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Comparison and Results of Artificial Bee Colony, Bat, Firefly and Genetic Algorithms on Selected Benchmark Functions

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Abstract— **Optimization has become an important research area in recent years. Many metaheuristic algorithms have been developed to solve mathematical optimization problems. Most of these algorithms have been inspired by nature to find optimal solutions to problems. Artificial Bee Colony (ABC) algorithm is a metaheuristic algorithm developed by mimicking the behavior of honey bees. Firefly algorithm has been developed based on fireflies in nature, while the Bat algorithm has been developed based on the behavior of bats. Genetic algorithms are based on the survival of the best by mimicking the evolutionary processes in nature. Benchmarking has an important role both in showing the efficiency of a new algorithm and in comparing the performance of existing algorithms. In addition, they are widely used to evaluate the advantages and disadvantages of algorithms under certain conditions. Benchmark functions have been developed to test the performance of algorithms. Some of these functions are two-dimensional while others are multi-dimensional. In this study, four different metaheuristic algorithms have been used to solve fifteen well-known different benchmark functions. Six of these functions are n-dimensional and nine are two-dimensional. The comparison of the performances of the algorithms has been made by evaluating the processing times and objective function values. Each benchmark function has been optimized in 50 independent iterations using the specified algorithms. Findings obtained as a result of calculations have been analyzed. As a result, considering both the objective function values and the processing times, it has been observed that the most successful algorithm is Artificial Bee Colony algorithm.**

Index Terms—**Artificial bee colony algorithm, Bat algorithm, Firefly algorithm, Genetic algorithm, Metaheuristic algorithm, Optimization.**

I. Introduction

Optimization can be defined as obtaining the best result under certain conditions. Mathematically, it can be expressed as the approximate finding of the smallest and largest values of a function.

Metaheuristic optimization can be explained as searching for solutions to optimization problems with the help of meta-heuristic algorithms. These problems can take place in many areas, from engineering to economics and even planning holidays.

Most daily life problems are actually non-linear problems that are expected to be realized under certain constraints. Metaheuristic algorithms promise to find approximate solutions to these problems. Their use in the solution of optimization problems is increasing day by day, both because they are relatively easier to apply than conventional methods and they give faster results. Accordingly, different metaheuristic algorithms are proposed. The performances of these algorithms differ, and academic studies are conducted to identify and compare these differences. Generally, there are two types of algorithm approaches. These are Evolutionary algorithms and Swarm based algorithms.

Evolutionary algorithms are algorithms developed on Darwin's survival principles of the best [1]. The most well-known type of evolutionary algorithm is Genetic algorithm. The concept of swarm intelligence was introduced by Beny in 1989 [2]. Artificial Bee Colony, Firefly and Bat algorithms used in this study are some of the swarm-based algorithms.

In this study, three swarm-based algorithms named Bat, Firefly and Artificial Bee Colony are used. As an evolutionary algorithm, Genetic Algorithm is used. Firefly algorithm was developed by Xin-She Yang of Cambridge University in 2007 [3]. It basically imitates the movements and behavior of fireflies in nature. Bat algorithm was developed by Xin-She Yang in 2010 [4]. It is a type of meta-heuristic algorithm that is based on imitating the behavior of bats in solving optimization problems. Artificial Bee Colony algorithm was developed in 2005 by D. Karaboga to be used in solving numerical optimization problems [5]. Genetic algorithms are algorithms aiming to find the best based on Darwin's evolutionary approach [6]. A study on the comparison of three of these algorithms was conducted by Tajmiruzzaman, Md & Asadujjaman in 2014 and the results obtained were evaluated [7].

