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Research article

An improved dung beetle optimizer algorithm for solving engineering optimization problems

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Abstract: To address the limitations of the dung beetle optimizer algorithm, such as its tendency to fall into local optima during the later phases of the iterative process, limited global exploration capability, and relatively slow convergence speed, this paper proposes a multi-strategy improved dung beetle optimizer algorithm. The improvement integrates the Sobol sequence, the nonlinear convergence factor, Lévy flight, the adaptive Cauchy–Gaussian hybrid mutation, and the greedy strategy. These improvements effectively enhance population diversity, the global exploration ability, and local exploitation performance. Specifically, the Sobol sequence is employed to initialize the population, thereby ensuring a more uniform and comprehensive population distribution. The nonlinear convergence factor is introduced to better balance the algorithm's global exploration and local exploitation. Lévy flight is applied to perturb the global best solution, improving the algorithm's ability to escape from local optima. Finally, the adaptive Cauchy–Gaussian hybrid mutation, combined with the greedy strategy, is designed to accelerate convergence and preserve elite individuals. To comprehensively evaluate the performance of the proposed algorithm, comparative experiments are conducted on the CEC2017 benchmark test set against seven widely recognized intelligent optimization algorithms. The experimental results demonstrate that the improved algorithm achieves superior performance in both optimization accuracy and convergence speed. Finally, the proposed algorithm is applied to actual engineering optimization problem, yielding the best results in all cases, thereby validating its effectiveness and practical applicability in solving complex optimization problem.

Keywords: dung beetle optimizer algorithm; optimization algorithm; optimization problem; strategy integration; industrial economy
Mathematics Subject Classification: 90C59

1. Introduction

For an extended period, optimization problems have constituted a major research focus. However, in the vast majority of engineering optimization problems, improving computational efficiency while obtaining optimal solutions under multiple complex constraints remains a significant challenge [1]. When dealing with optimization problems involving multiple variables and constraints, the solution space often contains multiple local optima, making it difficult for traditional numerical methods to achieve satisfactory results [2,3]. Swarm intelligence optimization algorithms, due to their few control parameters and strong generalization capabilities, are capable of performing global exploration on complex problems and are therefore widely used in various engineering applications [4,5]. In the realm of engineering optimization, such intelligent optimization algorithms have been extensively applied to areas such as power system optimization [6], engineering design [7], and path planning [8], yielding notable optimization outcomes. With the rapid advancement in this field, numerous novel intelligent optimization algorithms have been successively introduced, such as the ant colony optimizer (ACO) algorithm [9], spider wasp optimizer (SWO) [10], nutcracker optimizer algorithm (NOA) [11], whale optimizer algorithm (WOA) [12], artificial hummingbird algorithm (AHA) [13], and butterfly optimizer algorithm (BOA) [14]. Among these, the dung beetle optimizer (DBO) algorithm, introduced by Xue in 2022 [15], is a novel metaheuristic algorithm inspired by the social habits of dung beetles and exhibits significant optimization capability and operational flexibility. However, the DBO algorithm still has certain limitations, including a lack of diversity in the initial population and a tendency for the population to converge prematurely to local optima during the later phases of the iterative process.

In response to the limitations of the DBO algorithm during the optimization process, numerous scholars have conducted extensive research, primarily focusing on two main improvement approaches: algorithm fusion and hybrid strategies. On one hand, algorithm fusion can be implemented in two ways: Integrating the DBO algorithm with other intelligent optimization algorithms [16,17] or combining it with machine learning or deep learning techniques [18,19]. On the other hand, improvements based on hybrid strategies are mainly reflected in three aspects. First, enhancing the method used to initialize the population leads to a broader and more varied range of initial solutions, thereby accelerating the convergence speed and improving the final solution's quality [20,21]. Second, adaptive parameter adjustment allows the key control parameters to dynamically and nonlinearly vary with the population distribution, overcoming the issue of fixed parameter boundaries in the original algorithm and enhancing its capability to solve complex optimization problems [22,23]. Third, improvements through update mechanisms and position perturbation introduce randomness to the optimal solution or the entire population in the later iterations, effectively preventing premature convergence and maintaining algorithmic diversity [24,25].

Although the improved strategies proposed in the previous research enhance the global exploration and local exploitation capabilities of the DBO algorithm, several limitations persist in the algorithm itself. These include a lack of consideration for the distribution of the initial population and insufficient optimization performance during the later phases of the iterative process. These shortcomings result in an imbalance between global exploration and the local exploitation capabilities, accompanied by diminished convergence accuracy and reduced optimization efficiency. In response to these challenges, this paper proposes an improved dung beetle optimizer (IDBO) algorithm. First, in the early iterations, the Sobol sequence is introduced to improve the spatial distribution of the initial population, thereby enhancing the population's diversity. The excellent uniformity and traversal characteristics of the Sobol sequence effectively enhance the algorithm's exploration capability in the early iterations. Second, a nonlinear convergence factor is incorporated to balance the algorithm's global exploration and local exploitation capabilities, which increases in the early iterations and decreases in the subsequent iterations, thereby achieving a dynamic balance between exploration and exploitation. Third, in the later iterations, to prevent the algorithm from becoming trapped in local optima, Lévy flight is incorporated through its long-distance jumping behavior, thereby significantly improving its capacity for global exploration. Meanwhile, to further enhance the refined search capability, the adaptive Cauchy–Gaussian hybrid mutation, combined with the greedy strategy is applied for local exploitation, which enables the algorithm to converge rapidly. Finally, the proposed algorithm is evaluated through both theoretical analysis and practical experiments to validate its performance.

2. Dung beetle optimizer algorithm

The DBO algorithm represents a novel approach inspired by the foraging and navigational behaviors exhibited by dung beetles in their natural ecosystems. This algorithm is capable of identifying optimal solutions in complex scenarios, demonstrating its extensive applicability and practical significance [26,27]. Furthermore, the algorithm simulates the behaviors of four distinct types of dung beetles, namely the ball-rolling dung beetle, the reproductive dung beetle, the small dung beetle, and the thief dung beetle, each assigned according to a predefined proportion. Each individual dung beetle represents a solution, while the positions of these solutions are iteratively updated by following specific update rules associated with each group, resulting in the determination of the optimal solution. When applying the DBO algorithm, the population is divided into different types according to a certain proportion, with each individual performing its specialized role to collectively accomplish its foraging and reproductive objectives. According to the description of the algorithm [15], the ball-rolling dung beetles account for 20%, the reproductive dung beetles account for 20%, the small dung beetles account for 25%, and the thief dung beetles account for 35% of the total population. The detailed formula is presented below.

2.1. The ball-rolling dung beetle

The ball-rolling dung beetle imitates its fellow beetles, rolling dung balls in the sunlight to determine the optimal orientation. This rolling behavior can be categorized into two scenarios. Without obstacles, they persistently roll the dung ball; however, when dung beetles encounter obstacles, they perform a distinct reorientation behavior known as "dancing."

