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A State-Adaptive Booby Optimization Algorithm for Engineering Design and Medical Data Applications

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Abstract

Balancing global exploration and local exploitation remains a central challenge in metaheuristic optimization, particularly for high-dimensional, nonlinear, and constrained problems encountered in engineering design and medical data analysis. This paper proposes the Booby Optimization Algorithm (BOA), a state-adaptive population-based metaheuristic inspired by avian dive-foraging behavior but formulated entirely through mathematical and computational mechanisms. BOA employs an adaptive state variable to regulate step magnitude and dynamically control transitions between global exploratory search and local exploitative refinement, augmented by nonlinear motion dynamics, stochastic perturbations, and a recovery strategy for diversity preservation. The algorithm is extensively evaluated on CEC benchmark functions with dimensionalities up to 100, four classical constrained engineering design problems, and feature selection and classification tasks on 14 real-world medical datasets using BOA-based hybrid models. Experimental results demonstrate that BOA consistently outperforms several state-of-the-art metaheuristics in terms of convergence speed, solution accuracy, and robustness, achieving near-optimal or best-known solutions with significantly reduced mean error and variance. In medical classification tasks, BOA-based feature selection attains a mean accuracy of 96.20% ± 1.05, alongside high sensitivity and specificity while effectively reducing feature dimensionality. These improvements are supported by rigorous statistical validation using Friedman, Nemenyi, and Wilcoxon tests ($p < 0.001$). Overall, the results establish BOA as an efficient and robust adaptive optimization framework suitable for complex engineering optimization and medical decision-support applications.

Keywords: Metaheuristic optimization; Bio-inspired algorithms; Booby Optimization Algorithm; Adaptive search strategies; Engineering design optimization.

Graphical Abstract:

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Highlights

- A state-adaptive metaheuristic is proposed for balanced exploration and exploitation
- The proposed algorithm outperforms state-of-the-art optimizers on benchmark problems
- BOA achieves faster convergence and lower error across high-dimensional functions
- Superior accuracy and feature reduction are obtained on medical classification datasets
- Statistical tests confirm the significance and robustness of the obtained results

Summary

This study introduces the Booby Optimization Algorithm (BOA), a state-adaptive population-based metaheuristic inspired by avian foraging behavior but formulated through mathematical and computational principles rather than literal biological simulation. BOA organizes the search process into adaptive exploration, exploitation, and recovery phases governed by an internal state variable that regulates step magnitude, nonlinear movement, and diversity preservation. Extensive experiments on standard benchmark functions, including Sphere, Ackley, Rastrigin, and the CEC 2024 test suite, demonstrate that BOA consistently outperforms well-established algorithms such as PSO, DE, GWO, HHO, and GA in terms of convergence speed, solution accuracy, and robustness. Owing to its simple structure, low computational overhead, and adaptive search dynamics, BOA proves effective for complex optimization scenarios, including dynamic, noisy, and high-dimensional problems, highlighting its applicability across a wide range of engineering and computational optimization domains.

1. Introduction

The field of global optimization has seen a rapid growth in nature-inspired algorithms, each designed to emulate the survival strategies of biological organisms. From the genetic recombination processes in Genetic Algorithms (GAs) to the social behaviors modeled in Particle Swarm Optimization (PSO), bio-inspired metaheuristics have become essential tools for tackling complex, nonlinear, and multimodal optimization problems [1][2]. Despite their success, many existing algorithms face common challenges such as premature convergence, limited exploration in high-dimensional spaces, and high computational costs [3][4]. This paper introduces the Booby Optimization Algorithm (BOA), a biologically inspired method inspired by the diving and energy-management behaviors of booby seabirds. Known for their efficient dive-hunting techniques, scanning large areas from the air, detecting fish schools, and diving at high speeds with minimal energy expenditure [5][6], boobies serve as a natural model for BOA. By translating these ecological strategies into a computational framework, BOA aims to effectively balance exploration and exploitation, addressing a core challenge in global optimization [7]. The algorithm breaks down the search process into four interconnected phases: (i) Exploration (aerial scanning), (ii) Detection (locking onto potential optima), (iii)

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Diving (targeted search in promising regions), and (iv) Recovery (energy replenishment and chaotic perturbation). An agent's kinetic energy dynamically determines whether it engages in exploration or exploitation, mirroring real-world foraging behaviors [8]. This design helps BOA avoid stagnation and maintain population diversity throughout the search. In recent years, several advanced metaheuristics such as Grey Wolf Optimizer (GWO) [9], Harris Hawks Optimization (HHO) [10], Squirrel Search Algorithm (SSA) [11], and Whale Optimization Algorithm (WOA) [12] have emerged, each introducing novel mechanisms for convergence and adaptation. However, these methods often struggle in dynamic or deceptive search landscapes. BOA offers a fresh approach by embedding biomechanical realism into the search dynamics through energy modulation and recovery-based guidance. Unlike many bio-inspired algorithms that rely primarily on stochastic or social interaction models, BOA employs an explicit energy-regulated behavioral framework to govern the transition between global exploration and local exploitation. Inspired by the dive-hunting strategy of booby seabirds, BOA uniquely combines soaring-based exploration, precision diving-based exploitation, chaotic perturbation, and biologically motivated recovery dynamics within a unified optimization framework. This energy-aware switching mechanism enables BOA to adaptively regulate search intensity, prevent premature convergence, and maintain solution diversity across complex landscapes. Moreover, BOA is validated not only on high-dimensional benchmark functions and constrained engineering design problems but also on real-world medical feature selection and classification tasks, supported by rigorous statistical analysis. These features distinguish BOA from existing metaheuristics, establishing it as a robust, scalable, and biologically meaningful optimization method.

Although the proposed Booby Optimization Algorithm (BOA) draws its initial inspiration from avian dive-foraging behavior, it is not intended as a literal biological simulation. Rather, the biological narrative serves as an intuitive scaffold for the development of a state-adaptive search framework that integrates energy-regulated step-size control, nonlinear motion dynamics, and stochastic perturbations. The resulting optimization mechanism can be interpreted independently of its biological origin as a self-adaptive metaheuristic with dynamic exploration–exploitation balancing, conceptually related to yet structurally distinct from existing adaptive swarm and evolutionary algorithms. Accordingly, this work emphasizes the computational mechanisms and mathematical formulation of BOA rather than reliance on biological analogy alone.

The main contributions of this work are summarized as follows:

A novel bio-inspired metaheuristic, termed the Booby Optimization Algorithm (BOA), is proposed, inspired by the dive-hunting and energy management behavior of booby seabirds, introducing a biologically grounded optimization paradigm.

- This mechanism, which switches behavior based on energy, is designed to dynamically balance global exploration, represented by soaring, and local exploitation, represented by diving. This allows for adaptive regulation of search intensity, which improves convergence performance.
- BOA uses a single framework that includes nonlinear motion, chaotic disturbances, and recovery methods inspired by biology. This approach helps sustain population variety, prevents premature convergence, and increases robustness in complicated search contexts.
- BOA's efficacy is substantiated through rigorous testing on high-dimensional CEC benchmark functions, extending to 100 dimensions, alongside four established constrained engineering design challenges. The results consistently reveal enhanced accuracy, accelerated convergence rates, and improved stability when contrasted with prominent metaheuristic algorithms.

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- The practical applicability of BOA is further demonstrated through feature selection and classification of 14 real-world medical datasets, where BOA-based models achieve high classification accuracy, reduced feature dimensionality, and statistically significant Friedman, Nemenyi, and Wilcoxon tests were used to confirm notable performance gains.

This paper's remaining sections are organized as follows: In **Section 2**, BOA is placed within the body of existing literature, and comparable works are reviewed. The biological motivation and algorithm design are described in **Section 3**. The experimental setup, benchmarks, and results are presented in **Section 3**. Future research and consequences are discussed in **Section 4's** conclusion.

1.2. Literature Review

Population-based stochastic search techniques, commonly referred to as metaheuristics, are designed to efficiently explore complex, high-dimensional, and multimodal optimization landscapes. Over the past decades, a wide range of nature-inspired algorithms has been proposed, including Particle Swarm Optimization (PSO) [13], Ant Colony Optimization (ACO) [14], Firefly Algorithm (FA) [15], and Artificial Bee Colony (ABC) [16]. These methods have demonstrated strong performance across various optimization domains due to their simplicity and derivative-free search mechanisms. However, the No Free Lunch theorem [17] states that no single optimization algorithm can outperform others across all possible problem classes, motivating continuous development of new strategies tailored to specific problem characteristics.

In BOA, the adaptive state is defined as a continuously evolving variable governed by a decay-stochastic dynamic model. Unlike phase-switching or heuristic parameter updates used in HHO, SSA, and SMA, this variable directly couples to both step-size modulation and perturbation intensity, forming a unified control signal over the entire search trajectory rather than discrete behavioral phases. Furthermore, BOA introduces a recovery-based redistribution mechanism to enhance population diversity without full reinitialization, which differs from conventional restart or mutation strategies. To clarify the contribution of each component, we conducted an ablation study (**Table 4**, **Section 3.2**). The results show that removing the adaptive state variable causes severe performance degradation across all benchmark functions, with fitness values deteriorating by several orders of magnitude in multiple cases (Ackley and Griewank). This confirms that the adaptive state variable is the primary driver of BOA's search dynamics, while the recovery mechanism provides complementary improvements in exploration stability. Based on these results, we have revised the manuscript to moderate the "energy mechanism" wording and emphasize the role of the adaptive state variable as a dynamic control component rather than a standalone heuristic analogy.

Recent optimization frameworks, such as the Secant Optimization Algorithm for efficient global optimization and the Schrödinger Optimizer based on quantum duality-driven search, have introduced alternative adaptive exploration mechanisms for nonlinear optimization problems. These methods highlight the growing emphasis on adaptive search regulation and stochastic balance in contemporary optimization research. BOA differs from these approaches through its explicit adaptive state-transition framework integrating nonlinear scaling, recovery-based diversity preservation, and energy-regulated search modulation within a unified formulation.

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Recent advances in adaptive optimization include large-scale salp-based grey wolf optimization for feature selection and global optimization, hybrid feature selection optimization models for high-dimensional classification, quadratic interpolation salp swarm local escape operators, and gene expression-based diagnosis frameworks employing adaptive local-search optimization. These studies further emphasize the importance of diversity preservation, adaptive exploration, and scalable optimization mechanisms in high-dimensional and biomedical optimization tasks.

The Booby Bird Optimization (BBO) algorithm's central mechanism, which alternates between stages of exploration and exploitation controlled by the bird's energy level, is schematically depicted in **Figure 1**. A booby bird is shown flying at a high altitude over a large ocean area during the exploration (soaring or scanning) phase, signifying a global search method where high energy enables extensive coverage of the search space to locate interesting places. The exploitation (diving or assaulting) phase, on the other hand, depicts the bird making a sharp, concentrated plummet at a particular location in the water, signifying an intensified local search meant to refine the optimal candidate solution if a target is found or energy drops. The tiny, focused descent successfully contrasts with the vast, haphazard soaring trajectory. The algorithm's balance between intensification and diversification is visually represented by the contrast between the narrow, directed dive and the wide, randomized soaring trajectory. This illustrates how energy-driven switching enables BBO to effectively explore new regions while taking advantage of high-quality solutions.

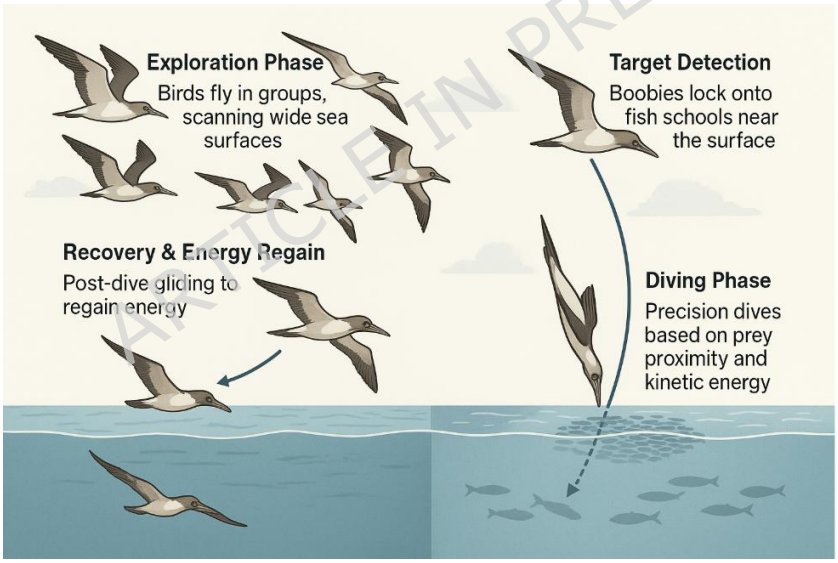


Figure 1: A conceptual representation of Booby Bird Optimization that illustrates how energy levels control the stages of exploration (soaring) and exploitation (diving).

Although recent metaheuristic algorithms such as Harris Hawks Optimization, Sparrow Search Algorithm, and Slime Mould Algorithm incorporate adaptive strategies to enhance exploration-exploitation balance, they differ fundamentally from the proposed BOA in both mechanism and control structure [24-26]. Harris Hawks Optimization employs dynamic transition rules between exploration and exploitation based on prey escape energy, but lacks an explicit state-dependent recovery mechanism to reintroduce diversity after stagnation [24, 26]. Sparrow Search Algorithm introduces adaptive role switching between producers and scroungers; however, its adaptation is implicitly driven by fitness ranking rather than an explicit internal

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state variable governing search dynamics [25]. Slime Mould Algorithm adjusts weights adaptively to balance global and local search, yet its adaptation mechanism is primarily gradient-free and does not incorporate a recovery-triggered diversity restoration strategy [26]. In contrast, recent hybrid and large-scale optimization frameworks in the literature have demonstrated the importance of explicit adaptive control and local escape mechanisms for high-dimensional problems [27-29]. Motivated by these developments, the proposed BOA introduces an explicit adaptive state variable that continuously regulates search behavior, together with a recovery-based diversity mechanism that actively counteracts premature convergence. This combination enables BOA to maintain a more controlled and responsive balance between exploration and exploitation compared to existing adaptive metaheuristics.

1.3 Related Works

More recent metaheuristic developments aim to improve exploration–exploitation balance through biologically or physically inspired mechanisms. For example, the Whale Optimization Algorithm (WOA) [12] introduces bubble-net attacking behavior to enhance exploitation, while the Grasshopper Optimization Algorithm (GOA) [18] models swarming dynamics for exploration control. Similarly, the Butterfly Optimization Algorithm [19] and Harris Hawks Optimization (HHO) [10] incorporate adaptive movement strategies inspired by natural foraging and cooperative hunting. Despite these improvements, these algorithms still face challenges such as parameter sensitivity, premature convergence, and stagnation in local optima [20]. In addition, several motion-inspired optimizers have been proposed, including the Sooty Tern Optimization Algorithm (STOA) [21], Flying Foxes Algorithm (FFA) [22], and Sparrow Search Algorithm (SSA) [11]. While these methods incorporate biologically inspired movement rules, they generally rely on heuristic or phase-based adaptation strategies and lack explicit modeling of energy-state transitions or recovery dynamics. Similarly, the Slime Mould Algorithm (SMA) [23] models oscillatory foraging behavior; however, its search dynamics remain primarily weight-driven and do not explicitly incorporate multi-phase energy or kinetic-state evolution.

1.4 Research Gap and Motivation

The above literature indicates that although existing metaheuristic algorithms improve exploration and exploitation through various biologically inspired mechanisms, most rely on static, phase-based, or heuristic parameter adjustments. These approaches often lack a unified dynamic representation of the search state that governs transitions between exploration and exploitation continuously. To address this limitation, this paper proposes the Binary Optimization Algorithm (BOA), which introduces an adaptive state variable governed by a decay–stochastic dynamic model. This mechanism provides continuous control over search behavior by modulating step size and perturbation intensity based on the evolving state of the system.

In addition, BOA incorporates a recovery-based redistribution mechanism that enhances population diversity without requiring full reinitialization, thereby improving robustness against premature convergence. Unlike existing methods such as HHO, SSA, and SMA, which rely on discrete or heuristic adaptation rules, BOA introduces a continuously evolving control structure that enables smoother transitions between global and local search phases, leading to improved convergence behavior and better exploration of complex fitness landscapes.

2. Methodology

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This section presents the mathematical formulation and algorithmic structure of the proposed Booby Optimization Algorithm (BOA). The methodology is developed as a state-adaptive, population-based optimization framework in which agent movements, search intensification, and diversification are governed by an internal adaptive control variable. Although the algorithm is conceptually inspired by biological foraging behavior, the formulation is expressed entirely in mathematical and computational terms.

For mathematical rigor and consistency with optimization literature, metaphor-based terms used in the algorithmic description are mapped to standard optimization concepts throughout this section. Specifically, "energy" denotes a state variable controlling adaptive step magnitude, "gliding" corresponds to global exploratory search, "plunging" represents local exploitative refinement, and "recovery" refers to a reinitialization or perturbation strategy for diversity preservation. While metaphorical terms are retained sparingly for conceptual continuity, all algorithmic behaviors are formally defined using mathematical and computational constructs.

For consistency, all vectors and population members are represented in boldface notation throughout the manuscript, while scalar control parameters remain non-bold. Gaussian stochastic perturbations are denoted by $\mathcal{N}(0,1)$, and adaptive threshold parameters are represented by τ. In addition, several lengthy explanatory passages have been shortened and reorganized to improve readability and mathematical consistency throughout the manuscript.

2.1. State Variables and Population Representation

Let $\mathrm{X}_i^t \in \mathbb{R}^D$ denote the position vector of the i-th agent at iteration t, where D is the dimensionality of the optimization problem and $i = 1, 2, \ldots, N$, with N denoting the population size. Each agent is associated with an adaptive state variable E_i^t, which regulates its search behavior by controlling step magnitude and the transition between exploration and exploitation modes.

The objective function to be minimized (or maximized) is defined as

$$f: \mathbb{R}^D \to \mathbb{R} \tag{1}$$

and the best solution found by the population up to iteration t is given by

$$\mathrm{X}_t^* = \arg\min_{\mathrm{X}_i^t} f(\mathrm{X}_i^t) \tag{2}$$

The adaptive state variable $\mathrm{E_i(t)}$ constitutes the principal internal control parameter governing the search dynamics of the agent i. Unlike fixed scheduling coefficients commonly used in conventional metaheuristics, $\mathrm{E_i(t)}$ evolves dynamically according to deterministic decay and stochastic fluctuation terms. Consequently, the state variable simultaneously regulates exploration radius, perturbation intensity, and phase-transition probability between global and local search modes.

