Modified Mountain Gazelle Optimizer Based on Logistic Chaotic Mapping and Truncation Selection

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Abstract - *In this study, a Modified Mountain Gazelle Optimizer (MMGO) algorithm is presented. The proposed algorithm was designed to improve the ability of MGO in solving high-dimensional problems, increase convergence speed, and enhance stability. The modification is based on the application of a logistics chaotic mapping at the initialization stage, a modified Migration pattern in the Search of Food (MSF) phase for diversity maintenance, and a controlling factor at the Territorial and Solitary Males (TSM) phase using the truncation selection technique. The proposed algorithm was implemented in MATLAB software and its performance was tested on 23 benchmark functions, and a real-life engineering problem to prove its efficiency and adaptability. The results of the MMGO were compared with those of the basic Mountain Gazelle Optimizer (MGO), Particle Swarm Optimization (PSO), and Gravitational Search Algorithm (GSA). The findings of the work indicated that the MMGO outperformed the other state-of-the-art algorithms in terms of both optimization accuracy and computational efficiency. The results demonstrated the effectiveness and robustness of the proposed MMGO algorithm, in solving high-dimensional optimization problems in engineering and other fields.*

Key Words: Mountain Gazelle Optimizer (MGO), logistics chaotic mapping, truncation selection technique, high-dimensional problem, optimization.

1. INTRODUCTION

The use of metaheuristic algorithms in finding optimal solutions to complex problems has seen wide applications in various fields such as engineering, finance, and computer science [1,2]. However, as the complexity and dynamism of the problem increase, metaheuristic algorithms often struggle to find the global optimum solution within a reasonable time frame and iterations [3-5]. To address this limitation, researchers have proposed modifications to metaheuristic algorithms to enhance their performance in solving complex optimization problems [6-8]. These modifications can improve the search efficiency of the metaheuristic algorithms, thereby enabling them to find better solutions. One such modification is the incorporation of problem-specific operators [9]. For instance, Ogun et al proposed a modified bull optimization algorithm for continuous optimization problems based on genetic operators [10], and Bing et al improved the Sparrow Search Algorithm (SSA) with a mutation strategy for global optimization [11].

Though these improved algorithms offer a promising avenue for solving complex problems, researchers are still in search of novel algorithms that exhibit robustness, flexibility, and the ability to handle diverse problem domains. Also, the dynamic nature of many real-world problems necessitates newly developed algorithms that are adaptive and can quickly respond to changing or evolving problem conditions [9,11]. The Mountain Gazelle Optimizer (MGO) developed by Benyamin et al [12] in 2022 is one of such algorithms. The MGO has been proven to handle problems characterized by high nonlinearity, and combinatorial complexity and has exhibited good performance when tested on some standard benchmark test functions and real-life engineering problems. However, similar to some other metaheuristic algorithms, it still suffers from optimization accuracy, slow convergence, and entrapment in suboptimal solutions when applied to complex high-dimensional optimization problems [12]. These high-dimensional and large-scale problems often exhibit a large number of variables, constraints, and interactions, making it difficult for the MGO to get an exact solution due to the exponential growth of the search space.

This is mainly associated with the poor quality of the initial population, lack of proper diversity maintenance mechanism, and lack of effective convergence control in the algorithm derivation [12]. However, in order to ensure the holistic application of this essential algorithm which is based on the social intelligence of mountain gazelles in the wildlife, there needs to be an improvement of its parameters to ensure its exploration and exploitation ability to deal with high dimensional problems.

Therefore, this paper proposes a Modified Mountain Gazelle Optimizer (MMGO), an improvement of the MGO algorithm to enhance its performance in solving high-dimensional engineering problems. Three modifications are incorporated. Firstly, a Logistic Chaotic mapping [13][14] is utilized to replace the random initialization in MGO to improve the quality of the initial population. Secondly, an operator is modified to maintain diversity in the population during the execution process to avoid suboptimal solutions [15]. Thirdly, a Truncation Selection Technique [16] is adopted to determine the value of the newly introduce parameter to control the convergence speed. The effectiveness of the

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proposed MMGO algorithm is established by benchmarking its performance against the original MGO and other state-of-the-art optimization algorithms, including PSO [8], and GSA [17].

The remainder of this paper is arranged as follows: the basic MGO algorithm is briefly described in section 2. In section 3, a detailed description of the three modifications is presented. Section 4 contains the test benchmark functions and the engineering problem, together with test parameters. Section 5: the results are presented and discussed. Finally, the conclusion and recommendations are presented in section 6.

2. MOUNTAIN GAZELLE OPTIMIZER (MGO)

2.1 Inspiration

The mountain gazelle is a type of gazelle that is native to the Arabian Peninsula and surrounding areas [12]. Although it has a large distribution range, its population density is quite low. The species is closely associated with the habitat of the Robinia tree species. Mountain gazelles are highly territorial and their territories are located at a significant distance from one another. They form three types of groups, including mother-offspring herds, young male herds, and single males with their territories. Male gazelles engage in regular battles, with the struggle for resources being more dramatic than the battles for the possession of females. Immature males use their horns more often in fights than adults or territorial males. Mountain gazelles migrate more than 120 km in search of food. They have a high running speed, with the ability to run a hundred meters at 80 km/h.