2.1.1. Rolling behavior

The formula for adjusting the rolling dung beetle's position without obstacles is as follows:

$$\begin{cases} x_i(t+1) = x_i(t) + \alpha \times k \times x_i(t-1) + b \times \Delta x \\ \Delta x = \left| x_i(t) - X^{\omega} \right| \end{cases} \qquad \rho \le \varphi, \tag{1}$$

where t denotes the number of the current iteration; $x_i(t)$ denotes the position of the ith dung beetle at iteration t; k denotes the deflection coefficient, where $k \in (0, 0.2]$; b denotes a random constant value, where $b \in (0, 1)$; α assumes a value of 1 or –1, depending on whether it deviates from the original direction; X^{ω} denotes the global worst position of individuals in the dung beetle population; Δx denotes the intensity of light; ρ is a random number, where $\rho\in[0, 1]$; and φ denotes the constant probability of encountering no obstacles, where $\varphi=0.9$.

2.1.2. Dancing behavior

When facing an obstacle that impedes progress, dung beetles execute a reorientation dance and establish an alternative path for continued locomotion. The corresponding position update mechanism is described as follows:

$$x_i(t+1)=x_i(t)+\tan(\theta)\left|x_i(t)-x_i(t-1)\right| \quad \rho>\varphi, \tag{2}$$

where θ denotes the random deflection angle and $\theta\in[0, \pi]$. When the value of θ is 0, $\pi/2$, or π, the spatial locations of the dung beetles shows no significant variation.

2.2. The reproductive dung beetle

The dung beetles primarily consume dung. Certain dung beetles convey dung balls to safe locations for reproduction. The area selected for spawning is dynamically modified based on the current optimal position. The mathematical formula used to define the safe area for reproduction is as follows.

$$\begin{cases} L_b^* = \max\left\{X^*(1-R), L_b\right\} \\ U_b^* = \min\left\{X^*(1+R), U_b\right\}, \\ R = 1 - t/T \end{cases} \tag{3}$$

where T denotes the maximum number of iterations; for the given optimization problem, L_b and U_b, indicate the minimum and maximum constraint values respectively; X^* denotes the current local optimal position; L_b^* and U_b^* represent the minimum and maximum limits of the solution domain, respectively; and R is the linear adjustment factor.

Female dung beetles exhibit selective behavior when choosing dung balls for spawning, embedding their eggs within these nutrient-rich substrates to provide an optimal developmental habitat for their offspring. Furthermore, according to Eq (3), the spatial distribution of dung beetles' spawning area exhibits substantial variation, primarily governed by parameter R. Consequently, the positional trajectory of the dung ball throughout the process of iterative optimization can be mathematically expressed as follows:

$$B_i(t+1)=x^* + b_1\left[B_i(t)-L_b^*\right]+b_2\left[B_i(t)-U_b^*\right], \tag{4}$$

where $B_i(t)$ denotes the position of the ith dung ball at iteration t, b_1 and b_2 are two independent random vectors of size $1\times D$, and D denotes the dimension of the optimization problem to be solved.

2.3. The small dung beetle

After hatching from the brood balls, dung beetle larvae, known as small dung beetles, begin their foraging activities. This foraging activity typically occurs within a defined area. The formula for the boundary of this area is as follows:

$$\begin{cases} L_b^* = \max\left\{X^b(1-R), L_b\right\} \\ U_b^* = \min\left\{X^b(1+R), U_b\right\} \end{cases}, \tag{5}$$

where x^b denotes the global optimal position, and L_b and U_b denote the lower and upper bounds of the foraging area, respectively.

The formula for the position update of the dung beetles during foraging is described as follows.

$$x_i(t+1) = x_i(t) + C_1 \cdot \left(x_i(t) - L_b^*\right) + C_2 \cdot \left(x_i(t) - U_b^*\right) \tag{6}$$

where C_1 follows a standard normal distribution, and C_2 represents a uniformly distributed random vector over the interval (0, 1).

2.4. The thief dung beetle

Some dung beetles exhibit theft behavior, whereby certain individuals steal dung balls from others for consumption or spawning. Theft typically occurs at favorable locations, and the position update mechanism is described as follows.

$$x_i(t+1) = x^b + S \cdot g \cdot \left(\left|x_i(t) - x^*\right| + \left|x_i(t) - x^b\right|\right) \tag{7}$$

where g is normally distributed, and S remains a fixed parameter.

3. Improved dung beetle optimizer algorithm

The improvements to the IDBO algorithm primarily incorporate the following five strategies. First, population diversity is enhanced by using the Sobol sequence, which ensures a more uniform and comprehensive distribution. Second, the nonlinear convergence factor strategy is introduced to modify the search range during the reproduction and foraging phases, successfully achieving a balanced optimization of the algorithm's overall performance. Third, the positions of thief dung beetles are adjusted by incorporating Lévy flight, which improves the algorithm's ability to explore the global search space. Fourth, the adaptive Cauchy–Gaussian hybrid mutation significantly boosts the algorithm's performance, enhancing convergence speed and accuracy. Finally, the greedy strategy focuses on retaining superior individuals, which significantly enhances the overall quality of the solution. This paper explores diverse improvement strategies and presents experimental validations that demonstrate the effectiveness of an enhanced algorithm.

3.1. Sobol sequence

The optimization performance and convergence rate of swarm intelligence algorithms are highly dependent on the initial spatial distribution of the population, as demonstrated in previous studies [28,29]. A uniformly distributed initial population can facilitate faster entry into the optimal region, thereby enhancing the algorithm's search accuracy. Traditionally, population initialization in such algorithms relies on random generation. Although this approach enables rapid population creation, the resulting spatial distribution is often irregular, leading to uneven dispersion of individuals and potential clustering effects [30,31]. With the advancement of population optimization techniques, researchers have employed chaotic mapping to generate the initial populations. By leveraging its randomness, ergodicity, and regularity, chaotic mapping improves the population's diversity by determining the initial positions of individuals more effectively than randomly generated populations. Chaotic mappings demonstrate significant sensitivity to the initial conditions and parameter values, resulting in uneven distributions within the initial populations, which manifest as clustered and sparse regions. The resulting unevenness may cause inadequate or excessively intensive exploration, which ultimately compromises the overall optimization efficiency of the population. To mitigate the influence of the initial positioning methods on the algorithm's performance, the initial population of dung beetles was generated utilizing the Sobol sequence, with the detailed mathematical formulation presented below.

$$x_i = L_b + S_n * (U_b - L_b), \tag{8}$$

where S_n is a random number generated by the Sobol sequence; $S_n \in [0, 1]$.

Assume the population size is set to 500. Three comparison diagrams for initializing the population are presented below (Figures 1–3).