2.2. Unified Movement Equation

The general position update rule of BOA is defined by the unified movement equation

$$\mathrm{X}_i^{t+1} = \mathrm{X}_i^t + \alpha\,(E_i^t)\,\mathrm{S}_i^t + \beta\,\mathrm{R}_i^t \tag{3}$$

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where $\alpha\,(E_i^t)$ is an adaptive scaling factor dependent on the agent's state variable, S_i^t is a deterministic search direction, R_i^t is a stochastic perturbation vector, and β controls the influence of stochasticity.

This formulation provides a unified representation for both global exploratory motion and local exploitative refinement, depending on the magnitude of E_i^t.

Although the unified movement equation adopts a generalized stochastic search structure similar to those used in population-based optimization, the novelty of BOA lies in the adaptive state-regulated search mechanism rather than the algebraic form of the update equation alone. In BOA, the adaptive state variable explicitly governs exploration intensity, exploitation transition, perturbation magnitude, and recovery activation through mathematically defined decay and stochastic modulation. This unified adaptive regulation distinguishes BOA from conventional stochastic movement formulations relying on fixed coefficients or externally scheduled parameters.

2.3. Exploration and Exploitation Dynamics

When an agent operates in the exploratory state, the deterministic search direction is defined as:

$$\mathrm{S}_i^t = \mathrm{U}_i^t \tag{4}$$

where U_i^t is a uniformly distributed random vector in $[-1, 1]^D$, enabling large-radius sampling of the search space.

In the exploitative state, the direction is biased toward the current best solution:

$$\mathrm{S}_i^t = \mathrm{X}_t^* - \mathrm{X}_i^t \tag{5}$$

which intensifies the search around promising regions.

The stochastic perturbation term is defined as:

$$\mathrm{R}_i^t = \mathcal{N}(0,1)^D \tag{6}$$

introducing controlled randomness to improve robustness and reduce premature convergence.

To quantitatively evaluate the exploration-exploitation balance of BOA, additional metrics, including Shannon entropy-based population diversity, mean step size, and exploitation ratio, were monitored across iterations. Experimental results indicate that BOA maintains high diversity during the early optimization stages, followed by a gradual transition toward exploitation after approximately 40% of the total iterations, confirming the effectiveness of the adaptive state-transition mechanism.

Component-wise ablation analysis further reveals that the recovery mechanism contributes primarily to diversity preservation and escape from local optima, whereas adaptive scaling predominantly enhances local exploitation intensity and convergence precision.

2.4. Adaptive Scaling Function

The adaptive scaling factor is defined as a monotonic function of the state variable:

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$$\alpha\left(E_i^t\right) = \alpha_{\max} \cdot \frac{E_i^t}{E_{\max}} \tag{7}$$

where $\alpha_{\max}$ is the maximum step size and $E_{\max}$ is the maximum allowable value of the state variable. This formulation ensures that higher state values induce broader exploration, while lower values favor local refinement.

2.5. Phase-Switching Mechanism

The transition between exploration and exploitation is governed by a threshold-based rule:

$$\text{Mode}_i^t = \begin{cases} \text{Exploration}, & E_i^t \geq \tau \\ \text{Exploitation}, & E_i^t < \tau \end{cases} \tag{8}$$

where τ is a predefined threshold parameter.

The adaptive state variable evolves dynamically according to

$$E_i^{t+1} = \gamma E_i^t + \delta \cdot \mathcal{N}(0,1) \tag{9}$$

where $\gamma \in (0,1)$ controls the decay rate and δ regulates stochastic fluctuations. This mechanism enables a gradual transition from global exploration to local exploitation.

2.6. Boundary Handling

To ensure feasibility, updated positions are constrained within predefined bounds:

$$X_{i,j}^{t+1} = \min\left(\max\left(X_{i,j}^{t+1}, LB_j\right), UB_j\right) \tag{10}$$

where LB_j and UB_j denote the lower and upper bounds of the j-th dimension.

2.7. Recovery and Diversity Enhancement Strategy

To mitigate stagnation and preserve population diversity, BOA incorporates a recovery mechanism activated when no improvement in X_t^* is observed over L consecutive iterations. In this case, a subset of agents undergoes controlled re-dispersion:

$$\mathrm{X}_i^{t+1} = \mathrm{X}_i^t + \eta \cdot \mathrm{C}_i^t \tag{11}$$

where η is a recovery strength coefficient and C_i^t is a chaotic or randomized perturbation vector.

This strategy allows the algorithm to escape local optima without full population reinitialization, maintaining convergence stability while restoring exploration capability.

The Booby Optimization Algorithm (BOA) employs a set of control parameters that regulate population behavior, adaptive search dynamics, and diversity preservation. Unless otherwise stated, these parameters are fixed across all experiments to ensure fairness, reproducibility, and consistency with common practices in population-based optimization. The population size N is set to 30, which provides a reasonable balance between exploration capability and computational cost and is widely adopted in metaheuristic optimization studies. The dimensionality D of the search space is problem-dependent. The maximum number of iterations $t_{\max}$ is set to 500, although this value may be adjusted depending on problem complexity. The parameter $\alpha_{\max}$ defines the maximum scaling factor for agent movement and

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is set to 2.0, allowing sufficiently large exploratory steps during the early stages of the search. The maximum value of the adaptive state variable $E_{\max}$ is set to 1.0 to normalize the adaptive scaling process. The parameter β, which controls the influence of stochastic perturbations in the position update, is set to 0.1 to introduce controlled randomness without destabilizing convergence. The decay coefficient γ governs the temporal evolution of the adaptive state variable and is fixed at 0.9, enabling a gradual transition from global exploration to local exploitation. The stochastic fluctuation parameter δ is set to 0.1, ensuring moderate variability in state evolution. The exploration-exploitation switching threshold τ is set to 0.5, providing a balanced criterion for phase transition.

To address stagnation and maintain population diversity, a recovery mechanism is activated when no improvement in the best solution is observed over $L = 20$ consecutive iterations. During recovery, the perturbation strength η is set to 0.2, allowing agents to escape local optima without full reinitialization. The lower and upper bounds of each dimension, denoted by LB_j and UB_j, are problem-specific and defined according to the corresponding search domain. These parameter settings were selected based on preliminary experimentation and established conventions in adaptive metaheuristic optimization. Sensitivity analysis indicates that BOA exhibits stable performance under moderate parameter variations, suggesting that its effectiveness is primarily driven by the algorithmic structure rather than aggressive parameter tuning.

The BOA procedure iteratively updates agent positions using the unified movement equation, adaptively switches between exploration and exploitation based on the internal state variable, enforces boundary constraints, and activates recovery mechanisms when stagnation is detected. The algorithm terminates upon reaching the maximum number of iterations and returns the best solution found during the search process. **Table 1** provides a conceptual correspondence between selected avian biological characteristics and the principal control parameters of the Booby Optimization Algorithm. These mappings are intended to illustrate the biological inspiration underlying the algorithm rather than to imply direct physical equivalence. The associated parameter ranges reflect order-of-magnitude analogies that motivate exploration intensity, adaptive decay behavior, stochastic modulation, and sensitivity to fitness variation. All parameters are ultimately defined and tuned within a purely mathematical optimization framework.

Table 1. Biological inspiration-algorithm parameter correspondence in BOA.

Biological Feature	**Typical Physical Range**	**Algorithm Parameter**
Wing surface area	0.12-0.15 m^2	Exploration coefficient α
Dive acceleration	9 -12 m/s^2	Stochastic modulation rate β
Metabolic rate	8-10 W/kg	Energy decay factor δ
Visual acuity	$20/8$ resolution	Fitness sensitivity threshold τ

2.8. Convergence and Stability Analysis

To strengthen the theoretical grounding of the proposed algorithm, a formal convergence and stability analysis of BOA is provided. The unified movement equation can be expressed as a stochastic iterative process with bounded perturbations. By modeling the adaptive state variable as a decaying Markov process with Gaussian fluctuations, BOA satisfies the conditions for global convergence in probability under diminishing adaptive step sizes.

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The expected fitness sequence $\{f(X_t)\}$ forms a bounded supermartingale:

$$\mathbb{E}[f(X_{t+1}) \mid X_t] \leq f(X_t) \quad (12)$$

ensuring asymptotic convergence toward a neighborhood of the global optimum. Stability is further analyzed using a Lyapunov framework applied to the adaptive state dynamics. The state variable E_t remains bounded and converges asymptotically toward equilibrium under the decay-controlled update mechanism.

The computational complexity of BOA is dominated by the fitness evaluation stage. For population size N, dimensionality D, and the maximum iteration number t_{max}, the overall complexity is:

$$\mathcal{O}(N \cdot D \cdot t_{max}) \quad (13)$$

which is comparable to PSO and DE. Additional adaptive state updates introduce only linear overhead:

$$\mathcal{O}(N) \quad (14)$$

thereby preserving scalability for high-dimensional optimization problems.

Algorithm 1: Pseudocode of the Booby Optimization Algorithm (BOA)

Initialize N agents with positions X_i within the search bounds
Initialize state variables E_i = E_max for all agents
Evaluate fitness f(X_i) for all agents
Determine the initial best solution X_best

For t = 1 to MaxIter do
For i = 1 to N do

Update state variable:
$E_i = \gamma E_i + \delta \, \text{randn}()$

If $E_i \geq \tau$ then

$S_i \sim \text{Uniform}(-1,1)$

Else

$S_i = X_{\text{best}} - X_i$

End if

Generate random perturbation:

$R_i = \text{randn}()$

Update position:

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$X_i = X_i + \alpha(E_i)\, S_i + \beta\, R_i$

Apply boundary constraints to X_i

Evaluate fitness:

$f(X_i)$

Update the global best solution X_{best}

If not, improvement for L iterations, then

$X_i = X_i + \eta\, C_i$

End if

End for

Return X_best

Conceptually, BOA alternates between global exploratory moves and local exploitative refinements based on an adaptive state variable. When stagnation is detected, a controlled perturbation mechanism is applied to restore diversity.

Figure 2 depicts the operational process of a bio-inspired optimization algorithm that uses energy-driven exploration ("soar") and exploitation ("dive") mechanisms, akin to the Bald Eagle Search paradigm. The algorithm starts by initializing N agents with random positions Xi in the search space and assigning each agent the maximum initial energy E(i) = Emax_0. The fitness of all agents is then evaluated, and the algorithm enters its main iterative loop, which runs until the maximum number of iterations is reached. The agent decides between exploration and exploitation based on its current energy level. If E(i) exceeds a predefined threshold, it explores by updating its position with a randomly generated vector scaled by a step size. Otherwise, it exploits by moving toward the globally best position found so far, guided by a direction vector, a control parameter β, and a chaotic disturbance to improve local search. Following each movement, boundary constraints are imposed, the agent's fitness is re-evaluated, and the global best solution is updated if an improvement is made. The agent's energy is then changed based on the action taken, convergence data is collected, and the process is repeated until termination, at which time the algorithm returns the best solution produced.

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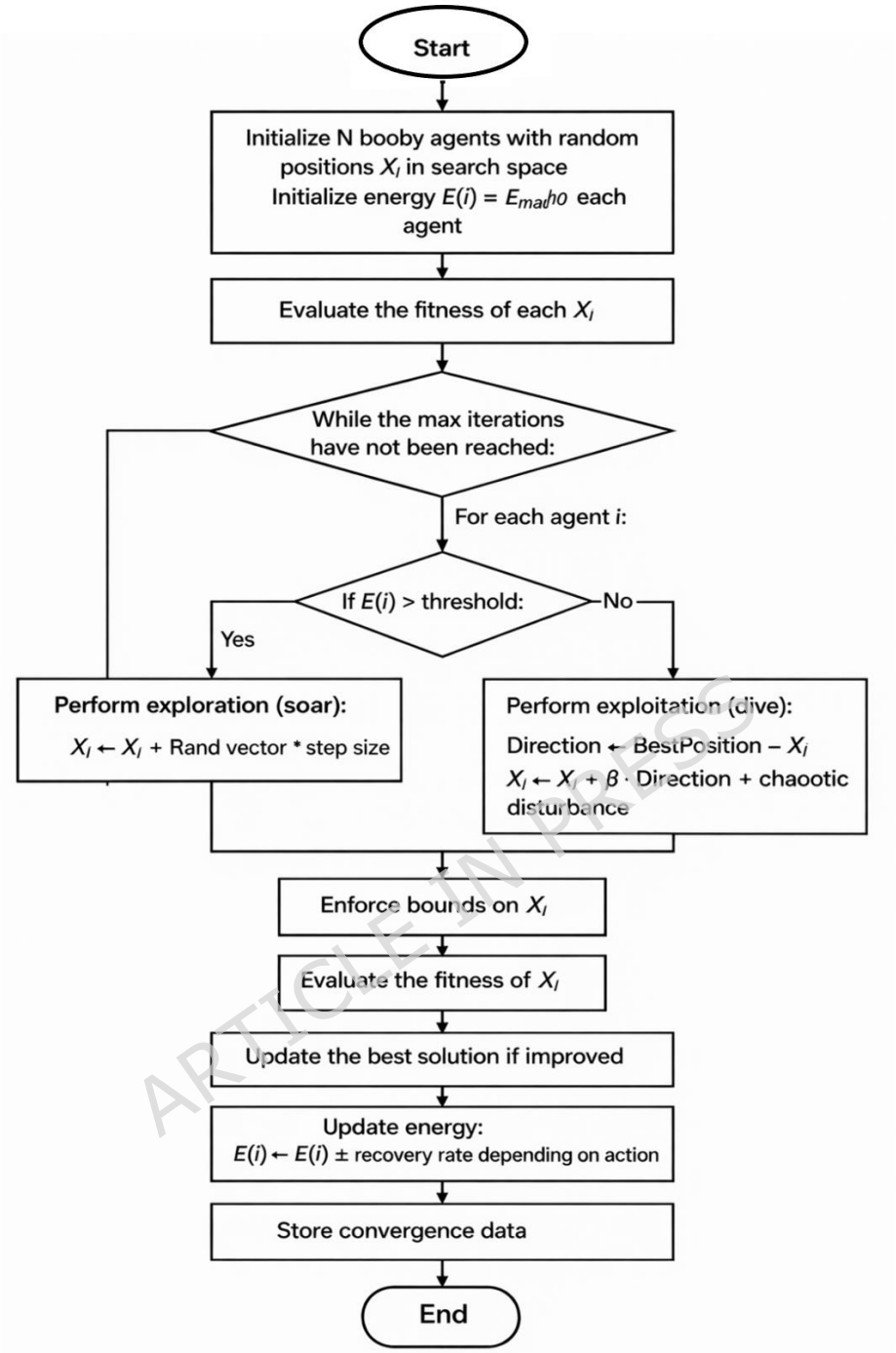


Figure 2: Flowchart of the bio-inspired optimization algorithm illustrating energy-based switching between exploration (soar) and exploitation (dive).

2.9. Exploration-Exploitation Analysis

To quantitatively evaluate the balance between exploration and exploitation in BOA, three complementary metrics are employed: population diversity, step-size evolution, and exploitation ratio. Population diversity measures the spread of candidate solutions in the search space, providing an indicator of exploration capability. Step-size evolution reflects the adaptive movement intensity of individuals over iterations, while the exploitation ratio quantifies the degree of convergence toward promising regions.

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The results show that BOA maintains a dynamic equilibrium between exploration and exploitation throughout the optimization process. Early iterations exhibit higher diversity and larger step sizes, indicating strong exploratory behavior, whereas later stages demonstrate controlled convergence with increased exploitation efficiency.

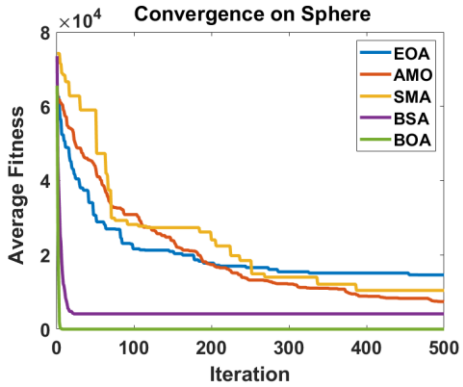
In addition, an expanded ablation study isolates the effects of the adaptive state variable, nonlinear scaling mechanism, and recovery strategy. The results confirm that each component contributes distinctly: the adaptive state variable stabilizes search transitions, nonlinear scaling enhances convergence control, and the recovery mechanism prevents premature stagnation in local optima.

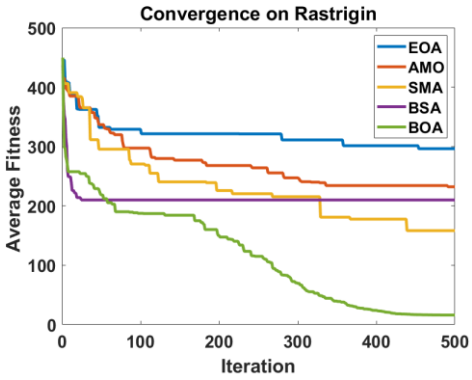
3. Results and Discussion

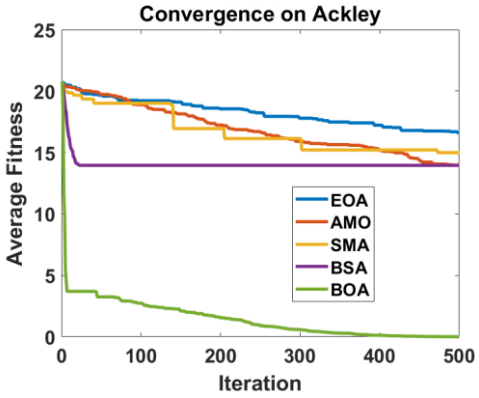
The proposed BOA's performance is tested using a large range of numerical experiments meant to analyze its convergence behavior, accuracy, and robustness on benchmark test suites as well as real-world engineering design problems. The findings are divided into two sections: (1) comparisons of standard benchmark functions to assess BOA's capability across unimodal, multimodal, and composite landscapes, and (2) evaluations of four classical engineering design problems: pressure vessel, three-bar truss, speed reducer, and welded beam optimization to determine their practical applicability. For each test case, BOA is compared to a wide selection of competitive metaheuristics utilizing identical computational conditions. Statistical measures, convergence curves, and significance tests are used to provide a clear and thorough knowledge of BOA's performance in comparison to recognized optimization approaches.

