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COMPARISON OF METAHEURISTIC ALGORITHMS WITH DIFFERENT PERFORMANCE CRITERIA

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ABSTRACT

Nature-inspired metaheuristic algorithms are widely used because they achieve successful results in difficult optimization problems. Their popularity has led to the development of new metaheuristics for solving different engineering problems. New metaheuristics lead scientific research by providing faster and more efficient results. In this study, Artificial Rabbit Algorithm (ARO), Dwarf Mongoose Algorithm (DMO) and Genetic Algorithm (GA), which are recently developed metaheuristics, are compared. According to the literature review, the performances of these three algorithms are compared for the first time. Single and multi-modal standard quality test functions were used to evaluate the algorithms. The results of the algorithms were checked by t-test to see if there is a significant difference in terms of the functions used. According to the results obtained, it was observed that ARO produced more successful results than the other algorithms compared. This shows that the newly developed metaheuristics can be used in many engineering problems.

Keywords: *Metaheuristic Algorithms, Artificial Rabbit Algorithm, Dwarf Mongoose Algorithm, Genetic Algorithm, Quality Test Functions*

METASEZGİSEL ALGORİTMALARIN FARKLI PERFORMANS KRİTERLERİ İLE KARŞILAŞTIRILMASI

ÖZET

Doğadan ilham alan metasezgisel algoritmalar, zor optimizasyon problemlerinde başarılı sonuçlar elde ettikleri için yaygın olarak kullanılır. Algoritmaların popülerliği farklı mühendislik problemlerinin çözümü için yeni metasezgisellerin geliştirilmesine olanak sağlamıştır. Yeni metasezgiseller, daha hızlı ve verimli sonuçlar sunarak bilimsel araştırmalara öncülük etmektedir. Bu çalışmada, yeni geliştirilen metasezgisellerden Yapay Tavşan Algoritması (Artificial Rabbit Algorithm, ARO), Cüce Firavun Algoritması (Dwarf Mongoose Algorithm, DMO) ve temel metasezgisellerden Genetik Algoritma (Genetic Algoritm, GA) kıyaslanmıştır. Literatür taramasına göre bu üç algoritmanın performansları ilk defa karşılaştırılmıştır. Algoritmalar değerlendirilirken tek ve çok modlu standart kalite testi fonksiyonları kullanılmıştır. Algoritmaların sonuçları kullanılan fonksiyonlar bakımından anlamlı bir fark olup olmadığı t-testi ile kontrol edilmiştir. Elde edilen sonuçlara göre, ARO'nun karşılaştırılan diğer algoritmalardan daha başarılı sonuçlar ürettiği gözlemlenmiştir. Bu durum yeni geliştirilen metasezgisellerin birçok mühendislik problemlerinde kullanılabileceğini göstermiştir.

Anahtar Kelimeler: *Metasezgisel Algoritmalar, Yapay Tavşan Algoritması, Cüce Fira-vun Algoritması, Genetik Algoritma, Kalite Testi Fonksiyonları*

1. Introduction

Metaheuristic algorithms (Metaheuristic Algorithm, MA) are an approach that has an impact on solving complex optimization problems and is generally based on heuristic methods [1]. They also have a wide range of applications and are used in many engineering problems in various fields. Due to their

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goal of finding the best result in these problems, their importance has been increasing in recent years [2]. The reasons for the popularity of MAs are their simplicity and ease of implementation [3].

The algorithms compared in this study are: Genetic Algorithm (GA), Artificial Rabbit Algorithm (ARO) and Dwarf Mongoose Algorithm (DMO). The contributions of the study are as follows:

• To the best our knowledge, the algorithms used in this study have been compared for the first time.

• The performance of the algorithms has been tested on various functions.

• According to experimental results, the best performance was obtained with the newly proposed ARO metaheuristic method.

The organization of the rest of the study is as follows: Detailed information about the algorithms is presented in Section 2. The functions and parameters used in the experiments are discussed in Section 3. Then simulation results are presented in Section 4. Statistical test results are provided in Section 5, finally the conclusions and information about future work are presented in Section 6.

