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REVIEW

A Comprehensive Review of Barnacles Mating Optimizer: Theoretical Foundation, Variants, Applications, and Future Research Directions

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ABSTRACT: As real-world optimization problems become more complex, the development of sophisticated and robust algorithms has become essential. Consequently, researchers are focusing on advanced optimization methods that efficiently explore the feasible solution space. This involves designing new high-performance algorithms or enhancing existing meta-heuristic methods by integrating advanced evolutionary strategies. Barnacles Mating Optimizer (BMO) is an evolutionary-based meta-heuristic algorithm inspired by the mating behavior of barnacles, incorporating Hardy–Weinberg principles and the sperm-cast mechanism. Introduced in 2020, BMO has attracted significant attention and has been successfully applied across diverse fields due to its simple design, ease of implementation, high flexibility, and efficient convergence. Therefore, this review provides an overview and synthesis of studies employing BMO. It begins with an introduction to BMO, describing its natural inspiration and optimization framework, followed by a discussion of its core operational procedures and theoretical foundations. The paper then presents a comprehensive analysis of recent BMO variants, systematically categorizing them into modified, multi-objective, and hybrid versions. It also examines BMO's diverse real-world applications, including power and control engineering, classification, image processing, wireless networks, forecasting, and signal processing. In addition, an updated performance evaluation of BMO is provided, comparing its effectiveness against recently published algorithms using the CEC2005 benchmark suite. Key strengths of BMO are highlighted, including its ability to balance exploration and exploitation, adaptability across problem domains, and its potential for hybridization with other optimization algorithms. Finally, potential enhancements and future research directions are outlined, including multi-objective variants, integration with deep learning, and parallel or distributed implementations.

KEYWORDS: Evolutionary algorithms; barnacles mating optimizer; meta-heuristics; engineering optimization; computational intelligence

1 Introduction

Optimization challenges are widespread across domains such as industry, transportation, robotics, telecommunications, and technology. Many of these challenges are nonlinear, high-dimensional, and often constrained by specific requirements [1]. An increase in the number of decision variables substantially increases the computational complexity of engineering problems. Traditional optimization techniques often become trapped in local optima when confronted with such large-scale challenges [2]. Classical algorithms, such as the simplex method and hill-climbing, are deterministic strategies that perform well for simpler tasks.

However, these conventional approaches rely on conditions such as continuity, differentiability, and linearity, which limit their applicability to more complex engineering problems [3].

Many engineering optimization problems encountered in practice involve complex objective functions with numerous closely spaced high-value local optima. Deterministic algorithms often struggle to escape these local optima, reducing the likelihood of finding the global best solution [4]. As engineering optimization problems become increasingly complex, there is a growing need for optimization methods to address these challenges effectively. Meta-heuristic techniques have attracted considerable interest due to their computational efficiency and capacity to deliver accurate, optimized solutions for a variety of complex real-world problems [5].

Meta-heuristic algorithms utilize a range of operators and adaptive strategies, but their effectiveness depends on satisfying two fundamental optimization principles: exploration and exploitation [6]. Exploration involves systematically scanning the search space to identify high-potential regions, while exploitation focuses on optimizing candidate solutions within these identified areas. Achieving a balanced equilibrium between these two mechanisms is crucial for improving solution quality, accelerating convergence, and enhancing the overall performance of the algorithm in complex problem spaces [7].

Inspired by natural and biological processes, meta-heuristic algorithms employ randomization to tackle complex optimization problems. Based on their foundational principles, these methods can be grouped into six main categories [8,9], including human-based, evolution-based, physics-based, mathematics-based, swarm-based, and chemistry-based meta-heuristic algorithms, as shown in Fig. 1.

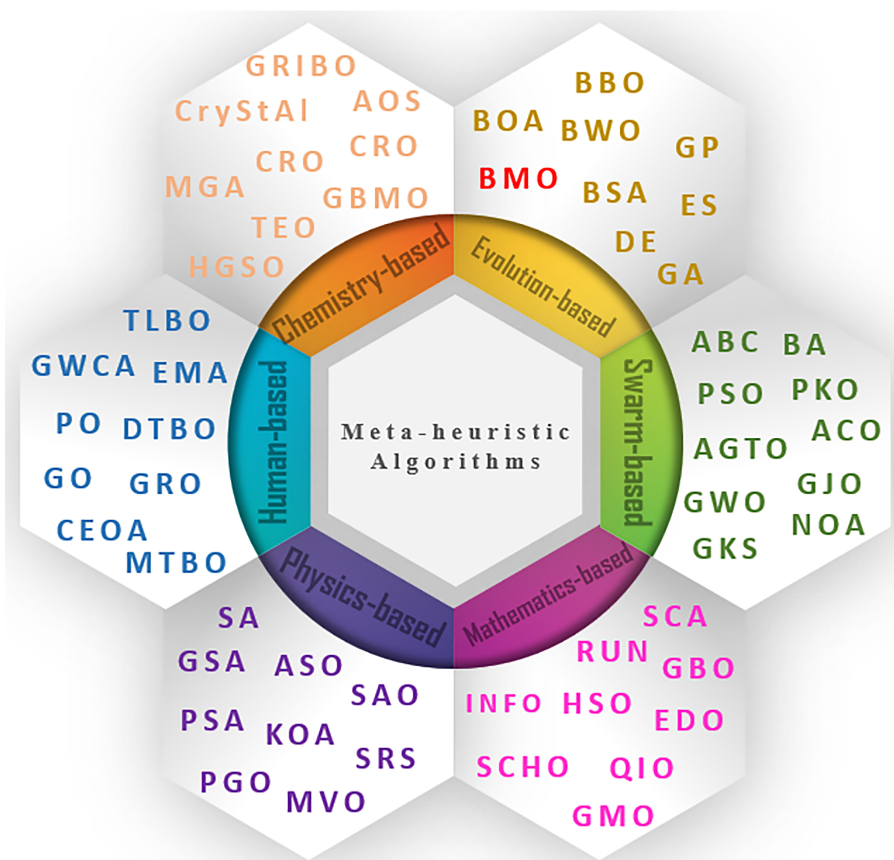


Figure 1: Classification of meta-heuristic algorithms.

Evolution-based methods, inspired by principles of genetics and natural selection, include prominent algorithms such as Differential Evolution (DE) [10] and the Genetic Algorithm (GA) [11]. DE leverages differences among population individuals to guide the search process toward optimal solutions through iterative convergence. GA mimics natural selection by employing crossover, mutation, and selection mechanisms to evolve candidate solutions toward optimal results. Additional evolution-based meta-heuristic algorithms include Evolutionary Strategy (ES) [12], Backtracking Search Algorithm (BSA) [13], Genetic Programming (GP) [14], Black Widow Optimization (BWO) [15], Bull Optimization Algorithm (BOA) [16], Biogeography-Based Optimization (BBO) [17] and so on.

Physics-based algorithms employ physical principles to model the behavior and interactions of search agents within the solution space. Notable examples include the Gravitational Search Algorithm (GSA) [18] and Simulated Annealing (SA) [19]. GSA, inspired by gravitational forces and celestial motion, updates the positions of search agents to converge toward the global optimum. Moreover, SA employs a probabilistic approach to escape local optima while randomly exploring the solution space, effectively mimicking the physical annealing process. Other significant techniques in this category include Atomic Search Optimization (ASO) [20], Kepler Optimization Algorithm (KOA) [21], Snow Ablation Optimizer (SAO) [22], PID-based Search Algorithm (PSA) [23], Special Relativity Search (SRS) [24], Plasma Generation Optimization (PGO) [25], Multi-Verse Optimizer (MVO) [26], and others.

Mathematics-based algorithms are grounded in mathematical operations, concepts, and principles. A notable example is the Sine Cosine Algorithm (SCA) [27], which uses transcendental cosine and sine functions. The Runge-Kutta Optimizer (RUN) [28] employs slope variations from the Runge-Kutta method to achieve global optimization. Other significant examples in this category include the Gradient-based optimizer (GBO) [29], Hyperbolic Sine Optimizer (HSO) [30], Geometric Mean Optimizer (GMO) [31], Quadratic Interpolation Optimization (QIO) [32], Exponential Distribution Optimizer (EDO) [33], weIghted meaN oF vectOrs (INFO) [34], Sinh Cosh Optimizer (SCHO) [35], and more.

Human-based methods draw inspiration from societal human activities and interactions. For example, Teaching-Learning-Based Optimization (TLBO) [36] mimics the dynamics of a traditional classroom environment, which models knowledge acquisition through teaching and learning phases. In the teacher phase, students learn from the best-performing individuals; in the learner phase, they acquire knowledge from their peers. Other notable human-based methods include the Great Wall Construction Algorithm (GWCA) [37], Exchange Market Algorithm (EMA) [38], Political Optimizer (PO) [39], Driving Training-Based Optimization (DTBO) [40], Growth Optimizer (GO) [41], Chief Executive Officer Election Algorithm (CEOA) [42], Team-Based Optimization (MTBO) [43], Gold Rush Optimizer (GRO) [44], and so on.

Chemistry-based methods are inspired by principles of chemical reactions, including molecular interactions, Brownian motion, and radiation phenomena. Notable examples include Gamma Ray Interactions-Based Optimization (GRIBO) [45], which models the energy loss processes of gamma rays; the Material Generation Algorithm (MGA) [46], which models key aspects of material chemistry; and the Crystal Structure Optimization Algorithm (CryStAl) [47], inspired by the principles of crystal structure formation. Other significant algorithms in this category include Atomic Orbital Search (AOS) [48], Chemical Reaction Optimization (CRO) [49], Henry Gas Solubility Optimization (HGSO) [50], Gases Brownian Motion Optimization (GBMO) [51], Thermal Exchange Optimization (TEO) [52], and others.

Finally, the swarm-based technique draws inspiration from the collective actions of animals and social insects. These methods often emulate processes such as prey searching for food, in which swarms depend on local interactions among members or on environmental signals. Particle Swarm Optimization (PSO) [53] is a pioneering algorithm that simulates the flocking behavior of birds. The Bees Algorithm (BA) [54] is another notable approach inspired by the natural foraging behavior of honeybees, in which they explore and exploit food sources. Similarly, the Artificial Bee Colony (ABC) algorithm [55] mimics the foraging behavior of honeybee swarms, where employed, onlooker, and scout bees collaborate to locate and optimize food sources. These methods demonstrate high adaptability and powerful search abilities when applied to diverse and complex optimization tasks. Other prominent algorithms in this category include the Artificial Gorilla Troops Optimizer (AGTO) [56], Ant Colony Optimization (ACO) [57], Nutcracker Optimization Algorithm (NOA) [58], Golden Jackal optimization (GJO) [59], Grey Wolf Optimizer (GWO) [60], Genghis Khan Shark (GKS) [61] and more.

In late 2019, Sulaiman et al. [62] introduced the Barnacles Mating Optimizer (BMO), an evolutionary-based algorithm inspired by the reproductive behavior of barnacles. By emulating these unique mating patterns, BMO employs an innovative search mechanism that is known for producing optimal or near-optimal solutions to complex optimization problems. Its strengths in maintaining population diversity, adapting to dynamic problem environments, and balancing exploration with exploitation have contributed to its growing prominence. According to Google Scholar metrics, citations of BMO have increased significantly since its introduction in late 2019. By November 2025, BMO had accumulated 450 citations, reflecting its growing recognition and substantial impact in addressing complex optimization problems. The significant increase in BMO citations reflects its growing recognition within the research community and demonstrates its effectiveness in addressing complex optimization challenges. Consequently, it has attracted considerable academic attention and inspired the development of numerous BMO variants. This paper provides a comprehensive review of BMO, its variants, and its applications across multiple disciplines, focusing on studies published from November 2019 to the present.

Beyond the notable increase in citations, the primary motivation for this study is that, to our knowledge, no comprehensive review or survey on BMO has yet been published. Therefore, this study aims to collect and critically evaluate the existing literature on BMO. This study is significant because it identifies, categorizes, and evaluates BMO and its variants, which have been applied to a wide range of optimization problems. The review examines BMO's real-world applications across various domains and provides insights to guide future research directions. The main contributions of this paper are summarized as follows:

- A comprehensive overview of BMO, including its mathematical formulation and core principles.
- An in-depth analysis of BMO variants, emphasizing modifications, multi-objective adaptations, and hybrid integrations.
- A review of application domains where BMO and its variants have been effectively applied.
- A comparative performance evaluation of BMO against recently published metaheuristic algorithms.
- Identification of future research directions, highlighting opportunities for algorithmic improvements and the exploration of new application areas.

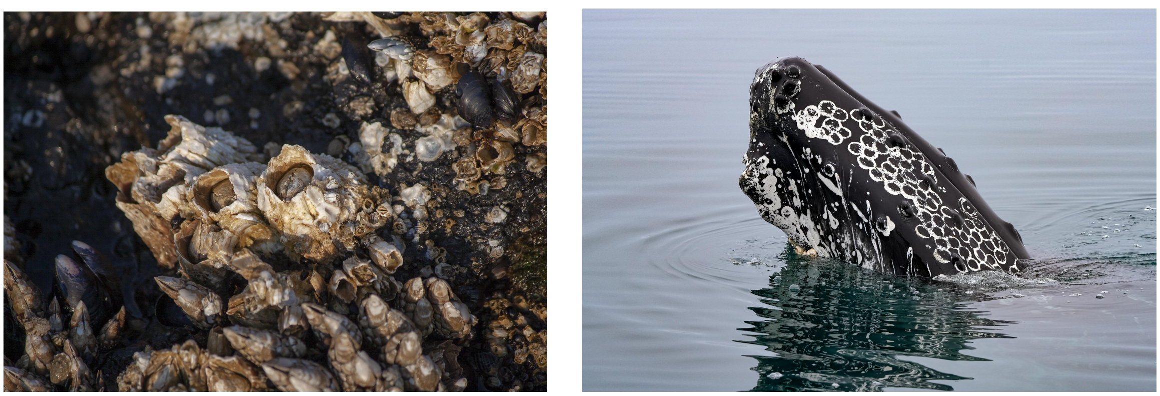
The structure of this paper is as follows: Following the introduction, Section 2 presents the foundational concepts, including the theoretical attributes and framework of the original BMO algorithm. Section 3 outlines the methodology used for the review. Section 4 provides a comprehensive review of research on BMO, covering modified, hybrid, and multi-objective variants. Section 5 examines the diverse applications of BMO and its variants across various domains. Section 6 introduces open-source tools related to BMO. Section 7 provides a comparative performance analysis of BMO against the latest published optimization algorithms using the CEC2005 benchmark functions. Section 8 offers a critical assessment of BMO's performance, identifying research gaps and limitations, while Section 9 discusses emerging opportunities and future research directions. Finally, Section 10 concludes the paper with a summary.

2 Theoretical Foundations of BMO Algorithm

This section presents an in-depth examination of the biological inspiration underlying the BMO algorithm and its mathematical formulations. It also explores the algorithm's computational complexity and key parameters, providing a thorough overview of BMO.

2.1 Inspiration

Barnacles are small crustaceans, typically gray or white, and are related to lobsters, crabs, and shrimp. They attach themselves to hard surfaces such as rocks, docks, ship hulls, and other stable structures, as illustrated in Fig. 2. Because they can settle on almost any solid object beneath the ocean's surface, they are widely distributed throughout the intertidal zone [63]. Barnacles reproduce by transferring sperm between individuals, resulting in fertilization of eggs that develop into free-swimming larvae. These larvae disperse through the water before settling in new habitats. Their reproductive season generally extends from mid-spring to late spring. After hatching, barnacle larvae are released into the water, where they search for a suitable hard surface on which to settle. Once attached, their protective shell plates continue to develop and harden around their bodies [64]. Barnacles also possess highly specialized reproductive structures that are proportionally long relative to their body size, enabling them to reproduce despite being permanently fixed in place. Relative to their body size, barnacles have the longest reproductive organs of any species. As unusual sessile animals that reproduce via internal fertilization, they face a trade-off: their organs must extend far enough to reach other individuals while remaining functional in turbulent water. Variation in organ length affects both the size of potential mating groups and the intensity of competition among nearby partners [65].



(a) (b)

Figure 2: Examples of barnacles in their natural environments. (**a**) Barnacles attached to coastal rocks.[1] (**b**) Barnacles attached to the skin of a whale.[2]

Leveraging the distinctive characteristics of barnacles, Sulaiman et al. [62] developed the Barnacles Mating Optimizer (BMO), drawing inspiration from natural reproductive strategies of barnacles. The algorithm translates these natural behaviors into mathematical models that guide the optimization process. Specifically, BMO models population dynamics by capturing how barnacles select mates and produce offspring, reflecting a balance similar to the Hardy–Weinberg principle in maintaining genetic-like stability during the search [62]. In BMO, the selection of parent barnacles is carried out randomly based on the biological variation in penis length, which determines mating reach and thus influences which individuals

[1] https://pixabay.com/photos/barnacles-sea-life-shell-clam-sea-4329795
[2] https://pixabay.com/photos/humpback-whale-ocean-iceland-8484783

contribute to new offspring [62]. The exploitation stage generates new candidate solutions through mechanisms inspired by the Hardy–Weinberg equilibrium, helping maintain structured diversity. In contrast, the exploration stage is modeled as a sperm-cast search, providing broad search coverage and enhancing the algorithm's ability to escape local optima [62].

2.2 Mathematical Model

The BMO algorithm consists of three main steps: initialization, selection, and reproduction. First, a population of barnacles is randomly generated in the search space, each representing a candidate solution whose fitness is evaluated. During selection, one parent is the best barnacle, while the second is chosen based on the penis length parameter, allowing either local mating for exploitation or sperm-cast mating for exploration. In reproduction, offspring are produced using the Hardy–Weinberg principle, combining parental traits with random factors for local exploitation, or adding perturbations to sperm-cast cases to enhance diversity. These steps are mathematically formulated as follows [62].

2.2.1 Initialization Phase

In population-based optimization methods, the process typically starts by generating an initial set of candidate solutions. Let n denote the total number of barnacles, and let the initial position of the i-th individual be defined as follows [62]:

$$\boldsymbol{X}_{i,j} = rand \times (ub_j - lb_j) + lb_j, \quad i = 1, 2, \cdots, n, \quad j = 1, 2, \cdots, d \tag{1}$$

where $X_{i,j}$ represents the j-th coordinate of the i-th barnacle's position, while d represents the number of dimensions in the problem. Additionally, ub_j and lb_j correspond to the upper and lower bounds of the j-th dimension, as defined by the problem constraints. Finally, $rand$ is a random variable drawn from a uniform distribution on $[0, 1]$.

2.2.2 Selection Phase

In the next phase of BMO, two parents (Dad and Mum) are selected to generate offspring. The selection process is primarily based on the length of their reproductive organs, denoted by pl, with individuals having longer pl values being more likely to be chosen. To promote exploitation, the algorithm randomly selects one barnacle as a parent based on its pl, ensuring that fertilization occurs with only a single partner at a time. Diversity is preserved through the sperm release mechanism, which is triggered whenever a barnacle selects a mating partner whose position index exceeds its own pl. The following equations mathematically describe this process [62].

$$b_M = rand\,(n) \tag{2}$$

$$b_D = rand\,(n) \tag{3}$$

where b_M and b_D represent the selected parents for reproduction within the population X, which consists of n individuals.

2.2.3 Reproduction Phase

In the final stage of the BMO mating process, the selected Dad and Mum produce offspring. The genetic contribution of each parent is evaluated using the Hardy–Weinberg principle. For the parental alleles D and M, the expected frequencies are $f(DD) = p^2$ and $f(MM) = q^2$ for the homozygous types, and $f(DM) = 2pq$ for the heterozygous type. These frequencies guide the determination of the genetic composition of the resulting offspring. The creation of a new barnacle, denoted X_i^{t+1}, is formally expressed by the following equation [62].

$$X_i^{t+1} = p \times X_{b_D}^t + q \times X_{b_M}^t \tag{4}$$

where p is a random value selected from the interval $[0, 1]$, and q is defined as equal to $1 - p$. These parameters represent the proportion of characteristics inherited by the new offspring X_i^{t+1} from the paternal barnacle (b_D) and the maternal barnacle (b_M). For example, if $p = 0.4$, the offspring inherits 40% of its traits from the father and the remaining 60% from the mother.

BMO shifts its search behavior into a more exploratory mode, referred to as the sperm-casting phase, when a specific condition is met in which both selected parents must have index values exceeding the predefined parameter pl. The mathematical operator describing this exploration mechanism is given in the following equation [62].

$$X_i^{t+1} = rand \times X_{b_M}^t \tag{5}$$

where $rand$ denotes a random variable uniformly distributed over the interval $[0, 1]$.

2.3 The Framework of BMO

BMO optimization process starts by randomly generating an initial population of candidate solutions. Using adaptive behavioral operators, the algorithm systematically explores the solution space, focusing on regions close to the current best solution or areas with high objective function values. Each candidate adjusts its position according to the best solution found globally by BMO up to the current iteration. This process is repeated iteratively until a predefined convergence or stopping criterion is satisfied. The overall procedure, including these steps, is summarized in the pseudo-code presented in Algorithm 1.

2.4 Computational Complexity

This subsection introduces the analysis of the time computational complexity of BMO. Analyzing the space and time complexities allows the algorithm's efficiency and resource consumption to be evaluated, providing a clear understanding of how each operation influences overall performance.

2.4.1 Time Complexity

The time complexity of the BMO algorithm depends on several key factors, including the population size (n, i.e., the number of barnacles), the problem dimension (d), the maximum number of iterations (T), and the computational cost of evaluating the fitness function (f). During the initialization phase, the computational complexity is $O(n)$, while the sorting operation also contributes $O(n)$. Evaluating the fitness function over all iterations adds $O(T \times n \times f)$ to the time complexity, and updating the population's positions contributes $O(T \times n \times d)$. The overall computational complexity of the BMO algorithm can be expressed as $O(n \times (2 + T \times (f + d)))$.

2.4.2 Space Complexity

This subsection examines the space complexity, focusing on the memory required to store variables, population data, and intermediate computations. Evaluating space complexity is essential for determining the algorithm's feasibility on systems with limited memory. The BMO algorithm has a space complexity of $O(n \times d)$, primarily due to the memory required to store the population's positions and fitness values across all dimensions. This storage allows the algorithm to track the locations of individual barnacles and their corresponding fitness evaluations within the search space.

Algorithm 1: Pseudo-code of BMO

Input: Initialization of parameters: lb, ub, d, n, T, and pl.
Initialize the population of barnacles X_i $(i = 1, 2, \ldots, n)$ by Eq. (1).
Assess the fitness of each barnacle in the population.
Start the process with $t = 1$.
while $t \leq T$ **do**
  for $i = 1$ to n **do**
    Choose the parent barnacles (Dad and Mum) according to Eqs. (2) and (3).
    Set $q = 1 - p$ and $p = C_n(i)$.
    if the parents' indices are equal to pl **then**
      for $j = 1$ to d **do**
        Generate offspring using Eq. (4).
      end for
    else
      for $j = 1$ to d **do**
        Generate offspring using Eq. (5).
      end for
    end if
  end for
  Ensure the new barnacle remains within the boundaries.
  Assess the current fitness.
  Update the best barnacle if it outperforms the previous best.
  $t \leftarrow t + 1$.
end while
Output: The best solution X_{best}.

2.5 Parameter Settings

According to the developers of the BMO, the algorithm is distinguished by its simple implementation and smooth convergence behavior. However, these advantages strongly depend on the appropriate tuning of its control parameters, which directly govern the balance between exploration and exploitation. In the standard BMO formulation, the key parameters include the penis length (pl), the population size (n), and the maximum number of iterations (T).

2.5.1 Role and Impact of the pl Parameter

To mitigate stagnation and enhance exploration of the search space, the pl parameter is employed in the BMO. In the original study, pl is recommended to be set to 50%–70% of the population size to achieve an effective balance between exploration and exploitation. This heuristic guideline is supported by empirical analyses of benchmark functions, such as the two-dimensional unimodal sphere function, in which intermediate values of pl (e.g., 5 to 7 for a population size of 10) promote convergence toward the global optimum. Such values enable sufficient local refinement through direct mating while introducing occasional randomization via sperm casting to preserve population diversity. Nevertheless, the optimal setting of pl remains problem-dependent. It requires further empirical tuning or sensitivity analysis for specific optimization scenarios to avoid excessive exploration, which may lead to inefficient dispersion, or over-exploitation, which can result in premature convergence to suboptimal regions.