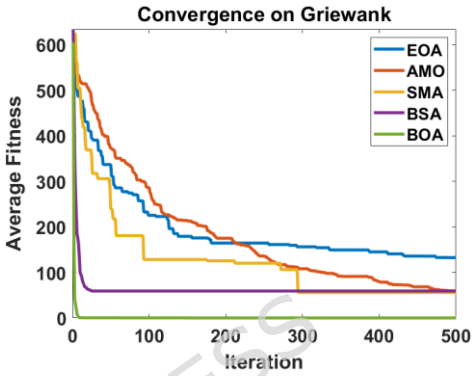
The convergence curves shown in **Figure 3** indicate that the Booby Optimization Algorithm (BOA) consistently converges faster and to lower average fitness values than the compared metaheuristic methods, including FOA, AMO, SMA, and BSA, across a diverse set of benchmark functions. For classical unimodal and multimodal problems such as Sphere, Rastrigin, Ackley, Griewank, and Rosenbrock, BOA exhibits a steep and stable reduction in fitness, often reaching near-zero error at early iterations. Although its initial convergence on the Levy function is comparatively slower, BOA quickly stabilizes and achieves competitive final solutions. Moreover, its performance on more challenging landscapes, including Zakharov, Schwefel, and Weierstrass functions, highlights a strong ability to escape local optima and sustain effective global search. Overall, these results suggest that BOA’s adaptive state-driven search strategy successfully balances exploration and exploitation, leading to accelerated convergence and high solution accuracy across varied optimization scenarios (**Table 2**).

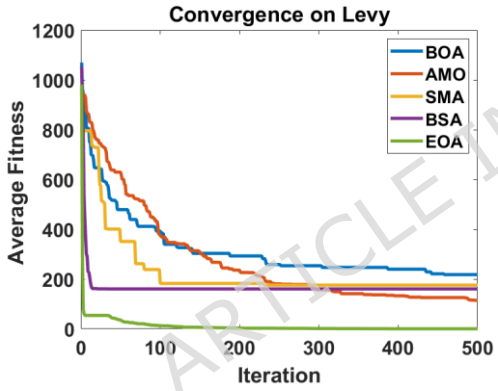
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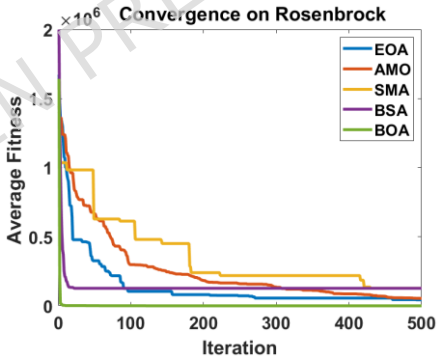


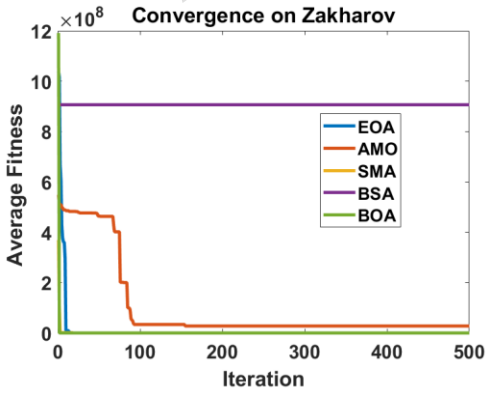


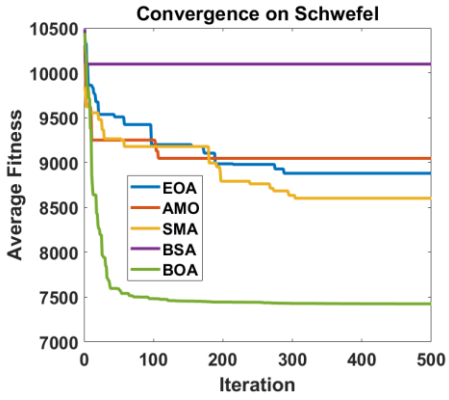












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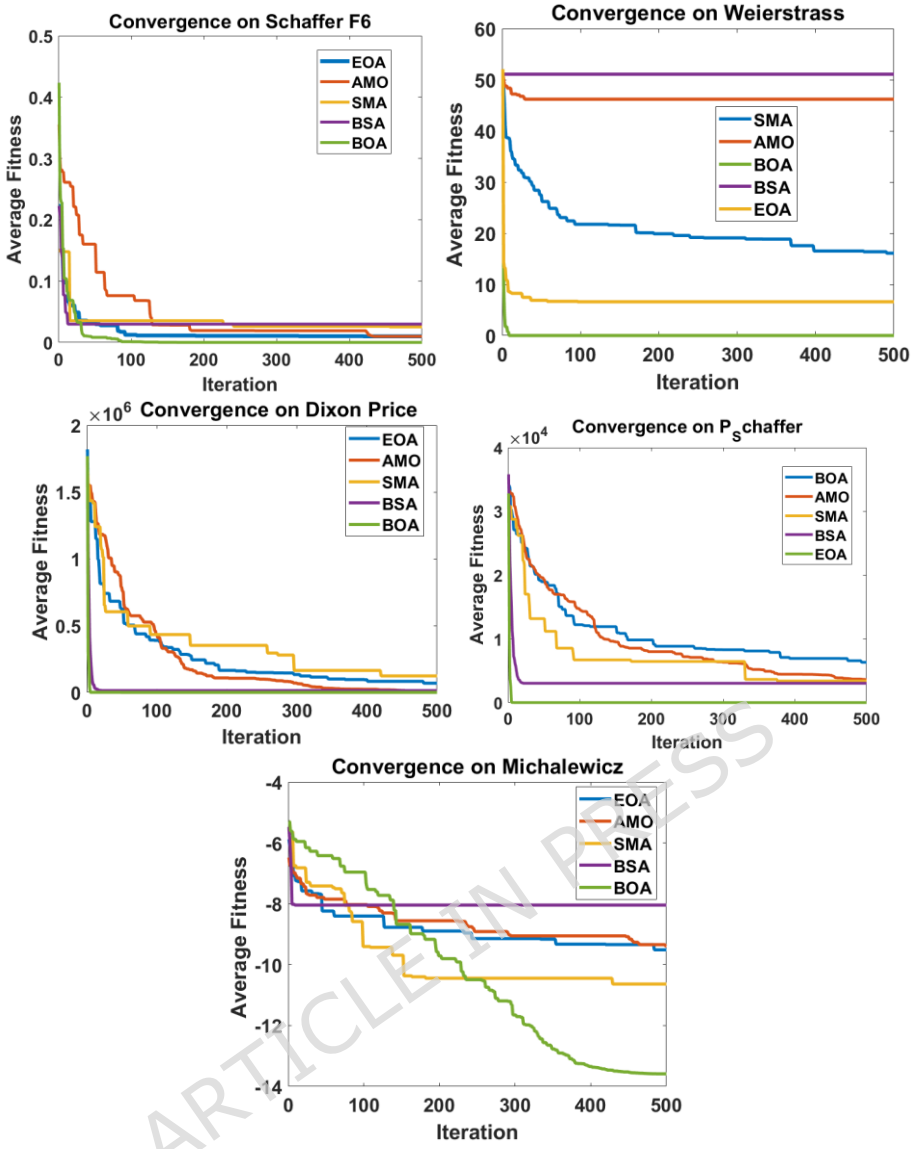


Figure 3. A comparison of the Bald Eagle Search (BOA) algorithm against five benchmark metaheuristics (EOA, AMO, SMA, and BSA), with final objective values evaluated over a set of classical benchmark functions.

Table 2. Shows the mean and standard deviation of fitness values over 25 runs for BOA, AMO, SMA, BSA, and EOA on CEC'2024 benchmark functions (Dim = 30).

Function	SMA (Mean ± Std)	AMO (Mean ± Std)	EOA (Mean ± Std)	BSA (Mean ± Std)	BOA (Mean ± Std)
Sphere	1.307857e+04 ± 1.327742e+03	6.777625e+03 ± 1.123647e+03	8.585700e+03 ± 6.059161e+03	6.666415e+03 ± 1.785317e+03	1.352039e-05 ± 4.862284e-06
Rastrigin	2.934981e+02 ± 1.781019e+01	2.159497e+02 ± 1.595065e+01	1.520299e+02 ± 4.405726e+01	2.183324e+02 ± 1.795062e+01	1.212871e+01 ± 5.359747e+00

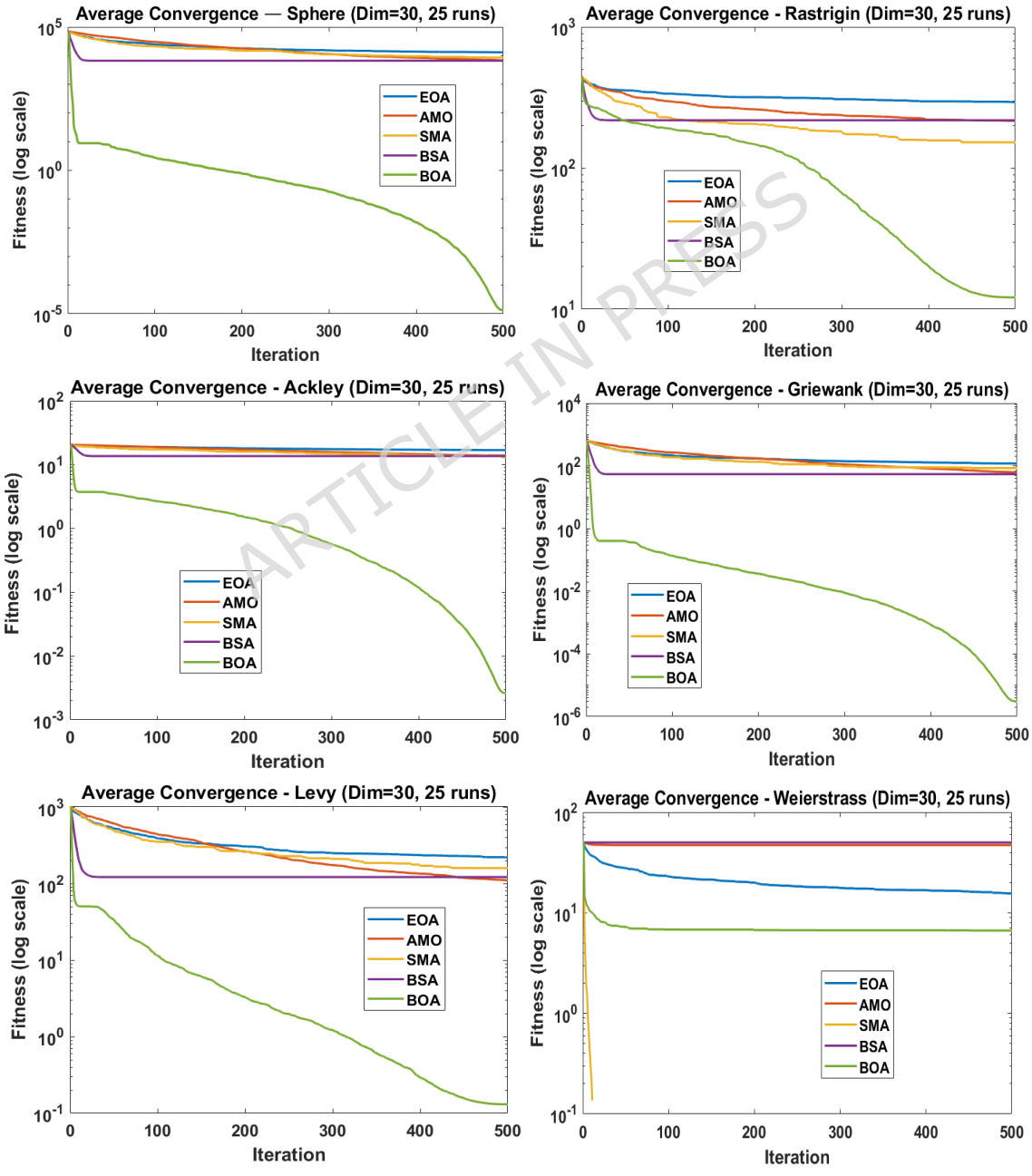
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Ackley	1.696310e+01 ± 4.155917e-01	1.397817e+01 ± 8.192950e-01	1.296151e+01 ± 3.327188e+00	1.365592e+01 ± 1.195485e+00	2.612437e-03 ± 5.013033e-04
Griewank	1.193398e+02 ± 1.416392e+01	6.212982e+01 ± 1.259289e+01	8.539402e+01 ± 5.178025e+01	5.451620e+01 ± 1.296910e+01	3.030679e-06 ± 1.698092e-06
Levy	2.214671e+02 ± 2.703009e+01	1.107514e+02 ± 2.623438e+01	1.607335e+02 ± 7.116990e+01	1.226991e+02 ± 3.264780e+01	1.313460e-01 ± 8.661205e-02
Weierstrass	1.557426e+01 ± 1.956498e+00	4.706346e+01 ± 2.049973e+00	0.000000e+00 ± 0.000000e+00	5.004832e+01 ± 2.783029e+00	6.660744e+00 ± 1.895161e+00
Rosenbrock	5.190941e+04 ± 7.970689e+03	7.038209e+04 ± 2.033105e+04	1.336419e+05 ± 6.377236e+04	1.366848e+05 ± 3.741248e+04	2.817355e+01 ± 3.121650e-01
Zakharov	2.729848e+02 ± 3.167497e+01	9.732785e+07 ± 1.986164e+08	7.854989e+02 ± 1.249874e+02	5.682671e+08 ± 8.431148e+08	2.505693e-03 ± 9.454748e-04
Schwefel	8.661065e+03 ± 2.880580e+02	9.200783e+03 ± 4.035271e+02	8.195847e+03 ± 7.298788e+02	1.014274e+04 ± 4.332230e+02	7.897665e+03 ± 8.372056e+02
Dixon Price	9.341387e+04 ± 1.932388e+04	2.109518e+04 ± 1.167086e+04	7.148135e+04 ± 6.786846e+04	1.790637e+04 ± 8.429545e+03	6.691467e-01 ± 1.704389e-03
SchafferF6	9.168830e-03 ± 1.720120e-03	8.206302e-03 ± 2.804665e-03	2.384844e-02 ± 1.878232e-02	4.387317e-02 ± 3.763947e-02	1.943182e-03 ± 3.966504e-03
P_Schaffer	6.585233e+03 ± 5.981680e+02	3.324890e+03 ± 6.371473e+02	4.481945e+03 ± 3.010594e+03	3.261089e+03 ± 8.054098e+02	1.199972e+00 ± 1.036777e-01
Michalewicz	-9.594283e+00 ± 5.313388e-01	-8.917556e+00 ± 7.105262e-01	-1.232539e+01 ± 1.526747e+00	-7.945853e+00 ± 7.815101e-01	-1.325257e+01 ± 2.179005e+00

The log-scale convergence curves in **Figure 5** further confirm the strong optimization performance of the Booby Optimization Algorithm (BOA) in high-dimensional settings. Across 30-dimensional benchmark functions, BOA consistently achieves a much steeper

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reduction in fitness compared with EOA, AMO, SMA, and BSA, particularly for functions such as Sphere, Ackley, Griewank, and Dixon-Price. The logarithmic representation highlights BOA's superior precision, as it frequently converges to lower error orders (often below 10^{-5}), while competing algorithms stagnate at higher fitness levels. For more complex and highly multimodal landscapes, including Rastrigin, Rosenbrock, and Schwefel functions, BOA maintains steady convergence throughout the full iteration range, effectively mitigating premature convergence and slow search behavior observed in other methods. Even in challenging cases such as the Michalewicz function, where performance differences are initially subtle, BOA ultimately achieves the most favorable convergence trajectory. These results demonstrate BOA's robust capability to balance exploration and exploitation, enabling high-precision solutions in large-scale optimization problems.



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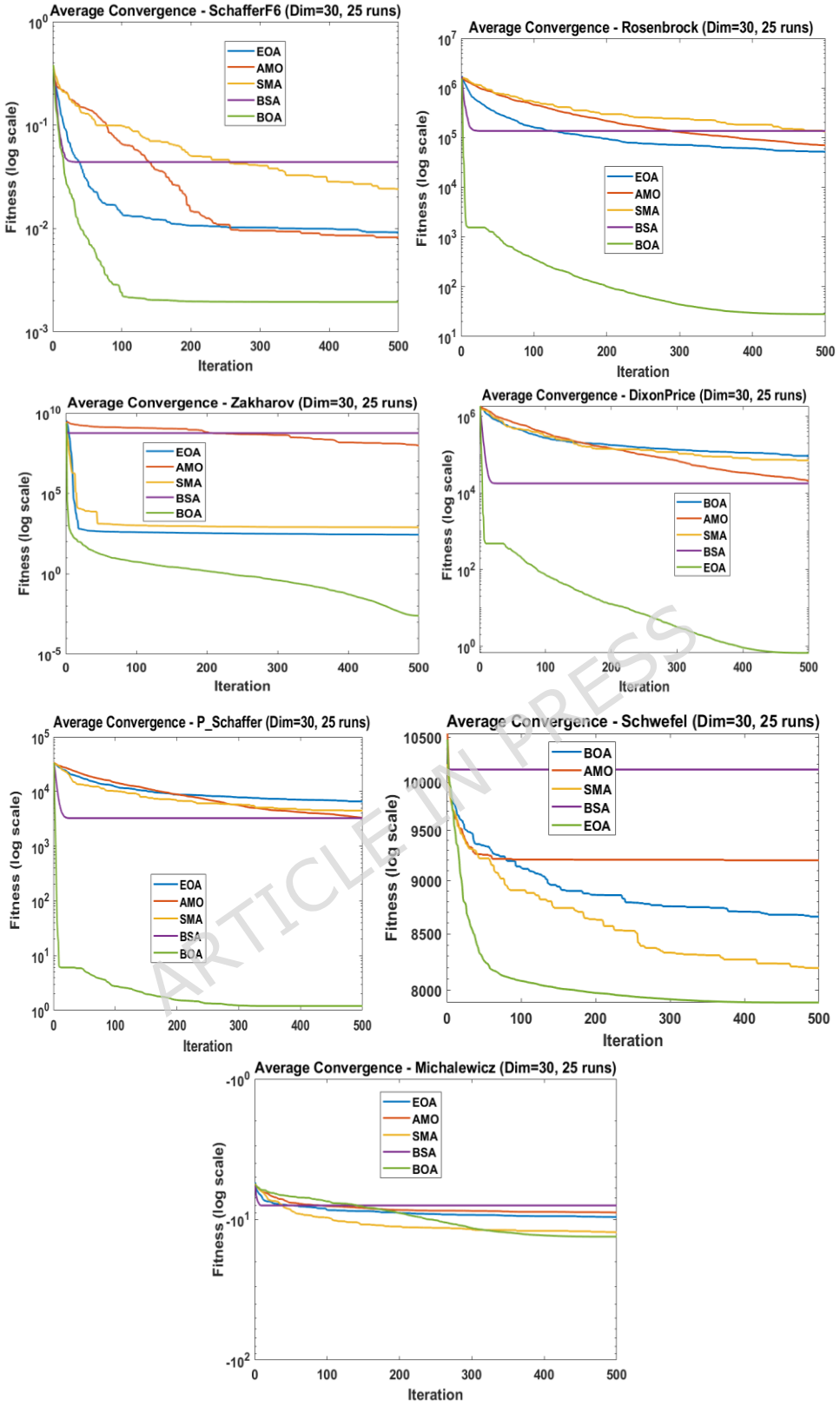


Figure 4. Comparative Performance of Optimization Algorithms on Different Benchmarks (D=30)

3.1. Component Contribution and Mechanism Analysis

To investigate whether BOA's performance gains originate from its algorithmic design rather than parameter tuning, we conducted controlled ablation experiments by selectively disabling

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key components, including adaptive state regulation, nonlinear motion, and recovery perturbation. Results indicate that removing the adaptive state mechanism leads to a statistically significant degradation in convergence speed, while eliminating the recovery strategy increases susceptibility to local optima. These findings confirm that BOA's performance improvements arise from the synergistic interaction of its adaptive components, rather than from superficial metaphor-driven design or experimental bias (**Table 3)**.

