Improved F-parameter Mountain Gazelle Optimizer (IFMGO): A Comparative Analysis on Engineering Design Problems

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Abstract - *This paper presents a comparative study of three metaheuristic algorithms: the Improved F-parameter Mountain Gazelle Optimizer (IFMGO), the Mountain Gazelle Optimizer (MGO), and the Particle Swarm Optimization (PSO) algorithm, applied to a selection of challenging engineering design problems. IFMGO, an advanced version of MGO, demonstrates enhanced exploration and exploitation capabilities owing to its inspiration from the social behavior of mountain gazelles. The algorithms were implemented in the MATLAB environment and evaluated on diverse engineering design problems, including the Pressure Vessel Design Problem (PVDP), the Spring Design Problem (SDP), the Three-bar Truss Design Problem (TTDP), the Cantilever Beam Design Problem (CBDP), and the Welded Beam Design Problem (WBDP). The primary objective is to investigate if IFMGO's improvements over MGO would lead to superior performance in solving engineering optimization problems. Our experimental results demonstrate that IFMGO indeed outperforms MGO across all the engineering design problems considered. Furthermore, IFMGO showcases competitive performance when compared to the well-established PSO algorithm, a testament to its efficacy as a tool for handling intricate engineering design challenges.*

Key Words: Algorithm, optimization, mountain gazelle, engineering design problems, metaheuristic algorithm.

1.INTRODUCTION

This In the pursuit of optimizing complex engineering design problems, metaheuristic algorithms have emerged as promising tools that can efficiently handle non-linear, multi-objective optimization challenges [1][2]. Among these algorithms, the Improved F-parameter Mountain Gazelle Optimizer (IFMGO) [3] presents a significant advancement over its predecessor, the Mountain Gazelle Optimizer (MGO) [4]. This paper aims to investigate and compare the performance of IFMGO, MGO, and Particle Swarm Optimization (PSO) on a set of diverse engineering design problems [3][4][5].

Engineering design optimization plays a pivotal role in various industries, including aerospace, mechanical, civil, and structural engineering, among others [6][7]. The main objective is to find the optimal design parameters that satisfy multiple objectives while considering a range of constraints. However, this task often presents a formidable challenge due to the presence of conflicting and competing objectives, coupled with the high dimensionality and non-linearity of the design space.

The IFMGO algorithm demonstrates superior exploration and exploitation capabilities in comparison to MGO, which is based on the social intelligence of mountain gazelles in the wildlife [4][8]. The enhancements introduced in the IFMGO aimed to address certain limitations present in the MGO, making it more adept at tackling complex, multi-dimensional engineering optimization problems.

To ascertain the performance of IFMGO in comparison to MGO and PSO, these algorithms have been implemented and tested using MATLAB software, a widely-adopted and robust computational environment. The choice of engineering design problems for evaluation includes the Pressure Vessel Design Problem, the String Design Problem, the Three-bar Truss Design Problem, the Cantilever Beam Design Problem, and the Welded Beam Design Problem [9][10][11]. These problems are well-known benchmarks in the field of engineering optimization, covering a diverse range of complexities and dimensions.

Initial results from our experimentation demonstrated that the IFMGO algorithm exhibits remarkable superiority over MGO in all the engineering design problems considered. Moreover, IFMGO demonstrates competitive performance compared to the well-established PSO algorithm. The objective of this paper is to shed light on the strengths and weaknesses of these algorithms, providing valuable insights for researchers and practitioners seeking efficient optimization strategies for engineering design tasks.

The subsequent sections of this paper will delve into the detailed methodology employed, the mathematical formulation of the IFMGO algorithm, the experimental setup, and comprehensive analyses of the obtained results. Finally, the implication of the findings in the context of engineering design optimization would be discussed and concluded with recommendations for future research avenues in the realm of metaheuristic algorithms.

This study, therefore, seeks to contribute to the growing body of knowledge in the field of engineering optimization and further establish the significance of the IFMGO algorithm as a powerful tool for tackling complex engineering design problems.

