Integration of the Genetic Algorithm with Mountain Gazelle Optimizer

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Abstract
This proposed algorithm provides a promising direction for improving the performance of nature-inspired optimization algorithms. In this approach, the Genetic Algorithm is used to address the limitations of the Mountain Gazelle Optimizer, which may suffer from premature convergence and a lack of exploitation in certain scenarios. By combining both algorithms, the hybrid approach often finds more accurate solutions to complex optimization problems. We conducted tests on benchmark functions, and the results show that the hybrid GAME algorithm outperforms the standalone GO and GA in terms of convergence speed, solution accuracy, and robustness.

Keywords— Genetic Algorithm, Hybridization**,** multimodal, optimization, meta-heuristic.

1. Introduction

In recent years, there has been a lot of interest in the ability of optimization algorithms inspired by nature to tackle difficult optimization issues [3]. Non-conventional meta-heuristic algorithms inspired by natural phenomena have been utilized recently to handle a number of challenging non-linear optimization problems because regular algorithms often fail in certain situations [1]. The great majority of MAs can be categorized into two main groups: those that are influenced by biological processes in nature and those that are entirely dependent on natural occurrences.

We created a hybrid optimization algorithm by combining the Genetic Algorithm (GA) with the Mountain Gazelle Optimizer (MGO). The Genetic Algorithm works by selecting the best solutions, mixing them (crossover), and making small changes (mutation) to improve results. When we added GA to the MGO process, the hybrid algorithm became better at both exploring new solutions and improving existing ones. This helps it find good answers more quickly and accurately.

To see how well the hybrid method works, we ran tests using standard benchmark problems. The results showed that the hybrid approach outperforms using just GA or MGO by themselves. It was faster, more accurate, and more reliable, especially for solving complex optimization problems. This study suggests using the Mountain Gazelle Optimizer and the Genetic Algorithm (GA) to get over these restrictions . With its selection, crossover, and mutation processes, GA, a well-known evolutionary algorithm, is excellent at preserving genetic variety. The hybrid strategy, known as GA-MGO, seeks to increase convergence dependability, prevent local optima, and improve global search capabilities by integrating GA components into the MGO framework.

DOI: https://doi.org/10.5281/zenodo.15605503

This study's goal is to assess how well the suggested GA-MGO hybrid algorithm performs on a collection of popular high-dimensional benchmark functions. The goal of the integration is to improve MGO's exploration capabilities without sacrificing its rate of convergence. To verify the efficacy of the suggested approach, experimental findings are contrasted with those of other conventional and hybrid optimization algorithms.

2. Literature Review

2.1FoundationsofDevelopmentandlgorithms

A metaheuristic optimization method called the Mountain Gazelle Optimizer was presented with the goal of increasing convergence speed and solution accuracy. The program successfully strikes a balance between exploration and exploitation since it is designed around the dynamic and adaptable movement patterns of gazelles [5]. By imitating gazelles' adaptive evasive strategies in the face of threats or barriers, MGO aims to decrease the probability of becoming caught in local optima. behavior into the process of optimization. By encouraging varied exploration in the early phases of optimization and fine-tuning in the latter stages, this integration greatly improves convergence speed and accuracy [2]. To further improve MGO's capacity to break out of local optima, especially in highly multimodal problem environments, spiral dynamics have also been added.

2.2 Challenges and Limitations of MGO

Despite its promising results, the MGO algorithm has several drawbacks, especially when dealing with complex multimodal or high-dimensional optimization problems. The premature trend of achieving the ideal MGO solution is one of the major drawbacks, particularly when population diversity decreases at the start of the search process. For this reason, the algorithm is trapped in a local optimizer and cannot explore sufficiently different and sometimes better regions of the search space. It is not very effective as it does not provide a mechanism for robust global exploration and diversity authority in situations where the fitness landscape is rough or misleading [3][4].

2.3 Comparative Performance Analysis

To address these challenges, researchers have proposed the integration of the Genetic Algorithm (GA) with the Mountain Gazelle Optimizer, resulting in a hybrid algorithm known as GA-MGO. The incorporation of GA's evolutionary operators such as selection, crossover, and mutation enhance population diversity and reinforces the global search capability of the hybrid model [2].