2.2 Mathematical Model of MGO

The MGO optimization algorithm is derived from the social behavior and habitats of mountain gazelles and is based on a mathematical model that incorporates key aspects of the gazelles' group life, including the behavior of bachelor male herds (BMH), maternity herds (MH), territorial and solitary males (TSM), and migration pattern in search of food (MSF) [12]. They are modelled mathematically, as follows.

Territorial Solitary Males (TSM):

Adult mountain gazelles create and protect their territories by engaging in a battle, and this phenomenon is modeled into equation 1 as follows.

$$TSM = male_{gazelle} - |(ri_1 \times HB - ri_2 \times X(t)) \times F| \times Cof_r \quad (1)$$

Where; ri_1 and ri_2 are random integers 1 or 2, $male_{gazelle}$ represents the position vector of the global solution (best male gazelle), and *HB, F,* Cof_r are given in equations (2), (3), and (4) respectively.

$$BH = X_{ra} \times r_1 + M_{pr} \times r_2, \qquad ra = \left\{ \tfrac{N}{3} .....N \right\} \quad (2)$$

X_{ra} is a random solution (young male) in the range of *ra*. M_{pr} is the average number of search agents randomly selected. *N* is the number of gazelles, and r_1 and r_2 are random values from a range of 0 and 1.

$$F = N_1(D) \times \exp\left(2 - Iter \times \left(\tfrac{2}{MaxIter}\right)\right) \quad (3)$$

N_1 is a random value in the problem dimension determined using a standard distribution, *Iter*, and *MaxIter* represents the iteration counter and the maximum iterations respectively.

In equation (4), *a* is calculated using equation (5). also, r_3 and r_4 are random values selected from a range of 0 to 1. N_2, N_3, and N_4 are random numbers in the normal range of the search space and have the problem dimension.

$$Cof_i = \begin{cases} (a+1) + r_3, \\ a \times N_2(D), \\ r_4(D), \\ N_3(D) \times N_4(D)^2 \times \cos((r_4 \times 2) \times N_3(D)), \end{cases} \quad (4)$$

$$a = -1 + Iter \times \left(\frac{-1}{MaxIter} \right) \quad (5)$$

Maternity Herds (MH):

Maternity herds play an important role in mountain gazelles' life as the mother provides immediate protection and grooming to her young ones. This is modelled in Equation 6 below.

$$MH = (BH + Cof_{1,r}) + (ri_3 \times male_{gazelle} - ri_4 \times X_{rand}) \times Cof_{1,r} \quad (6)$$

X_{rand} is a random vector position of a gazelle from the entire population, ri_3 and ri_4 are integers randomly selected from either 1 or 2.

Bachelor Male Herds (BMH):

Upon maturity, young adult males create their territories and turn to engage in a battle with the adult males for the possession of the female gazelles. This is formulated into equation (7).

$$BMH = (X(t) - D) + (ri_5 \times male_{gazelle} - ri_6 \times BH) \times Cof_r \quad (7)$$

X(t) is the position vector of the gazelle in the current iteration, ri_5, and ri_6 are integers of either 1 or 2. *D* is determined using equation (8), where r_6 is a randomly selected value from a range of 0 to 1.

$$D = \left(|X(t)| + |male_{gazelle}| \right) \times \left(2 \times r_6 - 1 \right) \quad (8)$$

Migration in Search of Food (MSF):

Mountain gazelles continuously look for food by traveling over long distances. This random movement is modelled in Equation (9) below.

$$MSF = \left(ub - lb \right) \times r_7 + lb \quad (9)$$

Where; *lb, and ub* are the lower and upper bounds of the search space respectively, and r_7 is a randomly determined value (0,1).

Algorithm 1: Pseudo-code of MGO

Inputs: the population size N, and maximum iterations
Output: Gazelle's location and fitness potential
Create a random population, X_i (i=1,2,..N)
Calculate Gazelle's fitness level.
While (the stopping condition is not met) **do**
  for (each Gazelle (X_i)) **do**
    Calculate TSM using equation (1)
    Calculate MH using equation (2)
    Calculate BMH using equation (3)
    Calculate MSF using equation (4)
    Calculate the fitness values of TSM, MH, BMH, and MSF
  end for
  Sort the entire population in ascending order according to fitness.
end while
Return $X_{bestGazelle}$, the Best Fitness value.

