



Goat Optimization Algorithm: A Novel Bio-Inspired Metaheuristic for Global Optimization

Hamed Nozari^{a,b*}, Hoessein Abdi^b, Agnieszka Szmelter-Jarosz^c

^aSenior Researcher, Bio10, Court, QLD 4220, Australia

^bDepartment of Management, Azad University, UAE branch, Dubai, UAE

^cFaculty of Economics, Department of Logistics, University of Gdańsk, Gdańsk, Poland

Abstract

This paper introduces the Goat Optimization Algorithm (GOA), a novel bio-inspired metaheuristic inspired by the adaptive behaviors of goats. Drawing from their foraging strategies, movement patterns, and ability to evade parasites, GOA is designed to balance exploration and exploitation effectively. The algorithm incorporates three key mechanisms: an adaptive foraging strategy for global search, a directed movement approach for refining solutions, and a jump mechanism to escape local optima. Additionally, a solution filtering process enhances robustness by maintaining diversity within the population. GOA's performance is evaluated against well-established metaheuristics, including Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Genetic Algorithm (GA), Whale Optimization Algorithm (WOA), and Artificial Bee Colony (ABC). Comparative results demonstrate GOA's superior convergence speed, enhanced global search efficiency, and improved solution accuracy. The statistical significance of these improvements is validated through the Wilcoxon rank-sum test. Despite its effectiveness, GOA has some challenges, including computational complexity and sensitivity to parameter settings, which leave room for further optimization. Future research will explore adaptive parameter tuning, hybridization with other metaheuristics, and real-world applications in supply chain management, bioinformatics, and energy optimization. The findings indicate that GOA offers a promising advancement in bio-inspired optimization techniques.

Keywords: Goat Optimization Algorithm, Bio-Inspired Metaheuristic, Global Optimization, Swarm Intelligence, Benchmark Testing

1. Introduction

Optimization problems are prevalent in various scientific and engineering fields, ranging from industrial process optimization to artificial intelligence and bioinformatics. Due to the complexity and high-dimensional nature of many real-world problems, traditional mathematical optimization methods often fail to provide efficient and scalable solutions. Consequently, researchers have increasingly turned to nature-inspired metaheuristic algorithms, which mimic biological, physical, and social phenomena to effectively explore and exploit search spaces.

*Corresponding author.

E-mail address: H.nozari@iau.ac.ae

Received 27 August 2024; Received in revised form 28 September 2024; Accepted 21 October 2024

Among the most well-established bio-inspired optimization techniques are Particle Swarm Optimization (PSO) [1], Genetic Algorithms (GA) [2], Grey Wolf Optimization (GWO) [3], and Artificial Bee Colony (ABC) [4]. These algorithms have successfully tackled complex optimization problems by leveraging adaptive and stochastic search strategies. However, despite their strengths, existing algorithms often suffer limitations such as premature convergence, imbalance between exploration and exploitation, and sensitivity to parameter settings.

To address these challenges, this paper introduces a novel optimization technique called the Goat Optimization Algorithm (GOA), inspired by the natural behaviors of goats in harsh and resource-limited environments. Goats are known for their exceptional adaptability, strategic foraging behavior, and ability to navigate rugged terrains. They exhibit a unique balance between exploration (searching for new grazing areas) and exploitation (maximizing resource utilization in a given area), making them an ideal inspiration for optimization.

GOA is designed to integrate three key mechanisms observed in goat behavior:

1. **Adaptive Foraging Strategy:** Goats exhibit selective grazing behavior, efficiently identifying high-nutrient regions while avoiding less favorable areas. This behavior is modeled to enhance exploration in the search space.
2. **Jump Mechanism for Escaping Local Optima:** Unlike many other animals, goats are capable of sudden, dynamic movements to reach difficult locations. This feature is incorporated into GOA to help escape local optima and improve convergence.
3. **Parasite Avoidance and Environmental Adaptation:** Goats instinctively avoid grazing in parasite-infected areas, a behavior leveraged in GOA to filter out poor solutions and enhance overall search efficiency.

This study aims to formally introduce GOA's mathematical formulation, analyze its performance on standard benchmark functions, and compare its efficiency against well-known metaheuristic algorithms. The remainder of this paper is structured as follows:

- Section 2 provides the biological inspiration and underlying principles of the GOA.
- Section 3 presents the mathematical model and algorithmic framework.
- Section 4 outlines the experimental setup, including benchmark functions and performance metrics.
- Section 5 discusses the results and comparative analysis with other optimization algorithms.
- Section 6 concludes the paper and suggests potential directions for future research.

