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A comprehensive survey of convergence analysis of beetle antennae search algorithm and its applications

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Abstract

In recent years, swarm intelligence optimization algorithms have been proven to have significant effects in solving combinatorial optimization problems. Introducing the concept of evolutionary computing, which is currently a hot research topic, into swarm intelligence optimization algorithms to form novel swarm intelligence optimization algorithms has proposed a new research direction for better solving combinatorial optimization problems. The longhorn beetle whisker search algorithm is an emerging heuristic algorithm, which originates from the simulation of longhorn beetle foraging behavior. This algorithm simulates the touch strategy required by longhorn beetles during foraging, and achieves efficient search in complex problem spaces through bioheuristic methods. This article reviews the research progress on the search algorithm for longhorn beetles from 2017 to present. Firstly, the basic principle and model structure of the beetle whisker search algorithm were introduced, and its differences and connections with other heuristic algorithms were analyzed. Secondly, this paper summarizes the research achievements of scholars in recent years on the improvement of longhorn whisker search algorithms. Then, the application of the beetle whisker search algorithm in various fields was explored, including function optimization, engineering design, and path planning. Finally, this paper summarizes the research achievements of scholars in recent years on the improvement of the longhorn whisker search algorithm, and proposes future research directions, including algorithm deep learning fusion, processing of multimodal problems, etc. Through this review, readers will have a comprehensive understanding of the research status and prospects of the longhorn whisker search algorithm, providing useful guidance for its application in practical problems.

Keywords Beetle antennae search algorithm · Swarm intelligence · Convergence analysis · Heuristic algorithm · Combinatorial optimization · Application

1 Introduction

In various academic domains, the pursuit of optimal solutions within a given array of choices or variables constitutes a fundamental endeavor. These optimization challenges primarily revolve around the maximization or minimization of a specific objective function, encompassing

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performance metrics, costs, benefits, and related criteria (Li et al. 2022; El-shafeiy et al. 2021). The ongoing progression of social technology underscores the increasing significance and intricacy inherent in optimization problems. Real-world quandaries often manifest as intricate conundrums characterized by nonlinearity, discreteness, and stringent constraints (Yue and He 2018, Lu et al. 2023, Yue et al. 2023, Xu et al. 2023, Cao et al. 2023a). Traditional methodologies, such as linear programming and gradient descent, have historically excelled in scenarios marked by attributes like continuity, differentiability, and monotonicity. Nevertheless, they are ill-suited to meet the contemporary demands of rapid computational speed and minimal error rates imposed by these multifaceted issues (El-shafeiy et al. 2021). The relentless pace of technological advancement has engendered heightened complexity across diverse industries. In light of these evolving challenges, the imperative emerges for optimization techniques that are not only more adaptive but also more efficient and versatile (Yue et al. 2021 Bai et al. 2022, Sun et al. 2022, Hu et al. 2023, Chen et al. 2023).

In response to the aforementioned challenges, a burgeoning domain of heuristic optimization techniques has rapidly evolved (Yue et al. 2023, Cao et al. 2023, Cao et al. 2022, Yue 2022). These methods draw inspiration from natural phenomena, biological processes, and collective dynamics, effectively transcending the confines of traditional methodologies (Khan et al. 2021a, Khan et al. 2022a Khan et al. 2022b). Noteworthy among these heuristic algorithms is the genetic algorithm (GA) (Khan and Li 2022), a model that emulates fundamental principles of evolution, including genetic inheritance, crossover, and mutation, in its quest for optimal solutions within intricate solution spaces. This approach finds its theoretical underpinning in the realm of evolutionary biology. The black hole algorithm (BHA) (Khan et al. 2023) adopts a scientific foundation by abstracting complex problems into optimization challenges and employing simulation to discern optimal solutions. In its execution, the BHA draws inspiration from the gravitational dynamics of celestial black holes. Similarly, the ant colony optimization (ACO) (Ijaz et al. 2022) leverages principles of collective intelligence, emulating the foraging behavior of ant colonies through the dissemination of pheromones and cooperative actions. This approach has proven particularly efficacious in addressing combinatorial optimization problems. Furthermore, the sphere of heuristic optimization has broadened its scope to encompass swarm intelligence-based algorithms, demonstrating substantial potential in addressing intricate problems. Prominent instances in this classification include particle swarm optimization (PSO) (Khan 2022), artificial bee colony (ABC) (Wei et al. 2021), and flower pollination algorithm (FPA) (Yang 2012). The assimilation of these heuristic methodologies serves to cultivate fresh perspectives and innovative resolutions for real-world challenges, thus enhancing the problem-solving milieu within the domain of optimization.

The Beetle Antennae Search algorithm (BAS), introduced by JIANG et al. in 2017, represents a noteworthy bio-inspired heuristic intelligent approach (Jiang and Li 2017). Drawing inspiration from the foraging behavior of beetles, this algorithm emulates the strategy employed by beetles, utilizing antennae to sense odor intensity and locate food sources, and transforms this behavioral paradigm into a mathematical model tailored for solving optimization challenges. BAS is distinguished by its elegant simplicity and efficient optimization mechanism. Within each iteration of the algorithm, BAS systematically approaches the optimal solution by leveraging the current position of individuals and their perception of pheromone values. This iterative process engenders a gradual convergence towards the global optimum, a hallmark of the BAS algorithm's prowess (Zhang et al. 2021). Over recent years, BAS has garnered extensive utilization in both engineering practice and academic research. Remarkably, it seamlessly integrates biological observations and adeptly balances local and global search strategies. BAS exhibits robust performance and resilience when addressing optimization problems, effectively replicating the motion and data exchange processes observed in beetle antennae. Moreover, owing to its versatility, BAS finds applicability across a diverse spectrum of domains, encompassing path planning, engineering design, and function optimization. As such, it furnishes practical and pragmatic solutions to real-world challenges, thereby affirming its relevance and utility.

The pioneering work in the development and application of the BAS algorithm extends to its innovative variants such as QBAS, CBAS, and DBAS. Each variant represents a significant enhancement in addressing complex problems across various domains. those research team stands at the forefront of the BAS algorithm's evolution, leveraging it across diverse domains. People have seamlessly integrated BAS into robotics (Yang and Slowik 2020, Yang et al. 2010, Yousif and Saka 2021), revolutionizing control and navigation. In portfolio optimization (Wang et al. 2019a, 2018), the bio-inspired techniques have redefined financial decision-making strategies. The contributions to control systems (Lin et al. 2018; Simon 2008) have significantly enhanced precision and efficiency in critical applications, including medical technology. Each of these achievements underlines the leadership in deploying BAS in innovative, impactful ways.

Since its inception, BAS has garnered substantial attention and scholarly investigation, both domestically and internationally, as it has effectively addressed a diverse spectrum of real-world optimization challenges. To expedite the algorithm's continued advancement in both research and practical applications, a comprehensive examination of BAS research spanning from its inaugural presentation in 2017 to the present is imperative. This exposition endeavors to elucidate the foundational principles and distinctive characteristics of the BAS algorithm, delving into its various modifications and enhancements, and providing comprehensive insights into its multifaceted applications across diverse industrial sectors. The discourse culminates with an overview of prospective avenues for future research endeavors.

This comprehensive review underwent a rigorous literature screening procedure, meticulously crafted to encompass the most representative and authoritative research contributions. The initial phase entailed an exhaustive exploration of pertinent literature within the Google Scholar database, employing the keyword "beetle tentacle retrieval" to identify the top 200 articles. A supplementary search was then conducted to identify highly cited articles of significant relevance. During the preliminary screening phase, papers not germane to the research theme were expeditiously excluded on the basis of their titles and abstracts. Subsequently, the literature selected following the initial screening underwent a thorough and meticulous examination in full-text form. This comprehensive assessment delved into various facets, including methodology, experimental design, results, and conclusions. The ultimate outcome of this rigorous curation process comprised a judiciously chosen ensemble of influential, highly cited, and authoritative papers within the realm of our research focus, which subsequently serve as the foundational references underpinning this review. The literature selection process of this paper covers the latest research results to ensure the comprehensiveness and timeliness of the review.

2 Beetle Antennae Search algorithm

2.1 Principle

BAS represents a heuristic optimization paradigm that amalgamates the simulation of beetle antennae behavior with fundamental optimization principles. Natural organisms, exemplified by beetles, are endowed with antennae characterized by their remarkable branching and curvilinear morphology, which afford them the capacity for efficient information transfer and sensing, even in demanding environmental contexts. The BAS algorithm, aspires to replicate the intricate functionality of beetle antennae, with the overarching objective of achieving effective optimization within solution spaces.

Within the realm of foraging, beetles confront a conundrum surrounding the precise location of sustenance. To address this uncertainty, they rely upon a pair of antennae situated on their cephalic region. The beetle's navigational strategy is elegantly simplistic: if the concentration of odor sensed by its left antenna surpasses that detected by the right, it proceeds towards the left; conversely, it maneuvers rightward when the right antenna's odor concentration prevails. This iterative process continues until the beetle accurately homes in on its sustenance source. A visual representation of the foraging behavior of beetles is presented in Fig. 1. The optimization quandary is conceptualized as the assignment of an olfactory value to every point within a three-dimensional spatial continuum, akin to a mathematical function, and draws its inspiration from the foraging proclivities of beetles. Notably, the odor values at each point align harmoniously with their respective function values. In the quest to identify the global point harboring the most elevated odor value, the dual antennae of beetles adeptly aggregate odor data from two proximate locations. This emulation of beetle antennae behavior emerges as a proficient strategy for achieving function optimization with notable efficiency.

2.2 Model

In BAS, the target function to be optimized is analogized to food, and the variables of the objective function correspond to the position of the beetle. When facing an unknown area, the beetle adopts a strategy of random searching. Function optimization is achieved by simulating the antennae behavior of beetles. For an optimization problem in an n-dimensional space, use

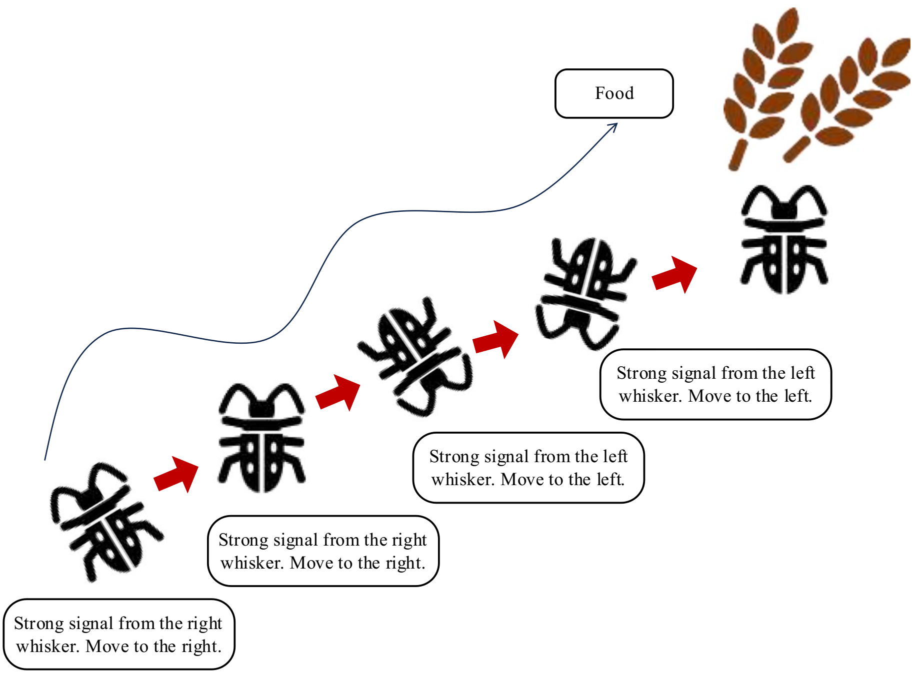


Fig. 1 schematic diagram of BAS bionic principle

x_{left} to represent the left antenna coordinate, x_{right} for the right antenna coordinate, x for the centroid coordinate, and d for the distance between the two antennae. After the beetle flies to a location, the orientation of its head is random. To simulate this behavior, the following formula is used to generate a random direction.

$$\vec{c} = \frac{\text{rand}(D, 1)}{\|\text{rand}(D, 1)\|} \tag{1}$$

where $\vec{c}$ represents the normalized direction vector, $\text{rand}(\cdot)$ denotes the random function, and D represents the dimensionality of the variable. The spatial coordinates calculation of the left and right antennae of the beetle are as follows:

$$\begin{aligned} x^t_{left} &= x^t + d^t \cdot \vec{c} \\ x^t_{right} &= x^t - d^t \cdot \vec{c} \end{aligned} \tag{2}$$

where x^t_{left} and x^t_{right} respectively represent the spatial coordinates of the left and right antennae of the beetle at t-time,x^t represents the centroid position of the beetle at t-time, and d^t is the distance between the two antennae at t-time. The concentration of odor at the left and right antennae at this time is calculated as follows:

$$\begin{aligned} f\left(x^t_{left}\right) &= f\left(x^t + d^t \cdot \vec{c}\right) \\ f\left(x^t_{right}\right) &= f\left(x^t - d^t \cdot \vec{c}\right) \end{aligned} \tag{3}$$

where $f(\bullet)$ is the fitness function, $f\left(x^t_{left}\right)$ represents the odor concentration of the left antenna of the beetle at t-time, and $f\left(x^t_{right}\right)$ represents the odor concentration of the right antenna of the beetle at t-time.

To explore the minimum of $f(\cdot)$, if $f\left(x^t_{left}\right) < f\left(x^t_{right}\right)$, the beetle moves in the direction of the left antenna; otherwise, it moves in the direction of the right antenna. To mimic the detection mechanism of the beetle, the following position update iterative model is generated:

$$x^{t+1} = x^t - \delta^t \cdot \vec{c} \cdot \text{sign}\left(f\left(x^t + d^t \cdot \vec{c}\right) - f\left(x^t - d^t \cdot \vec{c}\right)\right) \tag{4}$$

where δ^t is the search step size at t-time, and $\text{sign}(\cdot)$ is the sign function. To achieve convergence to the optimum after model iteration, update rules need to be set for the beetle's step size δ^t and the distance d^t between the two antennae.

$$d^t = a \cdot d^{t-1} + 0.01 \tag{5}$$

$$\delta^t = b \cdot \delta^{t-1} \tag{6}$$

where a is the decreasing factor for the step size δ^t, and b is the decreasing factor for the distance d^t. The initial values of δ and d, as well as the corresponding decreasing factors a and b, need to be selected based on the variable range of the objective function. Depending on the actual situation, specific values can also be adopted for δ^t and d^t. The morphology of the antennae imbues the search process with an inherent degree of stochasticity, concurrently directing it towards prospective optimal solutions. Through the emulation of this intricate search pattern, BAS algorithm demonstrates the capability to expeditiously navigate away from local optima within the solution space, facilitating a comprehensive exploration for superior global solutions.

2.3 Algorithm steps

The flowchart depicting the BAS algorithm is outlined below for reference. This comprehensive visualization provides a clear overview of the sequential steps involved in the execution of the algorithm.

The basic steps of the BAS algorithm are as follows:

Step 1: At the start of the algorithm, initialize individuals. The initial positions are randomly distributed in the search space. Establish random vectors for the orientations of the left and right antennae of the beetle, and normalize them.
Step 2: Calculate the spatial coordinates of the left and right antennae of the beetle.
Step 3: Determine the strength of the odor of the left and right antennae based on the set fitness function.
Step 4: Determine the position of the beetle after the next iteration update by comparing the odor strengths of the left and right antennae in Step 3.
Step 5: After each iteration, check whether the termination conditions are met, such as reaching the predetermined number of iterations or achieving solution stability. If the termination conditions are met, the algorithm ends; otherwise, go back to Step 2 for the next iteration.

2.4 Convergence analysis

In this section, a thorough analysis of the convergence of the BAS algorithm is undertaken. Notably, an in-depth examination of the concept of convergence is presented, laying the groundwork for understanding the algorithm's behavior in optimization tasks.

Definition 1 (Almost Sure Convergence) Almost sure convergence refers to the probability that a monotonically increasing sequence $\{f(x)\}_{t=1}^{\infty}$, converges to its infimum, f being 1 on a closed set $\Omega \in \mathbb{R}^n$.

The convergence analysis is based on Definition 1. Before the analysis, for ease of explanation, let $f_{bst}^t = \min_{x^j}\left\{f\left(x^j\right)\right\}$, where $j = 0, 1, \cdots, t$ and $f_{bst}^t = f\left(x_{bst}^t\right)$ are defined.

Lemma 1: For the BAS algorithm, f_{bst}^t does not increase. Proof: According to the principle of the beetle antennae search algorithm, at each time t, if $f\left(x^{t+1}\right) < f_{bst}$, then $f_{bst} = f\left(x^{t+1}\right)$. Therefore, the BAS algorithm ensures that f_{bst}^t does not increase.

Lemma 1 gives a deterministic conclusion that the BAS algorithm will not diverge in the long run.

Theorem 1: If the parameters of BAS are set reasonably, then BAS will converge almost surely Proof: Assuming that the parameters of the BAS algorithm are set reasonably, the probability that $P_{\Omega}\left(x^t + bsgn\left(f\left(x_r^t\right) - f\left(x_l^t\right)\right)\right)$is on the optimal solution x^* minimizing the optimization problem f is greater than 0 at each time t. $P_{\Omega}(\bullet)$ represents the projection on Ω. Let p_t denote the probability that x^t is not on the optimal solution x^* at time t. Then, we can obtain:

$$p\left(x_{bst}^t = x^*\right) >= 1 - p_0 p_1 \cdots p_t \tag{7}$$

Note that, under the above assumption, we know $0 \leq p_t < 1$. Therefore,

$$\lim_{t \to +\infty} \left(1 - p_0 p_1 \cdots p_t\right) = 1 - \lim_{t \to +\infty} p_0 p_1 \cdots p_t = 1 \tag{8}$$

Note that

$$p\left(x_{bst}^t = x^*\right) \leq 1 \tag{9}$$

Thus, by the squeeze theorem, we further obtain:

$$\lim_{t \to +\infty} p\left(x_{bst}^t = x^*\right) = 1 \tag{10}$$

Proof is completed.

Theorem 1 illustrates that through judicious selection of the step size, we can reliably guarantee the almost certain convergence of the BAS algorithm. This fundamental theorem underscores the importance of parameter tuning in optimizing the algorithm's convergence behavior.

This conclusion holds considerable significance for two main reasons. Primarily, it clarifies that the BAS algorithm exhibits convergence under specific step sizes. Secondly, when dealing with deterministic functions, this theorem helps elucidate why the BAS algorithm fail to produce an optimal solution, a common challenge faced by numerous bio-inspired algorithms in practice.

2.5 Comparison with Other Swarm Intelligence Algorithms

BAS, along with PSO(Khan 2022), ACO(Ijaz et al. 2022), GA(Khan and Li 2022), Firefly Algorithm (FA) (Yang and Deb 2014), Bat Algorithm (BA) (Geem et al. 2001), ABC(Wei et al. 2021) and similar algorithms, belong to the category of metaheuristic swarm intelligence optimization algorithms. This section embarks upon an exploration of the relative merits and drawbacks of the BAS algorithm vis-à-vis its counterparts, as well as delves into the specific problem domains wherein each algorithm finds its niche. Such an analysis is poised to illuminate the strengths and constraints inherent in these algorithms when applied to the multifaceted landscape of optimization challenges. The results are shown in Table 1.

The PSO algorithm draws its inspiration from avian flocking behavior, dynamically updating the position of each particle by facilitating the exchange of information amongst the members within the group. In comparison to the BAS, PSO exhibits a heightened aptitude for global exploration, albeit potentially at the expense of local search precision and convergence speed. BAS, conversely, distinguishes itself through its simplicity, featuring straightforward update rules that render parameter adjustments and implementation more accessible.

The ACO algorithm replicates the path selection propensities observed in foraging ants. ACO places paramount emphasis on the accumulation and subsequent evaporation of pheromones to steer the search process, rendering it well-suited for discrete optimization quandaries, such as path planning. When contrasted with BAS, ACO excels in addressing intricate discrete problems, whereas BAS excel in continuous space optimization, particularly within high-dimensional domains.

Table 1 Comparison between BAS and other algorithms

Algorithm	Advantage	Disadvantage	Application
BAS(Jiang and Li 2017)	Simplicity and ease of implementation of the algorithm	Convergence and accuracy are closely related to the parameters used	Function optimization, neural network training, combinatorial optimization, engineering design, classification problems
PSO(Khan 2022)	Easy to implement, fast convergence rate	Prone to local optima and premature convergence in later iterations, the algorithm is significantly influenced by parameters	Function optimization, multi-objective optimization, integer constraints, mixed integer constraint optimization, neural network training, signal processing, etc
ACO(Ijaz et al. 2022)	Positive feedback mechanism enhances global search capability, good robustness	Slow convergence speed, the efficiency of the algorithm significantly decreases for large-scale problems	Neural network training, combinatorial optimization, power system optimization, system and engineering design, etc
GA(Khan and Li 2022)	Strong global search capability	Prone to premature convergence and getting stuck in local optima	Combinatorial optimization and continuous optimization problems
FA(Yang and Deb 2014)	The algorithm is simple, requires minimal parameter tuning, and is easy to apply and implement	Parameter settings have a significant impact on convergence results	Combinatorial optimization, constraint optimization, multi-objective optimization, dynamic or noise optimization, engineering applications and classification, image processing, path planning, antenna design, etc
BA(Geem et al. 2001)	Simple model, fast convergence speed, few parameters	Premature convergence, low convergence accuracy	Engineering design, classification problems, fuzzy clustering, neural network training, combinatorial optimization, data mining, image processing, wireless sensors, power system optimization, particle filtering, etc
ABC(Wei et al. 2021)	Strong global convergence capability	Prone to stagnation, poor population diversity	Neural network training, combinatorial optimization problems, power system optimization, system and engineering design, etc

GA, a search paradigm that simulates the mechanisms of natural selection and genetic inheritance, propels populations towards optimal solutions through selection, crossover, and mutation operations. GA's versatility makes it an apt choice for a diverse array of challenges, especially in scenarios characterized by extensive solution spaces or intricate solution structures. In terms of solving straightforward or moderately complex optimization problems at a rapid pace and with relative simplicity, BAS surpasses GA, although GA holds advantages in maintaining population diversity and averting premature convergence.

