Available *online* at : http://jnte.ft.unand.ac.id/

Jurnal Nasional Teknik Elektro

| ISSN (Print) 2302-2949 | ISSN (Online) 2407-7267 |

Performance Enhancement of Elephant Herding Optimization Algorithm Using Modified Update Operators

Abdul-Fatawu Seini Yussif, Elvis Twumasi, Emmanuel Asuming Frimpong

Department of Electrical and Electronic Engineering, KNUST, Kumasi, Ghana

ARTICLE INFORMATION

Received: July 01, 2023
Revised: July 18, 2023
Accepted: July 18, 2023
Available online: July 31, 2023

KEYWORDS

Optimization, swarm intelligence, nature-inspired algorithm, elephant herding optimization, matriarch

CORRESPONDENCE

Phone: +233 248656932

E-mail: etwumasi.coe@knust.edu.gh

A B S T R A C T

This research paper presents a modified version of the Elephant Herding Optimization (EHO) algorithm, referred to as the Modified Elephant Herding Optimization (MEHO) algorithm, to enhance its global performance. The focus of this study lies in improving the balance between exploration and exploitation within the algorithm through the modification of two key operators: the matriarch updating operator and the separation updating operator. By reframing the equations governing these operators, the proposed modifications aim to enhance the algorithm's ability to discover optimal global solutions. The MEHO algorithm is implemented in the MATLAB environment, utilizing MATLAB R2019a. To assess its efficacy, the algorithm is subjected to rigorous testing on various standard benchmark functions. Comparative evaluations are conducted against the original EHO algorithm, as well as other established optimization algorithms, namely the Improved Elephant Herding Optimization (IEHO) algorithm, Particle Swarm Optimization (PSO) algorithm, and Biogeography-Based Optimization (BBO) algorithm. The evaluation metrics primarily focus on the algorithms' capacity to produce the best global solution for the tested functions. The proposed MEHO algorithm outperformed the other algorithms on 75% of the tested functions, and 62.5% under two specific test scenarios. The findings highlight the effectiveness of the proposed modification in enhancing the global performance of the Elephant Herding Optimization algorithm. Overall, this work contributes to the field of optimization algorithms by presenting a refined version of the EHO algorithm that exhibits improved global search capabilities.

INTRODUCTION

Several nature-inspired optimization algorithms have been proposed by researchers in the past years to solve optimization problems [1]. Out of the various categories, swarm intelligence (SI) based optimization algorithms stand out with the ability to search in large search spaces to avoid entrapment in local optima [2]. SI-based algorithms mimic the collective social behavior of living organisms or animals in nature. The well-organized behaviors portray local search intelligence that leads to intelligent global behavior for survival [1]. SI-based algorithms exploit the intelligent social behavior of such living organisms or animals to solve complex optimization problems with high accuracy [3]. Over the years, various SI-based optimization algorithms such as ant colony optimization (ACO) algorithm [4], particle swarm optimization (PSO) algorithm [5], artificial bee colony optimization (ABCO) algorithm [6], immune system optimization algorithm (ISA) [7], grey wolf optimization (GWO) algorithm [8], and elephant herding optimization (EHO) algorithm [9] have been developed.

The EHO algorithm is one of the SI-based metaheuristic optimization algorithms developed to mimic the herding behavior of elephants in their natural habitat in 2016 [9]. Among these algorithms, the EHO algorithm has been considered one of the algorithms with fast convergence and simplicity and has gained successful application for solving complex optimization problems. For instance, in [10], the EHO algorithm has been applied to support vector machine parameter tuning. It has also been applied in [11], to optimize a PI controller. Again, in [12] EHO algorithm has been applied to optimize heating ventilation, and air conditioning (HVAC) systems.

Despite the effectiveness exhibited by the EHO algorithm in solving some optimization problems, it has drawbacks of premature convergence and a high tendency of stagnation in local optimum solutions when used to solve complex optimization problems [13]. Therefore, there is a need for improvement to enhance its performance in producing global solutions. In [14], a chaotic approach is used to replace the random updating operators of clan members and replace the worst clan member in the original EHO. This produced improved results in determining the mean and standard deviation values of the solutions from thirty (30) runs. However, it performed poorly in attaining global optimal global solutions on benchmark functions compared to PSO and MFO. A levy flight strategy is used in reference [15] to modify the clan updating operator and to reduce the clan

https://doi.org/10.25077/jnte.v12n2.1085.2023

dependency on the matriarch of EHO. The levy strategy improved the quick convergence behavior of EHO but failed to relatively enhance its performance in obtaining global optima [16]. In [13], a modification to balance the exploitation and exploration in EHO is presented. It showed improvement in obtaining mean and standard deviations on benchmark functions. However, it performed poorly in obtaining global optima compared to BBO when tested on complex functions [17] [18].

Therefore, this work aims to enhance the performance of the EHO algorithm in solving complex optimization problems. Hence, a modification is proposed in this work to resolve the premature convergence as a result of entrapment in local optima [19] [20] and enhance the algorithm's ability to produce global optimal solutions when applied to optimization problems. The modification covers the equations for the matriarch updating operator and the separating updating operator. The rest of the work is presented in the following order. The method section presents the herding behavior of elephants, the standard elephant optimization (EHO) algorithm [21][22], the proposed modification, and the simulation test implementation. The results and discussion section presents simulation test results on benchmark functions and discussion. Finally, the paper is concluded in the conclusion section alongside recommendations.

Herding Behavior of Elephants:

Elephants are large mammals that have complex social lifestyles. Elephants are recognized for their huge body size and long multipurpose trunk. The African elephants are one of the traditionally recognized elephant breeds. A group of elephants live in smaller groups comprising female adult elephants and growing calves [9]. The smaller groups are called clans under the leadership of the strongest female adult elephant called the matriarch [23]. A clan moves in search of food where members' movement is influenced by the matriarch to ensure the maximum safety of the members. As a form of protection, the calves (baby elephants) usually move between the adult elephants. Male elephants on the other hand, gradually isolate themselves whiles growing up till they are completely separated from their clan while keeping communication through low-frequency vibrations [24].

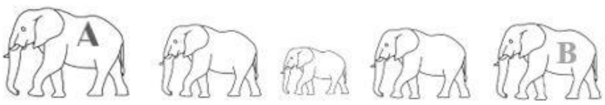

Figure 1. Elephant Clan

Fig. 1 depicts the elephant clan, with A as the matriarch, B as the growing male elephant, and the rest as female members.