2. Related Works

In this section, recent studies on metaheuristic in recent years are presented. The studies are as follows:

Alorf, in his study conducted in 2023, examined 57 recently proposed metaheuristic algorithms and compiled a list. He analyzed 26 of these algorithms through experiments. During the experiments, the usage and exploration capabilities of metaheuristics were compared using 50 single-modal and 50 multi-modal functions. To rank the metaheuristics, he employed the statistical Friedman average ranking test. According to the test results, Gradient-Based Optimizer (GBO), Political Optimizer, and Manta Ray Foraging Optimization algorithms were found to have superior usage and exploration capabilities. In terms of comparison functions, Marine Predators Algorithm (MPA), Forensic-Based Investigation, and Heap-Based Optimizer (HBO) algorithms were identified as the most balanced, while HBO, GBO, and Mayfly Algorithm were observed to be particularly suitable for solving engineering optimization problems [4].

In their study conducted in 2022, Cikan et al. implemented a new search algorithm, Equilibrium Optimizer (EO), to enhance reliability indices, increase voltage magnitudes, and reduce active power loss in power distribution networks for reconfiguration. The contributions of this study to the literature include the development of a novel algorithm for calculating reliability indices and providing a comprehensive perspective on solving the reconfiguration problem. The EO algorithm was analyzed on four different distribution test systems and compared with ten contemporary search algorithms. According to this comparison, EO demonstrated the best performance from various perspectives, such as having a lower error rate and successfully reaching the global optimum [5].

In their 2021 study, Gupta et al. analyzed the behavior of nine metaheuristic algorithms. The algorithms they utilized include the Salp Swarm Algorithm, Multi-Verse Optimizer (MVO), Moth-Flame Optimizer (MFO), Atom Search Optimization (ASO), Ecogeography-Based Optimization, Queuing Search Algorithm, EO, Evolutionary Strategy, and Hybrid Self-Adaptive Orthogonal Genetic Algorithm. These algorithms were evaluated using solution quality and convergence analysis on eight mechanical design problems. Additionally, the study demonstrated the broad applicability of the algorithms to real-world application problems [6].

In their 2023 study, Yiğit et al. utilized current metaheuristic algorithms to determine switching instants in Multilevel Inverters and to find switching angles for the Selective Harmonic Eliminationproblem. These algorithms include Ant Lion Optimization, Artificial Hummingbird Algorithm, Dragonfly Algorithm, Harris Hawk Optimization, MFO, Sine Cosine Algorithm, Flow

Direction Algorithm, EO, ASO, Artificial Electric Field Algorithm, and Arithmetic Optimization Algorithm. In the literature, commonly employed algorithms for solving these problems include MPA, Whale Optimization Algorithm, Grey Wolf Optimizer, Particle Swarm Optimization, MVO, Teaching–Learning-Based Optimization, and GA [7]. When all algorithms are compared in this study, MFO demonstrates superiority over many aspects compared to other algorithms [8].

In the 2022 study conducted by Altay, the recent metaheuristic algorithms, namely Harris Hawk Optimization Algorithm (HHO), Sparrow Search Algorithm (SSA), MVO, MPA and Coot Optimization Algorithm were analyzed on 23 different test functions, considering both single-modal and multi-modal scenarios. According to the findings of this study, the HHO algorithm exhibited good performance in the majority of single-modal quality functions, while the SSA algorithm performed well in five multi-modal functions, and the HHO algorithm showed good results in four multi-modal functions. For complex multi-modal quality functions, the algorithms tested produced similar results in four functions, whereas in the remaining five different functions, the MPA method demonstrated the best performance [9].