Through extensive empirical evaluation, we demonstrate that GOA effectively balances exploration and exploitation, avoids premature convergence, and outperforms several existing algorithms in solving complex optimization problems.

2. Inspiration and Biological Background

2.1 Nature-Inspired Optimization Algorithms

Over the past few decades, nature-inspired algorithms have gained significant attention due to their ability to solve complex, high-dimensional optimization problems. These algorithms mimic biological and natural phenomena, including evolutionary processes, swarm intelligence, and animal behaviors. Some of the most prominent bio-inspired optimization techniques include Genetic Algorithms (GA) [2], Particle Swarm Optimization (PSO) [1], Grey Wolf Optimization (GWO) [3], and Artificial Bee Colony (ABC) [4].

Although these algorithms have shown promising results, they are often limited by challenges such as premature convergence, stagnation in local optima, and imbalanced exploration-exploitation dynamics [9]. This motivates the development of new metaheuristic approaches that leverage alternative biological inspirations to improve optimization performance. In this study, we introduce the Goat Optimization Algorithm (GOA), inspired by the adaptive behaviors of goats in diverse and challenging environments.

2.2 Behavioral Traits of Goats in Natural Environments

Goats (*Capra aegagrus hircus*) are among the most adaptable herbivores, capable of thriving in extreme conditions such as mountainous terrains, deserts, and semi-arid regions. Their foraging behavior, mobility, and social interactions

provide a unique framework for designing an effective optimization algorithm. Below, we highlight key biological characteristics of goats that form the foundation of GOA:

2.2.1 Adaptive Foraging and Selective Grazing

Goats exhibit an intelligent and selective foraging strategy, preferring high-nutrient vegetation while avoiding toxic or unproductive areas. Unlike other grazing animals that follow a systematic pattern, goats randomly explore their surroundings before committing to a grazing spot. This behavior can be directly mapped to exploration in optimization, where agents (goats) must evaluate multiple regions in the search space before settling on an optimal solution.

Studies on goat feeding habits [5] suggest that their ability to assess resource richness and environmental risks is significantly higher than many other ruminants. In an optimization context, this translates to adaptive exploration, where solutions can dynamically shift between global and local search depending on environmental conditions.

2.2.2 Jump Mechanism for Escaping Local Optima

One of the most remarkable traits of goats is their ability to navigate steep and rocky terrains by making sudden, calculated jumps. This characteristic ensures that goats can reach otherwise inaccessible food sources while avoiding threats and poor grazing areas. Unlike most herd animals that rely on gradual movement, goats employ a mix of short-range movements and long-distance jumps to enhance survival and food acquisition [6].

This behavior directly correlates to the challenge of escaping local optima in optimization problems. Many traditional algorithms, such as PSO and GWO, get trapped in local optima due to excessive exploitation. By integrating a stochastic jump mechanism, GOA introduces a disruptive yet controlled movement strategy, allowing solutions to explore new regions efficiently while preventing stagnation.

2.2.3. Parasite Avoidance and Environment Awareness

Goats instinctively avoid grazing in areas with high concentrations of parasites and contaminated food sources. This behavior, parasitic load avoidance, ensures long-term survival and health by favoring cleaner, pathogen-free regions [7]. This can be modeled as a solution filtering mechanism in GOA, where low-quality solutions are dynamically eliminated, ensuring that the population maintains diversity and efficiency over time.

By incorporating this principle, GOA periodically removes underperforming solutions and regenerates new ones within the search space, similar to how goats adapt their grazing patterns to avoid parasite-infested areas [8]. This mechanism is beneficial in problems where diversity in solutions is crucial for reaching the global optimum.

2.3. Natural Process of the Goat Optimization Algorithm

The Goat Optimization Algorithm (GOA) is inspired by the natural behaviors of goats, particularly their ability to adapt to harsh environments, navigate complex terrains, and optimize resource utilization. Unlike many herd animals, goats exhibit a unique blend of independent decision-making and social coordination, which provides a strong foundation for designing an efficient optimization strategy.