2.5.2 Impact of the Population Size (n)

The population size plays a critical role in determining the performance of population-based metaheuristic algorithms. In the original BMO study, the population size (n) was fixed at 30 across all benchmark problems. However, subsequent studies have demonstrated that adopting a fixed population size, regardless of problem characteristics or dimensionality, lacks scientific justification. The existing literature indicates that dynamically adjusting the population size constitutes an effective adaptive strategy for achieving a more appropriate balance between exploration and exploitation. Consequently, the development of mechanisms for automatically identifying an optimal, problem-dependent population size (n) represents a challenging yet promising avenue for future research.

2.5.3 Impact of the Maximum Number of Iterations (T)

The maximum number of iterations significantly influences the performance of population-based metaheuristic algorithms. In the original BMO study, the maximum number of iterations (T) was fixed at 500 for all experiments. However, similar to the population size issue, employing a fixed iteration limit without accounting for problem complexity may lead to inefficiencies. For relatively simple problems, convergence may occur prematurely, resulting in unnecessary computational effort, whereas more complex search landscapes may require additional iterations to escape local optima and achieve higher-quality solutions. Prior studies have demonstrated that adaptive strategies for controlling the iteration limit based on convergence rate, fitness stagnation, or composite stopping criteria such as function evaluation budgets, can enhance both computational efficiency and solution quality. Consequently, developing adaptive mechanisms to determine the maximum number of iterations in BMO represents a promising research direction to improve its adaptability and performance across diverse optimization problems.

2.6 Performance Characteristics of BMO

BMO is a simple yet highly effective metaheuristic capable of solving diverse optimization problems across multiple domains. Its straightforward structure minimizes computational complexity while maintaining a robust balance between exploration and exploitation, enabling efficient navigation of the search space and rapid convergence to high-quality solutions. BMO is highly adaptable and can be extended or hybridized to tackle a wide variety of optimization problems. Its simplicity and flexibility make it effective across diverse domains, yet challenges remain. In large-scale or complex landscapes, BMO may stagnate or converge prematurely, sometimes becoming trapped in local optima if population diversity is insufficient. For certain problems, its convergence rate or solution accuracy may lag behind other metaheuristics. Moreover, BMO lacks inherent mechanisms to handle noisy and dynamic environments, limiting its robustness under changing or uncertain conditions.

3 Research Methodology

This section presents the methodology adopted for the literature review, including the selection of search keywords and databases, the inclusion and exclusion criteria, and the procedures used for study identification and synthesis. A broad range of publications on the BMO algorithm were analyzed to consolidate existing applications and variants, identify their strengths and limitations, and highlight potential directions for future research.

3.1 Search Keywords and Sources

The literature search focused on journals, book chapters, and conference proceedings from leading publishers to ensure reliability, with three major bibliographic databases serving as the primary sources, including:

- Google Scholar (https://scholar.google.com/).
- Scopus (https://www.scopus.com/).
- Web of Science (https://www.webofscience.com/).

The selected databases serve as primary sources due to their strong reputations and rigorous peer-review standards, ensuring that the included studies are based on credible and original research. For example, Scopus provides a comprehensive collection of resources across science, engineering, and technology, thereby enhancing the depth and breadth of our review of metaheuristic algorithms. In addition, Web of Science offers extensive coverage of multidisciplinary scholarly publications and citation indexing, which is crucial for tracing the impact and development of optimization algorithms such as BMO. Additionally, Google Scholar provides wide-ranging access to academic literature across multiple fields, including journal articles, theses, and preprints, facilitating comprehensive identification of BMO-related studies. Together, these databases provide a robust foundation for the literature review, covering a wide range of research areas while ensuring the relevance and reliability of the included publications.

Furthermore, the search keywords employed are presented in Fig. 3:

Figure 3: The most important keywords used for extracting and collecting BMO-related papers.

The keywords, including "Barnacles Mating Optimizer," "Barnacles Mating Optimiser", "Barnacles Mating Optimization", "Barnacles Mating Optimisation", "Barnacles Mating Algorithm", and "BMO Algorithm", were carefully selected to accurately identify publications focused on this bio-inspired optimization method, accounting for spelling and terminology variations. This selection directly supports the primary objective of investigating BMO's applications. Additionally, broader terms such as "Evolutionary Algorithms", "Optimization Algorithms", "Multi-objective Optimization", "Meta-heuristic Algorithms", and "Bio-inspired Algorithms" were included to capture related developments and extensions of BMO within the meta-heuristic domain, with emphasis on modified, hybrid, and multi-objective variants. This targeted strategy reinforces the central focus of our review. Table 1 summarizes the search strategy and keyword combinations used during the literature review.

Table 1: Summary of the search strategy and keyword combinations used during the literature review.

Item	Details
Databases Searched	-Scopus -Web of Science -Google Scholar
Search Keywords	-“Barnacles Mating Optimizer” -“Barnacles Mating Optimiser” -“Barnacles Mating Optimization” -“Barnacles Mating Optimisation” -“Barnacles Mating algorithm” -“BMO Algorithm” -“Evolutionary Algorithms” -“Optimization Algorithms” -“Multi-Objective Optimization” -“Meta-Heuristic Algorithms” -“Bio-Inspired Algorithms”
Search Techniques	Boolean operators (NOT, OR, AND) were used to combine keywords, refining the search results and facilitating the identification of relevant studies.
Fields Searched	Title, abstract, and keywords
Document Type	Peer-reviewed journal, book chapters, and conference papers
Timeframe for Publications	November 2019 to November 2025
Manual Search	Reference lists of key papers were manually examined to capture any additional relevant studies.

3.2 Exclusion and Inclusion Criteria

The inclusion criteria were established to guarantee the relevance and reliability of the selected publications. Priority was given to studies published in English in reputable peer-reviewed journals, conference proceedings, or book chapters. Eligible papers were required to specifically investigate BMO algorithm variants and demonstrate their practical, real-world applications. The literature search primarily covered the period from November 2019 to November 2025, starting with the formal journal publication of BMO in November 2019, which marked its rise to prominence and widespread adoption across multiple fields. This timeframe aligns with our objective of assessing recent modifications and applications while identifying their strengths and limitations. Initially, titles and abstracts were screened for relevance, followed by a full-text review to confirm the inclusion of novel BMO variants or practical applications addressing real-world problems. We also included a small number of highly influential studies outside the November 2019–November 2025 timeframe that represent key milestones, such as early conference versions that introduced BMO before its official journal publication, or studies that have received substantial citations within the field. Additionally, foundational works that first applied the BMO algorithm to specific domains were considered, even if published slightly earlier, to ensure a comprehensive assessment of its performance, versatility, and adoption across various fields.

The exclusion criteria were established to refine the selection process and ensure that only high-quality, highly relevant studies were included. Duplicate entries identified across multiple databases or platforms were removed, and publications outside the specified timeframe were excluded to maintain the review's focus on contemporary developments. Notably, studies in which BMO was not the primary focus were excluded, for example, papers that used BMO solely as a benchmark against other meta-heuristics or proposed theoretical enhancements without practical evaluation. This rigorous screening ensured that every included study either introduced an original BMO variant or focused on the development, refinement, implementation, and performance analysis of the BMO algorithm itself. Table 2 provides a summary of the exclusion and inclusion criteria used in selecting the studies.

Table 2: Criteria for including and excluding studies during selection.

	Inclusion	Exclusion
Scope	Studies applying or developing variants of the BMO algorithm for optimization problems, including its mechanisms, modifications, and real-world applications.	Studies focusing solely on other meta-heuristic or optimization algorithms without incorporating or centering on BMO.
Publication Date	Studies published between November 2019 and November 2025.	Studies published before November 2019.
Study Type	Empirical or case studies presenting performance metrics, benefits, limitations, or novel contributions related to BMO.	Studies lacking sufficient details on methods, algorithm settings, or performance metrics for BMO.
Language	Studies written in English.	Studies published in any language other than English.
Source	Peer-reviewed journals, book chapters, or reputable conference proceedings.	Non-peer-reviewed articles, grey literature, or opinion pieces.
Comparison to Baselines	Studies that compare BMO variants to baseline algorithms.	Studies that lack comparative analyses or performance benchmarking against other algorithms.

3.3 Paper Retrieval and Synthesis

Based on the predefined inclusion and exclusion criteria, this review considered only those research papers that met the established standards. From each selected study, the following information was extracted:

- Publication date: To examine study trends across different years.
- BMO variants employed: The specific modifications or extensions of the BMO algorithm (e.g., standard BMO, modified BMO, hybrid BMO, multi-objective BMO).
- Application domains: The type of optimization problems addressed (e.g., power and control engineering, classification, image processing, wireless networks) and their respective contexts.
- Comparative algorithms: Other metaheuristic or optimization methods compared against BMO and relative performance outcomes.

- Evaluation metrics: Performance measures such as convergence rate, solution quality, fitness value, computational time, robustness, etc.
- Advantages highlighted: Specific strengths noted in the study (e.g., faster convergence, better global optima exploration) beyond general challenges.
- Limitations and challenges: Primary issues faced when using BMO (e.g., parameter sensitivity, scalability, handling of constraints, premature convergence). Challenges and limitations: Key challenges identified in applying BMO (e.g., parameter sensitivity, scalability, handling of constraints, premature convergence).

The results were synthesized narratively, with studies categorized according to the type of BMO variant, the optimization problems tackled, and their reported performance outcomes.

4 Related Works on Standard BMO and Its Variants

The No Free Lunch (NFL) theorem [66] states that no optimization algorithm can consistently outperform all others across every problem category. Like other metaheuristic methods, BMO may encounter issues such as premature convergence, reduced population diversity, and an imbalance between exploration and exploitation. These limitations can cause the algorithm to become trapped in local optima when addressing a wide range of optimization problems. To overcome the limitations of the original BMO algorithm and enhance its overall performance, numerous variants have been proposed in the literature. These advancements enable BMO to address a broader range of optimization challenges across diverse application domains. Most studies focus on three main categories of enhancements: algorithmic modifications, hybridization with other optimization techniques, and multi-objective extensions, as illustrated in Fig. 4.

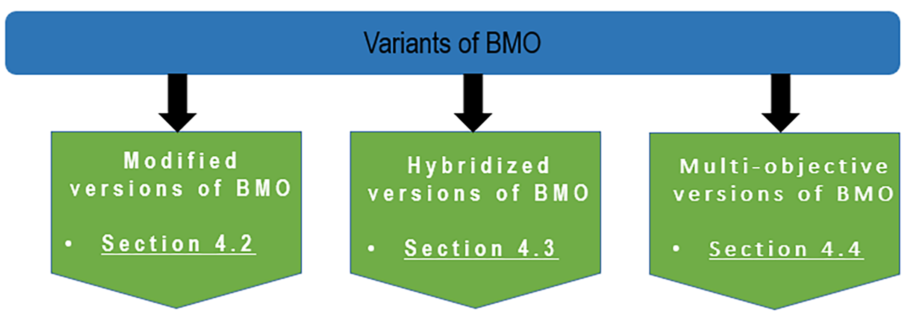


Figure 4: Classification of BMO variants.

4.1 Standard Version of BMO Algorithm

The standard BMO has been successfully applied to a variety of challenging optimization problems, providing a baseline for comparison and demonstrating reliable performance across multiple domains. This subsection reviews key studies on the standard BMO, highlighting its applications to challenging, non-trivial problems across various domains. For instance, Sulaiman et al. [67] applied BMO to the economic dispatch problem in power system operation, which aims to minimize generation costs while satisfying constraints such as prohibited operating zones, ramp rate limits, and generation capacity limits. The algorithm efficiently identified the optimal combination of generation units, achieving minimum costs for both the 6-unit and 15-unit test systems, and demonstrated performance comparable to that of contemporary optimization algorithms.

In another study, Sulaiman et al. [68] employed BMO for the combined economic and emission dispatch problem in power systems, which seeks to minimize generation costs and emissions simultaneously. By incorporating price penalty and weighting factors, BMO determined optimal generation schedules that balance these conflicting objectives while satisfying system constraints. Tested on 6- and 10-unit systems, the algorithm demonstrated an effective trade-off between cost reduction and emission minimization, highlighting its potential for multi-objective power system optimization.

Similarly, Sulaiman et al. [69] addressed economic emission-load dispatch problems using BMO. The algorithm was evaluated on 3-, 10-, and 40-unit systems, demonstrating competitive performance relative to other contemporary methods and effectively managing the challenges associated with economic emission load dispatch optimization.

In another study, Mustaffa et al. [70] employed BMO to predict short-term dengue outbreaks. The algorithm leveraged real-world Malaysian datasets, incorporating both historical case records and meteorological factors. Its predictive performance, evaluated using MAPE, MSE, and MAD, surpassed that of other metaheuristic methods, including the Moth Flame Optimizer and Grey Wolf Optimizer, demonstrating BMO's effectiveness in disease outbreak forecasting.

Furthermore, Choudhary et al. [71] addressed power flow scheduling problems in thermal power systems using BMO, accounting for nonlinear factors such as valve-point effects. The approach aimed to minimize generation costs while satisfying system constraints over a short-term scheduling horizon. Numerical simulations demonstrated that BMO achieved lower economic costs than other metaheuristic techniques, highlighting its effectiveness in handling complex power system optimization scenarios.

Additionally, Sulaiman et al. [72–74] conducted a series of studies applying BMO to solve the complex optimal power flow problem in power systems, which involves multi-modal, non-linear, and non-convex constraints. Across these works, BMO was employed to optimize multiple objectives, including minimizing generation costs, reducing power losses, mitigating voltage deviations, lowering emissions, and achieving combined cost-emission minimization, in systems integrating thermal generators with stochastic renewable sources such as solar PV, wind, and small hydro. The algorithm was rigorously tested on modified IEEE 30-bus and 57-bus systems, with comparative and statistical analyses against other recent metaheuristic methods demonstrating BMO's superior performance in balancing these objectives, providing reliable and efficient solutions, and highlighting its robustness as an alternative for addressing large-scale, constrained optimal power flow challenges in modern power networks.

Similarly, Sulaiman et al. [75] addressed the optimal reactive power dispatch problem in power systems using BMO, aiming to minimize system losses. By leveraging the Hardy-Weinberg principle and the barnacle sperm-cast process, the algorithm balanced exploration and exploitation while optimizing generator voltages, transformer tap settings, and reactive power compensation devices. Tested on the IEEE-30 and IEEE-118 bus systems, BMO demonstrated superior performance in reducing power losses compared to other established methods, highlighting its robustness in tackling complex optimal reactive power dispatch challenges.

In another work, Fakri et al. [76] implemented BMO for multilevel image thresholding to reduce the computational cost of multiple thresholds. Drawing inspiration from barnacle mating behavior, the algorithm optimized threshold selection using Otsu's between-class variance and Kapur's entropy functions, enabling detailed image segmentation into multiple classes. Comparative experiments demonstrated that BMO delivered effective and reliable results, highlighting its potential for image processing applications.

In another study, Sulaiman and Mustaffa [77] leveraged BMO to tackle the optimal chiller loading problem, focusing on minimizing power consumption in multi-chiller systems. The algorithm harnessed barnacle mating behavior, employing the Hardy–Weinberg principle for exploitation and the sperm-cast process for exploration to identify optimal solutions. Tested on three chiller configurations, BMO demonstrated superior energy savings compared to other established optimization methods, highlighting its potential for efficient energy management in air-conditioning systems.

Focusing on precise solar system modeling, Agwa et al. [78] determined unknown parameters in the three-diode model of solar generating systems using BMO. The algorithm minimized the root-mean-squared error between measured and modeled currents, enabling accurate performance characterization under varying irradiance, temperature, and load conditions. Validated on the Kyocera KC200GT and Copex P-120 systems, BMO achieved higher accuracy than other optimization methods in identifying all nine three-diode model parameters, demonstrating its effectiveness for real-world solar generation system applications.

Furthermore, Madhiarasan et al. [79] proposed BMO for efficient parameter extraction in photovoltaic cells and panels, including monocrystalline silicon, amorphous silicon, RTC France, PWP201, Sharp ND-R250A5, and Kyocera KC200GT. Using single- and double-diode models, the algorithm estimated PV parameters and was compared with existing methods. BMO achieved superior accuracy across six statistical metrics, including RMSE, MAPE, and MAE, while reducing computational time, running over 30 times faster than the hybrid successive discretization algorithm, demonstrating its effectiveness for both precise parameter estimation and rapid computation.

Lastly, Saari et al. [80] leveraged BMO to estimate the core size of magnetic nanoparticles via magnetization curve analysis. Using a non-regularized framework, the algorithm directly reconstructed magnetic moment distributions, minimizing differences between simulated and modeled curves. Compared to PSO, GA, SCA, and traditional non-negative least squares methods, BMO achieved higher accuracy, smoother distributions, and faster convergence.

4.2 Modified Versions of BMO Algorithm

Since its introduction in 2020, BMO has attracted increasing attention from researchers and practitioners across multiple fields. Numerous enhancements have been proposed by incorporating ideas from diverse search strategies and optimization techniques, leading to a variety of modified versions. In what follows, different modified versions of the BMO algorithm are highlighted, and their summaries are given in Table 3.

Table 3: Summary of BMO modification techniques.

SN	Strategy Used	Advantages	References
1	Self-adaptive parameter control	Enhances BMO's convergence behavior, stability, and localization accuracy by dynamically adjusting parameters during the search process	[81]
2	Elitism–crossover strategy	Improves information sharing, enhances exploitation, avoids local optima, and increases convergence accuracy and stability	[82]
3	Quasi-oppositional learning + chaotic mapping	Enhances population diversity, avoids local optima, accelerates convergence, and improves the overall robustness of the optimization process	[83–89]

(Continued)

Table 3 (continued)

SN	Strategy Used	Advantages	References
4	Lévy flight + logistic chaotic map	Enhances global exploration, increases population diversity, prevents premature convergence, and improves optimization accuracy and robustness	[90]
5	Laplacian-based crossover search + neighborhood-based wandering search	Enhances global diversification and local intensification, leading to improved balance between exploration and exploitation and higher solution accuracy	[91]
6	Logistic control model + chaotic mapping	Improves exploration–exploitation balance, enhances local search capability, increases robustness, and achieves more stable optimization performance	[92]
7	Tent chaos mapping + cosine control factor + Lévy flight	Enhances population diversity, balances exploration and exploitation, prevents premature convergence, and improves optimization accuracy	[93]
8	Dynamic opposition-based learning + triangular mutation	Enhances exploration efficiency, increases population diversity, prevents premature convergence, and strengthens BMO's adaptability and robustness in high-dimensional search spaces	[94]
9	Elite exponential probability strategy + Chebyshev chaotic map	Improves exploration–exploitation balance, enhances convergence speed, increases population diversity, and strengthens overall search efficiency	[95]
10	Variable genital length + improved offspring evolution + out-of-bounds correction mechanism	Enhances balance between exploration and exploitation, prevents invalid solutions near boundaries, and improves optimization stability and accuracy	[96]
11	Gaussian mutation + random flow toward the best solution	Improves population diversity, balances exploration and exploitation, prevents premature convergence, and enhances optimization accuracy	[97]
12	Variable genital length + improved offspring evolution + boundary-handling mechanisms	Improves the balance between exploration and exploitation, enhances stability near boundaries, and yields more accurate and robust optimization performance	[98]

4.2.1 Self-Adaptive BMO Algorithm

Purusothaman and Gopalakrishnan [81] introduced a Self-Adaptive BMO (SA-BMO) for node localization in wireless sensor networks. The method addresses challenges such as random node placement, fixed costs, and energy limitations through a two-phase strategy: first, optimal selection of target nodes based on inter-node displacement, and second, localization of remaining nodes using anchor nodes weighted by a recurrent neural network. The SA-BMO algorithm optimizes the localization process by minimizing an objective function that combines distances and anchor weights. Simulation results demonstrated that SA-BMO improves localization accuracy and network efficiency, making it a robust solution for wireless sensor network deployment and management.

4.2.2 Elitism-Crossover BMO Algorithm

Nasir et al. [82] developed an elitism-crossover BMO (ECBMO), a modified variant of the original BMO, to overcome issues with local optima and improve solution accuracy. The algorithm incorporates an elitism-crossover strategy, in which superior features from the best-so-far agent are inherited by newly generated offspring, while communication between the best agent and others is strengthened. ECBMO was evaluated on IEEE and CEC2014 benchmark functions, achieving higher accuracy and more precise convergence than the original BMO. The algorithm was also applied to optimize PID parameters for a buck converter, yielding superior voltage responses with reduced steady-state error and overshoot, demonstrating its effectiveness in both numerical benchmarks and real-world engineering applications.

4.2.3 Quasi-Oppositional Chaotic BMO Algorithm

Li et al. [83] introduced a variant of BMO called Converged BMO (CBMO) to optimize the sizing and control of fuel cell and battery systems in hybrid electric vehicles. This approach incorporates quasi-oppositional learning to accelerate convergence and a logistic chaotic map to maintain population diversity and avoid local optima. CBMO was applied to determine an optimal configuration that balances cost, reliability, and performance of the hybrid motor system. Simulation results highlighted the trade-offs between battery size, fuel cell lifetime, and fuel consumption, demonstrating that CBMO effectively improves optimization in complex energy management problems for hybrid electric vehicles.

In another study, Selim et al. [84] designed an enhanced version of BMO to solve the optimal allocation problem of distributed generators in radial distribution systems. To overcome issues such as local optima and slow convergence, the algorithm was improved by incorporating quasi-oppositional learning and chaotic maps, forming CQOBMO. The improved method was validated on 23 benchmark functions and then applied to minimize power and energy losses in distribution systems with uncertainties in distributed generator output and time-varying loads. Case studies on IEEE 33-bus and 69-bus systems demonstrated significant reductions in losses, with up to 68.86% loss reduction using photovoltaic distributed generators and up to 67.80% reduction when combined with battery energy storage.

Similarly, Mohammadnejad et al. [85] developed an Amended BMO (ABMO) for optimal base-station placement and transmission-power allocation in 5G wireless networks. The modified algorithm incorporates quasi-oppositional learning and a chaotic mapping strategy to enhance population diversity, avoid local optima, and improve convergence speed. By optimizing both the number of connected users and power efficiency, ABMO demonstrates superior performance compared to the original BMO and other state-of-the-art algorithms such as DE and RGA. Simulation results confirmed that ABMO effectively identifies the optimal base station locations and adjusts power levels, achieving statistically significant improvements in network coverage and energy efficiency.

In another work, Hai et al. [86] formulated a Converged BMO (CBMO) to optimize the operation of a microgrid with high penetration of renewable energy sources and plug-in hybrid electric vehicles. The study developed a single-objective model to minimize the total operating cost, leveraging a CBMO enhanced with quasi-oppositional and chaotic optimization strategies. Simulation results showed that CBMO outperformed conventional methods such as GA, PSO, and ICA in both cost reduction and convergence speed, achieving lower operating costs across different scenarios and significantly shorter mean simulation times.

Likewise, Hai et al. [87] designed a Converged BMO (CBMO) enhanced with quasi-oppositional and chaotic optimization strategies for the day-ahead scheduling of electric vehicles and responsive loads in a microgrid with wind and solar generation. The study formulated a two-stage optimization model to minimize generation, reserve, and startup costs while addressing fluctuations from renewable energy sources. Simulation results across three scenarios showed that CBMO significantly reduced operational costs compared to other methods.

In addition, Rawa et al. [88] developed a Converged BMO (CBMO) for seasonal short-term scheduling of a microgrid integrating energy storage and solar photovoltaic systems. The study defined a single-objective optimization problem to minimize the total operating cost while accounting for the effects of varying climatic conditions. To enhance CBMO's performance, quasi-oppositional and chaotic optimization strategies were incorporated. Simulation results demonstrated that CBMO not only outperformed several well-known algorithms in reducing cost across different weather scenarios but also achieved shorter mean simulation times.

Lastly, Hai et al. [89] designed a Converged BMO (CBMO) to address the day-ahead stochastic operation of a renewable energy-powered microgrid with high penetration of plug-in electric vehicles and plug-in hybrid electric vehicles. The study formulated the problem as a stochastic programming model to minimize the total operating and reliability costs, leveraging the unscented transform to capture system uncertainties. To enhance the performance of CBMO, quasi-oppositional and chaotic optimization strategies were incorporated. Simulation results demonstrated that the method efficiently manages the scheduling of distributed generation units and electric vehicles, reduces operating costs through V2G technology, and achieves superior performance compared to several well-known optimization algorithms.