BAS, in contrast to FA, demands fewer initial parameters, rendering it less susceptible to variations in parameter settings. With its concise core code comprising only four lines, BAS emerges as an easily implementable algorithm, compatible with a multitude of programming languages. Relative to BA and ABC, it exhibits enhanced efficiency and diminished complexity. Furthermore, its singular-beetle iteration contributes to lower time and space complexity, positioning it as a more efficient alternative in comparison to a majority of swarm intelligence algorithms.

In summation, BAS underscores its unique merits as an optimization problem solver, particularly celebrated for its algorithmic simplicity and ease of implementation. Nevertheless, its performance might not uniformly outshine other swarm intelligence algorithms, such as PSO, ACO, and GA, contingent upon the specific attributes and requisites of the problem at hand. Preliminary investigations substantiate the potential of BAS as a promising algorithm, warranting further in-depth exploration from both theoretical and practical perspectives. Fig. 2

3 Improvement of BAS

Although the BAS algorithm demonstrates good performance in various optimization problems, it still has shortcomings, such as slow convergence speed, low accuracy in handling high-dimensional complex problems, and a tendency to get stuck in local optima, resulting in poor optimization effects. To address these issues, scholars continuously refine and improve the algorithm. The main directions for improvement include parameter adjustments, introduction of adaptive mechanisms, hybrid heuristics, multi-objective optimization, and integration with deep learning, among others. Fig. 3

3.1 Parameter adjustment improved algorithm

These improved algorithms primarily focus on adjusting the parameters of the BAS algorithm, such as step size and individual expansion to population, to enhance algorithm performance. The main methods of improvement are shown in Table 2.

(1) Yousif and Saka extended the conventional BAS algorithm by incorporating the notion of beetle populations, thus unveiling the improved iteration known as the Enhanced Beetle Antennae Search (eBAS) algorithm (Price et al. 2005). The architectural framework of this algorithm bifurcates into two pivotal phases: an initialization phase and an iteration phase. The latter phase encompasses two essential components, namely, the beetle sensing phase and the beetle movement phase, illustrated in the precise procedural depiction provided in Fig. 3.

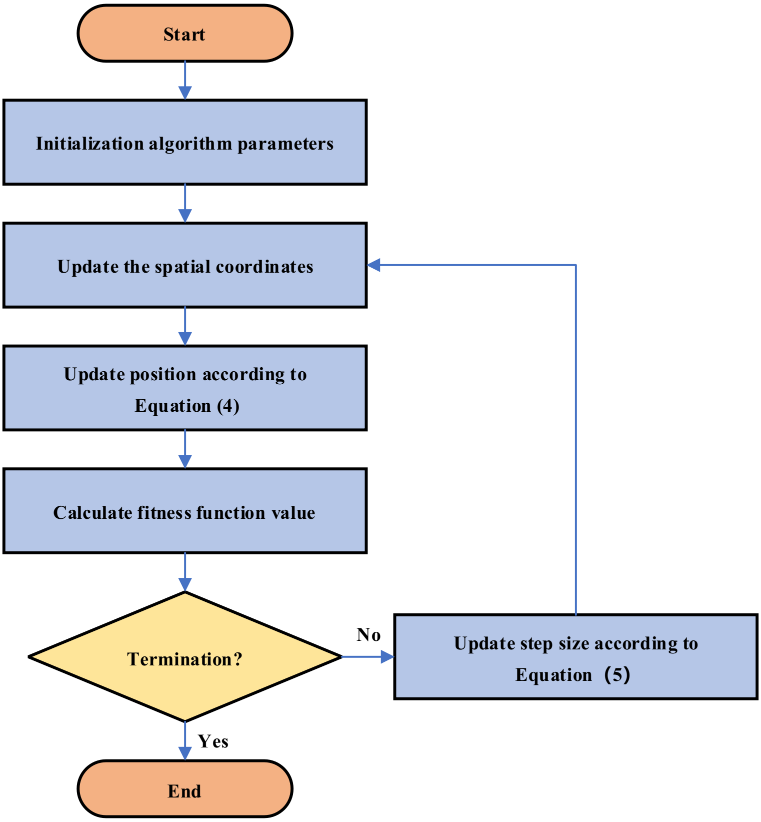


Fig. 2 BAS algorithm flow chart

During the initialization phase, the quantity of introduced beetle swarms aligns with the product of the number of problem design variables and the selected population size. The initial design variables allocated to each beetle group are assigned randomly. Furthermore, the initial positioning of individual beetles within the group is estimated through the application of the following formula:

$$x_{\mathrm{ij}} = x_d + \mathrm{rand}(1, k) \times \left(x_u - x_d\right)$$

where x_{ij} is the position of the j-th beetle in the i-th group, x_u and x_d are the upper and lower bounds of the variable, respectively, and k is the number of design variables. In the iteration phase, the new beetle position is updated using the following formula:

$$\begin{aligned} S &= x_j + \alpha\left(x_m - x_n\right) \\ S &= x_j - \alpha\left(x_m - x_n\right) \end{aligned} \tag{12}$$

where x_m and x_n are randomly selected beetles, x_j is the beetle position to be updated, and α is a random number between -1 and 1. Then, the position is updated based on the evaluation of the objective function. eBAS was compared with nine other metaheuristic algorithms, including BA, Biogeography-Based Optimization (BBO) (Qian et al. 2022), ABC, PSO, Cuckoo Search (CS) (Shao and Fan 2021), Harmony Search (HS) (Wu et al. 2020),

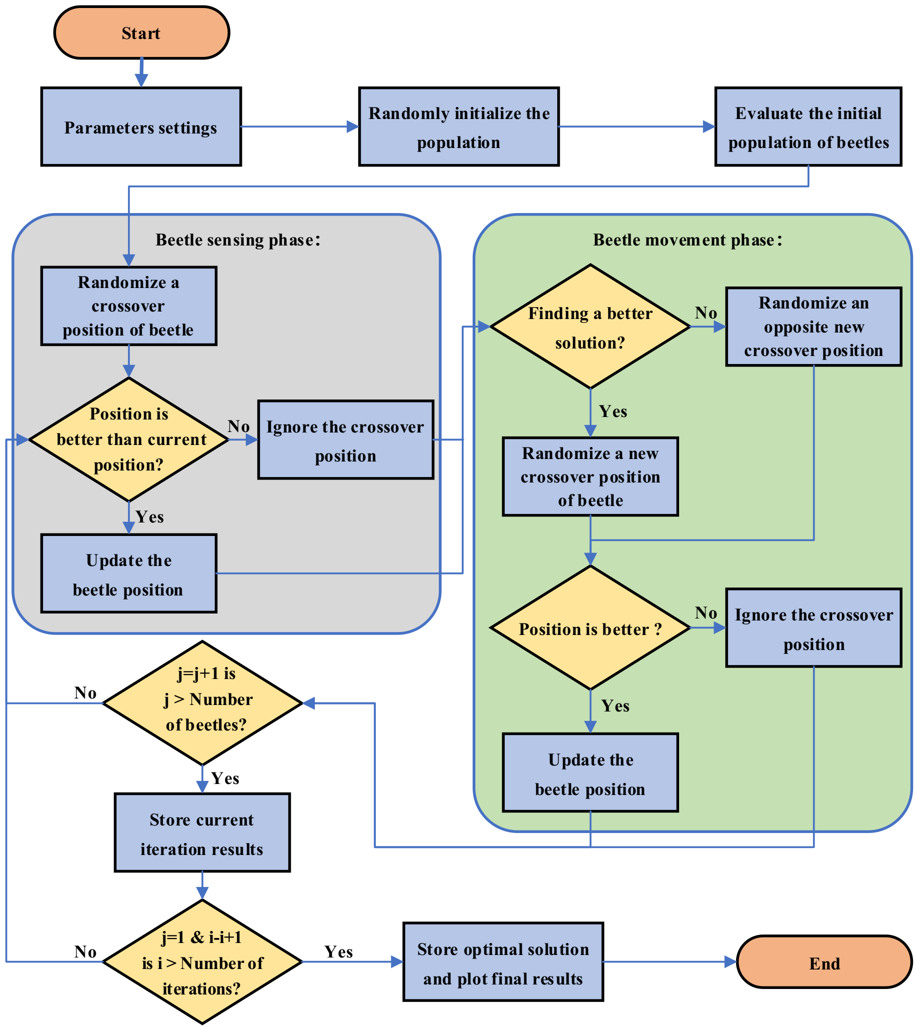


Fig. 3 Flow chart of eBAS algorithm

Differential Evolution (DE) (Mirjalili et al. 2014), Teaching–Learning-Based Optimization (TLBO) (Neshat et al. 2014), and FA. eBAS demonstrated exceptional performance in multiple optimization examples with continuous and/or discrete variables, especially in solving practical-sized problems with numerous design variables and complex constraints.

(2) Wang et al. focusing on the problem of spatial straightness evaluation, established a mathematical model and proposed an algorithm called Variable Step Beetle Antennae Search (VSBAS) (Rao et al. 2011). The key improvements of the algorithm are as follows: Introduction of variable step size: The original BAS was limited to a fixed step size, which affected its efficiency and accuracy in global and local search. To surmount this limitation, the authors have introduced a variable step size approach, thereby augmenting the algorithm's adaptability and computational accuracy.

Table 2 Summary of BAS parameter adjustment improved algorithms

Algorithm	Improvement Mechanism	Advantage	Disadvantage	Applicable Scenarios	Year
eBAS(Price et al. 2005)	Introduced the concept of beetle populations	Enhanced the global search capability of the algorithm	High computational complexity	Solving practical size problems with numerous design variables and complex constraints	2021
VSBAS(Rao et al. 2011)	Adopted variable step length method, dynamically adjusting the beetle's step length	Improved the global search capability	Increased computational complexity	Spatial straightness evaluation	2019
BSAS(Khan et al. 2020)	Introduced swarm intelligence methods and feedback-based step length update strategies	Enhanced the algorithm's global search capability	Neglected the impact of population on algorithm performance	High-dimensional problems, especially those with local minima issues	2018
BASL(Lin et al. 2020)	Conducts local search within a certain range of the current optimal solution	Enhanced local search capability	Increased the time complexity of the algorithm	Non-convex optimization problems	2018

Striking a balance between coarse and fine search: VSBAS initiates its quest with a coarse search phase, serving to delineate a broad search range, subsequently followed by a meticulous fine search conducted within this predefined range. This strategic maneuver harmonizes algorithmic accuracy with global convergence speed, thereby enhancing the overall efficiency of VSBAS.

Improvement in global convergence speed and accuracy: The modifications made to the BAS algorithm improve the convergence speed and accuracy. The experimental results in this paper show that VSBAS outperforms other methods such as GA and PSO in terms of accuracy and convergence speed.

(3) Wang et al. introduced swarm intelligence methods and a feedback-based step length update strategy, proposing the Beetle Swarm Antennae Search Algorithm (BSAS) (Khan et al. 2020). BSAS addressed issues in the BAS algorithm, such as over-reliance on the beetle's random direction and updating beetle position and step length during iterations. By allowing k beetles to move in k different directions, BSAS increases the likelihood of finding better solutions. Moreover, the algorithm adopted a feedback-based position and step length update strategy to improve efficiency and accuracy. BSAS introduced a probability constant p_δ to assess the impact of random direction selection on the search effect. This strategy is based on the assumption that, at the current step length, the probability of the beetle swarm missing the optimal solution is low. In most cases, if the beetles fail to discover a better objective function value, the algorithm will update the current step length. However, in rare cases, if the generated random number is less than p_δ, the step length δ and perception length d will remain unchanged, indicating that the algorithm considers the possibility of unexplored potential optimal solutions. The update of beetle positions occurs only when the swarm discovers a better solution. This improvement strategy enhances the algorithm's capability to handle high-dimensional problems. However, it overlooks the impact of population size on algorithm performance.

(4) Lin et al. proposed two different variant algorithms based on the BAS algorithm, which are the BAS with fitness value (BASF) algorithm and BAS with local fast search (BASL) algorithm(Lin et al. 2020). The BASL algorithm augments the algorithm's local search efficacy by orchestrating localized exploration in proximity to the present optimal solution, thereby facilitating the refinement of solutions with heightened precision. Conversely, the BASF algorithm integrates an update mechanism predicated on fitness values to steer the iterative adjustment of beetle positions, prioritizing the utilization of global fitness information for optimizing the search strategy, thereby enhancing the prospects of locating the global optimal solution. These refinements collectively strike a harmonious equilibrium, bolstering both the algorithm's local search prowess and global search strategy, thus fortifying its resilience and precision in tackling intricate optimization quandaries. Consequently, the BASL algorithm can be construed as a parameter adjustment-driven improvement, while the BASF algorithm embodies an adaptive mechanism-based refinement, with both enhancements oriented towards the augmentation of the original BAS algorithm's performance.

3.2 Adaptive mechanism introduces class improvement algorithm

The incorporation of an adaptive mechanism empowers the algorithm with the capacity to autonomously fine-tune parameters or strategies contingent upon the inherent characteristics of the problem at hand, thereby seamlessly aligning itself with the distinct solution requisites posed by diverse problem domains. The main improvement methods are shown in Table 3.

(1) Khan et al. proposed an ADAM-based improved BAS algorithm, named BAS-ADAM (Bertsimas and Tsitsiklis 1993). This algorithm introduces the ADAM update rule to adaptively adjust the step length in each iteration, with the step length update formula as follows:where x_{new} is the new solution generated after adaptively adjusting the step length, δ_0 is the initial step length, $\delta^t\left(\widetilde{\nabla}^t\right)$ is a function estimating the gradient value $\widetilde{\nabla}^t$, $\hat{y}^t$ and $\hat{e}^t$ are the corrected values of first-order momentum y and second-order momentum e at t-time. y^t and β^t represent the decay factors of first-order and second-order momenta at t-time, respectively. The principal merit of BAS-ADAM resides in its notable efficiency and expeditious convergence capability, rendering it particularly well-suited for the resolution of non-convex optimization challenges. Empirical substantiation has positioned BAS-ADAM as a superior performer in contrast to conventional BAS and PSO across a spectrum of benchmark problems. Nonetheless, it is essential to acknowledge that the employment of multiple search particles within the algorithm does introduce a modicum of augmented time complexity.

$$x_{\text{new}} = x^t + \delta^t\left(\widetilde{\nabla}^t\right) \tag{13}$$

$$\delta^t\left(\widetilde{\nabla}^t\right) = \delta_0 \frac{\hat{y}^t}{\sqrt{\hat{e}^t}} \tag{14}$$

$$\hat{y}^t = \frac{y^t}{1 - \beta^t} \tag{15}$$

$$\hat{e}^t = \frac{e^t}{1 - \gamma^t} \tag{16}$$

(2) Lin et al. proposed an improved version of BAS, named WSBAS (Rashedi et al. 2009), with the primary goal of enhancing the performance of the BAS algorithm in handling high-dimensional optimization problems. The algorithm introduces inertia weights, allowing for global search in the early stages and shifting to local search in the later stages, thereby balancing the needs for global exploration and local refinement, ultimately improving optimization accuracy. Noteworthy refinements extend to the individual level, diverging from the foundational BAS framework. Compared to the basic BAS, this approach pioneers a novel update mechanism for each individual beetle, thereby fortifying their individualized search capabilities. The principle is that larger inertia weight values can accelerate the beetles' search speed in new areas, while smaller weights in the later stages can enhance the beetles' local search capabilities. The update formula guiding these adaptations is articulated as follows:where $\omega_{\max}$ and $\omega_{\min}$ represent the maximum and minimum values of the inertia weight, respectively, and $t_{\max}$ is the maximum number of iterations. The WSBAS algorithm demonstrated superior comprehensive optimization performance over six other optimization algorithms on 15 benchmark functions. Its application in the ELD problem in power systems showcased its superiority. In comparison with other optimization algorithms such as PSO, WSBAS showed better overall optimization performance.

Table 3 Summary of BAS adaptive mechanism introduction improved algorithms

Algorithm	Improvement Mechanism	Advantage	Disadvantage	Applicable Scenarios	Year
BASF(Lin et al. 2020)	Introduction of optimal fitness values to update beetle positions	Increased stability and accuracy	Increased the time complexity of the algorithm	Non-convex optimization problems	2018
BAS-ADAM(Bertsimas and Tsitsiklis 1993)	Introduction of Adaptive Moment Estimation (ADAM) update rules to enhance step length adaptation	Faster convergence speed, superior to traditional BAS and PSO	Limited improvement in algorithm accuracy, still prone to local extremities	Non-convex optimization problems	2020
WSBAS(Rashedi et al. 2009)	Introduction of changing inertia weight strategy, employing early global search and later local search strategies	Enhanced global and local search capabilities	Increased computational complexity	15 benchmark functions and Economic Load Dispatch (ELD) in power systems	2020
EBAS(Arora and Singh 2019)	Introduced three enhancements: adaptive step reduction, current optimal update, and multi-directional sensing	Enhanced global and local search, faster convergence, and increased robustness	High computational complexity	Unbiased function optimization problems	2022
ENBAS(Wang et al. 2018)	Introduction of elite selection mechanism and neighbor movement strategy	Enhanced the global search ability and robustness of the algorithm	Requires parameter tuning, high computational complexity	8 benchmark functions; high-dimensional optimization problems	2021
FBAS(Li et al. 2019)	Introduction of a backup mechanism, simulating the evasive behavior of organisms when encountering obstacles	Improved global search capability, low time complexity	High computational complexity	Path planning problems	2020

$$\omega = \omega_{\min} + \frac{\left(\omega_{\max} - \omega_{\min}\right)\left(t_{\max} - t\right)}{t_{\max}} \tag{17}$$

$$x^{t+1} = \omega x^t - \delta^{t*} \vec{b}^* \operatorname{sign}\left(f\left(x_{rt}\right) - f\left(x_{lt}\right)\right) \tag{18}$$

(3) Qian et al. proposed an Enhanced Beetle Antennae Search algorithm (EBAS) based on BAS (Arora and Singh 2019). The EBAS algorithm elevates both the versatility and search efficiency of the original BAS through a triad of pivotal enhancements. Notably, the EBAS algorithm retains the utilization of a solitary beetle, mirroring the fundamental BAS paradigm, while concurrently attaining superior search performance and mitigating computational complexity, thereby rendering it amenable to seamless integration with other algorithmic frameworks.
Adaptive Step Size Calculation: In contrast to the conventional BAS, the EBAS algorithm governs step size dynamically by reference to the maximum value of the optimization range, denoted as 'R,' and a precision factor 'A' (e.g., 1/100). During the course of optimization, the step size gradually diminishes from 'R' to the minimum value, 'R*A,' thereby enhancing precision.
Efficient use of iterative information: In the standard BAS and its improved versions, the left and right solutions are only used to determine the direction of the next solution, not directly to update the solution. eBAS makes full use of the left and right solution information in each iteration to select the best solution to update the next position of the beetle and the historical optimal solution.

$$x^* = \begin{cases} x_l, \text{ if } min\left(\left[f\left(x_l\right), f\left(x_r\right), f(x^t)\right]\right) = f\left(x_l\right) \\ x_r, \text{ if } min\left(\left[f\left(x_l\right), f\left(x_r\right), f(x^t)\right]\right) = f\left(x_r\right) \\ x^t, \text{ if } min\left(\left[f\left(x_l\right), f\left(x_r\right), f(x^t)\right]\right) = f(x^t) \end{cases} \tag{19}$$

- Multi-directional sensing method: In each iteration, EBAS computes multiple pairs of left and right solutions, employing an optimal update strategy to designate the most favorable solution as the initial position for the beetle in the ensuing iteration, simultaneously updating the current optimal solution.

These improvements not only enhance the algorithm's performance in unbiased function optimization problems but also improve its applicability in practical engineering problems, such as social network contact competitions and scheduling issues. Despite potentially longer runtime, EBAS exhibits exceptional performance and flexibility in various optimization problems, becoming an effective tool for handling complex optimization issues.

(4) In response to the inherent limitations associated with the fundamental BAS algorithm, specifically pertaining to individual disparities and the dynamic processing of information, Shao and Fan have propounded a refined algorithm denoted as Enhanced Neighborhood-based BAS (ENBAS) (Wang et al. 2018). The crux of the ENBAS algorithm revolves around the orchestrated removal of underperforming individuals via elite selection mechanisms and the concomitant generation of novel beetles. This dual-pronged strategy serves the dual purposes of preserving population diversity and bolstering search capabilities. Concurrently, the neighbor movement strategy is instru-

mental in expanding the search ambit, amplifying the influence of optimally positioned individuals upon their less favorably situated counterparts. In ENBAS, to bring all individuals closer to the global optimal solution, the two update formulas (2) for the beetle antennae positions are modified to:

$$\begin{aligned} x^t_{left-new} &= x^t + d^t \cdot u_1 \\ x^t_{right-new} &= x^t - d^t \cdot u_2 \end{aligned} \tag{20}$$

where u_1 and u_2 are random numbers with a normal Gaussian distribution. The new position update formula (4) is adjusted to:

$$x^{t+1}_{new} = x_{best} - x_{best} \cdot u_3 \cdot \vec{c} \cdot \text{sign}\Big(f\Big(x^t_{left-new}\Big) - f\Big(x^t_{right-new}\Big)\Big)d^t \cdot u_2 \tag{21}$$

where u_3 is a random number with a normal Gaussian distribution. Experimental results show that this algorithm outperforms the original BAS in terms of solution accuracy, convergence speed, and stability.