2. METHOD

Improve F-parameter Mountain Gazelle Optimizer (IFMGO):

The Improved F-parameter Mountain Gazelle Optimizer (IFMGO) is an enhanced version of the Mountain Gazelle Optimizer (MGO) for more efficient performance in solving complex optimization problems [3]. The concept of this algorithm originated from mimicking the social life of mountain gazelles in the wildlife that included bachelor male herds (BMH), maternity herds (MH), territorial and solitary males (TSM), and the migration pattern of gazelles in search of food (MSF) [4]. The mathematical modeling of the IFMGO algorithm is presented as follows.

Mathematical Modelling of IFMGO

Territorial Solitary Male (TSM):

The adult male gazelles' mechanism of protecting their territories against intruders is mathematically modeled in equation (1).

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

Where;

ri_1 and ri_2: are random integers of either 1 or 2.

$male_{gazelle}$: is the position vector of the best male gazelle so far.

The values of *BH, F,* and Cof_r are determined using equations (2), (3), and (4).

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

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

$$F = randn(1,d) \times \exp(-Iter) \quad (3)$$

Where *d* represents the size of the problem dimension determined using a standard distribution. The *Iter* and *MaxIter* respectively represent the iteration count and the maximum iterations.

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

Where;

r_3 and r_4: represent random values within the range (0, 1).

N_2, N_3, and N_4: are set of randomly generated values with the size of the problem function.

The value of *a* is determined using equation (5) below at every iteration.

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

Maternity Herd (MH):

The intelligence behind the mother gazelle's act of protecting its offspring is mathematically modeled in equation (6).

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

Where;

X_{rand}: represents a vector position of a gazelle randomly selected from the population.

ri_3 and ri_4: are integers randomly chosen from (1, 2).

Bachelor Male Herds (BMH):

In part of the development process of the male gazelles, the young adult male ones create their territories and try winning female gazelles to join them. This behavior is modeled as equation (7).

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

Where;

X(t): is the position vector of the gazelle in the current iteration.

ri_5, and ri_6: are integers randomly from (1, 2).

r_6: is a randomly selected value from range (0 1).

The value of *D* is determined using equation (8) below.

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

Migration in Search of Food (MSF):

The foraging mechanism of mountain gazelles involves roaming to search the green pasture of their choice. This random movement is modeled in equation (9).

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

lb and ub represent the lower search boundary and the upper search boundary respectively. The value of r_7 is randomly chosen from (0,1). The pseudocode is presented below:

Pseudocode of IFMGO Algorithm

Inputs: *iteration counter (Iter), maximum iteration (MaxIter), population size (N).*

Output: *gazelle's position, and its fitness value*

Initialize random gazelle populations, X_i(i=1, 2, ...N)

Evaluate the fitness values of the population.

While *(Iter < MaxIter),* ***do***

for *(every gazelle, X_i)* ***do***

Calculate TSM using equation (1)

Calculate MH using equation (6)

Calculate BMH using equation (7)

Calculate MSF using equation (9)

Evaluate the fitness values of TSM, MH, BMH, and MSF.

End for

Output best gazelle, X_{best}, and its fitness value.

End while

Engineering Design Problems:

To effectively assess the performance of these algorithms on engineering design problems, some well-known standard engineering design problems have been considered in this study. They include the Pressure Vessel Design Problem (PVDP), the Spring Design Problem (SDP), the Three-bar Truss Design Problem (TTDP), the Cantilever Beam Design Problem (CBDP), and the Welded Beam Design Problem (WBDP) [12]. The details of each engineering design problem are presented as follows.

1. Pressure Vessel Design Problem (PVDP):

The PVDP is one of the standard engineering design benchmark functions for validating optimization algorithms developed for solving engineering problems [10]. The problem involves determining the values of four parameters: thickness (x_1), the thickness of the heads (x_2), the inner radius (x_3), and the length of the cylindrical section (x_4). The main objective of this design problem is to minimize the overall cost, subject to non-linear constraints of stress and yield criteria. The optimization problem is written as in equation (10).