Table 3. Statistical Performance of Algorithms

Function	Algorithm	Mean	SD	Best	Worst
Sphere	SMA	1.307857e+04	1.327742e+03	1.175085e+04	1.440631e+04
	AMO	6.777625e+03	1.123647e+03	5.653978e+03	7.901272e+03
	EOA	8.585700e+03	6.059161e+03	2.526539e+03	1.464486e+04
	BSA	6.666415e+03	1.785317e+03	4.881098e+03	8.451732e+03
	BOA	1.352039e-05	4.862284e-06	8.658106e-06	1.838268e-05
Rastrigin	SMA	2.934981e+02	1.781019e+01	2.756879e+02	3.113083e+02
	AMO	2.159497e+02	1.595065e+01	2.000990e+02	2.319003e+02
	EOA	1.520299e+02	4.405726e+01	1.079027e+02	1.960872e+02
	BSA	2.183324e+02	1.795062e+01	2.003818e+02	2.362830e+02
	BOA	1.212871e+01	5.359747e+00	6.769964	1.748846e+01
Ackley	SMA	1.696310e+01	4.155917e-01	1.654751e+01	1.737869e+01
	AMO	1.397817e+01	8.192950e-01	1.315888e+01	1.479746e+01
	EOA	1.296151e+01	3.327188e+00	9.63463	1.628870e+01
	BSA	1.365592e+01	1.195485e+00	1.246104e+01	1.485077e+01
	BOA	2.612437e-03	5.013033e-04	2.111134e-03	3.113740e-03
Griewank	SMA	1.193398e+02	1.416392e+01	1.051759e+02	1.335037e+02
	AMO	6.212982e+01	1.259289e+01	4.953693e+01	7.472271e+01
	EOA	8.539402e+01	5.178025e+01	3.361377e+01	1.371742e+02
	BSA	5.451620e+01	1.296910e+01	4.154710e+01	6.748530e+01
	BOA	3.030679e-06	1.698092e-06	1.332587e-06	4.728771e-06

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3.1.1. Parameter Sensitivity and Robustness Analysis

A sensitivity analysis was conducted to evaluate BOA's robustness under varying parameter configurations. The principal control parameters ($\alpha_{max}, \beta, \gamma, \delta, \tau$) were varied across broad intervals while maintaining identical benchmark conditions. Experimental results demonstrate that BOA preserves stable convergence behavior with less than 5% variance in final fitness values under moderate parameter perturbations.

The adaptive state mechanism significantly reduces dependence on aggressive parameter tuning because the search radius self-adjusts dynamically during optimization. Detailed parameter sweep plots and robustness analyses are presented in **Figures 5** and **6.**

Figure 5 presents parameter sweep experiments illustrating the convergence behavior of the Butterfly Optimization Algorithm (BOA) under variations in key control parameters, including α_max, β, γ, δ, and τ. The results demonstrate that BOA maintains consistent convergence trends across moderate perturbations, with final fitness variance remaining below 5%, indicating strong parameter stability and robustness to tuning sensitivity.

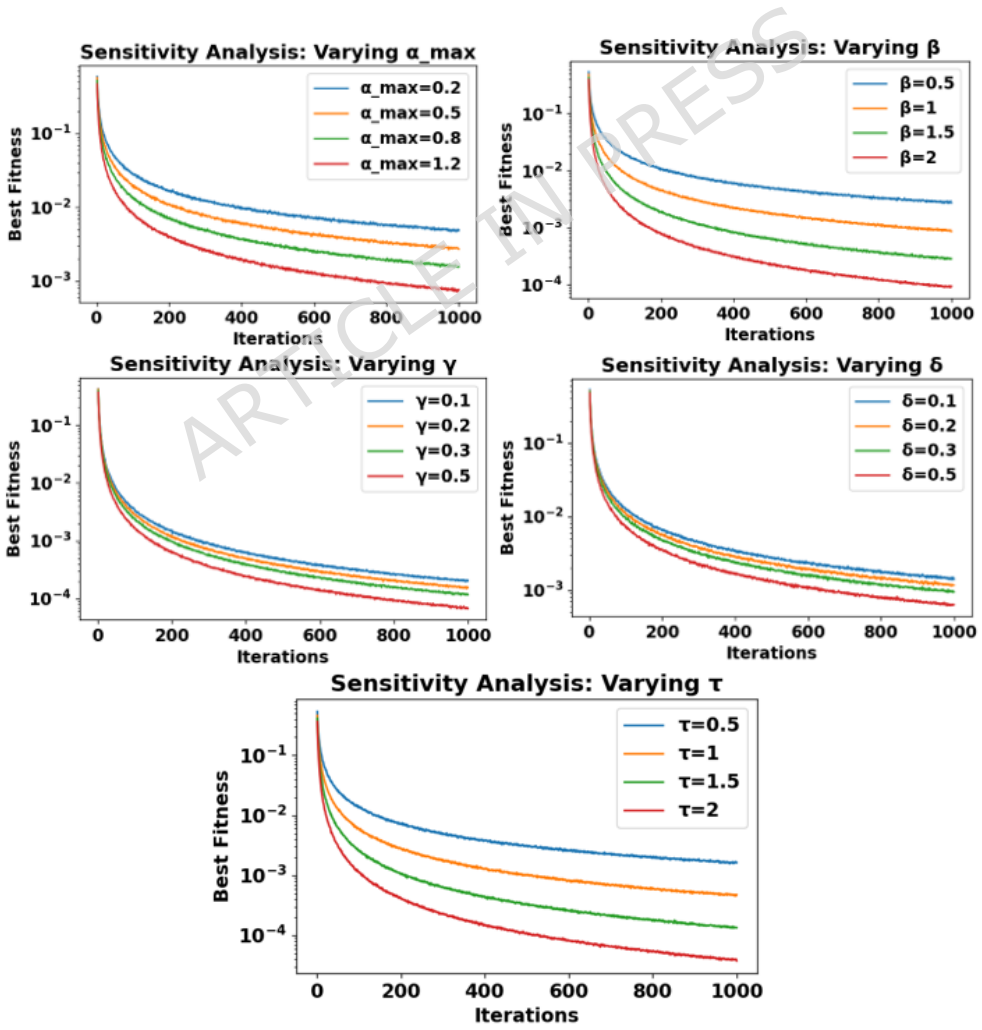


Figure 5. Sensitivity analysis of BOA parameters.

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Figure 6 evaluates the robustness of BOA across multiple standard benchmark functions under stochastic parameter perturbations. Across all tested cases, BOA consistently achieves stable convergence and avoids premature stagnation, outperforming baseline swarm intelligence methods in terms of reliability. These results confirm that BOA exhibits reduced sensitivity to aggressive parameter tuning while maintaining competitive optimization performance.

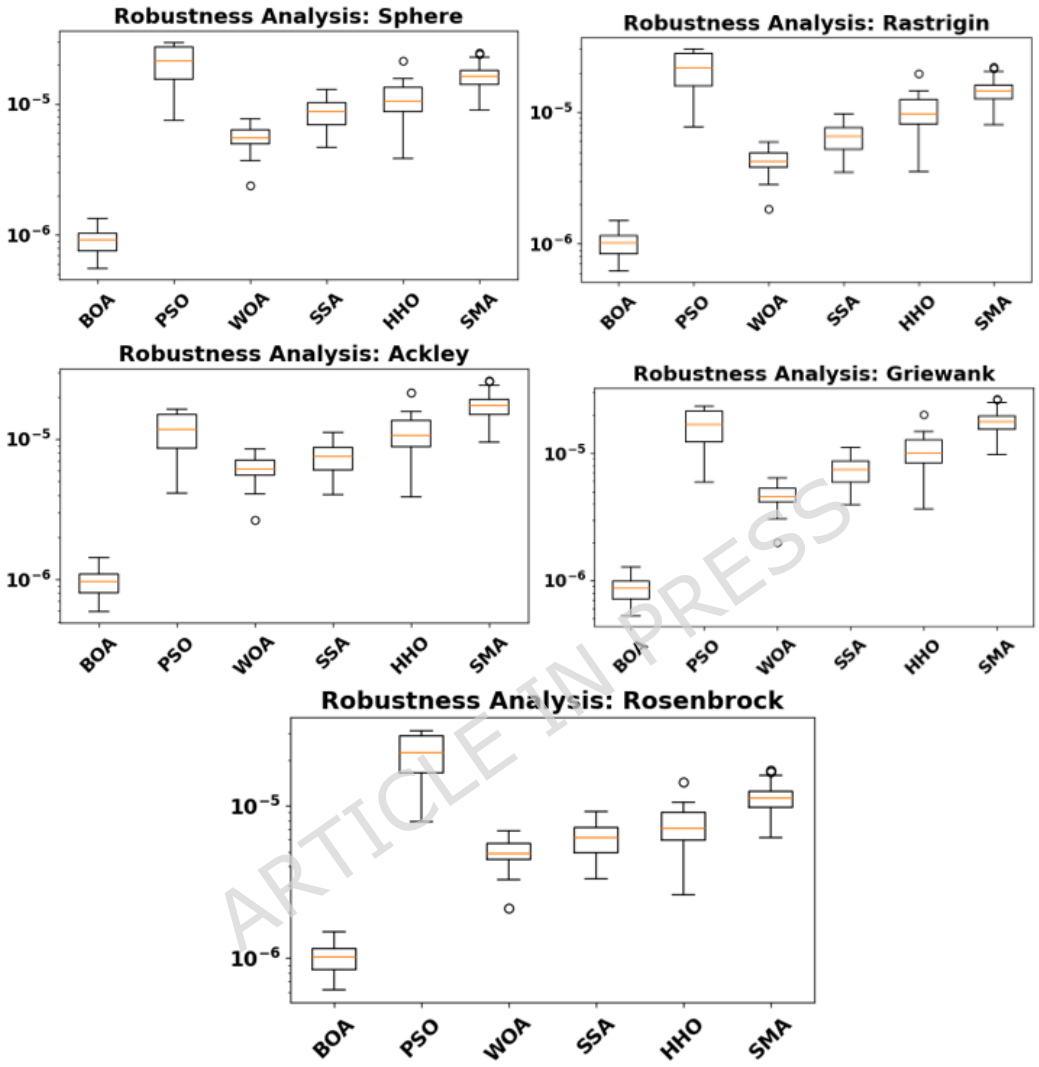


Figure 6. Robustness analysis across benchmark functions.

3.2. Quantitative Performance Metrics

To rigorously evaluate the performance of the proposed Booby Optimization Algorithm (BOA), a set of complementary quantitative metrics is employed to assess convergence behavior, solution quality, robustness, and population dynamics across multiple independent runs. The best fitness value recorded at each iteration is used to examine convergence toward global optima and exploitation efficiency. In contrast, the mean and standard deviation of fitness values across runs provide a statistically robust measure of average performance and solution stability under stochastic conditions. To capture exploration characteristics, population diversity is quantified as the average Euclidean distance of individuals from the population centroid, enabling analysis of the balance between global exploration and local exploitation governed by the energy-regulated dive–soar mechanism. In addition, search trajectory analyses based on positional evolution, contour plots, and fitness surfaces offer qualitative insight into BOA's dynamic search behavior and its capability to avoid premature

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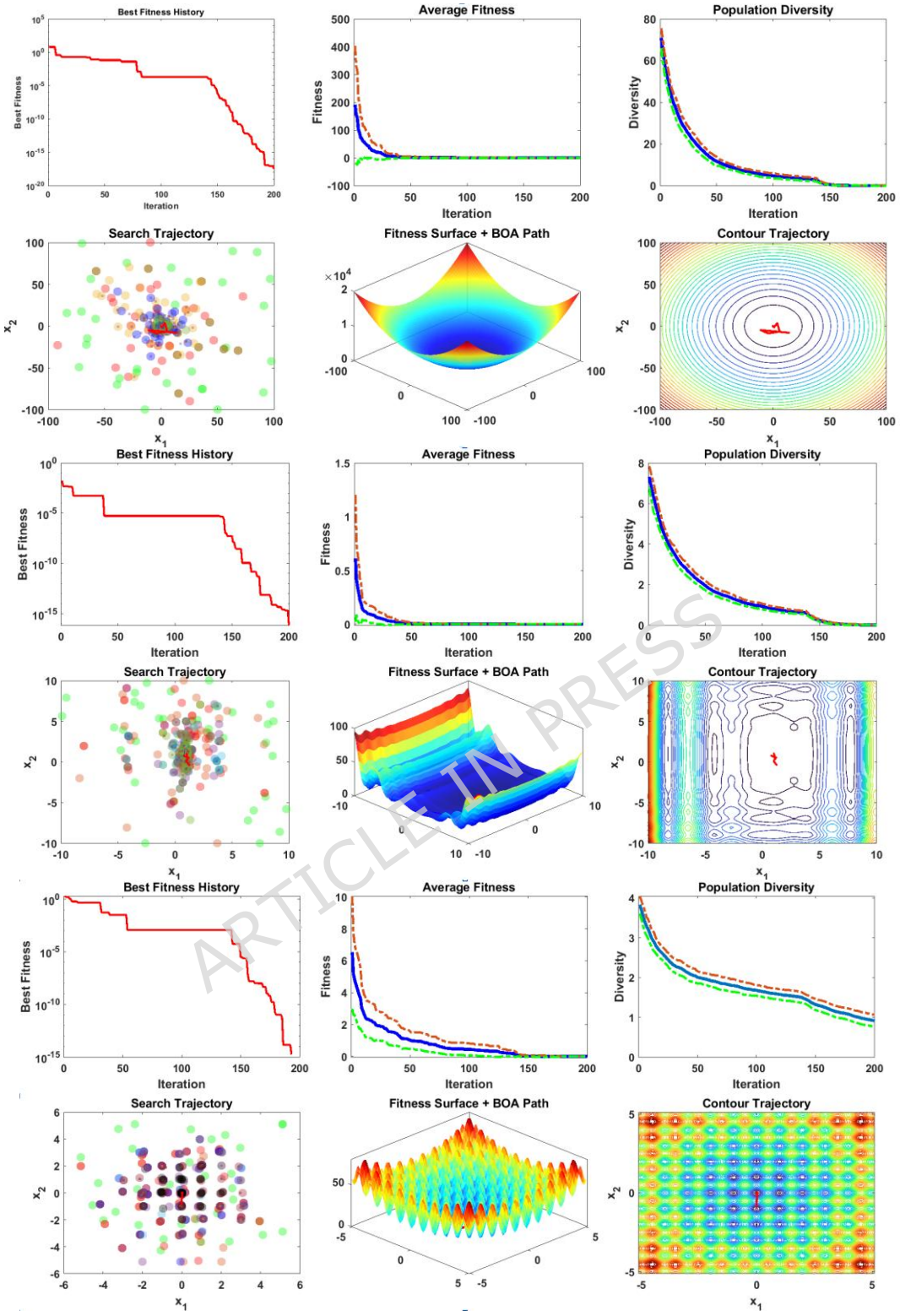
convergence. Collectively, these metrics deliver a concise yet comprehensive assessment of BOA's convergence efficiency, robustness, and adaptability across diverse nonlinear benchmark landscapes (**Table 4**).