3. PROPOSED MODIFICATION

To modify the basic mountain gazelle optimizer (MGO) to improve its performance in handling high-dimensional optimization problems, three approaches were used. Firstly, a logistic chaotic mapping [13] is adopted to generate the initial population of the algorithm in place of the random approach used in the traditional MGO. This is given in Equation (10) below.

$$X_i = lb + \left(ub - lb \right) \times X_{ch}(d), \qquad i = 1, \ldots, N \quad (10)$$

Where; X_{ch} is a set of values generated from the range 0 to 1 with the problem dimension using logistic chaotic mapping by equation (11).

$$X_{j+1} = r_j \times x_j \times \left(1 - x_j \right), \qquad j = 1, \ldots., d \quad (11)$$

Where; r_j is a randomly chosen value from the range of 3.5 to 4, x_0 is the initial value of x_j chosen as 0.5. Below is the pseudocode for X_{Ch}.

Initialize x_o (x_o =0.5), d, lb, ub, and N.
For i=1:N
  $r = 3.5 + \left(4 - 3.5 \right) \times rand;$
  For j=1:d
    Update the value X_{Ch} *according to equation (11).*
  End
  Update the value X_i *according to equation (10).*
End

Also, the update operator at the territorial and solitary male (TSM) phase, that is equation (12), is modified to increase the convergence speed of the MGO algorithm by introducing a controlling factor whose value is determined using the truncation selection technique in the genetic algorithm [16]. The updated operator is shown in equation (12).

$$TSM = male_{gazelle} - \beta \times \left| \left(ri_1 \times BH - ri_2 \times X\left(t \right) \right) \times F \right| \times Cof_r \quad (12)$$

Where $\beta \in \left(0,1 \right)$ is a controlling factor determined using the truncation selection technique based on the pseudocode given below.

Start
Select n, the sample size.
For i=1: n
  $x_i = rand();$
  Evaluate the performance of x_i *.*
End
Sort all values of x according to the performance from best to worst.
Select $\beta = x_1$, *where* x_1 *is the best x value.*
End

Finally, the update operator at the migrating to search for food (MSF) phase is modified by changing it to enhance its ability to search thoroughly within the search space for the continuous maintenance of good divergence in the population for high dimensional problems. The adopted approach has been applied in [5,15]. It is given in equation (13) below.

$$MSF = \left(ub - lb + 1 \right) \times r_7 + lb \quad (13)$$

Where *lb* and *ub*, are the lower and upper bounds of the search space, and r_7 is a random value selected from the range 0 to 1.

The flowchart of the propose modified MGO is shown in fig 1 below

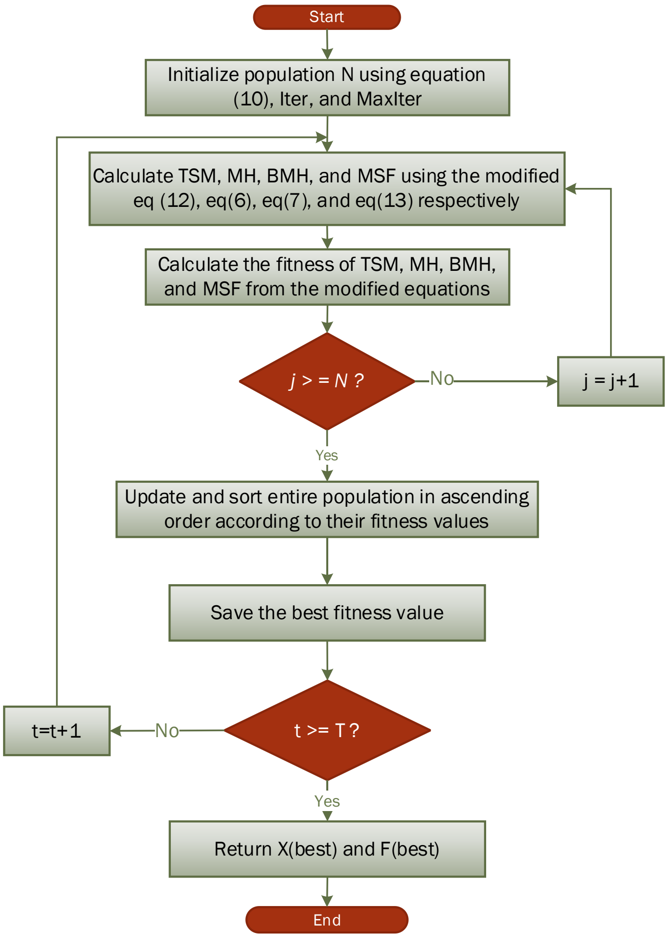


Fig-1: Flow Chart of MMGO algorithm

4. TESTING OF PROPOSED MMGO

Twenty-three (23) Standard benchmark test functions and the parameter estimation for FM sound wave optimization problem [12], were used to test the proposed modification to ascertain the effectiveness of its performance. The twenty-three (23) standard benchmark test functions that consist of third-teen (13) high-dimensional problems, and ten (10) fixed-dimensional problems were tested on. The results were compared to other three optimization algorithms, including original MGO [12], Particle Swarm Optimization (PSO) [8], and Gravitational Search Algorithm (GSA) [17]. The details of the functions are given in Table 1.