$$\min(f(x)) = 0.6224x_1x_3x_4 + 1.7781x_2x_3^2 \qquad (10)$$

Subject to:

$$\begin{cases} g_1(x) = -x_1 + 0.0193x_3 \le 0 \\ g_2(x) = -x_2 + 0.00954x_3 \le 0 \\ g_3(x) = -\pi x_3^2 x_4 - \frac{4\pi}{3}x_3^3 + 1,296,000 \le 0 \\ g_3(x) = x_4 - 240 \le 0 \end{cases} \qquad (11)$$

And search bounds of: $0.0625 \le X_1, X_2 \le 99 \times 0.0625$, $10 \le X_3$, and $X_4 \le 200$

2. Spring Design Problem (SDP):

The Spring Design Problem (SDP) is a continuous constrained design problem and the design is illustrated in Figure 1. The objective of the problem is to minimize the volume of a coil spring under a constant tension/compression load [11]. The problem focuses on three design variables. The mathematical formulation is presented in Equation (12).

$$\min(f(x)) = (x_3 + 2)x_2x_1^2 \qquad (12)$$

Subject to:

$$q_1(x) = 1 - \frac{x_2^3 x_3}{71785x_1^4} \le 0$$

$$q_2(x) = \frac{4x_2^2 - x_1x_2}{12566(x_2x_1^3 - x_1^4)} + \frac{1}{5108x_1^2} - 1 \le 0 \qquad (13)$$

$$q_3(x) = 1 - \frac{140.45x_1}{x_2^2 x_3} \le 0$$

$$q_4(x) = \frac{x_2 + x_1}{1.5} - 1 \le 0$$

The design upper and lower bounds for the variables are given below:

$$2 \le x_1 \le 15,\ 0.25 \le x_2 \le 1.3,\ 0.05 \le x_3 \le 2$$

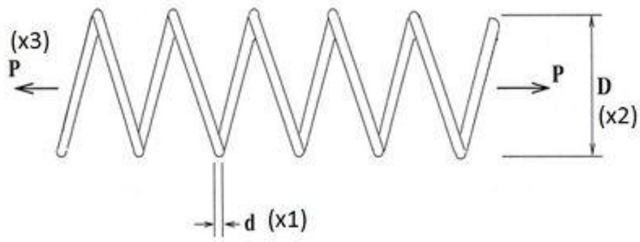

Fig -1: Schematic Diagram of Spring Design Problem

3. Three-bar Truss Design Problem (TTDP):

The design of the three-bar problem seeks to minimize the weight of the three-bar truss, which is illustrated in Figure 2 [13]. The objective function is mathematically formulated in Equation (14).

$$\min(f(x)) = (2\sqrt{2}x_1 + x_2) \times l \qquad (14)$$

Subject to:

$$g_1(x)=\frac{\sqrt{2}x_1+x_2}{\sqrt{2}x_1^2+2x_1x_2}P-\sigma\le 0$$

$$g_2(x)=\frac{x_2}{\sqrt{2}x_1^2+2x_1x_2}P-\sigma\le 0 \qquad (15)$$

$$g_3(x)=\frac{1}{\sqrt{2}x_2+x_1}P-\sigma\le 0$$

Where;

$$0\le x_1,\ x_2\le 1,\ l=100cm,\ P=2KN/cm^2,\ \sigma=2KN/cm^2$$

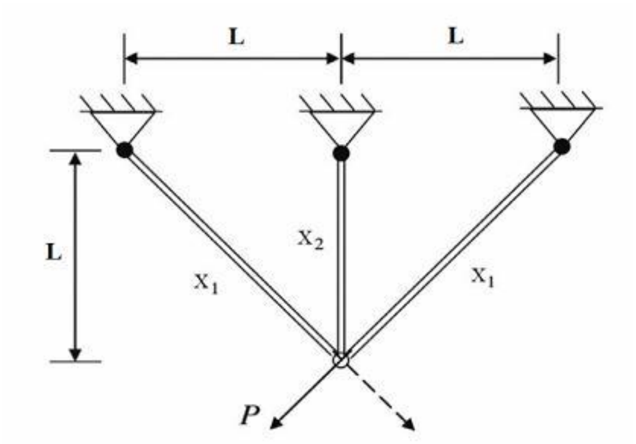

Fig -2: Three-bar Truss

4. Cantilever Beam Design Problem (CBDP):

Cantilever Beam Design is one of the widely used standard engineering design problems for validating the performance of nature-inspired optimization problems with the main aim of developing to solve engineering optimization problems [10]. The objective is to minimize the overall weight of the cantilever beam with square cross sections. It is formulated as shown in Equation (16).