This integration helps the algorithm escape local optima and maintain a healthier exploration–exploitation balance throughout the optimization process [5].

Compared to the standard MGO, the GA-MGO hybrid demonstrates improved convergence stability, solution accuracy, and robustness when applied to high-dimensional and complex optimization problems. Several studies have highlighted that this hybrid approach outperforms standalone MGO and other conventional algorithms across various benchmark functions.

Algorithms and Authors

Table 1: Algorithm, Authors & Year ofpublishing

Sr. No	Algorithm name	Author name	Year
1	Sine Cosine Algorithm	Seyedali Mirjalili	2016
2	Equilibrium Optimizer	Abdollah Asghari Varzaneh et al	2020
3	Differential Equation	Rainer Stom et al	1997
4	Backtracking Search Algorithm	P Civicioglu	2013
5	Particle Swarm Optimization	James Kennedy et al	1995
6	Slime Moul Algorithm	Mohammed H Saremi	2020

DOI: https://doi.org/10.5281/zenodo.15605503

7	Sunflower Evolutionary Optimization Algorithm	Osman K Erol	2021
8	Teaching Learning Based Optimization	Rao et al	2011

Fig 1: Classification diagram for Integration of the Genetic Algorithm with Mountain Gazelle Optimizer

3. Methodology

Actual Value

The Actual Value represents the original or true value of a solution, reflecting the outcome from a real-world scenario you're trying to optimize.

Hybrid Value

On the other hand, the Hybrid Value is the result that the Mountain Gazelle Optimizer Produces after running the algorithm to find an optimal.

Table 2 : Standard UM benchmark function

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Functions	Dimensions	Range	f_{min}
$F_1(S) = \sum_{m=1}^{z} S_m^2$	(10,30,50,100)	[-100 , 100]	0
$F_2(S) = \sum_{m=1}^{z} \lvert S_m \rvert + \prod_{m=1}^{z} \lvert S_m \rvert$	(10,30,50,100)	[-10 ,10]	0
$F_3(S) = \sum_{m=1}^{z} (\sum_{n-1}^{m} S_n)^2$	(10,30,50,100)	[-100 , 100]	0
$F_4(S) = max_m\{\lvert S_m \rvert, 1 \leq m \leq z\}$	(10,30,50,100)	[-100 , 100]	0
$F_5(S) = \sum_{m=1}^{z-1} [100(S_{m+1} - S_m^2)^2 + (S_m - 1)^2]$	(10,30,50,100)	[-38 , 38]	0
$F_6(S) = \sum_{m=1}^{z} ([S_m + 0.5])^2$	(10,30,50,100)	[-100 , 100]	0
$F_7(S) = \sum_{m=1}^{z} m S_m^4 + random\,[0,1]$	(10,30,50,100)	[-1.28, 1.28]	0

Functions	Dimension	Range	f_{min}
$F_8(S) = \sum_{m=1}^{z} - S_m sin(\sqrt{\lvert S_m \rvert})$	(10,30,50,100)	[-500,500]	-418.98295
$F_9(S) = \sum_{m=1}^{z} [S_m^2 - 10cos\,(2\pi S_m) + 10]$	(10,30,50,100)	[-5.12,5.12]	0
$F_{10}(S) = -20exp\,(-0.2\sqrt{(\frac{1}{z}\sum_{m=1}^{z} S_m^2)}) - exp\,(\frac{1}{z}\sum_{m=1}^{z} cos(2\pi S_m) + 20 + d$	(10,30,50,100)	[-32,32]	0
$F_{11}(S) = 1 + \sum_{m=1}^{z} \frac{S_m^2}{4000} - \Pi_{m=1}^{z} cos \frac{S_m}{\sqrt{m}}$	(10,30,50,100)	[-600, 600]	0
$F_{12}(S) = \frac{\pi}{z}\{10\,sin(\pi\tau_1) + \sum_{m=1}^{z-1}(\tau_m - 1)^2[1 + 10sin^2(\pi\tau_{m+1})] + (\tau_z - 1)^2\} + \sum_{m=1}^{z} u(S_m, 10,100,4)$ $\tau_m = 1 + \frac{S_m+1}{4}$ $u(S_m, b, x, i) = \begin{cases} x(S_m - b)^i & S_m > b \\ 0 & -b < S_m < b \\ x(-S_m - b)^i & S_m < -b \end{cases}$	(10,30,50,100)	[-50,50]	0
$F_{13}(S) = 0.1\{sin^2(3\pi S_m) + \sum_{m=1}^{z}(S_m - 1)^2[1 + sin^2(3\pi S_m + 1)] + (x_z - 1)^2[1 + sin^2 2\pi S_z)]$	(10,30,50,100)	[-50,50]	0