Table-1: Detail Information of Benchmark Functions

No	*Function*	*Search Range*	*Global Optimum*	*Dimension*
1	*F1*	*[-100, 100]*	*0*	*30*
2	*F2*	*[-10, 10]*	*0*	*30*
3	*F3*	*[-100, 100]*	*0*	*30*
4	*F4*	*[-100, 100]*	*0*	*30*
5	*F5*	*[-30, 30]*	*0*	*30*
6	*F6*	*[-100, 100]*	*0*	*30*
7	*F7*	*[-1.28, 1.28]*	*0*	*30*
8	*F8*	*[-500, 500]*	*-12,569*	*30*
9	*F9*	*[-5.12, 5.12]*	*0*	*30*
10	*F10*	*[-32, 32]*	*0*	*30*
11	*F11*	*[-600, 600]*	*0*	*30*
12	*F12*	*[-50, 50]*	*0*	*30*
13	*F13*	*[-50, 50]*	*0*	*30*
14	*F14*	*[-65.53, 65.53]*	*0.998*	*2*
15	*F15*	*[-5, 5]*	*0.00030*	*4*
16	*F16*	*[-5, 5]*	*-1.0316*	*2*
17	*F17*	*[-5, 0] [10, 15]*	*0.398*	*2*
18	*F18*	*[-5, 5]*	*3*	*2*
19	*F19*	*[0, 1]*	*-3.86*	*3*
20	*F20*	*[0, 1]*	*-3.32*	*6*
21	*F21*	*[0, 10]*	*-10.1532*	*4*
22	*F22*	*[0, 10]*	*-10.4028*	*4*
23	*F23*	*[0, 10]*	*-10.5363*	*4*

In addition to the above details, the proposed MMGO algorithm was implemented in MATLAB 2019a version using the standard parameters in reference [12]. These included 500 iterations and 30 runs for each test function. The following statistical information was extracted from the results and compared to that of the original MGO, PSO, and GSA; best solution (Best), worst solution (Worst), mean solution (Mean), and standard deviation of the solutions (STD).

To assess the performance of the proposed MMGO algorithm on handling high dimensional engineering problems, it was tested on the standard Parameter Estimation of FM Sound Wave optimization problem which is one of the challenging high-dimensional and multimodal engineering problems [12]. The proposed MMGO algorithm was tested on it to establish its superiority over other algorithms by comparison of their solutions.

The best solution of the problem is $f\left(X_{sol}\right)=0$, where $X_{sol}=\left\{a_1,\omega_1,a_2,\omega_2,a_3,\omega_3\right\}$.

The mathematical representation of the problem used as objective function is presented in equation 14.

$$f\left(X_{sol}\right)=\sum_{t=0}^{100}\left(y(t)-y_0(t)\right)^2 \tag{14}$$

Where,

$$y(t) = a_1.\sin\left(\omega_1.t.\theta + a_2.\sin\left(\omega_2.t.\theta + a_3.\sin\left(\omega_3.t.\theta\right)\right)\right) \quad (15)$$

$$y_0(t) = (1.0).\sin\left((5.0).t.\theta - (1.5).\sin\left((4.8).t.\theta + (2.0).\sin\left((4.9).t.\theta\right)\right)\right) \quad (16)$$

Where; $\theta = \dfrac{2\pi}{100}$

5. RESULTS AND DISCUSSIONS

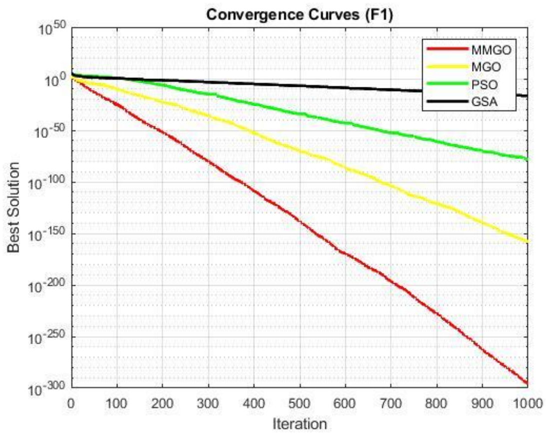
The outcome of the tests is as shown in table 2. Table 2 contains the simulation results of the proposed MMGO algorithm and other state-of-the-art optimization algorithms (MGO, PSO, and GSA). The comparison is based on the best results, worst results, mean, and standard deviation from repeated runs of thirty times. The proposed MMGO significantly outperformed MGO, PSO, and GSA in F1, F2, F3, F4, F5, F6, F7, F8, F9, F10, F11, F12, and F13. These functions are high-dimensional optimization test functions, implying that the proposed MMGO would outperform the others in real high-dimensional problems.