4.2.4 Multi-Strategy BMO Algorithm

Yang et al. [90] developed an improved BMO (IBMO) to optimally identify unknown parameters in proton exchange membrane fuel cell models. This variant enhances the original BMO by incorporating Lévy flights to improve exploration and a logistic chaotic map to increase population diversity and prevent premature convergence. IBMO was employed to minimize the sum of squared errors between experimental and estimated output voltages, and its performance was validated on Horizon 500W and NedSstack PS6 PEMFC stacks. Comparative results with other metaheuristic methods, including EPO, EHO, and WCO, showed that IBMO achieved the lowest error values, demonstrating superior accuracy, robustness, and reliability in modeling proton exchange membrane fuel cell systems.

In another work, Rizk-Allah and El-Fergany [91] proposed a novel BMO variant, named the Neighborhood Laplacian BMO (NLBMO), to enhance parameter optimization in solar cell diode models. NLBMO integrates two new search strategies including Laplacian-based crossover search for diversification and neighborhood-based wandering search for intensification to improve solution quality and balance global and local exploration. The algorithm was employed to optimize single-diode and double-diode models of various photovoltaic modules. Comparative results demonstrated that NLBMO significantly outperformed the original BMO and other state-of-the-art methods, achieving markedly lower RMSE across multiple PV models.

In another study, Li et al. [92] introduced an enhanced version of BMO that combines a logistic model and a chaotic mapping to improve optimization performance. This variant, known as LCBMO, dynamically adjusts algorithm parameters to balance exploration and exploitation and leverages chaotic sequences to strengthen local search. Subsequent studies have developed multiple derivatives of LCBMO and evaluated them on standard benchmark functions to identify the most effective configuration. Beyond numerical optimization, LCBMO has been successfully applied to complex real-world problems, such as multilevel color image segmentation, using Masi entropy as the objective function. Comparative analyses with alternative optimization methods and objective functions demonstrate the robustness and efficiency of this approach, with statistical tests confirming the significance of its performance improvements.

Similarly, Li et al. [93] designed an improved BMO (IBMO) for precise parameter identification in lithium-ion battery models and sensors. The study introduces an improved second-order RC model that incorporates battery hysteresis voltage to better capture dynamic behavior. To enhance convergence, IBMO integrates tent chaos mapping, a cosine control factor, and Lévy flight strategies. The approach is validated against standard benchmark functions and applied to two real battery operating conditions, achieving low root-mean-square errors (0.0431 and 0.0483) and minimal mean absolute percentage errors (0.38% and 0.56%).

Furthermore, Al-Qaness et al. [94] introduced a Dynamic Opposition-Based BMO with Triangular Mutation (DBMT) to enhance exploration and prevent premature convergence in high-dimensional Social IoT (SIoT) applications. Applied to resource allocation and decision-making tasks, DBMT demonstrated superior predictive accuracy and convergence stability on UCI and SIoT datasets, showing that opposition-based learning and mutation strategies significantly improve BMO's adaptability and robustness for large-scale heterogeneous IoT data.

Additionally, Zamli et al. [95] proposed the Elitist BMO (eBMO) to address the slow convergence and limited search efficiency of the original BMO. The eBMO enhances exploration and exploitation by using an elite exponential probability to guide the search between intensification via swap operations and diversification into new regions, while replacing random number generation with a Chebyshev map to improve solution quality. Applied to the generation of 8×8 substitution boxes, eBMO demonstrated competitive performance compared to existing methods.

Another example is provided by Ai et al. [96], who developed a Modified BMO (MBMO) to improve parameter estimation from self-potential anomalies in geophysical studies. MBMO incorporates a variable-genital-length strategy, an improved offspring evolution method, and an out-of-bounds correction mechanism, thereby enhancing its global exploration and local exploitation capabilities. Tested on both theoretical models and real self-potential datasets from Türkiye, Canada, India, and Germany, MBMO outperformed the original BMO in accurately estimating model parameters. Further validation on 11 challenging benchmark functions confirmed its effectiveness, highlighting MBMO as a reliable and robust tool for parameter estimation in complex geophysical and optimization problems.

Also, Jena et al. [97] designed an Enhanced BMO (EBMO) using an exponential information gain function for entropy-based multilevel thresholding in image segmentation. By incorporating Gaussian mutation and a random flow toward the best solution, EBMO balances exploration and exploitation, preventing premature convergence. Evaluated on benchmark functions and the CEC 2014 test suite, the method outperformed several algorithms, and in image segmentation, EBMO-EE improved PSNR, SSIM, FSIM, and UM values by 2%–4% over existing metaheuristics.

Lastly, Ai et al. [98] introduced a Modified BMO (MBMO) for joint inversion of active Rayleigh wave dispersion, refraction travel times, and vertical electrical sounding data to achieve reliable near-surface geophysical parameter estimation. MBMO enhances the standard BMO by incorporating variable genital length, improved offspring evolution, and boundary-handling mechanisms, enabling a better balance between global exploration and local exploitation. Tested on synthetic models and four real-world datasets from Türkiye, MBMO outperformed both the original BMO and PSO, providing more accurate and robust inversion results.

4.3 Hybridized Versions of BMO Algorithm

As previously mentioned, both the original BMO algorithm and its various modified versions have been successfully applied to a wide range of continuous and discrete optimization problems. Nevertheless, there are certain problem domains in which these algorithms have underperformed or failed to achieve the desired results. Consequently, to overcome these limitations, researchers often integrate multiple techniques to obtain improved solutions. Evidence from numerous studies indicates that hybrid approaches are generally more robust and consistently outperform traditional standalone methods [99]. The purpose of hybridization is to exploit the complementary strengths and added insights that arise from combining different algorithms. Recent studies applying BMO to complex optimization problems and real-world challenges indicate that the original BMO algorithm still requires further enhancements to achieve optimal performance. The following subsections provide a brief overview of hybrid versions that integrate the standard BMO with other algorithms or techniques, as reported in the literature.

4.3.1 Hybridization with Other Meta-Heuristics

The literature indicates that BMO has been integrated with various other metaheuristic algorithms to enhance its effectiveness and robustness. Table 4 summarizes the reported hybrid variants of BMO combined with different meta-heuristic methods. The following discussion offers a detailed examination of these hybrid BMO combinations.

Table 4: Summary of a literature review on hybrid BMO with other meta-heuristics.

SN	Model	Hybridized with	Advantages	Year	Refs.
1	BMO-CS	Cuckoo Search (CS)	Improved convergence; better stability; outperforms HHO, BMO, and BMOPSO	2021	[100]
2	SbBMO	Sine–Cosine Algorithm (SCA)	Better exploration–exploitation; higher accuracy	2022	[101]
3	HEBMO	Evolutionary Programming (EP)	Lower generation cost; handles outages; faster than EP, and BMO	2022	[102]
4	BMSCD	Sine–Cosine Algorithm (SCA) + Disruption Operator	High accuracy; strong robustness; avoids stagnation	2022	[103]
5	HBMDO	Dingo Optimizer (DO)	Improved energy efficiency and network lifetime	2023	[104]

(Continued)

Table 4 (continued)

SN	Model	Hybridized with	Advantages	Year	Refs.
6	High-level hyper-heuristic framework	Grey Wolf Optimizer (GWO) + Whale Optimization Algorithm (WOA)	Significant loss reduction; adaptive hyper-heuristic selection	2024	[105]
7	HMVO-BMO	Multiverse Optimizer (MVO)	Reduced power losses; handles EV randomness effectively	2024	[106]
8	MMRFO	Manta Ray Foraging Optimization (MRFO)	Improved modeling accuracy; better exploration	2024	[107]
9	High-level hyper-heuristic framework	Moth Flame Optimizer (MFO) + Teaching-Learning-Based Optimization (TLBO) + Gradient-Based Optimizer (GBO)	Better loss/cost reduction; adaptive metaheuristic selection	2024	[108]
10	Q-learning Hyper-Heuristic	Aquila Optimizer + Gradient-based Optimizer + Harris Hawks Optimization + Poor and Rich Optimization	Accurate predictions; strong exploration; optimal operator selection	2024	[109]
11	HEBMO	Evolutionary Programming (EP)	Lower cost; robust under stress; better than EP, and BMO	2024	[110]

Devarapalli et al. [100] proposed a hybrid Barnacles Mating–Cuckoo Search algorithm (BMO-CS) to address global optimization problems by enhancing the intensification capabilities of the original BMO through features from the CS algorithm. The method was first validated on standard benchmark functions, demonstrating efficient convergence to optimal solutions. BMO-CS was then applied to a complex electrical power system stability problem using a multi-objective formulation, outperforming traditional approaches and other metaheuristics, including HHO, BMO, and BMOPSO. The algorithm effectively improved system stability by shifting poles left in the s-plane and enhancing damping under fault conditions, highlighting its potential for solving challenging engineering optimization tasks.

Following this, Roslan et al. [101] introduced a Sine-based Barnacle Mating Optimization (SbBMO) algorithm, which enhances the standard BMO by introducing a sine-based position update strategy to guide barnacles toward the current best solution while dynamically adjusting step size. This modification improves the balance between exploration and exploitation in the search process. SbBMO was evaluated on 10-dimensional CEC2014 benchmark functions, showing significant gains in accuracy compared to the original BMO. Additionally, the algorithm was applied to optimize a Proportional-Derivative controller for an inverted pendulum system, where SbBMO demonstrated superior control performance, highlighting its effectiveness in both numerical optimization and engineering control applications.

Similarly, Abd Elaziz et al. [103] proposed an enhanced version of BMO to improve its optimization capability and clustering performance. The improved approach, termed BMSCD, integrates the Sine–Cosine Algorithm (SCA) and disruption operators into the traditional BMO framework to balance exploration and exploitation. The hybridization enables the algorithm to dynamically switch between BMO and SCA strategies based on the fitness value of candidate solutions, thereby reducing the risk of stagnation and premature convergence. Extensive experiments on standard benchmark functions and clustering datasets demonstrated that BMSCD outperforms several state-of-the-art algorithms in terms of accuracy, convergence speed, and robustness, confirming its efficiency in handling complex global optimization and clustering problems.

In another work, Reddy and Venkatram [104] applied a Hybrid Barnacle Mating Dingo Optimization (HBMDO) approach to enhance energy-aware routing in wireless body area networks with mobile and multiple sink nodes. The method integrates BMO with the dingo optimizer to optimally select cluster heads based on multi-objective criteria, including distance, energy, delay, transmission load, path loss, node trust, and packet delivery ratio. By leveraging this hybrid strategy, the routing protocol achieves improved energy efficiency and extended network lifetime, outperforming conventional wireless body area network routing approaches in both reliability and overall performance.

Furthermore, Sulaiman and Mustaffa [105] employed a high-level hyper-heuristic strategy that integrates BMO with the Grey Wolf Optimizer and the Whale Optimization Algorithm to solve the optimal power flow problem in power systems with renewable energy sources. The approach, called exponential Monte Carlo with counter, combines the strengths of these metaheuristic algorithms to minimize system losses. The method was validated on a modified IEEE-57 bus system, demonstrating that the hybrid hyper-heuristic strategy outperformed the individual low-level algorithms in terms of loss reduction. This study highlights the adaptability and efficiency of BMO when combined with other optimization techniques for complex power system problems involving renewable energy integration.

In another study, Razali et al. [106] introduced a hybrid optimization approach, HMVO-BMO, that combines the Multiverse Optimizer (MVO) and BMO to optimize plug-in electric vehicle charging scheduling in distribution grids. The method aims to minimize grid power losses while accounting for random plug-in electric vehicle arrival times and overnight home charging. Simulation studies on the IEEE 33-bus system under different electric vehicle penetration levels demonstrated that HMVO-BMO outperforms the individual MVO and BMO algorithms, providing more efficient and effective solutions for managing additional power demand from widespread EV adoption.

Moreover, Kasruddin et al. [107] utilized the Mating-based Manta Ray Foraging Optimization (MMRFO), an enhanced variant of the original MRFO algorithm that integrates barnacle-inspired mating strategies to improve offspring quality. By combining this mating behavior with existing Cyclone, Chain, and Somersault foraging strategies, MMRFO preserves communication between the best-performing agents and the rest of the population, enhancing exploration and exploitation. The algorithm was applied to optimize the parameters of a nonlinear fuzzy-Hammerstein model for an electric water heater, demonstrating improved dynamic modeling and more accurate output tracking compared to the standard MRFO. The study highlights MMRFO's potential for more complex optimization tasks, including fuzzy controller design and constrained multi-objective problems, illustrating the versatility of barnacle-inspired metaheuristics in engineering applications.

Following this, Sulaiman and Mustaffa [108] developed a hyper-heuristic framework for solving optimal power flow problems in systems with FACTS devices, including SVC, TCSC, and TCPS, aiming to reduce power losses and costs. The framework used two high-level strategies, including EMCQ and Randomly Select-Only Improving, to dynamically select among low-level metaheuristics, including BMO, MFO, TLBO, and GBO. Tested on a modified IEEE 30-bus system with thermal and wind generators, the approach demonstrated that leveraging BMO within the hyper-heuristic framework effectively improved optimal power flow, outperforming standalone metaheuristic methods.

Additionally, Turgut et al. [109] developed a Q-learning-enhanced hyper-heuristic framework integrating BMO with other metaheuristics to estimate the energy consumption of electric buses. Q-learning guided the selection of low-level optimizers including BMO, Aquila Optimizer, Gradient-based Optimizer, Harris Hawks Optimization, and Poor and Rich Optimization-based on performance. Evaluated on benchmark and real-world engineering problems, the framework effectively explored the search space, optimized parameters for a Multiple Linear Regression model, and produced highly accurate fuel consumption predictions.

Finally, Ismail et al. [102,110] developed and implemented a hybrid optimization approach called Hybrid Evolutionary-Barnacles Mating Optimization (HEBMO), which integrates Evolutionary Programming (EP) with the BMO to address both non-convex and convex economic dispatch problems in power systems, focusing on minimizing generation costs while ensuring reliability under various conditions such as line/generator outages and increased power demands. Tested on IEEE 30-bus and 57-bus reliability systems under base-case, stress, and outage scenarios, HEBMO demonstrated superior performance compared to standalone EP and BMO, achieving lower costs, faster computation, and more robust solutions, positioning it as an effective method for practical power system optimization.

4.3.2 Hybridization with Data Mining and Machine Learning

Integrating meta-heuristic algorithms with data mining techniques enhances machine learning performance and alleviates challenges associated with parameter tuning. Specifically, coupling BMO with models such as ANN and SVM has been shown to substantially improve outcomes in classification, regression, and forecasting tasks. For ANN, widely used for complex data problems, BMO serves as an effective optimizer for weights, learning rates, network layers, and neuron counts. In the case of SVM, BMO efficiently tunes key kernel parameters to maximize classification accuracy. Additionally, BMO has been hybridized with Decision Trees and Random Forests, optimizing critical hyperparameters to achieve higher accuracy in complex data mining applications. Table 5 summarizes documented hybrid BMO implementations with data mining techniques, followed by a detailed discussion of these integrated strategies.

Table 5: Summary of a literature review on hybrid BMO with data mining and machine learning models.

SN	Model	Hybridized with	Advantages	Year	Refs.
1	BMO-SVM	Support Vector Machine (SVM)	Effective gene selection; improved classification accuracy; outperforms GA, PSO, TSA, ABC	2021	[111]
2	BMO-LSSVM	Least Squares Support Vector Machine (LSSVM)	Hyperparameter optimization; better COVID-19 case prediction; more accurate than other hybrids	2021	[112]
3	BMO-RBFNN	Radial Basis Function Neural Network (RBFNN)	Accurate motor parameter estimation; reliable reactive power handling; outperforms GA	2021	[113]
4	BMO-NN	Artificial Neural Network (ANN)	Improved classification on stochastic data; lower MSE and runtime; enhanced training performance	2022	[114]

(Continued)

Table 5 (continued)

SN	Model	Hybridized with	Advantages	Year	Refs.
5	BMOHNN-ID	Hopfield Neural Network (HNN)	Higher intrusion detection accuracy and speed; robust IoT attack classification	2023	[115]
6	BMO-ANN	Artificial Neural Network (ANN)	Optimized weights/biases; lower MSE/RMSPE; better forecasting accuracy	2023	[116]
7	BMO-PSNN	Pi-Sigma Neural Network (PSNN)	Effective parameter tuning; improved convergence and prediction accuracy; lower average percentage error	2023	[117]
8	BMO-ANN	Artificial Neural Network (ANN)	Optimized for nonlinear/volatile time series; improved learning efficiency; better RMSE than DE+ANN/PSO+ANN	2024	[118]
9	BMO-PR/XGB/ LASSO	Polynomial Regression + Extreme Gradient Boosting + LASSO	Hyperparameter tuning; high accuracy for SC-CO_2 and niflumic acid solubility	2024	[119]
10	BMO-FFNN	Feed-Forward Neural Network (FFNN)	Optimized FFNN; better NMSE, RMSPE, MAPE; reliable battery SoC prediction	2025	[120]
11	VMD-BMO-ELM	Variational Mode Decomposition + Extreme Learning Machine (ELM)	Optimized ELM parameters; enhanced signal quality; accurate stock prediction	2025	[121]
12	BMO-CatBoost	CatBoost	Optimized hyperparameters; improved RMSE, MAE, R^2; robust battery SoC prediction	2025	[122]
13	BMO-KRR/DT/ RBF-SVM	Kernel Ridge Regression + Decision Tree Regression + RBF-SVM	Hyperparameter tuning; RBF-SVM best accuracy; models complex adsorption processes	2025	[123]
14	BMO-FFNN	Feedforward Neural Network (FFNN)	Optimized weights/biases; faster convergence; higher accuracy, precision, recall, F1-score for traffic prediction	2025	[124]
15	BMO-NN	Artificial Neural Network (ANN)	Optimized ANN; better RMSE, MAE, R^2; stable HVAC cooling load prediction	2025	[125]

(Continued)

Table 5 (continued)

SN	Model	Hybridized with	Advantages	Year	Refs.
16	BMO-Based Feature Selection	k-Means Clustering + Rule-Based System + Decision Tree Classifier	Feature selection improved accuracy/precision; robust multi-class botnet detection	2023	[126]
17	BMOML-TC	BERT + Beta Variational Autoencoder (VAE)	Optimized parameters; high sentiment classification accuracy; supports urban sustainability decision-making	2024	[127]

In their work, Houssein et al. [111] proposed a hybrid approach combining BMO with SVM for gene selection in cancer classification. This method leverages BMO's optimization capability to identify the most informative genes in microarray datasets, thereby enhancing the accuracy of distinguishing between normal and cancerous tissues and among different cancer types. The approach was tested on both binary and multi-class gene expression datasets, and comparative studies with other bio-inspired algorithms, including Genetic Algorithm, Particle Swarm Optimization, Tunicate Swarm Algorithm, and Artificial Bee Colony, demonstrated that BMO-SVM outperformed these methods, achieving higher predictive accuracy and better selection of relevant genes for classification.

In their work, Mustaffa and Sulaiman [112] introduced a hybrid approach combining BMO with Least Squares Support Vector Machines (LSSVM), named BMO-LSSVM, for predicting COVID-19 confirmed cases. In this model, BMO is used to optimize the hyperparameters of LSSVM, thereby enhancing the model's predictive performance. The method was applied to daily COVID-19 case data from China, and the experimental results demonstrated that BMO-LSSVM outperformed other hybrid approaches, yielding more accurate and reliable forecasts that can support timely prevention and control measures.

Similarly, Rajesh et al. [113] developed a hybrid approach combining BMO with a Radial Basis Function Neural Network (RBFNN), termed BMO-RBFNN, for efficient parameter estimation of induction motors. In this method, BMO optimizes machine parameters and addresses reactive power dispatch issues, while RBFNN models the motor's behavior under various operating conditions. The optimized parameters enable accurate estimation of both positive and negative sequence components, improving the assessment of motor performance. Simulation results in MATLAB/Simulink demonstrated that BMO-RBFNN outperforms conventional techniques, such as Genetic Algorithm, in terms of reliability and accuracy in parameter estimation.

In addition, Murugan and Baburaj [114] proposed applying nature-inspired metaheuristic algorithms, including BMO, to enhance machine-learning-based data-mining classification. In this study, BMO was used alongside Black Widow Optimization, Cuckoo Search, and Elephant Herd Optimization to train neural networks on stochastic datasets. The algorithms aimed to improve classification accuracy while reducing runtime and mean squared error. Results demonstrated that BMO and other bio-inspired optimizers effectively enhanced the neural network's performance, highlighting their potential for solving complex data mining and classification problems.

Moreover, Velumani and Kalimuthu [115] introduced BMO with a Hopfield Neural Network-based Intrusion Detection model (BMOHNN-ID) to enhance the security and reliability of Internet of Things (IoT) environments. The approach focuses on identifying and classifying various intrusion types that threaten IoT networks, which are increasingly used in smart cities, grids, and homes. The proposed method begins by preprocessing IoT data to ensure compatibility with learning, after which the Hopfield Neural Network (HNN) is used to accurately detect and classify intrusions. BMO is employed to fine-tune the HNN parameters, improving detection precision and convergence speed. Additionally, device-specific data, such as routing information, network flow, and topology, are analyzed through REST API modules to build detailed vulnerability profiles. Experimental results demonstrated that the BMOHNN-ID framework achieved superior performance in intrusion classification compared to existing methods, confirming its robustness and efficiency in securing IoT networks.

Furthermore, Mustaffa and Sulaiman [116] developed a hybrid BMO-ANN model in which BMO is used to optimize the ANN's weights and biases, thereby improving predictive performance. The approach was applied to forecast stock prices using time-series data, with six input variables for predicting the next-day closing price. Evaluation using Mean Squared Error (MSE) and Root Mean Squared Percentage Error (RMSPE) showed that BMO-ANN outperformed other hybrid optimization models, with the improvement statistically significant, demonstrating the effectiveness of BMO in enhancing ANN-based predictive models.

Additionally, Behera et al. [117] proposed a hybrid predictive framework that integrates BMO with the Pi-Sigma Neural Network (PSNN) to address the challenges of stock market forecasting. Due to the nonlinear and dynamic behavior of financial data, traditional optimization methods such as gradient descent often struggle to achieve robust convergence and high accuracy. In this study, BMO was employed to fine-tune the parameters of the PSNN, leading to the development of the BMO-PSNN model for predicting the closing prices of five major stock indices. The model's performance was assessed using the average percentage error (APE), and the comparative results showed that BMO-PSNN achieved significantly lower error rates than the conventional GD-PSNN approach. These findings demonstrate that the hybrid BMO-PSNN model effectively enhances prediction precision, demonstrating BMO's capability to handle complex, highly nonlinear optimization problems in financial market analysis.

In a related study, Behera et al. [118] introduced a hybrid forecasting framework that integrates BMO with ANN to address the inherent nonlinearity and volatility of financial time series data. In this study, BMO was employed to fine-tune the ANN's weights and biases, thereby improving the network's ability to capture complex temporal dependencies in exchange rate prediction. The resulting hybrid model, BMO+ANN, was evaluated on two major currency exchange rates and compared with other evolutionary-based neural models, including DE+ANN and PSO+ANN. Using the Root Mean Square Error (RMSE) as the primary evaluation metric, the experimental findings revealed that BMO+ANN achieved superior forecasting accuracy and robustness. This performance highlights BMO's capability to enhance the learning efficiency and predictive power of neural architectures for dynamic financial forecasting tasks.

Another example is provided by Li et al. [119], who proposed using BMO for hyperparameter tuning in predictive models estimating supercritical CO_2 (SC-CO_2) density and niflumic acid solubility. Three machine learning approaches including Polynomial Regression (PR), Extreme Gradient Boosting (XGB), and LASSO, were optimized with BMO to improve accuracy. PR showed the highest predictive capability for both SC-CO_2 density (R^2 = 0.99207) and niflumic acid solubility (R^2 = 0.96949), while XGB and LASSO also delivered competitive performance. The study demonstrates that BMO can effectively enhance model optimization, providing reliable predictions for pharmaceutical applications involving supercritical CO_2 as a solvent.

Also, Mustaffa and Sulaiman [120] proposed a hybrid approach combining Feed-Forward Neural Networks (FFNN) with BMO to improve the estimation of the State of Charge (SoC) of electric vehicle batteries. The BMO algorithm was used to optimize the FFNN parameters, enhancing prediction accuracy under varying operational conditions. The model was evaluated on BMW i3 journey data using NMSE, RMSPE, and MAPE. Results demonstrated that the BMO-FFNN achieved superior performance, with NMSE of 0.0954, RMSPE of 5.10%, and MAPE of 3.79%, outperforming other hybrid models using SSA, MFO, and WOA. This approach highlights the potential of BMO-enhanced neural networks for more reliable battery management in electric vehicles.

