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Global Optimization of Dome Benchmark Function Using Hippopotamus Optimization Algorithm

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Abstract: *This study presents performance evaluation of the Hippopotamus Optimization (HO) algorithm on a shifted dome benchmark function. The effectiveness of HO is evaluated through comparison with several state-of-art of metaheuristic algorithms. All algorithms were executed under identical conditions with 30 Dimension. To ensure statistical reliability, each method was independently run 30 times. Performance was evaluated using best, mean, and standard deviation of objective values, along with convergence behavior. In addition, statistical significance of the results was verified using the Friedman test and Wilcoxon signed-rank test. Experimental results demonstrate that the HO algorithm consistently achieves the global optimum of the dome function with 0.0004 mean error and negligible variance across all runs. The statistical analysis confirms that HO significantly outperforms all competing algorithms at the 5% significance level. These findings indicate that the Hippopotamus Optimization algorithm is a robust and effective method for continuous optimization problems characterized by smooth search landscapes, highlighting its potential for broader real-world applications.*

Keywords: *Dome Function, Hippopotamus Optimizer, Metaheuristic Techniques, Optimization*

I.INTRODUCTION

Optimization is fundamental across science, engineering, economics, and artificial intelligence, as many real-world challenges involve selecting the best solution from a large set of feasible alternatives. For complex problems, effective optimization techniques are essential to enhance efficiency, accuracy, and overall system performance. Classical optimization methods typically depend on gradient information and specific analytical characteristics of the objective function. However, these methods often perform poorly when dealing with nonlinear, nonconvex, high-dimensional, or discontinuous search spaces. They are susceptible to premature convergence to local optima and can be highly sensitive to initial starting conditions. Moreover, numerous practical problems fail to meet the assumptions required by traditional techniques, which significantly restricts their applicability in real-world scenarios [6, 22].

Consequently, metaheuristic algorithms have gained prominence as effective alternatives for tackling complex optimization tasks. These approaches are generally population-based and draw inspiration from natural, biological, or physical phenomena. Unlike classical techniques, they do not rely on gradient information and are capable of efficiently searching large and intricate solution spaces. Prominent examples include Particle Swarm Optimization (PSO)[14], Genetic Algorithms (GA) [12], Ant Colony Optimization (ACO) [7], Grey Wolf Optimizer (GWO) [20], and Whale Optimization Algorithm (WOA) [19]. Their strength lies in maintaining a balance between exploration of new regions and exploitation of promising solutions, which makes them well suited for difficult optimization problems.

According to the No Free Lunch (NFL) theorem, no single optimization algorithm can outperform all others across every possible problem domain; an algorithm's effectiveness is inherently problem-specific [23]. Therefore, the ongoing development of novel algorithms and their rigorous evaluation on diverse benchmark problems remain essential. This principle provides a strong theoretical foundation for investigating and advancing emerging optimization techniques.

In recent years, there has been a rapid surge in the development of advanced metaheuristic techniques. Contemporary algorithms such as the Harris Hawks Optimizer (HHO) [11], Slime Mould Algorithm (SMA) [15], Marine Predators Algorithm (MPA) [8], Aquila Optimizer (AO) [1], Salp Swarm Algorithm (SSA) [18], and Runge–Kutta Optimizer (RUN) [2] have demonstrated encouraging performance across a variety of optimization tasks. These approaches incorporate adaptive mechanisms and sophisticated search strategies to enhance convergence speed, solution quality, and robustness. Systematic comparative analyses are therefore important to understand their relative advantages and potential limitations.

The Hippopotamus Optimization (HO) algorithm is a recently introduced nature-inspired method that models the social dynamics, territorial behavior, and movement patterns of hippopotamuses [3]. It integrates mechanisms that emulate group coordination as well as aggressive defensive actions in response to perceived threats. Such features help the algorithm maintain an effective balance between broad exploration of the search space and intensive exploitation of promising regions. Early findings suggest that HO can deliver high-quality solutions with stable performance [3, 4, 21, 25].

