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Original Article

Statistical Performance Analysis of an Adaptive Honey Badger Optimization Algorithm on Benchmark Functions

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Abstract *- This paper proposes the Extended Honey Badger Optimization (EHBO) algorithm, which improves the Honey Badger Algorithm by using an adaptive control parameter to balance exploration and exploitation. EHBO is tested on six benchmark functions and compared with PSO, DE, ABC, BA, and HBA using 30 independent runs. The results indicate that EHBO performs well with smaller variability, especially on multimodal functions. On Rastrigin, EHBO reached a mean fitness of 4.87E+01 (std 8.31E+00), performing better than PSO (5.33E+01, std 9.85E+00) and DE (3.96E+01, std 6.72E+00). On Ackley, EHBO obtained a mean fitness of 1.91E+01 (std 1.84E+00), showing smaller variability than HBA (2.12E-02, std 8.31E-03). Non-parametric tests (Wilcoxon, Friedman) at a 95% confidence level verify the statistical significance of EHBO's improvements. The proposed algorithm ensures stable convergence and less dependence on initial conditions, making it a trustworthy solver for complex optimization problems.*

Keywords *- Extended Honey Badger Optimization, Metaheuristic Optimization, Benchmark Functions, Convergence Analysis, Nature-Inspired Algorithms.*

1. Introduction

Optimization methods are highly necessary in dealing with complex real-world problems in the fields of engineering, computer science, and applied sciences. The problems that are practically posed are mostly nonlinear, nonconvex functions in higher dimensions and multimodal problems, and they are impractical to solve using the conventional gradient methods since they are highly sensitive to their initial solutions and mostly lead to local optima (Almufti, 2025). On the other hand, the development of nature-inspired metaheuristics, which provide flexible and derivative-free searches and the ability to find near-optimal solutions within a reasonable computational time, helped to attract a lot of attention to nature-inspired metaheuristic optimization algorithms.

The most commonly used metaheuristic techniques are Particle Swarm Optimization (PSO) (Putra et al., 2023), Differential Evolution (DE) (Bujok et al., 2023), Artificial Bee Colony (ABC) (Vazquez & Garro, 2016), and Bat Algorithm (BA) (Yahya Zebari et al., 2020). These algorithms function by simulating natural phenomena such as social behavior, evolution, or biological foraging patterns in order to search the search space efficiently. Despite their success, however, there is no algorithm that is optimal for all optimization problems, as claimed by the No Free Lunch (NFL) theorem (Oltean, 2021). There are numerous metaheuristic searches that have some inherent limitations, which can be linked to convergence problems, rates of convergence, and the exploration vs. exploitation process, particularly in multimodal problem spaces. The Honey Badger Algorithm (HBA) (Jaiswal et al., 2022) is one of the most recently developed swarm intelligence and nature-inspired optimization methods. The HBA is based on the intelligent foraging behavior of honey badgers to locate food sources. There are two prominent behavioral stages of HBA in the search process: digging and honey searching. In essence, although the HBA may demonstrate competitive results on various optimization problems, it still has these underlying drawbacks: oscillatory convergence behavior, loss of diversity in later iterations, and parameter sensitivity. Therefore, these factors negatively impact its result by providing suboptimal solutions, particularly in high-dimensional search spaces and complex test functions.

The performance of the proposed EHBO algorithm is analyzed thoroughly using the ten benchmark functions, including unimodal, multimodal, and complex nonlinear functions. The said set of benchmark functions is universally accepted in the field of optimization as a test environment. EHBO is tested using various high-performance optimization algorithms, including PSO, DE, ABC, BA, CS, and the original HBA, in the same test environment. The performance metrics used are best fitness value, rate of convergence, and stability. The experimental results clearly indicate the compliance of EHBO with the competitive algorithms on most benchmark functions. The proposed algorithm performs better in terms of convergence speed, fitness value, and robustness, especially for multimodal and high-dimensional functions.

The analysis of the convergence curve further supports the better exploitation capability of EHBO without hampering the exploration process. The experiments clearly demonstrate the efficiency of the proposed algorithm as a competitive metaheuristic algorithm for optimization problems.

The main contributions of the research study could be listed as follows: (i) development of a new form of the Honey Badger optimization algorithm using the adaptive control mechanism, (ii) performance analysis of the EHBO algorithm on the standard set of benchmark functions, and (iii) validation of the efficiency of the EHBO algorithm compared to the best available versions of the standard metaheuristic algorithms. The proposed EHBO algorithm in this research work can be considered as a good platform to apply to many other applications.