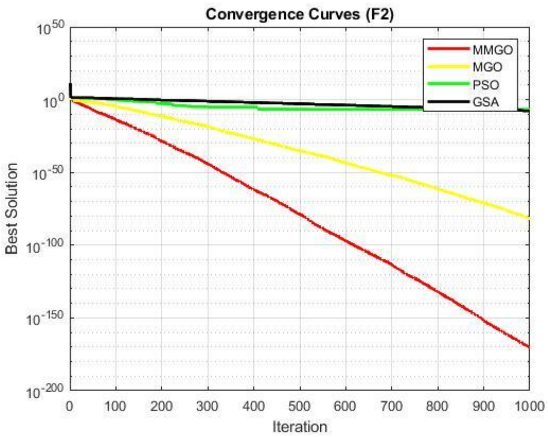
Table – 2: Results Comparison of Test Functions

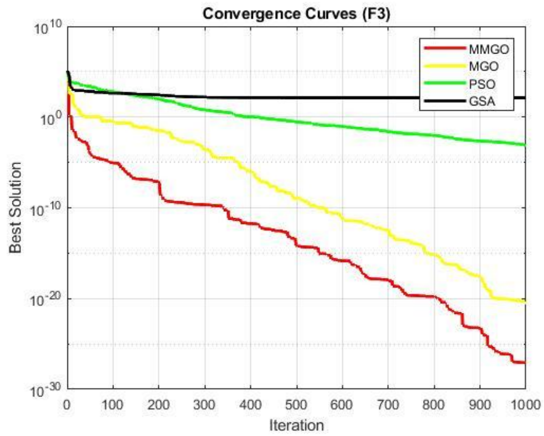
Fn	Para	MMGO	MGO	PSO	GSA
F1	Best	**6.39E-149**	2.41E-81	7.11E-09	1.46E-16
	Worst	**8.92E-137**	4.95E-71	7.36E-05	1.06E-15
	Mean	**3.34E-138**	4.74E-72	4.46E-06	4.04E-16
	STD	**1.63E-137**	1.34E-71	1.45E-05	2.27E-16
F2	Best	**3.15E-90**	1.67E-46	5.69E-06	5.78E-08
	Worst	**5.63E-84**	6.08E-41	2.05E-02	3.11E+00
	Mean	**4.64E-85**	3.91E-42	3.33E-03	1.87E-01
	STD	**1.34E-84**	1.19E-41	5.41E-03	6.02E-01
F3	Best	**4.46E-42**	3.53E-14	1.82E+01	4.95E+02
	Worst	**3.23E-12**	1.64E-07	3.48E+03	2.05E+03
	Mean	**1.10E-13**	6.82E-09	5.89E+02	1.11E+03
	STD	**5.89E-13**	2.98E-08	9.90E+02	3.91E+02
F4	Best	**1.99E-47**	5.25E-30	2.64E-01	3.99E+00
	Worst	**7.22E-39**	4.14E-22	2.10E+00	1.14E+01
	Mean	**2.47E-40**	1.59E-23	5.33E-01	7.96E+00
	STD	**1.32E-39**	7.54E-23	3.80E-01	1.79E+00
F5	Best	**0.00E+00**	0.00E+00	1.98E+01	2.31E+01
	Worst	**8.71E-29**	2.55E-22	1.08E+02	1.91E+02
	Mean	**6.56E-30**	1.19E-23	4.66E+01	6.38E+01
	STD	**1.71E-29**	4.95E-23	3.05E+01	4.53E+01
F6	Best	**3.49E-12**	4.81E-12	6.74E-09	1.83E-11
	Worst	**7.97E-07**	3.51E-08	4.11E-05	1.08E+01
	Mean	**3.90E-09**	4.54E-09	2.91E-06	5.96E-01
	STD	**1.67E-09**	7.65E-09	7.60E-06	2.29E+00
F7	Best	**2.45E-05**	3.24E-05	4.07E-02	3.36E-02
	Worst	**2.42E-03**	1.53E-03	1.56E-01	2.91E-01
	Mean	**5.38E-04**	5.59E-04	9.50E-02	1.11E-01
	STD	**3.14E-04**	3.89E-04	2.99E-02	5.09E-02
F8	Best	**-1.25E+04**	**-1.25E+4**	-3.31E+3	-3.15E+3
	Worst	**-1.25E+04**	**-1.25E+4**	-1.95E+3	-1.52E+3
	Mean	**-1.25E+04**	**-1.25E+4**	-2.59E+3	-2.39E+3
	STD	**5.21E-10**	3.99E-08	2.810E+2	3.48E+02
F9	Best	**0.00E+00**	**0.00E+0**	1.99E+01	1.59E+01
	Worst	**0.00E+00**	**0.00E+0**	7.26E+01	5.77E+01
	Mean	**0.00E+00**	**0.00E+0**	3.86E+01	3.25E+01
	STD	**0.00E+00**	**0.00E+0**	1.35E+01	9.91E+00
F10	Best	**8.881E-16**	8.88E-16	3.77E-06	8.08E-09
	Worst	**8.881E-16**	4.44E-15	2.41E+00	1.64E+00
	Mean	**8.881E-16**	1.71E-15	3.13E-01	1.38E-01
	STD	**0.00E+00**	1.53E-15	7.30E-01	4.25E-01
F11	Best	**0.00E+00**	0.00E+00	6.319E+1	2.236E+1
	Worst	**0.00E+00**	0.00E+00	1.037E+2	4.291E+1
	Mean	**0.00E+00**	0.00E+00	8.319E+1	3.195E+1
	STD	**0.00E+00**	0.00E+00	1.073E+1	5.336E+0
F12	Best	**1.570E-32**	1.57E-32	9.37E-11	6.51E-02
	Worst	**1.570E-32**	2.19E-25	1.56E+00	5.25E+00