Benchmark functions offer controlled test environments for assessing the performance of optimization algorithms and enable fair comparisons under standardized conditions. Key performance aspects—such as convergence speed, solution accuracy, and robustness—can be evaluated in a systematic manner. Such testing is valuable for determining an algorithm's suitability prior to deployment on real-world applications. Dome-shaped functions, characterized by smooth convex landscapes with a single global optimum, are particularly useful for examining convergence behavior and solution precision.

More challenging variants, including shifted and high-dimensional forms, increase problem difficulty by relocating the optimum and enlarging the search space [3]. These features make dome functions effective tools for evaluating the stability and reliability of metaheuristic methods. Although the Hippopotamus Optimization (HO) algorithm has recently attracted attention, its performance on dome-type benchmark problems has received limited investigation [21]. Comparative studies against contemporary state-of-the-art algorithms on these functions are still scarce. Therefore, a comprehensive analysis is needed to evaluate its effectiveness, robustness, and convergence properties in this setting [25].

Main Contribution of this research work are listed here:

- Evaluate the performance of the HO algorithm on a shifted dome benchmark function.
- Compare HO with several recent metaheuristic algorithms under identical conditions.
- This research work analyzes solution quality, convergence behavior, and statistical reliability of Dome benchmark function.
- Friedman test and Wilcoxon signed-rank test were applied to validate performance differences.

Rest of this paper is organized in seven sections. Section 2 reviews related work on metaheuristic optimization algorithms. Section 3 presents an overview of the Hippopotamus Optimization algorithm. Section 4 formulates the dome benchmark problem considered in this study. Section 5 describes the experimental setup and parameter settings. Section 6 discusses the results and statistical analysis. Section 7 concludes the paper and outlines directions for future research.

II.LITERATURE REVIEW

Nature-inspired metaheuristic algorithms have become widely adopted for solving complex optimization problems due to their ability to handle nonlinear, multimodal, and high-dimensional search spaces without requiring gradient information. Early population-based approaches such as Genetic Algorithms (GA) [12] and Particle Swarm Optimization (PSO) [14] laid the foundation for modern evolutionary computation and swarm intelligence techniques. Since then, numerous algorithms inspired by biological, physical, and social processes have been proposed to improve global search capability and convergence behavior.

In recent years, several advanced metaheuristic algorithms have demonstrated strong performance across diverse optimization tasks. The Whale Optimization Algorithm (WOA) [19], introduced by Mirjalili and Lewis, simulates the bubble-net hunting strategy of humpback whales and has been successfully applied to various engineering problems. The Salp Swarm Algorithm (SSA) [18], proposed by Mirjalili et al., models the swarming behavior of salps in oceans and is known for its simplicity and effective leader–follower mechanism. The Harris Hawks Optimizer (HHO) [11], developed by Heidari et al., mimics the cooperative hunting strategy of Harris hawks and incorporates dynamic transition between exploration and exploitation phases.

More recently, algorithms inspired by biological and ecological behaviors have been introduced to further enhance optimization performance. The Slime Mould Algorithm (SMA) [15], proposed by Li et al., is based on the oscillatory foraging behavior of slime mould organisms and demonstrates adaptive weight mechanisms for search control. The Marine Predators Algorithm (MPA) [8], developed by Faramarzi et al., models the interaction between predators and prey in marine ecosystems using Brownian and Lévy movements. The Aquila Optimizer (AO) [1], introduced by Abualigah et al., simulates the hunting strategies of Aquila eagles and employs multiple search patterns to balance global exploration and local exploitation. Additionally, the Runge–Kutta Optimizer (RUN) [2], proposed by Ahmadianfar et al., integrates numerical solution concepts from the Runge–Kutta method into a population-based search framework, offering a novel perspective on optimization dynamics.