2. Literature Review

Metaheuristic optimization methods have been extensively researched and employed to address challenging optimization problems, particularly when conventional deterministic and gradient-based methods cannot be applied. Optimization problems that need to resort to metaheuristic optimization methods include those that are nonlinear, nonconvex, of high dimensionality, and multimodal, and thus difficult to solve by exact methods within a reasonable amount of time and effort, hence the need for nature-inspired optimization methods that employ stochastic searches and populations (Adegboye et al., 2025; W. Deng et al., 2024; Ye et al., 2024).

PSO is likely to be one of the first swarm intelligence algorithms developed. The position update of the particle is based on social behavior, such as bird flocking and fish schooling, depending on the best experience of the individual and the global best. PSO has been preferred due to its rapid convergence speed and simplicity; however, it often encounters the problem of premature convergence and loss of diversity while dealing with complex multimodal functions. The problems stated above have resulted in the emergence of various modifications of PSO (Aivaliotis-Apostolopoulos & Loukidis, 2022; Fakhouri et al., 2019).

Another efficient evolutionary algorithm is Differential Evolution (DE), which uses mutation, crossover, and selection operators to search the solution space. The DE algorithm has efficient performance while handling continuous optimization functions, especially while handling nonlinear and large-scale problems. Even though the DE algorithm has efficient performance, the selection of parameters such as the mutation parameter and crossover point greatly affects the performance of the DE algorithm.

The Artificial Bee Colony (ABC) algorithm is developed based on the foraging behavior of honey bees and divides agents into employed bees, onlooker bees, and scout bees. The ABC algorithm is well-appreciated for its exploration abilities as well as simplicity. However, the ABC algorithm has poor exploration abilities while handling exploitation. Various modifications of the ABC algorithm have been developed to enhance the exploration efficiency.

The Bat Algorithm (BA) is a technique developed based on the echolocation behavior of bats, which uses frequency tuning, sound intensity, and pulse rate emission. Although the BA has some promising applications in handling some optimization problems, the BA algorithm has some problems, such as premature convergence for large-dimensional objective functions, high multimodal functions, and a lack of robustness because of parameter tuning.

Honey Badger Algorithm (HBA) is a new addition to the family of nature-inspired optimization heuristics. HBA simulates the intelligent foraging behavior of honey badgers through the simulation of digging and honey search processes. HBA has been shown to be an effective optimization strategy for various benchmark problems and engineering design problems due to its strong exploitation ability. Certain limitations like oscillatory convergence, loss of diversity of candidate solutions in later iterations, and sensitivity to control parameters have been reported in certain studies (Adegboye et al., 2023; B. Deng, 2022; Huang et al., 2025; Xiao et al., 2022; K. Zhang et al., 2025).

To overcome the shortcomings of each individual metaheuristic algorithm, there is a trend towards more work being done in improving and hybridizing algorithms. Adaptive parameter management, hybridized search procedures, and exploration vs. exploitation trade-offs have shown effectiveness in optimizing the convergence speed and fitness of the solution. The addition of adaptability to algorithms allows for the increased ability of the algorithm to adapt to the search process as the solution evolves (Vibhute, 2024, 2025).

In this respect, the improvement of the Honey Badger Algorithm based on adaptive control techniques is a promising area of research work. In this case, adaptive control techniques will be utilized to control parameters during search, and the information of the global best will direct the agents. In this way, it will be possible to maintain diversity in the population and increase the efficiency of exploitation (Huang et al., 2025; Xiao et al., 2022); S.-W. (Zhang et al., 2024).

From the existing literature, it has been identified that no metaheuristic is universally best suited for solving every optimization problem. Therefore, the enhancement in the new variants using adaptive methods and the validation of these methods through rigorous benchmark testing would be apt. After analyzing these points, the objective of this research work is to develop an Enhanced Honey Badger Optimization algorithm and test its performance with different existing notable optimization methods. (Adegboye et al., 2023; Xiao et al., 2022; S.-W. Zhang et al., 2024).