Our aim in this article is to compare the performances of these four algorithms using fifteen different benchmark functions. In the next sections of the article, firstly the Artificial Bee Colony, Firefly, Bat and Genetic algorithms are introduced and their working principles are explained. Then, the benchmark functions used are introduced. Finally, the performances of four algorithms are measured over the specified problems and the results are listed

II. Meta-Heuristic Algorithms and Optimization

A. *Firefly Algorithm*

Firefly Algorithm was developed by Xin-She Yang in 2007 [8]. It is a meta-heuristic algorithm based on fireflies' propensity for luminosity. In Firefly algorithm, fireflies are genderless. As a result, all fireflies can turn towards each other. The main factor in their orientation to each other is their brightness. In other words, fireflies with less brightness tend towards brighter ones. The brightness value is inversely proportional to the distance. Thus, other fireflies are less

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affected by fireflies at long distances. If a firefly cannot find a firefly brighter than itself, it moves randomly.
We can show the relationship between attractiveness and distance in (1);

$$\beta = \beta_0 e^{-\gamma r 2} \tag{1}$$

Where β is attractiveness value, β_0 is attractiveness value when $r = 0$ and γ is media light absorption coefficient.
We can express the motion of the firefly i as a result of being affected by the other firefly j, which is brighter than itself in (2);

$$x_i^{t+1} = x_i^t + \beta_0 e^{-\gamma r_{ij}^2}(x_j^t - x_i^t) + \alpha e_i^t \tag{2}$$

Where α is a random parameter and e_i^t is the vector created as a result of the normal distribution at time *t*.

B. Bat Algorithm

Bat algorithm was developed by Xin-She Yang in 2010. It is based on the behavior of small bats in nature to reach their prey. Bats use the resonance of sound to reach their prey. While searching for their prey, they send a fixed frequency $f_{\min}$. Yang shows the movement of a virtual bat in (3);

$$\begin{aligned} f_i &= f_{\min} + (f_{\max} - f_{\min})\beta \\ v_i^t &= v_i^{t-1} + (x_i^t - x_{best}) f_i \\ x_i^t &= x_i^{t-1} + v_i^t \end{aligned} \tag{3}$$

Where f_i is the frequency the bat uses when searching for its prey, $f_{\min}$ and $f_{\max}$ are smallest and largest values, x_i is the position of the bat in the solution space *i*, v_i is the speed of the bat, *t* is current iteration, β is a random vector plotted with a beta uniform distribution, x_{best} is global best solution.

C. Artificial Bee Colony Algorithm

Artificial Bee Colony algorithm was introduced by Derviş Karaboga in 2005 to find solutions to numerical optimization problems [9]. Firstly, food sources are determined randomly by the scout bees according to (4).

$$x_m = x_{\min} + (x_{\max} - x_{\min}) rand(0,1) \tag{4}$$

Where $x_{\max}$ and $x_{\min}$ are lower and upper bounds and a random number between 0 and 1 is generated by $rand(0,1)$.
In the second stage, employed bees reach their food sources. Then they find the neighboring food sources according to (5). Information on food sources is kept by employed bees and passed on to onlooker bees.

$$v_{ij} = x_{ij} + (x_{ij} - x_{kj}) rand(-1,1) \tag{5}$$

Where x_k is a randomly selected food source.
In the third stage, the profitability of the food source is calculated according to (6) for both itself and all food sources.

$$p_m = \frac{fit_m(x_m)}{\sum_{m=1}^{SN} fit_m(x_m)} \tag{6}$$

Where $fit_m(x_m)$ is the fitness of the food source.
In the fourth stage, neighboring food sources are found by onlooker bees according to (5).
In the last stage, after a certain number of cycles called limit, if the profitability of the food source cannot be further developed, a new food source is calculated by the scout bees according to (4).

D. Genetic Algorithm

Genetic algorithm was introduced by John Holland in 1975 with the aim of solving optimization and search problems [10]. It is based on the principle of finding the fittest value by imitating natural evolutionary processes. Each individual in the population has a chromosome set. Genetic operators such as mutation and crossover are used in each generation. Binary individuals to be crossed are selected according to their fitness values [11].