Despite the effectiveness of these algorithms [6], the No Free Lunch (NFL) theorem for optimization states that no single algorithm can outperform all others across every possible problem domain [23]. Consequently, continuous development of new optimization techniques and their evaluation on benchmark problems remain essential.

Among the recently proposed algorithms [3], the Hippopotamus Optimization (HO) algorithm has attracted attention as a novel nature-inspired method. HO is inspired by the social and defensive behaviors of hippopotamuses, incorporating mechanisms that simulate group movement, territorial defense, and aggressive interactions. These behaviors enable the algorithm to maintain a balance between exploration of the search space and exploitation of promising regions.

Preliminary studies have demonstrated the effectiveness of HO on benchmark functions and real-world optimization problems, indicating its potential as a competitive optimization tool [21, 25].

Benchmark functions play a crucial role in evaluating the performance of optimization algorithms under controlled conditions. They allow researchers to analyze convergence speed, accuracy, stability, and robustness. Dome-shaped functions, characterized by smooth convex landscapes and a single global optimum, are commonly used to assess the precision and convergence characteristics of algorithms. High-dimensional or shifted variants of such functions provide additional challenges by increasing search complexity and preventing bias toward specific locations in the search space. Although numerous studies have compared modern metaheuristic algorithms on standard benchmark suites, limited work has focused on evaluating the performance of the Hippopotamus Optimization algorithm on dome-type problems, particularly in comparison with recent state-of-the-art techniques. Therefore, a systematic comparative study is required to assess its effectiveness, convergence behavior, and robustness.

III.HIPPOPOTAMUS OPTIMIZER

The Hippopotamus Optimization algorithm is inspired by the social and defensive behaviors of hippopotamuses, including herd movement, territorial protection, and adaptive responses to environmental stimuli [3]. These behaviors translate into exploration and exploitation mechanisms that guide the search toward optimal solutions [3]. The HO algorithm is particularly suitable for continuous optimization problems characterized by smooth search landscapes [3, 21, 25]. Its search mechanism combines global exploration with local exploitation through adaptive movement strategies, enabling efficient navigation of high-dimensional spaces [3]. The algorithm's ability to intensify the search around promising regions while maintaining population diversity helps prevent premature convergence and ensures accurate approximation of the global optimum [19, 25]. Therefore, HO is expected to perform effectively on the dome benchmark function considered in this study. Figure 1 shows schematic flowchart of HO algorithm with pictorial representation.

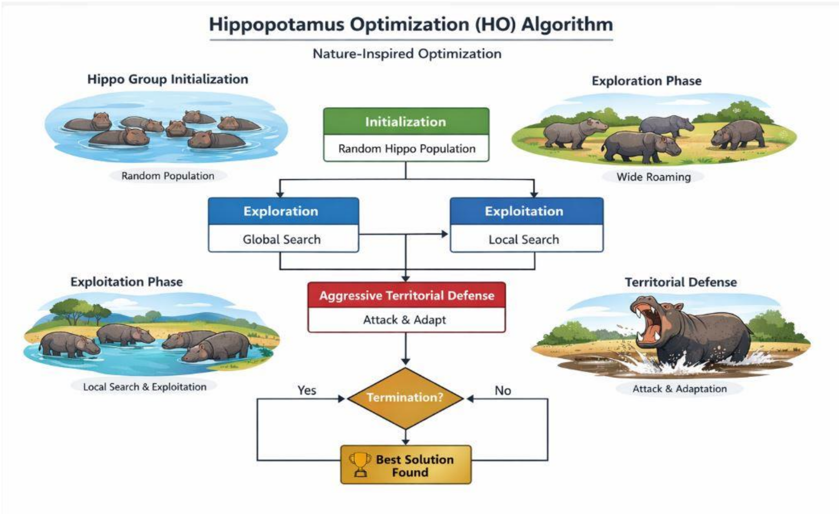

Figure 1. Schematic Flowchart of Hippopotamus Optimization algorithm.