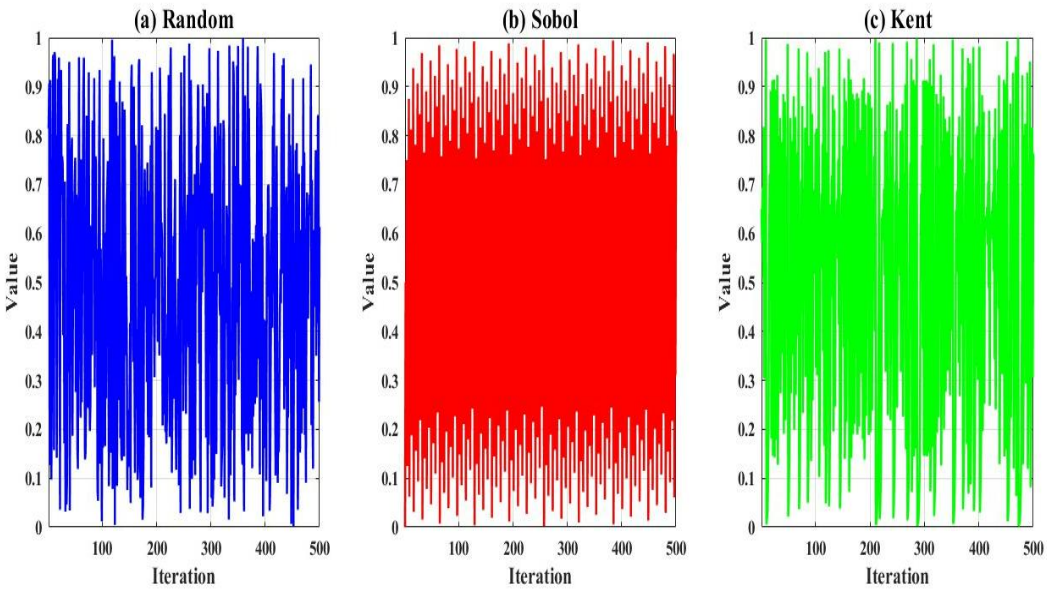

Figure 1. A comparison of sequence iterations across three population initialization methods.

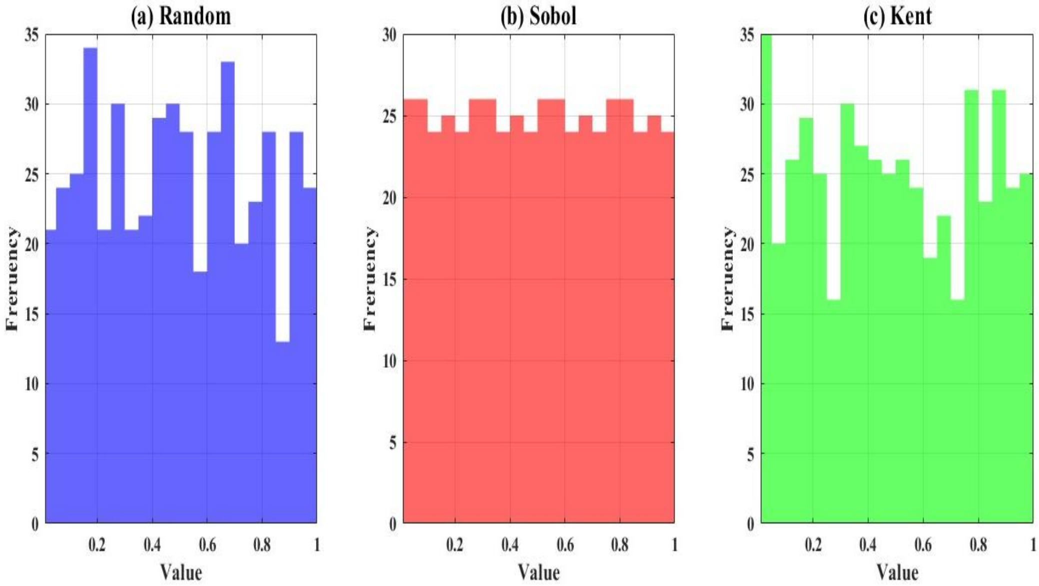

Figure 2. A comparison of histograms across three population initialization methods.

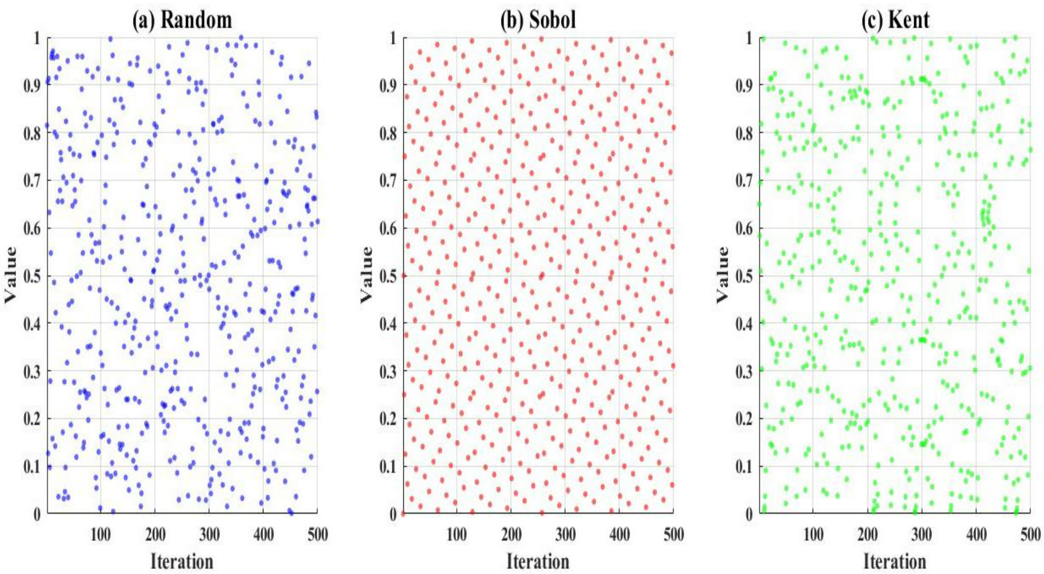

Figure 3. A comparison of scatter plots across three population initialization methods.

It can be observed from Figures 1–3 that the dung beetle population generated using the Sobol sequence exhibits a more uniform distribution, superior ergodicity, and more comprehensive coverage of the solution space compared with those generated by the other two methods, thereby preserving greater population diversity.

3.2. Nonlinear convergence factor

The DBO algorithm exhibits significant constraints due to its invariant parameter ranges during both the reproductive and feeding phases. During the spawning phase, small brood balls facilitate the clustering of newly generated individuals, effectively guiding them towards the optimal solution. This clustering mechanism, while accelerating convergence toward optimal solution, significantly reduces population diversity and increases the likelihood of early convergence to local optima. Similarly, if the foraging area is limited, the small dung beetles are confined to a small area around their parents' positions, which hampers their ability to reach the global optima. Consequently, fixed spawning and foraging ranges fail to accommodate the dynamic changes in the algorithm's optimization performance, which significantly contributes to premature convergence and entrapment in the optimal solution.

Given the perspectives above, we conducted an analysis to identify the limitations inherent in the DBO algorithm, particularly in its spawning and foraging stages. As indicated by Eqs (3)–(6), the boundary convergence factor R diminishes with increased iterations, resulting in a significant reduction in both the spawning and foraging areas for dung beetles. However, this linearly decreasing boundary convergence factor presents certain limitations. During the early phases of population iteration, the dung beetles require a rapid expansion of their spawning and foraging areas to enhance their global exploration capability; however, the small boundary convergence factor at this stage results in insufficient searching. Conversely, in the later iterations, the population needs to converge quickly, but the relatively large boundary convergence factor hinders the convergence speed. To tackle these restrictions, this paper proposes an enhanced boundary convergence factor that exhibits a nonlinear variation trend, aiming to achieve a more balanced overall performance of the algorithm. The boundary convergence factor has been updated as follows:

$$R' = (\cos(\pi * (t / T)) + 1) * 0.5 \tag{9}$$

The iterative curves of these factors were plotted for intuitive understanding and analysis, and the results are presented in Figure 4.