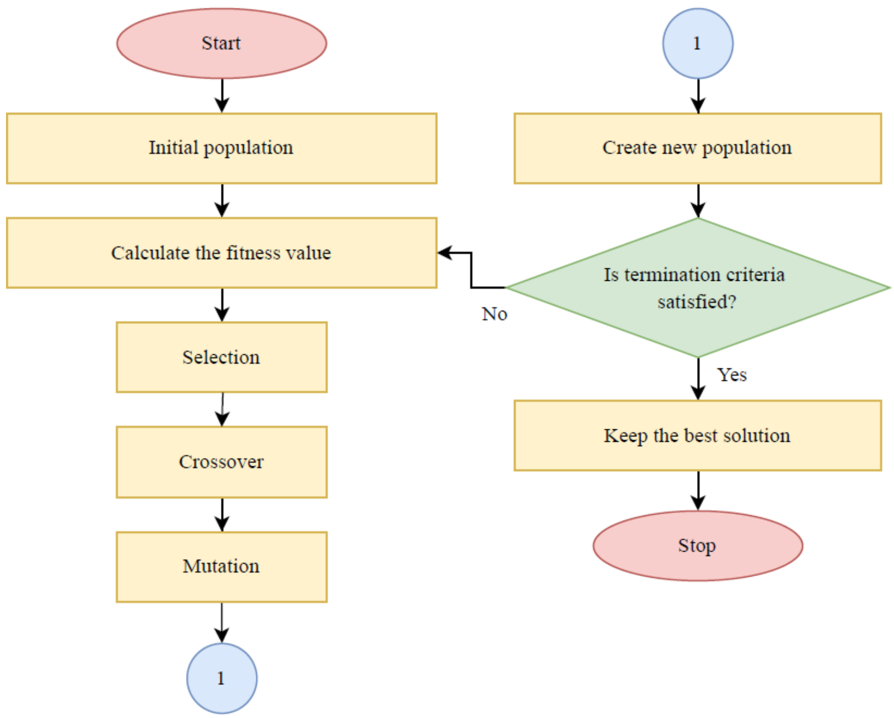

Figure 1. GA flowchart [11]

3. Algorithms

In this section, detailed information about metaheuristic algorithms to be used in the study is provided.

3.1. Genetic Algorithm

GA, a stochastic metaheuristic first proposed by John Holland in 1975 [10], is based on the concept of "survival of the fittest" as stated in Darwin's theory of evolution. Starting from a randomly selected initial population, the algorithm produces the next generation through genetic variations and selection processes. To find the best solution among generations, selection, crossover, and mutation operators are utilized. Solutions in a GA are encoded as fixed-length bit strings or specifically tailored to the problem. The solutions represent the chromosome, and the parameters represent the gene. The flowchart of the GA is provided in Fig. 1 [11]. A random initial population is created, fitness values are calculated, and subsequently, selection, crossover, and mutation operations are applied to generate a new population. When the termination criterion is satisfied, the algorithm terminates, presenting the best individual as the solution.

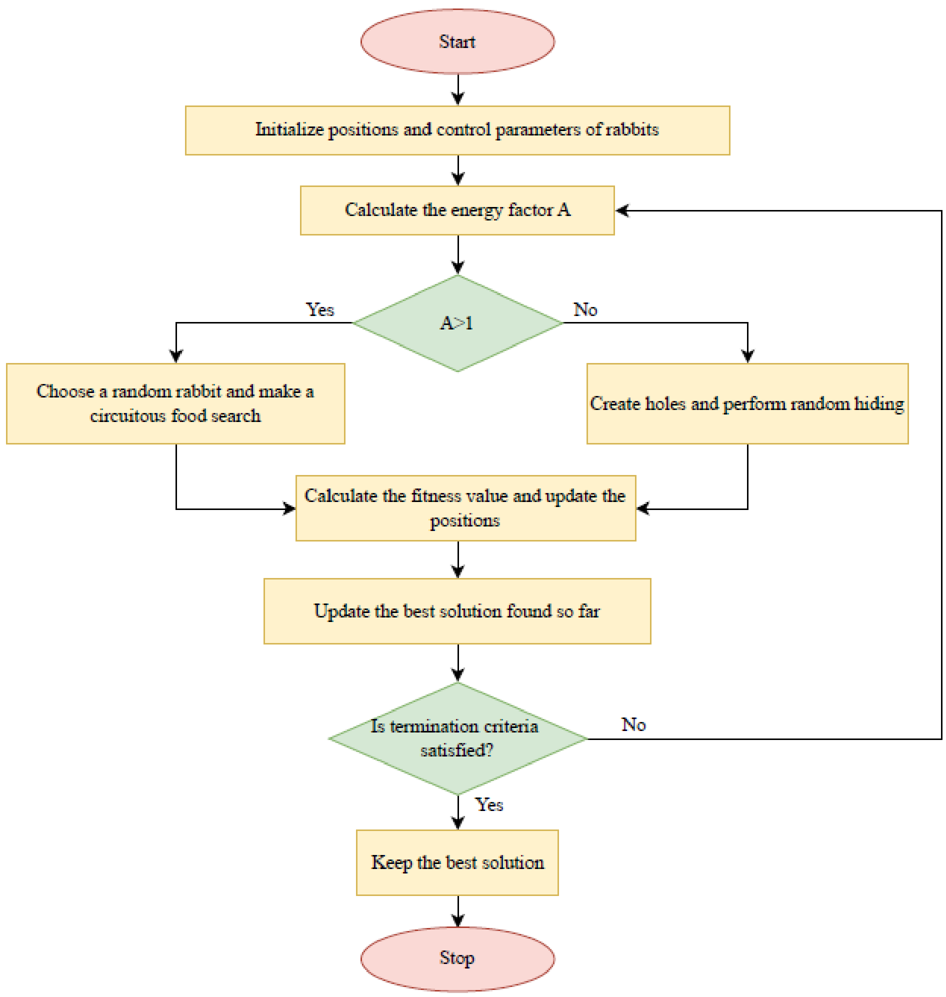

Figure 2. ARO flowchart [13]