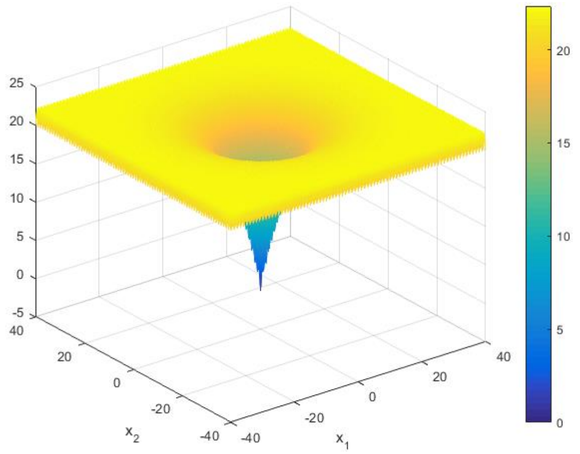
III. BENCHMARK FUNCTIONS

In this study, fifteen different well-known benchmark functions are used.

Ackley

$$f(\mathbf{x}) = f(x_1,...,x_n) = -ae^{-b\sqrt{\frac{\sum_{i=1}^n x_i^2}{n}}} - e^{\frac{\sum_{i=1}^n \cos(cx_i)}{n}} + a + e$$

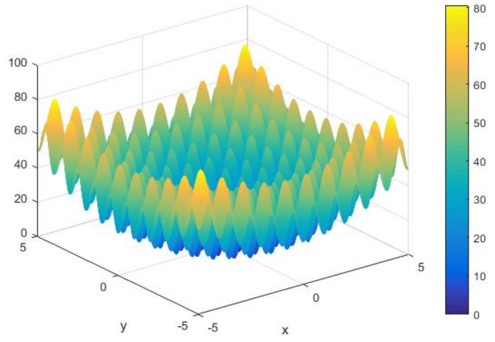
The function is continuous, not convex, n-dimensional, multimodal. $x_i \in [-32, 32]$ for all i=1,…,n. Global minimum at: f(x∗)=0 at x∗=(0,…,0).



Rastrigin

$$f(\mathbf{x}) = f(x_1,...,x_n) = 10n + \sum_{i=1}^n (x_i^2 - 10cos(2\pi x_i))$$

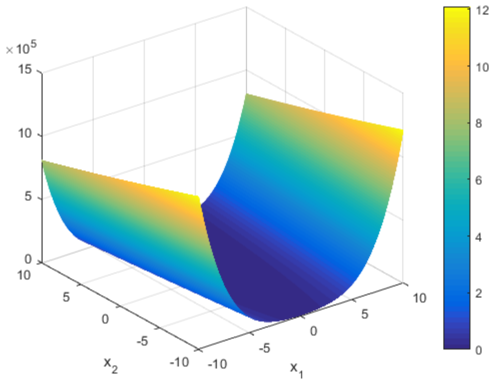
The function is continuous, convex, n-dimensional, multimodal, differentiable, separable. $x_i \in [-5.12, 5.12]$ for all *i*=1,…,*n*. Global minimum at: f(x∗)=0 at **x**∗=(0,…,0).



Rosenbrock

$$f(\mathbf{x}) = f(x_1,...,x_n) = \sum_{i=1}^{n-1}\left[b(x_{i+1}-x_i^2)^2 + (a-x_i)^2\right]$$

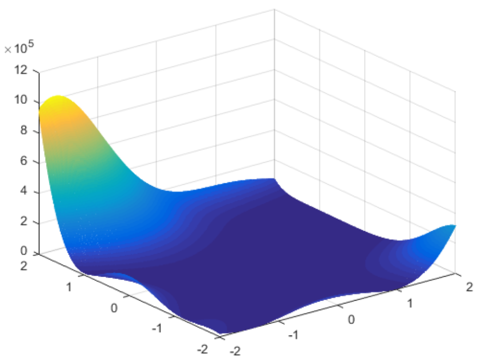
The function is continuous, non-convex, n-dimensional, multimodal, differentiable, non-separable. $x_i \in [-5, 10]$ for all i=1,…,n. Global minimum at: f(x∗)=0 at **x**∗=(1,…,1).