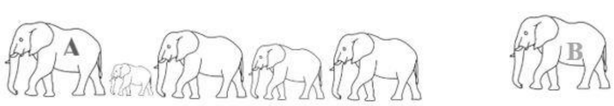

Figure 2. Male Separation

Fig. 2 shows the separation of a fully grown male elephant B and replacement by a newly born calf. The fully grown male elephant completely isolates itself from the clan, and the newborn calf is given a position to ensure maximum protection against predators.

The ideal position is between the two strongest female elephants in the clan, which is behind elephant A (Matriarch).

Original Elephant Herding Optimization (EHO) Algorithm:

The EHO algorithm mimics the herding behavior of elephants in nature and follows the movement pattern of elephants in various clans in searching for food [9]. EHO is based on two major phases; the Clan updating operator and the separating updating operator. It is guided by the following assumptions:

i. The elephant population is made of smaller groups called clans with a fixed number of members.
ii. Male elephants will isolate themselves from their clan and live far away in each generation.
iii. Elephants in each clan live together under the leadership of a matriarch (strongest female member).

Initialization:

At the start, random uniform distributed positions of N elephants' population are generated using equation 1. The population is grouped into smaller groups (clans) with an equal number of members.

$$x_j = x_{\min} + \alpha\left(x_{\max} - x_{\min} + 1\right) \times rand \tag{1}$$

where $x_{\min}$ and $x_{\max}$ are lower and upper bound of positions in the elephant population, and $rand \in [0,1]$ is a stochastic distribution.

Clan Updating Operator:

For a given clan *Ci*, the members live together under the matriarch's leadership. The new position of each member *j* in the next generation is influenced by the matriarch according to equation 2 [9].

$$x_{ci,j}^{t+1} = x_{ci,j}^{t} + \alpha\left(x_{best,ci}^{t} - x_{ci,j}^{t}\right) \times r \tag{2}$$

where $x_{new,ci,j}$ and $x_{ci,j}$ represent the new and old positions of clan members respectively, $x_{best,ci}$ represents the position of the matriarch, $\alpha \in [0,1]$ is a factor that determines the level of the matriarch's influence on the clan members' new position, $r \in [0,1]$ and is a factor randomly generated using a uniform distribution.

The matriarch's new position is updated by equation (3).

$$x_{best,ci}^{t+1} = \beta \times \left(x_{center,ci}^{t}\right) \tag{3}$$

where $\beta \in [0,1]$ is a factor for determining the influence of $x_{center,ci}$ the matriarch's new position, while $x_{center,ci}$ represents the clan center calculated using equation (4).

https://doi.org/10.25077/jnte.v12n2.1085.2023

$$x_{center,ci}^{t+1} = \frac{1}{n_{ci}} \times \sum_{j=1}^{n_c i} x_{ci,j,d}^{t} \tag{4}$$

where n_{ci} represents the number of elephants in the clan, and d is the dimension of the problem being solved in an interval $\left(1 \le d \le D\right)$.

Separating Operator:

The male elephant leaves the clan when it attains puberty. To ensure the elimination of the worst clan member, it is assumed that the weakest clan member implements the separation operator. The weakest member in each generation is replaced by a random elephant generated according to equation (5).

$$x_{worst,ci}^{t+1} = x_{\min} + \left(x_{\max} - x_{\min} + 1\right) \times rand \tag{5}$$

where $x_{\min}$ and $x_{\max}$ are lower and upper bound of positions in the elephant population, $x_{worst.ci}$ is the position of the worst individual in the clan, and $rand \in [0,1]$ is a stochastic distribution.

METHOD

Proposed Modification of Elephant Herding Optimization (MEHO) Algorithm:

Matriarch Updating Operator:

In EHO, the matriarch's new position is updated according to equation 3. All the clan members depend on the matriarch to update their positions while the matriarch depends on the clan center *($Ci_{center,\ ci}$)*. The clan center is the average of the position values of all clan members, calculated using Equation 4. However, the matriarch's position update is highly dependent on beta *(β)* and the clan center *($Ci_{center,\ ci}$)*. This high dependency on the clan center causes poor exploration in the global search space. To improve the global search, equation 3 is modified into Equation (6). The new matriarch position is updated from its previous position and the influence of the clan center. Beta *(β)* is a factor that represents the influence of the clan center. This enhances the global search ability of the algorithm.

$$x_{best,ci}^{t+1} = x_{best,ci}^{t} + \beta \times \left(x_{center,ci}^{t} - x_{best,ci}^{t}\right) \tag{6}$$

Separating Updating Operator:

In the original EHO, a separating operator is used to replace the worst clan member with a new one and randomly generates a position for it at each iteration using equation 5. However, the random nature of the replacement has no assurance of better replacement for the worst clan member and leads to poor convergence [16]. Based on the observation that the new member is actually a newly born calf into the clan and is usually positioned between female adult members for effective protection and grooming, a predefined position is proposed in this work for the new member according to equation (7). At each iteration, the new member is positioned between the two best/strongest clan members. This gives assured better replacement of the worst clan member to improve the convergence of the algorithm.

$$x_{worst,ci}^{t+1} = \frac{1}{2} \times \left(x_{best,ci}^{t} + x_{\sec-best,ci}^{t}\right) \times R \tag{7}$$

where $x_{best,ci}$ and $x_{\sec-best,ci}$ are the best two female members of the clan at the respective generation. R is a factor that gives the calf freedom to roam within a certain range of the assigned position. It is randomly generated within the range $[0.5, 1.01]$. The operators can be implemented by the following pseudo codes:

for *Ci =1 to $nClan$ (*for all clans in the population*) **do***
  for *j=1 to nCi (for all elephants in Ci)* ***do***
    Update $x_{ci,j}$ and generate $x_{new,ci,j}$ using Eq 2
   If *$x_{ci,j}$ = $x_{best,ci}$ then*
    Update $x_{ci,j}$ and generate $x_{new,ci,j}$ using Eq 6
   end if
  end for j
end for Ci

Figure 3. Pseudocode of clan updating operator

for *Ci =1 to $nClan$ (*all the clans in the elephant population*) **do***
  Replace the worst elephant in clan Ci using Eq 7.
end for Ci

Figure 4. Pseudocode of separating updating operator.