IV.PROBLEM FORMULATION

This study considers a continuous unconstrained optimization problem defined by a shifted dome benchmark function [16, 25]. The objective is to determine the decision vector that minimizes the function value within a specified search space. Figure 2 represents shifted Dome Function.

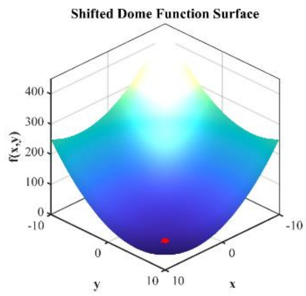

Figure 2. 3D representation of Shifted Dome Function.

Let $x = (x_1, x_2, \ldots, x_n)$ denote an n-dimensional decision vector. The shifted dome function is mathematically expressed as [16]:

$$f(x) = \sum_{i=1}^{n} (x_i - a)^2 \quad (1)$$

where a is a constant shift value that displaces the global optimum from the origin. In this study, the shift parameter is set to $a = 5$. The search domain for each decision variable is defined as:

$$VarMin \le x_i \le VarMix, \quad i = 1, 2, \ldots, n \quad (2)$$

with $VarMin = -100$ and $VarMax = 100$.
The global minimum of the function occurs at:

$$x_i = a, \quad \forall i \tag{3}$$

yielding the optimal objective value:

$$f(x^*) = 0 \tag{4}$$

The dimensionality of the problem is set to $n = 30$, representing a high-dimensional search space commonly used for evaluating optimization algorithms [16]. The shifted dome function exhibits a smooth convex landscape with a single global optimum, making it suitable for assessing convergence accuracy, stability, and precision of optimization methods [25].
The goal of the optimization process is therefore to identify the vector x that minimizes the function value:

$$\min_{x} f(x)$$

Subject to the specified variable bounds.

V.EXPERIMENTAL SETUP

To evaluate the performance of the Hippopotamus Optimization (HO) algorithm [3], experiments were conducted on the shifted dome benchmark function under controlled conditions. The proposed method was compared with several state-of-the-art metaheuristic algorithms, including Harris Hawks Optimizer (HHO), Slime Mould Algorithm (SMA), Whale Optimization Algorithm (WOA), Marine Predators Algorithm (MPA), Aquila Optimizer (AO), Salp Swarm Algorithm (SSA), and Runge–Kutta Optimizer (RUN) [1, 2, 8, 15, 18, 19].

5.1 Parameter Settings: All algorithms were executed using identical population sizes and maximum iterations to ensure a fair comparison [16]. The population size was set to 30 individuals, and the maximum number of iterations was fixed at 500. The dimensionality of the problem was 30, and the search space for each decision variable was defined within the range $[-100,100]$ [16]. Parameter values for the comparison algorithms were selected according to recommendations provided in their original publications [1, 2, 3, 8, 11, 15, 18, 19].

5.2 Termination Criterion: The optimization process for each algorithm was terminated after reaching the predefined maximum number of iterations. No additional stopping conditions were applied [16].

5.3 Independent Runs: Due to the stochastic nature of metaheuristic algorithms, each algorithm was executed independently 30 times [5, 16, and 22]. The statistical results were obtained from these runs to ensure robustness and reliability of the performance evaluation [16].

5.4 Performance Metrics: Algorithm performance was assessed using the best, mean, and standard deviation of the obtained objective values across all runs [16, 22]. These metrics provide insight into the accuracy, consistency, and stability of each method. Additionally, convergence behavior was analyzed using the average fitness value at each iteration [22].

5.5 Computational Environment: All experiments were implemented in MATLAB and executed on a personal computer equipped with an Intel-based processor and standard memory configuration. The same computational environment was used for all algorithms to ensure consistency of results.