Goldstein-Price

$$f(x,y) = [1+(x+y+1)^2(19-14x+3x^2-14y+6xy+3y^2)].$$
$$.[30+(2x-3y)^2(18-32x+12x^2+4y-36xy+27y^2)]$$

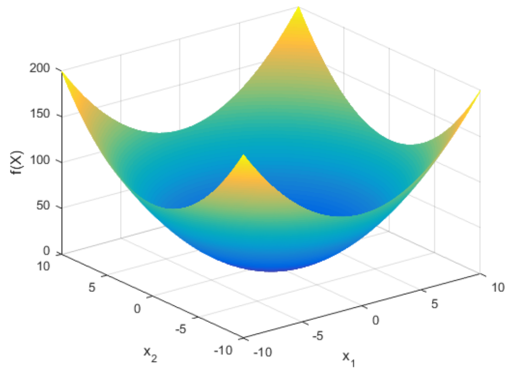
The function is continuous, non-convex, 2-dimensional, multimodal, differentiable, non-separable. x,y ∈[−2, 2]. Global minimum at: f(x∗)=3 at **x**∗=(0, -1).



Sphere

$$f(\mathbf{x}) = f(x_1,x_2,...,x_n) = \sum_{i=1}^{n} x_i^2$$

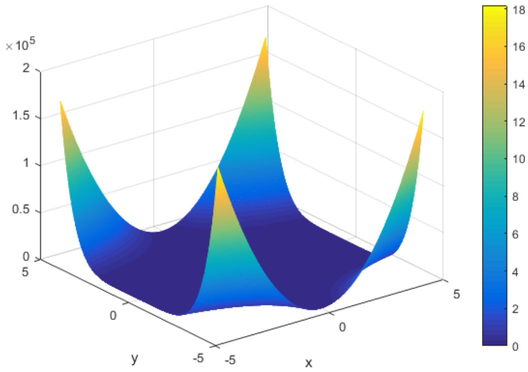
The function is continuous, convex, n-dimensional, unimodal, differentiable, separable. $x_i \in [-5.12, 5.12]$ for all i=1,…,n. Global minimum at: f(x∗)=0 at **x**∗=(0,…,0).



Beale

$$f(x,y) = (1.5-x+xy)^2 + (2.25-x+xy^2)^2 + (2.625-x+xy^3)^2$$

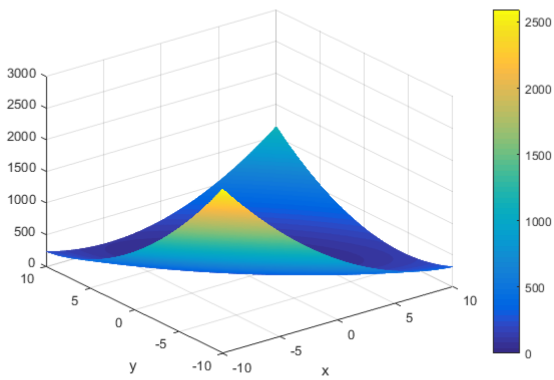
The function is continuous, non-convex, 2-dimensional, multimodal. x,y ∈[−4.5, 4.5]. Global minimum at: f(x∗)=0 at **x**∗=(3, 0.5).