$$\min(f(x))=0.0624(x_1+x_2+x_3+x_4+x_5) \qquad (16)$$

Subject to inequality:

$$g(x)=\frac{61}{x_1^3}+\frac{37}{x_2^3}+\frac{19}{x_3^3}+\frac{7}{x_4^3}+\frac{1}{x_5^3}-1\le 0 \qquad (17)$$

The limits for the five design variables are:

$$0.01\le x_i\le 100,\quad i=1,2,\ldots,5.$$

5. Welded Beam Design Problem (WBDP):

This is one of the several engineering design problems that gain substantial consideration in validating optimization algorithms. It is designed to minimize the cost based on shear stress constraints, beams' end deflection, bending stress in the beam, and buckling load on the bar [9]. The main objective is to design a welded beam with the least cost input, and the cost function is formulated as the objective function shown in Equation (18).

$$\min(f(x))=1.10471x_1^2x_2+0.04811x_3x_4(14.0-x_2) \qquad (18)$$

Subject to:

$$g_1(x)=\tau(x)-13000\le 0$$
$$g_2(x)=\sigma(x)-30000\le 0$$
$$g_3(x)=x_1-x_4\le 0$$
$$g_4(x)=0.1047x_1^2+0.04811x_3x_4\left(14+x_2\right)-5\le 0 \qquad (19)$$
$$g_5(x)=0.125-x_1\le 0$$
$$g_6(x)=\delta(x)-0.25\le 0$$
$$g_7(x)=6000-P_c(x)\le 0$$

Where:

$$\tau(x)=\sqrt{(\tau')_2+2\tau'\tau''\tfrac{x_2}{2R}+(\tau'')^2}$$

$$\tau'=\frac{6000}{\sqrt{2}x_1x_2}$$

$$\tau''=\frac{MR}{J}$$

$$M=6000(14+\tfrac{x_2}{2})$$

$$R=\sqrt{\frac{x_2^2}{4}+\left(\frac{x_1+x_3}{2}\right)^2}$$

$$J=2\left\{\sqrt{2}x_1x_2\left[\frac{x_2^2}{12}+\left(\frac{(x_1+x_3)}{2}\right)^2\right]\right\}$$

$$\sigma(x)=\frac{504000}{x_4x_3^2}$$

$$\delta(x)=\frac{2.1952}{x_3^3x_4} \qquad (20)$$

$$P_c(x)=64746.022(1-0.0282346X_3)X_3X_4^3$$

Test Implementation:

To establish a fair test comparison of the algorithms on the above detailed standard engineering design test problems, all the algorithms were coded in MATLAB environment (MATLAB R2019a) on the same laptop. For each engineering design problem, each algorithm is used to solve it in repetitions thirty (30) times, and the best results are recorded. The results of all three algorithms (IFMGO, MGO, and PSO) for each engineering design problem are recorded and compared in tabular forms. The parameter settings for the simulation are presented in Table 1.

Table-1: Parameter Settings for Simulation

Parameter	Value
Population Size (N)	30
Maximum Iterations	1000
Number of Runs	30

The computer used for the simulations possesses the following specifications as shown in Table 2.

Table-2: Specifications of Machine Used for Simulation

Specifications of Machine for Simulation	
Type	hp pavilion laptop computer
Processor	AMD A8-6410 APU
Memory (RAM)	4.00 Gigabyte (3.43 GB usable)
Clock Speed	2.00 GHz

3. RESULTS AND DISCUSSION

This section presents the simulation results to show the outcome of the experiment and establish a comprehensive comparative performance analysis of the various algorithms on the engineering design problems considered. To present the results concisely, it is presented under subsections according to the various engineering design problems.
Pressure Vessel Design Problem (PVDP):

Results from the test of algorithms on the PVDP are presented in Table 3. The original MGO algorithm produced the worst results of 6108.9319. The PSO algorithm produced a much better result of 6055.7985. However, the IFMGO algorithm, which is a modified version of MGO, exceptionally outperforms the PSO and produced the best solution value of 5897.7704. The result shows that the modification proposed in IFMGO has effectively improved the performance of the algorithm in solving the Pressure Vessel Design Problem.