(5) Wu et al. proposed the Fall-Back Beetle Antennae Search algorithm (FBAS) (Li et al. 2019) based on BAS, for intelligent path planning. The flowchart of the algorithm is shown in Fig. 4. FBAS introduces the setting of collision count C. If this iteration does not yield a new available optimal objective function value f_{bst}, i.e., $f\left(x_{\text{new}}\right) > f_{\text{bst}}$ and $x_{\text{new}} \in O$, it is determined that the beetle's movement has collided, and C increases by 1. When C exceeds the preset collision threshold C_n, the selection strategy for candidate points is changed to simulate retreat during the foraging process.

The innovation encapsulated within the Fallback Beetle Antennae Search (FBAS) algorithm resides in its incorporation of a fallback mechanism, which emulates the evasive strategies exhibited by organisms when confronted with obstacles. In practical terms, when the robot encounters an obstacle, it adeptly executes a strategic retreat to a safe distance and subsequently recalibrates its path to circumvent potential collisions. This adaptive maneuver not only imbues the path-planning process with heightened acumen but also engenders a reduction in time complexity, endowing the algorithm with the capacity to expeditiously chart collision-free trajectories. The efficacy of the FBAS algorithm underwent rigorous validation via simulation tests conducted within diverse environmental contexts. Comparative assessments against other algorithms underscored its superior performance. Fig. 4

3.3 Hybrid heuristic algorithm

Combining BAS with other optimization algorithms or heuristic search methods to construct hybrid algorithms. By integrating the advantages of multiple algorithms, the overall performance of the algorithm is improved. For example, combining PSO, ABC, FPA, Grey Wolf Optimizer (GWO) (Jian et al. 2019), ACO, Artificial Fish Swarm Algorithm (AFS) (Wang et al. 2019b), Simulated Annealing (SA) (Yang et al. 2020), Gravitational Search Algorithm (GSA) (Zhang et al. 2020a), and Butterfly Optimization Algorithm (BOA) (Zhang et al. 2020) with BAS to form new hybrid optimization strategies. Hybrid methods are becoming increasingly popular in the optimization field, using components of mixed leading optimization technologies to enhance the performance of traditional optimization algorithms. The main improvement methods are shown in Table 4.

3.3.1 Particle swarm optimization

Wang et al. identified a critical dependency of the BAS algorithm on the initial position of individuals. To overcome this limitation, they developed the Beetle Swarm Optimization (BSO) algorithm (Cheng et al. 2019), a novel approach that leverages the collective search strategies of PSO. This algorithm significantly enhances solution speed, precision, and robustness in various optimization challenges. BSO's unique integration of beetle-like foraging behaviors substantially augments group optimization efficacy, showcasing remarkable proficiency in complex scenarios such as engineering design and functional optimization. When benchmarked against established methodologies like PSO, GA, and the Grasshopper Optimization Algorithm (GOA) (Wu et al. 2019), BSO demonstrated superior capabilities across 23 test functions, notably excelling in stability and convergence speed, with practical applications evident in pressure vessel design and Himmelblau's optimization problem.

Li et al. innovatively synthesized the BAS and PSO algorithms to formulate the BAS-PSO hybrid algorithm (Zhang et al. 2022). This sophisticated algorithm initiates with the standard particle swarm technique to update particle positions and velocities, thereby maintaining

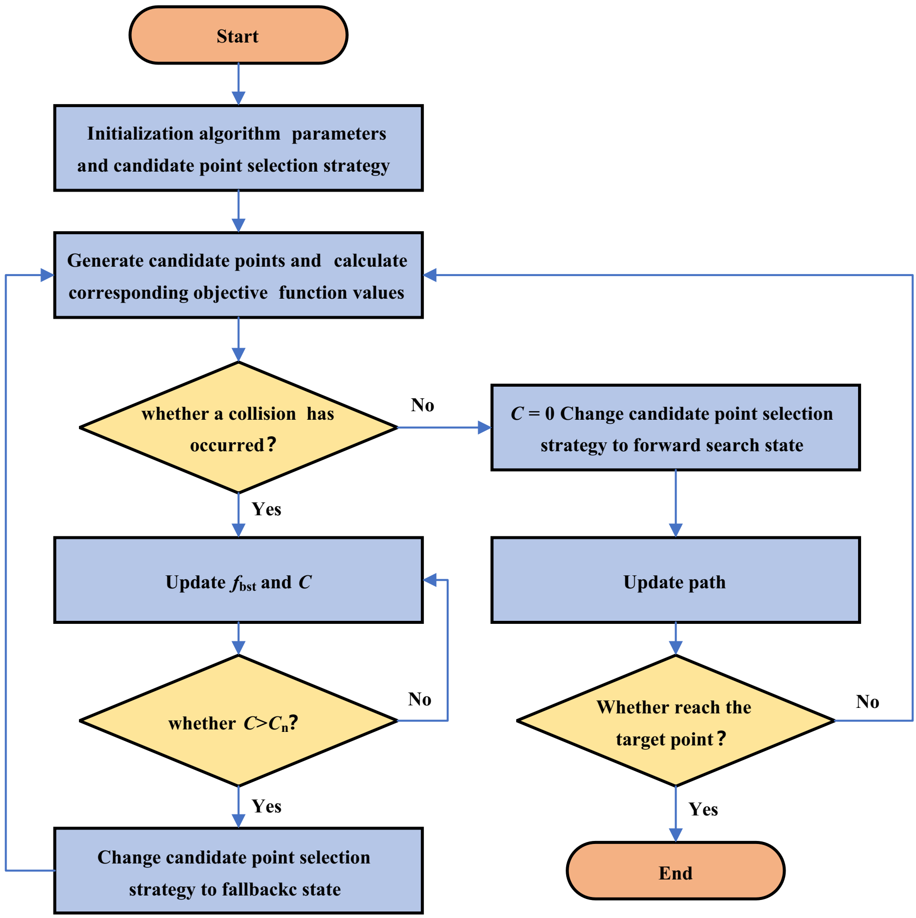


Fig. 4 Flowchart of the proposed FBAS algorithm

PSO's inherent strength in global search. In this hybrid model, each particle functions autonomously as a beetle, employing the BAS methodology for localized search, thus iterating until the discovery of an optimal solution. Despite its group-based approach necessitating multiple fitness evaluations, the BAS-PSO algorithm did not undergo subsequent refinements to reduce complexity, affecting its optimization speed. However, empirical studies revealed its enhanced optimization capacity in solving the Electric Load Dispatch (ELD) problem in power systems, outperforming traditional methods like PSO, GA, and the Chaos Optimization Algorithm (COA) (Khan et al. 2021). Further advancing this field, Jian et al. introduced the Beetle Antennae Particle Swarm Optimization (BAPSO) (Lei et al. 2019), tailored for resource coordination and scheduling challenges in edge computing. This evolved algorithm scales beetle individuals to a collective entity, integrating second-order oscillation and dynamic factors to augment the group mechanism. Such enhancements have proven effective in minimizing costs while optimizing the Quality of Experience (QoE). BAPSO's pivotal innovation lies in its application of swarm intelligence for resource allocation, merging advanced oscillation and dynamic factors to refine particle movement, thereby offering a more rapid and efficient solution to optimization problems. Wang et al. integrated the search strategy of Particle Swarm Optimization (PSO) with step lengths dictated by the Fibonacci sequence, culminating in the development of the PSO-Fibonacci-BAS algorithm (Zhou et al. 2022). This innovative approach underwent rigorous evaluation through performance tests on both unimodal and multimodal functions. The assessments, grounded in a tripartite criterion framework, revealed that the PSO-Fibonacci-BAS algorithm exhibits superior performance capabilities when contrasted with the conventional PSO and BAS algorithms. These findings, derived from comprehensive simulations, not only underscore the enhanced efficiency of the PSO-Fibonacci-BAS algorithm but also mark a significant advancement in the realm of optimization algorithms.

Yang et al. proposed a particle swarm optimization algorithm based on BAS, named the BASPSO algorithm (Fan et al. 2021). The core of the BASPSO algorithm is to introduce the strategy of the BAS algorithm into the PSO process. The crux of BASPSO lies in its strategic fusion of BAS's search mechanics within the PSO paradigm. This process initiates with each particle updating its position via the PSO methodology, followed by the employment of this new position as a baseline for enhanced local exploration utilizing BAS. Such iterative refinement enables the BASPSO algorithm to adeptly navigate and extricate itself from local optima, thereby markedly enhancing the optimization process in terms of efficacy and robustness. Empirical simulations, conducted across three distinct functions, underscore the superiority of BASPSO over traditional PSO. This comparative analysis reveals notable improvements in optimization performance and algorithmic resilience, affirming the potential of BASPSO in complex optimization scenarios.

Zhang et al. introduced the concept of beetle search into the particle swarm algorithm, proposing a combined the BAS algorithm and the PSO algorithm, namely the BAS-PSO algorithm (Yu et al. 2022), and applied it to multi-objective optimized robot path planning. This algorithm specifically addresses the limitations inherent in traditional PSO algorithms used for robot path planning, such as reduced search precision and a propensity for converging on local optima. By integrating the search strategy of BAS into the particle update mechanisms of PSO, BAS-PSO significantly enhances the optimization process. Each iteration within this framework sees particles dynamically self-adjusting in response to the environmental parameters, thereby streamlining the iterative process and augmenting the speed of search. Comparative simulations in the domain of path planning distinctly illustrate the superiority of BAS-PSO over conventional PSO, especially in terms of its enhanced stability and effectiveness. This approach offers a robust and efficient solution for complex multi-objective optimization challenges in robot path planning,

Table 4 Summary of BAS hybrid heuristic algorithms

Hybrid Algorithms	Algorithm	Improvement Mechanism	Advantage	Disadvantage	Applicable Scenarios	Year
PSO(Khan 2022)	BSO(Cheng et al. 2019)	Expanded individual search to population level, combining PSO's global search with BAS's local strategy	Performance superior to PSO, GA, GOA	Optimization results less effective than PSO for some multimodal functions	23 benchmark functions; pressure vessel and Himelblau's optimization problems	2018
	BAS-PSO(Zhang et al. 2022)	Combining PSO and BAS, PSO updates particle velocity and position, BAS for local search	Optimization effect superior to BAS and PSO	Optimization speed decreases, algorithm complexity increases	ELD problem	2019
	BAPSO(Lei et al. 2019)	Implemented group mechanism, introduced second-order oscillation and dynamic factors	Improved global search, reduced execution time	Increased time complexity	Edge computing resource coordination and scheduling issues	2019
	PSO-Fibonacci-BAS(Zhou et al. 2022)	Utilized particle swarm concept for search, employing the Fibonacci method to determine search step lengths	Outperforms PSO and BAS, achieving theoretical optimal values in 6 out of 8 test functions	Increased time complexity	Addressing complex, non-convex, high-dimensional, and non-linear optimization problems	2019
	BASPSO Fan et al. 2021)	Introduced BAS algorithm into PSO	Superior to BAS and PSO on three different multi-modal functions	Increased time complexity	Tackling intricate optimization with non-convex, high-dimensional, and non-linear constraints	2020
	BAS-PSO(Yu et al. 2022)	Combined BAS and PSO evolutionary algorithms	Superior to PSO in path planning tests	Experimental comparison only with PSO	Multi-objective optimization path planning	2020

Table 4 (continued)

Hybrid Algorithms	Algorithm	Improvement Mechanism	Advantage	Disadvantage	Applicable Scenarios	Year
ABC(Wei et al. 2021)	MBAS(Zhang et al. 2020b)	Merging ABC and BAS features, partitioning beetle swarm into searchers, followers, and explorers for tailored optimization strategies	Improved generalization performance	Increased computational load, longer computation time	ELM problem, complex data classification and regression problems	2020
	BAS-ABC(Jiang et al. 2020)	Determined bee advance direction from beetle search process	Faster than original ABC, more accurate than original ABC and PSO	Slightly lower accuracy than ABC on 50D Griewank and 100D Ackley functions	5 benchmark functions	2019
	BAS-ABC(Ni et al. 2022)	After BAS optimization, employing the optimal position as a food source in ABC	Swift convergence, surpasses BAS, ABC, and PSO-SSA	Increased computational complexity	Predicting software reliability model parameters	2022
FPA(Yang 2012)	BFPA(Zhou et al. 2020)	Used butterfly pollination strategy for global search, coupled with BAS for local search	Can converge to 0 on Rosenbrock, Schwefel 1.2 functions	Similar effect to PFA on Schwefel 2.21, optimization not prominent	5 benchmark functions	2019
	TBFPA(Kou et al. 2022)	Used BAS to assess and update positions in the neighborhood solution space calculated by FPA, employed uniform distribution sampling for initial population generation	Outperforms traditional FPA in convergence speed and global search	Initial population's impact from uniform distribution not isolated	Benchmark functions	2022

Table 4 (continued)

Hybrid Algorithms	Algorithm	Improvement Mechanism	Advantage	Disadvantage	Applicable Scenarios	Year
GWO(Jian et al. 2019)	BGWO(Kim et al. 2023)	Introduced grey wolf algorithm, incorporated cosine function-based dynamic control parameter update	Superior to GWO algorithm in search speed and robustness	Unable to converge to 0 on most benchmark functions	23 benchmark functions and designs for pressure vessels, welded beams, cantilever beams, and springs	2021
	BASGWO Yin and Deng 2022)	Incorporated BAS mechanism into grey wolf algorithm	Avoided algorithm falling into local optima	Requires more computational resources and time	Wireless Sensor Network (WSN) node localization problem	2022
ACO(Ijaz et al. 2022)	BCO(Saremi et al. 2017)	Used random direction to update ant states, effectively balancing individual search and group mechanism	Balanced adaptability and search efficiency, strong real-time performance	Incapable of estimating deviation between feasible and optimal solutions	NP-hard problems, Traveling Salesman, Quadratic Programming, and UAV path planning	2020
	LFS-BAS、ACO-BAS、SIO-BAS(Yang et al. 2014)	Introduced Local Fast Search (LFS), ACO initial path generation, Search Information Orientation (SIO)	LFS-BAS prevents local optima, ACO-BAS boosts efficiency, SIO-BAS balances speed, accuracy, and stability	Increased computational complexity	High real-time 3D path planning requirements	2020
AFS(Wang et al. 2019b)	AFS-MMSBAS (Wu and Zhang 2014)	Combined BAS and Artificial Fish Swarm Algorithm (AFS), introduced mutation and multi-step detection strategy (MMSBAS)	Increased convergence speed, enhanced global search capability	Performance influenced by function characteristics, less effective in low dimensions	High-dimensional optimization problems	2022

Table 4 (continued)

Hybrid Algorithms	Algorithm	Improvement Mechanism	Advantage	Disadvantage	Applicable Scenarios	Year
SA(Yang et al. 2020)	IBAS(Jiang and Li 2017)	Introduced adaptive factors, combined with Simulated Annealing algorithm	Faster convergence, higher precision, improved global search	High computational complexity	High-dimensional optimization problems	2020
	RWSAVSBAS(Zhang et al. 2020c)	Introduced random walk behavior of wolf pack algorithm and Simulated Annealing algorithm	Enhanced local search and global convergence capabilities	Requires parameter tuning	Geometric linkage errors in medical robots	2022
GSA(Zhang et al. 2020a)	BAS-GSA(Qian et al. 2021)	Combined BAS with Gravitational Search Algorithm (GSA)	Improved global and local search capabilities	High computational complexity	Image defect detection	2023
BOA(Zhang et al. 2020)	BAS-LBOA(Qian et al. 2021)	Used chaotic mapping, integrated Lévy flight rules, combined BOA with BAS	Enhanced global and local search capabilities	High computational complexity	High-dimensional optimization problems	2022

proving particularly beneficial for navigation systems where swift and precise trajectory determination is paramount.

3.3.2 Artificial bee colony algorithm

Zhang et al., based on the principles of the ABC algorithm, combined ABC and BAS algorithms to propose the Multi-Task Beetle Antennae Swarm Algorithm (MBAS) (Zhang et al. 2020b). This algorithm constructs a beetle particle swarm of size N in multi-dimensional space, dividing these beetle particles into three categories: searchers, followers, and explorers, based on a specific ratio. The searchers primarily focus on identifying the optimal solution within the solution space, employing BAS for position updates. Followers, in tandem, track specific searchers to probe for superior solutions near the existing global optimum. Conversely, explorers are tasked with random movements at fixed step lengths, a strategy designed to circumvent local optima. Significantly, the MBAS algorithm has been adeptly applied to Extreme Learning Machines (ELM), tackling the challenges of ill-conditioned problems that arise from randomly assigned input weights and biases. By adjusting these parameters in the ELM, the MBAS algorithm effectively reduces the condition number and regression error, thereby enhancing the model's generalization capabilities and ensuring more stable and reliable training outcomes. The strategy to expand the beetle swarm for greater diversity necessitates each beetle to undertake three separate fitness evaluations during the optimization process, consequently escalating the overall computational burden and time requirement.

Cheng et al. developed an enhanced version of the ABC algorithm, termed the BAS-based Artificial Bee Colony Algorithm (BAS-ABC) (Qian et al. 2022). This innovative method synergizes the BAS with ABC, specifically targeting the refinement of foraging bees' movement direction during food source search to elevate the efficiency of the algorithm. Rigorous evaluations through standard function tests revealed that BAS-ABC achieves a more rapid convergence and superior accuracy in comparison to the conventional ABC and PSO, albeit with a sensitivity to parameter configurations. Furthering this domain, Zhang et al. introduced an iteration of the BAS-ABC algorithm (Shao and Fan 2021),, which, upon deriving optimal adaptive values and positions via BAS, employs these positions as food source coordinates within the ABC framework. The algorithm executes BAS iterations commensurate with the number of food sources identified in ABC. This confluence of BAS's swift convergence and straightforward implementation with ABC's robust optimization capacity notably enhances parameter estimation in software reliability models. Empirical results indicate that the BAS-ABC hybrid algorithm markedly surpasses individual algorithms in accuracy, convergence speed, and stability, validating its utility in predicting software defects. Comparative assessments with other hybrid models, such as PSO-SSA, have further underscored BAS-ABC's multifaceted superiority. Nevertheless, this hybrid approach introduces greater complexity in implementation, and while the current research predominantly concentrates on the Group Object (GO) model, the algorithm's applicability across diverse software reliability models necessitates additional investigation.

3.3.3 Flower pollination algorithm

In an endeavor to rectify the limitations in convergence speed and accuracy of traditional FPA, Lei et al. introduced the butterfly pollination flower algorithm (BFPA) (Zhou et al. 2020). This innovative approach synergizes the butterfly pollination mechanism with the

BAS algorithm. The butterfly pollination strategy is applied to expedite the global search phase, while BAS is integrated during local search to adeptly navigate and evade local optima. Empirical analyses indicate that BFPA surpasses other advanced flower pollination algorithms in performance, although it exhibits comparable results to the conventional PFA on the Schwefel 2.21 function, lacking significant optimization enhancements. Notwithstanding its performance on specific tests, BFPA demonstrates improved efficacy on a broader range of test functions, particularly in contexts demanding elevated convergence speed and precision.

Zhou et al. proposed the BAS-based Flower Pollination Algorithm (TBFPA) (Kou et al. 2022) to overcome the slow convergence speed of the traditional FPA algorithm. This novel algorithm integrates the efficacy of the BAS with the traditional FPA. It employs BAS for scrutinizing the adjacent solution space of each solution generated by FPA, effectively refreshing the solution space proximal to the new positions of individuals. This refinement elevates the likelihood of identifying optimal solutions and expedites the convergence process. Moreover, TBFPA adopts a uniform distribution sampling technique for initial population generation, ensuring an equitable dispersion of initial solutions throughout the entire solution space. This strategy enhances the algorithm's early convergence and augments its capacity to bypass local optima at advanced stages. Experimental evaluations have established TBFPA's superiority over the conventional FPA, particularly in terms of convergence velocity and global search efficacy.

3.3.4 Grey wolf optimizer

Fan et al. sought to mitigate the issues of stagnation and susceptibility to local optima in the GWO due to its inherent lack of diversity and hierarchical limitations. They introduced an enhanced version, the Beetle-Grey Wolf Optimizer (BGWO) (Kim et al. 2023), integrating the BAS strategy with GWO. This novel approach, which equips the alpha wolf within the algorithm with simulated auditory sensing analogous to BAS foraging behavior, also incorporates a cosine function-based dynamic control parameter update strategy. Such refinements significantly elevate the global search capabilities of the algorithm, achieving a more effective balance between exploration and exploitation. Rigorous testing on 23 benchmark functions and application to four distinct engineering design challenges—namely, pressure vessel, welded beam, cantilever beam, and tension/compression spring designs—established BGWO's superior performance over traditional GWO, particularly in terms of search efficiency and robustness.

Addressing the complex node localization challenges in WSN, Yu et al. developed an innovative algorithm, the BAS-based Grey Wolf Optimizer (BASGWO) (Yin and Deng 2022). This algorithm reinterprets node localization as a function-constrained optimization problem and integrates the efficiency of the BAS mechanism into the grey wolf algorithm to enhance localization accuracy and stability. BASGWO commences with an advanced point set method for initializing the grey wolf population, thereby ensuring a robust starting point. It then employs the BAS strategy to augment the global search capabilities, effectively circumventing the grey wolf algorithm's tendency to converge on local optima during later iterations. Position updates within the algorithm are governed by the combined fitness values of the grey wolf and beetle antennae strategies, ensuring the identification of globally optimal solutions and facilitating precise localization of unknown nodes. Simulations validate the efficacy of BASGWO, showcasing its exceptional performance in WSN node localization, despite its increased demand for computational resources and time.

3.3.5 Ant colony optimization

Zhang et al. introduced the Beetle Colony Optimization (BCO) algorithm (Saremi et al. 2017), an innovative fusion of the BAS and ACO. BCO deviates from traditional ACO by adopting a unique ant state update mechanism that relies on random directional choices, thereby harmonizing the dichotomy of individualistic and collective search strategies. In practical applications, BCO has exhibited enhanced optimization speeds compared to ACO, particularly in resolving the Traveling Salesman Problem and achieving more efficient solutions in Quadratic Assignment Problems. Furthermore, its application in Unmanned Aerial Vehicle (UAV) path planning has led to broader search scopes and improved efficiency, thus augmenting real-time performance. Nevertheless, the inherent uncertainty in BCO's approach poses challenges in precisely quantifying the deviation of feasible solutions from the optimal solution.