Based on the detailed description given of the clan updating operator and the separating updating operator, figure 5 is a flowchart guide to the implementation of the proposed Modified Elephant Herding Optimization (MEHO) algorithm.

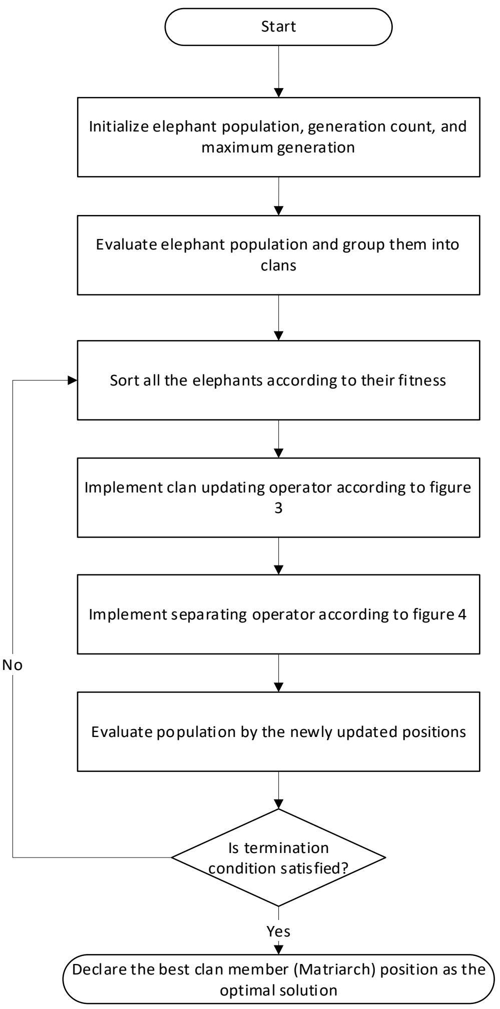

Figure 5. Implementation of MEHO

Testing of Proposed Modified Elephant Herding Optimization (Meho) Algorithm:

The proposed modification to the EHO algorithm, the MEHO algorithm, was tested on sixteen (16) standard benchmark functions. These functions were selected from IEEE CEC 2005, 2010, and 2014 picked from references [17]. Details of the benchmark functions used are shown in Tables 1 and 2.

Table 1. Details of Benchmark functions

Function	Benchmark Name	Range	Global Optima value	Dim
F1	Ackley	[-30, 30]	0	20
F2	Levy	[-10, 10]	0	20
F3	Griewank	[-600, 600]	0	20
F4	Perm O, D, Beta	[-30, 30]	0	20
F5	Perm D, Beta	[-30, 30]	0	20
F6	Rastrigin	[-5.12, 5.12]	0	20
F7	Sphere	[-5.12, 5.12]	0	20
F8	Trid	[-100, 100]	-1520	20
F9	Powell	[-4, 5]	0	20
F10	Styblinski-Tang	[-5, 5]	-783.3198	20
F11	Dixon-Price	[-10, 10]	0	20
F12	Sum of Different Powers	[-1, 1]	0	20
F13	Sum Squares	[-10, 10]	0	20
F14	Rosenbrock	[-5, 10]	0	20
F15	Zakharov	[-5, 10]	0	20
F16	Scwefel	[-500, 500]	0	20

Table 2. Scientific Equations of Benchmark Functions

Function	Equation
F1	$f(x) = -a\exp\left(-b\sqrt{\frac{1}{d}\sum_{i=1}^{d} x_i^2}\right) - \exp\left(\frac{1}{d}\sum_{i=1}^{d}\cos(cx_i)\right) + a + \exp(1)$ $i = 1, \ldots\ldots, d$
F2	$f(x) = \sin^2(\pi w_i) + \sum_{i=1}^{d-1}(w_i - 1)^2\left[1 + 10\sin^2(\pi w_i + 1)\right]$ $+(w_d - 1)^2\left[1 + \sin^2(2\pi w_d)\right]$ $w_i = 1 + \frac{x_i - 1}{4}, i = 1, \ldots\ldots, d$
F3	$f(x) = \sum_{i=1}^{d}\frac{x_i^2}{400} - \prod_{i=1}^{d}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$ $i = 1, \ldots\ldots, d$
F4	$f(x) = \sum_{i=1}^{d}\left(\sum_{j=1}^{d}(j + \beta)\left(x_j^i - \frac{1}{j^i}\right)\right)^2$ $i = 1, \ldots\ldots, d . j = 1, \ldots\ldots, d$
F5	$f(x) = \sum_{i=1}^{d}\left(\sum_{j}^{d}\left(j^i + \beta\right)\left(\left(\frac{x_j}{j}\right)^i - 1\right)\right)^2$ $i = 1, \ldots\ldots, d . j = 1, \ldots\ldots, d$
F6	$f(x) = 10d + \sum_{i=1}^{d}\left[x_i^2 - 10\cos(2\pi x_i)\right]$ $i = 1, \ldots, d$

https://doi.org/10.25077/jnte.v12n2.1085.2023

F7	$f(x)=\sum_{i=1}^{d} x_i^2 \quad i=1,....,d$
F8	$f(x)=\sum_{i=1}^{d}(x_i-1)^2-\sum_{i=2}^{d} x_i x_{i-1}$ $i=1,.......,d$
F9	$f(x)=\sum_{i=1}^{\frac{d}{4}}\left[(x_{4i-3}+10x_{4i-2})^2+5(x_{4i-1}-x_{4i})^2+(x_{4i-2}-2x_{4i-1})^4+10(x_{4i-3}-x_{4i})^4\right]$ $i=1,...,d$
F10	$f(x)=\frac{1}{2}\sum_{i=1}^{d}(x_i^4-16x_i^2+5x_i)$ $i=1,.....,d$
F11	$f(x)=(x_i-1)^2+\sum_{i=2}^{d} i(2x_i^2-x_{i-1})^2$ $i=1,.....,d$
F12	$f(x)=\sum_{i=1}^{d}\lvert x_i\rvert^{i+1}, i=1,....,d$
F13	$f(x)=\sum_{i=1}^{d} ix_i^2, i=1,......,d$
F14	$f(x)=\sum_{i=1}^{d-1}\left[100(x_{i+1}-x_i^2)^2+(x_i-1)^2\right]$ $i=1,...,d$
F15	$f(x)=\sum_{i=1}^{d} x_i^2+\left(\sum_{i=1}^{d}0.5ix_i\right)^2+\left(\sum_{i=1}^{d}0.5ix_i\right)^4$ $i=1,.....,d$
F16	$f(x)=418.9829d-\sum_{i=1}^{d} x_i\sin\left(\sqrt{\lvert x_i\rvert}\right)$ $i=1,......,d$

In addition to the test functions presented in Tables 1 and 2, the following parameter settings in Table 3 were used for the implementation of the proposed MEHO and the original EHO algorithms.