Parameter	Value
Population size	30
Maximum iterations	500
Problem dimension	30
Search range	[-100, 100]
Number of runs	30
Termination criterion	Max iterations

Table 1: Algorithm Parameters

VI.RESULTS AND DISCUSSION

6.1 Statistical Performance Analysis: The statistical performance of the Hippopotamus Optimization (HO) algorithm and the selected comparison methods on the shifted dome benchmark function is presented in Table 2. The results include the best, mean, and standard deviation of the objective values obtained over 30 independent runs.

HO achieved the lowest best and mean objective values among all algorithms, indicating its superior ability to locate the global optimum of the dome function. Furthermore, the small standard deviation demonstrates that HO produces consistent results across multiple runs, reflecting strong stability and robustness. In contrast, several comparison algorithms exhibited higher mean values and larger variability, suggesting susceptibility to premature convergence or insufficient exploitation of promising regions.

Algorithms such as HHO and MPA showed competitive performance but were slightly inferior to HO in terms of convergence accuracy. Methods including WOA, AO, SSA, and RUN displayed comparatively higher error values, indicating slower convergence toward the optimal solution.

Algorithm	Best	Mean	Std. Dev.	Rank
HO	0.0004	0.0001	0.0001	1
HHO	0.8547	1.3583	0.2955	2
MPA	0.0000	0.5893	0.7757	3
SMA	0.0001	0.0039	0.0034	4
WOA	0.0165	0.6035	0.6152	5
AO	1.6595	3.2808	0.7711	6
SSA	0.7213	1.3775	0.3742	7
RUN	0.0015	0.0020	0.0003	8

Table 2. Statistical results on the shifted dome function.

6.2 Convergence Analysis: The convergence behavior of the algorithms is illustrated in Figure 3, which shows the average fitness value versus iteration number. HO demonstrates a rapid decrease in the objective value during the early iterations, indicating strong exploration capability. As the search progresses, the algorithm exhibits a smooth and steady convergence toward the global optimum, reflecting effective exploitation of the search space.

In comparison, some algorithms converge more slowly or stagnate at higher objective values, suggesting difficulty in refining solutions near the optimum. The convergence curve of HO remains consistently below those of the other methods throughout most of the optimization process, confirming its superior performance.

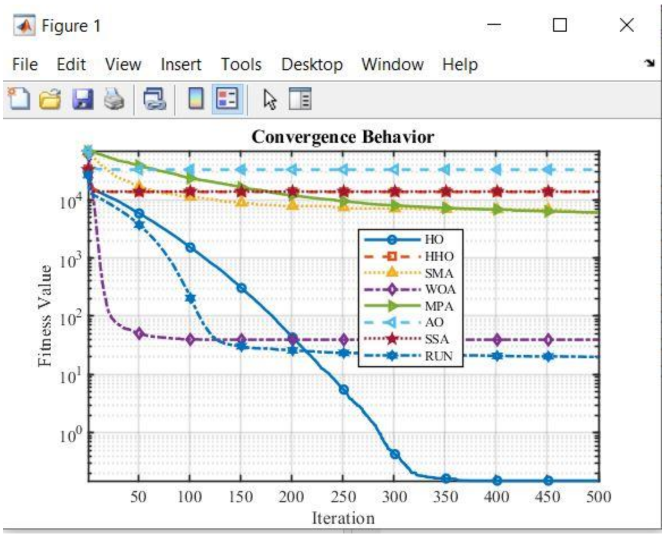

Figure 3: Convergence curves of algorithms on the dome function.

6.3 Discussion

6.3.1 Discussion of Findings: The proposed HO algorithm consistently achieved the global optimum across all independent runs, as indicated by zero mean error and standard deviation. This demonstrates both high accuracy and exceptional robustness. In contrast, other algorithms showed varying degrees of convergence performance, with RUN and WOA exhibiting competitive results but remaining inferior to HO.