Addressing the limitations of real-time performance and accuracy in three-dimensional (3D) path planning, Zhang et al. developed a refined heuristic algorithm grounded in BAS (Yang et al. 2014). This advanced algorithm integrates a trio of strategic mechanisms: Local Fast Search (LFS), ACO-based initial path generation, and Search Information Orientation (SIO). These mechanisms collectively work to expand the search range and enhance accuracy, whilst concurrently reducing time complexity. The LFS-BAS component accelerates path convergence through the delineation of specific bounded areas and rapid iterative exploration. In contrast, the ACO-BAS segment leverages ACO for efficient initial path generation. The SIO-BAS aspect, guided by search information, optimizes the balance between search speed, accuracy, and stability, thereby fostering consistent path searching and minimizing computational resource expenditure. Simulation tests have demonstrated that these augmented BAS algorithms surpass other intelligent algorithms in search precision and speed for 3D path planning, significantly bolstering adaptability across varied environments.

3.3.6 Artificial fish swarm algorithm

Ni et al. embarked on an innovative integration of the BAS algorithm with the Artificial Fish Swarm Algorithm (AFS), culminating in the development of a novel hybrid algorithm, AFS-Multi-Step BAS (AFS-MMSBAS) (Wu and Zhang 2014). This hybrid approach strategically employs AFS for initial global optimization and expeditious convergence, subsequently transitioning to an enhanced BAS algorithm for sustained optimization. The specific procedural dynamics of AFS-MMSBAS are depicted in Fig. 5. Central to this algorithm are two key enhancements: a mutation strategy and a multi-step detection strategy. The mutation strategy is designed to enable the simulated beetles to effectively circumvent local extremums, thereby enhancing the global search potential of BAS. Concurrently, the multi-step detection strategy propels the convergence rate of the algorithm, doing so by adaptively modulating the step length. This dual-strategy approach synergistically augments both the global search capabilities of BAS and the local search efficiency of AFS, resulting in an algorithm with improved performance metrics.

3.3.7 Simulated annealing algorithm

Zhou et al. developed an Improved Beetle Antennae Search algorithm (IBAS), which offers substantial enhancements in convergence velocity and accuracy for multi-dimensional optimization tasks (Jiang and Li 2017). IBAS achieves this marked acceleration in convergence by integrating adaptive factors, concurrently employing simulated annealing methods to amplify its proficiency in circumventing local optima, thus elevating its global search capabilities. Such refinements have rendered IBAS particularly effective in multi-dimensional function optimization, characterized by its swift convergence and heightened optimization precision. However, these advancements in IBAS come at the cost of increased computational complexity, attributable to the inclusion of these additional mechanisms.

Kou et al. introduced an innovative optimization algorithm—the Random Walk Simulated Annealing Variable Step Beetle Antennae Search Algorithm (RWSAVSBAS) (Zhang et al. 2020c), amalgamating the exploratory behaviors of the Wolf Pack Algorithm (WPA) (Chen et al. 2023) with simulated annealing and BAS. Drawing inspiration from WPA's stochastic roaming patterns, RWSAVSBAS augments BAS by incorporating 'random antennae' alongside the beetle's existing antennae, facilitating a tripartite antennae search. This enhancement significantly bolsters BAS's local search efficiency, although it does carry the inherent risk of entrapment in local optima due to the single-particle search characteristic of BAS. The integration of the Metropolis criterion from the simulated annealing algorithm fortifies the algorithm's capability to evade local optima, thereby solidifying its global search performance. In empirical studies involving the development and simulation of medical robot motion error models, RWSAVSBAS outperformed comparable algorithms in terms of convergence accuracy, underscoring its effectiveness and applicability in intricate optimization scenarios.

3.3.8 Gravitational search algorithm

Kim et al. introduced an advanced hybrid algorithm, termed BAS-GSA (Qian et al. 2021), which ingeniously amalgamates the BAS and Gravitational Search Algorithm (GSA) methodologies. This integration significantly enhances the effectiveness of parameter optimization processes. Specifically, the BAS-GSA algorithm is employed in conjunction with a two-dimensional Gabor filter for the automated detection of fabric defects, encompassing both training and detection phases. During the training phase, defect-free fabric images are processed using Gabor filters optimized by the BAS-GSA to ascertain the most efficacious filter parameters. Subsequently, in the detection phase, these optimized parameters are utilized to convolve the fabric images under inspection, with defects being pinpointed through binarization techniques. The empirical efficacy of this method is highlighted by its remarkable detection rate of up to 98%, underscoring its high efficiency and stability in identifying fabric defects. This attribute renders the BAS-GSA algorithm particularly conducive to industrial production settings, where it serves as a potent and precise instrument for automated quality control.

3.3.9 Butterfly optimization algorithm

Yin and Deng tackled the challenges of suboptimal accuracy and the propensity for converging on local optima in the BOA. They conceived an enhanced version, the Beetle Antennae Search-Improved Butterfly Optimization Algorithm (BAS-LBOA) (Qian et al. 2021). This advanced variant departs from conventional random initialization by employing chaos mapping to initialize butterfly agents, thereby achieving a more uniform distribution across the solution space. Additionally, chaos mapping is strategically utilized to derive pivotal parameters that govern both global and local search processes,

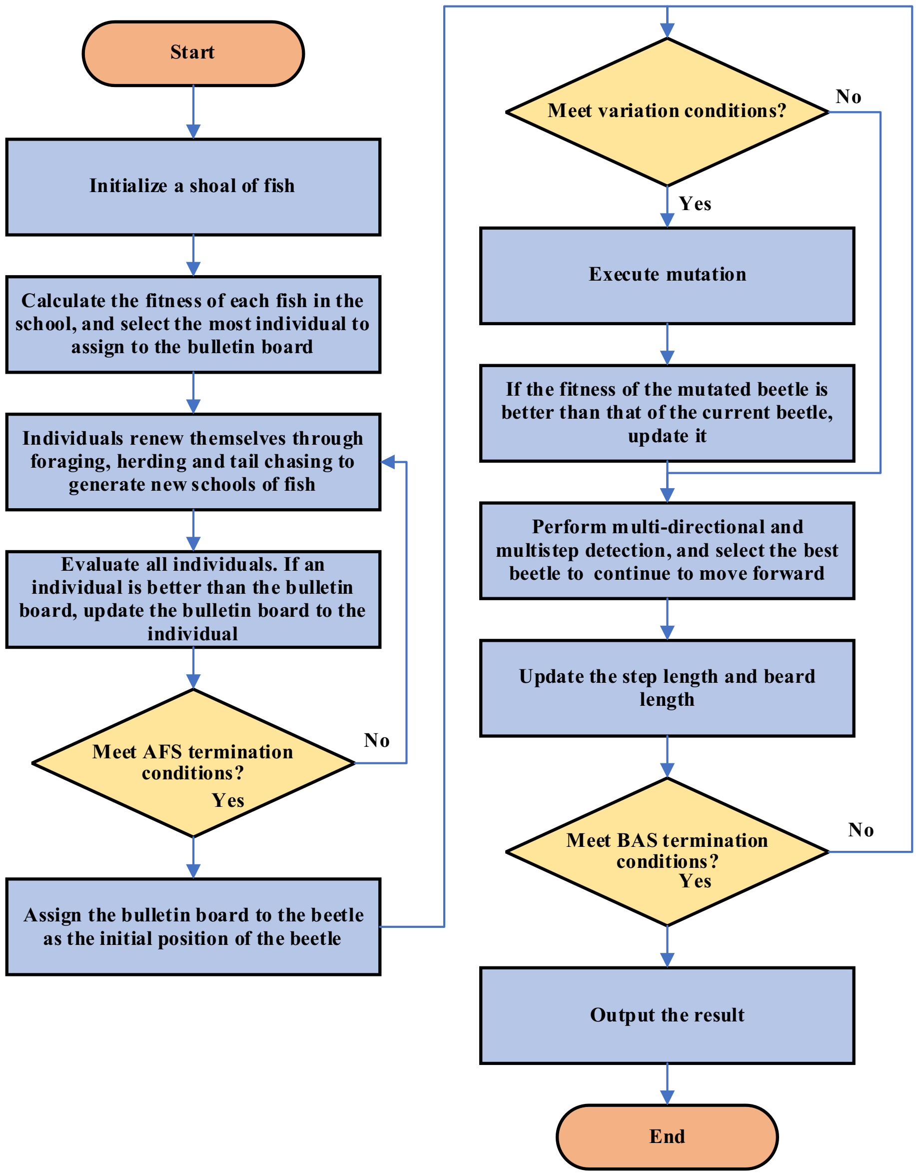


Fig. 5 AFS-MMSBAS algorithm flow chart

substituting the erstwhile random functions. A significant incorporation in BAS-LBOA is the integration of Lévy flight principles, which effectively forestalls search stagnation during advanced iterative stages. Moreover, the BAS mechanism is ingeniously embedded into the BOA's random search component, substantially bolstering search efficiency. Comparative analyses with various other intelligent algorithms have underscored BAS-LBOA's remarkable optimization performance, emphatically validating the efficacy of these improvement strategies.

3.4 Multi-objective optimization improved algorithms

For multi-objective optimization problems, researchers can design a multi-objective version of BAS, or combine it with multi-objective optimization methods to effectively handle multi-objective problems. The main improvement methods are summarized in Table 5.

Jiang et al. developed an innovative variant of the BAS algorithm, designated as BAS-WPT (Waly and Mohamed Ibrahim 2023), specifically tailored for multi-objective optimization challenges. This adaptation addresses the original BAS algorithm's limitation to single-objective tasks. BAS-WPT incorporates normalization techniques and penalty functions to simplify the algorithm's structure and extend its utility. The integration of normalization techniques streamlines parameter adjustment, and penalty functions adeptly manage infeasible solutions with minimal constraint violations. This refinement significantly improves the algorithm's capacity in handling constrained optimization scenarios. Empirical tests using the Pressure Vessel and Himmelblau Functions corroborated BAS-WPT's efficacy in multi-objective optimization contexts. Building upon BAS's success in intricate engineering problems, Zhang et al. introduced an expansion of BAS into the realm of multi-objective optimization engineering challenges, culminating in the Multi-Objective Beetle Antennae Search Algorithm (MOBAS)(Bao et al. 2023). MOBAS, an advanced iteration of BAS, employs an individual intelligence-based methodology for optimizing multiple objectives. The algorithm's proficiency was evaluated against four benchmark functions, where its performance was compared with other multi-objective optimization algorithms. Experimental results demonstrated MOBAS's remarkable computational efficiency and precision, successfully delineating the Pareto front in multi-objective optimization scenarios. Qian et al. introduced a novel approach, the New Multi-Objective Beetle Antennae Search Algorithm (NMBAS)(Jin et al. 2017), specifically designed to tackle the Multi-Objective Optimal Active Power Dispatch (MOAPD) problem. NMBAS ingeniously amalgamates the principles of NSGA-II and Multi-Objective Particle Swarm Optimization (MPSO) to deliver superior Pareto Fronts and Best Compromise Solutions in addressing MOAPD challenges. Additionally, they developed a BAS-BP fuel cost prediction network. This model, anchored in the BP network framework, attains multiple elite solutions of high quality by refining the BAS algorithm.

Qian et al. devised the Mixed Hybrid Beetle Antennae Search (MHBAS) algorithm (Khan et al. 2022), an enhanced version featuring an adaptively adjusted step factor, designed for multi-objective MOAPD problems. MHBAS integrates the initial optimization and mutation crossover mechanisms of the Multi-Objective Differential Evolution algorithm, thereby achieving superior population diversity. Furthermore, they introduced a BP flow prediction model based on basic fuel costs, which, when amalgamated with MHBAS, forms the novel MHBAS-BP method. This methodology not only yields high-quality scheduling solutions but also aligns with the expedited decision-making requirements. In addressing complex MOAPD issues, MHBAS-BP stands as a quintessential exemplar of advanced computer technology application.

3.5 Deep learning fusion improved algorithms

In an innovative integration of optimization and artificial intelligence, researchers have amalgamated BAS with deep learning technologies to forge advanced deep learning models that adeptly guide the search process. These models possess the capability to discern and learn from feature representations inherent in various problems, thereby enabling BAS

Table 5 Summary of BAS multi-objective optimization improved algorithms

Algorithm	Improvement Mechanism	Advantage	Disadvantage	Applicable Scenarios	Year
BAS-WPT(Waly and Mohamed Ibrahim 2023)	Normalization methods enable the extension of BAS to a broader form, applicable to multi-objective optimization	Optimal for multi-objective issues, no parameter adjustment needed	The optimization effect is not significant	Multi-objective optimization for Pressure Vessel and Himmelblau functions	2017
MOBAS(Bao et al. 2023)	Extended to multi-objective optimization problems	High computational efficiency	Lags behind Multi-objective Particle Swarm Optimization on ZDT 1, ZDT 2, and ZDT 3 functions	Four benchmark functions, multi-objective optimization problems	2020
NMBAS(Jin et al. 2017)	Integrates NSGA-II and Multi-objective PSO algorithms	Yields better Pareto Front and Best Compromise Solutions for MOAPD issues	Increased computational complexity	The MOAPD problem	2021
MHBAS(Khan et al. 2022)	Integrates initial optimization, Multi-objective Differential Evolution's mutation crossover, and FOSM method	Efficient solution, rapid convergence	Increased computational complexity	Nonlinear multi-objective optimal active power dispatch problem	2021

to navigate towards optimal solutions with enhanced intelligence and precision. The primary methodologies employed in this advancement are systematically outlined in Table 6, showcasing the strategic blend of BAS with the intricate mechanics of deep learning.

Wu et al. introduced a novel approach to NNC design, dubbed BASNNC (Gu et al. 2018),, which represents a departure from conventional neural network training methodologies. This technique uniquely employs the BAS algorithm for the optimization of NNC weights. Structurally, BASNNC is composed of three layers: the input layer, hidden layer, and output layer. Diverging from the traditional gradient descent approaches, BASNNC utilizes the BAS algorithm specifically to refine the weights interconnecting the hidden and output layers, as depicted in Fig. 6. This strategic application results in a marked enhancement in the classifier's computational speed. Through a series of numerical studies, applications in pattern classification, and comparative analyses with error backpropagation neural network models, it has been evidenced that BASNNC not only accelerates computational processing but also achieves superior classification accuracy.

Khan et al. have developed an advanced BAS with Zeroing Neural Network (BASZNN) algorithm (Weiss et al. 2016), which marks a significant improvement over the conventional BAS approach. By integrating delay factors and ZNN (Wang et al. 2020a), BASZNN enhances the calculation efficiency of the objective function. This innovation leads to notable increases in both computational efficiency and robustness. Merging BAS's random search trait with ZNN's parallel processing, BASZNN is adept at tackling a wide range of complex problems, including unconstrained, constrained, unimodal, multimodal, and real-world challenges. Furthermore, Khan et al. successfully employed BASZNN in multi-robot collaborative tasks within smart home settings, demonstrating its practical applicability and effectiveness (Gao et al. 2021).

In a groundbreaking study, Chen et al. applied the BAS algorithm to refine the initial parameters of CNN (Xu et al. 2020), introducing a novel BAS-optimized CNN methodology (Yu et al. 2023). This model, leveraging BAS's pre-training mechanisms, was deployed in the analysis and diagnosis of intracranial hemorrhage within medical imaging data. The experimental outcomes reveal that the BAS-optimized CNN (BAS-CNN) model surpasses conventional CNNs in both training speed and diagnostic precision. In a separate research endeavor, Waly and Ibrahim designed the Intelligent Beetle Antennae Search with Deep Transfer Learning (IBAS-DTL) model (Khan et al. 2021), aiming to advance the efficacy of Computer-Aided Diagnosis (CAD) systems in medical image classification. The IBAS-DTL combines deep transfer learning (He et al. 2022) with the Intelligent Beetle Antennae Search algorithm, thus enriching the model's generalization capabilities and its grasp of sophisticated problem domain nuances. The model employs an entropy-based weighted and first-order cumulative moment (EWFCM) technique for medical image segmentation, followed by feature extraction using DenseNet-121, and culminates with image classification via BAS and ELM models. Comparative testing on various benchmark medical imaging datasets has established the superior performance of IBAS-DTL in medical image classification.

Bao et al. innovatively merged the BAS with the Back Propagation Neural Network to create the BAS-BPNN thermal error prediction model (BAS-BP) (Jiming et al. 2019). This model harnesses BAS to finely tune the weights and thresholds of BPNN, thereby circumventing the issue of local minimization often encountered in conventional BPNN algorithms. This enhancement notably advances the mix rate and computational efficiency of the model. Employing machine temperature fluctuations and thermal error data, the BAS-BP model was formulated. It has been empirically demonstrated that BAS-BP exhibits substantial improvements in convergence speed, predictive accuracy, and robustness when compared with both traditional BPNN and Particle Swarm Optimization-enhanced BPNN models.

Table 6 Summary of BAS deep learning integration improved algorithms

Algorithm	Improvement Mechanism	Advantage	Disadvantage	Applicable Scenarios	Year
BASNNC(Gu et al. 2018)	Optimizing Neural Network Classifier (NNC) weights with BAS algorithm	Boasts quicker computation and enhanced classification accuracy	Increased computational complexity	Classification problems	2019
BASZNN(Weiss et al. 2016)	Incorporated delay factor and Zeroing Neural Network (ZNN), merging BAS's random search with ZNN's parallel processing	Improved computational efficiency and stability compared to BAS	High computational complexity	Covers unconstrained (unimodal, multimodal) and constrained (real-world) problems; apt for smart home multi-robot collaboration	2021
BAS-CNN(Yu et al. 2023)	Using BAS algorithm to optimize the initial parameters of Convolutional Neural Network (CNN)	Enhances training speed and diagnostic accuracy	Increases computational complexity compared to parameter tuning of the model	Medical image classification problems	2021
IBAS-DTL(Khan et al. 2021)	Combining transfer learning and BAS	Improved the performance of the classification model	High computational complexity	Medical image classification	2023
BAS-BP(Jiming et al. 2019)	Using BAS to find the optimal weights and thresholds of Back Propagation Neural Network (BPNN)	High accuracy, strong anti-interference ability, and robustness	High computational complexity	Thermal error modeling of CNC machines	2023

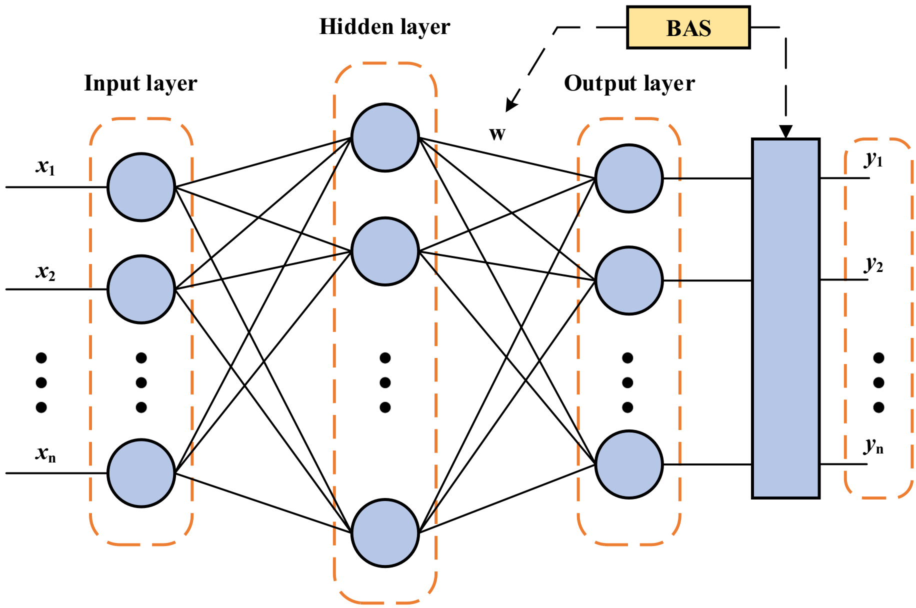


Fig. 6 Model structure of BASNNC

3.6 Other improved algorithms

Combining BAS with quantum theory, chaos concept, Lévy flight, ELM and other methods are used to improve the performance of the algorithm. The main improvement methods are shown in Table 7.

3.6.1 Quantum theory

Yu et al. introduced the Quantum-Based Beetle Swarm Optimization (QBSO) algorithm, a seminal advancement in optimization science, designed to navigate the complexities inherent in high-dimensional problems within the BAS paradigm (Rajagopal et al. 2021). The QBSO algorithm represents a quantum leap in encoding efficiency, successfully managing an expansive range of information within comparatively reduced population sizes. Central to its design is a novel position update mechanism, rooted in quantum mechanics, which effectively amalgamates the linear superposition of standard probabilities and deceptive states. This approach facilitates a sophisticated equilibrium between local and global search strategies, epitomized by a quantum-inspired revolving door technique. Additionally, the QBSO algorithm optimizes convergence velocity by implementing a dynamic search step size. Empirical assessments, particularly with a constrained population size of eight, underscore the QBSO algorithm's superior global convergence capabilities and its adeptness in addressing high-dimensional optimization challenges. This research transcends the limitations of traditional BAS algorithms, marking a groundbreaking integration of quantum computing methodologies with population-based intelligence algorithms, thus offering a novel pathway in tackling the intricacies of high-dimensional optimization.