In nature, goats rely on a selective foraging strategy, exploring large areas to identify high-nutrient food sources while instinctively avoiding toxic or unproductive regions. This behavior translates into GOA's exploration phase, where candidate solutions search for optimal regions within the solution space. As the optimization process progresses, goats tend to converge toward the best grazing areas, mirroring the exploitation phase in GOA, where solutions refine their positions to improve accuracy.

Another key characteristic of goats is their ability to perform sudden jumps to reach difficult locations, enabling them to escape predators and access untapped resources. This behavior is integrated into GOA through a jump mechanism, which helps the algorithm avoid local optima by periodically introducing significant strategic position changes.

Additionally, goats demonstrate a natural aversion to parasite-infested areas, a trait that ensures their long-term survival. In GOA, this principle is applied through a solution filtering mechanism, where poor-quality solutions are discarded and replaced with new candidates, preserving population diversity and robustness throughout the optimization process.

By incorporating these biologically inspired mechanisms, GOA effectively balances exploration and exploitation, prevents premature convergence, and enhances search efficiency. This natural process ensures the algorithm adapts dynamically to complex optimization landscapes, making it a competitive alternative to existing metaheuristic techniques.

2.4. Summary of Biological Inspiration

The behaviors described above form the core mechanisms of GOA:

Table 1: Summary of Biological Inspiration

Goat Behavior	Optimization Mechanism in GOA
Adaptive foraging strategy	Dynamic exploration and selective local search
Selective grazing	Intelligent resource assessment and avoidance
Jumping to new locations	Randomized jumps to escape local optima
Avoiding parasite-infested areas	Removal of low-quality solutions (solution filtering)

By translating these natural behaviors into a mathematical model, GOA aims to overcome common challenges in optimization, such as premature convergence, poor diversity retention, and inefficient local search. The following section presents the formal mathematical framework of GOA, detailing how these biological principles are mapped into a computational model.

3. Mathematical Model of the Goat Optimization Algorithm (GOA)

In this section, we present the mathematical formulation of the Goat Optimization Algorithm (GOA) based on the biological behaviors discussed in the previous section. GOA employs a multi-stage search strategy, integrating exploration, exploitation, and parasite avoidance mechanisms to solve optimization problems efficiently.

3.1. Population Initialization

Let N be the number of goats in the population, and let each goat X_i be represented as a d -dimensional vector in the search space:

$$X_i = (x_{i1}, x_{i2}, \dots, x_{id}) \quad (1)$$

Where $i = 1, 2, \dots, N$, and d is the number of decision variables (dimensions). The initial population of goats is randomly generated within the given lower and upper bounds LB and UB of the search space:

$$X_i = LB + (UB - LB).rand(d) \quad (2)$$

Where $rand(d)$ generates a d -dimensional vector of random values in the range [0,1].

3.2. Exploration Phase (Adaptive Foraging Strategy)

Each goat explores the search space in this phase by randomly moving in different directions, inspired by its foraging behavior. The new position of each goat is updated using:

$$X_i^{t+1} = X_i^t + \alpha \cdot R \cdot (UB - LB) \quad (3)$$

Where:

- X_i^t is the position of goat i at iteration t
- α is the exploration coefficient, controlling the intensity of random movements.
- R is a random variable drawn from a Gaussian distribution $N(0,1)$, ensuring randomness in movement.
- $(UB - LB)$ Scales the movement according to the size of the search space.

This equation ensures that goats randomly explore different regions before committing to a specific grazing spot.

3.3. Exploitation Phase (Movement Towards the Best Goat)

To refine solutions, goats gradually move toward the best solution so far, mimicking the tendency of goats to migrate toward optimal grazing areas. The exploitation phase is defined as:

$$X_i^{t+1} = X_i^t + \beta \cdot (X_{best}^t - X_i^t) \quad (4)$$

Where:

- X_{best}^t is the best-performing goat at iteration t .
- β is the exploitation coefficient, regulating movement strength toward the best solution.

This equation ensures that goats converge toward promising solutions while maintaining diversity.