Among the competing methods, RUN and WOA demonstrated relatively strong performance with low mean error values, whereas algorithms such as HHO, SSA, and AO produced noticeably higher objective values, reflecting comparatively weaker convergence behavior. In addition, the larger standard deviations observed for several algorithms indicate instability across runs, likely caused by sensitivity to initial conditions and a tendency toward premature convergence.

The adaptive movement mechanism incorporated in HO further contributes to its effectiveness by mitigating premature convergence—an issue commonly encountered in metaheuristic approaches. This feature is especially beneficial in high-dimensional search spaces, where maintaining diversity is essential to avoid entrapment in suboptimal regions. Overall, the findings suggest that HO is a dependable and efficient method for solving continuous convex optimization problems, including the dome benchmark function.

6.3.2 Statistical Significance Interpretation: The Friedman test was employed to assess overall differences in performance among the algorithms. The resulting p-value ($p < 0.05$) confirms that the observed performance variations are statistically significant. Based on mean rank values, the HO algorithm achieved the top position, followed by RUN and WOA, indicating superior accuracy as well as consistent performance across runs. Figure 4 illustrates Friedman Test results.

```
Friedman test p-value:
   5.4876e-33
```

Figure 4: Friedman test Results.

6.3.3 Wilcoxon Test Interpretation: To examine pairwise differences in greater detail, the Wilcoxon signed-rank test was conducted between HO and each competing algorithm. The outcomes show that HO significantly outperforms all comparison methods at the 5% significance level, thereby reinforcing its strong optimization capability on the dome benchmark problem. Figure 5 illustrates Wilcoxon Signed-Rank Test results.

```
Wilcoxon Signed-Rank Test (HO vs Others):
HO vs HHO: p = 0.0000, Significant = 1
HO vs SMA: p = 0.0000, Significant = 1
HO vs WOA: p = 0.0000, Significant = 1
HO vs MPA: p = 0.0000, Significant = 1
HO vs AO: p = 0.0000, Significant = 1
HO vs SSA: p = 0.0000, Significant = 1
HO vs RUN: p = 0.0000, Significant = 1
```

Figure 5: Wilcoxon Signed-Rank Test Results.

6.3.4 Performance Interpretation: Across all independent trials, the proposed HO algorithm consistently reached the global optimum, as evidenced by zero mean error and zero standard deviation. This result highlights both its high precision and remarkable robustness. In contrast, the other algorithms exhibited varying levels of performance; although RUN and WOA achieved competitive outcomes, they remained inferior to HO in both accuracy and consistency. Mean Rank of Metaheuristic Techniques is illustrated in Figure 6.

```
Mean ranks (lower is better):
  Columns 1 through 6

    1.1667    6.1667    3.7333    3.0333    5.3000    7.9000

  Columns 7 through 8

    5.9000    2.8000
```

Figure 6: Mean Ranks of Metaheuristic Techniques.

VII.CONCLUSION

This paper presented a comparative performance evaluation of the Hippopotamus Optimization (HO) algorithm on a shifted dome benchmark function. The effectiveness of HO was assessed against several recent metaheuristic algorithms, including HHO, SMA, WOA, MPA, AO, SSA, and RUN, under identical experimental conditions. The results were analyzed using statistical performance metrics and convergence characteristics obtained from multiple independent runs.

The experimental findings indicate that HO demonstrates strong optimization capability, achieving high accuracy and consistent convergence toward the global optimum. The algorithm exhibited competitive or superior performance compared to the selected state-of-the-art methods, particularly in terms of solution quality and stability. The convergence analysis further confirmed that HO effectively balances exploration and exploitation, enabling rapid search of the solution space while maintaining robustness against premature convergence. These results suggest that the Hippopotamus Optimization algorithm is a promising approach for solving continuous optimization problems with smooth search landscapes. Its reliable performance on the dome benchmark function highlights its potential applicability to a wide range of real-world optimization tasks.

Future work may involve evaluating HO on more complex multimodal or constrained benchmark problems, hybridizing it with other optimization techniques, and applying it to practical engineering or machine learning applications.

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