	Mean	**1.570E-32**	1.69E-26	2.49E-01	2.32E+00
	STD	**5.567E-48**	4.54E-26	3.71E-01	1.34E+00
F13	Best	**1.349E-32**	1.35E-32	2.92E-11	6.00E-02
	Worst	**1.349E-32**	6.40E-32	1.10E-02	3.43E+01
	Mean	**1.349E-32**	1.81E-32	2.56E-03	1.28E+01
	STD	**5.567E-48**	9.95E-33	4.72E-03	7.60E+00
F14	Best	**9.980E-01**	**9.98E-01**	**9.98E-01**	**9.98E-01**
	Worst	**9.980E-01**	**9.98E-01**	1.99E+00	1.47E+01
	Mean	**9.980E-01**	**9.98E-01**	1.33E+00	4.76E+00
	STD	**2.719E-17**	1.84E-16	4.76E-01	3.61E+00
F15	Best	**3.07E-04**	**3.07E-04**	**3.07E-04**	8.68E-04
	Worst	**1.22E-03**	1.22E-03	2.03E-02	1.18E-02
	Mean	**3.05E-04**	3.70E-04	1.28E-03	4.33E-03
	STD	**2.27E-04**	2.31E-04	3.63E-03	2.63E-03
F16	Best	**-1.032E-0**	-1.032E-0	-1.032E-0	-1.032E-0
	Worst	**-1.032E-0**	-1.032E-0	-1.032E-0	-1.032E-0
	Mean	**-1.032E-0**	-1.032E-0	-1.032E-0	-1.032E-0
	STD	**5.296E-17**	4.79E-16	6.38E-16	5.83E-16
F17	Best	**3.97E-01**	**3.97E-01**	**3.97E-01**	**3.97E-01**
	Worst	**3.97E-01**	**3.97E-01**	**3.97E-01**	**3.97E-01**
	Mean	**3.97E-01**	**3.97E-01**	**3.97E-01**	**3.97E-01**
	STD	**0.00E+00**	**0.00E+0**	**0.00E+0**	**0.00E+00**
F18	Best	**3.00E+00**	**3.0E+00**	**3.0E+00**	**3.00E+00**
	Worst	**3.00E+00**	**3.0E+00**	**3.0E+00**	**3.00E+00**
	Mean	**3.00E+00**	**3.0E+00**	**3.0E+00**	**3.00E+00**
	STD	**1.108E-15**	1.41E-15	2.05E-15	4.77E-15
F19	Best	**-3.86E+0**	**-3.86E+0**	**-3.86E+0**	**-3.86E+0**
	Worst	**-3.86E+0**	**-3.86E+0**	**-3.86E+0**	**-3.86E+0**
	Mean	**-3.86E+0**	**-3.86E+0**	**-3.86E+0**	**-3.86E+0**
	STD	**2.146E-15**	2.25E-15	2.404E-3	2.49E-15
F20	Best	**-3.32E+0**	**-3.32E+0**	**-3.32E+0**	**-3.32E+0**
	Worst	**-3.32E+0**	**-3.32E+0**	-2.956E-0	**-3.32E+0**
	Mean	**-3.32E+0**	**-3.32E+0**	-3.238E-0	**-3.32E+0**
	STD	**1.603E-15**	6.032E-2	1.014E-1	1.695E-2
F21	Best	**-10.1532**	**-10.1532**	**-10.1532**	**-10.1532**
	Worst	**-10.1532**	**-10.1532**	-2.6305	-2.6829
	Mean	**-10.1532**	**-10.1532**	-6.7321	-5.2432
	STD	**0.0000**	**0.0000**	3.5630	3.5442
F22	Best	**-10.4029**	**-10.4029**	**-10.4029**	**-10.4029**
	Worst	**-10.4029**	**-10.4029**	-2.7519	-2.7659
	Mean	**-10.4029**	**-10.4029**	-6.7370	-10.1484
	STD	**0.0000**	**0.0000**	3.5639	1.3943
F23	Best	**-10.5364**	**-10.5364**	**-10.5364**	**-10.5364**
	Worst	**-10.5364**	**-10.5364**	-2.4217	-2.4217
	Mean	**-10.5364**	**-10.5364**	-7.2984	-9.9954
	STD	**0.0000**	**0.0000**	3.7994	2.0588