3.2. Artificial Rabbit Algorithm

ARO is a recent metaheuristic proposed by Wang et al. in 2022 [3]. This algorithm consists of exploration and exploitation phases. Exploration involves searching for new solutions in different regions. Exploitation aims to increase suitability by utilizing existing solutions and making improvements to them [12]. ARO has two main strategies. The first strategy is food foraging, and the second strategy is random hiding. These strategies represent the stages of exploration and exploitation, respectively. The transition between the two stages occurs based on energy shrink.

Rabbits are generally in the exploration phase in the early stages of iterations, as their energy levels are high. During this exploration phase, rabbits feed on grass in distant areas to prevent predators from finding their nests. In the subsequent stages of the iteration, they engage in exploitation as their energy decreases. During this stage, rabbits usually build multiple nests around to hide from predators and hunters. Later, they complete the exploitation by selecting one of these nests randomly.

Flowchart of algorithm, as seen in Fig. 2. Firstly, the positions of the rabbits and the control parameters are initialized. The energy of each rabbit is calculated, and based on this, exploration or exploitation is performed. The fitness value is calculated, and the positions are updated again. This loop is repeated until the iteration count is completed, and the process is terminated while retaining the best solution [13].

3.3. Dwarf Mongoose Algorithm

DMO is an algorithm developed by Agushaka et al. in 2022, inspired by the cooperation and organizational abilities of the dwarf mongoose to solve complex problems [14].

In this algorithm, the dwarf mongoose is divided into three social groups: alpha (female), scouts and babysitters. In DMO, the fitness value of each individual is calculated, and the best one is selected as the alpha based on this value. From the members of the population, scout groups and babysitters are formed by selecting randomly. The scouts inform the alpha about the newly found hill to stay. The flowchart of the DMO is provided in Fig. 3. The alpha initiates the search for food, evaluates the exploration route, the distance covered, and assesses the suitable spot to rest. A switch between the scout group and the babysitters for hunting is made, and this exchange process is referred to as the exploitation stage. Dwarf mongooses do not return to the ancient dwelling area and they explore new habitat areas, thus learning the entire region. In this way, the exploration phase is conducted [15].