Likewise, Yu [121] introduced a hybrid model integrating Variational Mode Decomposition (VMD), Extreme Learning Machine (ELM), and BMO for accurate copper price prediction. In this approach, VMD decomposes historical OHLC price data to enhance signal quality, while BMO optimizes the ELM parameters for improved forecasting. The VMD-BMO-ELM model was evaluated using multiple performance metrics, including R^2, RMSE, MAPE, RAE, and RSE, and demonstrated superior prediction accuracy compared to baseline methods. These results indicate the model's effectiveness as a reliable tool for investors, policymakers, and stakeholders in the metals market.

Beyond this, Sulaiman et al. [122] developed a hybrid methodology integrating BMO with the CatBoost algorithm to enhance the accuracy and robustness of State of Charge estimation in electric vehicle batteries. Using an extensive dataset from 72 BMW i3 driving trips, the study implemented comprehensive preprocessing, including outlier removal, imputation of missing values, and feature normalization. BMO was employed to optimize CatBoost parameters, including the learning rate, tree depth, regularization, and bagging temperature, and its performance was compared with PSO-, GA-, and WOA-based CatBoost models. The BMO-CatBoost approach achieved superior results, with an RMSE of 6.1031, an MAE of 4.1303, and an R^2 of 0.8211, demonstrating improved predictive accuracy and reliability. These findings highlight BMO's effectiveness in enhancing battery management systems and its potential for real-world electric vehicle applications.

Following this, Lv and Wang [123] proposed a hybrid modeling framework that combines computational fluid dynamics (CFD) with ML techniques to predict chemical concentration distributions during adsorption processes. The study employed Kernel Ridge Regression (KRR), Decision Tree Regression (DT), and Radial Basis Function Support Vector Machine (RBF-SVM) models, with hyperparameters optimized using the BMO algorithm. BMO-enhanced optimization improved model accuracy, and the RBF-SVM achieved the best performance with an R^2 of 0.9537, an RMSE of 3.5136, and an MAE of 1.5326. The results highlight the potential of integrating BMO with ML models to accurately capture complex spatial dependencies in solute transport and adsorption processes.

In the same context, Mustaffa et al. [124] proposed a hybrid traffic prediction model that integrates a Feedforward Neural Network (FFNN) with BMO to enhance traffic class prediction. In this approach, BMO optimizes the network's weights and biases, improving both accuracy and convergence speed. The model was tested on a dataset with four traffic classes—low, normal, high, and heavy—and compared with FFNN models optimized by Particle Swarm Optimization, Whale Optimization Algorithm, and Harmony Search Algorithm. Results showed that the BMO-FFNN achieved the highest accuracy, precision, recall, and F1-score while converging faster than the other metaheuristic-based models, demonstrating its superior capability for reliable and efficient traffic prediction.

Following this, Sulaiman et al. [125] proposed a hybrid approach combining BMO with ANN (BMO-NN) for accurate cooling load prediction in commercial chiller systems. The model leverages seventeen operational parameters, including temperature, flow rates, and electrical data, to capture complex nonlinear relationships. BMO-NN was evaluated against other metaheuristic-based neural networks, including PSO-NN, ACO-NN, SMA-NN, and RSA-NN, as well as the traditional ADAM optimizer, using RMSE, MAE, and R^2 metrics. The results demonstrated that BMO-NN achieved superior accuracy and stability, with an RMSE of 2.8551, an MAE of 1.8273, and an R^2 of 0.7440. SHAP analysis highlighted the algorithm's ability to effectively prioritize key electrical and thermal features, confirming its effectiveness for proactive energy management in HVAC systems.

Another contribution was made by Zaheer et al. [126], who proposed a hybrid machine learning framework for detecting botnet attacks in network traffic, leveraging features extracted using BMO. The approach combines k-means clustering, rule-based systems, and decision tree classifiers to enhance detection accuracy and robustness. Experiments on the CTU-13 dataset demonstrated that BMO-based feature selection significantly improved the performance of the hybrid model, achieving accuracies of 99.32% for k-means, 99.11% for the decision tree, and 97.14% for the rule-based system, with high precision across all classifiers. This study highlights the effectiveness of integrating BMO with machine learning algorithms for real-world cybersecurity applications.

Lastly, Alahmari [127] proposed a novel approach, BMOML-TC, that integrates BMO with machine learning techniques for Twitter sentiment analysis to support sustainable urban living. The method employs BERT for feature extraction from tweets and a beta Variational Autoencoder (VAE) for classification, while BMO is used to automatically optimize model parameters. Evaluation on benchmark datasets demonstrated that BMOML-TC effectively classifies tweets, capturing public opinions and sentiments with high accuracy, thereby providing valuable insights for decision-making in urban sustainability initiatives.

4.3.3 Hybridization with Deep Learning Models

Integrating BMO with deep learning models such as CNN, LSTM, GRU, and DBN effectively addresses complex tasks, including image classification, time series analysis, and natural language processing. BMO optimizes key parameters such as weights, learning rates, number of layers, and units, thereby improving model accuracy, convergence speed, and feature selection. For CNNs, commonly used in image processing, challenges arise in selecting the number and size of filters and convolutional layers, as well as the number of learning parameters, where BMO provides effective optimization. LSTM and GRU, well-suited for sequential and time-series data, benefit from BMO-driven tuning of memory units, layers, and learning rates. Table 6 summarizes reported hybrid BMO implementations with deep learning models, followed by a detailed discussion of these integrated approaches.

Table 6: Summary of a literature review on hybrid BMO with deep learning models.

SN	Model	Hybridized with	Advantages	Year	Refs.
1	BMO-DBN	DBN + BiLSTM	Improves attack detection and network throughput and enables efficient data offloading	2020	[128]
2	DAE-BMO-RF	Deep Autoencoder and Random Forest	Enhances classification accuracy, sensitivity, and specificity in MRI brain tumor analysis	2021	[129]
3	BMODTL-BMPC	Deep Transfer Learning (NasNetLarge) and ELM	Improves accuracy and reliability in malaria parasite detection and classification	2022	[130]
4	BMODL-MICM	ShuffleNetv2 and Elman Neural Network	Enhances X-ray image classification accuracy and convergence speed	2023	[131]

(Continued)

Table 6 (continued)

SN	Model	Hybridized with	Advantages	Year	Refs.
5	BMO-FFNN	Feed-Forward Neural Network	Improves state-of-charge prediction accuracy and reliability for EV batteries	2023	[132]
6	BMO-DL	ANN, RNN, LSTM, and GRU	Enhances weight and bias optimization and improves temperature forecasting accuracy	2024	[133]
7	BMO-Transfer Learning	ResNet, Inception, Inception-ResNet, MobileNet, and BiLSTM-Autoencoder	Achieves near-perfect botnet detection and enhances model interpretability with XAI	2024	[134]
8	DCNN-BMO	Deep Convolutional Neural Network with Semantic Image Segmentation and Guided Attention	Improves feature selection and achieves high accuracy in early liver disease prediction	2025	[135]
9	BMO-CRNN	Cascaded Recurrent Neural Network	Enhances hyperparameter optimization and achieves high accuracy for COVID-19 detection	2021	[136]
10	BMO-CNN	Convolutional Neural Network	Improves drought prediction accuracy using vegetation indices	2022	[137]
11	CSM-FFDNN	Deep Neural Network with Fractal Feature Extraction	Improves signal modulation recognition accuracy and optimizes DNN hyperparameters	2022	[138]
12	BMO-HCNN-LSTM	CNN-LSTM	Enhances SOC estimation accuracy and optimizes hyperparameters for battery modeling	2022	[139]
13	GSAAN-BMO-SA-OPR	Graph Sample and Aggregate Attention Network	Improves recommendation accuracy and optimizes network for sentiment classification	2023	[140]
14	OLiST-BMO	Lite Swin Transformer with CNN	Enhances brain MRI classification accuracy and optimizes hyperparameters	2024	[141]
15	BMO-BiLSTM	Bidirectional LSTM	Enhances feature selection and achieves high accuracy for intrusion detection	2025	[142]

(Continued)

Table 6 (continued)

SN	Model	Hybridized with	Advantages	Year	Refs.
16	CNN-LSTM-BMO	CNN-LSTM	Improves chiller power consumption forecasting accuracy and convergence speed	2025	[143]
17	DBM-LSTM	LSTM	Enhances intrusion detection accuracy and optimizes LSTM for signal separation in DOFS	2025	[144]
18	BMO-GBLRU	Gated Bernoulli Logmax Recurrent Unit with LIBED	Improves hotspot detection accuracy and feature selection in PV systems	2024	[145]
19	SEM-TPS	Bi-GRNN and Type II Fuzzy Logic System	Enhances energy management efficiency and traffic flow prediction accuracy	2022	[146]

In their work, Gopalakrishnan et al. [128] introduced integrating BMO with deep learning models to enhance cybersecurity and traffic management in Mobile Edge Computing (MEC) networks. BMO optimizes a Deep Belief Network (DBN) for cyberattack detection, forming a hybrid BMO-DBN model. The system, DLTPDO-CD, also includes BiLSTM-based traffic prediction and adaptive sampling cross-entropy for efficient data offloading. Simulations showed that the BMO-optimized framework improves attack-detection accuracy and network throughput, demonstrating its effectiveness for complex deep-learning tasks in IoT and edge computing.

Similarly, Anantharajan and Gunasekaran [129] developed a hybrid method combining a Deep Autoencoder (DAE) with BMO and a Random Forest (RF) classifier for brain tumor segmentation and classification in MRI images. The approach employs weighted fuzzy kernel-based metrics for feature segmentation, while BMOA tunes the autoencoder's parameters to enhance classification accuracy. When implemented in MATLAB and evaluated on MRI datasets, the DAE-BMOA-RF framework achieved higher accuracy, sensitivity, and specificity than existing methods, demonstrating the effectiveness of BMO variants in medical image analysis.

A further study by Dutta et al. [130], which proposed a hybrid framework, BMODTL-BMPC, integrating BMO with Deep Transfer Learning for automated malaria parasite detection and classification. The method applies Gaussian filtering to remove noise, followed by Graph Cuts segmentation to identify affected regions. BMO optimizes feature extraction using the NasNetLarge model, while an Extreme Learning Machine (ELM) performs classification. Experiments on benchmark datasets show that BMODTL-BMPC outperforms recent methods in accuracy and reliability, demonstrating the effectiveness of BMO variants in biomedical image analysis.

In another work, Kumar and Ponnusamy [131] introduced BMODL-MICM, a hybrid framework that combines BMO with a deep-learning-based model to improve medical X-ray image classification. The approach applies Wiener filtering for noise removal, uses ShuffleNetv2 for feature extraction, and employs BMO to fine-tune hyperparameters, enhancing convergence and predictive reliability. An Elman Neural Network (ENN) performs the final classification. Experiments on benchmark X-ray datasets showed that

BMODL-MICM achieved 99.67% accuracy, outperforming existing deep learning methods and demonstrating the effectiveness of BMO in optimizing medical imaging models.

In a related study, Mustaffa and Sulaiman [132] developed a hybrid BMO-DL approach for accurate estimation of the state of charge (SoC) in Nissan Leaf batteries. BMO is used to optimize the hyperparameters of a deep learning model that predicts SoC from voltage, current, and charge inputs. Experiments showed that BMO-DL achieves lower error rates and higher reliability than conventional methods, demonstrating its effectiveness in improving electric vehicle battery management and operational efficiency.

In the same context, Mustaffa et al. [133] designed a hybrid forecasting model for Earth surface temperature by combining Deep Learning (DL) with BMO to optimize weights and biases. Trained on a global temperature dataset, the model was compared with DL models optimized using PSO, HSA, ACO, and the classical ARIMA method. Evaluation using MAE, RMSE, and R^2 showed that the BMO-optimized DL model achieved superior predictive accuracy, demonstrating the effectiveness of BMO in improving time-series forecasting for environmental applications.

In another study, Saheed and Chukwuere [134] proposed an explainable ensemble transfer learning framework for detecting zero-day botnet attacks in the Internet of Vehicles (IoV). The model integrates SHAP for interpretability and combines a bidirectional LSTM with autoencoders (BiLAE) for dimensionality reduction. At the same time, BMO optimizes hyperparameters for deep learning models, including ResNet, Inception, Inception-ResNet, and MobileNet. This approach enables efficient detection without the need for large labeled datasets. Experiments showed near-perfect performance, with up to 100% accuracy, precision, recall, and F1-score in internal networks, and 99.88% accuracy in multi-class external networks, outperforming existing methods. The XAI component enhances transparency, supporting real-time, scalable IoV cybersecurity applications.

Likewise, Shanmugaraja et al. [135] introduced a deep learning framework combined with BMO for early prediction of liver disease. The model integrates a deep convolutional neural network (DCNN), semantic image segmentation (SIS), and a guided attention mechanism to extract high-density features from CT images. BMO optimizes feature selection, enhancing the model's ability to detect asymmetric patterns and subtle tissue abnormalities. The DCNN-BMO model classifies liver CT scans into five disease categories, achieving 98.04% accuracy, demonstrating its effectiveness in supporting early diagnosis and monitoring of liver disease.

Another investigation was carried out by Shankar et al. [136], which developed a hybrid COVID-19 diagnosis framework, BMO-CRNN, combining a Cascaded Recurrent Neural Network (CRNN) with BMO. BMO optimizes CRNN hyperparameters, including learning rate, batch size, activation function, and epoch count, improving classification performance on chest X-ray images. Preprocessing enhances image quality, while CRNN extracts deep features for detection. Experiments showed that BMO-CRNN achieves 97.01% sensitivity, 98.15% specificity, 97.31% accuracy, and 97.73% F-measure, outperforming existing methods and demonstrating the effectiveness of BMO in medical diagnostics.

In the same context, Sardar et al. [137] designed an ensemble framework combining Convolutional Neural Networks (CNNs) with BMO to improve drought prediction. The model uses vegetation indices such as NDVI, SAVI, ARVI, and EVI from satellite data to classify drought severity as low, moderate, or severe. Integrating BMO into the CNN enhances predictive performance, demonstrating the effectiveness of hybrid metaheuristic–deep learning approaches for complex environmental forecasting.

In another work, Venugopal et al. [138] developed a communication signal modulation recognition framework, CSM-FFDNN, that combines fractal feature extraction with deep neural networks. The model employs the Sevcik Fractal Dimension (SFD) to capture signal characteristics, while BMO optimizes DNN hyperparameters to enhance classification performance. Experiments show that CSM-FFDNN achieves higher recognition accuracy and outperforms existing state-of-the-art methods across multiple evaluation metrics in modulation signal classification.

A further study by Pughazendi et al. [140], which proposed a Graph Sample and Aggregate Attention Network optimized with BMO (GSAAN-BMO-SA-OPR) for sentiment-based online product recommendation. BMO is used to optimize the network for classifying customer feedback such as excellent, good, very good, bad, and very bad. Experiments on the Amazon product dataset showed improved performance across MSE, MAE, MAPE, accuracy, precision, recall, and F-score, demonstrating the effectiveness of BMO in enhancing recommendation systems and big data analytics.

Similarly, Gade et al. [141] introduced an improved Lite Swin Transformer (OLiST) model for brain MRI analysis, combining CNN-extracted local features with the transformer's global feature-extraction capability. BMO was used to optimize hyperparameters and enhance performance. Evaluated on open-source brain tumor MRI datasets from Kaggle, the OLiST-BMO model achieved superior classification accuracy and efficiency compared to other transfer learning methods, demonstrating the potential of BMO-assisted hybrid deep learning models in medical image analysis.

In another study, Venkata et al. [142] designed a BMO-BiLSTM framework for intrusion detection in complex networks. The model uses preprocessing steps like missing data handling, categorical encoding, and SMOTE/ADASYN for class balancing. BMO performs feature selection, reducing dimensionality and improving efficiency, while Bi-LSTM captures bidirectional temporal dependencies for accurate classification. Experiments on NSL-KDD and BoT-IoT datasets showed binary accuracies of 98.12% and 99.46%, with strong multi-class performance, outperforming conventional and deep learning methods in precision, recall, F1 Score, and AUC-ROC.

Beyond this, Sulaiman and Mustaffa [143] proposed a CNN-LSTM-BMO framework to forecast chiller power consumption in commercial buildings. BMO fine-tunes model parameters to handle non-linear and temporal complexities. Compared with GA, PSO, ACO, and DE, the model achieved the lowest RMSE of 0.5523, the highest R^2 of 0.9435, and 27% faster convergence. SHAP analysis identified temperature-related features as key predictors, demonstrating that BMO-enhanced deep learning can improve energy forecasting and HVAC optimization.

Following this, Yang and Yang [144] introduced a dynamic BMO-enhanced LSTM (DBM-LSTM) framework to improve intrusion detection in distributed optical fiber sensors. BMO adaptively tunes the LSTM model, enhancing the separation of true disturbances from background noise after preprocessing and wavelet-based feature extraction. Tested on various real-world disturbance types, DBM-LSTM achieved high classification accuracy, demonstrating the effectiveness of BMO in enhancing signal interpretation for IoT-based infrastructure monitoring.

In a related study, Kumar and Reddy [145] developed a BMO-based hybrid framework for hotspot detection in PV systems. The approach combines a Log Inverse Bilateral Edge Detector (LIBED) with a Gated Bernoulli Logmax Recurrent Unit (GBLRU) to analyze thermal images. Images are enhanced using CLAHE and α-Modified Histogram Blending, followed by LIBED-based contour detection and feature extraction. BMO selects the most relevant features for GBLRU classification, while a Haversine Self-Organizing Map (HSOM) isolates defective hotspots. Experiments showed the model achieved over 97% accuracy and 94% efficiency, outperforming existing PV fault detection methods.

Lastly, Hamza et al. [146] designed SEM-TPS, an energy management and traffic flow prediction framework for autonomous vehicles. The model integrates a Type-II Fuzzy Logic System (T2FLS) with BMO to optimize the membership functions and uses a bidirectional GRNN (Bi-GRNN) to accurately predict traffic flow. Experiments showed that SEM-TPS improves energy efficiency and prediction accuracy, outperforming existing state-of-the-art methods for autonomous vehicle systems.

4.3.4 Hybridization with Domain-Specific Optimization Methods

BMO has been effectively hybridized with domain-specific optimization techniques to address complex engineering and scientific problems. By integrating BMO with algorithms or models tailored to specific domains, such as power system optimization, renewable energy management, industrial process control, or time-series forecasting, hybrid approaches combine the strengths of both methods. BMO provides global exploration and adaptive parameter tuning, while the domain-specific component offers problem-specific guidance, constraint handling, or objective modeling. This synergy improves solution quality, convergence speed, and robustness across diverse applications. Table 7 summarizes reported hybrid BMO implementations with domain-specific optimization methods, followed by a detailed discussion of these integrated strategies.

Table 7: Summary of a literature review on hybrid BMO with domain-specific optimization methods.

SN	Model	Hybridized with	Advantages	Year	Refs.
1	Grey-BMO	Grey-level mapping for image contrast enhancement	Improves visual quality, outperforms state-of-the-art, versatile for preprocessing	2020	[147]
2	BSS-BMO	Sequence optimization for t-way software testing	Reduces test suite size, effective for small sequences	2021	[148]
3	MPPT-BMO	MPPT for TEG systems	High tracking efficiency, extracts more energy, fast convergence	2021	[149]
4	SF-BMO	Superiority of Feasible solution for OPF	Reduces generation cost, effective constraint handling, reliable solution	2022	[150]
5	BMO-ANFC	Adaptive Neuro-Fuzzy Controller	Improves performance, extends device lifetime, better fault management	2022	[151]
6	BMO-SMA	Second Moving Average for geophysical inversion	Handles ill-posed problems, robust convergence, efficient exploration	2022	[152]
7	BMO-CFOID-FOPIDN	Cascade FOPID and PIDN controller for multi-microgrid AGC	Minimizes frequency and tie-line deviations, robust under uncertainties	2022	[153]
8	BMOA-AWJC	Abrasive water jet cutting process optimization	Improves kerf taper, surface quality, and precision	2023	[154]
9	BMO-OCR	Optimal coordination of overcurrent relays	Minimizes relay tripping time; improves system reliability	2023	[155]

(Continued)

Table 7 (continued)

SN	Model	Hybridized with	Advantages	Year	Refs.
10	BMO-MRPID	Multi-Resolution PID controller for hybrid stepper motors	High precision; rapid response; robust under uncertainties	2024	[156]
11	DCT-BMO	Discrete Cosine Transform for UAV fault detection	Efficient real-time detection; low prediction error	2025	[157]
12	SES-BMO	Single Exponential Smoothing for time series forecasting	Improves forecast accuracy; robust parameter selection; timely predictions	2025	[158]
13	FL-BMO	Fuzzy logic for WSN clustering and routing	Improves network lifetime; energy efficiency; packet delivery and throughput	2025	[159]
14	Modified BMO	HVAC chiller optimization (manual on/off control + continuous cycles + filtering/sorting)	Handles chiller constraints; smooth load cycles; up to 11% energy savings; reliable HVAC optimization	2025	[160]

In their work, Ahmed et al. [147] applied BMO to image contrast enhancement by formulating it as an optimization problem using grey-level mapping. Evaluated on benchmark datasets such as Kodak, MIT-Adobe FiveK, H-DIBCO, and standard images, the method achieved superior contrast enhancement compared to state-of-the-art techniques. BMO was also effective as a preprocessing step for image binarization, demonstrating its versatility in image processing applications.

Similarly, Zamli and Kader [148] introduced the Barnacle Sequence Strategy (BSS), a BMO-based method for sequence-based t-way software testing. The approach optimizes input ordering to enhance interaction coverage among software components. Experiments showed that BSS achieves competitive test suite sizes for small interaction strengths and limited event sequences, matching or outperforming existing strategies.

Following this, Tariq et al. [149] proposed a BMO-based Maximum Power Point Tracking (MPPT) strategy for centralized thermoelectric generator systems under nonuniform temperature conditions. The optimized model achieved 99.93% tracking efficiency, extracted 5.6% more energy than competing methods, and reduced voltage fluctuations, thereby improving stable grid connectivity. BMO reached the global optimum within 18 iterations, converging 53.7% faster than PSO, confirming its reliability and efficiency in challenging operating conditions.

In another work, Sulaiman et al. [150] developed an SF-BMO approach that integrates the Superiority of Feasible Solution (SF) technique with the Barnacles Mating Optimizer to solve the optimal power flow problem with cost minimization. By effectively handling constraints without penalty functions, SF-BMO avoids trial-and-error tuning. Tests on the IEEE 30-bus system showed that SF-BMO achieves lower generation costs and outperforms other SF-based metaheuristic methods in optimal power flow optimization.

In a related application, Priya et al. [151] designed a hybrid BMO-ANFC approach to enhance the lifetime of power electronics in brushless DC drives. BMO optimizes the adaptive neuro-fuzzy controller by considering motor speed and semiconductor temperature to improve reliability and prevent early faults. Experimental results show that BMO-ANFC outperforms conventional controllers, offering enhanced performance, extended device lifetime, and more effective management of high-power switching operations.

In another study, Ai et al. [152] applied BMO to nonlinear geophysical inverse problems, representing its first use in geophysical parameter estimation. BMO effectively handles ill-posed and non-unique problems without requiring an accurate initial model. Validated on synthetic and real magnetic anomaly datasets, with SMA preprocessing to remove regional anomalies, BMO demonstrated superior convergence, robustness, and stability compared to standard PSO, highlighting its potential for geophysical inversion and parameter estimation.

Beyond this, Peddakapu et al. [153] developed a BMO-optimized control strategy for multi-microgrid systems to reduce frequency and tie-line power fluctuations caused by renewable intermittency and load variations. The approach employs a cascade CFOID–FOPIDN controller for secondary automatic generation control, with BMO tuning its parameters to enhance stability. Simulations incorporating diverse energy sources and uncertainties showed that the proposed controller significantly minimizes deviations and improves dynamic performance, demonstrating its effectiveness in microgrid stabilization.