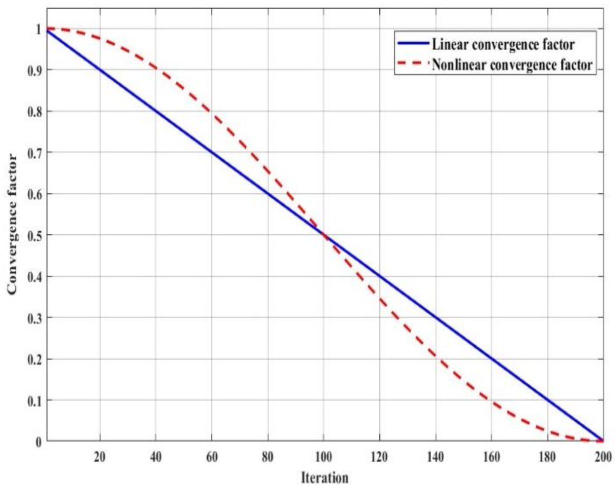

Figure 4. A comparison of the convergence factor before and after improvement.

As illustrated in Figure 4, during the initial phases, the population exhibits high diversity, which broadens the global exploration scope. Meanwhile, compared with the linear convergence factor, the linear convergence factor, the nonlinear convergence factor has a higher initial value and exhibits a slower rate of decrease. Consequently, the algorithm's global exploration ability is enhanced. In the later iterations, population diversity gradually diminishes, allowing for a more refined local search. As a result, the marked decline in the nonlinear convergence factor not only reinforces the algorithm's capability for local exploitation but also promotes accelerated convergence. Therefore, the enhanced convergence factor ensures a balance in the algorithm's performance.

The proposed nonlinear convergence factor improves the local exploration ability of dung beetles in both the spawning and foraging phases, leading to the following modified formulation.

$$\begin{cases} L_b' = \max\left\{x^*(1-R'), L_b\right\} \\ U_b' = \min\left\{x^*(1+R'), U_b\right\} \end{cases}, \tag{10}$$

$$B_i(t+1) = x^* + b_1\left[B_i(t) - L_b'\right] + b_2\left[B_i(t) - U_b'\right], \tag{11}$$

$$\begin{cases} L_b' = \max\left\{x^b(1-R'), L_b\right\} \\ U_b' = \min\left\{x^b(1+R'), U_b\right\} \end{cases}, \tag{12}$$

$$x_i(t+1) = x_i(t) + C_1 \cdot \left(x_i(t) - L_b'\right) + C_2 \cdot \left(x_i(t) - U_b'\right). \tag{13}$$

3.3. Lévy flight

Lévy flight represents a stochastic movement pattern that follows a power law distribution, distinct from Gaussian random walks, and is defined by alternating phases of localized exploration and sporadic long-range jumps [32–34]. This unique movement pattern originates from the optimized foraging behaviors developed through the evolution of natural organisms, such as albatrosses and bees. It has since become a key technique in intelligent optimization algorithms for overcoming the limitations of local optima. In function optimization, the Lévy flight mechanism facilitates frequent long-range jumps, which significantly enhances the algorithm's ability to avoid being trapped in local optima [35], thereby preserving its global exploration capability and maintaining population diversity.

The role of the thief dung beetle in the algorithm is primarily to explore new, potentially viable, and unoccupied regions or to attempt to "steal" resources from existing individuals within the population. The long-distance jumping behavior associated with Lévy flight endows this search strategy with a more extensive and efficient random search pattern. Therefore, this paper uses Lévy flight to enhance the position update process of the thief dung beetles. Specifically, according to Eq (7), the initial position updating strategy of the thief dung beetle primarily depends on the positional differences between two randomly selected individuals, along with a normally distributed random disturbance term. Although this approach exhibits a certain level of exploratory capability, its step size variation is relatively moderate, which may limit its efficacy in escaping local optima when addressing intricate multimodal optimization challenges. More importantly, the purpose of incorporating Lévy flight is to replace the random step length ($S * g$) in the original update formula with a step length ($L(\beta)$) generated through Lévy flight. This improvement in the formula enables the thief dung beetle to expand its search range to areas farther away from the current population concentration, which may potentially contain superior solutions, enhancing its global exploration capability. The specific formula is presented below.

$$L(\beta) = u / |v|^{1/\beta}, \tag{14}$$

$$\sigma = \left[\frac{\Gamma(1+\beta)\sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right)\times 2^{\frac{\beta-1}{2}}} \right]^{\frac{1}{\beta}}, \tag{15}$$

where $u \sim N(0, \sigma^2)$, $v \sim N(0, 1)$, and $\Gamma(x)=(x-1)!$; β is commonly assumed to be 1.5, $\beta \in (1, 3]$.

The DBO algorithm incorporates Lévy flight to optimize the position update mechanism of thief dung beetles. The modified formula is displayed in the subsequent expression.

$$x_i(t+1) = X^b + L(\beta)\cdot\left(\left|x_i(t) - X^*\right| + \left|x_i(t) - X^b\right|\right). \tag{16}$$

In a two-dimensional coordinate system, the initial point was iterated 500 times using the Lévy flight strategy, with α set to 1.5 and β set to 1. The flight path is illustrated as follows (Figure 5).

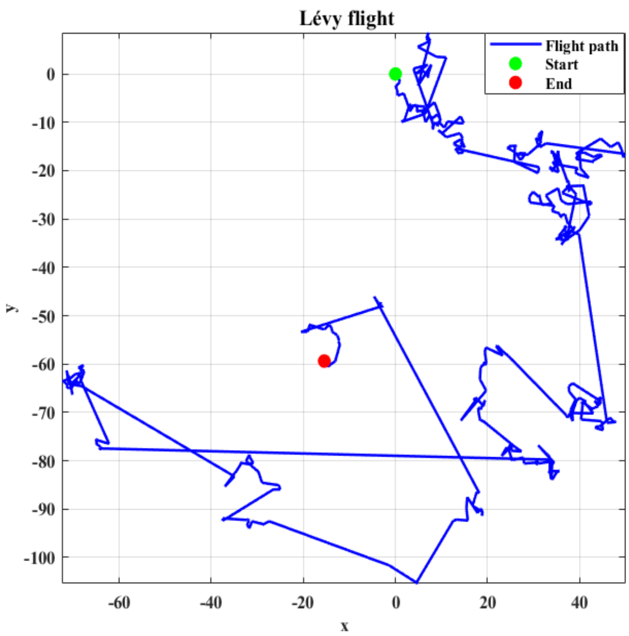

Figure 5. The flight path of Lévy flight.

The results depicted in Figure 5 demonstrate that employing Lévy flight markedly expands the exploration scope of the algorithm across the solution space, consequently improving its ability to discover global optima.