Booth

$$f(x,y) = (x+2y-7)^2 + (2x+y-5)^2$$

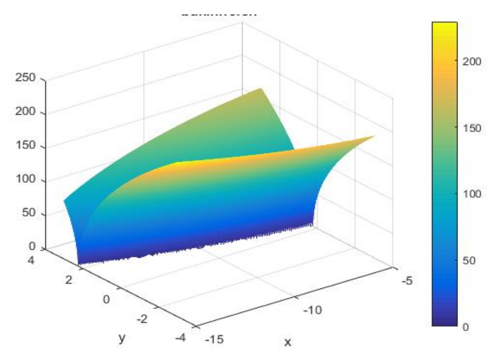
The function is continuous, convex, 2-dimensional, unimodal, differentiable, non-separable. x,y ∈[−10, 10]. Global minimum at: f(x∗)=0 at **x**∗=(1, 3).



Bukin N.6

$$f(x,y) = 100\sqrt{|y-0.01x^2|} + 0.01|x+10|$$

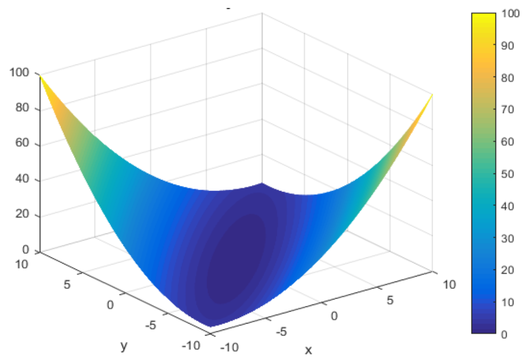
The function is continuous, convex, 2-dimensional, unimodal, differentiable, non-separable. x∈[−15, 5], y ∈[−3, 3]. Global minimum at: f(x∗)=0 at **x**∗=(-10,13).



Matyas

$$f(x,y) = 0.26(x^2 + y^2) - 0.48xy$$

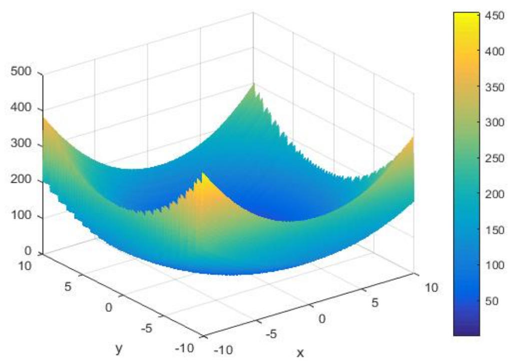
The function is continuous, convex, 2-dimensional, unimodal, differentiable, non-separable. x,y∈[−10, 10]. Global minimum at: f(x∗)=0 at **x**∗=(0, 0).



Levi N. 13

$$f(x,y) = sin^2(3\pi x) + (x-1)^2(1+sin^2(3\pi y)) + \\ +(y-1)^2(1+sin^2(2\pi y))$$

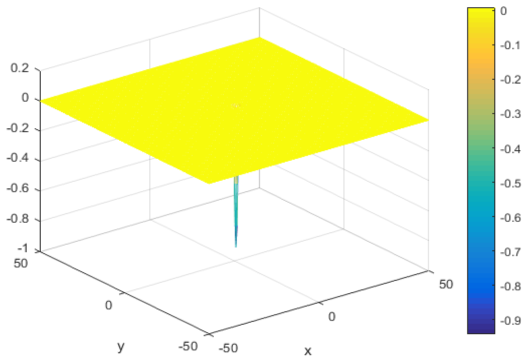
The function is continuous, non-convex, 2-dimensional, multimodal, differentiable, non-separable. x,y∈[−10, 10]. Global minimum at: f(x∗)=0 at **x**∗=(1, 1).