Table 3. Parameters for simulation

Parameter	Value
α	0.5
β	0.1
Population size	50
Number of Clans	5
Maximum Iteration	100
Number of Runs	30

To establish fair assessment, the simulation test on each benchmark function was repeated 30 times and the best result and the mean of the results were extracted. The test results were compared with those of the other optimization algorithms considered under two scenarios as follows:

i. The first scenario compares test results of the proposed modified elephant herding optimization (MEHO) algorithm with existing results of the original EHO and a variant (Improved Elephant Herding Optimization -IEHO) picked from reference [17]. The best optimal solution value and mean solution values are considered under this comparison.
ii. The second scenario compares the simulation results of the proposed modified elephant herding optimization (MEHO) with that of the particle swarm optimization (PSO) algorithm, and biogeography-based optimization (BBO) algorithm. The best optimal solution values and convergence characteristics are considered in this comparison.

The simulations were carried out in MATLAB environment (R2019a) using a Hp Pavilion laptop with the following specifications:

Processor: AMD A8-6410 APU with AMD Radeon R5 Graphics 2.00 GHz
Install memory (RAM): 4.00 GB (3.43 GB usable)
System type: Windows 10 Pro 64-bit Operating System, ×64-based processor.

RESULTS AND DISCUSSION

The test results are presented under two headings; scenario one and scenario two. Scenario 1 compared the best optimal results and the mean of the results of the proposed MEHO with the original EHO and a variant IEHO picked from the literature [17]. Scenario 2 compared the best optimal results and convergence characteristics of the proposed MEHO with that of the original EHO, Particle Swarm Optimization (PSO) algorithm, and Biogeography-Based Optimization (BBO) algorithms simulated on the same computer under the same conditions.

Scenario 1: Comparison in Terms of Best Optimal Solution and Mean Solution.

Table 4 contains the results for the first scenario. From this result, the proposed MEHO algorithm significantly outperformed the other algorithms by producing the best and mean global solutions on F1, F2, F3, F6, F7, F9, F10, F11, F12, F13, F14, and F16. The EHO algorithm produced the best performance in F8, while the IEHO algorithm showed best performance in F4, F5 and F15. The proposed MEHO algorithm performed exceptionally better than the EHO algorithm and the IEHO algorithm in most of the benchmark functions, that is twelve out of the sixteen test functions. The percentage representation is illustrated in Figure 6.

Table 4. Results comparison of MEHO to other modifications in the literature

Func	Parameter	EHO	IEHO	MEHO
F1	Best	1.180E-3	1.6206E-7	**6.1491E-8**
	Mean	1.760E-3	1.8291E-7	**1.1817E-7**
F2	Best	1.188E+0	1.1062E+0	**9.3156E-1**
	Mean	1.726E+0	1.2556E+0	**9.5606E-1**
F3	Best	5.490E-5	1.546E-12	**3.3307E-16**
	Mean	9.920E-3	1.967E-12	**3.8195E-16**
F4	Best	5.2042E+2	**1.3015E+2**	5.8008E+3
	Mean	1.6488E+3	**1.1605E+3**	5.8008E+3
F5	Best	5.9493E+45	**2.2499E+40**	6.865E+49
	Mean	1.6488E+48	**4.5413E+45**	1.5588E+51
F6	Best	1.890E-5	5.6843E-13	**1.4211E-13**
	Mean	3.750E-5	6.7757E-13	**4.8033E-13**
F7	Best	7.110E-8	7.9159E-13	**6.7403E-15**
	Mean	1.600E-7	1.9958E-12	**2.1035E-14**
F8	Best	**-3.0143E+1**	-2.7480E+1	1.3236E+1
	Mean	**-6.6518E+0**	-1.0112E+1	1.3301E+1
F9	Best	9.340E-7	4.0067E-14	**3.437E-14**
	Mean	5.650E-6	5.6644E-14	**1.2249E-13**
F10	Best	-5.2071E+2	-4.9804E+2	**-4.0783E+2**
	Mean	-4.4716E+2	-4.7391E+2	**-4.0268E+2**
F11	Best	7.8796E+1	7.21209E-1	**7.2101E-1**
	Mean	9.0060E+1	8.6529E-1	**8.3335E-1**
F12	Best	6.2295E-13	1.9276E-24	**1.5737E-24**
	Mean	6.0716E-12	3.2128E-24	**9.1319E-24**
F13	Best	2.2385E-6	5.1272E-14	**1.0775E-14**
	Mean	4.7144E-6	6.3831E-14	**4.0734E-14**
F14	Best	1.8703E+1	1.8748E+1	**1.8702E+1**
	Mean	1.8781E+1	1.8768E+1	**1.8728E+1**
F15	Best	3.5785E-5	**6.3818E-13**	2.7959E-10
	Mean	9.3992E-4	**1.2104E-12**	6.1273E-10
F16	Best	4.7589E+3	3.4122E+3	**2.7404E+3**
	Mean	5.9121E+3	4.5861E+3	**3.0802E+3**

Figure 6 compared the percentage performance of the EHO algorithm, IEHO algorithm, and the proposed MEHO algorithm in which the MEHO outperformed the other algorithms in twelve (12) functions, representing 75% of the total standard benchmark functions tested. Also, the EHO algorithm outperformed the other algorithms in 6.25% of the total functions tested, while the IEHO algorithm outperformed the others in 18.75% of the total benchmark functions tested. This performance by the proposed MEHO algorithm shows the positive impact of the modifications introduced in the matriarch updating and the separating updating operators, relative to the original version and the existing variant.