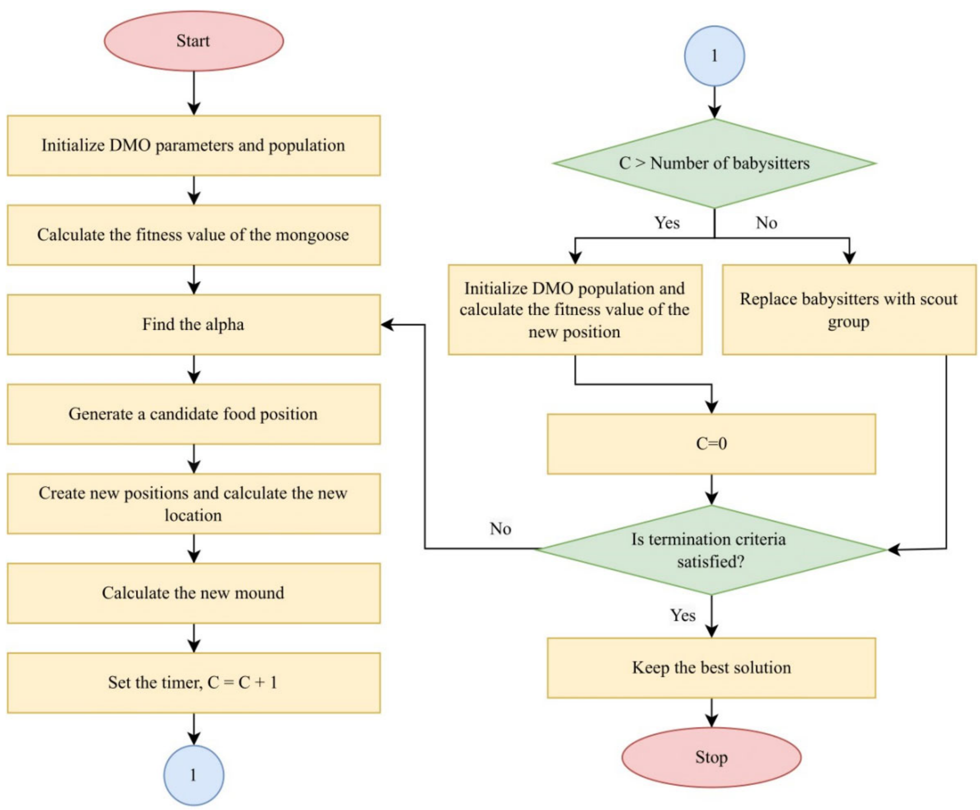

Figure 3. DMO flowchart [15]

4. Experimental Design

In this section, the test functions and parameter values used in the comparison of algorithms are presented.

4.1. Functions

In the study, algorithms were compared using four different quality test functions. The functions were selected from two main groups: single-modal and multi-modal [16]. The groups are given in Table 1. F_1 and F_2 are single-modal test functions, while F_3 and F_4 are multi-modal test functions [17]. The dimension of all functions has been set to 30 in the experiments.

The range given in the table is the valid range of values for each component of the inputs, and different range values are provided for each function. F_{min} represents the minimum value of a function. The minimum value is set to zero for all functions [18]. The graphs of the functions used are given in Fig. 4.

Table 1. Test functions

Function	Range	f_{min}
$F_1(x) = \sum_{i=1}^{n} x_i^2$	[-100,100]	0
$F_2(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	[-10,10]	0
$F_3(x) = 418.9829n + \sum_{i=1}^{n} -x_i \sin\left(\sqrt{\lvert x_i \rvert}\right)$	[-500,500]	0
$F_4(x) = \sum_{i=1}^{n} \left[x_i^2 - 10\cos(2\pi x_i) + 10\right]$	[-5.12,5.12]	0

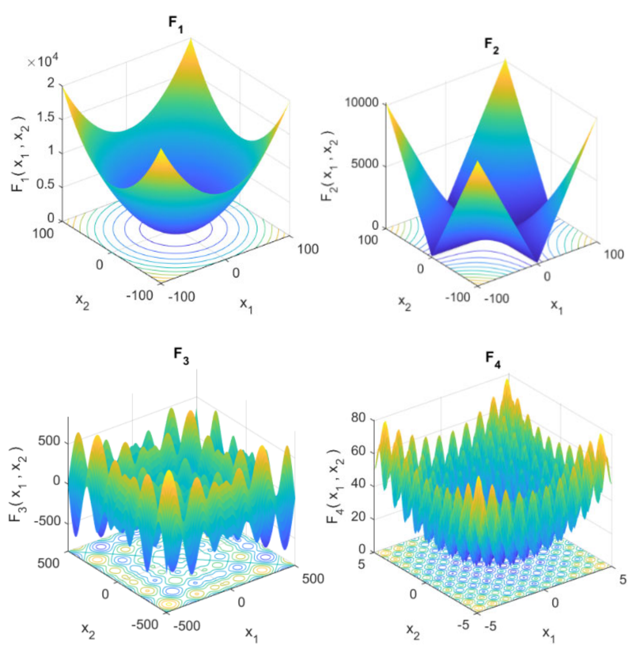

Figure 4. Quality test functions

4.2. Parameters

The parameters used in algorithms are provided in Table 2. The number of genes indicates the number of variables. Genes are represented as bit sequences within a chromosome. Also, P_c denotes the crossover probability, and P_m represents the mutation probability in GA. Babysitters are a DMO specific parameter. However, ARO does not have any specific control parameters unique to the algorithm.