Khan et al. have proposed the Quantum Beetle Antenna Search (QBAS) algorithm, a quantum modification of the traditional BAS framework (Yan et al. 2023). This cutting-edge algorithm synthesizes quantum computing principles, facilitating operations at the quantum level. Demonstrating remarkable efficacy, the QBAS algorithm particularly shines in resolving complex financial problems, with a pronounced proficiency in portfolio optimization scenarios. However, it is crucial to recognize that the algorithm incurs significant computational costs and extended processing times when handling large datasets, highlighting potential areas for future refinement.

3.6.2 Chaos mapping

Ma et al. introduced the Chaotic Disturbance Beetle Antenna Search (CDBAS) algorithm, an enhanced variant of the traditional BAS algorithm, incorporating a chaotic perturbation mechanism (Gu and Wang 2022). This innovative algorithm modifies the beetle's position using a chaotic mechanism, optimizing the iterative search process to efficiently pinpoint regions of higher global fitness values. Comparative analyses employing seven distinct test functions revealed that CDBAS surpasses its predecessor in optimization efficacy, convergence velocity, and precision. When applied to image enhancement, CDBAS demonstrated its ability to significantly improve image clarity and depth of hierarchical information. Despite the increased complexity introduced by the chaotic mechanism, the contribution of CDBAS in augmenting algorithmic performance and broadening its application spectrum is noteworthy, offering fresh insights into the evolution and utility of optimization algorithms.

Yin and Deng addressed the multi-objective optimization network reconfiguration challenge in distribution networks, arising from fluctuations in power and customer load demands, by developing the Chaotic Disturbed Beetle Antenna Search (CDBAS) algorithm (Lu et al. 2023). Distinct from its predecessors, CDBAS employs chaotic mapping for initialization, replacing the conventional random approach, and integrates grey-objective decision-making techniques to prioritize beetles. This strategy enhances system static voltage stability and voltage quality. The algorithm's efficacy and practicality were validated through simulations on IEEE 33, 69, and 118 bus test networks. The CDBAS algorithm's ingenuity lies in its adeptness at multi-objective optimization, simultaneously boosting computational efficiency and enhancing system performance.

Gao et al. advanced this field further by proposing the Chaos Beetle Antenna Search (CBAS) algorithm, a synergy of logistic chaotic mapping and the BAS algorithm (Zhang et al. 2023). Complementing this, they introduced an innovative soft measurement model for the complex Polyvinyl Chloride (PVC) aggregation process, merging CBAS with the Elman neural network. This method, focusing on the objective function, leverages the uniform traversal properties of chaotic sequences alongside the efficient search capabilities of the BAS algorithm to train the Elman neural network. Simulation results corroborate that this integrated approach substantially enhances model prediction accuracy.

3.6.3 Lévy flight

Xu et al. introduced the Lévy Flight Adaptive Beetle Antenna Search (LABAS) algorithm, an innovative enhancement of the conventional BAS algorithm, integrating Lévy flight dynamics and an adaptive strategy (Zivkovic et al. 2021). LABAS significantly augments search efficacy and algorithmic stability by amalgamating elite individual updating,

Table 7 Summary of BAS algorithms and their applicable scenarios

Type	Algorithm	Improvement Mechanism	Advantage	Disadvantage	Applicable Scenarios	Year
Quantum theory	QBSO(Rajagopal et al. 2021)	Improved search with quantum gates adjusting probabilities and variable step sizes for faster convergence	Surpasses PIO, SOA, GWO, and BSO in performance	Inability to trade off accuracy and convergence speed	Dealing with high-dimensional optimization problems with low population sizes	2023
	QBAS(Yan et al. 2023)	Incorporating the principles of quantum computing technology	Outperforms PSO and GA in efficiency and speed	Triple objective function calculation increases cost and time	Portfolio selection issues in finance	2021
Chaos mapping	CDBAS(Gu and Wang 2022)	Utilizing Chaos Mechanisms to Disrupt the Position of the Tenebrae	Outperforms BAS in performance, convergence speed, and accuracy	Increased algorithmic complexity	7 test functions; image enhancement	2019
	CDBAS(Lu et al. 2023)	Introducing Chaotic Perturbation and Gray Goal Decision Making Techniques	Solving multi-objective optimization diversifies algorithms and avoids local optima	Subject to initial parameters and chaotic perturbations, requiring parameter tuning	8 benchmark functions; multi-objective network reconfiguration problem	2020
	CBAS(Zhang et al. 2023)	Incorporating logistic chaos mapping in BAS	Prevents the algorithm from falling into a local optimum and improves the convergence speed	High computational complexity	Elman neural network soft measurement model for polyvinyl chloride polymerization process	2021
Lévy flight mechanism	LABAS(Zivkovic et al. 2021)	Combining Elite Updating, Contrastive Learning, Lévy Flight, and Adaptive Step Size	Outperforms traditional BAS algorithms and other comparative algorithms	Unstable on specific benchmarks; unsuitable for multi-objective and discrete optimization	Complex Optimization Problems with Multiple Class Attributes	2020
	IBAS(Zhang et al. 2020d)	The Lévy flight mechanism was introduced, employing inertia, normalization, and elite selection features	Enhanced localized search capabilities	Requires parameter tuning	15 benchmark functions and 4 classical engineering problems	2022

Table 7 (continued)

Type	Algorithm	Improvement Mechanism	Advantage	Disadvantage	Applicable Scenarios	Year
ELM	MBAS-ELM (Ma et al. 2020)	Combined ELM and Multi-task Beetle Antenna Search (MBAS) algorithms	Distributed and autonomous LSN routing with multi-task beetle antenna search algorithm	Requires parameter tuning	Routing in dynamic environments with variable topologies, link fluctuations, and imbalanced communication loads	2021
	IBAS-ELM(Hu and Zhang 2021)	IBAS algorithm combined with ELM	Improved modeling accuracy	High computational complexity	Forecast of water levels in front of pumping stations	2023
	BAS-RLS(Ghosh and Martinsen 2021)	Introducing BAS to determine the optimal number of hidden layer neurons in the Recurrent-ELM model	Improving the accuracy and intelligence of SOC estimation	Requires parameter tuning and high computational complexity	Battery State of Charge Estimation	2019
Others	HBSO(Mirjalili and Lewis 2016)	Enhancing BAS with a multi-beetle model and integrating it with Dijkstra's algorithm	Improved algorithmic efficiency	High computational complexity	4PL routing problem	2023
	CBSO(Mirjalili 2015)	Combining the notion of complex order operators	Improved modeling accuracy	Requires parameter tuning	Improving the accuracy of battery models	2023
	CESBAS(Xu et al. 2022)	The Cauchy variational operator and the Cauchy perturbation variational operator are introduced	Optimized prediction model with improved prediction performance	Weak convergence on the two benchmark functions to the improved BAS	6 benchmark functions, COVID-19 classification problem	2021
	DBAS(Dhiman and Kaur 2019)	Introduced with damping factor	Improved adaptability and stability of algorithms	Increased time complexity	Clustering task	2020

a generalized adversarial learning approach, Lévy flight incorporation, and adaptive step size modification. Distinctly, LABAS utilizes elite individuals for population information update, diverging from traditional individual optimization methods, and employs a generalized adversarial learning strategy for initializing populations and refining elite individuals. The incorporation of Lévy flights in LABAS markedly enhances the algorithm's exploratory capabilities, characterized by frequent short-range searches interspersed with sporadic extensive jumps and substantial directional shifts, thus circumventing local optima. Additionally, an adaptive step-size mechanism addresses the parameter setting challenges inherent in the original BAS, utilizing variables with superior fitness values for updating the beetle's current position. Empirical evaluations on benchmark functions demonstrate that LABAS outperforms both the traditional BAS and various other algorithms, despite some instability noted in specific functions like the Griewank function. LABAS's emphasis on overcoming parameter setting challenges through adaptive step-size strategies and the integration of Lévy flights significantly bolsters its global search capabilities, rendering it efficacious for complex, multi-class attribute optimization tasks. However, LABAS is currently not suited for multi-objective and discretized optimization problems. He et al. proposed the Improved Beetle Antenna Search (IBAS) Algorithm, integrating Lévy flight dynamics, to enhance local search capabilities (Zhang et al. 2020d). The IBAS algorithm incorporates Lévy flight mechanisms along with inertia, normalization, and elitist selection, thereby refining the algorithm's efficiency and precision. Striking a balance between effectiveness and efficiency, IBAS has shown commendable performance across 15 benchmark functions and four classical engineering problems. While the algorithm's performance is somewhat dependent on parameter settings and require further optimization, it has demonstrated significant potential for application in real-world engineering challenges, such as predicting laser energy in micro-laser-assisted turning. Specifically tailored for single-solver heuristic optimization problems, the IBAS algorithm is particularly apt for enhanced local search requirements in fields like engineering optimization and function optimization.

3.6.4 Extreme learning machine

In a novel approach to optimizing Low Earth Orbit (LEO) satellite communication networks, Rajagopal et al. have developed the MBAS-ELM model (Ma et al. 2020), integrating the Extreme Learning Machine (ELM) with the Multi-task Beetle Antenna Search (MBAS) algorithm (Zhang et al. 2020b). This innovative model leverages ELM for predicting traffic at the Earth traffic circulation level, while employing the MBAS algorithm for traffic forecasting and routing decisions at satellite nodes (SNs). The synergistic use of these technologies in the MBAS-ELM model markedly enhances the precision and reliability of routing decisions. Empirical evaluations demonstrate that the MBAS-ELM model outperforms comparative models in several key metrics, including average delay, packet loss rate, and queuing delay. This method is particularly effective in managing the routing challenges of LEO satellite networks in complex scenarios characterized by dynamic topologies, frequent link alterations, and uneven communication loads. Nonetheless, the model necessitates meticulous selection and fine-tuning of algorithmic parameters for optimal performance. Yan et al. introduced the innovative IBAS-ELM water level prediction model, a fusion of the IBAS algorithm and the ELM (Hu and Zhang 2021).. This model enhances the BAS algorithm by diversifying the search direction and integrating optimal individual and Lévy flight strategies. Importantly, the IBAS algorithm is utilized to fine-tune the weights and biases of the ELM, thereby elevating the model's predictive accuracy. Tested on the Jiaodong water transfer project in China, the IBAS-ELM model demonstrates exceptional precision in water level prediction at two pumping stations, significantly reducing mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE), while increasing Nash's efficiency coefficient (NSE), compared to other existing models.

Gu and Wang proposed the Beetle Antenna Search Optimization Recurrent Limit Learning Machine (BAS-RLS) as an innovative methodology for estimating the state-of-charge (SOC) of batteries (Ghosh and Martinsen 2021). This method ingeniously integrates the fixed hidden layer weight model of the ELM with the recursive least squares algorithm. By incorporating a time delay line into the recursive ELM model, BAS-RLS captures the dynamic characteristics of batteries with enhanced precision. The integration of the BAS algorithm in this context serves to optimally determine the number of neurons in the hidden layer, thereby augmenting both the accuracy and intelligence of SOC estimations. Comparative analyses reveal that the BAS-RLS model achieves superior accuracy in SOC estimations when contrasted with traditional methodologies.

3.6.5 Others

Lu et al. introduced the hybrid beetle swarm optimization (HBSO) algorithm, through the development of a multi-beetle model and its integration with Dijkstra's algorithm (Mirjalili and Lewis 2016). Aimed at solving complex fourth party logistics (4PL) routing problems, HBSO outperformed genetic algorithms (GA), PSO, and BAS in efficiency and accuracy across three case studies. Zhang et al. proposed a complex-order beetle swarm optimization (CBSO) algorithm (Mirjalili 2015) based on the BSO algorithm (Cheng et al. 2019). CBSO updates the velocity formulation based on the concept of the CO operator, and introduces the mutation operation into the BSO algorithm that can capture the memory of particles and alleviate the problem of the algorithm falling into local optimum. Experimental results show that CBSO can significantly improve the modeling accuracy of lithium-ion batteries. Zivkovic et al. introduced the Cauchy variational operator and the Cauchy perturbation variational operator and proposed the CESBAS algorithm (Xu et al. 2022), which was combined with machine learning and the adaptive neuro-fuzzy inference system (ANFIS), and was applied to improve the prediction accuracy of the number of new cases in the case of a COVID-19 epidemic. By using the enhanced BAS algorithm to determine the parameters of ANFIS, the CESBAS method optimizes the prediction model and effectively solves the problems existing in the traditional method. Tests on the COVID-19 epidemic dataset show that CESBAS performs well in predicting the number of new cases and outperforms other algorithms in terms of prediction accuracy and speed. Zhang et al. proposed a beetle antenna search algorithm (DBAS) with a damping factor (Dhiman and Kaur 2019) and a new spectral clustering algorithm combined with an improved Gaussian kernel function. The algorithm improves the stability and adaptability of the results by adaptively selecting the scale parameters using a Gaussian kernel function based on the nearest neighbor distance information. Meanwhile, the introduction of DBAS solves the instability problem of K-means random initialization of cluster centers in the clustering stage. Experiments on diverse datasets validate its efficacy. More studies on the improved BAS algorithm can be found in the literature (Fan et al. 2023, Li et al. 2022, Khan et al. 2021).

4 Algorithm Simulation Comparison and Analysis

In order to comprehensively verify the performance effect of BAS, the experiment selected 12 standard test functions with different characteristics for comparison testing, which are mainly divided into three categories: single-peak benchmark test function, mainly used to test the algorithm's local development ability; multi-peak test function, which has more local extreme value points. The group intelligence algorithm is easy to fall into the local optimum during the optimization process, which is mainly used to test the ability of the algorithm to jump out of the local extreme value and the global exploration ability. The test functions are shown in Table 8 below.

In order to verify the optimization effect of BAS and the improvement of BAS, it was compared with PSO (Khan 2022), GWO (Jian et al. 2019), Whale Optimization Algorithm (WOA) (Khan et al. 2022), GOA (Wu et al. 2019), Ant Lion Optimizer (ALO) (Zhou et al. 2021), Snake Optimization (SO) (Jiang et al. 2021), Basic BAS, BOA (Zhang et al. 2020), Sooty Tern Optimization Algorithm (STOA)(Wang et al. 2020), Choas Lévy flight BAS (ChoasLBAS), and Butterfly-Tweaked BAS (BTBAS). The effect of the algorithmic improvements can be objectively reflected by performing 30 comparison experiments on 12 typical benchmark test functions. In order to record some fair results, all algorithms are set with the same initial conditions. Due to the large number of benchmark functions, the dimension is 30. In order to ensure fairness and reduce the chance of the results, the basic parameters of each algorithm were kept consistent with the original literature. Since the dimensionality of the algorithms also affects the optimization performance of the algorithms, in order to verify the effectiveness of the algorithms as well as the ability of low-dimensional and high-dimensional solutions more comprehensively, the optimal value (min), the standard deviation (std), the mean (mean), the median (med), the worst value (worst), and the simulation elapsed time (time) of each test function for 30 experiments were recorded, and the results of the algorithms' iterative runs are shown in Fig. 7. Tables 9 and 10 show the test results of the 11 algorithms.

In order to more intuitively reflect the superiority of the Tennessee whisker search algorithm, it is ensured that the average convergence curves of different benchmark functions are obtained for the 11 algorithms with the same number of iterations and dimension of 30. By comparing the results with other algorithms, it is verified that the improved Tennessee whisker algorithm shows superior solution performance with better global convergence whether the improved BAS algorithm is solving single-peak or multi-peak functions. From the convergence curves of functions F3, F4, F6, F11 and F12, it can be seen that the fitness values of the algorithm at the beginning of the iteration are better than the other algorithms, indicating that the initialization of the population with chaotic mapping improves the quality of the Tennessee whiskers population. The convergence curve of the basic BAS algorithm has a local stagnation, while the BTBAS algorithm adopts the fusion butterfly search strategy to regulate the global search and local development ability, compared with other algorithms have enough global search ability to avoid the algorithm prematurely convergence, so that the BTBAS algorithm has a faster convergence speed and better solving accuracy.

According to the results in Tables 9 and 10, it can be seen that the standard deviation can reflect the dispersion of the dataset, and if the value of the standard deviation is smaller, the stability of the optimization is better. It can be found that the basic BAS and improved BAS algorithms have better overall stability on the single-peak function, proving that BTBAS and ChoasLBAS are still fruitful. Overall, the improved BAS algorithm outperforms the other algorithms in solving the single peak function. The proposed improved BAS algorithm can focus on the optimal case in problems with mean index, although it is slightly inferior in

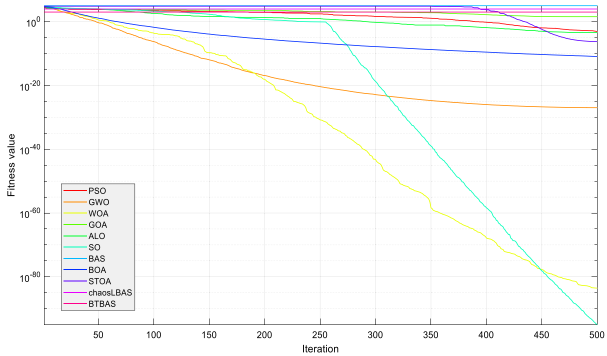
Table 8 Test Functions

Function	Equation	Dim	Bounds	Optimum
F1	$\sum_{i=1}^{d} x_i^2$	30	[-100,100]	0
F2	$\sum_{i=1}^{d} \left(\sum_{j=1}^{i} x_j \right)^2$	30	[-100,100]	0
F3	$\max\{ \lvert x_i \rvert, 1 \le i \le d \}$	30	[-100,100]	0
F4	$\sum_{i=1}^{d-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	30	[-10,100]	0
F5	$\sum_{i=1}^{d} (\lvert x_i + 0.5 \rvert)^2$	30	[-100,100]	0
F6	$\sum_{i=1}^{d} i x_i^4 + rand(0,1)$	30	[-1.28,1.28]	0
F7	$\sum_{i=1}^{d} \lvert x_i \sin(x_i) + 0.1 x_i \rvert$	30	[-10,100]	0
F8	$-20\exp\left(-0.2 \sqrt{\frac{1}{d} \sum_{i=1}^{d} x^2} \right) - \exp\left(\frac{1}{d} \sum_{i=1}^{d} \cos(2\pi x_i) \right) + 20 + \exp(1)$	30	[-5.12,5.12]	0
F9	$\frac{1}{4000} \sum_{i=1}^{d} x_i^2 - \prod_{i=1}^{d} \cos \frac{x_i}{\sqrt{i}} + 1$	30	[-32,32]	0

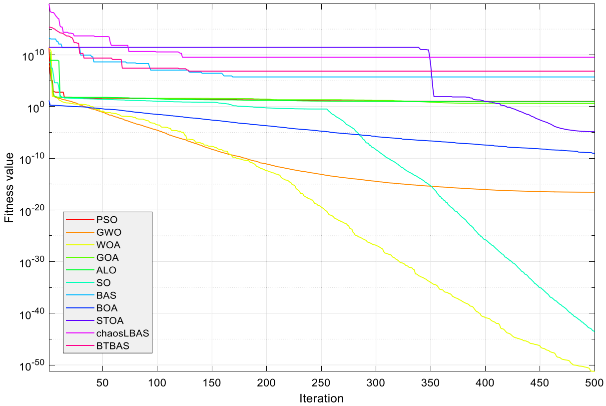
Table 8 (continued)

Function	Equation	Dim	Bounds	Optimum
F10	$F12 = \frac{\pi}{d}\left\{10\sin(\pi y_1) + \sum_{i=1}^{d-1}(y_i - 1)^2[1 + 10\sin^2(\pi y_{i+1})] + (y_n - 1)^2\right\} + \sum_{i=1}^{d} u\left(x_i, 10, 100, 4\right)$ $y_i = 1 + \frac{x_i+1}{4} u\left(x_i, a, k, m\right) = \begin{cases} k(x_i - a)^m, x_i > a \\ 0, -a < x_i < a \\ k(-x_i - a)^m, x_i < -a \end{cases}$	30	[-600,600]	0
F11	$0.1\left\{\sin^2(3\pi x_1) + \sum_{i=1}^{d-1}(x_i - 1)^2[1 + \sin^2(3\pi x_i + 1)] + (x_n - 1)^2[1 + \sin^2(2\pi x_n)]\right\} + \sum_{i=1}^{d} u(x_i, 5, 100, 4)$	30	[-50,50]	0
F12	$\sum_{i=1}^{11}\left[a_i - \frac{x_i(b_i^2+b_i x_2)}{b_i^2+b_i x_3+x_4}\right]^2$	30	[-5,5]	0.0003

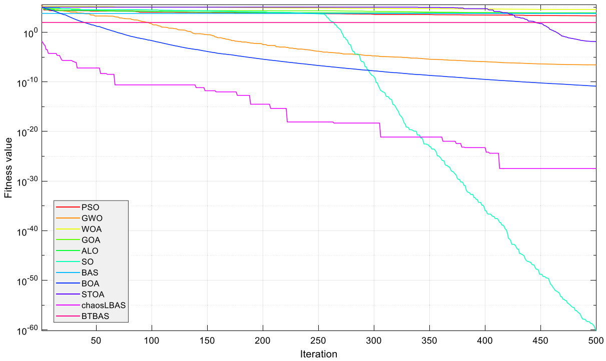
Fig. 7 Test function optimization results for 11 algorithms



F1



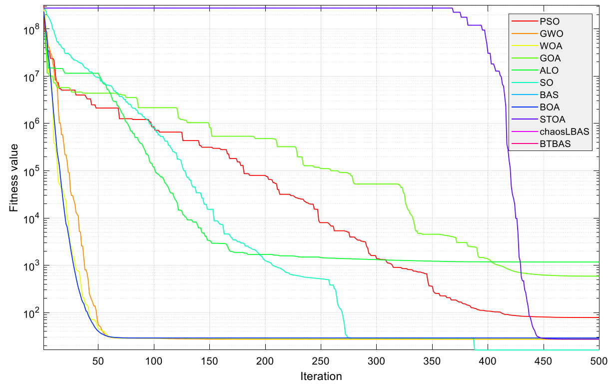
F2



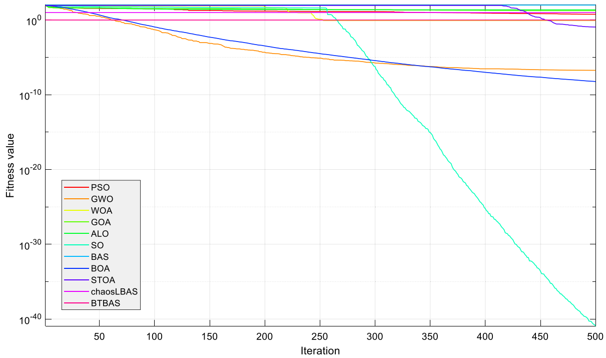
F3

stability. The experimental results show that the improved BAS algorithm is the best method to handle the benchmark task in 30 independent runs. As can be seen from the data in Tables 9 and 10, the improved BAS algorithm ranks high on average when dealing with functions with different peaks, and the rest of the rankings are, in order, WOA, GWO, BOA, SO, ALO, GOA, STOA, BOA, and PSO. The experimental results show that the improved OLCGOA algorithm is the best algorithm to deal with the 30 benchmark tasks in 30 independent runs. This finding also shows that the application of CLS and OL strategies in OLCGOA improves the efficiency to a great extent.