3.4. Adaptive Cauchy–Gaussian hybrid mutation

In intelligent optimization algorithms, introducing perturbations to the optimal position through a mutation strategy is a commonly adopted approach for performance enhancement. Typical perturbation strategies include Cauchy mutation and Gaussian mutation. Cauchy mutation exhibits a heavy-tailed distribution [36], allowing for the generation of larger mutation step lengths, whereas Gaussian mutation produces perturbations that are more concentrated around the mean. Consequently, Cauchy mutation facilitates global exploration, while Gaussian mutation enhances local exploitation. Consequently, depending solely on a single mutation approach may result in an inadequate balance between exploratory and exploitative behaviors. To overcome this constraint, the present study introduces an enhanced approach utilizing a hybrid mutation mechanism that adaptively integrates Cauchy and Gaussian distributions. The enhanced mutation strategy significantly boosts the algorithm's performance by augmenting population diversity and accelerating convergence efficiency. The modified formula is presented below.

$$\begin{cases} X_{new} = X_b \cdot [w_1 \cdot Cauchy(0,1) + (1-w_1) \cdot \ Gassian(0,1)] \\ w_1 = 1 - \sin(0.5\pi t / T) \end{cases}, \tag{17}$$

where X_{new} denotes the new individual after perturbation and w_1 is the inertia weight.

3.5. Greedy strategy

Although new individuals are generated by perturbing the optimal position, there is no guarantee that the quality of these solutions will be superior to the global optimum. To enhance the algorithm's local exploitation efficiency, the greedy strategy is adopted to maintain high-quality candidates, ensuring the preservation of optimal solutions and improving computational performance.

$$X_b = \begin{cases} X_{new} \ , & f(X_{new}) < f(X_b) \\ X_b \ , & otherwise \end{cases}, \tag{18}$$

where $f(x)$ denotes the fitness function.

A common approach is to formulate the fitness function using the mean square error derived from the objective function. A smaller error value corresponds to a higher fitness value, indicating the higher quality of the resulting individual solution. The greedy strategy is applied to update the global optimal solution by evaluating and comparing the fitness values of solutions both prior to and following the mutation operation.

3.6. Flowchart of the IDBO algorithm

The flowchart depicting the IDBO algorithm's procedural framework is shown below (Figure 6).

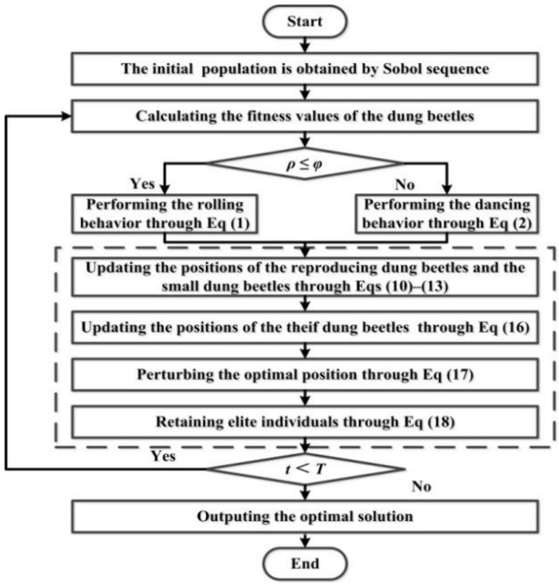

Figure 6. The flowchart of the IDBO algorithm.

3.7. Verification of the algorithm's performance

To assess the optimization efficacy and robustness of the IDBO algorithm, this paper conducts a comparative analysis with eight metaheuristic algorithms: The sparrow search algorithm (SSA) [37], the grey wolf optimizer (GWO) algorithm [38], the Harris hawk optimizer (HHO) algorithm [39], the honey badger algorithm (HBA) [40], the genetic algorithm (GA) [41], the particle swarm optimizer (PSO) algorithm [42], the DBO algorithm, and the IDBO algorithm. The maximum iteration count was set at 400 generations, while a consistent population size of 60 individuals was maintained. The parameter settings of the comparison algorithms are as follows (Table 1).

Table 1. The parameter settings of the comparison algorithms.

Algorithm	Parameter settings
SSA	ST=0.6, PD=0.2, SD=0.1
GWO	r_1= rand(), r_2= rand(), C=2 * r_2
HHO	$E_0 \in (-2,2)$, J=2×(1−rand())
HBA	β=6, C=2
GA	p_c=0.6, p_m=0.3
PSO	w=0.7, c_1=1.2; c_2=1.2
DBO	$k \in (0,0.2]$, $b \in (0,1)$, $\rho \in [0,1]$, φ=0.9, $\theta \in [0, \pi]$

3.7.1. Benchmark test function

To rigorously assess the efficacy of the IDBO algorithm, this paper employs a series of standardized benchmark test functions for a comparative performance analysis. Considering that the CEC2005 test function set has been widely used in earlier studies, its effectiveness and representativeness have become limited in reflecting current algorithms' capabilities. To address increasingly complex optimization problems, the CEC2017 test function set was adopted to thoroughly and systematically evaluate the algorithm's performance, which is currently the most comprehensive and widely accepted benchmark in the research field [43,44]. Detailed information on the CEC2017 test function set is shown in Table 2.

Table 2. CEC2017 test function set.

Type	Functions	Description	Optima
Unimodal functions	F1	Shifted and rotated bent cigar function	100
	F3	Shifted and rotated Zakharov function	300
Multimodal functions	F4	Shifted and rotated Rosenbrock's function	400
	F5	Shifted and rotated Rastrigin's function	500
	F6	Shifted and rotated expanded Scaffer's F6 function	600
	F7	Shifted and rotated Lunacek Bi_Rastrigin function	700
	F8	Shifted and rotated non-continuous Rastrigin's function	800
	F9	Shifted and rotated Levy function	900
	F10	Shifted and rotated Schwefel's function	1000
Hybrid functions	F11	Hybrid function 1 (N=3)	1100
	F12	Hybrid function 2 (N=3)	1200
	F13	Hybrid function 3 (N=3)	1300
	F14	Hybrid function 4 (N=4)	1400
	F15	Hybrid function 5 (N=4)	1500
	F16	Hybrid function 6 (N=4)	1600
	F17	Hybrid function 6 (N=5)	1700
	F18	Hybrid function 6 (N=5)	1800
	F19	Hybrid function 6 (N=5)	1900
	F20	Hybrid function 6 (N=6)	2000
Composite functions	F21	Composite function 1(N=3)	2100
	F22	Composite function 2(N=3)	2200
	F23	Composite function 3(N=4)	2300
	F24	Composite function 4(N=4)	2400
	F25	Composite function 5(N=5)	2500
	F26	Composite function 6(N=5)	2600
	F27	Composite function 7(N=6)	2700
	F28	Composite function 8(N=6)	2800
	F29	Composite function 9(N=3)	2900
	F30	Composite function 10(N=3)	3000

Note: The F2 function has been officially removed and the algorithm operates in the 30 or 50 dimensional optimization space.