Functions	Dimensions	Range	f_{min}
$F_{14}(S) = [\frac{1}{500} + \sum_{n=1}^{2} 5 \frac{1}{n + \sum_{m=1}^{z}(S_m - b_{mn})^6}]^{-1}$	2	[-65.536, 65.536]	1
$F_{15}(S) = \sum_{m=1}^{11} [b_m - \frac{S_1(a_m^2 + a_m S_2)}{a_m^2 + a_m S_3 + S_4}]^2$	4	[-5, 5]	0.00030
$F_{16}(S) = 4S_1^2 - 2.1S_1^4 + \frac{1}{3}S_1^6 + S_1S_2 - 4S_2^2 + 4S_2^4$	2	[-5, 5]	-1.0316
$F_{17}(S) = (S_2 - \frac{5.1}{4\pi 2}S_1^2 + \frac{5}{\pi}S_1 - 6)^2 + 10(1 - \frac{1}{8\pi})cosS_1 + 10$	2	[-5, 5]	0.398
$F_{18}(S) = [1 + (S_1 + S_2 + 1)^2 (19 - 14S_1 + 3S_1^2 - 14S_2 + 6S_1S_2 + 3S_2^2)] \times [30 + (2S_1 - 3S_2)^2 (18 - 32S_1 + 12S_1^2 + 48S_2 - 36S_1S_2 + 27S_2^2)]$	2	[-2,2]	3
$F_{19}(S) = -\sum_{m=1}^{4} d_m\,exp\,(-\sum_{n=1}^{3} S_{mn}(S_m - q_{mn})^2)$	3	[1, 3]	-3.32
$F_{20}(S) = -\sum_{m=1}^{4} d_m\,exp\,(-\sum_{n=1}^{6} S_{mn}(S_m - q_{mn})^2)$	6	[0, 1]	-3.32
$F_{21}(S) = -\sum_{m=1}^{5}[(S - b_m)(S - b_m)^T + d_m]^{-1}$	4	[0,10]	-10.1532
$F_{22}(S) = -\sum_{m=1}^{7}[(S - b_m)(S - b_m)^T + d_m]^{-1}$	4	[0, 10]	-10.4028
$F_{23}(S) = -\sum_{m=1}^{7}[(S - b_m)(S - b_m)^T + d_m]^{-1}$	4	[0, 10]	-10.5363