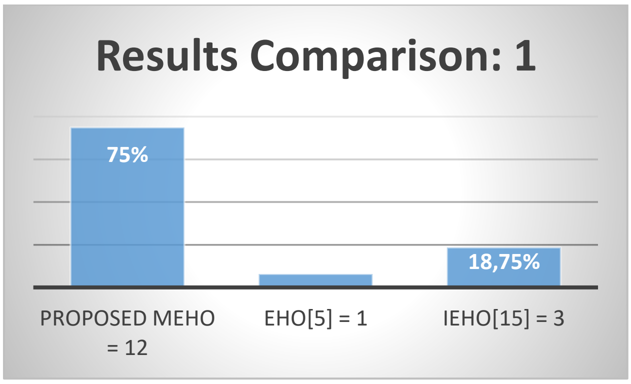

Figure 6. Percentage comparison with literature.

Scenario Two: Comparison in Terms of Best Optimal Solution and Convergence Characteristics.

Table 5 contains simulation test results of the four algorithms (PSO, BBO, EHO, and MEHO) based on their ability to produce the best global solutions on the sixteen benchmark test functions. These results seek to establish the performance of the proposed MEHO algorithm relative to PSO and BBO algorithms, and these are some well-known existing metaheuristic optimization algorithms. The proposed MEHO algorithm performed exceptionally better than the other optimization algorithms in F1, F3, F6, F7, F9, F10, F11, F12, F13, and F15. The PSO algorithm performed better in F8, and finally, the BBO algorithm performed better than the other algorithms in F2, F4, F5, F14, and F16. The proposed MEHO algorithm exhibited its superiority by performing better on more of the standard benchmark test functions than the others. The percentage performance is illustrated in Figure 7.

Table 5. Results comparison of MEHO with other algorithms

Fun	PSO	BBO	EHO	MEHO
F1	1.708E+1	8.541E+0	1.030E-3	**6.149E-8**
F2	4.414E-7	**6.379E-9**	1.191E+0	9.315E-1
F3	1.478E-2	1.478E-2	8.016E-8	**3.330E-16**
F4	5.343E-1	**3.102E-1**	6.258E+2	5.801E+3
F5	2.560E+12	**3.062E+1**	7.508E+49	6.86E+49
F6	3.0687E+0	5.084E-5	1.112E-5	**1.421E-13**
F7	4.0453E-7	4.485E-8	8.615E-8	**6.740E-15**
F8	**-2.100E+2**	-2.998E+1	9.184E+0	1.323E+1
F9	1.6334E-4	6.634E-5	1.488E-6	**3.437E-14**
F10	-3.774E+2	-1.675E+2	-3.792E+2	**-4.08E+2**
F11	1.602E+0	8.010E-1	8.734E-1	**7.210E-1**
F12	6.093E-12	1.331E-13	1.046E-12	**1.573E-24**
F13	5.049E-5	2.0293E-8	7.6209E-6	**1.077E-14**
F14	5.464E+0	**3.942E+0**	1.8749E+1	1.870E+1
F15	1.367E-2	5.7608E-5	1.725E-5	**2.796E-10**
F16	4.029E+3	**2.075E+3**	4.770E+3	2.740E+3

https://doi.org/10.25077/jnte.v12n2.1085.2023

In Figure 7, the proposed MEHO algorithm performed exceptionally better than the other algorithms with the highest percentage of 62.50% of the total number of benchmark functions tested. The PSO algorithm performed well in 6.25% of the functions, and the BBO algorithm performed better in 31.25% of the total functions. The proposed MEHO algorithm exhibited its superiority with the highest percentage performance of 62.50%.

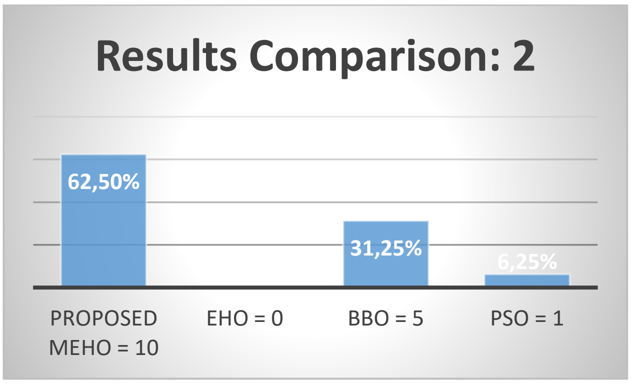

Figure 7. Results comparison with different algorithms

Figures 8, 9, 10, 11, 12, and 13 compared the convergence characteristics of the proposed MEHO algorithm, EHO algorithm, BBO algorithm, and PSO algorithm when tested on the **Ackley benchmark function, Griewank benchmark function, Rastrigin benchmark function, Sphere benchmark function, Powell benchmark function, and Dixon-Price benchmark function** respectively. In Figure 8, it is observed that the proposed MEHO algorithm exhibited a smooth convergence to the best global solution. It is also observed in Figures 9, 10, 11, 12, and 13 that the proposed MEHO algorithm showed good convergence curves that were able to avoid entrapment in local optimal solutions, and effectively searched towards obtaining the best global optimal solutions. This shows the enhancement of the proposed modifications on the two update operators in the original EHO algorithm.

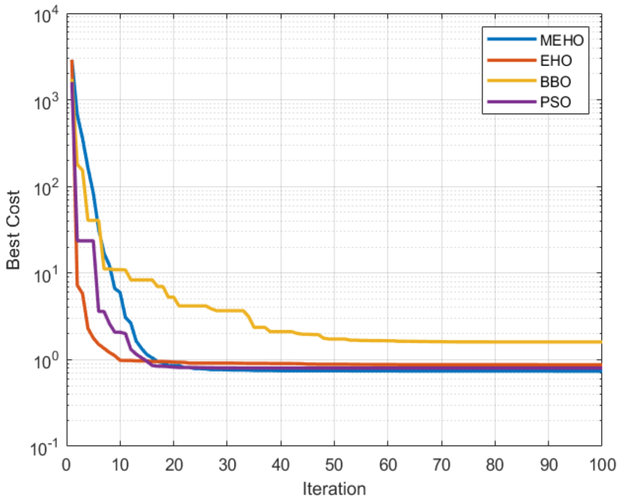

Figure 8. Convergence curves for Ackley function (F1)