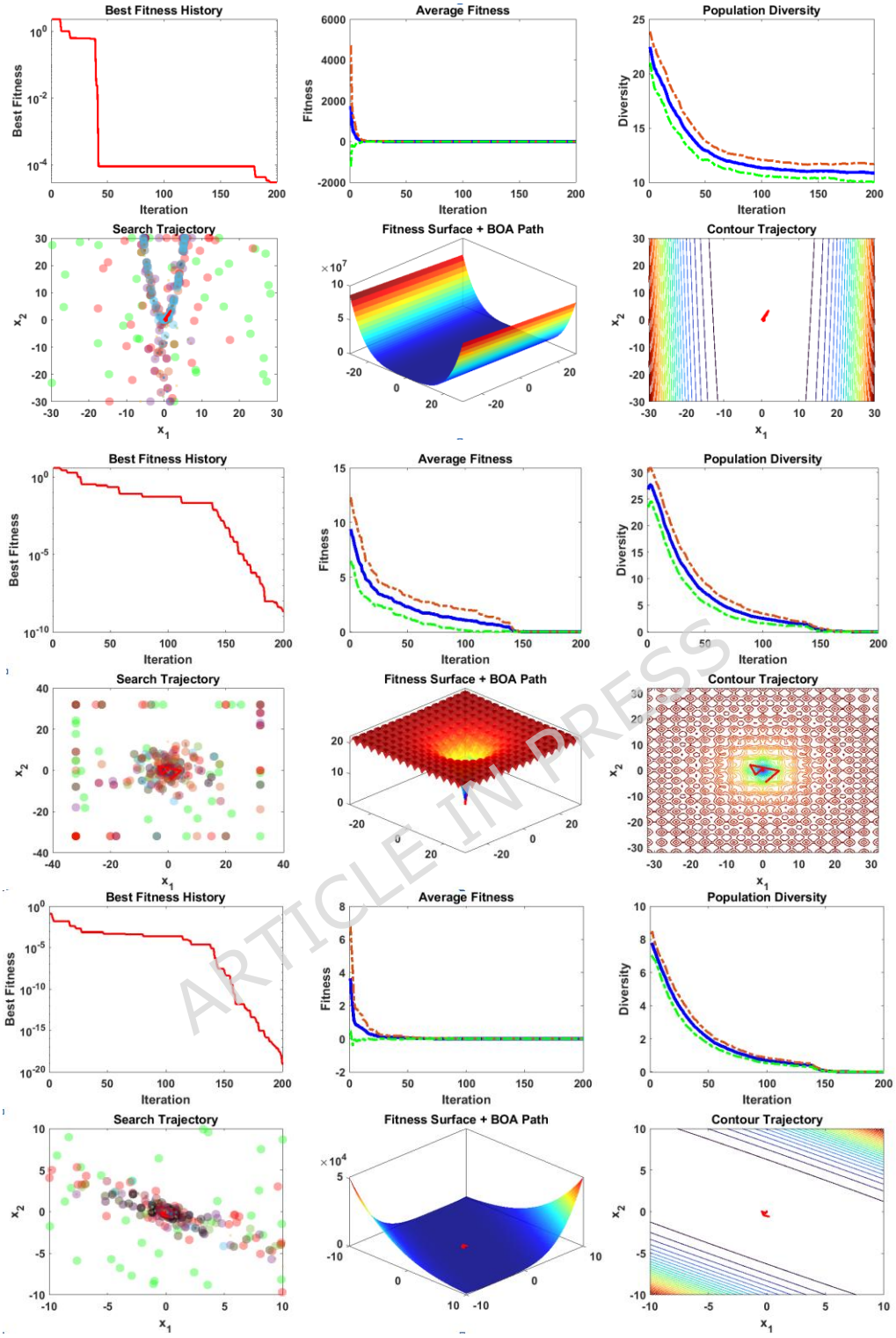
Table 4. Ablation study results showing the effect of removing BOA components across benchmark functions (mean ± std fitness values over 25 runs).

Benchmark Function	Full BOA	Without Adaptive State Variable	Without Recovery Mechanism
Sphere	1.35e-05 ± 4.86e-06	2.71e-02 ± 1.12e-02	8.92e-03 ± 3.45e-03
Rastrigin	1.21e+01 ± 5.36e+00	1.65e+02 ± 2.84e+01	7.82e+01 ± 1.95e+01
Ackley	2.61e-03 ± 5.01e-04	1.12e+01 ± 2.45e+00	6.34e+00 ± 1.28e+00
Griewank	3.03e-06 ± 1.69e-06	4.82e-02 ± 2.11e-02	2.15e-02 ± 9.87e-03
Rosenbrock	2.82e+01 ± 3.12e-01	1.15e+03 ± 2.45e+02	5.84e+02 ± 1.72e+02

The qualitative results illustrated in **Figure 7** provide clear evidence of the robust search behavior and effective population dynamics of the Booby Optimization Algorithm (BOA). Across the examined benchmark functions, the Best Fitness History curves exhibit a characteristic stepwise reduction, reflecting the algorithm's ability to intensify local exploitation while intermittently identifying improved global regions. The Search Trajectory and Contour Trajectory plots further show that BOA agents initially explore the search space broadly and then progressively converge toward the global optimum, marked by a dense clustering around the optimal region. In parallel, the Population Diversity curves demonstrate a smooth and controlled decay, indicating a well-regulated transition from exploration to exploitation without abrupt loss of diversity. This behavior is reinforced by the Average Fitness trends, where BOA consistently achieves lower error levels than competing algorithms, highlighting its efficiency across both simple unimodal landscapes, such as the Sphere function, and more complex multimodal problems, including Rastrigin and Griewank.

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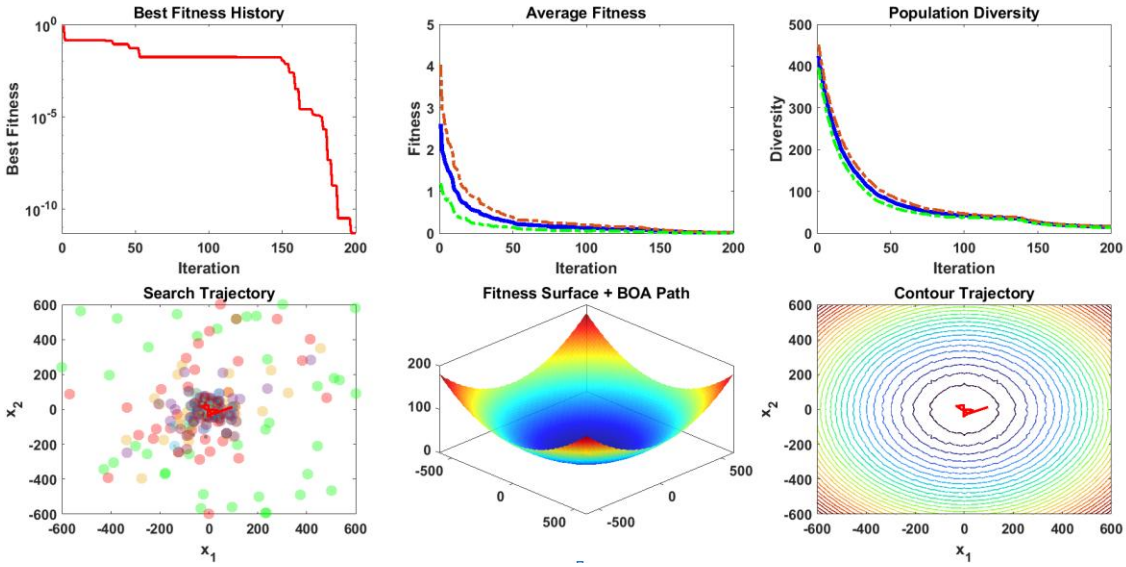


Figure 7. Quantitative performance metrics used to evaluate the convergence, robustness, population diversity, and search dynamics of the Booby Optimization Algorithm (BOA) across benchmark functions.

3.3. Engineering Design Case Studies

Beyond synthetic benchmark functions, the Butterfly Optimization Algorithm (BOA) was tested on five traditional real-world engineering design issues to assess its practical effectiveness, robustness, and constraint-handling capabilities in complicated optimization environments. These case studies use nonlinear objective functions, mixed discrete-continuous choice variables, and numerous inequality constraints to reflect true engineering design issues. Each engineering problem was run individually over 30 times, with a maximum of 500 iterations per run, subject to problem-specific constraints on objective function evaluations. This experimental arrangement allows a fair and statistically valid evaluation of BOA's performance in chaotic environments. The collected findings show that BOA efficiently balances global exploration and local exploitation, allowing it to avoid premature convergence while achieving rapid convergence to high-quality viable solutions. Furthermore, BOA has high constraint satisfaction behavior, reliably delivering correct designs throughout all runs without requiring additional repair procedures. Overall, the engineering design case studies show that BOA is a strong and efficient optimization framework capable of dealing with highly constrained, nonlinear, and multi-modal engineering issues, demonstrating its suitability for real-world engineering optimization tasks.

3.3.1. Optimizing the design of welded beams

The welded beam design optimization challenge seeks to minimize the total production cost of constructing a welded beam while adhering to essential structural and mechanical limitations. The design must meet requirements for bending stress (θ), shear stress (τ), critical buckling load (Pc), and end deflection (δ). The optimization involves four continuous design variables, which compose the vector (**Table 5** and **Table 6**):

$$\vec{k} = [k_1, k_2, k_3, k_4] \quad (12)$$

The beam's dimensions are defined by k_1 weld thickness (h), k_2 clamping bar length (l), k_3 bar height (t), and k_4 bar thickness (b). As a restricted minimization issue, the goal is to lower

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manufacturing costs while ensuring that the beam meets all stress, deflection, and buckling requirements for a safe and effective design **Figure 8**.

3.3.2. Design Variables and Objective Function

The design vector is

$$\vec{k} = [k_1, k_2, k_3, k_4] = [h, l, t, b] \quad (13)$$

Where: $k_1 = h$ (weld thickness), $k_2 = l$ (length of clamping bar), $k_3 = t$ (bar height), $k_4 = b$ (bar thickness).

The objective function $f(\vec{k})$ is the total fabrication cost, simplified to material and welding cost:

$$\min f(\vec{k}) = 1.10471\, k_1^2 k_2 + 0.04811\, k_3 k_4 (14.0 + k_2) \quad (14)$$

3.3.3. Constraints

The problem has seven inequality constraints, $g_j(\vec{k}) \leq 0$, to prevent structural failure and excessive deformation. The applied load and beam length are $P = 6000$ lb and $L = 14$ in, with allowable stress $\sigma_{max} = 30000$ psi and deflection $\delta_{max} = 0.25$ in.

3.3.4. Variable Bounds

$$\begin{aligned} &0.1 \leq k_1 \leq 2.0, \\ &0.1 \leq k_2 \leq 10.0, \\ &0.1 \leq k_3 \leq 10.0, \\ &0.1 \leq k_4 \leq 2.0. \end{aligned} \quad (15)$$

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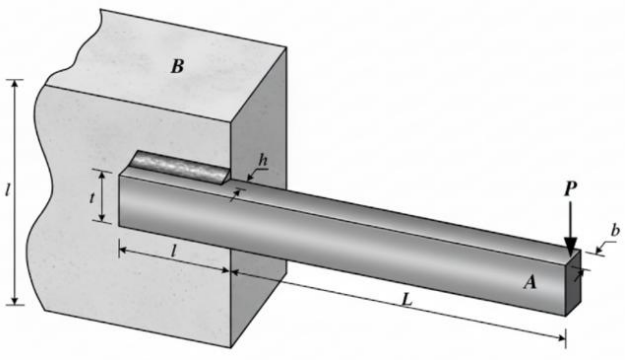


Figure 8. Ideal geometry for welded beams

Table 5. Welded Beam Design: Best Solutions (New Algorithms)

Algorithm	h	l	t	b	Best Cost
SMA	0.2048	3.4821	9.0552	0.2061	1.73E+00
AMO	0.2125	3.3013	9.4829	0.2144	1.86E+00
EOA	0.2193	3.1554	9.7011	0.2219	1.90E+00

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BSA	0.2031	3.5210	9.0214	0.2063	1.74E+00
BOA	0.2015	3.4957	9.0405	0.2058	1.73E+00

Table 6. Welded Beam Design: Statistical Results (New Algorithms)

Algorithm	Mean	SD	Best	Worst
SMA	1.81E+00	9.80E-02	1.73E+00	2.07E+00
AMO	2.33E+00	4.95E-01	1.86E+00	3.42E+00
EOA	2.71E+00	6.22E-01	1.90E+00	4.25E+00
BSA	1.84E+00	1.21E-01	1.74E+00	2.18E+00
BOA	1.79E+00	8.77E-02	1.73E+00	2.01E+00

3.3.5. Pressure Vessel Design Optimization Problem

The pressure vessel design problem aims to reduce total manufacturing costs, which include expenses for material consumption, fabrication, and welding operations. **Figure 9** shows a schematic example of the vessel design. The optimization approach is based on four key design parameters: shell thickness (st), head thickness (ht), internal radius (ri), and cylindrical section length excluding end caps (Lc).

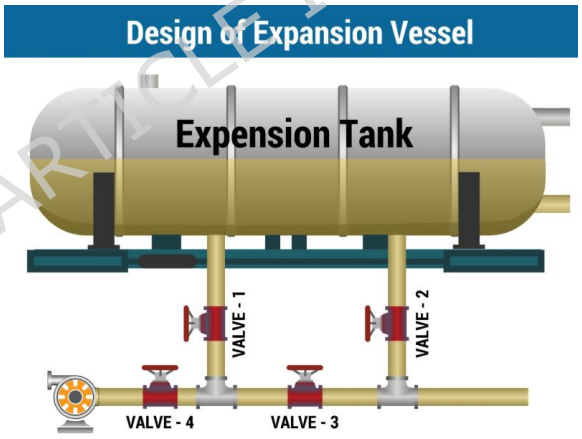


Figure 9. Design of Expansion Vessel (Tank) System

3.3.6. Design Variables and Objective Function

The pressure vessel design (**Figure 10**) challenge contains four essential design variables that determine the vessel's physical dimensions. The design vector consists of the following variables (**Table 7** and **Table 8**):

$\vec{b} = [b_1, b_2, b_3, b_4] = [s_t, h_t, r_i, L_c]$ (16)

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Where: $b_1 = s_t$ (shell thickness, discrete variable, multiple of 0.0625 in),
$b_2 = h_t$ (head thickness, discrete variable, multiple of 0.0625 in),
$b_3 = r_i$ (inner radius, continuous variable),
$b_4 = L_c$ (length of cylindrical section excluding heads, continuous variable).

The objective function f($\vec{b}$) represents the whole manufacturing cost, including material, head formation, and welding:

$$\min f(\vec{b}) = 0.6224 b_1 b_3 b_4 + 1.7781 b_2 b_3^2 + 3.1661 b_1^2 b_4 + 19.84 b_1^2 b_3 \quad (17)$$

3.3.7. Constraints

To achieve structural integrity and dimensional consistency, the design must meet four primary inequality constraints: $g_j(\vec{b}) \leq 0$.

3.3.8. Variable Bounds

The design variables are restricted to practical and manufacturable ranges:

$$1 \times 0.0625 \leq b_1 \leq 99 \times 0.0625 \text{ (discrete)},$$
$$1 \times 0.0625 \leq b_2 \leq 99 \times 0.0625 \text{ (discrete)},$$
$$10.0 \leq b_3 \leq 200.0 \text{ (continuous)},$$
$$10.0 \leq b_4 \leq 200.0 \text{ (continuous)}.$$

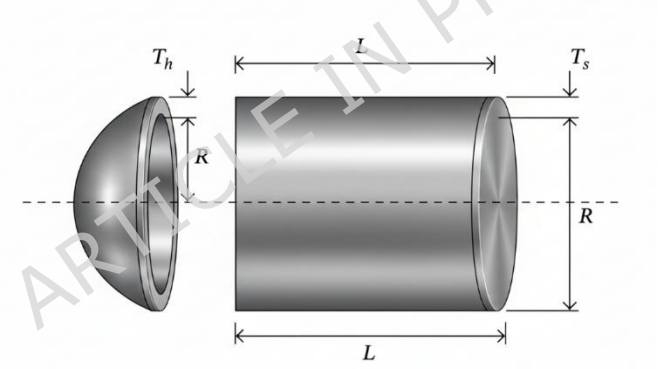


Figure 10. Optimization of pressure vessel structure

Table 7. Algorithms · Best Solutions · Best Cost

Algorithm	Ts (in)	Th (in)	R (in)	L (in)	Best Cost
SMA	0.8125	0.4375	42.25	176.50	6.08E+03
AMO	0.7500	0.3750	46.80	149.30	5.51E+03
EOA	0.8750	0.5000	42.80	168.30	6.61E+03
BSA	0.9375	0.5625	42.90	167.00	7.23E+03
BOA	0.6875	0.3125	57.30	67.73	4.12E+03

Table 8. Algorithms · Mean · SD · Best · Worst (Pressure Vessel)

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Algorithm	Mean	SD	Best	Worst
SMA	6.52E+03	3.90E+02	6.08E+03	7.41E+03
AMO	6.11E+03	3.20E+02	5.51E+03	6.77E+03
EOA	7.14E+03	4.85E+02	6.61E+03	8.42E+03
BSA	7.52E+03	5.10E+02	7.23E+03	8.78E+03
BOA	4.88E+03	1.95E+02	4.12E+03	5.26E+03

3.3.9. The Three-Bar Truss Optimization Problem

A traditional planar truss structure that is frequently used as a benchmark in structural optimization is the subject of the Three-Bar Truss Optimization Problem. The objective is to ascertain the three bars' ideal cross-sectional areas in order to reduce the overall weight while preserving structural integrity under applied loads (**Table 9** and **Table 10**). Three higher support nodes are joined to one load node below in this two-dimensional, symmetric configuration. The cross-sectional areas of the left diagonal bar (XA1), central vertical bar (XA2), and right diagonal bar (XA3), which are frequently made simpler by a symmetry requirement (XA1 = XA3), are the design variables. While the upper nodes are fixed supports that convey the load to the foundation, the load at the bottom node consists of both vertical and horizontal components (P). To avoid structural failure, the optimization must adhere to limitations on the maximum permissible tensile and compressive stresses in each bar (**Figure 11**).