Table-3: Results of Algorithms on PVDP

Name of Algorithm	X1	X2	X3	X4	F(x)
PSO	0.8703583	0.4284147	45.09629	142.7209	**6055.7985**
MGO	0.8947789	0.4404352	46.3616	130.1125	**6108.9319**
IFMGO	0.7805281	0.386001	40.4248	198.799	**5897.7704**

Spring Design Problem (SDP):
Table 4 contains the results of the algorithms on the Spring Design Problem, and it shows a very competitive outcome from all three algorithms. However, the MGO produced the worst result of 0.014116, followed by the PSO with 0.013013, and the best result among the three algorithms of 0.012708 is produced by the IFMGO. This as well showed the superior performance of IFMGO in handling the Spring Design Problem.

Table-4: Results of Algorithms on SDP

Name of Algorithm	X1	X2	X3	F(x)
PSO	0.05618	0.47469	6.6855	**0.013013**
MGO	0.060979	0.62414	4.0823	**0.014116**
IFMGO	0.0501768	0.321414	13.7041	**0.012708**

Three-bar Truss Design Problem (TTDP):
In the Three-bar Truss Design Problem (TTDP), all the algorithms produced very close outcomes. However, the IFMGO algorithm produced the best result of 263.8959, a very small margin from that of the PSO algorithm of 263.8991. The original MGO algorithm produced the least good results of 263.9041 as shown in Table 5.

Table-5: Results of Algorithms on TTDP

Name of Algorithm	X1	X2	F(x)
PSO	0.79077	0.40234	**263.8991**
MGO	0.78534	0.41775	**263.9041**
IFMGO	0.78845	0.4089	**263.8959**

Cantilever Beam Design Problem (CBDP):
The results on the Cantilever Beam Design Problem (CBDP) in Table 6 show that the IFMGO algorithm produced the best result with a value of 1.3400. However, both the original

MGO algorithm and the PSO algorithm produced very competitive results of 1.3405 and 1.3403 respectively.

Table-6: Results of Algorithms on CBDP

Name of Algorithm	X1	X2	X3	X4	X5	F(x)
PSO	6.009	5.2663	4.4544	3.5637	2.1855	**1.3403**
MGO	6.0354	5.4124	4.3968	3.4774	2.1605	**1.3405**
IFMGO	6.0129	5.3089	4.4961	3.5031	2.1527	**1.3400**

Welded Beam Design Problem (WBDP):
On the Welded Beam Design Problem (WBDP), the PSO algorithm produced 1.4829, the MGO algorithm produced 1.5766, and the IFMGO produced 1.473 as shown in Table 7. Here, another competitive result was obtained with the best produced by the IFMGO to show its superiority, followed by the PSO algorithm, and finally the original MGO algorithm.

Table-7: Results of Algorithms on WBDP

Name of Algorithm	X1	X2	X3	X4	F(x)
PSO	0.18001	2.5008	9.5847	0.18312	**1.4829**
MGO	0.21403	2.1015	8.8515	0.21443	**1.5766**
IFMGO	0.18298	2.4073	9.5818	0.18298	**1.4730**

4. CONCLUSIONS AND RECOMMENDATION

A comparative analysis of the performance of the PSO algorithm, MGO algorithm, and IFMGO algorithm on engineering design problems is conducted to assess the performance of the IFMGO relative to the other two algorithms. The IFMGO algorithm exceptionally performed better than the MGO algorithm, and slightly better than the PSO algorithm. By this performance, it is concluded that the IFMGO is superior to the MGO and the PSO in solving complex engineering optimization problems.

The IFMGO algorithm is therefore recommended for adoption in the field of engineering for solving optimization problems. For instance, optimizing the integration of renewable energy and energy storage devices in electrical distribution networks.

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