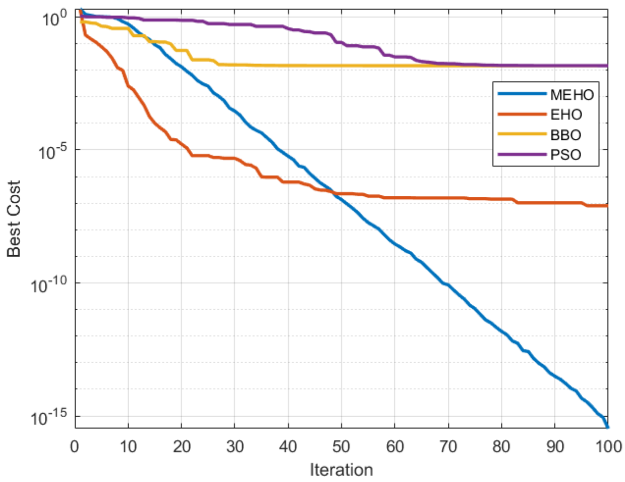

Figure 9. Convergence curves for Griewank function (F3)

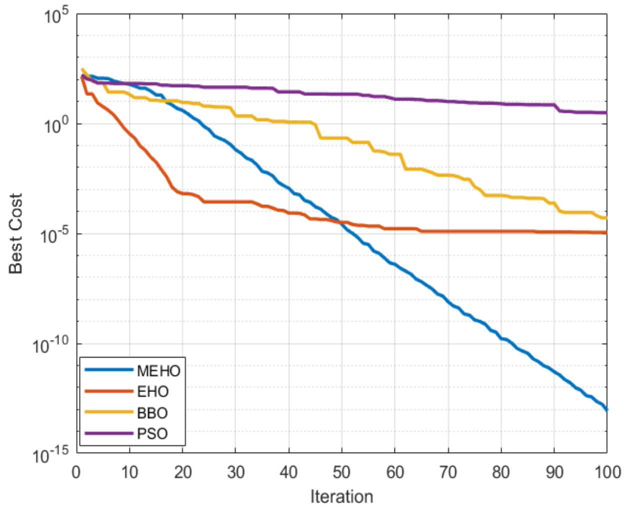

Figure 10. Convergence curves for Rastrigin function (F6)

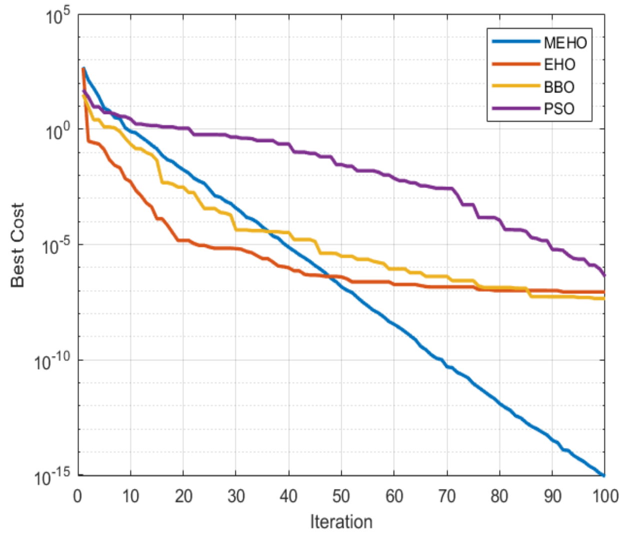

Figure 11. Convergence curves for Sphere function (F7)

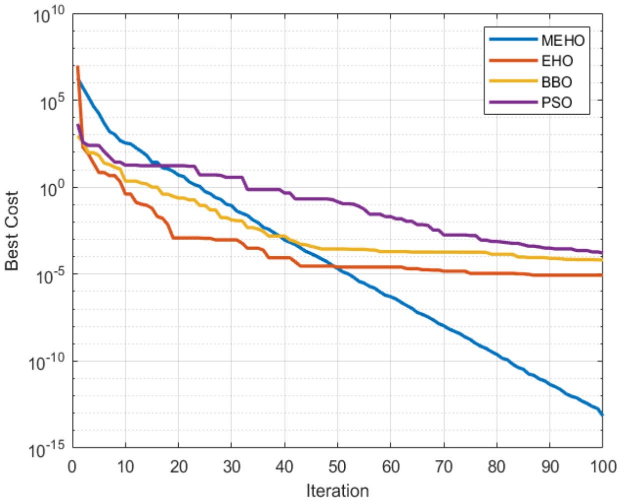

Figure 12. Convergence curves for Powell function (F9)

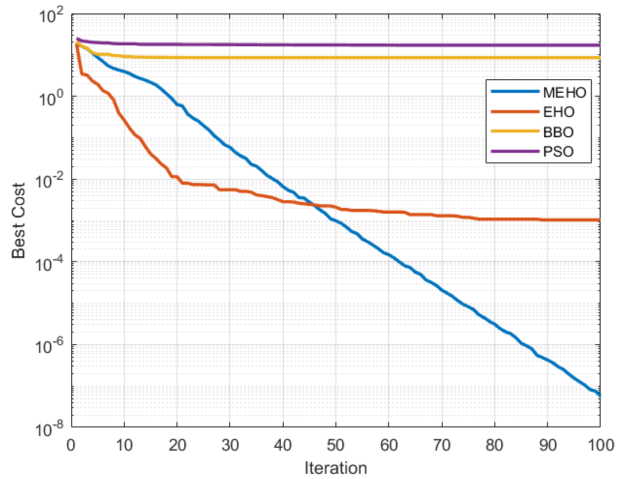

Figure 13. Convergence curves for the Dixon-Price function (F11)

CONCLUSION AND RECOMMENDATION

In this paper, a modification of elephant herding optimization (MEHO) to enhance its performance in finding the best global optimal solutions is presented. A modification of the matriarch updating operator and the separating updating operator of the EHO is carried out. Simulation results, in a MATLAB environment, on standard benchmark test functions showed 75% success in producing the best optimal solutions and the mean solutions compared with those of the original EHO and an improved version, IEHO. Also, 62.50% success in producing the best optimal solutions and efficient convergence characteristics have been achieved compared to simulated results of the PSO algorithm and BBO algorithm. These performances have justified the effectiveness of the proposed MEHO algorithm. It is therefore concluded that the modification proposed has enhanced the performance of the elephant herding optimization (EHO) technique in finding globally optimal solutions for optimization problems.

The proposed modified elephant herding optimization (MEHO) algorithm is recommended for researchers to adopt in solving optimization problems. For instance, it can be adapted for the optimal placement and sizing of compensation devices in power systems.

REFERENCES

[1] T. Dokeroglu, E. Sevinc, T. Kucukyilmaz, and A. Cosar, “A survey on new generation metaheuristic algorithms,” *Comput. Ind. Eng.*, vol. 137, no. August, p. 106040, 2019, doi: 10.1016/j.cie.2019.106040.