Table 2. Parameters

Control parameters	**Algorithms**		
	GA	**ARO**	**DMO**
Number of genes	30	-	-
P_c	0.80	-	-
P_m	0.20	-	-
Number of babysitters	-	-	3
Alpha female vocalization	-	-	2
Population size	100	100	100
Maximum number of iterations	200	200	200

Table 3. Simulation results of quality test functions

Functions	**Algorithms**	**ARO**	**DMO**	**GA**
F_1	**Mean**	**1.93E-23**	1.41E+03	3.52E+04
	Std	2.91E-23	2.06E+02	3.88E+03
	Best	**1.43E-27**	1.05E+03	2.80E+04
	Worst	9.25E-23	1.76E+03	4.14E+04
	Rank	**1**	2	3
F_2	**Mean**	**1.50E-13**	8.56E+01	1.23E+04
	Std	1.55E-13	1.70E+01	1.64E+04
	Best	**2.86E-15**	5.84E+01	1.07E+02
	Worst	4.67E-13	1.17E+02	5.76E+04
	Rank	**1**	2	3
F_3	**Mean**	**2.73E+03**	7.50E+03	3.72E+05
	Std	3.88E+02	2.47E+02	2.84E+02
	Best	**1.88E+03**	6.94E+03	3.71E+05
	Worst	3.26E+03	7.90E+03	3.73E+05
	Rank	**1**	2	3
F_4	**Mean**	**0.00E+00**	2.61E+02	9.24E+03
	Std	0.00E+00	1.57E+01	3.26E+01
	Best	**0.00E+00**	2.16E+02	9.17E+03
	Worst	0.00E+00	2.81E+02	9.28E+03
	Rank	**1**	2	3
Total rank		**4**	8	12

5. Simulation Results

The algorithms were run independently 30 times in the study. The algorithms were implemented on the MATLAB R2023a platform, utilizing a machine with the following specifications: Core i5-8250U CPU, 1.6 GHz speed, and 8GB RAM. The simulation results of the quality test functions are provided in Table 3. All runs of functions are presented in the table, showing the mean, standard deviation, best, and worst results. In the table, algorithms that produce the highest mean and best value are highlighted in bold. Rankings are based on the means.

When considering the mean and best performances of all functions, ARO stands out as the most successful algorithm. Following ARO, the other best performing algorithm in terms of the solutions it generates is DMO. There are significant differences between the means of DMO and GA as well. For instance, in the function F_3, GA has a mean that is 3.65E+05 higher than DMO. Therefore, in all functions, GA has produced worse solutions than both algorithms. Furthermore, the low values of standard deviation in the algorithms indicate that the results of the convergence are close to each other and the difference between them is minimal. As in the other criteria, ARO has the lowest value in standard deviations. Moreover, ARO reached the optimal value of zero in the F_4 function. Even the worst values of ARO in each function produced better results than the best values of the other algorithms. At the same time, ARO has the lowest value in total ranks. This proves that ARO is the most successful algorithm in all functions.

6. t-test Results

t-test is a hypothesis test used in statistical analysis to determine the significance of the difference between two groups [19]. In this study, a one-tailed t-test has been used. The significance level in the t-test has been set at 5%. In the results, a value of h equal to 1 and p-values less than 0.05 indicate a significant difference between the two algorithms [20]. The statistical test results of the algorithms across all runs for each function used are provided in Table 4. The values of h have been bolded in the table.

In the right-tailed t-test, the algorithm on the right of the two given algorithms gives the minimum value. By referring to Table 3, three distinct pairs have been formed. According to the t-test results in the 1st and 2nd pairs, ARO, DMO, and GA have produced better results respectively. When comparing the results of DMO and GA, it is evident that DMO has performed better.

Table 4. t-test results

Functions	**DMO-ARO**		**GA-ARO**		**GA-DMO**	
	p	***h***	**p**	***h***	**p**	***h***
F_1	0.00E+00	**1.00E+00**	0.00E+00	**1.00E+00**	0.00E+00	**1.00E+00**
F_2	0.00E+00	**1.00E+00**	1.53E-04	**1.00E+00**	1.63E-04	**1.00E+00**
F_3	0.00E+00	**1.00E+00**	0.00E+00	**1.00E+00**	0.00E+00	**1.00E+00**
F_4	0.00E+00	**1.00E+00**	0.00E+00	**1.00E+00**	0.00E+00	**1.00E+00**

7. Conclusion

In this study, metaheuristics ARO, DMO, and GA are compared for the first time. Experiments are conducted on four different quality test functions using these algorithms. The success of the algorithms is evaluated using statistical t-tests to determine whether the differences are significant. According to the test results, it is observed that overall, in all functions, ARO consistently produces better results by generating minimum values compared to both DMO and GA. The order of algorithm success is ARO, DMO and GA. This situation indicates that suggesting and developing different metaheuristics could lead to better results. Future researches aims to compare various metaheuristic algorithms on diverse functions.

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