A further study by Rajamani et al. [154] used BMO to optimize abrasive water jet cutting of fiber-intermetallic laminates. By tuning process parameters such as traverse speed, waterjet pressure, and nozzle height, the method improved cut quality metrics, including kerf taper, surface roughness, and kerf deviation. The results demonstrate the effectiveness of BMO for enhancing machining precision and surface quality in difficult-to-machine composite materials.

Also, Jamal and Shamsuddin [155] employed BMO to optimize overcurrent relay coordination in power systems. BMO tunes the time dial setting and plug setting to minimize total relay tripping time while maintaining the required coordination time interval. Tested on the IEEE 8-bus system with IEC-based IDMT characteristics, BMO outperformed GA and PSO, demonstrating its effectiveness in improving power system protection reliability.

Another example is provided by Deepa et al. [156], which introduced a BMO-based Multi-Resolution PID (MRPID) controller to improve speed regulation of hybrid stepper motors under variable operating conditions. BMO fine-tunes MRPID parameters to achieve high precision and fast response. The system uses a low-voltage, low-current converter to drive the VSI powering the hybrid stepper motor efficiently. MATLAB simulations comparing BMO-MRPID with ANFIS and MFO demonstrated superior dynamic performance, including a rise time of 0.0007 s, settling time of 0.1 s, and minimal steady-state error, highlighting its robustness and accuracy for industrial and robotic motion control.

Following this, Zakaria et al. [157] proposed a single-stage UAV fault detection framework that integrates BMO with the discrete cosine transform (DCT) to reduce the complexity of traditional multi-stage FDI systems. Their approach designs a BMO-driven fitness function that evaluates specific harmonic peaks namely the 3rd, 5th, and 7th to identify abnormal behavior in UAV operation. Validated through Software-in-the-Loop simulations, the method demonstrated strong real-time potential, achieving an optimal 5-second analysis window and low prediction errors. The study shows that combining BMO with frequency-domain features can provide an efficient and accurate anomaly-detection mechanism, offering a streamlined alternative to enhance UAV reliability and operational safety.

In another work, Aziz et al. [158] proposed a hybrid SES-BMO model that combines Single Exponential Smoothing with BMO to optimize both the smoothing parameter and initial value for improved time series forecasting. The approach achieved an average 8-day forecast accuracy of 90.2%, ranging from 83.7% to 98.8%. The study also highlighted the advantage of Repeated Time-Series Cross-Validation over traditional data-splitting methods for rapid decision-making, demonstrating BMO's effectiveness in enhancing parameter selection for practical forecasting applications.

Likewise, Renaldo Maximus and Balaji [159] designed a hybrid FL-BMO approach for energy-efficient clustering and routing in wireless sensor networks. Fuzzy logic manages uncertainties in sensor data, while BMO optimizes cluster head selection based on residual energy, intracluster distance, sink proximity, and cluster balance. A nature-inspired hybrid cross-layer routing strategy (NiHCLR-SFO) further optimizes path selection. Simulations showed that FL-BMO outperforms existing protocols, improving network lifetime, packet delivery, and throughput while reducing energy consumption, delay, and packet loss, demonstrating its effectiveness for reliable wireless sensor network performance.

Finally, Thou et al. [160] developed a modified BMO for optimal chiller loading in HVAC systems, addressing maintenance and breakdown challenges. The method allows manual control of chiller on/off statuses and introduces continuous optimization cycles with filtering and sorting of the best load distributions. Results showed comparable performance to the original BMO at high cooling loads and up to 11% energy savings at lower loads, enhancing both reliability and practical applicability for efficient building energy management.

4.3.5 Multi-Strategy Hybridization of BMO

BMO can be effectively combined with multiple strategies simultaneously, forming multi-strategy hybrid frameworks. These approaches integrate metaheuristics, machine learning, deep learning, and domain-specific optimization techniques, along with algorithmic enhancements, to exploit the complementary strengths of each component. In such hybrids, BMO typically provides global exploration and adaptive parameter tuning, while other strategies contribute predictive modeling, problem-specific guidance, or local exploitation. The combination of these methods has been shown to improve convergence speed, solution quality, robustness, and adaptability to complex real-world problems. Table 8 summarizes representative multi-strategy hybridization of BMO, which are discussed in detail in the following to highlight their design principles and effectiveness.

Table 8: Summary of a literature review on hybrid BMO with multi-strategy methods.

SN	Model	Hybridization between	Advantages	Year	Refs.
1	IBMO-SVM	SVM + BMO improvements (Gaussian mutation, logistic modeling, refraction-learning)	Improved convergence accuracy and stability; better exploration–exploitation balance; superior performance on high-dimensional datasets	2021	[161]
2	BM-BOA	BMO + BOA + NN/CNN + Weber LBP	Improved segmentation and classification accuracy, efficient and reliable detection	2021	[162]
3	JB-BMO	BMO + Jaya + CNN + LWGP descriptor	Improved feature extraction and classification, optimized CNN performance	2021	[163]
4	Improved BMO-SVM	SVM + BMO improvements (Dynamic Search Scope, Self-Reproduction, Lévy Flight) + fuzzy mutual information	High classification accuracy, effective feature reduction, improved fault detection	2021	[164]

(Continued)

Table 8 (continued)

SN	Model	Hybridization between	Advantages	Year	Refs.
5	BND-BMOML	ENN + BMO + CSO	Efficient feature selection, high detection accuracy, improved IoT security	2022	[165]
6	IBMO-SVM	SVM + BMO improvements (cubic chaotic mapping, hyperbolic sinusoidal control factor, Gauss–Cosey variation)	Improved exploration–exploitation, faster convergence, high accuracy in SOC estimation	2022	[166]
7	MBMODL-WD	DenseNet-121 + ENN + BMO improvements (self-population-based initialization) + Gabor filtering	High accuracy, robust and efficient, improved exploration–exploitation	2022	[167]
8	MDL-BADDC	Deep Stacked Autoencoder + QOBMO + Krill Herd Algorithm	Improved feature selection, high accuracy, reliable diagnosis	2022	[168]
9	HR-BMSO	CNN + Attention-based LSTM + BMO + Rat Swarm Optimization	Optimized deep learning parameters, high accuracy and F1-score, effective bug prediction	2023	[169]
10	IBMO-LSSVM	LSSVM + BMO improvements (Levy flight-enhanced sperm cast)	Superior forecasting accuracy, improved exploration, effective epidemic prediction	2023	[170]
11	D-HGBMO	Deep Belief Network + DNN + ELM + LSTM + Hybrid Grasshopper-BMO	Enhanced feature optimization, improved ensemble prediction accuracy, effective multi-disease prediction	2023	[171]
12	HBM-BSO	ResNet150 + LSTM + DNN + BMO + Bird Swarm Optimization	Optimized deep learning parameters, improved classification accuracy, effective plant disease detection	2023	[172]
13	HDAG-CBMO	BMO improvements (Chaotic initialization) + Hierarchical data aggregation	Improved network lifetime, better energy efficiency, reduced response time	2023	[173]
14	OFWNN-RDD	DenseNet121 + FWNN + BMO improvements (self-population-based initialization) + Gabor filtering	High accuracy, improved convergence and solution quality, effective road damage detection	2023	[174]

(Continued)

Table 8 (continued)

SN	Model	Hybridization between	Advantages	Year	Refs.
15	EBMOHDL-WC	MobileNetv2 + hybrid DL classifier + Elitist BMO	Optimized deep learning parameters, improved classification accuracy, effective smart waste management	2023	[175]
16	IBMOLSSVM	LSSVM + BMO improvements (Gauss distribution)	Improved prediction accuracy and stability, effective COVID-19 forecasting	2023	[176]
17	CNN–BMO	CNN + BMO + Sparrow Search Algorithm + vegetation indices (NDVI, ARVI, SAVI, EVI)	Improved feature extraction, higher accuracy, faster convergence, effective drought assessment	2024	[177]
18	OC-RSRGM	BMO improvements + Optimal Fuzzy c-Means + Rough Set theory + Hadoop MapReduce	Efficient big data handling, avoids local optima, accurate classification	2024	[178]
19	I-BMHBA	Autoencoder + CNN + RBF + GRU + BMO + Honey Badger Algorithm	Improved feature selection, enhanced MSP prediction accuracy, better profit recommendations	2024	[179]
20	NIMADL-HDA	CLSTM + BMO + Prairie Dog Optimization	Effective feature selection, improved accuracy and robustness, reliable healthcare data analysis	2024	[180]
21	HWW-BMO	ELM + LSTM + BMO + Water Wave Optimization + word-to-vector features	Optimized feature weights and deep learning parameters, improved prediction accuracy, effective chatbot interactions	2024	[181]
22	BMO-RBF	RBF + BMO + TLBO + MPA + other ML models	Reliable crude oil viscosity predictions, effective handling of complex datasets	2024	[182]
23	ABMO-ANN	ANN + Adaptive BMO	Improved forecasting accuracy, reduced MAPE, better RMSE and correlation, effective microgrid management	2024	[183]
24	CBMO-ANFIS	Adaptive Neuro-Fuzzy Inference System (ANFIS) + BMO improvements (Quasi-oppositional learning and chaotic mapping)	Fast convergence; high stability; accurate global MPP tracking; 99.3% tracking efficiency under varying irradiance and temperature	2024	[184]

(Continued)

Table 8 (continued)

SN	Model	Hybridization between	Advantages	Year	Refs.
25	SO-C-BMO-LSSVM	Least Squares Support Vector Machine (LSSVM) + BMO improvements (environmental constraints and selective opposition)	Hyperparameter tuning of LSSVM; improved convergence and forecasting accuracy; effective for multimodal/non-convex time-series problems	2025	[185]
26	BCOBMO-DL	Self-attention BiGRU + BMO improvements (Fractal Chaotic Oppositional BMO) + Reptile Search Algorithm + Blockchain	Improved detection accuracy and robustness, ensures data privacy, effective IoT security	2025	[186]
27	HBBSO-RDBN	RDBN (DBN + RNN) + BMO + Beetle Swarm Optimization + preprocessing (median filtering, CLAHE)	Optimized hyperparameters, improved accuracy and robustness, effective oral cancer detection	2025	[187]
28	ADT-BMO	AA-DTCN-SC + BERT + TransformerNet + Text CNN + BMO + DTBO	Enhanced feature selection and parameter tuning, improved intent recognition accuracy, efficient and scalable chatbot	2025	[188]
29	BMO-DRFE	Deep Residual Fuzzy Encoder + BMO + Kho-Kho Optimization + ReliefF	High prediction accuracy, effective feature selection, precise crop yield forecasting	2025	[189]
30	ADT-BMO	AA-DTCN-SC + BERT + TransformerNet + Text CNN + BMO + DTBO	Improved feature selection and fusion, enhanced intent recognition accuracy and precision, contextually accurate chatbot responses	2025	[190]

In their work, Jia and Sun [161] developed IBMO-SVM, a hybrid model that combines an improved BMO (IBMO) with SVM to enhance feature selection and kernel parameter tuning. IBMO incorporates Gaussian mutation, logistic modeling, and refraction learning to improve convergence, stability, and the exploration–exploitation balance. Validated on 23 benchmark functions and 20 real-world datasets, including high-dimensional cases, IBMO-SVM outperformed standard BMO-SVM and six state-of-the-art methods, demonstrating superior accuracy and robustness, especially for high-dimensional data.

Similarly, Mondal et al. [162] proposed BM-BOA, a hybrid meta-heuristic that combines BMO and the Butterfly Optimization Algorithm (BOA) for automated diagnosis of pulmonary emphysema. BM-BOA optimizes lung segmentation using a multi-objective function based on image variance and entropy and fine-tunes activation functions in NN and CNN classifiers. Features are extracted via Weber local binary patterns, and the model classifies lungs into normal, mild, moderate, and severe emphysema. Experiments on benchmark and real-time datasets showed that BM-BOA improves segmentation and classification accuracy, offering an efficient and reliable emphysema detection system.

In another work, Mahesh et al. [163] introduced a hybrid JB-BMO algorithm combining Jaya and Barnacles Mating Optimization for content-based medical image retrieval and classification. The method uses an optimized Local Weber and Gradient Pattern descriptor for feature extraction, enhanced with JB-BMO to improve retrieval accuracy. For classification, an improved CNN is employed, with JB-BMO tuning the activation functions and the number of training epochs. Experiments on public medical image datasets showed that this hybrid approach outperforms existing methods, demonstrating the effectiveness of BMO variants in optimizing both feature extraction and deep learning classification.

Also, Liang et al. [164] developed a hybrid BMO-SVM approach for soft fault diagnosis in analog circuits. The improved BMO incorporates Dynamic Search Scope, Self-Reproduction, and Lévy Flight to enhance parameter optimization, while fuzzy mutual information with minimum redundancy and maximum relevance reduces feature dimensionality. Experiments on UCI datasets and circuit tests showed high classification accuracy of 92.9% for distributed fault parameters and 99.07% for fixed parameters, outperforming other optimization-based classifiers and demonstrating their effectiveness in fault detection.

Subsequently, Alrayes et al. [165] proposed BND-BMOML, a hybrid BMO–machine-learning model for botnet detection in IoT networks. BMO is used for feature selection, an ENN performs detection, and chicken swarm optimization optimizes hyperparameters. By standardizing data and selecting relevant features, the model efficiently distinguishes normal from malicious IoT activities. Experiments on benchmark datasets showed that BND-BMOML outperforms existing methods, demonstrating BMO's effectiveness in enhancing IoT security.

In a related study, Liu et al. [166] introduced an IBMO-SVM framework for accurate state-of-charge estimation in lithium-ion batteries. The improved BMO integrates a cubic chaotic mapping, a hyperbolic sinusoidal control factor, and a Gauss–Cosey variation to enhance the exploration–exploitation balance and convergence. IBMO optimizes SVM parameters for precise state-of-charge prediction. Comparative tests showed superior convergence and performance, with the IBMO-SVM model achieving low error rates and high correlation, demonstrating its reliability for battery management systems.

In another work, Albraikan et al. [167] developed MBMODL-WD, a hybrid framework combining a Modified Barnacles Mating Optimizer with Deep Learning for automated weed detection in agriculture. The system applies Gabor filtering for noise reduction, DenseNet-121 for feature extraction, and a self-population-based BMO for hyperparameter optimization, with an ENN for classification. Simulations demonstrated that MBMODL-WD achieves 98.99% accuracy, outperforming other deep learning methods and proving its robustness and efficiency for innovative agriculture applications.

Another example is provided by Malibari et al. [168], who formulated MDL-BADDC, a hybrid framework that combines BMO variants with deep learning to achieve accurate atherosclerosis diagnosis and classification. The approach uses Quasi-Oppositional BMO (QOBMO) for optimal feature selection, a deep stacked autoencoder for classification, and the Krill Herd Algorithm to fine-tune model parameters. Experiments on three biomedical benchmark datasets showed that MDL-BADDC outperforms conventional methods, achieving higher accuracy and reliability in medical diagnosis.

Following this, Gupta et al. [169] proposed HR-BMSO, a hybrid Rat–Barnacle Mating Swarm Optimization approach for software bug prediction. The method integrates HR-BMSO with a CNN for feature extraction and an Attention-based LSTM for classifying software modules as faulty or non-faulty, thereby addressing class imbalance. Experiments showed that the model achieves high accuracy and F1 Score, outperforming conventional methods, demonstrating the effectiveness of BMO-based variants in enhancing predictive performance for software engineering tasks.

In another study, Ahmed et al. [170] introduced an improved BMO (IBMO) for epidemic time-series forecasting, enhancing the exploration phase of the original BMO by incorporating Lévy flight into the sperm cast mechanism. The IBMO was then hybridized with LSSVM to form the IBMO-LSSVM model, which was applied to forecast COVID-19 trends in Malaysia. Benchmarking against standard test functions and other well-known algorithms demonstrated that the proposed approach achieves superior accuracy in most cases and maintains competitive performance in others, highlighting its effectiveness for both optimization and predictive modeling tasks.

Similarly, Anish and Joe Prathap [171] developed a multi-disease prediction framework combining deep feature extraction with a hybrid metaheuristic optimizer. Features from the Restricted Boltzmann Machine layers of a Deep Belief Network are optimized using the Deviation-based Hybrid Grasshopper–BMO (D-HGBMO) method. The optimized features are fed into an ensemble of Deep Neural Networks, Extreme Learning Machines, and LSTMs to predict multiple diseases simultaneously. D-HGBMO-based feature tuning and ensemble weighting significantly improved prediction accuracy, demonstrating the effectiveness of BMO variants in complex healthcare applications.

In a related application, Sahu and Minz [172] designed a hybrid Barnacle Mating–Bird Swarm Optimization (HBM-BSO) integrated with a deep learning ensemble (Res-LSTMDN) for multi-disease classification of plant leaves. The approach combines adaptive image segmentation with ResNet150, LSTM, and DNN, while HBM-BSO optimizes the parameters of LSTM and DNN to enhance classification accuracy. Experimental results demonstrated that the proposed method significantly outperforms existing models in precision and other performance metrics, highlighting the effectiveness of BMO-based hybrid optimization for agricultural disease detection applications.

Also, Nalayini and Prakash [173] formulated a hierarchical data aggregation strategy for Fog-enabled IoT networks using a Chaotic BMO(HDAG-CBMO). The approach enhances network lifetime and energy efficiency by optimizing node selection based on factors such as residual energy, neighbor distance, and centroid degree. A chaotic-based initialization improves the starting positions of the barnacle population, while a learning-based data offloading method reduces response time for IoT requests. Simulation results demonstrate that HDAG-CBMO effectively balances energy consumption and extends the operational lifetime of Fog-assisted IoT systems.

Likewise, Alamgeer et al. [174] proposed an optimal Fuzzy Wavelet Neural Network-based Road Damage Detection (OFWNN-RDD) method for flood management that integrates a modified BMO (MBMO) for hyperparameter tuning. The approach uses Gabor filtering for noise reduction and DenseNet121 for feature extraction from remote sensing images. MBMO enhances the standard BMO by incorporating self-population-based initialization to improve convergence and solution quality. Finally, the FWNN classifier identifies road damage, and simulation results demonstrate that OFWNN-RDD achieves superior accuracy, reaching 98.56%, outperforming existing methods in flood-related road damage detection.

In a related study, Vijayalakshmi et al. [175] introduced an Elitist BMO with a Hybrid Deep Learning model (EBMOHDL-WC) to enhance smart waste management in IoT-enabled environments. The method integrates EBMO to optimize hyperparameters of the MobileNetv2 feature extraction model and employs a hybrid deep learning classifier for accurate waste classification. Experimental evaluation on a Kaggle garbage dataset demonstrated that the proposed approach outperforms conventional methods, highlighting its potential for improving efficiency and accuracy in smart city waste management applications.

Subsequently, Ahmed et al. [176] developed IBMOLSSVM, a hybrid BMO model enhanced with a Gauss distribution and integrated with LSSVM to predict COVID-19 cases and vaccination trends. The approach uses BMO's exploration–exploitation balance, improved via Gauss distribution, to optimize LSSVM hyperparameters. Tested on real-world data from Malaysia, the model demonstrated superior accuracy and stability compared to conventional BMO, neural networks, and other hybrid forecasting methods, proving its effectiveness for real-time epidemiological predictions.

An additional contribution came from Chaudhari et al. [177], who formulated a hybrid deep-learning and bio-inspired-optimization framework for agricultural drought assessment using satellite imagery and vegetation indices (NDVI, ARVI, SAVI, EVI). The model combines CNN with the Sparrow Search Algorithm (SSA) and BMO, treating vegetation indices as the optimization population to enhance feature extraction. On data from the Kolar region, CNN–BMO achieved 94% accuracy with faster convergence than a standalone CNN, demonstrating that BMO improves efficiency and predictive performance for remote sensing–based agricultural monitoring.

Another example is provided by Bhukya and Sadanandam [178], who proposed OC-RSRGM, an Optimal Clustering with Rough Set-Based Rule Generation Model for big data classification in a MapReduce environment. The approach combines Optimal Fuzzy c-Means clustering with an enhanced BMO to avoid local optima, followed by Rough Set-based rule generation for classification. Implemented on Hadoop MapReduce, OC-RSRGM effectively handles continuous and uncertain data, providing accurate insights. Experiments showed a computation time of 5.43 s, demonstrating the efficiency of integrating BMO with fuzzy clustering and Rough Set theory.

In a related study, Visnu Darsini and Babu [179] developed an intelligent framework for predicting crop Minimum Support Price (MSP) using the Intensity-based Barnacle Mating Honey Badger Algorithm (I-BMHBA). The approach integrates deep learning and optimization: crop data are processed through an autoencoder and CNN to extract features, which are then refined via I-BMHBA-based feature selection. The selected features are used to train an optimized RBF–GRU network for MSP prediction and profit analysis. Results showed that I-BMHBA improves prediction accuracy and profit recommendations compared to benchmark models, demonstrating its potential for smart agricultural decision-making.

In another work, Halawani et al. [180] introduced NIMADL-HDA, a hybrid framework combining metaheuristic optimization and deep learning for cardiovascular disease detection and classification. Healthcare data are standardized using Z-score normalization, and BMO is applied for feature selection to reduce dimensionality while retaining key medical attributes. A CLSTM network performs classification, and the Prairie Dog Optimization (PDO) algorithm fine-tunes hyperparameters. Validation on benchmark datasets showed that NIMADL-HDA outperforms conventional methods in accuracy, precision, and robustness, demonstrating the effectiveness of BMO-based optimization in healthcare analytics.

Also, Magoo and Singh [181] designed an intelligent chatbot framework using Hybrid Water Wave–Barnacle Mating Optimization (HWW-BMO) to improve query understanding and response accuracy. User queries are preprocessed into weighted feature vectors, which are optimized by HWW-BMO and fed into a hybrid H-ExtLSTM model for intent detection and response prediction. Optimizing both ELM and LSTM parameters via HWW-BMO enhances performance. Experiments across multiple datasets showed that the framework outperforms existing methods, demonstrating the effectiveness of combining BMO with Water Wave Optimization for natural language processing tasks.

A further study by Adnan et al. [182], who designed predictive models for the apparent viscosity of waxy crude oils using metaheuristic-optimized machine learning, including BMO. The study analyzed 622 experimental values under polymer-free and polymer-doped conditions. Models included BMO-optimized RBF networks, TLBO, MPA, tree-based methods, and Gaussian Process Regression (GPR). GPR achieved the highest accuracy, while BMO-RBF models also provided reliable predictions. Outlier detection via the

Leverage method confirmed data validity, highlighting the potential of BMO and related metaheuristics for modeling complex petroleum properties.

In a related application, Indira et al. [183] introduced a hybrid ABMO-ANN model for short-term load forecasting in microgrids. The Adaptive BMO (ABMO) optimizes feature selection and ANN parameters, overcoming limitations of conventional static methods. The proposed ABMO-ANN method demonstrated superior performance compared to regression tree (RT), support vector machine (SVM), standalone ANN, and PSO-based ANN models, achieving substantial reductions in mean absolute percentage error (MAPE) and improvements in root mean square error (RMSE), correlation coefficient, symmetric MAPE, and agreement index.

Also, Al-Dhaifallah et al. [184] proposed an efficient MPPT method for PV systems by integrating a Converged BMO (CBMO) with an Adaptive Neuro-Fuzzy Inference System (ANFIS). CBMO was applied offline to obtain optimal voltage values under varying irradiance and temperature conditions, which were then used by ANFIS to predict the optimal operating voltage in real time. The CBMO–ANFIS model was implemented in MATLAB/Simulink and evaluated under diverse climatic scenarios. The results demonstrated fast convergence, high stability, and a tracking efficiency of 99.3%, outperforming conventional MPPT techniques.

In another work, Ahmed et al. [185] introduced the Selective Opposition-Based Constrained Barnacle Mating Optimizer (SO-C-BMO), which enhances the original BMO by incorporating environmental constraints and selective opposition to improve exploration, convergence speed, and solution quality. Its effectiveness was validated through real-world case studies, showing faster convergence and superior statistical results. Furthermore, SO-C-BMO was coupled with a Least Squares Support Vector Machine (LSSVM) to form SO-C-BMO-LSSVM, which accurately tuned LSSVM hyperparameters for time-series forecasting. Thanks to its selective opposition mechanism, the approach effectively handles multimodal and non-convex problems, outperforming several well-known metaheuristics in both accuracy and convergence behavior.

Subsequently, Alrayes et al. [186] developed BCOBMO-DL, a hybrid model that combines blockchain and deep learning to enhance IoT security. Data are preprocessed using linear scaling normalization, and COBMO performs optimal feature selection. Detection is handled by a self-attention BiGRU model incorporating fractal theory, with hyperparameters tuned via the Reptile Search Algorithm (RSA). Evaluation on the NSLKDD dataset showed that BCOBMO-DL outperforms existing methods, providing higher accuracy and robustness in detecting sophisticated cyberattacks while ensuring data privacy.