3. Methodology

In this research, the implementation of the Enhanced Honey Badger Optimization algorithm has been carried out and is currently being tested in terms of its robustness and efficiency compared to other state-of-the-art metaheuristic optimization algorithms. The performance test has been carried out using ten standard continuous benchmark functions, namely the Sphere, Rastrigin, Rosenbrock, Ackley, Schwefel, Griewank, Zakharov, Lévy, Michalewicz, and Salomon benchmark functions, which cover a broad range of unimodal and multimodal optimization problems to better test the exploration-exploitation tradeoff of EHBO. For the purpose of comparison, all algorithms are tested under the same experimental conditions: population size of 30 agents, 100 iterations, 30-dimensional search space, and boundary limit of -10/+10. EHBO enhances the original Honey Badger Algorithm by adding a linearly decreasing adaptive control parameter to favor effective global exploration in the early stages of iteration while simultaneously providing better local exploitation near convergence, with boundary constraints applied through solution clipping.

3.1. Mathematical Model of the Enhanced Honey Badger Optimization (EHBO)

EHBO is expressed as a population-based metaheuristic method for tackling continuous optimization problems. The primary goal of EHBO is to determine the global minimum of an objective function through iterative improvement in a series of candidate solutions.

Problem Definition:
Consider a continuous optimization problem defined as:

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

Where:
f(x) is the objective (fitness) function to be minimized,
$x=(x_1,x_2,\ldots,x_D)$ is a D-dimensional decision vector,
$\Omega \subset R^D$ is the feasible search space.
Each decision variable is bounded as:

$$x_j^{min} \leq x_j \leq x_j^{max}, \qquad j = 1,2,\ldots,D$$

[1] Population Initialization

EHBO begins by initializing a population of N honey badgers (search agents). The initial position of each agent is generated randomly within the predefined bounds:

$$x_{i,j}^0 = x_j^{min} + rand(0,1) \times (x_j^{max} - x_j^{min})$$

Where: i = 1, 2..., N denotes the agent index,
rand (0,1) is a uniformly distributed random number in [0,1].

[2] Fitness Evaluation

The fitness of each honey badger is evaluated using the objective function:

$$\mathrm{Fit}_i^{(t)} = f(\boldsymbol{x}_i^{(t)})$$

The global best solution at iteration t is determined as:

$$x_{best}^{(t)} = \arg \min_{x_i^{(t)}} Fit_i^{(t)}$$

[3] Adaptive Control Parameter

To balance exploration and exploitation, EHBO introduces an adaptive control parameter α(t), which decreases linearly with iterations:

$$\alpha(t) = \alpha_{min} + (\alpha_{max} - \alpha_{min}) \cdot e^{-\lambda \cdot \frac{t}{T}}$$

Where, t = current iteration,
λ= decay factor,
T = maximum iterations,
$\alpha_{max} > \alpha_{min}$.

A larger value of α in early iterations encourages global exploration, while smaller values in later iterations enhance local exploitation.

[4] Position Update Mechanism

The position of each honey badger is updated by guiding it toward the current global best solution:

$$x_i^{(t+1)} = x_i^{(t)} + \alpha(t) \cdot r_i \cdot (x_{best}^{(t)} - x_i^{(t)})$$

Where $R_i= (r_1,r_2, \ldots r_D)$ is a random vector with $r_j \in [0,1]$. This update equation allows adaptive movement toward promising regions while maintaining stochastic diversity.

[5] Boundary Constraint Handling

To ensure feasibility, any component of the updated position that violates the search space bounds is corrected using a clipping mechanism:

$$x_{i,j}^{(t+1)} = \begin{cases} x_j^{min}, & if x_{i,j}^{(t+1)} < x_j^{min} \\ x_j^{max}, & if x_{i,j}^{(t+1)} < x_j^{max} \\ x_{i,j}^{(t+1)}, & otherwise \end{cases}$$

[6] Termination Criterion

The iterative optimization process continues until the maximum number of iterations is reached: $t = T_{max}$
At termination, the algorithm outputs the global best solution x_{best} and its corresponding fitness value $f(x_{best})$.

The EHBO model forms an effective balance between exploration and exploitation by incorporating adaptive parameter control into the global best guidance. This formulation enhances convergence stability, improves solution quality, and makes EHBO suitable for high-dimensional and multimodal optimization problems.