[2] Z. Meng, G. Li, X. Wang, S. M. Sait, and A. R. Yıldız, “A Comparative Study of Metaheuristic Algorithms for Reliability-Based Design Optimization Problems,” *Arch. Comput. Methods Eng.*, vol. 28, no. 3, pp. 1853–1869, 2021, doi: 10.1007/s11831-020-09443-z.

[3] X. S. Yang, “Swarm intelligence based algorithms: A critical analysis,” *Evol. Intell.*, vol. 7, no. 1, pp. 17–28, 2014, doi: 10.1007/s12065-013-0102-2.

[4] R. Jangra and R. Kait, “Analysis and comparison among Ant System; Ant Colony System and Max-Min Ant System with different parameters setting,” *3rd IEEE Int. Conf.* , pp. 1–4, 2017, doi: 10.1109/CIACT.2017.7977376.

[5] R. M. Golubovićć, D. I. Olćan, and B. M. Kolundžija, “Particle swarm optimization algorithm and its modifications applied to EM problems,” *8th Int. Conf. Telecommun. Mod. Satell. Cable Broadcast. Serv. TELSIKS 2007, Proc. Pap.*, pp. 427–430, 2007, doi: 10.1109/TELSKS.2007.4376029.

[6] W. Gao, S. Liu, and L. Huang, “A global best artificial bee colony algorithm for global optimization,” *J. Comput. Appl. Math.*, vol. 236, no. 11, pp. 2741–2753, 2012, doi: 10.1016/j.cam.2012.01.013.

[7] T. Liu, F. W. Cao, and Y. Zhou, “Optimization design algorithm based on artificial immune system for mechanical systems,” *2nd Int. Symp. Electron. Commer. Secur. ISECS 2009*, vol. 1, no. 1, pp. 612–615, 2009, doi: 10.1109/ISECS.2009.214.

[8] S. Mirjalili, S. M. Mirjalili, and A. Lewis, “Grey Wolf Optimizer,” *Adv. Eng. Softw.*, vol. 69, pp. 46–61, 2014, doi: 10.1016/j.advengsoft.2013.12.007.

[9] G. G. Wang, S. Deb, and L. D. S. Coelho, “Elephant Herding Optimization,” *Proc. - 2015 3rd Int. Symp. Comput. Bus. Intell. ISCBI 2015*, pp. 1–5, 2016, doi: 10.1109/ISCBI.2015.8.

[10] E. Tuba and Z. Stanimirovic, “Elephant herding optimization algorithm for support vector machine parameters tuning,” *Proc. 9th Int. Conf. Electron. Comput. Artif. Intell. ECAI 2017*, vol. 2017-Janua, pp. 1–4, 2017, doi: 10.1109/ECAI.2017.8166464.

[11] M. F. El-Naggar, M. I. Mosaad, H. M. Hasanien, T. A. AbdulFattah, and A. F. Bendary, “Elephant herding algorithm-based optimal PI controller for LVRT enhancement of wind energy conversion systems,” *Ain Shams Eng. J.*, vol. 12, no. 1, pp. 599–608, 2021, doi: 10.1016/j.asej.2020.07.013.

[12] H. Moayedi, M. A. Mu’azu, and L. K. Foong, “Novel swarm-based approach for predicting the cooling load of residential buildings based on social behavior of elephant herds,” *Energy Build.*, vol. 206, p. 11, 2020, doi: 10.1016/j.enbuild.2019.109579.

[13] A. A. K. Ismaeel, I. A. Elshaarawy, E. H. Houssein, F. H. Ismail, and A. E. Hassanien, “Enhanced Elephant Herding Optimization for Global Optimization,” *IEEE Access*, vol. 7, pp. 34738–34752, 2019, doi:

https://doi.org/10.25077/jnte.v12n2.1085.2023

10.1109/ACCESS.2019.2904679.

[14] E. Tuba, R. Capor-Hrosik, A. Alihodzic, R. Jovanovic, and M. Tuba, "Chaotic elephant herding optimization algorithm," *SAMI 2018 - IEEE 16th World Symp. Appl. Mach. Intell. Informatics Dedic. to Mem. Pioneer Robot. Antal K. Bejczy, Proc.*, vol. 2018-Febru, no. February, pp. 213–216, 2018, doi: 10.1109/SAMI.2018.8324842.

[15] H. Xu *et al.*, "Application of elephant herd optimization algorithm based on levy flight strategy in intrusion detection," *Proc. 2018 IEEE 4th Int. Symp. Wirel. Syst. within Int. Conf. Intell. Data Acquis. Adv. Comput. Syst. IDAACS-SWS 2018*, pp. 16–20, 2018, doi: 10.1109/IDAACS-SWS.2018.8525848.

[16] S. S. Chippagiri, S. Pemmada, and N. R. Patne, "Distribution Network Reconfiguration and Distributed Generation Injection Using Improved Elephant Herding Optimization," pp. 1–6, 2020, doi: 10.1109/stpec49749.2020.9297805.

[17] M. A. Elhosseini, R. A. El Sehiemy, Y. I. Rashwan, and X. Z. Gao, "On the performance improvement of elephant herding optimization algorithm," *Knowledge-Based Syst.*, vol. 166, pp. 58–70, 2019, doi: 10.1016/j.knosys.2018.12.012.

[1] T. Dokeroglu, E. Sevinc, T. Kucukyilmaz, and A. Cosar, "A survey on new generation metaheuristic algorithms," Comput. Ind. Eng., vol. 137, no. August, p. 106040, 2019, doi: 10.1016/j.cie.2019.106040.

[2] Z. Meng, G. Li, X. Wang, S. M. Sait, and A. R. Yıldız, "A Comparative Study of Metaheuristic Algorithms for Reliability-Based Design Optimization Problems," Arch. Comput. Methods Eng., vol. 28, no. 3, pp. 1853–1869, 2021, doi: 10.1007/s11831-020-09443-z.

[3] X. S. Yang, "Swarm intelligence based algorithms: A critical analysis," Evol. Intell., vol. 7, no. 1, pp. 17–28, 2014, doi: 10.1007/s12065-013-0102-2.

[4] R. Jangra and R. Kait, "Analysis and comparison among Ant System; Ant Colony System and Max-Min Ant System with different parameters setting," 3rd IEEE Int. Conf. , pp. 1–4, 2017, doi: 10.1109/CIACT.2017.7977376.