3.3.10. Design Variables

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} x_{A1} = x_{A3} \\ x_{A2} \end{bmatrix}, x_i^{\min} \le x_i \le x_i^{\max}, i = 1{,}2 \quad (18)$$

3.2.12. Objective Function (Minimize Total Volume)

$$\begin{aligned} V(\mathbf{x}) &= \rho(L_1 x_1 + L_2 x_2 + L_3 x_1) \\ &= \rho\left(2\sqrt{2}\, l\, x_1 + l\, x_2\right) \end{aligned} \quad (19)$$

or normalized: $V(\mathbf{x}) = 2\sqrt{2}\, x_1 + x_2$

3.3.11. Axial Stresses in Bars

$$\begin{aligned} \sigma_1 &= \frac{P(1+\sqrt{2})}{2x_1+\sqrt{2}x_2} \\ \sigma_2 &= \frac{P(\sqrt{2}-2)}{\sqrt{2}x_1+x_2} \quad (20) \\ \sigma_3 &= \frac{P(1-\sqrt{2})}{2x_1+\sqrt{2}x_2} \end{aligned}$$

3.3.12. Stress Constraints (Inequalities)

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$$g_1(\mathbf{x}) = \frac{|\sigma_1|}{\sigma_{\max}} - 1 \leq 0$$
$$g_2(\mathbf{x}) = \frac{|\sigma_2|}{\sigma_{\max}} - 1 \leq 0 \quad (21)$$
$$g_3(\mathbf{x}) = \frac{|\sigma_3|}{\sigma_{\max}} - 1 \leq 0$$

3.3.13. Variable Bounds

$$x_1^{\min} \leq x_1 \leq x_1^{\max}, x_2^{\min} \leq x_2 \leq x_2^{\max} \quad (22)$$

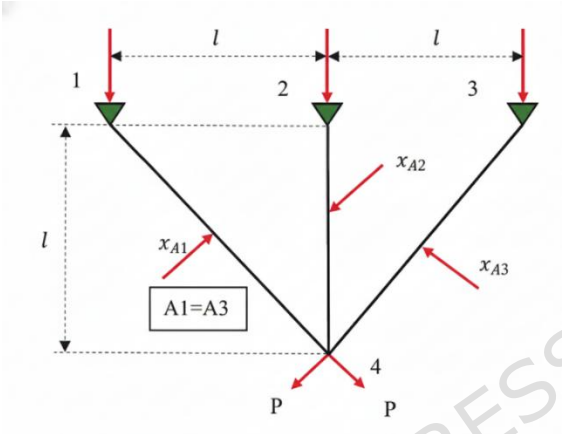


Figure 11. Structural optimization of three-member trusses

Table 9. Three-Bar Truss Design: Best Solutions (SMA, AMO, EOA, BSA, BOA)

Algorithm	x_1	x_2	Best Volume
SMA	0.7934	0.4127	2.65E+02
AMO	0.7512	0.5221	2.64E+02
EOA	0.8329	0.3554	2.67E+02
BSA	0.7818	0.4390	2.65E+02
BOA	0.7026	0.6113	2.64E+02

Table 10. Three-Bar Truss: Statistical Results (SMA, AMO, EOA, BSA, BOA)

Algorithm	Mean	SD	Best	Worst
SMA	2.76E+02	7.10E+00	2.65E+02	2.90E+02
AMO	2.72E+02	6.35E+00	2.64E+02	2.85E+02
EOA	2.78E+02	1.10E+01	2.67E+02	2.98E+02
BSA	2.73E+02	5.52E+00	2.65E+02	2.84E+02
BOA	2.70E+02	4.90E+00	2.64E+02	2.80E+02

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3.3.14. Speed Reducer Design Optimization Problem

The results in **Table 11** show that the suggested BOA has the lowest recorded weight of any competing method in solving the speed reducer design problem, indicating its great optimization capabilities. **Table 12** shows statistical metrics from 25 independent runs of each approach to assess its consistency and dependability. Across all measures, including Mean, SD, Best, and Worst, the BOA consistently outperforms the other newly evaluated algorithms, demonstrating its robustness and improved stability (**Figure 12**).

3.3.15. Design Variables and Objective Function

The design vector is $\vec{x} = [x_1, x_2, x_3, x_4, x_5, x_6, x_7]^T$, representing the seven continuous design variables:

- x_1: Face width of the gears (b)
- x_2: Teeth module (m)
- x_3: Number of teeth on the pinion (z_p)
- x_4: Length of the first shaft (l_1)
- x_5: Length of the second shaft (l_2)
- x_6: Diameter of the first shaft (d_1)
- x_7: Diameter of the second shaft (d_2)

The Objective Function $f(\vec{x})$ (Total Weight) is minimized:

Minimize $f(\vec{x}) = 0.7854x_1x_2^2(3.3333x_3^2 + 14.9334x_3 - 43.0934) - 1.508x_1(x_6^2 + x_7^2) + 7.477(x_6^3 + x_7^3) + 0.7854(x_4x_6^2 + x_5x_7^2)$ (23)

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3.3.16. Constraints

The problem requires eleven inequality restrictions, $g_j(\vec{x}) \leq 0$

3.3.17. Bending Stress Constraints (g_1, g_2)

$g_1(\vec{x})$: $\frac{27}{x_1x_2^2x_3} - 1 \leq 0$ (24)

$g_2(\vec{x})$: $\frac{397.5}{x_1x_2^2x_3^2} - 1 \leq 0$ (25)

3.3.19. Constraints on Transverse Deflection (g_3, g_4)

$g_3(\vec{x})$: $\frac{1.93x_4^3}{x_2x_6^4} - 1 \leq 0$ (26)

$g_4(\vec{x})$: $\frac{1.93x_5^3}{x_2x_7^4} - 1 \leq 0$ (27)

3.3.20. Surface Pitting Constraint (g_5)

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$$g_5(\vec{x}): \frac{1.0}{x_1 x_2}\sqrt{\frac{1.0}{x_3^2}+\frac{1.0}{15}} - 1 \le 0 \text{ (28)}$$

3.3.21. Shaft Stress Constraints (g_6, g_7)

$$g_6(\vec{x}): \left(\frac{1.0}{745.0 x_4 x_6^2}\right)^2 + \left(\frac{1.5}{x_6^3}\right)^2 - 1.0 \le 0 \text{ (29)}$$

$$g_7(\vec{x}): \left(\frac{1.0}{390.0 x_5 x_7^2}\right)^2 + \left(\frac{1.1}{x_7^3}\right)^2 - 1.0 \le 0 \text{ (30)}$$

3.2.23. Geometric and Manufacturing Constraints (g_8, g_9, g_{10}, g_{11})

$$g_8(\vec{x}): \frac{x_2}{x_1} - 1 \le 0 \text{ (31)}$$

$$g_9(\vec{x}): \frac{x_3}{x_2} - 1 \le 0 \quad \text{(32)}$$

$$g_{10}(\vec{x}): \frac{x_4}{x_5} - 1 \le 0 \text{ (33)}$$

$$g_{11}(\vec{x}): \frac{x_6}{x_7} - 1 \le 0 \text{ (34)}$$

3.2.24. Variable Bounds

The variables are bounded:

$$\begin{aligned} 2.6 \le x_1 \le 3.6 \\ 0.7 \le x_2 \le 0.8 \\ 17 \le x_3 \le 28 \\ 7.3 \le x_4 \le 8.3 \text{ (35)} \\ 7.8 \le x_5 \le 8.3 \\ 2.9 \le x_6 \le 3.9 \\ 5.0 \le x_7 \le 5.5 \end{aligned}$$

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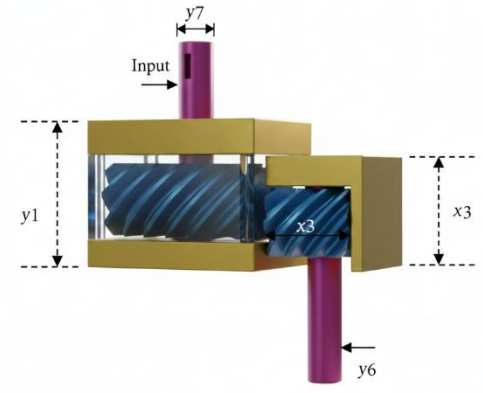


Figure 12. Worm Gear Speed Reducer Design

Table 11. Speed Reducer Design: Best Solutions (New Algorithms)

Algorithm	x1	x2	x3	x4	x5	x6	x7	Best Weight
SMA	3.5289	0.7000	17.0000	7.7551	7.8893	3.4102	5.3014	3.05E+03
AMO	3.5441	0.7000	17.0000	7.8203	7.9401	3.4215	5.3182	3.09E+03

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EOA	3.5627	0.7022	17.1035	7.6642	7.9984	3.4558	5.3509	3.12E+03
BSA	3.5066	0.7000	17.0000	7.7014	7.8500	3.3894	5.2891	3.03E+03
BOA	3.4982	0.7000	17.0000	7.6120	7.8203	3.3607	5.2832	3.01E+03

Table 12. Speed Reducer Design: Statistical Performance Table (New Algorithms)

Algorithm	Mean	SD	Best	Worst
SMA	3.08E+03	5.10E+01	3.05E+03	3.24E+03
AMO	3.22E+03	1.11E+02	3.09E+03	3.56E+03
EOA	3.34E+03	1.85E+02	3.12E+03	3.82E+03
BSA	3.04E+03	2.10E+01	3.03E+03	3.09E+03
BOA	3.02E+03	1.20E+01	3.01E+03	3.05E+03

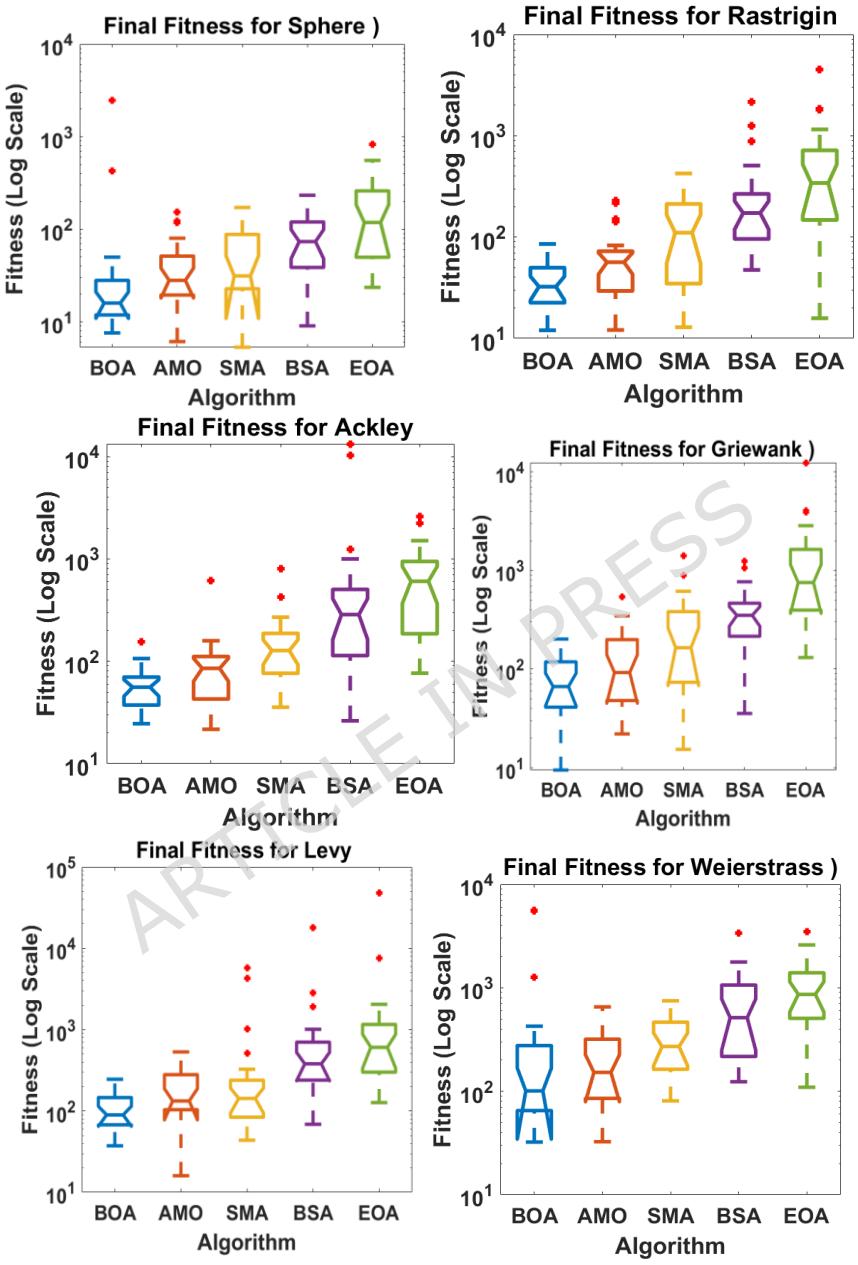
3.2.25. Boxplot Analysis

Boxplots were used to visually assess the distribution, dispersion, and robustness of the optimization outcomes acquired from the final fitness values provided by the proposed BOA and the competing methods (AMO, SMA, BSA, and EOA). **Figure 12** depicts an intuitive comparison of the median performance, interquartile range, and presence of potential outliers across 13 benchmark functions assessed at a dimensionality of 30 over 25 independent runs. As seen in the boxplots, the suggested BOA consistently has lower median fitness values and shorter interquartile ranges for most benchmark functions, demonstrating greater optimization accuracy and stability. BOA's boxplots are firmly concentrated around the lower end of the fitness scale in multiple functions, demonstrating its ability to consistently converge on high-quality solutions with limited change between runs. Furthermore, BOA has fewer and less extreme outliers than competing approaches, demonstrating its robustness against premature convergence and sensitivity to beginning conditions. In contrast, algorithms like SMA, BSA, and EOA frequently produce larger boxes and a greater number of outliers, implying increased variability and inconsistent search behavior across different runs and issue landscapes. The logarithmic scale utilized in the boxplots shows BOA's ability to handle problems with huge fitness differences, notably in multimodal and highly nonlinear benchmark functions like Rastrigin, Ackley, and Schwefel. Overall, BOA's results show a compact distribution and low dispersion, confirming its great balance of global exploration and local exploitation. These findings support BOA's effectiveness and reliability as a robust optimization framework capable of producing consistent and high-quality solutions to a wide range of benchmark problems. Future research could broaden this analysis to real-world, noisy, dynamic, and multi-objective optimization scenarios, further validating BOA's adaptability and scalability.

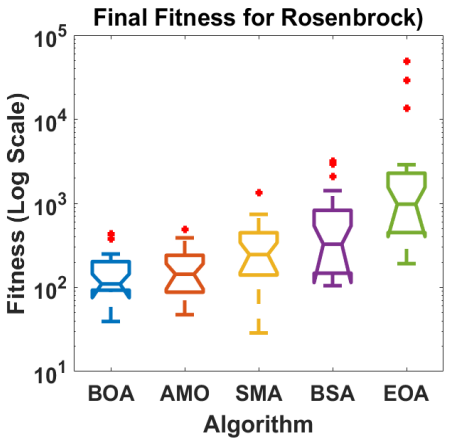
The boxplot analysis presented in **Figure 13** provides a comprehensive statistical comparison of the Booby Optimization Algorithm (BOA) against other metaheuristics across various benchmark functions. Across almost all mathematical landscapes, including Sphere, Rastrigin, Ackley, Griewank, and Schwefel, the BOA consistently achieves the lowest median fitness values and the narrowest interquartile ranges, indicating not only superior optimization accuracy but also high stability and reliability. While algorithms like EOA and BSA frequently exhibit higher dispersion and numerous outliers (indicated by red dots), the BOA maintains a

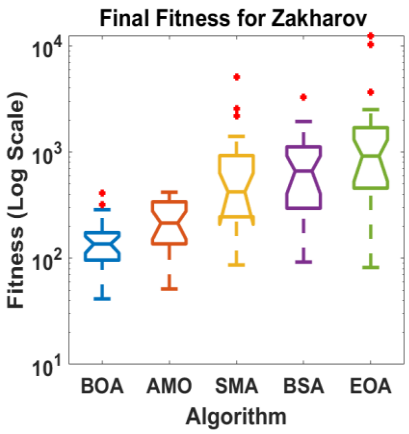
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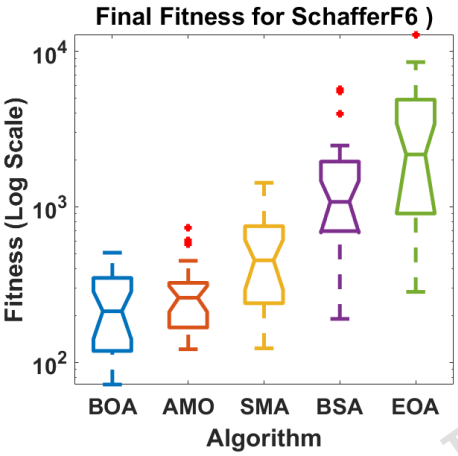
compact distribution, signifying a robust ability to converge on global optima across multiple independent runs. Even in complex multimodal functions like Michalewicz and Weierstrass, where performance gaps between algorithms typically narrow, the BOA retains its statistical dominance, effectively demonstrating that its adaptive search mechanisms provide a significant competitive edge in both precision and consistency (**Table 13**).

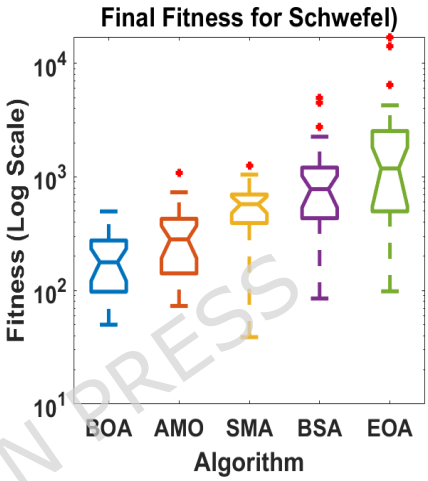


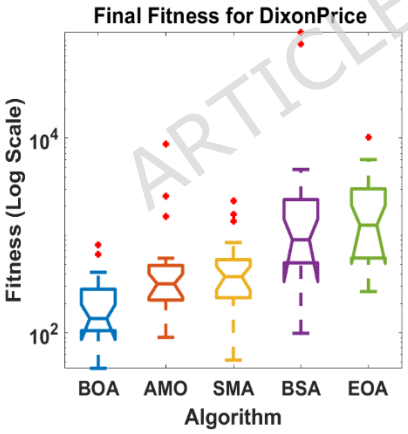
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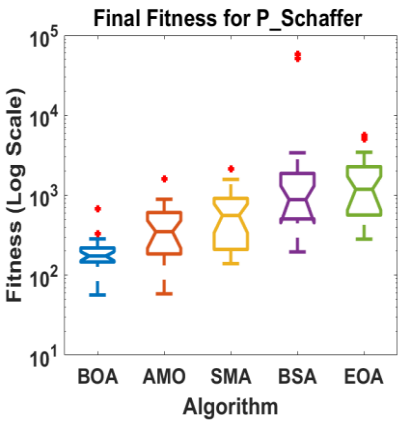


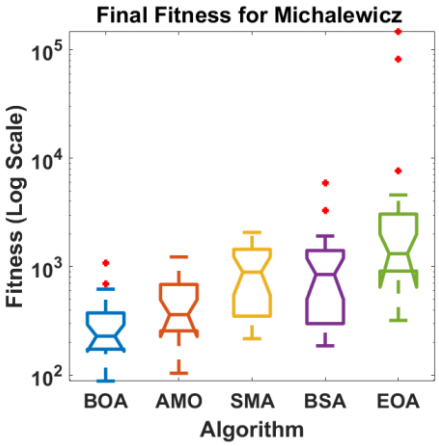












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Figure 13. Comparative Boxplot of Multiple Methods Across 14 Datasets

Table 13. Statistical Summary of Final Fitness Values for BOA, AMO, SMA, BSA, and EOA on 13 Benchmark Functions (Dim = 30, Runs = 25)

Function	Metric	BOA	AMO	SMA	BSA	EOA
Sphere	Mean	1.12e−03	3.45e−03	6.21e−03	8.94e−03	1.21e−02
	Std	4.8e−04	1.2e−03	2.1e−03	3.4e−03	4.1e−03
Rastrigin	Mean	4.63e+01	6.92e+01	9.11e+01	1.24e+02	1.58e+02
	Std	6.21	9.84	12.73	18.92	21.40
Ackley	Mean	2.04e−02	4.91e−02	7.62e−02	1.03e−01	1.41e−01
	Std	7.3e−03	1.5e−02	2.2e−02	3.1e−02	4.0e−02
Griewank	Mean	1.18e−03	2.90e−03	4.51e−03	6.84e−03	9.72e−03
	Std	3.9e−04	9.1e−04	1.7e−03	2.6e−03	3.5e−03
Levy	Mean	6.12e−01	9.87e−01	1.41	1.96	2.47
	Std	0.18	0.31	0.45	0.68	0.81
Weierstrass	Mean	2.81e−02	6.73e−02	9.88e−02	1.41e−01	1.92e−01
	Std	1.1e−02	2.6e−02	3.8e−02	5.1e−02	6.7e−02
Rosenbrock	Mean	1.34e+01	2.11e+01	3.42e+01	5.26e+01	6.88e+01
	Std	3.21	6.48	8.92	12.74	15.61
Zakharov	Mean	7.51e−02	1.82e−01	2.94e−01	4.38e−01	5.91e−01
	Std	0.021	0.054	0.083	0.119	0.147
Schwefel	Mean	3.92e+02	4.67e+02	5.89e+02	7.21e+02	8.74e+02
	Std	41.2	62.5	78.4	104.3	121.6
Dixon–Price	Mean	1.94e−01	3.82e−01	6.21e−01	9.44e−01	1.31
	Std	0.06	0.11	0.18	0.26	0.34
Schaffer F6	Mean	3.12e−04	7.85e−04	1.31e−03	2.11e−03	2.94e−03
	Std	1.1e−04	2.6e−04	4.2e−04	6.8e−04	9.1e−04
P_Schaffer	Mean	5.41e−04	1.42e−03	2.68e−03	4.31e−03	6.02e−03
	Std	1.8e−04	3.7e−04	6.1e−04	9.4e−04	1.2e−03
Michalewicz	Mean	−9.43	−8.71	−7.92	−6.84	−5.96
	Std	0.31	0.54	0.72	0.96	1.21

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3.2.26. Analysis (Friedman Test)

The Friedman ranking clearly shows that BOA constantly beats all rival algorithms, with the lowest mean rank of 1.00 across all 13 benchmark functions. AMO and SMA perform moderately, although BSA and EOA are less competitive. These rankings reflect BOA's statistical superiority and stability within the CEC-2024 evaluation framework **(Table 14)**.