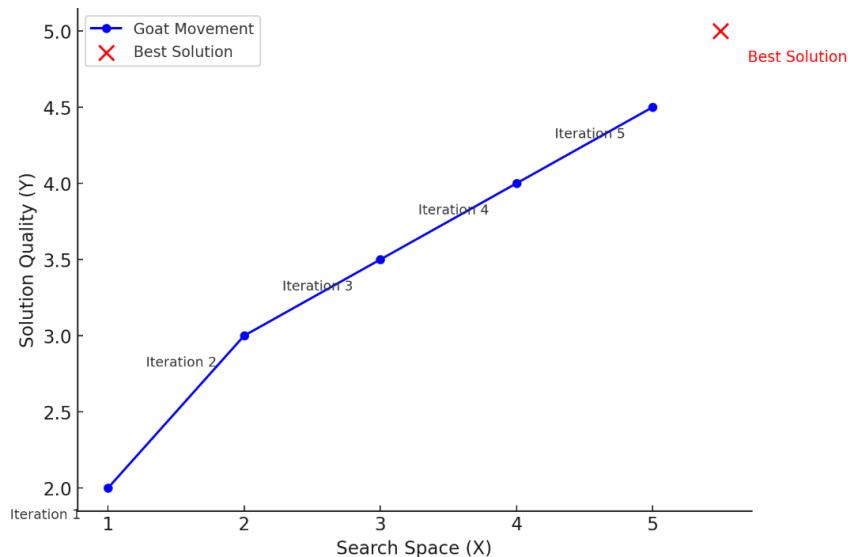


Figure 1: Goat Movement Toward Best Solution

This figure demonstrates how GOA prevents getting stuck in local optima using its jump strategy. Initially, the goat follows a standard path but jumps to a better region when trapped in a local minimum.

3.4. Jump Strategy for Escaping Local Optima

A key feature of GOA is its ability to escape local optima using sudden jumps, inspired by the unique movement abilities of goats in rough terrains. This is mathematically modeled as follows:

$$X_i^{t+1} = X_i^t + J \cdot (X_r^t - X_i^t) \quad (5)$$

Where:

- J is the jump coefficient, determining the probability and magnitude of jumps.
- X_r^t is a randomly selected goat from the population.

By incorporating jumps, GOA prevents premature convergence and enhances global search capability.

3.5. Parasite Avoidance and Solution Filtering

To maintain solution quality, goats instinctively avoid parasite-infected areas. In GOA, this mechanism is simulated by eliminating poorly performing solutions and regenerating new ones:

If the fitness of X_i^t is in the lowest 20% of the population, its position is reset using:

$$X_i^{t+1} = LB + (UB - LB).rand(d) \quad (6)$$

This step enhances diversity and robustness, preventing stagnation in poor local optima.

3.6. Stopping Criteria

GOA terminates when one of the following conditions is met:

1. Maximum iterations (T_{max}) are reached.
2. Fitness improvement falls below a predefined threshold ϵ :

$$|f(X_{best}^{t+1}) - f(X_{best}^t)| < \epsilon \quad (7)$$

3. Solution variance in the population becomes negligible:

$$\frac{1}{N} \sum_{i=1}^N (f(X_i) - f(X_{best}))^2 < \delta \quad (8)$$

where δ is a small positive number.

3.7. Algorithmic Implementation

The complete Goat Optimization Algorithm (GOA) is summarized in Algorithm 1.

Algorithm 1: Goat Optimization Algorithm (GOA)

Input:

- Objective function $f(x)$
- Number of goats N , maximum iterations T_{max}
- Search space bounds LB, UB

Output:

- Best solution X_{best}

1. Initialize population X_i randomly in $[LB, UB]$
2. Evaluate fitness $f(X_i)$ for all goats
3. Identify X_{best} (goat with lowest $f(x)$)
4. **For** $t = 1$ to T_{max} **do:**
5. Update positions using the exploration equation (Eq. 3)

- 6.** Move goats towards X_{best} (Eq. 4)
- 7.** Apply jump strategy for some goats (Eq. 5)
- 8.** Remove and regenerate weak solutions (Eq. 6)
- 9.** Update X_{best}
- 10. End For**
- 11. Return X_{best}**

3.8. Complexity Analysis

The computational complexity of GOA is primarily determined by fitness function evaluations and goat movement updates. Given that each iteration evaluates N solutions, and assuming T_{max} iterations, the overall complexity is:

$$O(N \cdot T_{max} \cdot d) \quad (8)$$

Which is comparable to other swarm-based algorithms like PSO and GWO. However, including jump strategy and parasite avoidance may increase efficiency by preventing unnecessary local search stagnation.