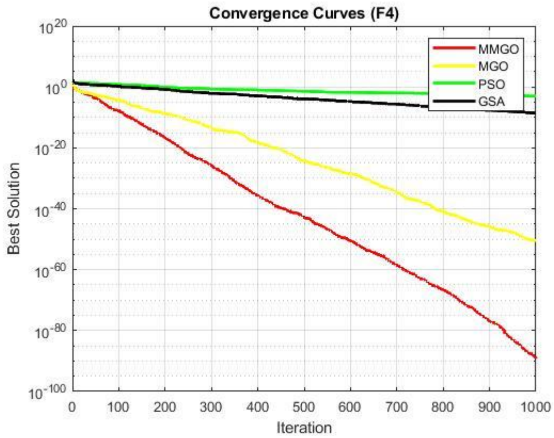
Also, MMGO maintained the best results produced by MGO, and improve the worst value, mean value, and standard deviation in F14, F15, F16, F17, F18, F19, F20, F21, F22, and F23. These consist of fixed-dimensional optimization benchmark functions, and this implies that the proposed MMGO has the potential to perform efficiently on real fixed-dimensional problems.

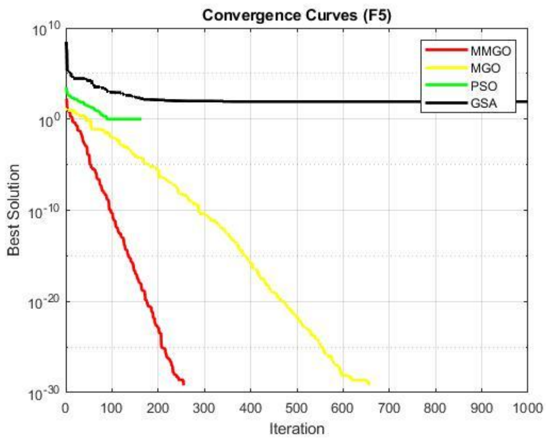
In addition, the convergence characteristics of MMGO, MGO, PSO, and GSA are plotted on the high-dimensional functions and presented as F1 to F12. It is observed in the curves that MMGO converges very fast and produced the best or optimal solutions with fewer iterations compared to the other optimization algorithms (MGO, PSO, and GSA). This confirms that the proposed MMGO is suitable for real-life optimization problems that require fast convergence with less iteration.