3.7.2. Analysis of algorithm optimization capability

To eliminate the influence of randomness, each of the eight algorithms above was independently executed on the benchmark functions for 30 independent runs. Each algorithm was iterated 400 times for every run. The average result across these 30 runs was used as the final performance value for each algorithm. The corresponding evaluation criteria include four indicators: The minimum value, standard deviation, average, and median. These indicators are designed to gauge the algorithm's capability in solving optimization problems. The experimental data are summarized below.

Table 3. The result of algorithm optimization (Dim=30).

Functions	Statistic	SSA	GWO	HHO	HBA	GA	PSO	DBO	IDBO
	Min	1.367E+04	1.054E+08	7.255E+07	2.406E+04	2.836E+09	9.003E+03	2.003E+10	**2.860E+02**
	Std	7.258E+04	2.556E+09	2.020E+08	3.636E+05	5.337E+09	2.047E+09	4.656E+09	**2.663E+03**
F1	Avg	6.970E+04	2.316E+09	3.760E+08	3.032E+05	9.513E+09	1.145E+09	2.855E+10	**2.928E+03**
	Median	4.971E+04	1.731E+09	3.413E+08	1.578E+05	9.768E+09	1.904E+07	2.849E+10	**1.886E+03**
	Worse	2.816E+05	1.183E+10	8.363E+08	1.266E+06	2.430E+10	7.988E+09	3.842E+10	**9.646E+03**
	Min	4.410E+04	4.110E+04	3.600E+04	2.420E+04	1.540E+05	**2.170E+04**	6.590E+04	4.710E+04
	Std	**7.210E+03**	1.420E+04	8.100E+03	7.620E+03	7.080E+04	1.880E+04	2.230E+04	2.190E+04
F3	Avg	5.600E+04	5.770E+04	5.110E+04	**3.680E+04**	2.880E+05	5.180E+04	8.980E+04	8.360E+04
	Median	5.650E+04	5.430E+04	5.240E+04	**3.510E+04**	2.920E+05	5.080E+04	8.810E+04	8.480E+04
	Worse	6.820E+04	8.390E+04	6.470E+04	**5.290E+04**	4.120E+05	8.940E+04	1.770E+05	1.360E+05
	Min	4.866E+02	5.140E+02	5.780E+02	4.710E+02	9.840E+02	4.791E+02	3.790E+03	**4.706E+02**
	Std	2.430E+01	5.170E+01	9.410E+01	2.970E+01	3.829E+02	4.900E+01	1.513E+03	**1.210E+01**
F4	Avg	5.117E+02	6.093E+02	6.912E+02	5.182E+02	1.488E+03	5.434E+02	6.284E+03	**5.103E+02**
	median	5.158E+02	6.112E+02	6.779E+02	5.180E+02	1.510E+03	5.328E+02	6.203E+03	**5.148E+02**
	Worse	5.580E+02	7.159E+02	1.036E+03	6.074E+02	2.422E+03	6.495E+02	9.087E+03	**5.226E+02**
	Min	6.313E+02	5.839E+02	7.012E+02	5.793E+02	8.220E+02	5.867E+02	7.915E+02	**5.717E+02**
	Std	5.190E+01	3.570E+01	3.460E+01	2.740E+01	4.630E+01	3.990E+01	2.470E+01	**1.240E+01**
F5	Avg	7.532E+02	6.264E+02	7.682E+02	6.245E+02	8.999E+02	6.657E+02	8.391E+02	**6.136E+02**
	Median	7.547E+02	6.296E+02	7.682E+02	6.196E+02	8.990E+02	6.751E+02	8.420E+02	**6.166E+02**
	Worse	8.234E+02	7.238E+02	8.276E+02	6.794E+02	9.795E+02	7.334E+02	8.755E+02	**6.334E+02**
	Min	6.368E+02	6.046E+02	6.517E+02	6.055E+02	6.817E+02	6.136E+02	6.610E+02	**5.982E+02**
	Std	9.300E+00	3.600E+00	6.800E+00	6.400E+00	1.560E+01	1.140E+01	5.800E+00	**1.937E-03**
F6	Avg	6.521E+02	6.109E+02	6.656E+02	6.146E+02	7.096E+02	6.322E+02	6.705E+02	**5.833E+02**
	Median	6.511E+02	6.099E+02	6.653E+02	6.142E+02	7.086E+02	6.307E+02	6.704E+02	**6.002E+02**
	Worse	6.654E+02	6.179E+02	6.800E+02	6.283E+02	7.393E+02	6.594E+02	6.812E+02	**6.003E+02**
	Min	1.067E+03	8.343E+02	1.194E+03	8.282E+02	1.337E+03	8.288E+02	1.180E+03	**8.222E+02**
	Std	8.020E+01	5.040E+01	4.300E+01	5.830E+01	1.317E+02	4.460E+01	3.460E+01	**1.370E+01**
F7	Avg	1.245E+03	8.867E+02	1.287E+03	9.126E+02	1.541E+03	9.105E+02	1.224E+03	**8.595E+02**
	Median	1.260E+03	8.731E+02	1.293E+03	8.928E+02	1.526E+03	9.069E+02	1.215E+03	**8.593E+02**
	Worse	1.334E+03	1.023E+03	1.370E+03	1.036E+03	1.768E+03	1.010E+03	1.304E+03	**8.823E+02**
	Min	9.373E+02	8.675E+02	9.381E+02	**8.613E+02**	1.051E+03	8.737E+02	1.025E+03	8.823E+02
	Std	3.150E+01	3.370E+01	2.700E+01	1.930E+01	4.330E+01	3.750E+01	2.270E+01	**1.640E+01**
F8	Avg	9.812E+02	9.056E+02	9.852E+02	**9.030E+02**	1.777E+03	9.317E+02	1.071E+03	9.150E+02
	Median	9.786E+02	**8.990E+02**	9.873E+02	9.042E+02	1.171E+03	9.236E+02	1.067E+03	9.179E+02
	Worse	1.053E+03	9.964E+02	1.031E+03	**9.324E+02**	1.258E+03	1.033E+03	1.111E+03	9.385E+02
	Min	3.639E+03	1.365E+03	6.804E+03	1.548E+03	3.361E+03	1.700E+03	5.880E+03	**9.004E+02**
	Std	4.134E+02	6.084E+02	9.342E+02	8.753E+02	2.061E+03	1.060E+03	1.303E+03	**8.003E+01**
F9	Avg	5.333E+03	2.101E+03	8.544E+03	2.641E+03	6.111E+03	3.709E+03	8.176E+03	**9.005E+02**
	Median	5.451E+03	1.918E+03	8.807E+03	2.611E+03	5.369E+03	3.439E+03	8.232E+03	**9.007E+02**
	Worse	5.571E+03	3.717E+03	1.022E+04	4.544E+03	1.015E+04	6.245E+03	1.060E+04	**9.028E+02**
F10	Min	4.101E+03	**3.372E+03**	5.128E+03	3.946E+03	6.689E+03	3.925E+03	7.093E+03	6.136E+03
	Std	7.477E+02	1.082E+03	6.573E+02	1.076E+03	7.643E+02	6.880E+02	6.380E+02	**5.269E+02**