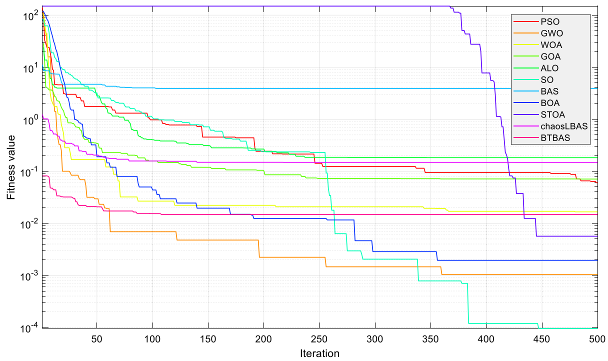
Fig. 7 (continued)



F4



F5

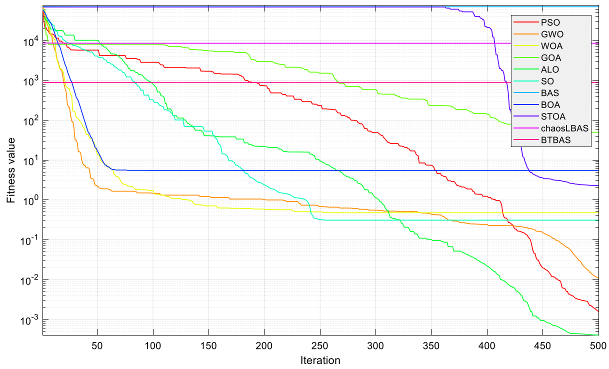


F6

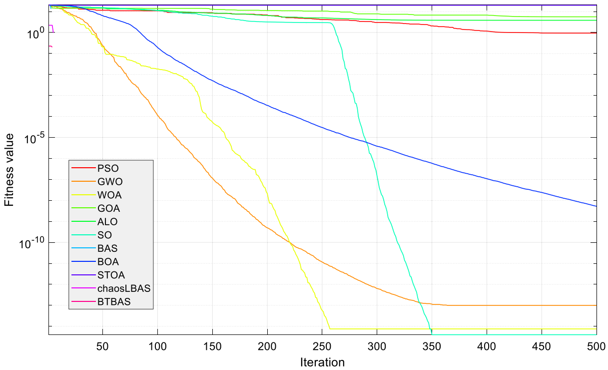
5 Applications of BAS

BAS algorithms have been playing an increasingly important role as an efficient optimization tool in various fields. The applications of BAS algorithms are broad and diverse, including robotics, energy systems and environmental monitoring, manufacturing and industrial engineering, construction civil and geo-engineering, network communication and information technology, path planning and transportation systems, and finance

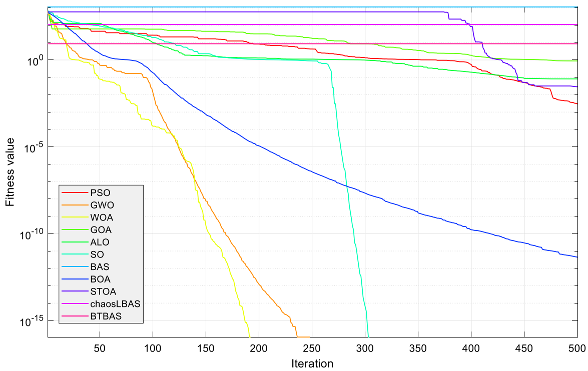
Fig. 7 (continued)



F7



F8

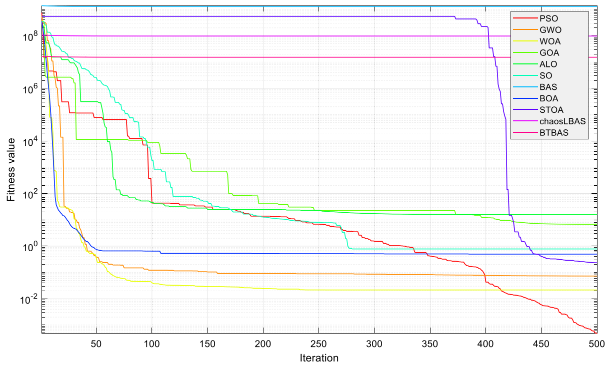


F9

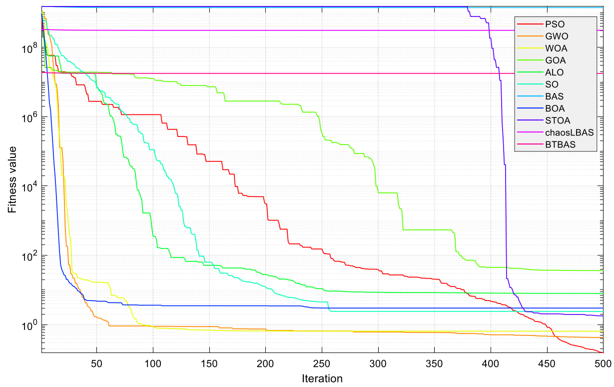
and economics, among others. Figure 8 shows a comprehensive categorization of BAS applications in different fields.

The algorithm has been effectively applied in many studies, showing its potential and practical value in solving complex optimization problems. These innovations not only bring ideas for solving complex optimization problems, but also open up new avenues for future research and applications. The application is specifically organized in Table 11, and a focused overview of the applications will be given in this chapter.

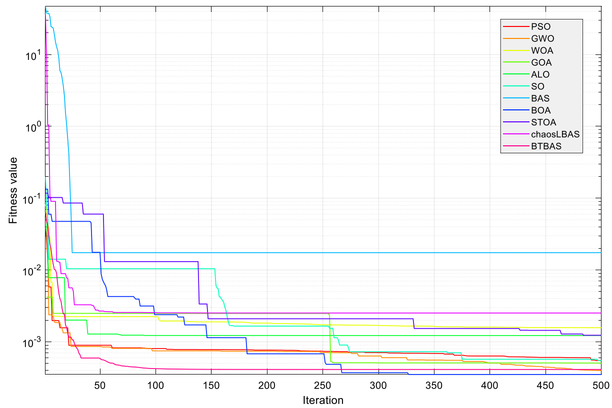
Fig. 7 (continued)



F10



F11



F12

5.1 Robotics and automation

In robotics, the utilization of BAS algorithms has gained prominence due to their simplicity and effectiveness in parameter optimization. BAS algorithms facilitate the reduction of kinematic parameter errors in robots, enhance the construction of dynamic models, and significantly improve search efficiency and accuracy. This application of BAS has been

Table 9 Comparison of the optimal values of the six algorithms

Function		PSO	GWO	WOA	GOA	ALO	SO
F1	min	-2.52E-02	-6.51E-15	-3.69E-41	-1.89E+00	-1.34E-02	-1.80E-48
	std	1.15E-02	6.98E-15	3.95E-40	7.70E-01	5.95E-03	5.05E-49
	mean	2.73E-03	2.46E-15	1.26E-40	2.05E-01	-1.65E-04	3.95E-50
	med	2.11E-03	6.94E-15	1.63E-41	2.53E-01	2.99E-04	-2.56E-50
	worse	4.59E-02	8.21E-15	1.39E-39	2.25E+00	9.98E-03	1.89E-48
	time	3.69E-02	6.50E-02	2.46E-02	2.37E+01	5.63E+00	4.81E-02
F2	min	-4.94E+01	-2.39E-04	-5.94E+01	-7.28E+01	-5.36E+01	-3.38E-31
	std	1.44E+01	1.61E-04	3.14E+01	2.85E+01	2.82E+01	1.13E-31
	mean	-1.10E-01	-3.55E-06	-1.06E+00	9.60E-03	9.94E-02	1.32E-32
	med	1.74E+00	-4.04E-05	-2.99E+00	7.75E+00	6.62E+00	-1.08E-33
	worse	3.51E+01	2.68E-04	5.75E+01	5.78E+01	4.64E+01	3.52E-31
	time	1.25E-01	1.51E-01	1.20E-01	2.15E+01	5.32E+00	1.31E-01
F3	min	-5.72E+00	-1.82E-07	-8.35E-01	-1.73E+01	-2.25E+01	-1.17E-41
	std	3.55E+00	1.76E-07	3.34E-01	1.27E+01	1.84E+01	4.86E-42
	mean	-1.02E+00	2.03E-08	2.49E-01	-7.10E-01	5.60E-02	-1.20E-42
	med	-4.64E-01	1.53E-07	2.73E-01	-1.94E+00	-5.18E-01	-1.37E-42
	worse	5.49E+00	1.82E-07	8.35E-01	1.73E+01	2.25E+01	9.00E-42
	time	3.94E-02	7.09E-02	5.90E-02	2.15E+01	5.22E+00	5.07E-02
F4	min	-5.52E-03	-8.68E-04	1.87E-05	-1.66E+00	-3.28E+00	1.07E+00
	std	3.56E-01	1.49E-01	1.02E-01	2.14E+00	2.17E+00	0.00E+00
	mean	3.24E-01	4.81E-02	3.70E-02	6.29E-01	3.35E-01	1.07E+00
	med	1.26E-01	2.47E-03	1.24E-02	2.79E-01	2.52E-02	1.07E+00
	worse	9.35E-01	6.80E-01	5.19E-01	1.11E+01	1.13E+01	1.07E+00
	time	5.55E-02	7.87E-02	3.79E-02	2.14E+01	5.19E+00	6.20E-02
F5	min	-5.16E-01	-5.11E-01	-5.94E-01	-3.00E+00	-5.07E-01	-7.11E-01
	std	7.37E-03	1.91E-02	1.24E-01	1.30E+00	3.75E-03	1.03E-01
	mean	-5.01E-01	-4.96E-01	-4.68E-01	-6.95E-01	-5.00E-01	-4.93E-01
	med	-5.01E-01	-4.98E-01	-4.99E-01	-6.89E-01	-5.00E-01	-5.06E-01
	worse	-4.79E-01	-4.02E-01	-5.33E-02	1.28E+00	-4.94E-01	-1.06E-01
	time	3.87E-02	6.58E-02	2.47E-02	2.13E+01	5.21E+00	5.02E-02
F6	min	-2.57E-01	-1.14E-01	-1.24E-01	-3.45E-01	-2.81E-01	-3.14E-02
	std	1.03E-01	3.64E-02	6.84E-02	1.19E-01	1.37E-01	1.20E-02
	mean	1.70E-02	-3.91E-03	1.08E-02	-2.91E-02	3.40E-03	9.90E-04
	med	2.85E-02	1.91E-03	4.76E-03	-4.35E-02	-1.38E-02	1.33E-04
	worse	2.19E-01	7.63E-02	1.68E-01	1.73E-01	1.95E-01	3.03E-02
	time	9.22E-02	1.17E-01	7.67E-02	2.18E+01	5.31E+00	9.84E-02
F7	min	-5.00E+02	-5.00E+02	6.50E+01	-3.03E+02	-5.00E+02	4.20E+02
	std	3.29E+02	2.83E+02	7.50E+01	2.44E+02	0.00E+00	5.78E-14
	mean	1.75E+02	-4.29E+01	4.02E+02	1.09E+02	-5.00E+02	4.20E+02
	med	4.21E+02	-7.34E+01	4.21E+02	1.34E+02	-5.00E+02	4.20E+02
	worse	4.21E+02	4.53E+02	4.27E+02	4.23E+02	-5.00E+02	4.20E+02
	time	5.87E-02	7.87E-02	3.62E-02	2.17E+01	5.29E+00	6.50E-02

Table 9 (continued)

Function		PSO	GWO	WOA	GOA	ALO	SO
F8	min	-7.22E-01	-3.56E-14	-9.02E-15	-2.83E+00	-1.94E+00	-3.06E-15
	std	1.98E-01	2.53E-14	2.50E-15	1.42E+00	1.07E+00	1.17E-15
	mean	3.23E-03	-3.92E-15	-6.38E-17	6.22E-01	-3.25E-02	-9.17E-17
	med	-1.72E-04	-1.39E-14	-3.18E-17	8.89E-01	-5.81E-04	5.16E-17
	worse	7.86E-01	3.23E-14	4.45E-15	3.76E+00	1.94E+00	1.94E-15
	time	4.98E-02	7.01E-02	2.87E-02	2.16E+01	5.29E+00	5.30E-02
F9	min	-1.10E+00	-1.02E+00	-1.29E+00	-7.71E+00	-9.00E+00	-1.08E+00
	std	4.91E-02	4.11E-01	2.97E-01	4.51E+00	7.21E+00	3.20E-01
	mean	9.00E-04	-8.55E-09	-2.22E-09	-1.47E-01	1.31E-03	1.18E-09
	med	-7.19E-04	-1.35E-08	-1.12E-09	-1.95E-01	9.95E-03	7.05E-10
	worse	2.18E-01	4.29E-08	2.18E-08	9.91E+00	3.12E+00	2.94E-08
	time	5.87E-02	7.93E-02	3.81E-02	2.18E+01	5.34E+00	6.09E-02
F10	min	-1.10E+00	-1.02E+00	-1.29E+00	-7.71E+00	-9.00E+00	-1.08E+00
	std	4.91E-02	4.11E-01	2.97E-01	4.51E+00	7.21E+00	3.20E-01
	mean	-9.97E-01	-7.97E-01	-8.92E-01	3.98E-01	-3.66E-01	-1.92E-01
	med	-1.00E+00	-9.98E-01	-9.87E-01	6.51E-01	-1.01E+00	-4.70E-02
	worse	-9.00E-01	3.78E-02	8.16E-04	7.23E+00	1.02E+01	2.71E-01
	time	1.90E-01	2.13E-01	1.66E-01	2.17E+01	5.59E+00	2.35E-01
F11	min	3.41E-01	-6.69E-03	2.51E-02	-5.00E+00	-2.48E+00	-3.38E-01
	std	2.21E-01	3.45E-01	3.87E-01	3.17E+00	1.60E+00	3.61E-01
	mean	9.75E-01	8.39E-01	7.63E-01	-4.45E-01	1.05E+00	2.72E-01
	med	9.99E-01	9.89E-01	7.44E-01	-2.16E-01	1.15E+00	2.60E-01
	worse	1.34E+00	1.04E+00	1.51E+00	4.82E+00	3.76E+00	1.38E+00
	time	1.91E-01	2.09E-01	1.67E-01	2.17E+01	5.36E+00	1.90E-01
F12	min	1.72E-01	1.83E-01	-5.00E+00	1.73E-01	-5.00E+00	1.69E-01
	std	4.39E-01	1.71E-01	2.52E+00	3.66E-01	2.45E+00	3.27E-01
	mean	6.14E-01	3.30E-01	-3.30E+00	5.31E-01	-3.06E+00	4.71E-01
	med	5.31E-01	2.81E-01	-4.28E+00	4.54E-01	-3.75E+00	3.89E-01
	worse	1.22E+00	5.77E-01	3.42E-01	1.04E+00	2.83E-01	9.36E-01
	time	2.44E-02	2.65E-02	2.11E-02	2.98E+00	7.79E-01	2.40E-02

instrumental in advancing the field of robotics, particularly in parameter optimization and dynamic modeling.

In terms of robot parameter optimization and calibration, Fan et al. introduced an innovative approach for calibrating kinematic parameter errors in industrial robots (Li et al. 2020). This method ingeniously combines the Levenberg–Marquardt (LM) algorithm with BAS, utilizing an enhanced Denavit-Hartenberg model to establish the robot's kinematic framework. Initial calibration is performed using the LM algorithm, followed by precise optimization through BAS. Empirical findings demonstrate a notable reduction in kinematic parameter errors and a consequent improvement in localization accuracy. Complementing this, Li et al. developed a method for calibrating industrial robot arms, integrating BAS with an extended Kalman filter (Sun et al. 2019a). This approach, featuring a novel

Table 10 Comparison of the optimal values of the five algorithms

Function		BAS	BOA	STOA	ChoasLBAS	BTBAS
F1	min	-8.51E+01	-1.12E-06	-5.83E-05	-9.70E+01	-9.66E+01
	std	6.15E+01	5.97E-07	4.41E-05	5.94E+01	5.56E+01
	mean	-3.27E-01	-3.05E-07	-9.06E-06	2.94E+00	3.14E+00
	med	8.87E+00	-2.81E-07	-2.75E-05	1.73E+01	7.06E+00
	worse	8.82E+01	9.08E-07	6.51E-05	9.53E+01	9.02E+01
	time	6.79E-03	4.97E-02	5.63E-02	7.17E-03	5.68E-03
F2	min	-9.91E+01	-1.13E-06	-5.29E-02	-9.51E+01	-8.81E+01
	std	6.17E+01	8.02E-07	3.04E-02	5.96E+01	5.36E+01
	mean	-5.89E+00	2.37E-08	8.90E-04	-6.98E+00	7.11E+00
	med	-1.16E+01	3.51E-08	2.22E-04	-3.62E+00	2.36E-01
	worse	9.83E+01	1.55E-06	5.55E-02	9.34E+01	9.91E+01
	time	7.72E-03	2.16E-01	1.39E-01	8.95E-03	5.69E-03
F3	min	-9.71E+01	-5.69E-09	-1.13E-01	-9.59E+01	-9.13E+01
	std	6.42E+01	3.30E-09	8.10E-02	5.55E+01	6.40E+01
	mean	-3.54E+00	1.50E-10	-1.99E-02	1.77E+01	2.31E+00
	med	-1.22E+01	1.38E-10	-2.70E-02	2.23E+01	-2.41E+00
	worse	9.71E+01	4.81E-09	1.12E-01	9.59E+01	9.68E+01
	time	8.20E-03	4.63E-02	5.59E-02	6.31E-03	5.58E-03
F4	min	-2.51E+01	-6.14E-03	-1.36E-02	-2.85E+01	-2.73E+01
	std	1.67E+01	3.14E-03	1.47E-01	1.89E+01	1.52E+01
	mean	3.71E+00	1.11E-03	4.54E-02	1.76E+00	7.20E-01
	med	3.72E+00	6.81E-04	1.05E-03	-1.78E+00	2.02E+00
	worse	2.99E+01	6.98E-03	6.72E-01	2.81E+01	2.70E+01
	time	1.79E-02	7.04E-02	6.88E-02	1.04E-02	9.64E-03
F5	min	-9.38E+01	-4.52E-01	-5.46E-01	-9.22E+01	-9.79E+01
	std	4.89E+01	1.89E-01	2.31E-01	5.29E+01	5.42E+01
	mean	5.32E+00	-1.16E-01	-3.43E-01	-1.22E+01	-9.36E+00
	med	1.56E+00	-1.21E-01	-4.76E-01	-1.40E+01	-1.38E+01
	worse	9.50E+01	1.93E-01	1.44E-02	7.58E+01	8.66E+01
	time	7.86E-03	4.51E-02	5.61E-02	6.97E-03	5.31E-03
F6	min	-8.28E-01	-6.77E-02	-1.18E-01	-6.81E-01	-6.33E-01
	std	5.06E-01	3.82E-02	4.86E-02	4.01E-01	4.46E-01
	mean	-6.43E-02	9.30E-04	-9.66E-03	8.23E-02	2.35E-02
	med	-1.99E-03	1.54E-03	-9.46E-03	1.14E-01	1.40E-01
	worse	9.74E-01	6.10E-02	8.76E-02	7.67E-01	5.94E-01
	time	1.18E-02	1.50E-01	1.09E-01	1.18E-02	1.06E-02
F7	min	-4.67E+02	4.32E+01	-5.00E+02	-4.73E+02	-4.74E+02
	std	2.74E+02	2.74E+02	2.43E+02	3.20E+02	2.93E+02
	mean	6.83E+00	1.09E+02	-4.29E+02	-4.27E+01	-5.26E+00
	med	-7.97E+01	-2.73E+02	-5.00E+02	-1.30E+01	-6.38E+01
	worse	4.01E+02	4.84E+02	5.00E+02	4.98E+02	4.97E+02
	time	9.58E-03	2.18E-01	6.76E-02	7.50E-03	6.29E-03

Table 10 (continued)

Function		BAS	BOA	STOA	ChoasLBAS	BTBAS
F8	min	-2.92E+01	-3.47E-09	-3.20E+01	-3.00E+01	-3.19E+01
	std	1.69E+01	1.34E-09	3.15E+01	1.84E+01	2.01E+01
	mean	3.99E+00	4.30E-12	2.34E-01	1.26E+00	-3.90E+00
	med	6.51E+00	-2.24E-10	3.51E+00	6.52E+00	-4.49E+00
	worse	2.91E+01	3.07E-09	3.20E+01	3.10E+01	3.01E+01
	time	7.88E-03	6.35E-02	6.60E-02	7.63E-03	6.43E-03
F9	min	-4.87E+01	-1.27E+00	-1.10E+00	-4.78E+01	-3.76E+01
	std	2.73E+01	4.99E-01	4.65E-01	2.63E+01	3.10E+01
	mean	-9.94E+01	2.28E-07	3.45E-01	-1.89E+02	8.34E+01
	med	-1.23E+02	1.75E-07	6.39E-04	-2.99E+02	6.73E+01
	worse	5.97E+02	4.00E-06	5.43E+00	4.06E+02	5.94E+02
	time	8.54E-03	7.75E-02	7.38E-02	7.46E-03	6.59E-03
F10	min	-4.87E+01	-1.27E+00	-1.10E+00	-4.78E+01	-3.76E+01
	std	2.73E+01	4.99E-01	4.65E-01	2.63E+01	3.10E+01
	mean	-8.71E+00	-2.92E-01	-5.17E-01	-8.11E+00	8.86E+00
	med	-1.05E+01	-3.34E-01	-6.32E-01	-1.53E+01	1.05E+01
	worse	4.83E+01	7.43E-01	5.65E-02	4.00E+01	4.84E+01
	time	4.24E-02	3.55E-01	2.03E-01	2.34E-02	2.31E-02
F11	min	-4.35E+01	-7.79E-03	-5.78E-02	-4.83E+01	-4.52E+01
	std	2.58E+01	3.78E-03	3.98E-01	3.29E+01	2.68E+01
	mean	-1.19E+00	1.68E-03	3.71E-01	-3.32E+00	-5.12E+00
	med	1.55E+00	1.42E-03	3.19E-01	-1.11E+01	-5.69E+00
	worse	4.84E+01	7.46E-03	1.01E+00	4.94E+01	4.48E+01
	time	2.37E-02	3.33E-01	1.99E-01	2.28E-02	2.21E-02
F12	min	3.64E-01	1.10E-01	-5.00E+00	-3.20E+00	2.24E-01
	std	1.03E+00	8.11E-02	2.45E+00	3.18E+00	1.38E+00
	mean	1.65E+00	1.96E-01	-3.03E+00	2.69E-01	1.44E+00
	med	1.87E+00	1.85E-01	-3.71E+00	-6.58E-02	1.20E+00
	worse	2.51E+00	3.06E-01	2.80E-01	4.41E+00	3.15E+00
	time	5.72E-03	4.73E-02	2.33E-02	5.00E-03	4.18E-03

quadratic interpolated beetle antenna search algorithm, significantly enhances calibration accuracy.