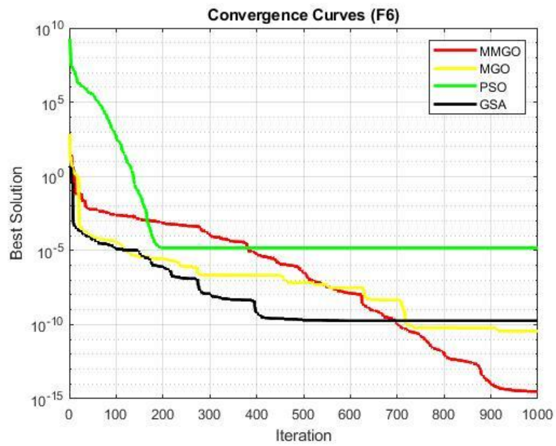


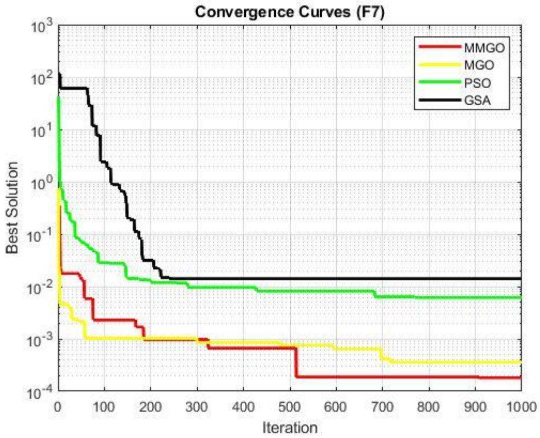


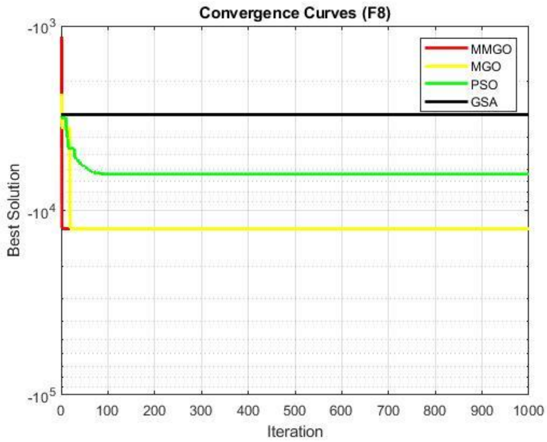


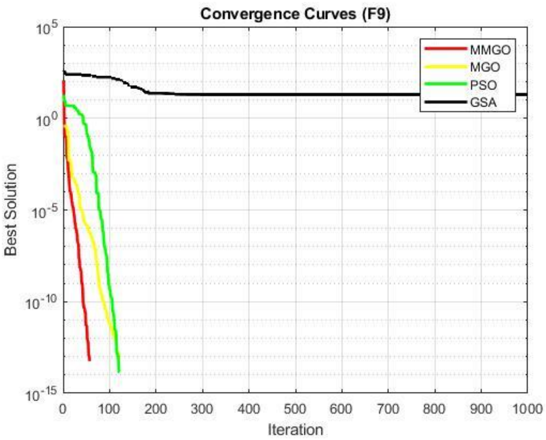


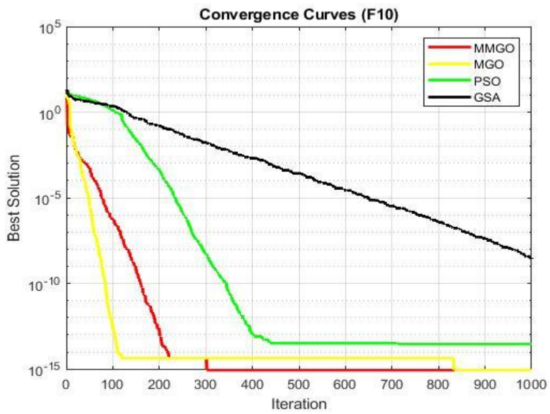


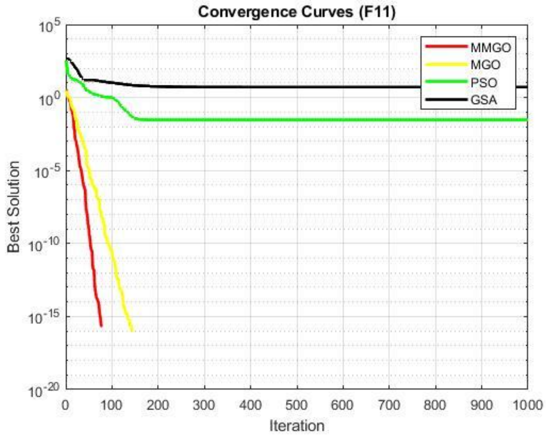


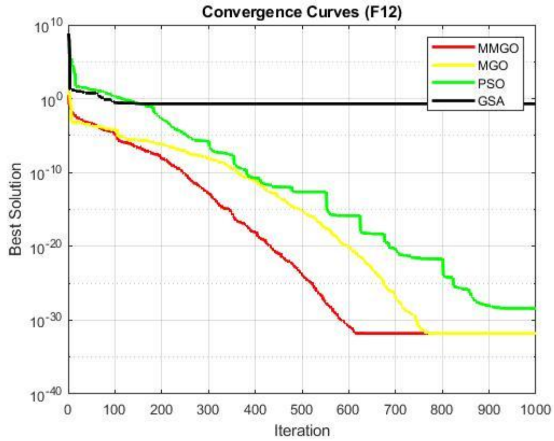












Finally, the result from the test on the parameter estimation of FM sound wave is presented in Table 3 below. It is compared with that of the original MGO, PSO, and GTO picked from literature [12], and it is shown from the results that MMGO outperformed them with competitive results.

Table -3: Results Comparison of Engineering Test Problem

Algorithm	MMGO	MGO	PSO	GTO
X(1)	-1.0000	1.0000	0.8563	-1.0000
X(2)	-5.0000	5.0000	4.9215	-5.0000
X(3)	-1.5000	-1.5000	-1.1521	-1.5000
X(4)	-4.8000	4.8000	2.4955	-4.8000
X(5)	2.0000	-2.0000	-4.9331	2.0000
X(6)	-4.9100	-4.9000	-2.4247	-4.9000
Maximum Cost	**5.97E-28**	4.56E-28	11.20E+00	6.02E-28

6. CONCLUSION

An improved version of the traditional MGO algorithm called modified mountain gazelle optimizer (MMGO) is presented. The modified MGO introduces three modifications at the initialization, the migration to search for food (MSF) phase, and the territorial and solitary male (TSM) phase. The proposed MMGO has been compared with the original MGO, PSO, and GSA on 23 standard benchmark test functions. The proposed MMGO outperformed the other algorithms on all 23 test functions in terms of quality results, fast convergence, and stability. It also avoided stagnation in local optimal or suboptimal solutions.

The proposed MMGO algorithm is recommended for application in solving high-dimensional engineering problems, such as optimal integration of shunt compensators in distribution systems, optimal integration of distribution generations, and optimal placement of sectionalizing switches in power systems. Also, MMGO can be applied to optimization problems in the field of control systems that require fast convergence.

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