Following this, Saraswathi and Murali Bhaskaran [187] proposed HBBSO-RDBN, a hybrid deep learning model for oral cancer detection that combines a Recurrent Deep Belief Network (RDBN) with metaheuristic optimization. Preprocessing uses median filtering and CLAHE to reduce noise, while RDBN integrates a DBN and an RNN architecture to improve classification. Hyperparameters, including the learning rate, number of epochs, and number of hidden neurons, are optimized using Hybrid Beetle–Barnacle Swarm Optimization (HBBSO), which merges BMO with Beetle Swarm Optimization. Experiments show HBBSO-RDBN outperforms PSO-RDBN, GWO-RDBN, BSO-RDBN, and BMO-RDBN, achieving higher accuracy and robustness in oral cancer detection.

Similarly, Kathole et al. [188] designed an educational chatbot using deep learning optimized with ADT-BMO, a hybrid Barnacles Mating Optimizer. ADT-BMO enhances feature selection, fusion, and tuning of hidden neurons, activation functions, and epochs for the AA-DTCN-SC network, refining features from BERT, TransformerNet, and Text CNN. The model achieves accurate intent recognition and context-aware responses, outperforming DTCN, RNN, and Bi-LSTM in accuracy, efficiency, and scalability for intelligent educational support.

In another work, Shikalgar et al. [189] developed a deep residual fuzzy encoder framework enhanced with BMO for crop yield prediction. Crop data are preprocessed via random drop imputation, normalization, and outlier detection, with feature selection using ReliefF, where BMO optimizes the number of neighbors. Kho-Kho Optimization (KKO) fine-tunes fuzzy encoder hyperparameters. The hybrid model achieved 95.6% accuracy, a 10% false discovery rate, and an F1 Score of 89.85%, demonstrating practical and reliable agricultural yield forecasting.

Finally, Nair and Azath [190] introduced an educational chatbot using deep learning optimized with ADT-BMO to improve intent recognition and response relevance. Student queries are converted into vector representations via BERT, TransformerNet, and Text CNN, and ADT-BMO performs weighted feature selection and fusion. The fused features feed into an AA-DTCN-SC network, whose parameters are also optimized by ADT-BMO. The system achieves 85.4% accuracy and 92.6% precision, outperforming traditional chatbot methods.

4.4 Multi-Objective Versions of BMO Algorithm

Unlike traditional single-objective optimization, multi-objective optimization must address multiple objectives simultaneously, requiring the algorithm to manage trade-offs among conflicting objectives. This requirement substantially increases the challenge of identifying solutions that can be regarded as optimal [191]. In such situations, identifying a single definitive optimal solution becomes challenging, as coordinated strategies are required to achieve the best possible outcomes. Consequently, tackling problems that involve multiple objectives simultaneously is regarded as one of the most demanding tasks in optimization. Researchers have sought to enhance BMO's capability to address multi-objective problems by introducing several modifications that extend its strong performance in single-objective optimization. The following paragraph presents the various multi-objective adaptations of the BMO algorithm.

In their work, Abd Razak et al. [192] extended the single-objective BMO to a Multi-Objective BMO (MOBMO) by integrating non-dominated sorting and crowding distance mechanisms to generate Pareto-optimal solutions while preserving diversity. The algorithm was tested on standard multi-objective benchmarks, showing improved accuracy and competitive diversity relative to existing methods. MOBMO was further applied to tuning the PD controller for an inverted pendulum, outperforming the multi-objective water cycle algorithm in solution accuracy while maintaining comparable diversity.

Following this, Lakkshmanan et al. [193] used BMO within a Multi-Objective Metaheuristics with Intelligent Deep Learning (MOM-IDL) framework for early diagnosis of pancreatic tumors. The algorithm optimized multi-level thresholding for image segmentation and fine-tuned FSVM parameters, enabling effective handling of conflicting objectives in segmentation accuracy and classification performance. Experiments on benchmark datasets demonstrated that BMO significantly improved both segmentation and classification compared to state-of-the-art methods, underscoring its utility for multi-objective optimization in medical imaging applications.

Similarly, Bhasha and Reddy [194] proposed an Opposition-based Multi-Objective BMO (O-BMO) for hyperspectral image super-resolution that integrates NSSR, ADWT, and a deep CNN. O-BMO was employed to fine-tune the parameters of NSSR and CNN, optimizing multiple objectives, including PSNR and SSIM. Experimental results on benchmark datasets demonstrated significant performance gains, with up to 38.8% improvement in PSNR, highlighting the effectiveness of BMO in handling multi-objective optimization for high-quality hyperspectral image reconstruction.

Furthermore, Ismail et al. [195] developed a Multi-objective Hybrid Evolutionary Programming–BMO (MOHEBMO) to address the combined economic and environmental dispatch problem in power systems.

The algorithm simultaneously minimizes fuel cost and emissions using a weighted-sum strategy to achieve a balanced trade-off. Tested on the IEEE 57-Bus system with practical constraints, MOHEBMO demonstrated superior convergence, solution quality, and robustness compared to existing multi-objective methods. The hybridization enhanced the algorithm's ability to explore diverse solutions while maintaining an effective balance between exploration and exploitation in complex multi-objective optimization scenarios.

In another study, Ismail et al. [196] applied MOHEBMO to address non-convex combined economic-emission dispatch problems in power systems. When tested on the IEEE 30-bus system under practical operational constraints, MOHEBMO outperformed existing multi-objective optimization methods, demonstrating superior solution quality, convergence behavior, and robustness. These findings underscore its effectiveness in tackling complex multi-objective optimization challenges in real-world power system applications.

Additionally, Fan et al. [197] proposed an Improved BMO (IBMO) for optimizing a hybrid renewable energy system with wind, photovoltaic, and hydropower sources. IBMO incorporates a quasi-oppositional mechanism to enhance convergence and uses Pareto Front solutions to balance trade-offs between power output stability and energy efficiency. The algorithm outperformed NSGA-II and the original BMO, demonstrating superior convergence and effective multi-objective optimization under varying climatic conditions.

Finally, Norouzi et al. [198] proposed a Modified BMO (MBMO) for the optimal placement of switches and distributed generation units in power distribution networks, aiming to maximize reliability indices (SAIDI, SAIFI) and minimize operational costs. MBMO integrates opposition-based learning and a self-adaptive population strategy to enhance diversity, convergence speed, and global search capability. Results showed that MBMO outperformed NSGA-II and SPEA2, demonstrating its effectiveness and robustness in complex multi-objective optimization for power distribution systems.

5 Application Areas of BMO and Its Variants

The BMO algorithm has demonstrated high effectiveness in addressing a wide range of real-world optimization problems across various engineering and computational domains. Its applications include power and control engineering, forecasting, image Processing, signal processing, and other fields. These problems often involve complex optimization tasks with diverse search-space dimensions and varying computational requirements.

On the other hand, to overcome the limitations of existing metaheuristics in addressing complex optimization problems, the original BMO was developed and subsequently enhanced to broaden its practical applicability. To better handle the diverse characteristics and complexities of solution landscapes, numerous modifications and hybridization strategies have been proposed. Table 9 summarizes studies that have applied the classical BMO across different domains, while Table 10 presents investigations using various BMO variants along with their respective application areas. Additionally, Fig. 5 provides a visual overview of the distribution of BMO applications across multiple fields.

Table 9: Application domains of classical BMO.

Domain	Problem	Year	Research Works
Power and Control	-Economic Dispatch (minimize generation cost under constraints)	2019	Sulaiman et al. [67]

(Continued)

Table 9 (continued)

Domain	Problem	Year	Research Works
Engineering	-Combined Economic and Emission Dispatch (minimize cost and emissions simultaneously)	2019	Sulaiman et al. [68]
	-Economic Emission-Load Dispatch	2020	Sulaiman et al. [69]
	-Power Flow Scheduling with Valve-Point Effects	2021	Choudhary et al. [71]
	-Optimal power flow optimization	2021	Sulaiman et al. [72]
	-Optimal power flow optimization	2021	Sulaiman and Mustaffa [73]
	-Optimal power flow optimization	2021	Sulaiman and Mustaffa [74]
	-Optimal reactive power dispatch optimization	2022	Sulaiman et al. [75]
	-Optimal Chiller Loading (minimize power consumption)	2022	Sulaiman and Mustaffa [77]
	-Parameter extraction in three-diode solar model	2022	Agwa et al. [78]
	-Parameter extraction in PV modules	2022	Madhiarasan et al. [79]
Forecasting	-Short-term dengue outbreak prediction	2020	Mustaffa et al. [70]
Image Processing	Multilevel image thresholding for image segmentation	2022	Fakri et al. [76]
Signal Processing	-Core size estimation of magnetic nanoparticles	2023	Saari et al. [80]

Table 10: Application domains of BMO variants.

Domain	Problem Solved	Year	Research Works
Power and Control	-PD controller tuning for inverted pendulum using multi-objective optimization	2020	Abd Razak et al. [192]
	-Power system stability optimization	2021	Devarapalli et al. [100]
	-Maximum Power Point Tracking for thermoelectric generator system	2021	Tariq et al. [149]
	-Parameter estimation of induction motors	2021	Rajesh et al. [113]
	-Soft fault diagnosis in analog circuits	2021	Liang et al. [164]
	-PD controller optimization for an inverted pendulum	2022	Roslan et al. [101]
	-Non-convex economic dispatch optimization in power systems	2022	Ismail et al. [102]

(Continued)

Table 10 (continued)

Domain	Problem Solved	Year	Research Works
	-State of charge estimation for lithium-ion batteries	2022	Liu et al. [166]
	-State of Charge estimation for hybrid and electric vehicle batteries	2022	Vellingiri et al. [139]
	-Energy management and traffic flow prediction for autonomous vehicles	2022	Hamza et al. [146]
	-Optimal Power Flow optimization	2022	Sulaiman et al. [150]
	-Lifetime enhancement of power electronics in brushless DC drives	2022	Priya et al. [151]
	-Frequency and tie-line power stabilization in multi-microgrid systems	2022	Peddakapu et al. [153]
	-Optimal placement of switches and distributed generation units to maximize reliability and minimize cost	2022	Norouzi et al. [198]
	-Optimal placement of switches and distributed generation units to maximize reliability and minimize cost	2022	Norouzi et al. [198]
	-Non-convex combined economic-emission dispatch under operational constraints	2023	Ismail et al. [196]
	-Combined economic and environmental dispatch with multiple conflicting objectives	2023	Ismail et al. [195]
	-Optimizing abrasive water jet cutting process parameters for composite materials	2023	Rajamani et al. [154]
	-Optimal coordination of overcurrent relays in power systems	2023	Jamal and Shamsuddin [155]
	-State of Charge estimation for Nissan Leaf batteries	2023	Mustaffa and Sulaiman [132]
	-Optimal power flow optimization	2024	Sulaiman and Mustaffa [105]
	-Convex economic dispatch optimization in power systems	2024	Ismail et al. [110]
	-Energy consumption modeling and optimization for electric buses	2024	Turgut et al. [109]
	-State of Charge estimation for electric vehicle batteries	2024	Sulaiman et al. [199]
	-Speed regulation of hybrid stepper motors	2024	Deepa et al. [156]
	-Optimal power flow optimization	2024	Sulaiman and Mustaffa [108]
	-Maximum power point tracking for PV systems under varying irradiance and temperature	2024	Al-Dhaifallah et al. [184]

(Continued)

Table 10 (continued)

Domain	Problem Solved	Year	Research Works
	-Parameter optimization of a nonlinear fuzzy-Hammerstein model	2024	Kasruddin et al. [107]
	-Optimal PEV charging scheduling in distribution grids	2024	Razali et al. [106]
	-Hotspot detection in PV systems from thermal image	2024	Kumar and Reddy [145]
	-State of Charge estimation for electric vehicle batteries	2025	Mustaffa and Sulaiman [120]
	-Optimal chiller loading considering maintenance and breakdowns	2025	Thou et al. [160]
	-State of Charge estimation for electric vehicle batteries	2025	Sulaiman et al. [122]
Forecasting	-COVID-19 case prediction	2021	Mustaffa and Sulaiman [112]
	-Drought severity prediction using satellite vegetation indices	2022	Sardar et al. [137]
	-COVID-19 cases and vaccination trend prediction	2023	Ahmed et al. [176]
	-Stock price prediction	2023	Mustaffa and Sulaiman [116]
	-Stock market closing price prediction	2023	Behera et al. [117]
	-Epidemic forecasting	2023	Ahmed et al. [170]
	-COVID-19 cases and vaccination trend prediction	2024	Ahmed et al. [185]
	-Earth surface temperature forecasting	2024	Mustaffa et al. [133]
	-Crop price prediction	2024	Visnu Dharsini and Babu [179]
	-Predicting apparent viscosity of waxy crude oils	2024	Adnan et al. [182]
	-Short-term load forecasting in microgrids	2024	Indira et al. [183]
	-Agricultural drought severity prediction using satellite imagery	2024	Chaudhari et al. [177]
	-Currency exchange rate prediction	2024	Behera et al. [118]
	-Prediction of SC-CO_2 density and niflumic acid solubility	2024	Li et al. [119]
	-Copper price prediction	2025	Yu [121]
	-Prediction of chemical concentration distributions in adsorption processes	2025	Lv and wang [123]
	-Traffic class prediction	2025	Mustaffa et al. [124]
	-Cooling load prediction in commercial chiller systems	2025	Sulaiman et al. [125]

(Continued)

Table 10 (continued)

Domain	Problem Solved	Year	Research Works
	-Chiller power consumption forecasting in commercial buildings	2025	Sulaiman and Mustaffa [143]
	-Crop yield prediction	2025	Shikalgar et al. [189]
	-Time series forecasting	2025	Aziz et al. [158]
Image Processing	-Image contrast enhancement	2020	Ahmed et al. [147]
	-Brain tumor segmentation and classification in MRI images	2021	Anantharajan and Gunasekaran [129]
	-COVID-19 diagnosis from chest X-ray images	2021	Shankar et al. [136]
	-Automated pulmonary emphysema diagnosis	2021	Mondal et al. [162]
	-Medical image retrieval and classification	2021	Mahesh et al. [163]
	-Malaria parasite detection and classification in blood smear images	2022	Dutta et al. [130]
	-Super-resolution of hyperspectral images optimizing PSNR and SSIM	2022	Bhasha and Reddy [194]
	-Early diagnosis of pancreatic tumors via multi-level image segmentation and classification	2022	Lakkshmanan et al. [193]
	-Weed detection and classification in agricultural images	2022	Albraikan et al. [167]
	-Medical X-ray image classification	2023	Kumar and Ponnusamy [131]
	-Multi-disease classification of plant leaves	2023	Sahu and Minz [172]
	-Road damage detection from remote sensing images	2023	Alamgeer et al. [174]
	-Brain tumor classification from MRI images	2024	Gade et al. [141]
	-Early liver disease classification from CT images	2025	Shanmugaraja et al. [135]
	-Oral cancer detection	2025	Saraswathi and Murali Bhaskaran [187]
Classification	-Gene selection for cancer classification	2021	Houssein et al. [111]
	-Feature selection	2021	Jia and Sun [161]
	-Data clustering optimization	2022	Abd Elaziz et al. [103]
	-Improving neural network-based data classification	2022	Murugan and Baburaj [114]
	-Atherosclerosis diagnosis and classification	2022	Malibari et al. [168]
	-Feature selection	2023	Gupta et al. [169]
	-Multi-disease prediction	2023	Anish and Joe Prathap [171]

(Continued)

Table 10 (continued)

Domain	Problem Solved	Year	Research Works
	-Waste classification in IoT-enabled smart environments	2023	Vijayalakshmi et al. [175]
	-Sentiment-based online product recommendation	2023	Pughazendi et al. [140]
	-Big data classification using rough set and clustering	2024	Bhukya and Sadanandam [178]
	-Twitter sentiment analysis for urban sustainability	2024	Alahmari [127]
	-Cardiovascular disease detection and classification	2024	Halawani et al. [180]
	-Chatbot intent detection and response prediction	2024	Magoo and Singh [181]
	-Student intent recognition for educational chatbots	2025	Kathole et al. [188]
	-Student intent recognition for educational chatbots	2025	Nair and Azath [190]
Networking	-Cyberattack detection and traffic management in MEC networks	2020	Gopalakrishnan et al. [128]
	-Botnet attack detection in IoT networks	2022	Alrayes et al. [165]
	-Zero-day botnet attack detection in Internet of Vehicles	2020	Saheed and Chukuwuere [134]
	-Energy-aware routing in Wireless Body Area Networks	2023	Reddy and Venkatram [104]
	-Intrusion detection in IoT networks	2023	Velumani and Kalimuthu [115]
	-Botnet attack detection in network traffic	2023	Zaheer et al. [126]
	-Energy-efficient data aggregation in Fog-enabled IoT networks	2023	Nalayini and Prakash [173]
	-Intrusion detection in complex network environments	2025	Venkata et al. [142]
	-Intrusion detection in IoT networks	2025	Alrayes et al. [186]
	-Energy-efficient clustering and routing in wireless sensor networks	2025	Renaldo Maximus and Balaji [159]
Signal Processing	-Modulation recognition of communication signals	2022	Venugopal et al. [138]
	-Intrusion detection in distributed optical fiber sensor systems	2025	Yang and yang [144]
	-UAV fault detection	2025	Zakaria et al. [157]

(Continued)

Table 10 (continued)

Domain	Problem Solved	Year	Research Works
Others	-Sequence-based t-way test suite generation optimizing input ordering for interaction coverage	2021	Zamli and kader [148]
	-Nonlinear geophysical parameter estimation and inversion for magnetic anomaly datasets	2022	Ai et al. [152]

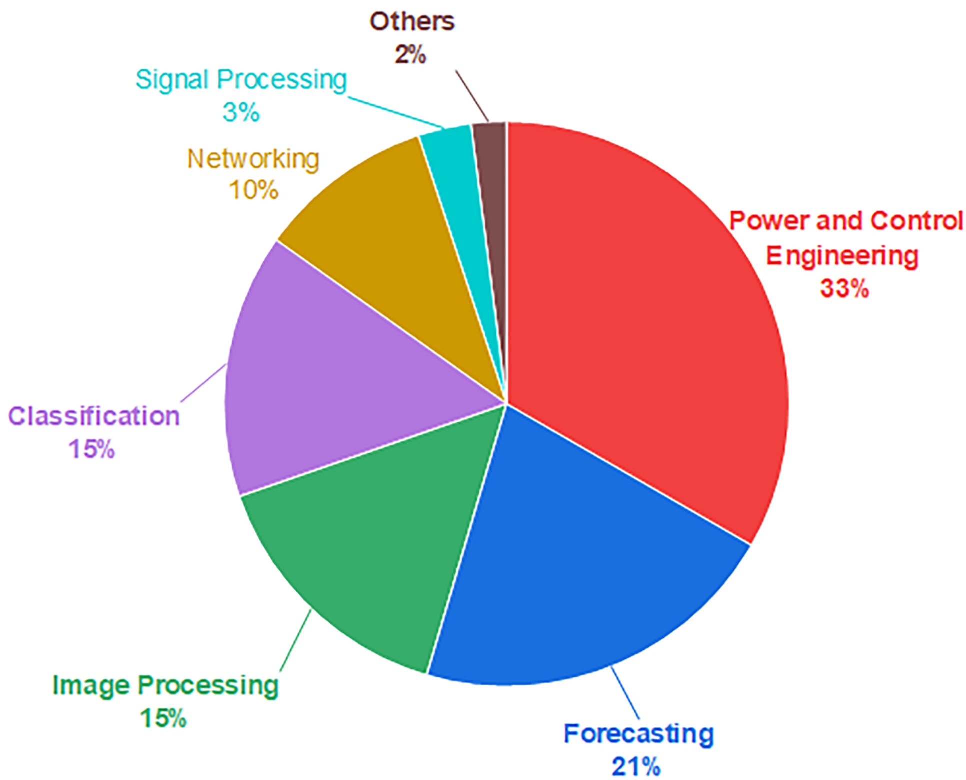


Figure 5: Application areas of BMO and its variants.

6 Open Source Implementations of BMO Algorithm

BMO algorithm has recently garnered considerable interest from researchers seeking to apply it in a wide range of domains. To ensure a thorough overview, this study provides detailed information along with references to all publicly available open-source implementations. Since its introduction, BMO has been implemented in MATLAB and made publicly available as open-source software[3]. This implementation has been widely used to evaluate numerous benchmark test functions, significantly contributing to its broad adoption. Additionally, a Python implementation of the BMO algorithm has been developed within the MEALPY library [200] and is available on GitHub[4]. MEALPY is one of the most comprehensive collections of metaheuristic algorithms worldwide, including BMO, and provides several key functionalities:

[3] http://ee.ump.edu.my/herwan/index.php/research/barnacles-mating-optimizer-bmo
[4] https://github.com/thieu1995/mealpy

- Provides user-friendly interfaces for configuring and executing the BMO algorithm.
- Includes a wide range of standard benchmark functions for algorithm testing and performance evaluation.
- Provides frameworks for extending BMO to multi-objective problems using popular strategies such as NSGA-II and MOEA/D.
- Ensures that results can be reliably reproduced, supporting validation and comparison of algorithmic performance.
- Facilitates easy modification or hybridization with other meta-heuristic techniques, promoting further research and experimentation.

Moreover, many researchers have applied BMO and its variants to address a variety of optimization problems, making their implementations publicly accessible. For instance, Jena et al. [97] proposed an enhanced BMO variant by incorporating directed random movement toward the current best solution and a Gaussian mutation operator, with the source code freely accessible online[5]. Similarly, Ahmed et al. [147] developed an efficient contrast enhancement method named iEBMO, based on the BMO algorithm, and have shared the complete source code on GitHub[6].

For the remaining studies reviewed in this paper, where the source code of the proposed BMO variants was not publicly available, the algorithms were independently implemented in MATLAB based on the methodological descriptions provided in the original publications. MATLAB was selected because it is the platform most commonly used in BMO-related research, which offers a relatively uniform implementation environment across studies. However, it should be noted that detailed reporting of software versions, hardware specifications, and random seed settings is not consistently provided in the literature, which may limit the exact reproducibility of some reported results.

7 Performance Evaluation of BMO Algorithm

Since its introduction, many metaheuristic algorithms have emerged to tackle increasingly complex optimization problems. To provide an updated evaluation of BMO, this section compares its performance with recently published metaheuristics using the CEC2005 benchmark suite [201], a widely accepted standard for algorithm assessment. This comparison highlights BMO's current performance, revealing its strengths and weaknesses relative to modern approaches and offering insights into its competitiveness and potential avenues for further enhancement.

7.1 Benchmark Description and Parameter Settings

The optimization literature provides a rich set of benchmark test functions. To thoroughly evaluate the performance of BMO, a diverse set of functions with varying characteristics and complex search landscapes was selected. In particular, the well-established CEC2005 test suite [201], comprising 23 functions, was employed in this study, as summarized in Tables 11–13. The primary objective of these benchmarks is the minimization of fitness values. The CEC2005 functions are categorized into three groups: unimodal (F_1–F_7), multimodal (F_8–F_{13}), and fixed-dimensional multimodal (F_{14}–F_{23}). Unimodal functions contain a single global optimum, multimodal functions feature multiple local optima in addition to a global one, and fixed-dimensional multimodal functions have a constant dimensionality. These benchmarks are widely used to assess the effectiveness and efficiency of metaheuristic algorithms in global optimization.

[5] https://www.mathworks.com/matlabcentral/fileexchange/159558-enhanced-barnacle-mating-optimization-algorithm-ebmo
[6] https://github.com/ahmed-shameem/Projects

Table 11: Unimodal test functions.

Functions	D	Range	F_{best}
$F_1(x) = \sum_{i=1}^{n} x_i^2$	30	$[-100, 100]$	0
$F_2(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	30	$[-10, 10]$	0
$F_3(x) = \sum_{i=1}^{n} \left(\sum_{j-1}^{i} x_j \right)^2$	30	$[-100, 100]$	0
$F_4(x) = \max_i \{\lvert x_i \rvert, 1 \le i \le n\}$	30	$[-100, 100]$	0
$F_5(x) = \sum_{i=1}^{n-1} \left[100 \left(x_{i+1} - x_i^2 \right)^2 + (x_i - 1)^2 \right]$	30	$[-30, 30]$	0
$F_6(x) = \sum_{i=1}^{n} ([x_i + 0.5])^2$	30	$[-100, 100]$	0
$F_7(x) = \sum_{i=1}^{n} i x_i^4 + \text{random}[0, 1)$	30	$[-128, 128]$	0

Table 12: Multimodal test functions.