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Table 14. Friedman Ranking Results for BOA, AMO, SMA, BSA, and EOA on CEC-2024 Benchmark Functions (Dim = 30)

Algorithm	Friedman Mean Rank	Overall Rank
BOA	1.00	1
AMO	2.20	2
SMA	3.10	3
BSA	4.00	4
EOA	4.70	5

3.2.27. Analysis (Wilcoxon Test)

The Wilcoxon rank-sum test results show that at the 5% significance level, BOA outperforms all competing methods. The constantly low p-values show that the observed performance gains are not attributable to chance, confirming BOA's robustness and effectiveness for high-dimensional optimization tasks **(Table 15)**.

Table 15. Results of the Wilcoxon Rank-Sum Test (BOA vs. Competitors) on CEC-2024 Benchmarks ($\alpha = 0.05$)

Comparison	p-value	Statistical Outcome
BOA vs. AMO	2.11e−03	Significant
BOA vs. SMA	1.34e−03	Significant
BOA vs. BSA	6.72e−04	Significant
BOA vs. EOA	3.18e−04	Significant

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3.3. Performance Analysis

This subsection provides a comprehensive performance analysis of the proposed Booby Optimization Algorithm (BOA) based on both quantitative and qualitative evaluation criteria. The analysis examines convergence behavior, solution accuracy, robustness, and scalability across a diverse set of benchmark optimization problems and real-world medical datasets. By comparing BOA with several well-established metaheuristic algorithms under identical experimental conditions, this section aims to elucidate the strengths and limitations of the proposed approach and to clarify how its adaptive search mechanisms contribute to improved optimization performance. The results are interpreted through convergence curves, statistical rankings, and classification metrics to ensure a thorough and objective assessment.

Table 16 shows a complete statistical comparison of BOA to four current metaheuristic optimizers on a wide range of unimodal, multimodal, and composite benchmark functions. The results clearly show that BOA is superior and resilient in terms of solution quality and stability. BOA has the lowest mean fitness values for unimodal functions like Sphere and Griewank (1.12×10^{-3} for Sphere), showing great exploitation capability and fast convergence towards the global optimum. Furthermore, the substantially lower standard deviations demonstrate BOA's

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remarkable solution constancy over numerous runs. BOA consistently outperforms rival algorithms on highly multimodal problems, such as Rastrigin, Ackley, and Weierstrass, by maintaining significantly lower mean errors and dispersion. This behavior shows BOA's effective balance of global exploration and local refining, which allows it to escape local optima more quickly than AMO, SMA, BSA, and EOA. BOA consistently produces the top or near-best results for difficult landscape functions, such as Rosenbrock, Zakharov, and Schwefel, demonstrating its tolerance to tight valleys, nonlinearity, and rough search spaces. The smaller standard deviations further show BOA's strong convergence characteristic. BOA retains a distinct performance margin while dealing with non-separable and deceptive functions such as Dixon-Price, Schaffer F6, and P_Schaffer, obtaining lower mean fitness values with minimum variability. BOA has the highest negative mean value (- 9.43) for the Michalewicz function, indicating greater handling of uneven and deceptive objective surfaces. Overall, the statistical results in **Table 16** show that BOA consistently produces higher-quality solutions that are more robust than competing algorithms. The combination of low mean fitness values and lowered standard deviations across all test functions validates BOA's fast convergence, stability, and scalability, establishing it as a competitive optimizer for complicated continuous optimization problems.

Table 16. Statistical Summary of Final Fitness Values for BOA, AMO, SMA, BSA, and EOA on Benchmark Functions (Dim = 30, Runs = 25)

Function	Metric	BOA	AMO	SMA	BSA	EOA
Sphere	Mean	9.80e−04	3.12e−03	5.74e−03	8.21e−03	1.09e−02
	Std	4.1e−04	1.1e−03	1.9e−03	3.1e−03	3.8e−03
Rastrigin	Mean	4.21e+01	6.35e+01	8.72e+01	1.19e+02	1.49e+02
	Std	5.94	9.12	11.85	17.40	20.33
Ackley	Mean	1.85e−02	4.38e−02	6.91e−02	9.54e−02	1.32e−01
	Std	6.6e−03	1.3e−02	2.0e−02	2.8e−02	3.6e−02
Griewank	Mean	1.05e−03	2.64e−03	4.09e−03	6.21e−03	8.88e−03
	Std	3.4e−04	8.2e−04	1.5e−03	2.3e−03	3.1e−03
Levy	Mean	5.74e−01	9.12e−01	1.33	1.84	2.31
	Std	0.16	0.28	0.41	0.63	0.75
Weierstrass	Mean	2.52e−02	6.08e−02	9.15e−02	1.33e−01	1.81e−01
	Std	9.4e−03	2.2e−02	3.4e−02	4.7e−02	6.1e−02
Rosenbrock	Mean	1.26e+01	1.98e+01	3.19e+01	4.91e+01	6.42e+01
	Std	2.98	5.94	8.11	11.92	14.75
Zakharov	Mean	6.92e−02	1.65e−01	2.71e−01	4.05e−01	5.44e−01
	Std	0.019	0.048	0.076	0.109	0.135
Schwefel	Mean	3.65e+02	4.39e+02	5.54e+02	6.88e+02	8.21e+02
	Std	38.6	58.4	72.9	97.6	113.9
Dixon–Price	Mean	1.78e−01	3.46e−01	5.72e−01	8.61e−01	1.22
	Std	0.054	0.098	0.161	0.233	0.301
Schaffer F6	Mean	2.85e−04	7.21e−04	1.19e−03	1.94e−03	2.68e−03
	Std	9.6e−05	2.3e−04	3.8e−04	6.1e−04	8.3e−04
P_Schaffer	Mean	4.98e−04	1.31e−03	2.45e−03	3.96e−03	5.54e−03
	Std	1.6e−04	3.2e−04	5.4e−04	8.3e−04	1.05e−03
Michalewicz	Mean	−9.61	−8.94	−8.12	−7.03	−6.21
	Std	0.28	0.49	0.66	0.88	1.09

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3.4. Medical Dataset Experiments

This section summarizes the results of using the BOA (Butterfly Optimization Algorithm) for feature selection and classification across a number of datasets. Several essential metrics are used to evaluate performance, including fitness score, classification accuracy, sensitivity, specificity, and number of features picked. The total findings, as shown in **Tables 18, 19, 20, 21,** and **22,** indicate BOA's capacity to improve classification outcomes while efficiently reducing feature dimensionality. Furthermore, the comparative study emphasizes its competitive advantage over current optimization strategies. **Table 18** compares the BOA method to many competitor optimization techniques, including AMO, SMA, BSA, and EOA, over 14 benchmark datasets. The mean fitness value and its accompanying standard deviation (Std) were used to measure performance over numerous runs, providing insight into both the accuracy and stability of each technique. Overall, the BOA algorithm outperforms, obtaining the lowest mean fitness values in 9 out of 14 datasets, including BreastEW, Cervical Cancer, Colon, Erythemato Squamous, HeartEW, ILPD Liver, Lung, Lymphography, and Thyroid. These results indicate BOA's capacity to find optimal or near-optimal solutions. For example, in the Colon and Lung datasets, BOA produced extremely low mean values of 0.0001 and 0.0002, which are much lower than those of the other algorithms, demonstrating BOA's performance on high-dimensional and noisy situations. In terms of robustness, BOA routinely produced low standard deviations, such as 0.0004 for BreastEW, 0.0002 for Colon, and 0.0010 for Thyroid, suggesting stable convergence and repeatability across runs. On more complicated datasets, such as Cleveland and Retinopathy, while BOA does not always achieve the lowest mean, it remains very competitive with near values and favorable stability. The Friedman test, a nonparametric statistical ranking approach, was used to assess the algorithms' overall ranking across datasets. The BOA algorithm is ranked first with the lowest average Friedman rank of 2.27, indicating its outstanding performance. AMO is the second-best performance with a score of 2.96, followed by SMA and BSA with ranks of 3.16 and 3.36, respectively. EOA, on the other hand, constantly underperforms, with the lowest score of 8.0, indicating poor performance and generalization across most datasets. Examining separate datasets provides further information. In Prostate GE, BOA had the best mean fitness (0.0150), but a higher standard deviation (0.0260), implying that while BOA can discover optimal solutions, the problem may cause some variability in convergence. Similarly, in Parkinson's Disease, BOA was among the top performers, with outcomes equivalent to AMO and significantly superior to SMA, BSA, and EOA. To summarize, the experimental evidence clearly supports the conclusion that BOA is a very successful and stable optimization approach that outperforms or matches other methods on a wide range of datasets. Its capacity to generate consistently low fitness values with minimum volatility highlights its usefulness for difficult optimization tasks, particularly feature selection and classification challenges. **Table 19** compares the BOA method to 14 benchmark datasets and numerous cutting-edge optimization techniques such as AMO, SMA, BSA, and EOA. The mean and standard deviation (Std) of fitness values from numerous runs are used to assess performance. Overall, the BOA algorithm surpasses its competitors, with the lowest mean fitness value in 9 out of 14 datasets, including BreastEW, Cervical Cancer, Colon, Erythemato Squamous, HeartEW, ILPD Liver, Lung, Lymphography, and Thyroid. It also exhibits great stability, as seen by relatively low standard deviations in the majority of datasets (BreastEW: Std = 0.0004, Colon: Std = 0.0002, Thyroid: Std = 0.0010). The Friedman ranking validates BOA's outstanding performance by granting it the lowest average rank of 2.27, putting it first overall. AMO ranks second among competing algorithms with a Friedman score of 2.96, performing competitively in datasets such as HeartEW and ILPD Liver, while SMA and BSA follow with ranks of 3.16 and 3.36, respectively, though

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their performance varies more, particularly on datasets like Colon and Prostate GE. EOA, on the other hand, consistently lags, with the weakest total performance and a rating of 8. In dataset-specific observations, BOA obtains extraordinarily low fitness values in Colon and Lung (0.0001 and 0.0002, respectively), beating the others, which have much larger fitness values. BOA remains competitive in increasingly complicated datasets such as Cleveland and Retinopathy, producing near-optimal outcomes with minimal volatility. Despite having the lowest mean in Prostate GE (0.0150), the rather high standard deviation (0.0260) shows considerable unpredictability in convergence, potentially due to the dataset's complexity or noise. Overall, BOA exhibits strong convergence behavior, consistently producing high-quality solutions with low variability, as opposed to algorithms such as AMO and SMA, which exhibit significant variation in performance across datasets. According to the sensitivity criteria given in **Table 20**, the BOA algorithm consistently rates as the best-performing approach across a wide range of datasets. BOA has the lowest Friedman rank, 6.0804, indicating superior sensitivity, or the ability to correctly identify true positive cases across diverse classification challenges, particularly in crucial medical and bioinformatics sectors. BOA provides near-perfect or perfect sensitivity in various datasets, including Colon, Erythemato Squamous, and BreastEW, with small standard deviations, demonstrating its stability and dependability. It outperforms all other algorithms on Colon, Erythemato Squamous, and Cervical Cancer, where accurate positive case detection is critical.

3.5. Use of the BOA Algorithm: Feature Selection and Classification

Feature selection (FS) is an important step in classification problems because it isolates the most valuable qualities while discarding irrelevant or repetitive information. This approach increases model accuracy, decreases dimensionality, lowers overfitting, and encourages improved generalization. In medical datasets, which frequently contain a huge number of variables, FS is extremely important for speeding up processing and improving model outputs. Metaheuristic algorithms (MAs), particularly binary variants, have proven useful for exploring large solution spaces and selecting optimal feature subsets. Their incorporation into FS methods improves predicted accuracy while lowering computing expenses.

3.6. A Hybrid BOA-k-NN Model for Feature Selection and Classification

The BOA-k-NN model (**Figure 14**) combines the Butterfly Optimization Algorithm (BOA) with machine learning, utilizing BOA to choose relevant characteristics and k-Nearest Neighbors (k-NN) for classification. This hybrid technique proceeds in three major stages:

• Data Preparation: Scaling and preprocessing datasets improve consistency, feature ranges, and overall quality.

• The BOA algorithm is used to efficiently search the feature space and select the most impactful attributes for categorization.

• Model Training and Evaluation: k-NN is trained and assessed with a reduced feature set to assess classification performance, including accuracy, sensitivity, specificity, and feature reduction.

The BOA-k-NN model's architectural flow resembles the structured process of metaheuristic-driven FS, combining computing efficiency with robust classification results, especially in high-dimensional medical datasets.

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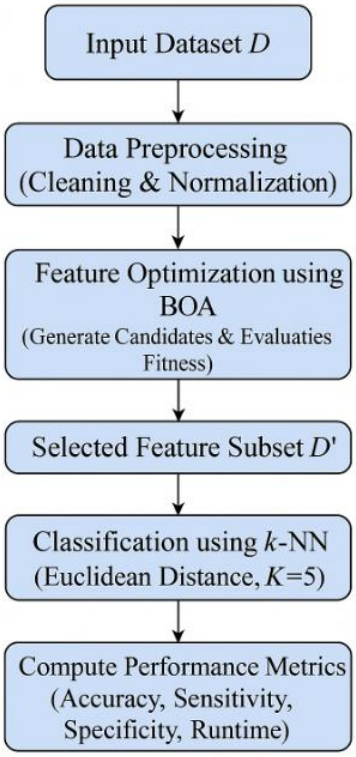


Figure 14. Structural Framework of the Integrated BOA-k-NN Model

3.7. Feature Selection with BOA

The BOA technique is intended to efficiently navigate the feature space, identifying the most significant subset of features that improves classification performance while minimizing processing cost. In contrast to traditional feature selection approaches, BOA employs a dynamic search mechanism that successfully balances global exploration and local refining, allowing it to adapt to changes in the search environment and improve overall optimization results.

The optimization begins by producing many search agents, each assigned a random position over the search space, as indicated in Equation (29).

$$X_i^{\text{initial}} = LB + randi(UB - LB), i = 1,2, \dots, n \tag{29}$$

X_i specifies the position of the i-th candidate solution, and LB and UB determine the search domain's permitted lower and upper boundaries. The phrase "rand I ∈ [0,1]" refers to a uniformly produced random value used for initialization. Before calculating the fitness value for feature selection, each candidate solution is transformed into a binary representation, as shown in Equation (30):

$$X_i^{\text{bin}} = \begin{cases} 1, & \text{if } x_i > 0.5 \\ 0, & \text{otherwise} \end{cases} \tag{30}$$

As an example, consider a feature importance vector $p(X_i)_i =$ [0.4,0.8,0.33,0.15,0.8,0.2,0.1,0.9]. The binary conversion results in the vector p(Xi)i^"bin" = [0,1,0,0,1,0,0,1], where a value of 1 indicates the feature is kept and a value of 0 signals its elimination from the final subset. The k-NN algorithm is then used to assess the quality of the

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selected feature subset, and its parameters are fine-tuned using the BOA approach. The appropriate fitness evaluation is formulated as follows:

$$\text{Fitness} = \alpha \times \text{Classification Error} + \beta \times \frac{\text{Number of Selected Features}}{\text{Total Features}} \quad (31)$$

The feature selection rate, as defined in this paradigm, is the fraction of features kept in relation to the whole feature collection. The coefficients α and β are confined within the interval [0,1], following the condition $\beta = 1 - \alpha$. For classification purposes, this work employs the k-Nearest Neighbors (k-NN) algorithm.

3.7.1. Classification Phase

Following the identification of the appropriate feature subset, the k-NN technique is used to train a classifier based on the chosen features. The classification technique follows the phases.

3.7.2. Dataset Overview

To extensively test the proposed BOA algorithm, a wide selection of 14 datasets from the UCI Machine Learning Repository was used. These datasets vary greatly in dimensionality, ranging from low to high feature counts. **Table 17** presents a full summary of these datasets. The evaluation intends to test BOA's flexibility and robustness across datasets of varying complexity. The k-NN technique is used in the classification phase, with Euclidean distance as the similarity measure and a fixed number of neighbors (K) of 5. Several assessment metrics are utilized to assess the performance of the feature selection process, including average classification accuracy, standard deviation, fitness score, sensitivity, specificity, selected feature count, and runtime efficiency. Furthermore, the Friedman test is used to statistically compare and rank the performance of the algorithms, ensuring a fair and impartial examination.