In the realm of robot dynamics, Khan et al. (Zhu et al. 2018) formulated BAS as an RNN-type controller for the tracking control of redundant robotic manipulators. They extended it to mobile robotic systems under various real-world constraints, i.e., Obstacle avoidance (Zhu et al. 2018), Remote Center of Motion (RCM) (Zhang et al. 2019b), and nonholonomic vehicle models (Lyu et al. 2022a). Khan et al. applied the BAS algorithm for trajectory optimization in a 5-link biped robot (Fei and He 2019). Diverging from conventional methodologies that separately address trajectory generation and robust control, this research integrates these aspects into a singular optimization challenge, resolving it in real-time with BAS. The study underscores the algorithm's capability in modeling complex dynamics. Additionally, Khan et al. proposed a neural network model combining beetle

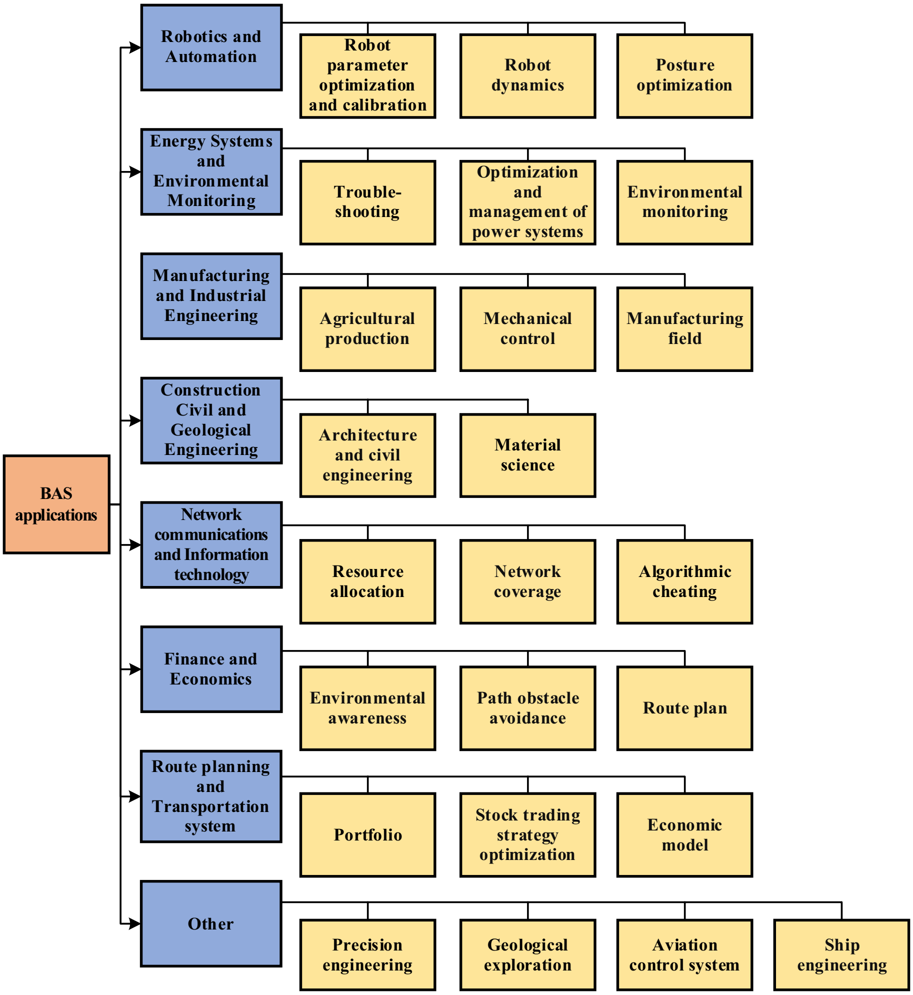


Fig. 8 Classification of BAS applications

antenna search with a continuous time nulling neural network (ZNNBAS) to address quadratic optimization in real-time redundancy resolution (Fuyin and Jian 2023). Applied to a 7-degree-of-freedom robotic arm, the algorithm demonstrated successful trajectory tracking under real-time conditions, highlighting its efficacy and practical application. Zhou et al. presented an enhanced beetle swarm optimization algorithm for the intelligent navigation control of autonomous navigation robots (Ghosh et al. 2020). This algorithm, merging the search mechanism of a single beetle with particle swarm optimization, dynamically adjusts step factors and inertia weights to optimize trajectory navigation control in a sailboat mathematical model. Its effectiveness was confirmed through navigation tests using a small autonomous sailing robot prototype. In another study focusing on attitude optimization, Jiang et al. proposed the Robotic Arm Beetle Antenna Search Attitude Optimization (BASAO) method (Liu et al. 2023). Utilizing a wearable wireless body sensor network (WWBSN), BASAO achieves dynamic attitude configuration for manipulators. The

Table 11 Applications of BAS algorithm

Areas	Author	Year	Specific direction
Robotics and Automation	Fan(Li et al. 2020)	2023	Error calibration of industrial robot kinematic parameters
	Li(Sun et al. 2019a)	2022	Robot Arm Calibration Method
	Khan(Fei and He 2019)	2021	Trajectory optimization of a 5-link biped robot
	Khan(Fuyin and Jian 2023)	2022	Solution to the quadratic optimization problem for redundant parsing
	Khan(Zhu et al. 2018)	2019	The tracking control of redundant robotic manipulators
	Zhou(Ghosh et al. 2020)	2021	Intelligent Navigation Control for Autonomous Navigation Robots
	Jiang(Liu et al. 2023)	2021	Robotic Arm Beetle Antenna Search Attitude Optimization
Energy Systems and Environmental Monitoring	Wang (Gao et al. 2022)	2020	Intelligent Fault Diagnosis of Rolling Bearing Failures in Wind Turbines
	Li(Fu et al. 2021)	2020	Rolling bearing fault diagnosis method
	Sun(J., Bai,, et al. 2022)	2019	Vibration Reduction Strategies for Rotating Machinery Systems
	Fei(Fan et al. 2019)	2019	Prediction of dissolved gas content in power transformers
	N.I.(Lin et al. 2019)	2023	Harmonic Control Strategies for Unified Power Quality Conditioner (UPQC)
	Zhu(Xiao et al. 2023)	2018	Energy optimization models for microgrids
	Ghosh(Y., Zhang,, et al. 2023)	2020	Optimal power output in combined cycle power plants
	Liu(Huang et al. 2022)	2023	Transmission network performance optimization
	Gao(Yang and Peng 2020)	2022	Water Quality Assessment of Municipal Rivers
	Hu (Li et al. 2023)	2021	Optimization of wind speed forecast accuracy
Manufacturing and Industrial Engineering	Bai(Sun et al. 2019a)	2022	Liquid Fertilizer Variable Speed Application Control System
	Fan(Sun et al. 2019b)	2019	Optimization of electrohydraulic position servo control systems
	Lin (Zhang et al. 2019a)	2019	DC motor speed control system design
	Xiao(Sun et al. 2019b)	2023	Turning production process optimization
	Zhang(Huang et al. 2020)	2023	Scheduling Problems in Intelligent Production Lines
	Huang(Li et al. 2019)	2022	Estimation of Dynamic Modulus (DM) of Asphalt Mixtures

Table 11 (continued)

Areas	Author	Year	Specific direction
Civil and Geological Engineering	Yang(Jiamei, et al. 2023)	2020	Bridge Sensor Position Optimization
	Li(Li et al. 2023)	2023	Intelligent prediction of rock bursts in tunnels
	Sun(Song 2018)	2019	Prediction of unconfined compressive strength of coal concretions
	Sun(Sabahat et al. 2022)	2019	Determination of Young's Modulus of Sprayed Slurry Coal Concrete
	Zhang(Xiao et al. 2019)	2019	Mechanical Properties of Lightweight Self-Compacting Concrete
	Sun(Khan et al. 2022c)	2020	Pervious Concrete Performance Testing
	Huang(Tang and Wu 2023)	2019	Predicted permeability of pervious concrete
Network Communications and Information Technology	Li(Wang et al. 2023a)	2019	Resource allocation in cooperative communication in UAV networks
	Chen(Wu, et al. 2019)	2023	Network performance optimization of UAV-assisted network systems
	Li(Deng et al. 2023)	2023	Containerized Application Scheduling Algorithm Optimization in Kubernetes Cloud
	Song(Gu et al. 2020)	2018	WSN Coverage Issues
	Sabahat(Xie et al. 2019)	2022	IoT Positioning Methods
	Xiao(Xie et al. 2019)	2019	Adaptive Zero Watermarking Algorithm with Enhanced Singular Value Decomposition
	Khan(Liu and Chen 2022)	2022	Deep Convolutional Neural Networks for Image Classification Attacks
	Tang(Lin et al. 2019)	2023	blind source separation algorithm
	Wang(Wang et al. 2023b)	2023	Optimization of ICP algorithm in point cloud alignment
Path Planning and Traffic Systems	Wu(Yu et al. 2023)	2019	Intelligent Path Planning for UAV Sensing and Obstacle Avoidance
	Deng(Liang et al. 2022)	2023	Intelligent Guided Path Tracking and Collision Avoidance for Unmanned Sailboats
	Gu(Zha et al. 2023)	2020	Path planning supported by radiation protection technology
	Xie(Chen et al. 2018)	2019	Predictive collision avoidance methods for surface ships

Table 11 (continued)

Areas	Author	Year	Specific direction
	Xie(Katsikis and Mourtas 2021)	2019	Ship collision avoidance methods
	Liu (Katsikis et al. 2020)	2022	Adaptive control method for active lift and sink compensation system
	Lin(Medvedeva et al. 2021)	2019	Global Path Planning Method for Robots
	Wang(Khan et al. 2022)	2023	UAV 3D Path Planning
	Yu(Khan et al. 2022a)	2023	Mobile Robot Path Planning
	Liang(Li et al. 2021)	2022	Path planning for vehicles
	Zha(Wang et al. 2023)	2023	Global path planning for unmanned watercraft
Finance and Economics	Wang(Huang et al. 2020)	2021	Portfolio problem solving
	Chen (Li et al. 2021)	2018	Portfolio Optimization Algorithm
	Katsikis(Cao et al. 2023)	2021	Binary optimal tangent portfolio (BOTPCC) problem solving
	Katsikis(Lin et al. 2023)	2020	Time-Varying Nonlinear Programming (TV-NLP) Problem Solving
	Medvedeva(Xie et al. 2018)	2021	Solution of the Randomized Time-Varying Knapsack Problem (RTVKP)
	Khan(Yue et al. 2020)	2020	The intended Markowitz model for portfolio optimization
	Khan(Wang et al. 2020b)	2022	The portfolio optimization problem
	Khan(Mei et al. 2022)	2022	Financial fraud by listed companies
Others	Li(Khan et al. 2022b)	2021	Thermal error prediction model for high-speed electric spindles
	Wang(Xu et al. 2020)	2023	FOG random error compensation method
	Li(Fan et al. 2020)	2021	Error problems in detection and localization of magnetic anomaly signals
	Cao(Xiang and Zhu 1630)	2023	Detection of geochemical anomalies associated with iron mineralization
	Lin(Yin and Ma 2018)	2023	Trajectory tracking of quadrotors
	Xie(Wu et al. 2021)	2018	Marine Diesel Engine Speed Control

method introduces empirical guidance and an inner-loop step self-attenuation mechanism, enhancing search efficiency and accuracy. This approach has shown promising results in WWBSN pose planning.

5.2 Energy systems and environmental monitoring

Within the realms of energy and environment, the BAS algorithm has emerged as a pivotal tool for fault diagnosis, optimization of energy systems, and enhancement of environmental monitoring processes. BAS contributes significantly to elevating energy utilization efficiency, diminishing energy consumption, and bolstering the precision and effectiveness of environmental monitoring. Wang et al. have pioneered an intelligent fault diagnosis methodology for wind turbine rolling bearing faults, integrating the Mahalanobis semi-supervised mapping manifold learning algorithm with a BAS-enhanced Support Vector Machine (BAS-SVM) (Gao et al. 2022). This innovative approach involves extracting multi-scale information from rolling bearing vibration signals using multi-scale arrangement entropy, followed by dimensionality reduction through Mahalanobis semi-supervised mapping, and subsequent classification via the BAS-SVM classifier. Complementing this, Li et al. introduced an enhanced selective integrated deep learning method for rolling bearing fault diagnosis that synergizes deep learning with BAS (Fu et al. 2021). This method adeptly utilizes BAS for adaptive selection of optimal category thresholds within the Enhanced Weighted Voting (EWV) combination strategy, thereby augmenting fault diagnosis performance.

In the sphere of rotating machinery systems, Sun et al. devised a vibration damping strategy for active magnetic levitation bearing (AMB) systems (Bai et al. 2022). This strategy employs the Tennessee whisker search algorithm, coupled with the BAS algorithm, to identify and optimize the coefficients of compensating currents, effectively mitigating centrifugal force vibrations. In power system optimization and management, Fei and He developed a hybrid kernel correlation vector regression model (BASA-MkRVR), employing BAS to fine-tune kernel and control parameters (Fan et al. 2019). This model predicts dissolved gas content in power transformers with heightened accuracy. Additionally, N.I. and Hu demonstrated the efficacy of BAS in enhancing the harmonic control strategy of a unified power quality conditioner (UPQC) (Lin et al. 2019). The optimization of QPIR controller parameters via BAS markedly improves the system's dynamic response and control precision, as evidenced by simulation results, which showed superior performance compared to a PI control strategy based on neural network algorithms.

Addressing microgrid energy management, Zhu et al. formulated a multi-objective microgrid energy optimization model, aiming to minimize operational and pollutant treatment costs (Xiao et al. 2023). Utilizing BAS for problem-solving, the method showed feasibility and effectiveness in microgrid energy management. Ghosh et al. extended the application of BAS by proposing a data-driven cascaded feedforward neural network-assisted BAS algorithm (Zhang et al. 2023), which significantly enhances the optimal power output of combined cycle power plants (CCPP). Liu et al. introduced the Stochastic Fractal Beetle Antennae Algorithm (SFBA) (Huang et al. 2022), employing an elite inverse learning methodology and a leader multivariate learning strategy. This novel approach ensures a balance between global exploration and local exploitation in optimizing the performance of transmission networks (TN), achieved through the introduction of a beetle population and elite member.

In the environmental monitoring sector, Gao et al. optimized a municipal river water quality assessment model using an enhanced beetle tentacle search algorithm (Yang and Peng 2020). This methodology provided precise water quality assessments, underscoring the versatility of BAS in environmental monitoring applications. Furthermore, Fu et al. proposed a novel composite wind speed prediction method (Li et al. 2023). This method combines variational modal decomposition (VMD), phase space reconstruction (PSR), and the Volterra series model with an improved beetle antenna search (DEBAS), showcasing its applicability in obtaining reliable wind speed predictions.

5.3 Manufacturing and industrial engineering

In the field of manufacturing and industrial engineering, BAS is used to optimize the parameters of the production process, such as controller parameters, optimal selection, and intelligent scheduling. Through BAS, the manufacturing process can be optimized to reduce the production cost and increase the production efficiency.

In the field of agriculture, Bai et al. (Sun et al. 2019a) developed a BAS-based variable-speed application control system for liquid fertilizers in response to the problems of fertilizer application accuracy and flow uniformity of liquid fertilizer applicators in the field. The system further optimized the PID controller parameters by establishing a mathematical model of the variable fertilizer application control system for liquid fertilizers, which significantly improved the fertilizer application accuracy and response speed. Similarly, Fan et al. (Sun et al. 2019b) used BAS to optimize the PID parameters in an electro-hydraulic position servo control system, which effectively improved the performance of the electro-hydraulic position servo control system, and especially achieved significant results in suppressing external interference. In terms of mechanical control, in order to solve the parameter setting problem of a double-closed-loop DC motor governor, Lin et al. (Zhang et al. 2019a) proposed a DC motor speed control system design method based on improved BAS. The method effectively improves the robustness and response speed of the system by combining the multi-beetle strategy and PID control to adjust and update the position of the beetle swarm using the fitness value.

In the manufacturing field, Xiao et al. (Sun et al. 2019b) used BAS for the optimal selection of low-carbon and high-efficiency turning production equipment. By analyzing the carbon emissions and efficiencies of multiple types of machining equipment, a computational model of carbon emissions and efficient production of multiple types of machining equipment was established. The researchers used the BAS algorithm to calculate the carbon emissions and efficiencies of different equipment, which provided quantitative advice to enterprises on the selection of low-carbon production equipment. This not only improves production efficiency but also reduces carbon emissions. For the scheduling problem of smart production lines, Zhang et al. (Huang et al. 2020) developed a BAS-based scheduling method for smart production lines with minimum waiting time and minimum completion time as the optimization objectives. The method significantly reduces the production time and equipment waiting time and improves the efficiency of the production line while considering multiple constraints. In addition, Huang et al. (Li et al. 2019) utilized an improved BAS algorithm to estimate the dynamic modulus of asphalt mixtures. The researchers prevented the algorithm from falling into local optimum prematurely by introducing Lévy flight weights and inertia weights, which improved the search efficiency. Experimental results showed that the model demonstrated reliability and validity in accurately assessing and predicting the DM of asphalt mixtures used in the Mechanical Empirical Pavement Design Guide (MEPDG).

5.4 Civil and geological engineering

In the domains of construction, civil, and geological engineering, the Beetle Antenna Search (BAS) algorithm has been instrumental in optimizing sensor layouts, predicting tunnel rockbursts, and testing material properties. BAS has notably enhanced the accuracy of engineering model construction, the determination of modulus, and the precision of material measurements. Yang and Peng have made significant advancements in the field of construction and civil engineering by optimizing bridge sensor layouts (Jiamei, et al. 2023). Their innovative approach, integrating the aspen whisker search algorithm with a swarm evolutionary competition mechanism, showcased rapid convergence and robust global optimization capabilities, particularly in the context of large bridge sensor placement. Additionally, Fei et al. developed a hybrid model combining BAS with a BPNN for the intelligent prediction of rockbursts in tunnels (Li et al. 2023). This model achieved an impressive prediction accuracy of 94.3% in rockburst forecasting. Complementing this, Sun et al. employed BPNN and BAS to enhance an unconfined compressive strength prediction model for coal concretions, surpassing traditional methods such as multivariate regression, logistic regression, and support vector machines in modeling nonlinear relationships (Song 2018). In a pursuit to increase the efficiency of determining the Young's modulus of shotcrete sprayed coal concrete, Sun et al. employed BAS to fine-tune the hyperparameters of Support Vector Machines (SVMs) (Sabahat et al. 2022), resulting in the development of an optimized SVM-BAS model. This model demonstrated greater reliability, accuracy, and time efficiency compared to baseline models like BPNN, LR, and MLR in predicting the Young's modulus of coal concrete.

In the field of materials science, Zhang et al. addressed the mechanical properties of lightweight self-compacting concrete (Xiao et al. 2019). They proposed a random forest (RF) model based on a tensile whisker search algorithm to tackle the challenges posed by traditional uniaxial compressive strength (UCS) testing methods, which are often time-consuming and costly. Their algorithmic model successfully resolved these testing inefficiencies. Similarly, Sun et al. introduced a BAS-based evolutionary support vector regression method for predicting the performance of pervious concrete (Khan et al. 2022c). The empirical results indicated that this method outperforms traditional approaches in both accuracy and efficiency. Furthermore, Huang et al. combined BAS with a random forest algorithm to predict the permeability of pervious concrete (Tang and Wu 2023). This study highlighted the efficacy of BAS in adjusting the random forest hyperparameters, providing a viable solution for accurate permeability prediction.