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Functions	Statistic	SSA	GWO	HHO	HBA	GA	PSO	DBO	IDBO
	Avg	5.563E+03	**4.889E+03**	6.079E+03	5.308E+03	7.861E+03	4.996E+03	8.272E+03	7.038E+03
F10	Median	5.494E+03	**4.658E+03**	6.091E+03	5.361E+03	7.905E+03	5.042E+03	8.460E+03	7.157E+03
	Worse	7.054E+03	7.716E+03	7.791E+03	7.898E+03	9.100E+03	**6.575E+03**	9.115E+03	7.827E+03
	Min	1.175E+03	1.329E+03	1.280E+03	1.196E+03	3.992E+03	1.174E+03	2.755E+03	**1.163E+03**
	Std	6.760E+01	7.955E+02	1.262E+02	6.600E+01	7.880E+03	6.050E+01	1.438E+03	**2.860E+01**
F11	Avg	1.304E+03	2.126E+03	1.480E+03	1.285E+03	1.351E+04	1.273E+03	5.015E+03	**1.218E+03**
	Median	1.293E+03	1.839E+03	1.463E+03	1.275E+03	1.261E+04	1.282E+03	4.682E+03	**1.213E+03**
	Worse	1.437E+03	3.932E+03	1.746E+03	1.457E+03	4.285E+04	1.381E+03	7.727E+03	**1.284E+03**
	Min	1.968E+05	1.088E+06	5.325E+06	9.024E+04	3.632E+06	**2.641E+04**	5.484E+08	6.552E+04
	Std	1.267E+06	6.303E+07	2.209E+07	9.533E+05	2.967E+08	1.712E+08	2.322E+09	**8.879E+05**
F12	Avg	1.821E+06	6.148E+07	3.641E+07	**8.074E+05**	1.972E+08	5.747E+07	5.782E+09	1.021E+06
	Median	1.774E+06	3.021E+07	3.576E+07	**4.193E+05**	9.572E+07	6.881E+05	5.643E+09	7.744E+05
	Worse	5.106E+06	2.055E+08	8.020E+07	4.193E+06	1.329E+09	6.157E+08	9.999E+09	**3.446E+06**
	Min	3.155E+03	7.356E+04	1.351E+05	6.102E+03	4.638E+05	6.370E+03	1.376E+08	**2.225E+03**
	Std	1.608E+04	5.205E+07	1.082E+06	3.050E+04	7.961E+07	2.609E+07	2.290E+09	**1.563E+04**
F13	Avg	1.831E+04	1.434E+07	8.953E+05	4.056E+04	4.787E+07	1.122E+07	2.547E+09	**1.774E+04**
	Median	1.182E+04	2.028E+05	6.547E+05	3.624E+04	1.400E+07	3.438E+04	1.606E+09	**1.165E+04**
	Worse	5.634E+04	2.305E+08	5.260E+06	1.155E+05	3.064E+08	7.168E+07	8.629E+09	**4.821E+04**
	Min	6.348E+03	2.132E+04	1.695E+04	4.024E+03	2.352E+05	**1.994E+03**	8.594E+04	2.855E+03
	Std	9.353E+04	7.162E+05	1.428E+06	**3.164E+04**	6.825E+06	7.519E+04	5.328E+05	2.444E+05
F14	Avg	1.037E+05	7.681E+05	1.428E+06	**3.490E+04**	6.511E+06	5.684E+04	6.969E+05	1.311E+05
	Median	9.390E+04	5.656E+05	9.658E+05	3.120E+04	4.821E+06	**2.642E+04**	6.661E+05	5.276E+04
	Worse	4.291E+05	2.519E+06	5.211E+06	**1.037E+05**	2.873E+07	2.743E+05	2.022E+06	1.114E+06
	Min	1.731E+03	2.001E+04	4.633E+04	2.153E+03	7.321E+04	2.608E+03	3.469E+05	**1.671E+03**
	Std	7.678E+03	5.654E+05	4.170E+04	2.776E+04	8.030E+06	1.659E+04	6.254E+06	**4.733E+03**
F15	Avg	8.142E+03	3.158E+05	9.653E+04	2.241E+04	2.729E+06	1.438E+04	5.773E+06	**5.628E+03**
	Median	6.159E+03	9.149E+04	9.063E+04	1.250E+04	4.977E+05	6.731E+03	3.533E+06	**3.967E+03**
	Worse	3.004E+04	2.318E+06	2.180E+05	1.217E+05	3.644E+07	6.099E+04	2.245E+07	**1.678E+04**
	Min	2.203E+03	2.168E+03	2.645E+03	2.229E+03	2.913E+03	2.210E+03	3.077E+03	**2.079E+03**
	Std	4.103E+02	4.242E+02	4.825E+02	3.509E+02	4.003E+02	3.177E+02	4.383E+02	**1.927E+02**
F16	Avg	2.914E+03	2.694E+03	3.410E+03	2.755E+03	3.690E+03	2.697E+03	3.996E+03	**2.528E+03**
	Median	2.780E+03	2.567E+03	3.288E+03	2.759E+03	3.679E+03	2.710E+03	4.059E+03	**2.533E+03**
	Worse	3.747E+03	3.783E+03	4.588E+03	3.641E+03	4.611E+03	3.243E+03	4.675E+03	**2.870E+03**
	Min	2.126E+03	1.923E+03	2.305E+03	1.908E+03	2.331E+03	1.800E+03	2.202E+03	**1.756E+03**
	Std	2.300E+02	1.296E+02	2.103E+02	2.467E+02	1.896E+02	2.037E+02	2.492E+02	**1.005E+02**
F17	Avg	2.556E+03	2.135E+03	2.672E+03	2.368E+03	2.701E+03	2.209E+03	2.809E+03	**1.883E+03**
	Median	2.539E+03	2.115E+03	2.657E+03	2.349E+03	2.741E+03	2.213E+03	2.823E+03	**1.894E+03**
	Worse	2.888E+03	2.449E+03	3.103E+03	2.789E+03	3.071E+03	2.498E+03	3.326E+03	**2.092E+03**
	Min	1.127E+05	1.123E+05	2.152E+05	7.419E+04	8.326E+05	**4.274E+04**	1.006E+06	1.043E+05
	Std	1.264E+06	4.502E+06	5.988E+06	3.119E+05	1.542E+07	**2.334E+05**	2.860E+06	1.256E+06
F18	Avg	1.294E+06	2.955E+06	5.199E+06	3.807E+05	1.403E+07	**2.605E+05**	4.935E+06	1.179E+06
	Median	9.317E+05	1.406E+06	2.682E+06	2.543E+05	7.182E+06	**1.564E+05**	4.311E+06	7.578E+05
	Worse	5.282E+06	1.913E+07	2.012E+07	1.150E+06	5.505E+07	**7.839E+05**	9.595E+06	5.429E+06