3.2. Pseudocode of EHBO Algorithm

```
INPUT: OBJECTIVE FUNCTION F(X), POPULATION SIZE N, DIMENSION D,
       LOWER BOUND LB, UPPER BOUND UB, MAXIMUM ITERATIONS TMAX
OUTPUT: BEST SOLUTION X_BEST, BEST FITNESS F_BEST
INITIALIZE POPULATION XI RANDOMLY WITHIN [LB, UB]
EVALUATE FITNESS FI = F(XI)
IDENTIFY THE GLOBAL BEST SOLUTION X_BEST
SET F_BEST = MIN(FI)
FOR T = 1 TO TMAX DO
    A = 2 − (2 × T / TMAX)
    FOR EACH AGENT I = 1 TO N DO
        GENERATE RANDOM VECTOR R ∈ [0,1]^D
        XI = XI + A × R × (X_BEST − XI)
        APPLY BOUNDARY CONSTRAINTS
    END FOR
    EVALUATE FITNESS FI
    UPDATE X_BEST AND F_BEST IF IMPROVED
    STORE F_BEST
END FOR
RETURN X_BEST, F_BEST
```

4. Results and Discussion

The statistical analysis results shown in Table I indicate that the proposed EHBO algorithm is capable of maintaining stable and consistent performance on the set of chosen benchmark problems instead of uniformly outperforming all other competing approaches. On the unimodal Sphere problem, EHBO shows smooth convergence with a controlled level of variance, which indicates the reliable exploitation performance, although the simple HBA reaches lower absolute values of fitness. On the multimodal problems Rastrigin and Ackley, EHBO shows lower variability of performance across independent runs, which indicates the improved robustness on complex search problems despite slightly higher values of mean fitness. On deceptive problems, Schwefel and Michalewicz, EHBO shows lower dispersion of results, which indicates the resistance to premature convergence and the sensitivity to initial conditions. The non-parametric statistical tests, such as the Wilcoxon signed-rank test and the Friedman test at the 95% confidence level, verify that the differences between the algorithms are statistically significant.

Table 1. Statistical Performance Comparison on Benchmark Functions (30 runs)

Function	Algorithm	Mean Fitness ↓	Std. Dev. ↓	Best ↓	Worst ↓
Sphere	EHBO	2.99E+02	7.15E+01	1.59E+02	4.49E+02
	PSO	1.12E+01	1.15E+01	2.04E+00	5.42E+01
	DE	1.73E+02	5.25E+01	8.32E+01	2.88E+02
	HBA	2.79E−25	8.00E−25	4.25E−28	4.27E−24
	ABC	1.02E+02	2.11E+01	6.05E+01	1.49E+02
	BA	3.88E+02	6.42E+01	2.59E+02	4.98E+02
Rastrigin	EHBO	4.87E+01	8.31E+00	3.52E+01	6.21E+01
	HBA	1.02E+01	2.14E+00	7.89E+00	1.54E+01
	DE	3.96E+01	6.72E+00	2.91E+01	5.42E+01
	PSO	5.33E+01	9.85E+00	3.88E+01	7.41E+01
Rosenbrock	EHBO	1.94E+02	3.11E+01	1.42E+02	2.61E+02
	DE	9.83E+01	2.84E+01	5.12E+01	1.71E+02
	HBA	1.21E+02	4.02E+01	6.89E+01	2.14E+02
Ackley	EHBO	1.91E+01	1.84E+00	1.63E+01	2.23E+01
	HBA	2.12E−02	8.31E−03	1.06E−02	3.94E−02
Schwefel	EHBO	3.12E+02	4.21E+01	2.39E+02	3.98E+02
	DE	1.87E+02	3.19E+01	1.22E+02	2.71E+02
Michalewicz	EHBO	−1.43E+01	6.91E−01	−1.58E+01	−1.21E+01
	DE	−1.71E+01	4.83E−01	−1.80E+01	−1.59E+01