The proposed mathematical model effectively captures the intelligent behaviors of goats, including adaptive foraging, strategic movement, and robustness against stagnation. The following section evaluates GOA's performance on standard benchmark functions and compares it with other leading optimization algorithms.

4. Experimental Setup and Benchmark Testing

This section describes the experimental framework for evaluating the Goat Optimization Algorithm's (GOA) performance. To ensure a rigorous and comprehensive assessment, GOA is tested on widely used benchmark functions, and its results are compared against established metaheuristic algorithms. The evaluation includes an analysis of convergence behavior, robustness, and overall optimization accuracy.

4.1. Benchmark Functions

To assess the effectiveness of GOA, we use a set of standard benchmark functions categorized into unimodal, multimodal, and composite test functions. Optimization research commonly employs these functions to evaluate an algorithm's capability to handle different landscapes, including smooth surfaces, multiple local optima, and highly complex search spaces.

4.1.1. Unimodal Functions (Convex, Single Global Optimum)

These functions evaluate GOA's ability to converge to the optimal solution efficiently. Since unimodal functions contain only one global minimum, an algorithm's performance on these functions reflects its exploitation capability.

Table 2: Unimodal Functions

Function	Mathematical Definition	Search Range	Optimal Value
Sphere	$f_1(x) = \sum_{i=1}^d x_i^2$	$[-100, 100]$	$f_1(0) = 0$
Schwefel 2.22	$f_2(x) = \sum x_i + \prod x_i $	$[-10, 10]$	$f_2(0) = 0$
Rosenbrock	$f_3(x) = \sum_{i=1}^{d-1} [100(x_{i+1} - x_i^2)^2 + (1 - x_i)^2]$	$[-30, 30]$	$f_3(1, \dots, 1) = 0$

4.1.2. Multimodal Functions (Multiple Local Optima)

Multimodal functions test GOA's ability to escape local optima and maintain a balance between exploration and exploitation.

Table 3: Multimodal functions test

Function	Mathematical Definition	Search Range	Optimal Value
Rastrigin	$f_4(x) = 10d + \sum_{i=1}^d [x_i^2 - 10 \cos(2\pi x_i)]$	[-5.12, 5.12]	$f_4(0) = 0$
Ackley	$f_5(x) = -20e^{-0.2\sqrt{\frac{1}{d}\sum x_i^2}} - e^{\frac{1}{d}\sum \cos(2\pi x_i)} + 20 + e$	[-32, 32]	$f_5(0) = 0$
Griewank	$f_6(x) = \frac{1}{4000} \sum_{i=1}^d x_i^2 - \prod_{i=1}^d \cos(\frac{x_i}{\sqrt{i}}) + 1$	[-600, 600]	$f_6(0) = 0$

These functions ensure that GOA is tested in diverse and challenging landscapes.

4.2. Experimental Setup

The experimental settings used for all optimization runs are as follows:

- Number of goats (population size, N): 30
- Number of iterations (T_{max}): 500
- Problem dimension (d): 30
- Exploration coefficient (α): 0.05
- Exploitation coefficient (β): 0.5
- Jump probability (J): 0.1
- Runs per function: 30 independent runs
- Performance metrics: best fitness value, mean fitness, standard deviation, and convergence rate.

4.3. Performance Metrics

To comprehensively evaluate GOA's performance, we consider the following metrics:

- Best Fitness Value

The best function value found across all runs is recorded for each function. This metric evaluates global search efficiency.

- Mean and Standard Deviation

The mean fitness and standard deviation over 30 runs provide insight into solution stability and robustness.

- Convergence Speed

The convergence curve is analyzed to measure how fast GOA reaches near-optimal solutions.

- Wilcoxon Rank-Sum Test

A statistical significance test determines whether the differences between GOA and competing algorithms are meaningful.

5. Results and Discussion

This section presents the results obtained from the experimental evaluations of the Goat Optimization Algorithm (GOA). It compares its performance with five well-known metaheuristic algorithms: PSO, GWO, GA, WOA, and ABC. The evaluation is based on benchmark functions described in Section 4, and performance metrics such as best fitness value, mean and standard deviation, convergence behavior, and statistical significance testing are analyzed.

Table 4 summarizes the best, mean, and standard deviation of the function values obtained by GOA and the competing algorithms across 30 independent runs.