5.5 Network communications and information technology

In networking and communication, the application of the BAS algorithm has proven crucial in addressing challenges such as resource allocation, network coverage, and algorithm spoofing. BAS has demonstrated capabilities to enhance resource allocation, augment localization accuracy, and improve overall algorithm performance. In the context of cooperative communication within UAV networks, Li et al. developed a method that integrates BAS with the variation operator of GA (Wang et al. 2023a). This method leverages the mutation operator of GA for antennae position mutation, effectively optimizing the search for the best solution. Concurrently, Chen et al. tackled UAV auxiliary network deployment and resource allocation by merging BAS with PSO, circumventing the limitations of PSO in local optimum convergence (Wu, et al. 2019). Their simulation results indicated superior network performance of this hybrid algorithm compared to standalone PSO and RA algorithms within UAV auxiliary network systems. Further, Li et al. introduced an enhanced BAS-based scheduling algorithm to address containerized application scheduling in Kubernetes cloud (Deng et al. 2023). This optimization significantly reduced costs in the deployment of communication-intensive and periodically changing web applications.

In wireless sensor network coverage, Song combined BAS with PSO, achieving improved network coverage and enhancing the standard PSO algorithm's performance in specific applications (Gu et al. 2020). Sabahat applied a BAS-based approach to IoT localization, effectively addressing the accuracy issues of GPS-free node localization and showcasing the strengths of BAS in network localization (Xie et al. 2019). Xiao et al. proposed an adaptive zero watermarking algorithm for enhanced singular value decomposition (BN-SVD) (Xie et al. 2019), utilizing BAS to optimize the parameter β, thereby enhancing adaptivity. This application of BAS in BN-SVD successfully addressed issues related to watermark distortion and false alarms. Moreover, Khan et al. employed the BAS algorithm to perturb individual pixels in images to spoof deep CNN architectures like LeNet-5 and ResNet (Liu and Chen 2022), using the CIFAR-10 dataset. Their findings revealed BAS's simplicity and efficiency, highlighting its potential in security applications.

Tang and Wu developed a BAS-based blind source separation algorithm (Lin et al. 2019), introducing stepwise attenuation factors to enhance BAS's optimization performance. This resulted in higher convergence and accuracy, particularly in separating independent and non-independent source signals, outperforming traditional methods and proving especially effective in image blind source separation. Addressing the challenges of the time-consuming Iterative Closest Point (ICP) algorithm and the stringent initial position requirements in point cloud alignment, Wang et al. proposed an improved method combining BAS with ICP (Wang et al. 2023b). By incorporating aspects of the moth flame optimization algorithm in the coarse alignment stage, the method significantly enhanced the initial pose estimation of point cloud pairs.

5.6 Path planning and traffic systems

The BAS algorithm has exhibited notable efficacy in unmanned and intelligent path planning, distinguished by its expansive search range and rapid processing capabilities. Wu et al. introduced the Obstacle Avoidance Beetle Antenna Search (OABAS) algorithm (Yu et al. 2023), a significant advancement in UAV sensing and obstacle avoidance. OABAS, surpassing traditional bio-heuristic algorithms, reconciles the challenge of high computational complexity with the necessity for real-time path planning by offering a broad search range and swift execution speed. Experimental simulations with UAVs not only validated the effectiveness of the OABAS algorithm but also confirmed its superiority in comparison to other bio-heuristic algorithms. Deng et al. proposed a BAS-optimized path tracking and collision avoidance guidance method for unmanned sailing ships (Liang et al. 2022). This method adeptly determines the optimal heading angle to minimize the total cost function, thereby efficiently achieving path tracking and collision avoidance in marine navigation.

In the realm of environment sensing and path avoidance, Tan et al. developed a radiation-aware motion model and a radiation avoidance algorithm using BAS (Zha et al. 2023). This approach provides an effective protective strategy for radiation workers and robots. Xie et al. formulated a predictive collision avoidance method for surface ships (Chen et al. 2018), integrating an improved BAS with PSO algorithm, significantly enhancing the timeliness and reliability of ship collision avoidance. In another study, Xie et al. combined model predictive control (Katsikis and Mourtas 2021), an enhanced Q-learning beetle swarm antenna search algorithm, and neural networks to devise an innovative ship collision avoidance method, offering a real-time and reliable solution. Furthermore, Liu et al. presented an adaptive control method for active heave compensation systems that merge BAS and neural networks, addressing ship stability issues in harsh sea conditions (Katsikis et al. 2020).

In global path planning, Lin et al. introduced a BAS-based method for mobile robots (Medvedeva et al. 2021), which substantially improves the speed and obstacle avoidance performance of robot path planning. This method involves comparing multiple paths at each point and selecting the most efficient route closest to the theoretical optimal path. Wang et al. demonstrated enhanced path planning performance in complex 3D environments with their 3D path planning algorithm for UAVs (Khan et al. 2022), which fuses PSO and BAS. Yu et al. integrated BAS with the water flow potential field method to develop an efficient path planning method for mobile robots (Khan et al. 2022a), characterized by reduced time consumption, significant optimization, and resistance to local optima, thereby offering a practical solution for diverse path planning scenarios. Liang et al. proposed the improved VBAS algorithm (Li et al. 2021), which increases path planning reliability by incorporating map safety thresholds, virtual target points, and path smoothing. Lastly, Zha et al. enhanced the stability and success rate of global path planning for unmanned watercraft by introducing a maximum turning angle constraint through an improved BAS algorithm (Wang et al. 2023).

5.7 Finance and economics

In the realms of finance and economics, the utilization of BAS algorithms has gained increasing prominence, particularly in portfolio optimization, stock trading strategy enhancement, and economic model parameter refinement. These applications of BAS have significantly bolstered financial transaction benefits, mitigated investment risks, and optimized the accuracy of economic model predictions. Wang et al. innovatively proposed a hybrid Aspen Whisker Search Sine–Cosine Algorithm, integrated with nonlinear inertia weights (Huang et al. 2020). This algorithm is designed to assist investors in achieving stable returns and risk diversification. The convergence of the algorithm is expedited by updating nonlinear inertia weights of aspen locations and amalgamating them with the sine–cosine method, thereby enhancing the efficiency and stability of portfolio management in the real stock market context. Chen et al. developed the Beetle Swarm Optimization (BSO) algorithm (Li et al. 2021), a fusion of BAS and standard PSO. BSO inherits the global search capabilities of PSO while incorporating BAS's local search strategy, effectively diminishing risk and circumventing the pitfalls of local optima. This algorithm exhibits robust performance in addressing constrained multidimensional function optimization, rendering it a potent tool for portfolio problem-solving.

Katsikis and Mourtas demonstrated the applicability of BAS in solving the Binary Optimal Tangent Portfolio (BOTPCC) problem under basis constraints, showcasing BAS's efficacy in complex financial domains (Cao et al. 2023). Katsikis et al. further advanced this field by proposing an online solution for time-varying nonlinear programming problems (Lin et al. 2023), employing BAS to address time-varying least-cost portfolio insurance issues under transaction costs. Medvedeva et al. introduced a novel approach to the stochastic time-varying knapsack problem (RTVKP), conceptualizing it as a time-varying integer linear programming (TV-ILP) problem (Xie et al. 2018). This method employs a binary BAS algorithm that transitions to a TV-ILP approach for combinatorial optimization, offering an effective online resolution for RTVKP. Additionally, this study extends the application of RTVKP to finance by transforming it into a portfolio insurance problem, with empirical simulations demonstrating its superiority over traditional methodologies.

Khan et al. applied BAS to solve the intended Markowitz model for portfolio optimization by introducing transaction cost and nonlinear cardinality constraints in the original model (Yue et al. 2020). Addressing the non-convex tax-aware portfolio optimization challenge, traditionally approximated as a convex problem, Khan et al. introduced the Nonlinear Activated Beetle Antenna Search (NABAS) algorithm (Wang et al. 2020b), an innovative nondeterministic meta-heuristic based on BAS. NABAS employs a specific gradient estimation measure to navigate the search space, enhancing convergence speed and eluding local minima. This method has shown promising results on simulated stock data from 20 companies on the NASDAQ stock market. In another significant contribution, Khan et al. applied BAS to a financial fraud detection framework for publicly traded companies (Mei et al. 2022). By designing an optimization problem focused on a nonlinear decision function and maximizing recall, they achieved effective fraud detection by minimizing the loss function. Testing on a benchmark dataset published by the SEC Accounting and Audit Enforcement revealed BAS as a potent method for fraud detection.

5.8 Other applications

In the realm of precision engineering, Li et al. have pioneered a method that integrates the BAS algorithm with a BP neural network for constructing a thermal error model of high-speed electric spindles (Khan et al. 2022b). This approach employs fuzzy clustering and grey correlation analysis to develop a predictive model, and utilizes BAS for the optimization of weights and thresholds within the BP neural network. Experimental assessments, utilizing temperature and axial thermal drift data across various rotational speeds, have demonstrated notable enhancements in the predictive accuracy and robustness of the model. Wang et al. introduced a novel stochastic error compensation method for Fiber Optic Gyroscopes (FOG) (Xu et al. 2020), leveraging Support Vector Regression (SVR) optimized by an Untraceable Kalman Filter (UKF) with an Adaptive Beetle Antenna Search (ABAS) algorithm. This method refines BAS by incorporating an adaptive attenuation factor and assembles a hybrid model composed of SVR, VMD, a sliding window method, and UKF. This composite approach significantly elevates the Durbin-Watson value of the model while concurrently reducing noise intensity. Furthermore, Li et al. tackled the challenge of detecting and localizing magnetic anomalous signals in vector sensors, such as fluxgate magnetometers (Fan et al. 2020). By developing a three-error calibration model based on the BAS algorithm, they successfully balanced accuracy with computational efficiency, illustrating the potential of BAS in high-precision sensor applications.

In geological exploration, Cao et al. employed BAS and a competitive mechanism to refine a random forest model for detecting geochemical anomalies linked to iron mineralization (Xiang and Zhu 2022). This optimized model demonstrated considerable superiority in analyzing geochemical data, with an inherent ability to autonomously adjust parameters and identify the global optimal solution, thereby markedly improving geochemical anomaly detection performance. In the field of aeronautical control systems, Lin et al. proposed an enhanced BAS algorithm for optimizing controller parameters in quadrotor trajectory tracking amid bounded external disturbances (Yin and Ma 2018). By integrating historical information and dynamically updating step sizes and search ranges, this algorithm substantially improves optimization speed, control efficiency, and effectively minimizes error and overshoot. In marine engineering, Xie et al. devised a novel speed control method for marine diesel engines (Wu et al. 2021). This method adeptly manages load and model parameter perturbations in diesel engines by combining an adaptive state compensation extended state observer with backstepping and BAS for online parameter optimization. Further research and applications of the BAS algorithm are extensively documented in references (Zhang et al. 2019b; Lyu et al. 2022a, 2022b; Liao and Zhang 2020; Li et al. 2020; Katsikis et al. 2021; Liao et al. 2022; Mourtas et al. 2023; Brajević et al. 2021; Cheng et al. 2020; Zheng et al. 2020; Khan et al. 2019, 2021b, 2020a, 2020b).

6 Challenges and future works

This review meticulously explores the diverse applications of the BAS algorithm as delineated in current research, with a particular focus on the principles underlying these algorithms. Illustrative data, as presented in Fig. 9, reveal the integration of BAS algorithms across a spectrum of disciplines, highlighting their successful implementation in solving pertinent engineering challenges. Furthermore, Fig. 10 provides a quantitative analysis of research publications in various fields from 2017 to 2023, indicating a marked increase in the development and application of BAS algorithms since 2019. Notably, the bulk of this research is concentrated in areas such as robotics engineering, path planning, and finance. The trajectory of the BAS algorithm since its inception underscores its broad applicability and adaptability. Looking forward, the algorithm shows promise for integration into emerging fields driven by societal needs. This adaptability positions the BAS algorithm as a versatile tool in the evolving landscape of technological and scientific research, capable of addressing complex problems in new and diverse application domains.

The BAS algorithm has demonstrated superior convergence accuracy and speed relative to various other optimization algorithms in the realm of engineering optimization. However, it has been observed that in the latter stages of optimization, BAS tends to converge on local optima. This limitation has catalyzed the development of numerous enhanced versions of the BAS algorithm, aimed at refining its accuracy. These enhancements encompass modifications of parameters such as step length and the inter-whisker distance of the algorithm's metaphorical 'beetles', as well as advancements in hybrid algorithm techniques. Despite these improvements, the applicability of the enhanced BAS algorithm is not universal across all optimization scenarios. Consequently, further simulation experiments are essential to ascertain the specific conditions and boundaries within which these refined algorithms can operate most effectively. This recognition of the BAS algorithm's limitations and the subsequent iterative improvements underscore a dynamic and responsive approach to algorithm development in optimization research. The ongoing refinement of the BAS algorithm illustrates the necessity for continuous evaluation and adaptation, particularly in the face of diverse and complex engineering challenges. Future research endeavors must therefore focus not only on enhancing the algorithm but also on thoroughly testing its efficacy across a multitude of application scenarios to determine its most suitable and effective use cases.

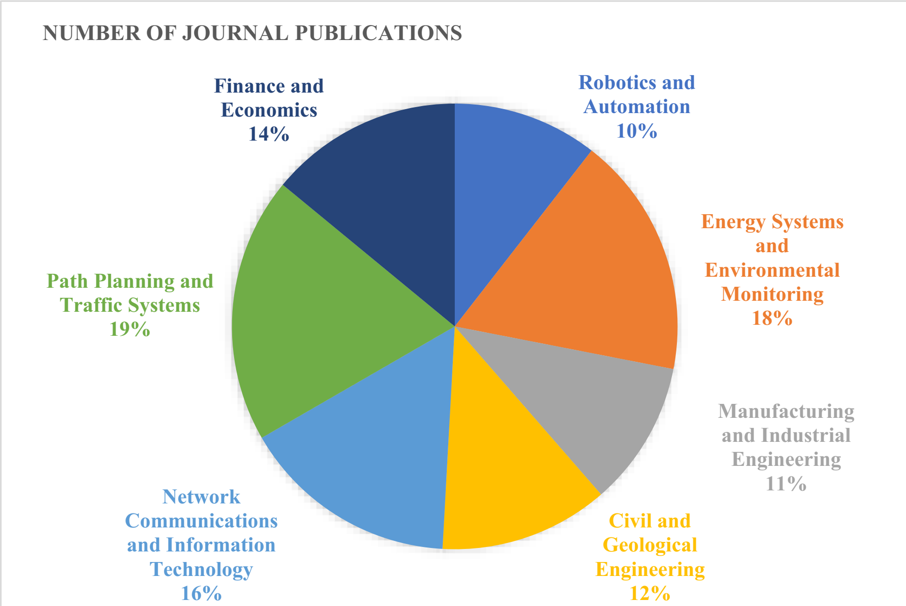


Fig. 9 Core application of BAS algorithm

The BAS algorithm, characterized by its simplicity and efficiency, holds significant promise in theoretical research, refinement, and practical application. Presently, the BAS algorithm is extensively deployed in domains such as electrical engineering, control systems, and artificial intelligence, where it has yielded noteworthy results. Nevertheless, the algorithm is not without its limitations. These include a constrained capability for individual optimization, a propensity to converge on local optima in high-dimensional problems, and a pronounced reliance on parameter settings. Given these challenges, a concerted effort toward the further theoretical and practical enhancement of the BAS algorithm is of paramount importance. Looking ahead, the research trajectory of the BAS algorithm can be strategically directed along three critical avenues. First, addressing the inherent limitations in individual optimization to expand its applicability in complex problem-solving scenarios. Second, developing robust strategies to prevent the convergence on local optima, especially in high-dimensional contexts. And third, reducing the algorithm's dependency on parameter settings, thereby increasing its adaptability and ease of use. These focal points will not only drive the evolution of the BAS algorithm but will also significantly contribute to the broader field of optimization algorithms.

(1) Theoretical investigations into the BAS algorithm remain limited, yet are crucial, particularly given the algorithm's sensitivity to parameter settings. A comprehensive analysis of how various parameters, such as step length and the inter-whisker distance of Tenebrionidae, impact the algorithm's iterative process is essential. Theoretical explorations in this domain could lead to the development of more effective parameter rules or automated parameter adjustment mechanisms. Moreover, a detailed theoretical examination of the BAS algorithm's global and local search capabilities is imperative. Such an analysis would elucidate the effects of its optimization mechanisms, providing valuable theoretical insights for algorithmic refinement. Further, an in-depth study of other characteristics, including convergence, stability, and complexity, is vital for a holistic understanding of the BAS algorithm's performance. These

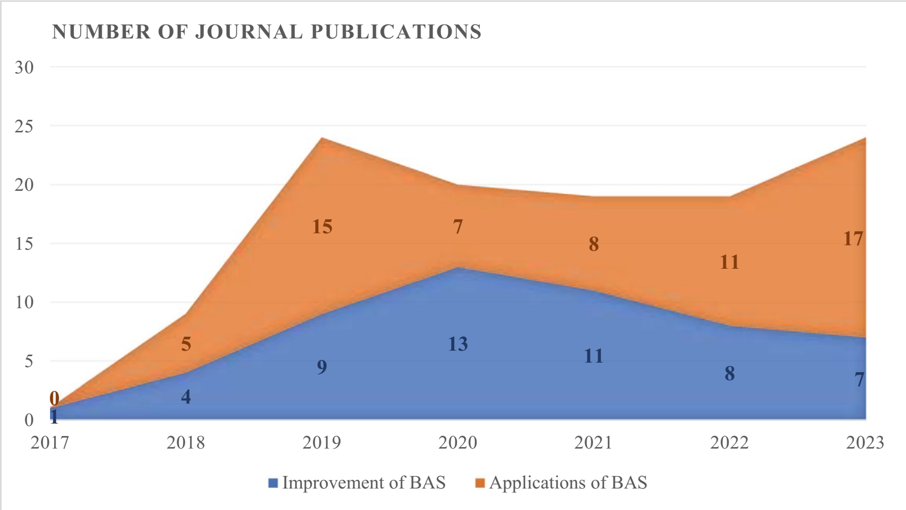


Fig. 10 Research progress of BAS algorithm

factors, once thoroughly analyzed, could significantly augment the theoretical foundation of the BAS algorithm. Such an enriched theoretical base will not only enhance our comprehension of the BAS algorithm but also pave the way for its advanced development and more widespread application in various optimization scenarios.

(2) Research on the enhancement of the BAS algorithm has evolved from focusing on single entities to encompassing entire populations. The efficacy of initial solutions within the Tennessee whisker population is pivotal, greatly influencing the convergence speed and accuracy of the algorithm. However, there is a noticeable scarcity of research on methods that improve initial population solutions. Potential strategies, such as the implementation of chaotic mapping, reverse learning, Sobol sequences, and good point sets, warrant consideration. The design of hybrid algorithms represents a critical advancement in this field. Integration of BAS with other algorithms, known for their high convergence accuracy, could significantly boost search performance and provide a more comprehensive theoretical basis for the enhanced algorithm. Nonetheless, the problem's dimensionality must be carefully considered in these designs. A notable limitation of the BAS algorithm is the absence of mutation mechanisms, which constrains its further development. To address this, perturbation mechanisms such as Cauchy and Gaussian variations, as well as the incorporation of exchange operators, could be explored to augment population diversity. Such enhancements are anticipated to improve the algorithm's capacity to escape local optima. Future research should consider the development of novel algorithms, drawing inspiration from theories across different disciplines. Simultaneously, it is crucial that the design of new algorithms not only enhances search performance but also maintains the time efficiency and universality of the algorithm.

(3) Applied Research on Beetle Antenna Search Algorithm: The integration of deep learning with the BAS algorithm represents a compelling research trajectory. This hybridization could manifest in various forms, such as employing BAS to refine the parameters of deep neural networks, or conversely, utilizing deep learning methodologies to augment the search strategies inherent in BAS. Another critical area of investigation is the treatment of multimodal optimization problems. Here, the focus would be on the further enhancement of

algorithms to more effectively navigate and leverage the plethora of local optima within a given problem space. Additionally, in the context of escalating computational demands, the application of BAS algorithms within parallel computing and distributed systems emerges as a vital area of exploration. This approach is anticipated to significantly bolster the capacity for managing large-scale datasets and expedite the resolution of complex computational problems. Such developments in BAS algorithm research could substantially contribute to the field of optimization, aligning with the evolving needs of computational efficiency and advanced problem-solving.

7 Conclusions

The BAS algorithm, as a meta-heuristic optimization technique, holds significant research value and finds extensive application across various domains. However, it's essential to acknowledge certain limitations and constraints that shape its utility and effectiveness. One such constraint lies in the algorithm's reliance on parameter settings, where suboptimal choices impact its convergence behavior and solution quality. Additionally, the algorithm's performance be influenced by the complexity and dimensionality of the problem space, with scalability concerns arising in highly nonlinear or high-dimensional optimization scenarios.

Despite these constraints, the BAS algorithm stands out for its robustness, simplicity in implementation, and minimal control parameter requirements compared to alternative algorithms. This comprehensive review offers a detailed analysis of the BAS algorithm's foundational principles and existing research landscape, shedding light on its strengths and limitations. By exploring the biological inspiration behind the algorithm and its implementation nuances, we gain a deeper understanding of its operational mechanisms and potential challenges.

Furthermore, this paper delves into various enhancements and adaptations made to the BAS algorithm, along with its diverse applications across different systems. It is evident that while the BAS optimization algorithm and its variants exhibit unique characteristics, their efficacy varies across different problem domains. Thus, it becomes imperative to acknowledge the algorithm's adaptability limitations and explore avenues for improvement and refinement.

Looking ahead, the future of BAS research holds promise for theoretical advancements, interdisciplinary collaborations, and broader applications. By addressing the identified constraints and leveraging the algorithm's strengths, researchers can pave the way for more versatile and effective optimization techniques. This review serves not only to synthesize existing knowledge but also to inspire continued exploration and innovation in optimization algorithms, positioning the BAS algorithm as a cornerstone for future advancements across diverse fields.

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Declarations

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