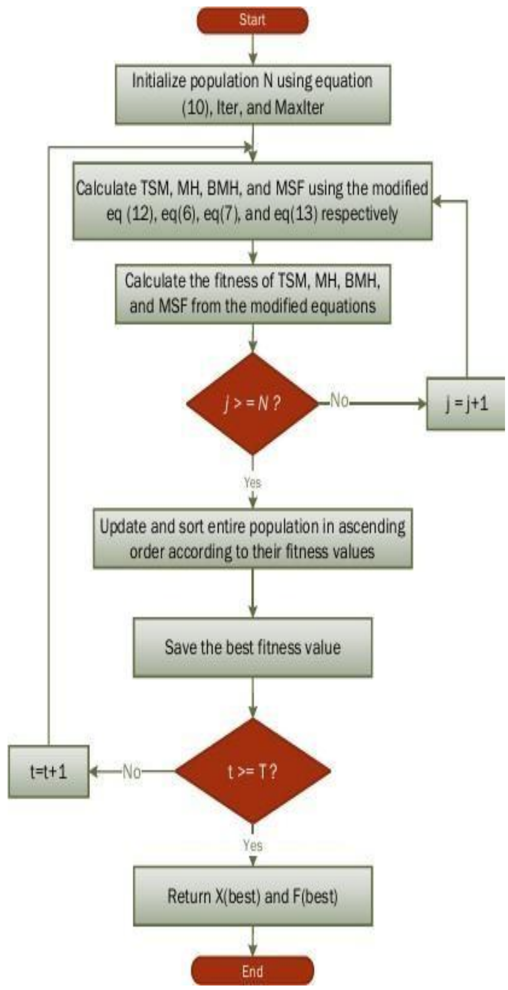


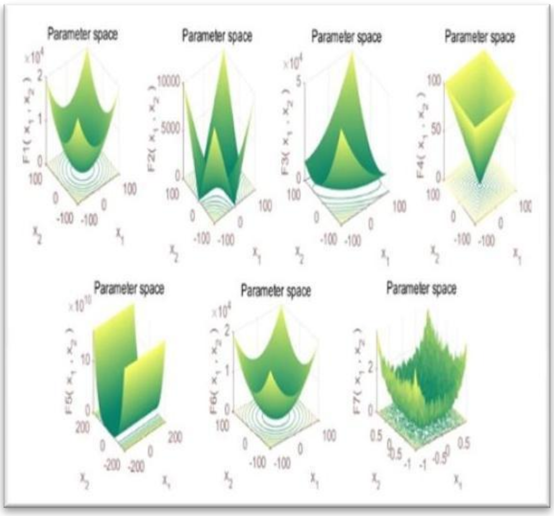
fig 2: Flowchart

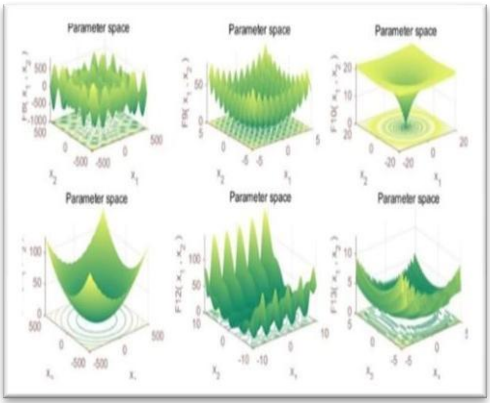
DOI: https://doi.org/10.5281/zenodo.15605503

4. Result

By using existing algorithms, we can apply new approaches to achieve better improvements. After applying these approaches, they provide optimized results and enhance the algorithm's performance. By implementing hybridization with a genetic algorithm, we can further improve efficiency In the diagram below, we perform the test function on the existing Mountain Gazelle Optimizer algorithm. Additionally, we perform the test function on the integration of the Genetic Algorithm with Mountain Gazelle Optimizer.

By comparing both, we can conclude that the reviewed Mountain Gazelle Optimizer algorithm provides better and more optimized results.





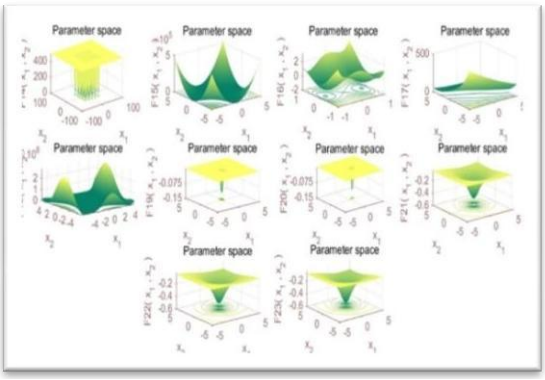
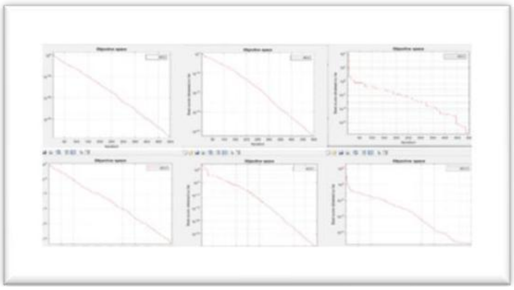