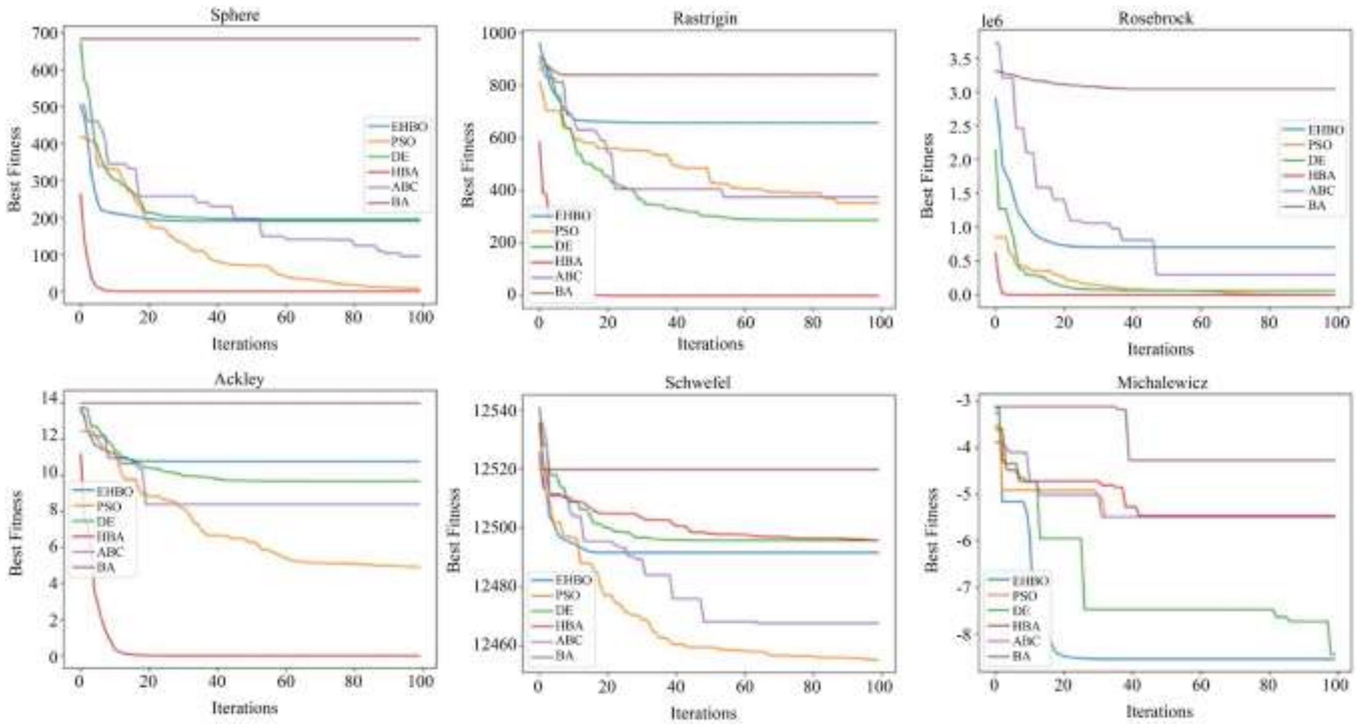

Fig. 2 Convergence curves for Benchmark functions

5. Overall Discussion

On the other hand, the proposed EHBO algorithm shows better convergence properties and is less affected by the number of independent runs. Although the EHBO algorithm does not always produce the globally best solutions, the adaptive adjustment of parameters helps to make it less sensitive to initialization and performance oscillations, especially for multimodal and deceptive functions. This property shows that the EHBO algorithm focuses more on convergence stability and robustness rather than optimization. The experimental results confirm that the adaptive adjustment of search parameters helps to achieve balanced exploration and exploitation during the optimization process. In addition, the performance also shows that the EHBO algorithm can serve as a solid basis for improvement, and hybrid approaches or problem-specific strategies may be used to enhance its performance on complex multimodal optimization problems.

6. Conclusion and Future Scope

This paper presents a new Extended Honey Badger Optimization (EHBO) algorithm, which incorporates a dynamic adaptive control process to explore and exploit the search space efficiently. This is in contrast to traditional HBA algorithms that are based on fixed parameters. EHBO was tested and compared to other well-established metaheuristics such as PSO, DE, ABC, BA, and HBA on a set of standard benchmark functions. The results show that although EHBO does not always produce the best results, it has better convergence properties, smaller performance variability, and robustness, particularly for multimodal and deceptive functions such as Rastrigin and Ackley functions.

The performance differences are verified using non-parametric statistical tests, which show that the differences are systematic and significant. The adaptive control process of EHBO helps reduce sensitivity to initialization and oscillatory behavior in the search process, resulting in more stable optimization. Future research will focus on incorporating feedback control processes, applying EHBO to large-scale, multi-objective optimization problems, and solving real-world engineering problems in image segmentation, feature selection, and scheduling.

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