Functions	D	Range	F_{best}
$F_8(x) = \sum_{i=1}^{n} -x_i \sin\left(\sqrt{\lvert x_i \rvert}\right)$	30	$[-500, 500]^d$	$-418.9829 \times$ n
$F_9(x) = \sum_{i=1}^{n} \left[x_i^2 - 10\cos(2\pi x_i) + 10 \right]$	30	$[-5.12, 5.12]^d$	0
$F_{10}(x) = -20exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - exp\left(\frac{1}{n}\sum_{i=1}^{n} cos(2\pi x_i)\right) + 20 + e$	30	$[-32, 32]^d$	0
$F_{11}(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	30	$[-600, 600]^d$	0
$F_{12}(x) = \frac{\pi}{d}\left\{10\sin(\pi y_1) + \sum_{i=1}^{d-1} (y_i - 1)^2 \left[1 + 10sin^2(\pi y_{i+1})\right] + (y_d - 1)^2\right\} + \sum_{i=1}^{d} U(x_i, 10, 100, 4)$ $y_i = 1 + \frac{x_i + 1}{4}$ $U(x_i, a, k, m) = \begin{cases} k(x_i - a)^m & x_i > a \\ 0 & -a < x_i < a \\ k(-x_i - a)^m & x_i < -a \end{cases}$	30	$[-50, 50]^d$	0
$F_{13}(x) = 0.1\left\{sin^2(3\pi x_1) + \sum_{i=1}^{d} (x_i - 1)^2 \left[1 + sin^2(3\pi x_i + 1)\right] + (x_d - 1)^2 \left[1 + sin^2(2\pi x_d)\right]\right\} + \sum_{i=1}^{d} U(x_i, 5, 100, 4)$	30	$[-50, 50]^d$	0

Table 13: Fixed-dimension multimodal test functions.

Functions	D	Range	F_{best}
$F_{14}(x) = \left[\frac{1}{500} + \sum_{i=1}^{25} \frac{1}{i + \sum_{j=1}^{2} \left(x_j - a_{j,i}\right)^6}\right]^{-1}$	2	$[-65, 65]^d$	1
$F_{15}(x) = \sum_{i=1}^{d} \left[a_i - \frac{x_1\left(b_i^2 + b_i x_2\right)}{b_i^2 + b_i x_3 + x_4}\right]^2$	4	$[-5, 5]^d$	0.00030
$F_{16}(x) = 4x_1^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1 x_2 - 4x_2^2 + 4x_2^4$	2	$[-5, 5]^d$	-1.0316
$F_{17}(x) = \left(x_2 - \frac{5.1}{4\pi^2}x_1^2 + \frac{5}{\pi}x_1 - 6\right)^2 + 10\left(1 - \frac{1}{8\pi}\right)cosx_1 + 10$	2	$[-5, 5]^d$	0.398
$F_{18}(x) = \left[1 + (x_1 + x_2 + 1)^2 \left(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1 x_2 + 3x_2^2\right)\right] \times \left[30 + (2x_1 - 3x_2)^2 \times \left(18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1 x_2 + 27x_2^2\right)\right]$	2	$[-2, 2]^d$	3

(Continued)

Table 13 (continued)

Functions	D	Range	F_{best}
$F_{19}(x) = -\sum_{i=1}^{4} a_i exp\left(-\sum_{j=1}^{3} b_{ij}\left(x_j - p_{ij}\right)^2\right)$	3	$[1,3]^d$	−3.86
$F_{20}(x) = -\sum_{i=1}^{4} a_i exp\left(-\sum_{j=1}^{6} b_{ij}\left(x_j - p_{ij}\right)^2\right)$	6	$[0,1]^d$	−3.32
$F_{21}(x) = -\sum_{i=1}^{5}\left[(X - a_i)(X - a_i)^T + c_i\right]^{-1}$	4	$[0,10]^d$	−10.1532
$F_{22}(x) = -\sum_{i=1}^{7}\left[(X - a_i)(X - a_i)^T + c_i\right]^{-1}$	4	$[0,10]^d$	−10.4028
$F_{23}(x) = -\sum_{i=1}^{10}\left[(X - a_i)(X - a_i)^T + c_i\right]^{-1}$	4	$[0,10]^d$	−10.5363

The performance of the BMO algorithm was statistically evaluated and benchmarked against several recently proposed high-performing optimization algorithms, namely Water Uptake and Transport in Plants (WUTP) algorithm [202], Mirage Search Optimization (MSO) [203], Fungal Growth Optimizer (FGO) [204], Educational Competition Optimizer (ECO) [205], Newton-Raphson-based Optimizer (NRBO) [206], RIME optimization algorithm (RIME) [207], Aquila Optimizer (AO) [208], and Arithmetic Optimization Algorithm (AOA) [209]. For a fair comparison, the parameter settings of all competing algorithms were kept exactly as recommended by their original authors. All methods were run for a maximum of 500 iterations with a population size of 30 (i.e., 30 randomly initialized candidate solutions). Each algorithm was independently executed 30 times on every test function.

A comprehensive set of performance metrics was employed to conduct a rigorous evaluation. These include the mean and standard deviation (Std) of the fitness values to assess solution accuracy and stability, the Wilcoxon rank-sum test [210] for statistical significance analysis, and the Friedman test [211] for ranking the overall performance of the algorithms. These statistical tools ensure a precise, reliable, and unbiased comparison among the different optimization methods. All experiments were performed on a computer equipped with an Intel Core i7-1255G7 processor running at up to 4.70 GHz, 32 GB of RAM, and Windows 11 Pro operating system. The MATLAB R2024a environment was used to implement and execute all algorithms and procedures.

7.2 Statistical Results

This subsection presents a rigorous and in-depth analysis of the comparative performance of BMO against a set of recently proposed metaheuristic algorithms on the CEC2005 benchmark suite. Table 14 reports the statistical results over 23 benchmark functions using two key performance indicators: the mean fitness value obtained over 30 independent runs and the corresponding standard deviation, which quantifies the robustness and stability of each method.

Table 14: Comparison results over 23 benchmark functions.

Fun.	Indice	WUTP	MSO	FGO	ECO	NRBO	RIME	AO	AOA	BMO
F_1	Mean	8.3772E−01	4.0919E−03	1.4790E+04	6.2196E−51	2.8640E+04	1.9964E+00	3.5353E−106	3.9517E−17	0.0000E+00
	Std	4.9546E−01	2.9446E−03	4.5899E+03	3.2967E−50	2.6204E+04	9.0006E−01	1.9363E−105	2.1644E−16	0.0000E+00
	Rank	6	5	8	3	9	7	2	4	1
F_2	Mean	6.1785E−01	1.2161E−02	1.3681E+04	3.5043E−25	1.3264E+12	1.2466E+00	1.2227E−54	0.0000E+00	6.1236E−287
	Std	1.8982E−01	1.2971E−02	7.3922E+04	1.8686E−24	3.7778E+12	8.3640E−01	6.6968E−54	0.0000E+00	0.0000E+00
	Rank	6	5	8	4	9	7	3	1	2
F_3	Mean	2.9149E+04	3.1133E+03	4.5381E+04	1.6933E−50	9.0193E+04	1.2731E+03	3.5238E−116	8.4390E−03	0.0000E+00
	Std	5.9432E+03	1.0577E+03	1.1368E+04	8.4127E−50	4.3060E+04	4.7324E+02	1.9285E−115	1.7743E−02	0.0000E+00
	Rank	7	6	8	3	9	5	2	4	1
F_4	Mean	8.4807E+00	2.5386E+01	4.9675E+01	7.1051E−25	1.2170E−119	8.8651E+00	3.3343E−54	2.4999E−02	5.1117E−288
	Std	2.4449E+00	5.6716E+00	5.3282E+00	3.8914E−24	6.6088E−119	3.9324E+00	1.8263E−53	2.0667E−02	0.0000E+00
	Rank	6	8	9	4	2	7	3	5	1
F_5	Mean	2.6584E+02	2.1629E+02	1.5875E+07	2.7358E+01	1.3620E+08	7.4545E+02	5.7709E−03	2.8447E+01	2.7791E+01
	Std	3.2069E+02	2.5359E+02	6.3157E+06	4.6979E−01	8.4460E+07	9.0046E+02	1.1548E−02	2.8090E−01	3.3584E−01
	Rank	6	5	8	2	9	7	1	4	3
F_6	Mean	8.7713E−01	3.8264E−03	1.4551E+04	8.2783E−03	1.5700E+04	2.0876E+00	1.4920E−04	3.2683E+00	4.1156E−01
	Std	7.4545E−01	2.9819E−03	3.4890E+03	8.7361E−03	2.1245E+04	8.2280E−01	2.9892E−04	2.5311E−01	2.3657E−01
	Rank	5	2	8	3	9	6	1	7	4
F_7	Mean	4.7762E−02	1.0321E−01	8.8146E+00	2.8929E−04	8.3662E−03	4.3461E−02	9.5300E−05	8.5249E−05	3.0812E−05
	Std	1.3558E−02	3.7029E−02	3.6874E+00	2.3163E−04	9.2566E−03	1.9766E−02	8.3499E−05	8.0742E−05	3.1960E−05
	Rank	7	8	9	4	5	6	3	2	1
F_8	Mean	−5.3390E+03	−9.1765E+03	−3.7116E+03	−1.1268E+04	−1.2210E+04	−1.0091E+04	−7.9781E+03	−5.2677E+03	−7.8393E+03
	Std	4.6775E+02	4.8568E+02	3.2222E+02	8.1534E+02	5.3560E+02	6.0468E+02	3.8156E+03	4.6112E+02	1.0062E+03
	Rank	7	4	9	2	1	3	5	8	6
F_9	Mean	2.0649E+02	5.0523E+01	2.7601E+02	0.0000E+00	4.6786E+01	6.4300E+01	0.0000E+00	0.0000E+00	0.0000E+00
	Std	1.5466E+01	1.4201E+01	2.6364E+01	0.0000E+00	9.4766E+01	1.5206E+01	0.0000E+00	0.0000E+00	0.0000E+00
	Rank	8	6	9	1	5	7	1	1	1
F_{10}	Mean	1.9962E+01	1.5977E+00	1.6138E+01	4.4409E−16	4.4409E−16	2.1876E+00	4.4409E−16	4.4409E−16	4.4409E−16
	Std	8.6791E−03	7.5582E−01	1.1144E+00	0.0000E+00	0.0000E+00	4.0748E−01	0.0000E+00	0.0000E+00	0.0000E+00
	Rank	9	6	8	1	1	7	1	1	1

(Continued)

Table 14 (continued)

Fun.	Indice	WUTP	MSO	FGO	ECO	NRBO	RIME	AO	AOA	BMO
F_{11}	Mean	8.5156E−01	2.3865E−02	1.3920E+02	0.0000E+00	0.0000E+00	9.4611E−01	0.0000E+00	2.3234E−01	0.0000E+00
	Std	1.3328E−01	1.8250E−02	2.6731E+01	0.0000E+00	0.0000E+00	9.9553E−02	0.0000E+00	1.4972E−01	0.0000E+00
	Rank	7	5	9	1	1	8	1	6	1
F_{12}	Mean	5.0118E−01	6.4203E−01	1.2849E+07	3.7257E−03	2.4404E+08	2.8414E+00	3.7849E−06	5.1978E−01	1.6280E−02
	Std	9.4730E−01	7.3059E−01	1.0710E+07	1.9526E−02	2.0526E+08	1.5956E+00	5.3055E−06	3.9061E−02	1.2381E−02
	Rank	4	6	8	2	9	7	1	5	3
F_{13}	Mean	1.2511E+00	1.9147E−01	4.3415E+07	1.7294E−02	4.9941E+08	2.2257E−01	1.6418E−05	2.8418E+00	2.7837E+00
	Std	2.2999E+00	5.2389E−01	2.1513E+07	3.1218E−02	4.5657E+08	9.1660E−02	2.1295E−05	1.0542E−01	7.0279E−01
	Rank	5	3	8	2	9	4	1	7	6
F_{14}	Mean	9.9800E−01	6.6590E+00	4.6401E+00	1.5262E+00	1.0162E+00	9.9800E−01	2.5320E+00	9.7378E+00	1.0358E+01
	Std	3.2643E−15	5.0259E+00	2.7814E+00	1.1251E+00	8.0890E−02	3.2301E−12	3.3009E+00	4.1741E+00	3.3188E+00
	Rank	1	7	6	4	3	2	5	8	9
F_{15}	Mean	3.4147E−03	5.1717E−03	1.0314E−02	6.9612E−04	1.2955E−03	5.2808E−03	4.4778E−04	1.2060E−02	4.5656E−04
	Std	6.7631E−03	8.0769E−03	6.2635E−03	3.7172E−04	4.5614E−04	8.4662E−03	7.4103E−05	2.0300E−02	1.8085E−04
	Rank	5	6	8	3	4	7	1	9	2
F_{16}	Mean	−1.0316E+00	−1.0316E+00	−1.0068E+00	−1.0316E+00	−1.0179E+00	−1.0316E+00	−1.0312E+00	−1.0316E+00	−1.0316E+00
	Std	5.2156E−16	6.4539E−16	2.8072E−02	7.3200E−10	1.3378E−02	1.3580E−07	4.6697E−04	1.1063E−07	6.7752E−16
	Rank	1	2	9	4	8	5	7	6	3
F_{17}	Mean	3.9789E−01	3.9789E−01	4.1419E−01	3.9789E−01	4.3463E−01	3.9789E−01	3.9809E−01	3.9789E−01	3.9789E−01
	Std	0.0000E+00	0.0000E+00	2.4963E−02	0.0000E+00	3.9006E−02	2.0410E−08	2.7535E−04	6.1041E−08	1.5955E−06
	Rank	1	1	8	1	9	4	7	5	6
F_{18}	Mean	−3.8628E+00	−3.8370E+00	−3.8447E+00	−3.8628E+00	−3.6600E+00	−3.8628E+00	−3.8564E+00	−3.8520E+00	−3.8625E+00
	Std	2.4491E−15	1.4113E−01	1.2163E−02	1.2043E−13	1.9002E−01	2.6463E−07	4.6797E−03	4.1735E−03	1.4390E−03
	Rank	1	8	7	2	9	3	5	6	4
F_{19}	Mean	−3.8628E+00	−3.8356E+00	−3.6396E+00	−3.8628E+00	−3.8628E+00	−3.8628E+00	−3.8564E+00	−3.8517E+00	−3.8625E+00
	Std	2.4028E−15	2.8690E−02	1.8254E−01	4.2177E−07	3.3334E−09	2.3557E−15	4.7115E−03	4.2180E−03	1.4390E−03
	Rank	2	8	9	4	3	1	6	7	5
F_{20}	Mean	−3.2943E+00	−3.2784E+00	−2.9282E+00	−3.2546E+00	−2.1874E+00	−3.2784E+00	−3.1808E+00	−3.0380E+00	−3.2594E+00
	Std	5.1146E−02	5.8273E−02	1.5856E−01	5.9923E−02	3.7239E−01	5.8287E−02	9.0063E−02	9.6197E−02	8.2144E−02
	Rank	1	2	8	5	9	3	6	7	4

(Continued)

Table 14 (continued)

Fun.	Indice	WUTP	MSO	FGO	ECO	NRBO	RIME	AO	AOA	BMO
F_{21}	Mean	−5.0552E+00	−6.3250E+00	−2.3430E+00	−1.0153E+01	−1.0033E+01	−7.8799E+00	−1.0145E+01	−3.5419E+00	−5.0552E+00
	Std	1.3897E−15	3.6908E+00	7.9917E−01	1.2656E−03	1.9379E−01	2.9119E+00	1.5450E−02	1.2577E+00	9.0336E−16
	Rank	6	5	9	1	3	4	2	8	6
F_{22}	Mean	−6.0121E+00	−6.3441E+00	−2.9396E+00	−9.3353E+00	−1.0320E+01	−8.6985E+00	−1.0394E+01	−3.5653E+00	−5.3188E+00
	Std	2.0600E+00	3.4352E+00	1.2968E+00	2.8519E+00	2.5641E−01	2.9748E+00	1.8001E−02	1.4543E+00	1.1083E+00
	Rank	6	5	9	3	2	4	1	8	7
F_{23}	Mean	−7.4798E+00	−6.6378E+00	−2.8663E+00	−7.6198E+00	−1.0484E+01	−8.4609E+00	−1.0527E+01	−3.7157E+00	−5.1285E+00
	Std	2.7411E+00	3.8317E+00	1.0528E+00	3.7717E+00	7.8584E−02	3.2578E+00	9.3524E−03	1.5923E+00	8.6573E−09
	Rank	5	6	9	4	2	3	1	8	7
Friedman mean rank		4.8696	5.3913	7.6957	2.7391	5.8261	5.0870	3.1304	5.5652	3.6087
Result		4	6	9	1	8	5	2	7	3

A close inspection of Table 14 clearly reveals the superior exploitation capability of BMO on unimodal functions. In particular, BMO consistently attains the global optimum or near-optimal solutions on multiple functions, including F_1, F_3, F_4, and F_7, outperforming most of the compared algorithms. The near-zero mean errors combined with negligible standard deviations demonstrate not only high accuracy but also remarkable consistency, indicating that BMO can reliably converge to optimal regions without being affected by stochastic variations. This behavior highlights the efficiency of its local search mechanism and its ability to intensify the search around promising solutions.

For multimodal functions, BMO continues to demonstrate a clear competitive advantage. Remarkably, it achieves the best mean fitness values on F_8, F_9, and F_{10}, outperforming all other compared algorithms on these functions. These results indicate that BMO not only maintains strong exploration capabilities but also effectively balances exploration with exploitation to navigate complex landscapes and avoid premature convergence. While a few algorithms show marginally better performance on other multimodal functions, BMO consistently delivers high-quality solutions across the category, confirming its reliability in complex, multimodal optimization scenarios.

In the case of fixed-dimension multimodal functions, BMO demonstrates consistently stable and competitive performance across the entire set. These functions, characterized by highly irregular landscapes and limited dimensionality, present significant challenges for metaheuristic algorithms due to the increased likelihood of local optima traps. Despite this, BMO maintains robust performance, achieving results that are often comparable to or slightly below the best-performing algorithms on individual functions. While a few algorithms may outperform BMO on specific functions, the overall performance profile indicates that BMO does not suffer from substantial performance degradation. Its consistent convergence patterns and relatively low standard deviation values across these functions underscore its reliability and robustness, even in the presence of complex and deceptive landscapes.

A Friedman rank test was performed across all benchmark functions to rigorously assess the overall efficiency of BMO, with the results presented in the last row of Table 14. This non-parametric statistical method enables a comprehensive performance comparison, where lower mean ranks indicate superior performance. The results demonstrate that BMO consistently achieves a top-tier position, securing a mean rank of 3.6087, which places it among the best-performing algorithms. While a few algorithms, such as ECO and AO, achieve slightly lower mean ranks, BMO outperforms several recently proposed methods, including MSO, NRBO, RIME, and AOA, confirming its competitive advantage and robustness across diverse problem landscapes.

7.3 Convergence Performance Analysis

Convergence analysis serves as a fundamental tool for evaluating both the robustness and efficiency of optimization algorithms. Fig. 6 depicts the convergence trajectories of all compared methods on selected representative CEC2005 benchmark functions, offering a detailed view of their search behavior and convergence rates. This visualization highlights how quickly and reliably each algorithm approaches high-quality solutions, providing valuable insights into their relative optimization performance across different problem landscapes. Analysis of the convergence curves shows that BMO consistently delivers strong performance across diverse benchmark functions, with a steady decrease in fitness values that reflects a well-balanced exploration–exploitation strategy. In many cases, BMO demonstrates stable convergence patterns with limited oscillations, indicating reliable search dynamics. However, variations in convergence speed can be observed depending on the function characteristics, where other algorithms may exhibit comparable or faster convergence in certain instances. Overall, the convergence profiles indicate that BMO remains competitive in terms of convergence speed and stability when compared to other recently published algorithms.

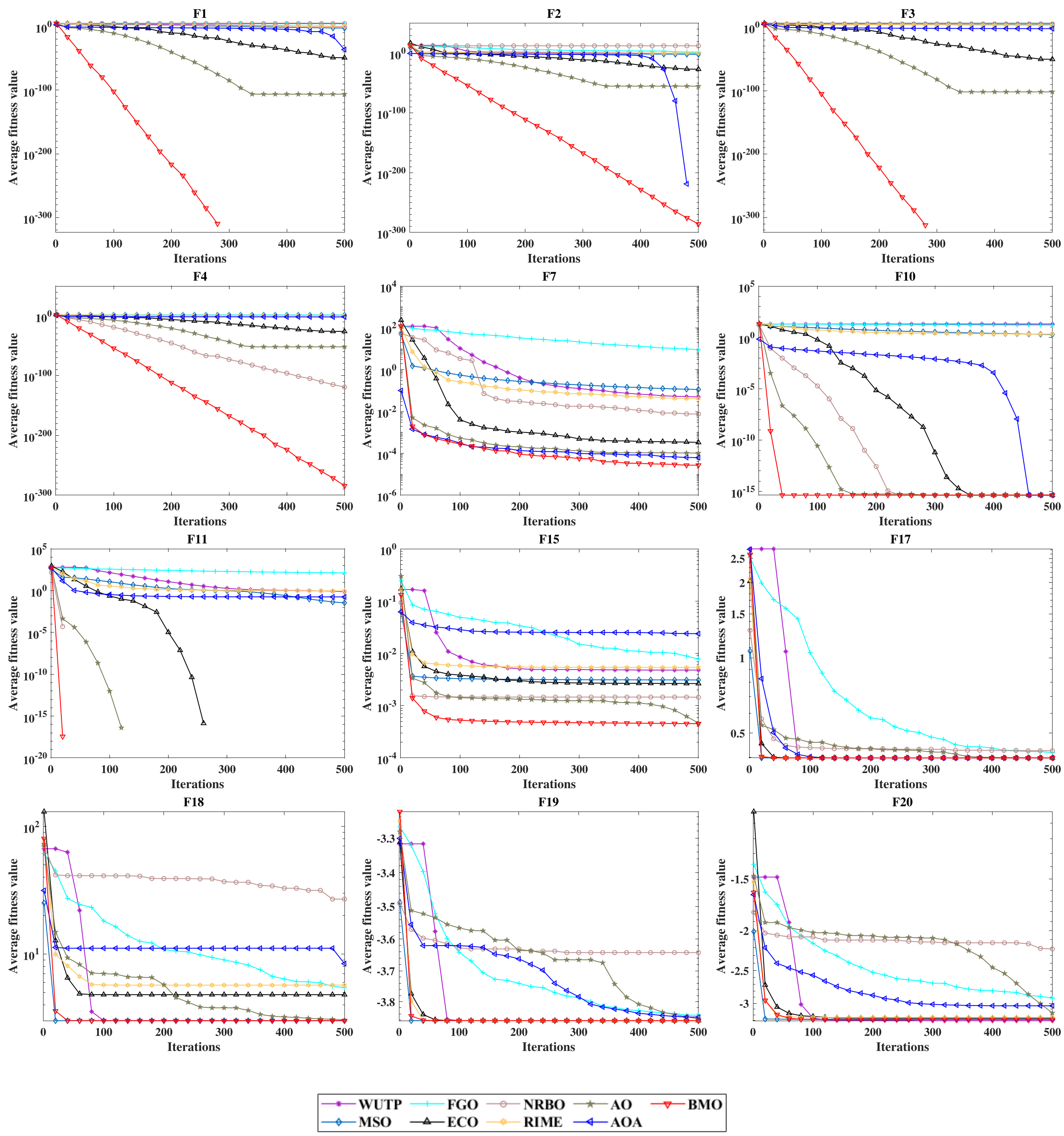


Figure 6: Convergence curves of compared meta-heuristics on representative functions from the CEC2005 benchmark.

