{ij} = X_{ij} + \Phi_{ij}\left(X_{ij} - X_{kj}\right) \tag{2}$$

In onlooker bee stage, an onlooker bee evaluates the information received from all employed bees and chooses the new source in relation with the probability value. As in the employed bee stage, if the new source has a better amount of nectar, the information of previous position is deleted from the memory and the new source information is saved in the memory. Selection of the new source by an onlooker bee is related to the p probability value given in (3). Here, $fitness_i$ refers to the fitness value evaluated by the employed bee of i^th solution. SN shows to the number of food sources.

$$P_i = \frac{fitness_i}{\sum_{j=1}^{SN} fitness_j} \tag{3}$$

In the ABC algorithm, abandoned food source is replaced with a new food source by scout bee. This is realized by creating a random position. The scout bee uses (1) for a new food source. If a position cannot be developed in the number of control parameters called as "limit", it is assumed that this food source is abandoned.

B. Adaptive and Hybrid Artificial Bee Colony (aABC)

Karaboga and Kaya [11] have presented a novel solution generating mechanism by utilizing arithmetic crossover and adaptive neighborhood radius and it is given in (4). In this study, this algorithm is utilized.

$$V_{ij} = x_{ij}\gamma + x_{gj}\left(1-\gamma\right) + B_i\phi_{ij}\left(x_{ij} - x_{kj}\right) \tag{4}$$

γ is the crossover ratio and takes a value in the range [0.5, 1]. X_g is the best solution. Here, B_i expresses the adaptive neighbor radius obtained using the failure counter belonging to i^th solution and is calculated using (5).

$$B_i = \left(\frac{1}{1+trial_i}\right)^{\alpha} \tag{5}$$

Here, $trial_i$ is the failure counter belonging to i^th solution. α is the adaptability coefficient and is between [0, n]. n is a positive real number.

III. Simulation Results

In this study, the performance of aABC algorithm is evaluated on numerical optimization test problems. In the scope of the applications, 6 test functions (SumSquares, Rosenbrock, Step, Powell, Levy and Ackley) given in TABLE I are used. The obtained results are compared with standard ABC algorithm.

The control parameter values are the same in aABC and ABC algorithms. Colony size (S) is 50 and the dimension of the problem (D) is 100. The number of evaluations is 100.000. The limit value is determined by (S * D) / 2. The α and γ control parameter values of aABC algorithm are determined according to [11]; α=0.5 and γ=0.7 are taken for all problems. Each application is run 30 times and mean fitness values are calculated.

The results found with aABC algorithm for SumSquares, Rosenbrock, Step, Powell, Levy, and Ackley functions are given in TABLE II. At the same time, they are compared with standard ABC algorithm. Here, average fitness value and standard deviation values are given. When the results are examined, it is seen that more effective results are obtained with aABC algorithm. The best performance increase is obtained on Step function. With aABC algorithm, performance gains are respectively 58%, 47%, 64%, 78% and 87% on SumSquares, Rosenbrock, Powell, Levy and Ackley functions. However, the lowest standard deviation values are found by utilizing aABC algorithm. This shows that the results found by using aABC algorithm are more robust.

The Wilcoxon signed rank test is used to determine the significance of the results. The obtained p values are presented in TABLE III. The analyzes are performed according to $p = 0.05$ level. On Sum Squares, Rosenbrock, Powell and Ackley functions, p values are respectively found as 0.047, 0.001, 0.000 and 0.000. These values are less than 0.05. This shows that there is a meaningful difference. In other functions, although aABC algorithm is better, no significant results are found. For Step function, p is 0.139. In addition, p is determined as 0.221 for Levy function.

TABLE II and III show that aABC algorithm has a good solution quality. Besides the quality of the solution, convergence is also important. So, the convergence graphs of ABC and aABC algorithm are compared in Fig. 1. The convergence rate of the aABC algorithm for all functions is found to be better.

IV. Conclusion

In this study, the performance of the aABC algorithm, one of the variants of the ABC algorithm, is evaluated in solving numerical optimization problems. In aABC algorithm, the solution generating mechanism has arithmetic crossover and adaptive neighborhood radius. These two modifications have improved the convergence speed and solution quality of the aABC algorithm. In general, it has been observed that the proposed algorithm is more effective than standard ABC algorithm.

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