Fig: 3 Parameter Spaces for the Function 1 to function 23



DOI: https://doi.org/10.5281/zenodo.15605503

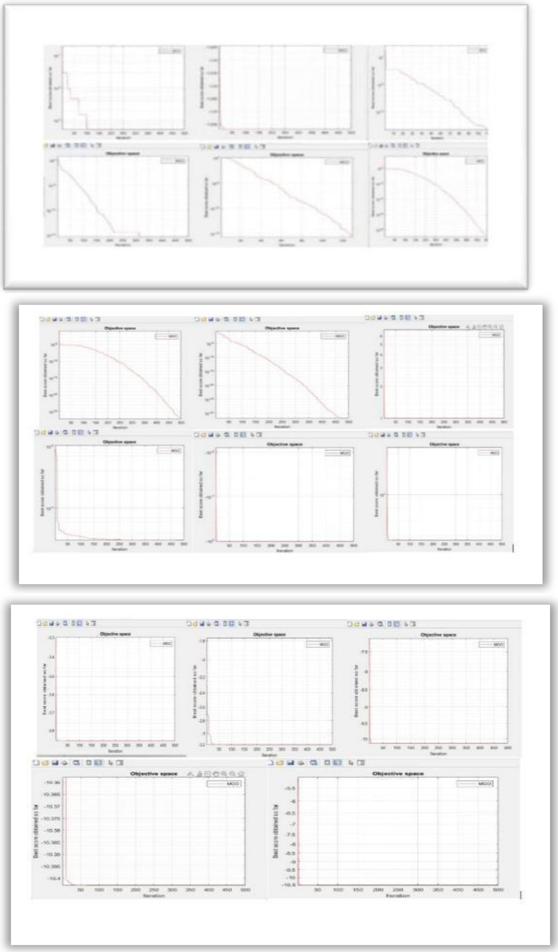


Fig 4: Graphs for the Function 1 to function 2

Table 3: Result of Function 1 to Function 23

5. Conclusion

Both Actual and Hybrid Values were used in this study to evaluate the performance of 23 test functions; the Hybrid Value showed how well a hybrid optimization algorithm that blends local and global search techniques worked. With the lowest Hybrid Value of -**9429.329**, the results show that Function F8 produced the best optimal solution under a minimization objective.

While not as good as F8, other functions including F1, F22, and F23 also showed good performance with hybrid values around -10.5.

Function Name	Actual Value	Hybrid Value
F1	1.3746e-75	-10.5364
F2	1.4299e-45	0.015036
F3	1.3693e-09	0.015036
F4	4.304e-26	29.9455
F5	1.2485e-28	28.0437
F6	4.1225e-10	0.0041524
F7	4.1225e-10	0.053953
F8	4.1225e-10	-9429.329
F9	4.1225e-10	21.3584
F10	4.4409e-16	0.061984
F11	0	0.061984
F12	0	7.1728
F13	0	0.004021
F14	0	6.9033
F15	0.00030749	0.00096214
F16	0.00030749	-1.0316
F17	0.00030749	
F18	0.00030749	3.0001
F19	-3.8628	-3.8628
F20	-3.8628	-3.322
F21	-10.1532	-3.322
F22	-10.1532	-10.4029
F23	-10.1532	-10.5364

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Reliable convergence was highlighted by functions F19 to F23, which demonstrated consistency between Actual and Hybrid Values.
The best performances in a maximizing setting were F4 and F5. Considerably, the results demonstrate how well the hybrid strategy works to produce excellent results in a variety of optimization scenarios.

SummaryofOptimalFunctions (Minimization Focus):

Function	Hybrid Value
F8	-9429.329
F1	-10.5364
F22	-10.4029
F23	-10.5364
F19	-3.8628
F20	-3.322
F21	-3.322

6. References

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