7.4 Boxplot Behavior Analysis

Boxplots provide a powerful means to visualize the distribution and key statistical properties of performance data. The plot divides the dataset into four segments, emphasizing the first quartile, median, and third quartile. The edges of the box represent the lower and upper quartiles, while the whiskers typically extend to the minimum and maximum values. A more compact box reflects lower variability and greater consistency in results across repeated experiments. Fig. 7 shows the boxplots of the results for selected representative CEC2005 benchmark functions with diverse characteristics. The proposed BMO consistently produces narrower boxplots with more competitive distributions compared to the other algorithms across the majority of the functions. This reflects BMO's strong performance in terms of both solution quality and stability.

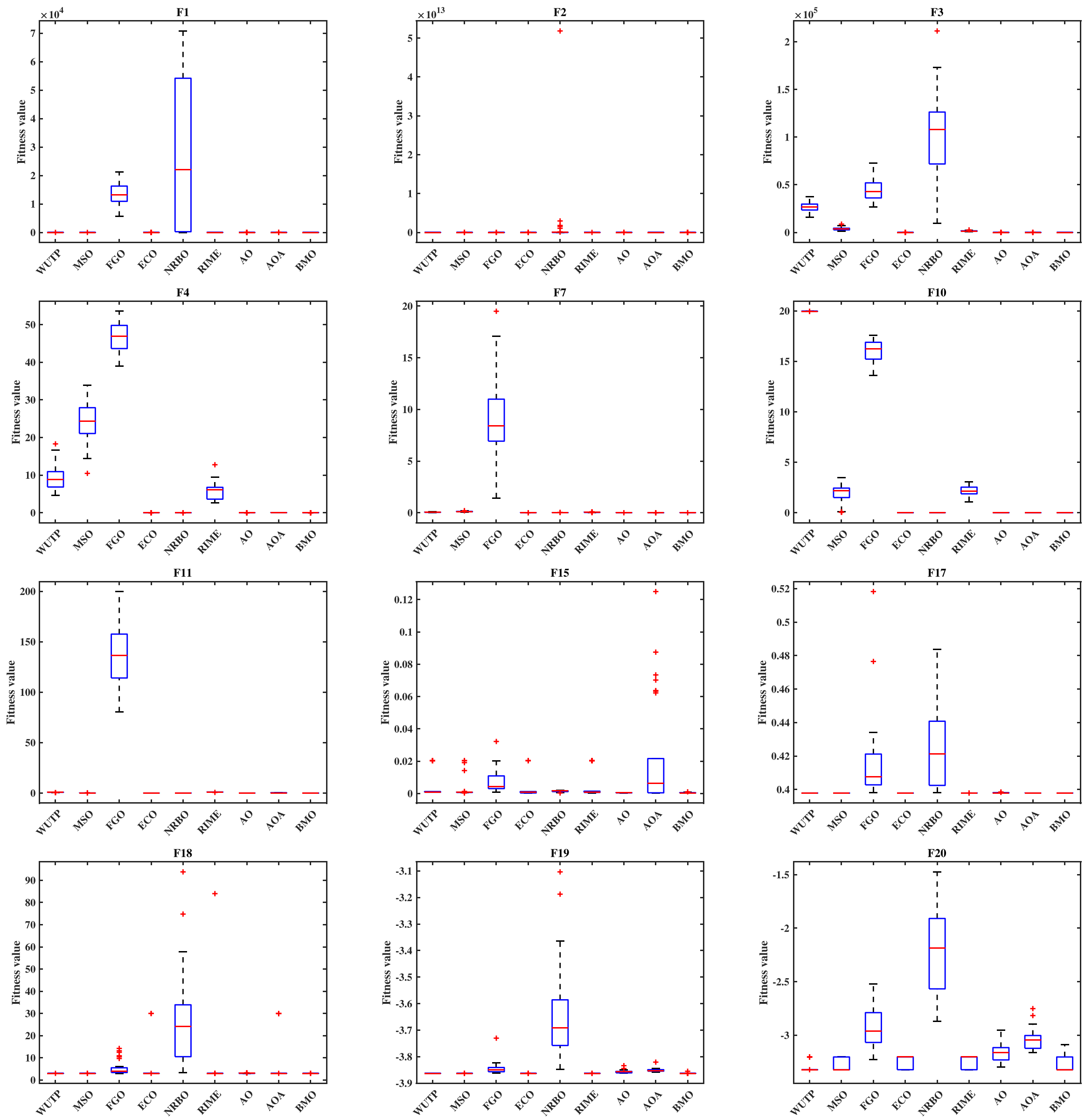


Figure 7: Box-plot charts on representative functions from the CEC2005 benchmark.

7.5 Wilcoxon Rank Test Analysis

The Wilcoxon rank-sum test is a non-parametric statistical procedure widely employed to assess and compare the performance of optimization algorithms [210]. This test produces a p-value, which indicates whether the observed performance differences between two algorithms are statistically significant. In the present study, BMO was benchmarked against several recently proposed optimization algorithms to provide a comprehensive and up-to-date performance evaluation. Table 15 summarizes the p-values obtained from pairwise Wilcoxon rank-sum tests between BMO and the competing methods: WUTP, MSO, FGO, ECO, NRBO, RIME, AO, and AOA. A significance level of 0.05 was adopted, where p-values below 0.05 denote statistically significant performance differences, while values above this threshold indicate no significant difference. A p-value of 1 corresponds to identical statistical performance, whereas NaN is reported when the test cannot be conducted due to uniform results across all independent runs. Overall, the results demonstrate that BMO exhibits competitive performance relative to several recent metaheuristic algorithms, achieving statistically significant improvements on numerous benchmark functions while showing comparable performance in other cases. These findings underscore that BMO remains a robust and competitive optimization strategy despite the advent of newer algorithms.

Table 15: Wilcoxon rank-sum results of BMO against recent optimizers over the CEC2005 benchmark functions.

BMO vs.	WUTP	MSO	FGO	ECO	NRBO	RIME	AO	AOA
F_1	6.0589E−13	6.0589E−13	6.0589E−13	6.0589E−13	6.0589E−13	6.0589E−13	6.0589E−13	6.0589E−13
F_2	1.5099E−11	1.5099E−11	1.5099E−11	1.5099E−11	1.5099E−11	1.5099E−11	1.5099E−11	1.0000E+00
F_3	6.0589E−13	6.0589E−13	6.0589E−13	6.0589E−13	6.0589E−13	6.0589E−13	6.0589E−13	6.0589E−13
F_4	1.5099E−11	1.5099E−11	1.5099E−11	1.5099E−11	1.5099E−11	1.5099E−11	1.5099E−11	1.5099E−11
F_5	1.5099E−11	5.3328E−08	1.5099E−11	9.9988E−01	1.5099E−11	1.5099E−11	1.0000E+00	5.0523E−09
F_6	1.0262E−03	1.0000E+00	1.5099E−11	1.0000E+00	3.2639E−08	5.4683E−11	1.0000E+00	1.5099E−11
F_7	1.5099E−11	1.5099E−11	1.5099E−11	1.5984E−09	1.5099E−11	1.5099E−11	2.4713E−05	8.3988E−04
F_8	1.8449E−11	1.0000E+00	1.5099E−11	1.0000E+00	1.0000E+00	1.0000E+00	6.7869E−02	1.5099E−11
F_9	6.0589E−13	6.0589E−13	6.0589E−13	NaN	6.0589E−13	6.0589E−13	NaN	NaN
F_{10}	6.0589E−13	6.0589E−13	6.0589E−13	NaN	NaN	6.0589E−13	NaN	NaN
F_{11}	6.0589E−13	6.0589E−13	6.0589E−13	NaN	NaN	6.0589E−13	NaN	6.0589E−13
F_{12}	1.2193E−09	1.2861E−07	1.5099E−11	1.0000E+00	1.5099E−11	1.5099E−11	1.0000E+00	1.5099E−11
F_{13}	1.0000E+00	1.0000E+00	1.5099E−11	1.0000E+00	1.5099E−11	1.0000E+00	1.0000E+00	9.9998E−01
F_{14}	1.0000E+00	9.9986E−01	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.4918E−01
F_{15}	3.5423E−09	3.5215E−07	1.5099E−11	8.2357E−02	4.4455E−10	9.3042E−07	2.1702E−01	9.3408E−06
F_{16}	2.6795E−09	1.0710E−02	6.0589E−13	8.4134E−10	6.0589E−13	6.0589E−13	6.0589E−13	6.0589E−13
F_{17}	3.3371E−01	3.3371E−01	8.6013E−13	3.3371E−01	8.6013E−13	2.2809E−11	8.6013E−13	2.2809E−11
F_{18}	5.9722E−04	1.0534E−01	4.9341E−12	3.1042E−07	2.5906E−12	5.9747E−11	2.6406E−11	5.4890E−12
F_{19}	4.4253E−05	6.1048E−12	2.8859E−12	5.9747E−11	5.9747E−11	3.9655E−05	1.9367E−11	4.4343E−12
F_{20}	9.9974E−01	9.9794E−01	3.4948E−11	4.6886E−03	1.4251E−11	1.1094E−02	9.2801E−05	3.5108E−10
F_{21}	2.5740E−13	6.3950E−01	6.0589E−13	1.0000E+00	1.0000E+00	9.9999E−01	1.0000E+00	9.5697E−08
F_{22}	3.3074E−05	3.8544E−01	2.2732E−07	9.9997E−01	1.0000E+00	9.9979E−01	1.0000E+00	2.7229E−05
F_{23}	8.7451E−01	8.0517E−01	3.6257E−08	2.0281E−01	1.0000E+00	9.8993E−01	1.0000E+00	5.5539E−07

8 Critical Analysis of BMO Algorithm Theory

BMO has emerged as a powerful meta-heuristic owing to its nature-inspired foundation based on barnacle mating behavior, its simple and efficient structure, and its competitive performance across a wide range of optimization problems. By mimicking the mating behavior of barnacles through structured parent selection and reproduction mechanisms, where exploitation is achieved through direct mating within a specified pl range and exploration is promoted via sperm casting beyond this range, BMO maintains an effective balance between local exploitation and global exploration. These distinctive characteristics enable BMO to compete effectively with well-established metaheuristics such as GA, PSO, MFO, and SCA in solving complex problems across domains, including power systems, image processing, feature selection, and energy optimization.

One of the key strengths of BMO lies in its minimal reliance on control parameters and its simple implementation, making it particularly accessible for both academic research and real-world applications.

Its flexible structure enables effective hybridization with other methods and supports straightforward algorithmic enhancements. Moreover, its robust global search capability has demonstrated strong performance across a wide range of optimization tasks, including discrete, continuous, and constrained problems.

Despite its strengths, BMO has certain limitations. Notably, its reliance on fixed parameters limits the algorithm's adaptability when addressing dynamic or time-varying optimization environments. Additionally, the absence of an elitism strategy in BMO may result in the loss of high-quality solutions during iterations. The algorithm is also susceptible to premature convergence in complex or high-dimensional search spaces and demonstrates relatively limited local exploitation capabilities for fine-tuning near-optimal solutions. Finally, like all metaheuristic algorithms, BMO is subject to the NFL theorem [66], which states that no single optimization method can outperform all others across every possible problem type. Enhanced performance on specific problem classes leads to reduced effectiveness on others when considered across the full spectrum of optimization tasks. A summary of these advantages and drawbacks is provided in Table 16.

Table 16: Advantages and drawbacks of BMO.

Strengths	Limitations
1. Exhibits a relatively fast convergence rate	1. Lacks a formal theoretical guarantee of convergence
2. Suitable for a wide range of optimization problems	2. Requires careful tuning of multiple parameters
3. Easily hybridized with other meta-heuristic algorithms	3. Susceptible to premature convergence in some cases
4. Applicable to both continuous and discrete search spaces	4. Originally developed for continuous optimization problems
5. Demonstrates strong local neighborhood search capability	5. Exploration–exploitation balance depends on the pl parameter
6. Low likelihood of being trapped in local optima	6. Sensitive to population size and iteration settings
7. Provides an effective global search mechanism	
8. Notable for flexibility, robustness, and scalability	
9. Minimal dependence on initial solution selection	
10. Original implementation readily available by the authors	
11. Computationally efficient for practical applications	
12. Effective hybridization with ML and DL models	

To address these challenges, various strategies emphasizing algorithm enhancement and hybridization have been proposed. Hybrid methods integrate different techniques to balance exploration, which broadly searches the solution space, and exploitation, which intensively refines solutions in promising regions. Conversely, adaptive techniques seek to dynamically tune parameters, enhancing the algorithm's flexibility across diverse problem domains. By leveraging the strengths of complementary methods, these approaches improve the overall efficiency, effectiveness, and robustness of metaheuristic algorithms. Combining the inherent strengths of the BMO algorithm with those of other algorithms enhances both the exploration of the search space and the exploitation of promising solutions. These hybrid approaches improve overall optimization performance and promote the development of versatile, robust algorithms capable of effectively tackling complex optimization problems.

Based on the benchmark functions presented in Section 7, BMO demonstrates strong performance on both unimodal and multimodal functions. In these problem categories, BMO consistently achieves high-precision solutions with low variability, reflecting its effective balance between exploration and exploitation. However, for fixed-dimension multimodal functions, the performance is less consistent. While BMO remains competitive, it does not consistently dominate these functions and shows room for improvement in navigating highly irregular and deceptive search landscapes. This observation highlights a key area for further algorithmic enhancement, particularly in strengthening global search capabilities and adaptive strategies for complex, fixed-dimensional optimization problems.

The evaluation of multi-objective BMO variants in the literature reveals a lack of standardized performance assessment criteria. While several studies employ established multi-objective optimization metrics, such as hypervolume (HV), inverted generational distance (IGD), and generational distance (GD), to quantitatively assess convergence and solution diversity, a substantial number of works rely on alternative evaluation approaches. These include problem-specific objective values, visual inspection of Pareto fronts, or weighted aggregation strategies. Although such measures may be informative within individual application contexts, they do not provide a consistent basis for cross-study or cross-algorithm comparison. As a result, when standard multi-objective performance metrics are absent, comparisons with other multi-objective optimization algorithms remain largely qualitative, incomplete, and potentially misleading. This underscores the need for unified experimental frameworks and standardized evaluation metrics in future multi-objective BMO studies, which would enhance reproducibility, fairness of comparison, and the overall rigor and maturity of the research field.

Reviewed BMO studies cover diverse application domains, each using different evaluation metrics. For example, accuracy and Peak Signal-to-Noise Ratio (PSNR) are common in classification and image processing, while Root Mean Square Error (RMSE) or Mean Absolute Error (MAE) are often reported in forecasting and engineering optimization. Many studies, however, do not provide complete statistical indicators, limiting fair cross-study comparison. Future work should adopt standardized reporting, including mean and standard deviation over multiple runs, best and worst results, convergence plots, and computational cost, to improve reproducibility, transparency, and comparability.

An important practical consideration in evaluating BMO variants is their computational overhead, which is often underreported in the literature. Most studies do not provide explicit time complexity analyses, runtime measurements, or publicly available code, limiting direct efficiency comparisons. Original and modified BMO implementations generally have low computational cost due to their simple structure and few control parameters, while hybrid variants, especially those incorporating deep learning, advanced local search, or additional operators, tend to require higher computational effort. This trade-off between performance gains and runtime highlights the need for future studies to systematically report computational complexity, runtime, and accuracy and efficiency for meaningful evaluation.

Population size is a key factor influencing convergence, solution diversity, and computational efficiency in population-based algorithms such as BMO. Most studies related to BMO adopt a fixed population size, typically $n = 30$, following standard benchmarking practices rather than tailoring it to problem dimensionality or landscape complexity. While fixed settings facilitate reproducibility and comparison, they may limit performance on high-dimensional or complex problems. Adaptive or dimension-scaled population sizing strategies offer potential improvements, but systematic validation for BMO remains limited. Exploring dynamic population sizing could enhance convergence speed, solution quality, and computational efficiency, strengthening BMO's competitiveness across diverse optimization scenarios.

Understanding the strengths and limitations of the BMO algorithm is crucial for researchers and practitioners, particularly when applying it to specific optimization problems and domains. Therefore, by carefully evaluating the factors that affect the algorithm's performance, researchers can determine the most suitable enhancements or hybrid strategies to achieve optimal results. This underscores the importance of ongoing efforts to develop variants and hybrid versions of the BMO algorithm, which are vital for unlocking its full potential. These innovations not only improve its performance but also enhance its adaptability across a wide range of optimization problems.

9 Potential Future Research Lines

Over the past few years, a variety of meta-heuristic techniques have been developed to address complex optimization problems that traditional gradient-based methods cannot effectively handle. However, many of these algorithms lack true innovation and are often adapted versions of existing techniques presented under new metaphors. This rapid growth has also led to an increase in survey studies, most of which aim to establish benchmarking criteria for selecting suitable algorithms for specific problem contexts. Yet many of these surveys provide only superficial assessments, which may lead to misleading interpretations and suboptimal algorithm choices. Therefore, a rigorous and critical review is essential for identifying and selecting the most appropriate algorithms, considering factors such as problem-specific suitability, control parameter settings, ease of implementation, and overall robustness. In line with these criteria, the following subsections are organized to guide current research and inform future developments in meta-heuristics, in general, and specifically for BMO algorithm.

9.1 Adaptive Parameter Control Mechanisms

In optimization, it is well established that an algorithm's performance is strongly influenced by the choice of its parameters. Parameter control refers to how these settings affect the balance between exploration and exploitation during the search process. Consequently, BMO's control parameters (particularly the pl parameter) present a valuable opportunity for further research, with potential adjustments implemented via self-adaptive, adaptive, or deterministic strategies.

9.2 Hybridization with Other Meta-Heuristics

This review indicates that most hybrid BMO variants have been developed by combining BMO with other metaheuristics, particularly SCA, CS, EP, GWO, and several additional methods. Consequently, investigating hybridization opportunities between BMO and recently proposed meta-heuristic algorithms could be highly beneficial. Such hybrid frameworks may exploit complementary search strategies to improve the balance between exploration and exploitation, enhance convergence behavior, and increase robustness across different optimization problems. Therefore, exploring new hybrid structures remains a promising direction for further improving the performance and applicability of BMO.

9.3 Multi/Many-Objective Extensions

Numerous studies have explored the use of BMO for solving multi-objective optimization problems. In these settings, BMO can be integrated with established multi-objective frameworks, such as NSGA-II and MOEA/D, to address problems involving conflicting objectives. MOEA/D tackles multi-objective problems by decomposing them into a set of scalar subproblems that are optimized simultaneously. In contrast, NSGA-III extends the NSGA-II framework to efficiently handle many-objective problems by employing reference points to maintain population diversity. Selecting an appropriate stopping criterion is also crucial, as it directly influences solution quality and convergence behavior. Future research could focus on systematically evaluating stopping criteria tailored to specific problems and frameworks, which may improve the performance and reliability of BMO in multi-objective optimization.

9.4 Handling High-Dimensional Problem Environments

BMO's performance in high-dimensional data classification and computationally intensive tasks has recently attracted significant attention. In particular, BMO has shown promising results in feature selection applications. However, the large search space remains a major challenge when applying BMO to high-dimensional datasets containing tens of thousands of features. Consequently, novel strategies are required to reduce the number of selected features while maintaining or improving classification accuracy.

9.5 Integration with Deep Learning Techniques

Artificial intelligence, particularly deep learning, is a rapidly expanding field that has achieved remarkable results across various domains. Recently, BMO has been applied in deep learning applications, motivating further research to explore its potential and develop robust strategies for integrating it into the training process. This includes optimizing neural network hyperparameters such as batch size, learning rate, and regularization coefficients.

9.6 Parallel and Distributed Implementations

Parallel and distributed computing techniques have been widely adopted in modern computational systems, including multicore processors, cluster environments, and cloud-based infrastructures [212]. These approaches enable multiple computations to be performed simultaneously, significantly accelerating optimization processes and improving scalability when dealing with large-scale or computationally demanding problems. In this context, developing parallel or distributed versions of the BMO algorithm represents a promising research direction. For instance, candidate solution evaluations or population updates could be executed concurrently across multiple processing units, which may reduce computational time and improve the algorithm's efficiency when solving complex optimization tasks.

9.7 Applications in Emerging Domains

As discussed in Section 5, BMO has demonstrated effectiveness in numerous real-world applications. Nevertheless, considerable opportunities remain to extend its use to emerging and complex optimization domains. In particular, BMO could be applied to problems in big data analytics, cybersecurity optimization, and smart city systems, where large volumes of data and dynamic environments require efficient search strategies. Additionally, classical combinatorial problems such as the traveling salesman problem and modern AI-related tasks, including hyperparameter tuning for large language models and drone swarm path planning, represent promising areas for future exploration. Expanding BMO to these emerging domains may further demonstrate its flexibility and effectiveness in addressing diverse and challenging optimization problems.

9.8 Ablation Analysis of Multi-Strategy BMO Variants

Many recent BMO variants incorporate multiple improvement strategies, such as Lévy flights, chaotic maps, adaptive parameters, or hybrid search operators, with the aim of enhancing exploration and exploitation capabilities. Although these multi-strategy approaches often report improved performance on benchmark problems, most studies do not perform ablation analyses to determine the individual contribution of each component. Consequently, it remains difficult to identify which mechanisms are primarily responsible for the observed improvements. Conducting systematic ablation studies, where each strategy is evaluated independently and in different combinations, would provide clearer insights into their respective roles. Such analyses could facilitate a more rigorous understanding of multi-strategy BMO designs and support the development of more effective and well-justified algorithmic improvements.

9.9 Jupyter Notebook–Based Demonstrations for BMO

Despite the availability of several open-source implementations of BMO, most are distributed as standalone scripts that require prior familiarity with the algorithm and the programming environment. Interactive Jupyter notebooks could provide a more accessible format by combining executable code, explanations, and visualizations within a single document. Such demonstrations could illustrate the key steps of the BMO algorithm, parameter configuration, and example applications, while also presenting graphical outputs such as convergence curves or Pareto fronts. Providing notebook-based examples would enhance transparency, improve reproducibility, and facilitate the practical adoption of BMO in research and applied optimization tasks.

10 Conclusion

This study provides an extensive review of the current literature on the Barnacles Mating Optimizer (BMO), highlighting its versatility across core principles, theoretical foundations, algorithmic variants, performance-enhancement strategies, and a wide range of practical applications, with particular emphasis on significant advancements achieved in recent years. As a prominent evolution-inspired computational method, BMO has received numerous enhancements that integrate novel concepts and advanced operators, reinforcing its position along with that of its extended variants as a distinctive and innovative branch within evolutionary computation. Its simple structure and minimal reliance on prior knowledge of the objective function have contributed to its growing popularity, encouraging extensive research efforts to further refine the algorithm. These efforts have produced a variety of improvements aimed at enhancing both effectiveness and computational efficiency, including advanced initialization methods, adaptive control-parameter schemes, population size adjustments, and the incorporation of diverse evolutionary procedures.

This review highlights that BMO's optimization performance is significantly improved when combined with other algorithms or enhanced with specialized operators. Moreover, the reviewed studies demonstrate BMO's remarkable adaptability across a variety of fields, such as power and control engineering, classification, image processing, wireless network optimization, scheduling, forecasting, and signal processing, consistently exhibiting robust convergence, solution stability, and population diversity. To address its inherent limitations, later algorithmic enhancements have introduced new parameters or combined BMO's core mechanisms with elements from other metaheuristics. Researchers have applied BMO successfully to a wide array of practical problems, including constrained/unconstrained optimization, multi- and many-objective scenarios, and complex engineering design challenges. Overall, the literature confirms BMO's strong performance across numerous benchmark and real-world cases, reinforcing its ability to deliver high-quality and reliable solutions.

Nonetheless, it is important to acknowledge several inherent limitations of BMO, including sensitivity to initial population settings, occasional loss of population diversity, suboptimal convergence rates, risk of premature convergence, and challenges with scalability on complex and large-scale problems. The various improved BMO variants discussed in this review provide valuable insights into these specific shortcomings and offer a clearer understanding of the method's overall behavior and performance. Understanding these limitations enables practitioners and researchers to make informed decisions regarding the adoption of BMO, its configuration, or the selection of the most appropriate variant for a given optimization problem. Moreover, systematically addressing these weaknesses facilitates the development of more robust, efficient, and versatile versions of the method, strengthening its practical impact and applicability across various domains.

Moving forward, BMO's performance can be enhanced by focusing on high-dimensional problems and developing dynamic parameter-adaptation strategies to enable more flexible responses to complex search spaces. Integrating BMO with machine learning and deep learning could enable self-learning optimization, while applications in emerging areas like quantum computing, smart grids, and cybersecurity may open new research and practical opportunities.

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