Easom

$$f(x,y) = -cos(x)cos(y)e^{(-(x-\pi)^2-(y-\pi)^2)}$$

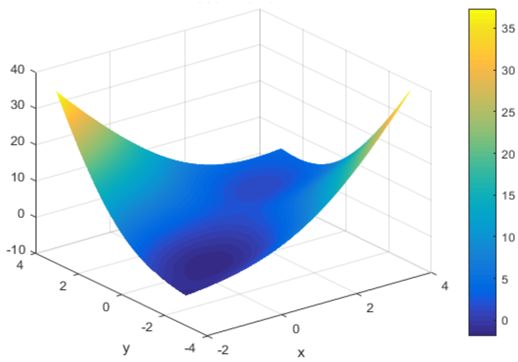
The function is continuous, non-convex, 2-dimensional, multimodal, differentiable, separable. x,y∈[−100, 100]. Global minimum at: f(x∗)=-1 at **x**∗=(π, π).



McCormick

$$f(x,y) = sin(x+y) + (x-y)^2 - 1.5x + 2.5y + 1$$

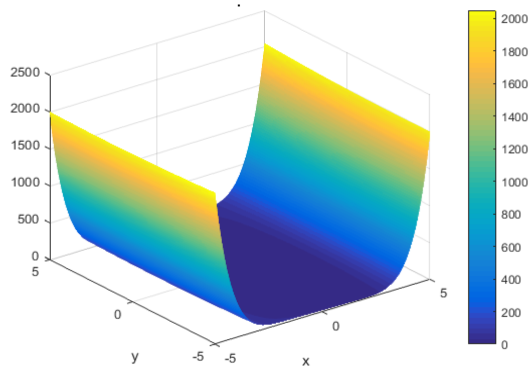
The function is continuous, convex, 2-dimensional, multimodal, differentiable, non-scalable. x∈[−1.5, 4], y ∈[−3, 3]. Global minimum at: f(x∗)≈−1.9133 at **x**∗=(−0.547,−1.547).



Three-HumpCamel

$$f(x,y) = 2x^2 - 1.05x^4 + \frac{x^6}{6} + xy + y^2$$

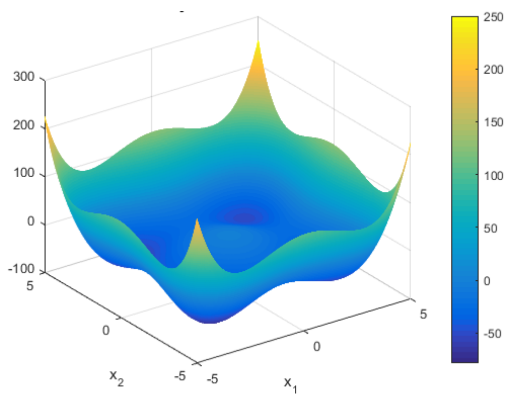
The function is continuous, non-convex, 2-dimensional, unimodal, differentiable, non-separable. x,y∈[−5, 5]. Global minimum at: f(x∗)=0 at **x**∗=(0, 0).



Styblinski-Tank

$$f(\mathbf{x}) = f(x_1,...,x_n) = \frac{1}{2}\sum_{i=1}^{n}(x_i^4 - 16x_i^2 + 5x_i)$$

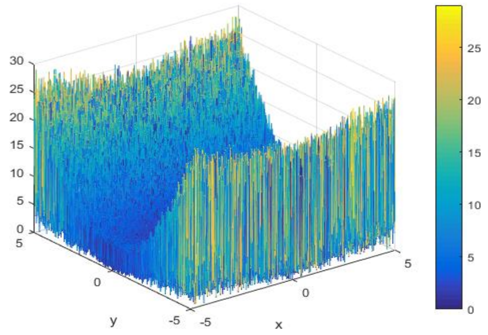
The function is continuous, non-convex, n-dimensional, multimodal. **x**∈[−5, 5]. Global minimum at: f(x∗)=−39.16599 0 at x∗=(−2.903534,…,−2.903534)



Xin-SheYang

$$f(\mathbf{x}) = f(x_1,\ldots,x_n) = \sum_{i=1}^{n} \epsilon_i |x_i|^i$$

The function is continuous, non-convex, n-dimensional, multimodal. **x**∈[−5, 5]. Global minimum at: f(x∗)=0 at x∗=(0,…,0)