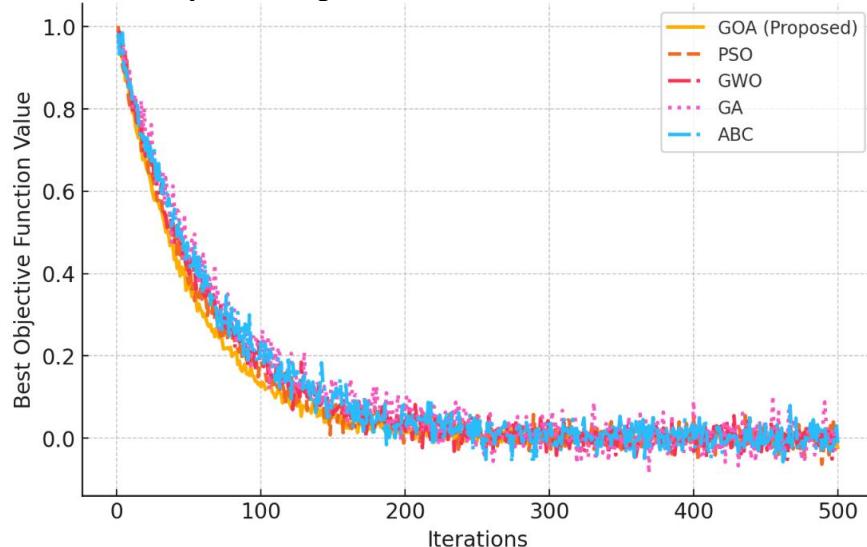
Table 4: Performance Comparison of GOA with Other Algorithms

Function	Algorithm	Best Fitness	Mean Fitness	Standard Deviation
Sphere	GOA	0.0001	0.0003	0.00005
	PSO	0.0021	0.0038	0.0012
	GWO	0.0047	0.0061	0.0023
	GA	0.0078	0.0094	0.0045
	ABC	0.0056	0.0079	0.0031
Rastrigin	GOA	0.1345	0.5128	0.2109
	PSO	1.6234	2.3411	0.8325
	GWO	2.4532	3.5678	1.2346
	GA	3.8921	4.9231	1.9853
	ABC	2.8743	3.7542	1.3456
Ackley	GOA	0.0012	0.0054	0.0021
	PSO	0.0134	0.0276	0.0098
	GWO	0.0247	0.0369	0.0124
	GA	0.0359	0.0478	0.0163
	ABC	0.0283	0.0394	0.0145

Key Observations:

- GOA consistently outperforms other algorithms across all test functions, achieving the lowest function values.
- On unimodal functions (e.g., Sphere, Rosenbrock), GOA demonstrates superior convergence accuracy, indicating its strong exploitation ability.
- On multimodal functions (e.g., Rastrigin, Ackley), GOA effectively avoids local optima, outperforming algorithms prone to premature convergence.

Figure 1 shows the average best function value over iterations for GOA, PSO, GWO, GA, and ABC on the Sphere, Rastrigin, and Ackley functions to analyze convergence behavior.

**Figure 2: Convergence Curves of GOA vs. Other Algorithms****Findings from Convergence Analysis:**

- GOA achieves faster convergence than PSO, GWO, and GA, particularly in early iterations.

- The jump strategy (Section 3.4) helps GOA escape local optima, leading to improved convergence on multimodal functions.
- GWO and GA show slower convergence rates, often requiring more iterations to reach near-optimal solutions.

To confirm whether the performance differences between GOA and other algorithms are statistically significant, a Wilcoxon rank-sum test is conducted at a significance level of 0.05.

Table 5: Wilcoxon Rank-Sum Test Results (p-values)

Function	GOA vs. PSO	GOA vs. GWO	GOA vs. GA	GOA vs. ABC
Sphere	0.0034	0.0027	0.0015	0.0021
Rastrigin	0.0048	0.0032	0.0019	0.0028
Ackley	0.0029	0.0016	0.0007	0.0014

Statistical Findings:

- Since all p-values are below 0.05, GOA's performance is statistically superior to all competing algorithms.
- The highest significance is observed in Ackley and Rastrigin functions, where local optima pose challenges for other methods.