[5] R. M. Golubovićć, D. I. Olćan, and B. M. Kolundžija, "Particle swarm optimization algorithm and its modifications applied to EM problems," 8th Int. Conf. Telecommun. Mod. Satell. Cable Broadcast. Serv. TELSIKS 2007, Proc. Pap., pp. 427–430, 2007, doi: 10.1109/TELSKS.2007.4376029.

[6] W. Gao, S. Liu, and L. Huang, "A global best artificial bee colony algorithm for global optimization," J. Comput. Appl. Math., vol. 236, no. 11, pp. 2741–2753, 2012, doi: 10.1016/j.cam.2012.01.013.

[7] T. Liu, F. W. Cao, and Y. Zhou, "Optimization design algorithm based on artificial immune system for mechanical systems," 2nd Int. Symp. Electron. Commer. Secur. ISECS 2009, vol. 1, no. 1, pp. 612–615, 2009, doi: 10.1109/ISECS.2009.214.

[8] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey Wolf Optimizer," Adv. Eng. Softw., vol. 69, pp. 46–61, 2014, doi: 10.1016/j.advengsoft.2013.12.007.

[9] G. G. Wang, S. Deb, and L. D. S. Coelho, "Elephant Herding Optimization," Proc. - 2015 3rd Int. Symp. Comput. Bus. Intell. ISCBI 2015, pp. 1–5, 2016, doi: 10.1109/ISCBI.2015.8.

[10] E. Tuba and Z. Stanimirovic, "Elephant herding optimization algorithm for support vector machine parameters tuning," Proc. 9th Int. Conf. Electron. Comput. Artif. Intell. ECAI 2017, vol. 2017-Janua, pp. 1–4, 2017, doi: 10.1109/ECAI.2017.8166464.

[11] M. F. El-Naggar, M. I. Mosaad, H. M. Hasanien, T. A. AbdulFattah, and A. F. Bendary, "Elephant herding algorithm-based optimal PI controller for LVRT enhancement of wind energy conversion systems," Ain Shams Eng. J., vol. 12, no. 1, pp. 599–608, 2021, doi: 10.1016/j.asej.2020.07.013.

[12] H. Moayedi, M. A. Mu'azu, and L. K. Foong, "Novel swarm-based approach for predicting the cooling load of residential buildings based on social behavior of elephant herds," Energy Build., vol. 206, p. 11, 2020, doi: 10.1016/j.enbuild.2019.109579.

[13] A. A. K. Ismaeel, I. A. Elshaarawy, E. H. Houssein, F. H. Ismail, and A. E. Hassanien, "Enhanced Elephant Herding Optimization for Global Optimization," IEEE Access, vol. 7, pp. 34738–34752, 2019, doi: 10.1109/ACCESS.2019.2904679.

[14] E. Tuba, R. Capor-Hrosik, A. Alihodzic, R. Jovanovic, and M. Tuba, "Chaotic elephant herding optimization algorithm," SAMI 2018 - IEEE 16th World Symp. Appl. Mach. Intell. Informatics Dedic. to Mem. Pioneer Robot. Antal K. Bejczy, Proc., vol. 2018-Febru, no. February, pp. 213–216, 2018, doi: 10.1109/SAMI.2018.8324842.

[15] H. Xu et al., "Application of elephant herd optimization algorithm based on levy flight strategy in intrusion detection," Proc. 2018 IEEE 4th Int. Symp. Wirel. Syst. within Int. Conf. Intell. Data Acquis. Adv. Comput. Syst. IDAACS-SWS 2018, pp. 16–20, 2018, doi: 10.1109/IDAACS-SWS.2018.8525848.

[16] S. S. Chippagiri, S. Pemmada, and N. R. Patne, "Distribution Network Reconfiguration and Distributed Generation Injection Using Improved Elephant Herding Optimization," pp. 1–6, 2020, doi: 10.1109/stpec49749.2020.9297805.

[17] M. A. Elhosseini, R. A. El Sehiemy, Y. I. Rashwan, and X. Z. Gao, "On the performance improvement of elephant herding optimization algorithm," Knowledge-Based Syst., vol. 166, pp. 58–70, 2019, doi: 10.1016/j.knosys.2018.12.012.

[18] H. Muthusamy, S. Ravindran, S. Yaacob, and K. Polat, "An improved elephant herding optimization using sine–cosine mechanism and opposition based learning for global optimization problems," Expert Syst. Appl., vol. 172, no. October 2020, p. 114607, 2021, doi: 10.1016/j.eswa.2021.114607.

[19] N. S. Guptha, V. Balamurugan, G. Megharaj, K. N. A. Sattar, and J. D. Rose, "Cross lingual handwritten character recognition using long short term memory network with aid of elephant herding optimization algorithm," Pattern Recognit. Lett., vol. 159, pp. 16–22, 2022, doi: 10.1016/j.patrec.2022.04.038.

[20] M. A. S. Ali et al., "Classification of Glaucoma Based on Elephant-Herding Optimization Algorithm and Deep Belief Network," Electron., vol. 11, no. 11, 2022, doi: 10.3390/electronics11111763.

[21] T. Bezdan, S. Milosevic, K. Venkatachalam, M.

Zivkovic, N. Bacanin, and I. Strumberger, “Optimizing Convolutional Neural Network by Hybridized Elephant Herding Optimization Algorithm for Magnetic Resonance Image Classification of Glioma Brain Tumor Grade,” 2021 Zooming Innov. Consum. Technol. Conf. ZINC 2021, pp. 171–176, 2021, doi: 10.1109/ZINC52049.2021.9499297.

[22] H. Hakli, “BinEHO: a new binary variant based on elephant herding optimization algorithm,” Neural Comput. Appl., vol. 32, no. 22, pp. 16971–16991, 2020, doi: 10.1007/s00521-020-04917-4.

[23] Y. Duan, C. Liu, S. Li, X. Guo, and C. Yang, “Gradient-based elephant herding optimization for cluster analysis,” Appl. Intell., vol. 52, no. 10, pp. 11606–11637, 2022, doi: 10.1007/s10489-021-03020-y.

[24] J. Li, H. Lei, and A. H. Alavi, “10.3390@Math8091415.Pdf,” 2020.

https://doi.org/10.25077/jnte.v12n2.1085.2023