IV. EXPERIMENTAL RESULTS

The experiments in this study are carried out using a Dell computer which has an Intel i7 7700HQ 2.8GHZ processor and 16 GB of RAM. Six of the benchmark functions used are n-dimensional and the rest are two-dimensional. For n-dimensional functions, the number of dimensions is determined as 10 and used in the same way in all tests. The parameter values of the algorithms used are shown in Table 1. All functions are tested on specified algorithms, each containing 50 iterations. The objective function values obtained as a result of the tests are shown in Table 2, and the processing times of the algorithms are shown in Table 3

Table 1 Parameter values of four algorithms

Firefly	Bat	Artificial Bee Colony	GeneticAlgorithm
α (randomness): 0.5	**A0 (loudness):** 1.8	**Foodsource :**40	**Number of population:** 100
γ(absorption): 1	**α:** 0.9	**Number of employed bees:** 40	**Crossover rate:** 0.8
β0: 1	**r0 (pulse rate):** 0.9	**Number of outlooker bees:** 40	**Mutation rate:** 0.05
βmin: 0.2	**γ:** 0.9	**Limit :** 100	
	Qmin (minimum frequency): 0 **Qmax (maximum frequency):** 2		

Table 2 Objective function values obtained after 50 iterations

Function	Dim	Bat			Firefly			ABC			Genetic		
		Best	**Worst**	**Mean**	**Best**	**Worst**	**Mean**	**Best**	**Worst**	**Mean**	**Best**	**Worst**	**Mean**
Ackley	10	10.645	14.564	12.245	2.876E-05	0.0009	0.0004	1.1391E-10	1.333E-07	**8.627E-09**	1.416E-13	0.007	0.0006
Rastrigin	10	0.994	4.974	2.653	3.194E-09	0.994	0.033	0	4.945E-12	**3.379E-13**	0	0.994	0.165
Rosenborg	10	2.745E-11	3.148	0.256	2.299E-10	7.915E-08	**1.710E-08**	0.0001	0.0574	0.0099	0.001	1.902	0.265
Goldenstein Price	2	3.000	3.000	3.000	3.000	3.000	3.000	3.000	3.000	3.000	3.000	3.031	3.003
Sphere	10	6.237E-07	1.470E-06	9.938E-07	9.898E-08	9.901E-07	4.859E-07	1.590E-19	1.371E-17	**4.512E-18**	0.0015	0.0114	0.005
Beale	2	7.069E-12	1.482E-09	**2.946E-10**	2.360E-12	2.859E-09	9.379E-10	1.336E-05	0.006	0.0013	1.191E-08	0.043	0.014
Booth	2	3.341E-11	1.508E-09	**4.401E-10**	4.274E-10	2.248E-08	7.406E-09	2.506E-07	0.0009	5.784E-05	9.273E-19	1.703E-05	1.631E-06
Bukin	2	0.005	0.139	0.068	0.038	0.251	0.126	2.8046E-05	0.0015	**0.0004**	9.469E-06	0.003	0.0014
Matyas	2	3.731E-13	6.179E-11	**1.822E-11**	3.684E-12	1.210E-09	2.563E-10	3.280E-06	0.0048	0.0005	2.498E-27	3.223E-05	1.096E-06
Levi N. 13	2	3.163E-10	9.666	1.506	1.249E-09	1.332E-07	4.107E-08	1.761E-19	2.052E-16	**2.617E-17**	8.224E-23	6.721E-06	5.479E-07
Easom	2	-0.999	0	-0.1	-0.999	0	-0.46	-0.999	-2.048	-0.639	-0.999	-1.615	**-0.799**
McCormick	2	-1.913	-1.810	-1.875	-1.913	-1.913	-1.913	-1.913	-1.913	-1.913	-1.913	-1.913	-1.913
Three-Hump Camel	2	1.975E-12	0.298	0.019	1.791E-11	2.165E-09	**7.488E-10**	2.879E-14	1.881E-08	1.717E-09	2.154E-19	2.401E-06	9.712E-08
Styblinski-Tank	10	-39.166	-39.166	-39.166	-39.166	-39.166	-39.166	-39.166	-39.166	-39.166	-39.166	-39.166	-39.166
Xin-SheYang	10	0.041	0.136	0.063	0.0417	0.0417	0.0417	2.371E-05	0.329	0.0127	4.610E-14	0.0017	**0.0002**