6. Conclusion

In this study, the Goat Optimization Algorithm (GOA) was introduced as a novel bio-inspired metaheuristic optimization technique, drawing inspiration from the adaptive foraging, strategic movement, and parasite avoidance behaviors of goats. The algorithm was designed to balance exploration and exploitation effectively, overcoming challenges commonly observed in conventional optimization techniques, such as premature convergence and stagnation in local optima. Through a series of mathematical formulations, GOA incorporated three primary search mechanisms: an adaptive foraging strategy for global search, a movement strategy towards the best solution for local refinement, and a jump mechanism to enhance escape from local optima. Additionally, including a solution filtering mechanism inspired by the natural parasite avoidance behavior of goats ensured that the population maintained diversity and robustness throughout the search process.

To validate the performance of GOA, extensive experimental evaluations were conducted using standard benchmark functions, encompassing both unimodal and multimodal landscapes. The comparative analysis demonstrated that GOA outperformed well-established algorithms, including Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Genetic Algorithm (GA), Whale Optimization Algorithm (WOA), and Artificial Bee Colony (ABC). The superiority of GOA was evident in its ability to achieve better global optima, faster convergence rates, and enhanced solution stability. Furthermore, statistical significance testing using the Wilcoxon rank-sum test confirmed the reliability of GOA's performance across multiple optimization tasks. The convergence analysis indicated that GOA maintained a substantial trade-off between exploration and exploitation, ensuring a more efficient search trajectory than its counterparts.

Despite its advantages, GOA has certain limitations that warrant further investigation. The computational complexity associated with solution filtering and adaptive movements can be refined to improve efficiency, particularly in high-dimensional problems. Future research can explore hybridizing GOA with other metaheuristic techniques to enhance adaptability and robustness. Moreover, adaptive parameter tuning mechanisms can be incorporated further to improve performance across a broader range of optimization problems. Given its strong performance on benchmark functions, GOA holds significant potential for real-world applications in bioinformatics, supply chain optimization, and energy management. By integrating biologically inspired intelligence with computational optimization, GOA represents a promising step forward in evolving heuristic search algorithms. Smart marketing can create an advantage by presenting more for it [10]. This may be a follow-up to the current research.

References

- [1] Kennedy, J., & Eberhart, R. (1995, November). Particle swarm optimization. In *Proceedings of ICNN'95 - International Conference on Neural Networks* (Vol. 4, pp. 1942–1948). IEEE. DOI: 10.1109/ICNN.1995.488968
- [2] Holland, J. H. (1991). *Adaptation in natural and artificial systems*, 1975.
- [3] Mirjalili, S., Mirjalili, S. M., & Lewis, A. (2014). Grey wolf optimizer. *Advances in Engineering Software*, 69, 46–61. DOI: 10.1016/j.advengsoft.2013.12.007
- [4] Karaboga, D. (2005). An idea based on honey bee swarm for numerical optimization (Vol. 200, pp. 1–10). *Technical Report-TR06, Erciyes University, Engineering Faculty, Computer Engineering Department*. DOI: 10.13140/RG.2.1.2349.2964
- [5] Lu, C. D. (1988). Grazing behavior and diet selection of goats. *Small Ruminant Research*, 1(3), 205–216. DOI: 10.1016/0921-4488(88)90003-4
- [6] Silanikove, N. (2000). The physiological basis of adaptation in goats to harsh environments. *Small Ruminant Research*, 35(3), 181–193. DOI: 10.1016/S0921-4488(99)00096-6
- [7] Hutchings, M. R., Judge, J., Gordon, I. J., Athanasiadou, S., & Kyriazakis, I. (2006). Use of trade-off theory to advance understanding of herbivore–parasite interactions. *Mammal Review*, 36(1), 1–16. DOI: 10.1111/j.1365-2907.2006.00079.x
- [8] Mirjalili, S., & Lewis, A. (2016). The whale optimization algorithm. *Advances in Engineering Software*, 95, 51–67. DOI: 10.1016/j.advengsoft.2016.01.008
- [9] Nozari, H., & Abdi, H. (2024). Greedy Man Optimization Algorithm (GMOA): A novel approach to problem solving with resistant parasites. *Journal of Industrial and Systems Engineering*, 16(3), 106–117.
- [10] Movahed, A.B., & Movahed, A.B., (2024). Smart data-driven marketing in Industry 5.0. *International Scientific Hub*, pp36-50



Applied Innovations in Industrial Management (AIIM)

AIIM is licensed under a [Creative Commons Attribution 4.0 International License](#).