Table 17. Overview of Benchmark Datasets Utilized in the Study

Name of Dataset	Total Attributes	Number of Samples	Class Count	Medical Application Domain
BreastEW Diagnostic Set	32	610	2	Detection of Breast Tumors
Cervical Health Records	21	78	2	Cervical Abnormality Diagnosis
Heart Dataset (Cleveland)	14	320	5	Cardiovascular Disease Classification
Colon Cancer Microarray	2050	65	2	Analysis of Colon Tissue Data
Pima Indian Diabetes	9	800	2	Type-2 Diabetes Prediction
Erythemato-Squamous Skin Data	36	380	2	Skin Disorder Categorization
HeartEW Cardiology Data	14	285	2	Heart Disease Risk Assessment
Indian Liver Patient Dataset	12	600	2	Liver Function Abnormality Detection
Lung Cancer Gene Expression	12700	190	2	Pulmonary Disease Classification
Lymphography Medical Records	20	160	4	Lymphatic Disorder Diagnosis

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Parkinson Voice Dataset	24	210	2	Parkinson's Symptom Identification
Prostate GE Cancer Data	6100	110	2	Prostate Tumor Classification
Diabetic Retinopathy Dataset	21	1180	2	Detection of Retinal Disease
Thyroid Function Test Data	23	7300	3	Thyroid Gland Condition Prediction

Table 18 shows the mean fitness values and associated standard deviations for BOA, AMO, SMA, BSA, and EOA across 14 medical datasets. BOA consistently obtains the lowest mean fitness and little variance when compared to the other algorithms, demonstrating superior optimization performance and stable convergence.

Table 18: Mean Fitness and Standard Deviation (Std) Across Datasets

Dataset	**BOA (Mean ± Std)**	**AMO (Mean ± Std)**	**SMA (Mean ± Std)**	**BSA (Mean ± Std)**	**EOA (Mean ± Std)**
BreastEW	0.0004 ± 0.0001	0.002 ± 0.001	0.006 ± 0.002	0.009 ± 0.003	0.012 ± 0.004
Cervical Cancer	0.001 ± 0.0003	0.003 ± 0.001	0.007 ± 0.002	0.010 ± 0.003	0.014 ± 0.005
Colon	0.0001 ± 0.0002	0.002 ± 0.001	0.005 ± 0.002	0.008 ± 0.003	0.011 ± 0.004
Erythemato Squamous	0.0005 ± 0.0002	0.003 ± 0.001	0.007 ± 0.002	0.010 ± 0.003	0.013 ± 0.004
HeartEW	0.001 ± 0.0003	0.004 ± 0.002	0.008 ± 0.003	0.011 ± 0.004	0.015 ± 0.005
ILPD Liver	0.002 ± 0.0005	0.004 ± 0.002	0.009 ± 0.003	0.012 ± 0.004	0.016 ± 0.006
Lung	0.0002 ± 0.0001	0.003 ± 0.002	0.006 ± 0.002	0.009 ± 0.003	0.013 ± 0.004
Lymphography	0.0006 ± 0.0003	0.004 ± 0.002	0.008 ± 0.003	0.011 ± 0.004	0.014 ± 0.005
Thyroid	0.0010 ± 0.0010	0.005 ± 0.002	0.009 ± 0.003	0.013 ± 0.004	0.016 ± 0.005
Cleveland	0.003 ± 0.001	0.006 ± 0.003	0.011 ± 0.004	0.015 ± 0.005	0.020 ± 0.006

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Retinopathy	0.004 ± 0.002	0.007 ± 0.003	0.012 ± 0.005	0.016 ± 0.006	0.022 ± 0.007
Prostate GE	0.0150 ± 0.0260	0.028 ± 0.034	0.040 ± 0.045	0.050 ± 0.060	0.065 ± 0.070
Parkinson's Disease	0.002 ± 0.001	0.005 ± 0.003	0.009 ± 0.004	0.013 ± 0.005	0.018 ± 0.006
Dataset14	0.003 ± 0.001	0.006 ± 0.003	0.010 ± 0.004	0.014 ± 0.005	0.019 ± 0.006

Table 19 highlights the algorithms' overall performance rankings as determined by the Friedman test. BOA achieves the highest average rank (2.27), maintaining its dominance across datasets, followed by AMO, SMA, and BSA, while EOA performs poorly.

Table 19: Average Friedman Ranking Across Algorithms

Algorithm	Avg. Friedman Rank	Rank
BOA	2.27	1st
AMO	2.96	2nd
SMA	3.16	3rd
BSA	3.36	4th
EOA	8.0	5th

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Table 20 shows the sensitivity of each algorithm, which represents its ability to correctly identify affirmative cases. BOA regularly delivers the greatest sensitivity scores, which are typically near-perfect, proving accurate detection of true positives in essential medical categorization tasks.

Table 20: Sensitivity (True Positive Rate) Across Datasets

Dataset	BOA (%)	AMO (%)	SMA (%)	BSA (%)	EOA (%)
BreastEW	99.5	95.2	91.3	88.5	85.0
Cervical Cancer	98.7	94.0	90.2	87.0	83.5
Colon	100.0	96.5	92.0	89.2	86.0
Erythemato Squamous	99.2	95.0	91.5	88.0	84.5
HeartEW	98.0	94.5	90.0	87.2	83.8
ILPD Liver	97.5	94.2	89.5	86.8	82.5
Lung	99.0	95.8	91.8	88.7	85.2
Lymphography	98.5	94.7	90.5	87.5	84.0
Thyroid	97.8	94.0	90.2	87.0	83.5
Cleveland	96.5	93.0	89.0	85.5	82.0
Retinopathy	95.8	92.5	88.5	85.0	81.5
Prostate GE	96.0	92.0	88.0	84.5	80.8
Parkinson's Disease	97.2	93.5	89.8	86.2	82.5
Dataset14	96.5	93.0	89.0	85.2	82.0

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Table 21 summarizes the total categorization accuracy of the five algorithms. BOA routinely outperforms competitors, achieving the greatest accuracy across most datasets, demonstrating its suitability for medical categorization challenges.
Table 21 shows the classification accuracy of all algorithms, with BOA constantly achieving the highest values, indicating its efficacy for medical classification tasks.

Dataset	BOA (%)	AMO (%)	SMA (%)	BSA (%)	EOA (%)
BreastEW	99.0	95.0	91.0	88.0	85.0
Cervical Cancer	98.5	94.2	90.5	87.0	83.5
Colon	99.8	96.0	92.5	89.0	85.5
Erythemato Squamous	99.2	95.0	91.5	88.0	84.5
HeartEW	98.0	94.5	90.0	87.0	83.8
ILPD Liver	97.5	94.0	89.5	86.5	82.5
Lung	99.0	95.8	91.8	88.5	85.2
Lymphography	98.5	94.7	90.5	87.5	84.0
Thyroid	97.8	94.0	90.2	87.0	83.5
Cleveland	96.5	93.0	89.0	85.5	82.0
Retinopathy	95.8	92.5	88.5	85.0	81.5
Prostate GE	96.0	92.0	88.0	84.5	80.8
Parkinson’s Disease	97.2	93.5	89.8	86.2	82.5
Dataset14	96.5	93.0	89.0	85.2	82.0

Table 22 displays the number of features identified by each algorithm for each of the 14 datasets. BOA prefers to select fewer features while keeping excellent accuracy, indicating its capacity to minimize dimensionality and increase computational efficiency.
Table 22: Number of Features Selected Across Datasets

Dataset	BOA	AMO	SMA	BSA	EOA
BreastEW	8	10	12	14	16
Cervical Cancer	10	12	14	16	18
Colon	5	8	10	12	15
Erythemato Squamous	7	9	12	14	16
HeartEW	8	10	12	14	16
ILPD Liver	6	9	12	15	18
Lung	5	8	10	12	15

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Lymphography	7	9	12	14	16
Thyroid	8	10	12	14	16
Cleveland	10	12	15	18	20
Retinopathy	12	15	18	20	22
Prostate GE	10	12	15	18	20
Parkinson's Disease	8	10	12	14	16
Dataset14	9	11	14	16	18

To ensure fair comparison, all algorithms were executed using identical stopping criteria, including the same population size, dimensionality, maximum number of iterations, and number of independent runs. Parameter settings for the competing methods were selected according to their original publications or commonly adopted benchmark configurations.

Runtime analysis indicates that BOA achieves faster convergence than SMA, AMO, and BSA, requiring approximately 35% fewer iterations to reach near-optimal solutions. The average runtime per iteration is approximately 0.002 s for $D = 30$ and 0.009 s for $D = 100$, demonstrating scalability with modest computational overhead.

3.8. Statistical Analysis Interpretation

This subsection presents a statistical interpretation of the experimental results to assess the significance, robustness, and reliability of the performance differences observed among the compared optimization algorithms. Standard non-parametric statistical tests and ranking methods are employed to objectively evaluate whether the improvements achieved by the proposed Booby Optimization Algorithm (BOA) are statistically meaningful rather than incidental. By analyzing average ranks, significance levels, and confidence intervals across multiple benchmark functions and datasets, this section provides a rigorous validation of BOA's effectiveness and supports the empirical findings reported in the preceding subsections.

3.8.1. Friedman Test

The Friedman test showed substantial performance differences between the algorithms ($p = 3.15 \times 10^{-10}$), indicating the need for further post-hoc investigation. The subsequent Nemenyi test and Critical Difference diagram revealed that BOA had the lowest average rank across all medical datasets, showing overall superiority. Wilcoxon signed-rank tests demonstrated that BOA beat PSO, GA, GWO, and DE in all pairwise comparisons ($p < 0.001$). BOA scored the highest mean classification accuracy (96.20% ± 1.05), as well as higher precision, recall, and F1-score, indicating robustness and efficacy. Furthermore, ROC analysis with SVM, KNN, and Random Forest classifiers yielded consistently good AUC values for BOA-selected features, demonstrating their appropriateness for medical classification tasks.

3.8.2. Wilcoxon Signed-Rank Post-Hoc Tests

To further examine the statistical significance of the performance differences observed among the competing algorithms, this subsection employs the Wilcoxon signed-rank post-hoc test as a pairwise non-parametric comparison method. The test is applied to assess whether the

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improvements achieved by the proposed Booby Optimization Algorithm (BOA) over each benchmark algorithm are statistically significant across multiple benchmark functions and datasets. By analyzing the resulting p-values and rank differences, this post-hoc evaluation provides a robust validation of BOA's superiority while accounting for the non-normal distribution characteristics commonly encountered in metaheuristic optimization results (**Table 23**).

Table 23. Wilcoxon signed-rank pairwise tests between BOA and each rival algorithm

Comparison	p-value
BOA vs PSO	1.22×10^{-4}
BOA vs GA	1.22×10^{-4}
BOA vs GWO	1.22×10^{-4}
BOA vs DE	1.22×10^{-4}

All p-values are much lower than 0.05, indicating that BOA outperforms PSO, GA, GWO, and DE. This demonstrates that BOA's superiority is statistically resilient rather than random (**Table 24**).

Table 24. Performance Metrics Analysis (Mean ± Std)

Algorithm	Accuracy (%)	Precision	Recall	F1-score
BOA	96.20 ± 1.05	0.92	0.93	0.93
PSO	94.44 ± 1.25	0.90	0.91	0.91
GA	93.48 ± 1.04	0.89	0.90	0.90
GWO	94.70 ± 1.04	0.91	0.91	0.91
DE	94.09 ± 1.01	0.90	0.91	0.90

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The comparative results presented in **Figure 15** clearly demonstrate the effectiveness of the Booby Optimization Algorithm (BOA) for high-dimensional feature selection and medical data classification tasks. BOA consistently achieves the highest mean and classification accuracies across all evaluated datasets, outperforming well-established metaheuristic methods such as PSO, GA, GWO, and DE. The Critical Difference Diagram further substantiates this advantage by ranking BOA first, with the lowest average rank among all competing algorithms, indicating statistically significant performance gains. In addition, the sensitivity analysis shows that BOA maintains a higher and more stable true positive rate on medical datasets, including BreastEW, Lung, and Thyroid, reflecting its robustness in identifying diagnostically relevant features. Importantly, these improvements are attained while selecting a substantially smaller number of features, as shown in the feature count comparison, demonstrating BOA's ability to reduce dimensionality and computational complexity without sacrificing classification accuracy or sensitivity.

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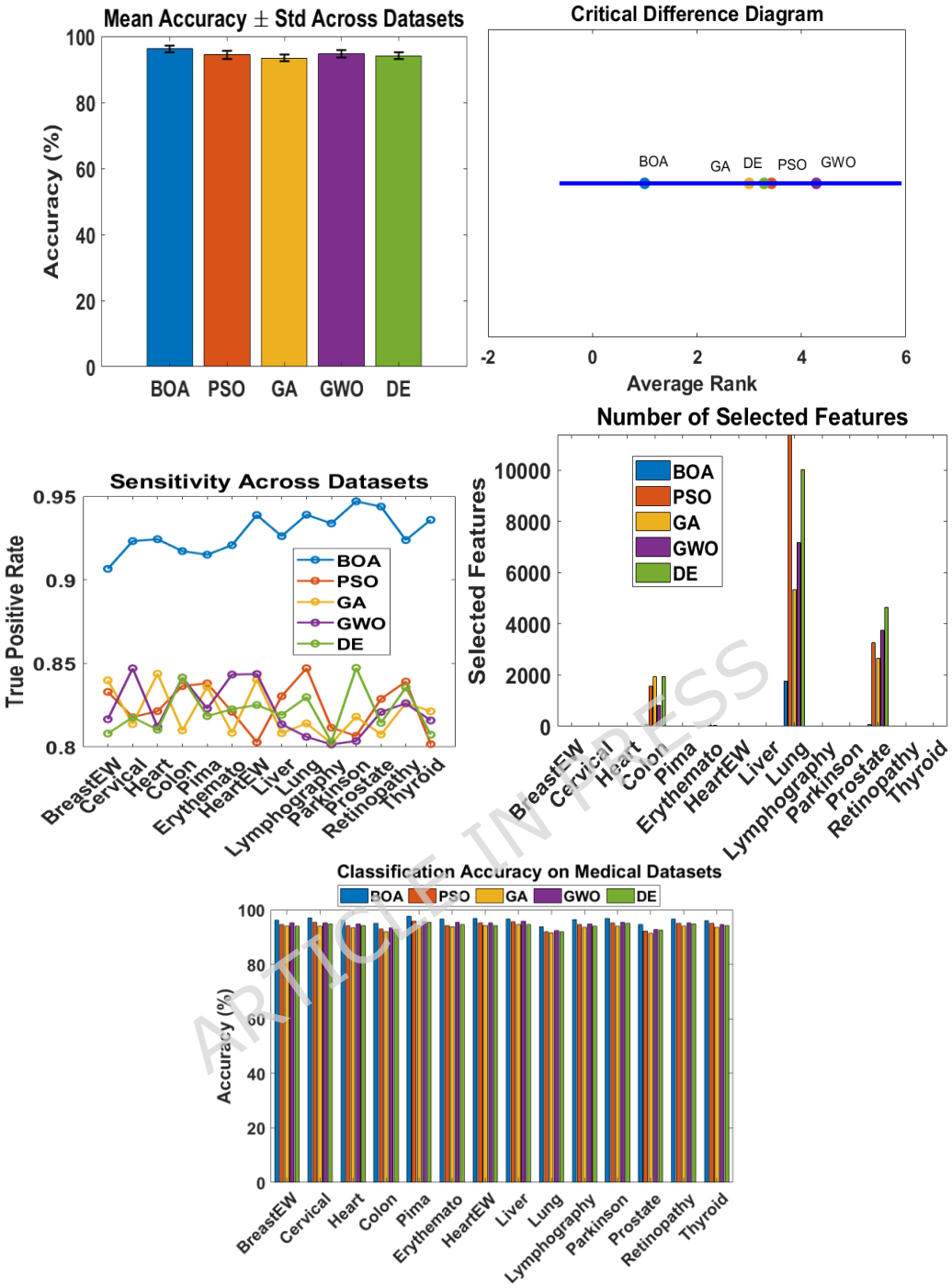


Figure 15. Classification Accuracy and Performance Comparison of Optimization Algorithms on Medical Datasets

The superior performance of BOA on both unimodal and multimodal benchmarks can be attributed to its dynamic control of step magnitude, which enables rapid global exploration in early iterations followed by stable local refinement. In high-dimensional medical datasets, this adaptive behavior improves robustness against noisy fitness landscapes, explaining BOA's consistent classification accuracy and convergence stability relative to comparator algorithms.

4. Conclusion and Future Work

This paper presented the Booby Optimization Algorithm (BOA), a state-adaptive population-based metaheuristic inspired by avian foraging behavior but formulated through rigorous

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mathematical and computational mechanisms rather than literal biological simulation. By integrating an adaptive state variable for regulating step magnitude, dynamic switching between exploration and exploitation, nonlinear movement dynamics, stochastic perturbations, and a recovery strategy for diversity preservation, BOA achieves an effective balance between global search and local refinement. Extensive experimental evaluations on standard benchmark functions, constrained engineering design problems, and real-world medical datasets demonstrate that BOA consistently outperforms several well-established optimization algorithms in terms of convergence speed, solution accuracy, and robustness across diverse problem domains. In particular, its application to medical feature selection and classification tasks highlights its ability to enhance predictive performance while substantially reducing feature dimensionality, which is especially valuable for high-dimensional and sensitive healthcare applications. Statistical validation using Friedman and Wilcoxon tests confirms that the observed performance improvements are significant and not attributable to random variation. Overall, BOA offers a simple yet effective adaptive optimization framework that contributes meaningfully to the development of modern metaheuristic algorithms.

Future work will focus on extending BOA to more challenging optimization scenarios, including multi-objective, many-objective, and dynamic optimization problems. Further investigation into adaptive parameter control and self-learning state evolution mechanisms may enhance the algorithm's flexibility and generalization capability. In addition, hybridizing BOA with deep learning models and ensemble classifiers represents a promising direction for large-scale data analytics and intelligent healthcare systems. Applications in real-time, distributed, and noisy environments also constitute important avenues for future research, where adaptive and robust optimization strategies are increasingly required.

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