Table 3 Processing times of four algorithms

Function	Dim.	Bat			Firefly			ABC			Genetic		
		Best	Worst	Mean	Best	Worst	Mean	Best	Worst	Mean	Best	Worst	Mean
Ackley	10	0.737	1.199	0.785	1.365	2.416	1.583	0.335	0.416	0.353	0.228	0.476	0.299
Rastrigin	10	0.684	1.188	0.769	1.326	1.917	1.5	0.333	0.46	0.36	0.225	0.337	0.242
Rosenborg	10	0.705	1.014	0.893	1.345	2.005	1.439	0.333	0.372	0.348	0.222	0.324	0.245
Goldenstein Price	2	0.863	0.971	0.917	0.554	0.77	0.626	0.464	0.712	0.516	0.439	0.564	0.479
Sphere	10	1.023	1.547	1.157	1.384	2.485	1.603	0.348	0.462	0.365	0.331	0.604	0.383
Beale	2	0.636	0.848	0.673	0.522	0.818	0.594	0.4	0.532	0.442	0.321	0.573	0.445
Booth	2	0.426	0.705	0.492	0.476	0.718	0.513	0.371	0.489	0.429	0.188	0.371	0.263
Bukin	2	0.523	0.866	0.587	0.502	0.767	0.532	0.371	0.493	0.423	0.233	0.367	0.251
Matyas	2	0.421	0.656	0.455	0.471	0.578	0.494	0.356	0.432	0.372	0.194	0.293	0.206
Levi N. 13	2	0.832	1.014	0.878	0.56	0.742	0.604	0.433	0.647	0.479	0.357	0.639	0.519
Easom	2	0.573	0.946	0.679	0.311	0.759	0.485	0.392	0.518	0.426	0.254	0.372	0.265
McCormick	2	0.382	0.522	0.406	0.464	0.682	0.498	0.364	0.474	0.385	0.18	0.353	0.215
Three-HumpCamel	2	0.59	0.878	0.654	0.503	0.899	0.625	0.389	0.66	0.412	0.265	0.353	0.281
Styblinski-Tank	10	0.857	1.494	0.99	1.363	2.354	1.583	0.363	0.585	0.405	0.208	0.295	0.224
Xin-SheYang	10	1.524	1.877	1.606	1.518	2.5	1.673	0.405	0.509	0.425	0.304	0.395	0.320

V. CONCLUSIONS

In this study, four metaheuristic algorithms have been compared using fifteen different benchmark functions. As a result of the tests, the best objective function values have been obtained using the Artificial Bee Colony algorithm in five of the benchmark functions, while three have been obtained using Bat algorithm, two using Firefly algorithm, and two using Genetic algorithm. Very close values have been obtained in the other three benchmark functions. By observing both the processing times and the obtained objective function values, it can be interpreted that Artificial Bee Colony algorithm has the best performance among other algorithms. The best processing times in all functions have been obtained using Genetic algorithm. Artificial Bee Colony has the second-best processing times. While Bat algorithm gave better results than Firefly algorithm in two-dimensional functions, Firefly algorithm performed better in n-dimensional functions. It has been observed that Bat algorithm works faster than Firefly algorithm. In future studies, optimization problems can be diversified. In addition, the performance of the algorithms can be compared by increasing the number of iterations and dimensions.

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