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Functions	Statistic	SSA	GWO	HHO	HBA	GA	PSO	DBO	IDBO
	Min	2.083E+03	3.308E+04	1.070E+05	2.168E+03	4.004E+05	2.086E+03	9.872E+06	**1.989E+03**
	Std	1.349E+04	9.591E+06	1.114E+06	7.825E+03	4.052E+06	**4.576E+03**	1.335E+08	9.072E+03
F19	Avg	1.027E+04	4.069E+06	1.342E+06	8.879E+03	3.179E+06	**7.157E+03**	1.836E+08	8.829E+03
	Median	**4.010E+03**	1.176E+06	8.922E+05	6.377E+03	1.359E+06	5.566E+03	1.553E+08	5.326E+03
	Worse	5.343E+04	4.185E+07	3.961E+06	2.628E+04	1.337E+07	**1.560E+04**	6.097E+08	3.636E+04
	Min	2.281E+03	2.233E+03	2.310E+03	2.218E+03	2.586E+03	2.300E+03	2.473E+03	**2.044E+03**
	Std	2.473E+02	1.522E+02	2.136E+02	1.946E+02	2.669E+02	1.830E+02	1.864E+02	**1.395E+02**
F20	Avg	2.715E+03	2.388E+03	2.800E+03	2.502E+03	3.012E+03	2.599E+03	2.837E+03	**2.298E+03**
	Median	2.767E+03	2.337E+03	2.867E+03	2.474E+03	3.008E+03	2.614E+03	2.842E+03	**2.312E+03**
	Worse	3.136E+03	2.660E+03	3.107E+03	2.955E+03	3.490E+03	2.939E+03	3.124E+03	**2.573E+03**
	Min	2.444E+03	2.365E+03	2.463E+03	**2.212E+03**	2.680E+03	2.394E+03	2.385E+03	2.380E+03
	Std	4.334E+01	4.179E+01	5.372E+01	5.309E+01	5.256E+01	3.748E+01	7.864E+01	**1.280E+01**
F21	Avg	2.526E+03	2.420E+03	2.592E+03	**2.405E+03**	2.759E+03	2.442E+03	2.585E+03	2.413E+03
	Median	2.522E+03	**2.407E+03**	2.591E+03	2.409E+03	2.757E+03	2.437E+03	2.608E+03	2.413E+03
	Worse	2.623E+03	2.515E+03	2.688E+03	2.476E+03	2.887E+03	2.530E+03	2.669E+03	**2.439E+03**
	Min	2.302E+03	2.462E+03	2.745E+03	2.303E+03	3.521E+03	2.417E+03	4.610E+03	**2.300E+03**
	Std	2.037E+03	1.635E+03	1.514E+03	2.769E+03	2.124E+03	2.000E+03	6.438E+02	**2.847E+02**
F22	Avg	5.932E+03	4.353E+03	6.866E+03	5.270E+03	8.088E+03	4.554E+03	5.865E+03	**3.895E+03**
	Median	6.372E+03	4.934E+03	7.341E+03	6.455E+03	8.862E+03	4.295E+03	5.944E+03	**2.304E+03**
	Worse	8.467E+03	9.164E+03	8.849E+03	8.648E+03	1.052E+04	7.488E+03	6.762E+03	**6.555E+03**
	Min	2.765E+03	2.726E+03	3.036E+03	2.711E+03	3.065E+03	2.817E+03	3.024E+03	**2.703E+03**
	Std	9.018E+01	2.952E+01	1.187E+02	4.907E+01	8.786E+01	6.670E+01	9.583E+01	**2.035E+01**
F23	Avg	2.940E+03	2.766E+03	3.220E+03	2.794E+03	3.236E+03	2.932E+03	3.188E+03	**2.752E+03**
	Median	2.928E+03	2.760E+03	3.189E+03	2.786E+03	3.243E+03	2.927E+03	3.200E+03	**2.754E+03**
	Worse	3.123E+03	2.807E+03	3.466E+03	2.913E+03	3.395E+03	3.042E+03	3.357E+03	**2.788E+03**
	Min	2.970E+03	**2.874E+03**	3.170E+03	2.886E+03	3.329E+03	2.975E+03	3.250E+03	2.923E+03
	Std	1.043E+02	5.757E+01	1.434E+02	1.781E+02	1.031E+02	7.629E+01	9.264E+01	**1.209E+01**
F24	Avg	3.119E+03	**2.933E+03**	3.402E+03	3.077E+03	3.505E+03	3.114E+03	3.397E+03	2.942E+03
	Median	3.093E+03	**2.915E+03**	3.396E+03	3.027E+03	3.488E+03	3.105E+03	3.375E+03	2.945E+03
	Worse	3.396E+03	3.089E+03	3.787E+03	3.578E+03	3.724E+03	3.276E+03	3.595E+03	**2.963E+03**
	Min	2.887E+03	2.934E+03	2.930E+03	2.887E+03	3.577E+03	2.887E+03	3.517E+03	**2.884E+03**
	Std	1.624E+01	3.958E+01	4.245E+01	1.173E+01	3.798E+02	3.391E+01	2.133E+02	**8.362E+00**
F25	Avg	2.902E+03	3.003E+03	3.008E+03	2.909E+03	4.068E+03	2.927E+03	3.979E+03	**2.892E+03**
	Median	2.897E+03	2.994E+03	3.013E+03	2.911E+03	4.050E+03	2.926E+03	3.989E+03	**2.889E+03**
	Worse	2.942E+03	3.082E+03	3.072E+03	2.925E+03	5.326E+03	3.017E+03	4.260E+03	**2.921E+03**
	Min	2.914E+03	3.962E+03	4.082E+03	2.924E+03	6.666E+03	4.024E+03	6.944E+03	**2.857E+03**
	Std	1.059E+03	3.290E+02	1.095E+03	9.684E+02	9.004E+02	1.384E+03	6.681E+02	**2.265E+02**
F26	Avg	6.494E+03	4.783E+03	8.326E+03	5.171E+03	8.013E+03	5.183E+03	7.997E+03	**4.526E+03**
	Median	6.454E+03	4.753E+03	8.519E+03	5.151E+03	7.897E+03	5.339E+03	7.942E+03	**4.553E+03**
	Worse	8.055E+03	5.399E+03	9.355E+03	7.150E+03	1.072E+04	7.361E+03	9.498E+03	**4.845E+03**
	Min	3.226E+03	3.221E+03	3.303E+03	3.226E+03	3.581E+03	3.247E+03	3.355E+03	**3.201E+03**
F27	Std	3.936E+01	2.787E+01	1.890E+02	1.245E+02	2.133E+02	3.145E+01	1.534E+02	**4.734E+00**
	Avg	3.280E+03	3.254E+03	3.537E+03	3.310E+03	3.852E+03	3.298E+03	3.627E+03	**3.213E+03**

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Functions	Statistic	SSA	GWO	HHO	HBA	GA	PSO	DBO	IDBO
F27	Median	3.277E+03	3.254E+03	3.519E+03	3.270E+03	3.787E+03	3.299E+03	3.617E+03	**3.215E+03**
	Worse	3.373E+03	3.339E+03	3.949E+03	3.722E+03	4.302E+03	3.361E+03	3.907E+03	**3.218E+03**
	Min	3.220E+03	3.261E+03	3.357E+03	3.215E+03	3.754E+03	3.238E+03	4.613E+03	**3.213E+03**
	Std	2.638E+01	1.088E+02	7.592E+01	2.836E+01	5.766E+02	5.812E+01	3.338E+02	**1.907E+01**
F28	Avg	3.256E+03	3.419E+03	3.460E+03	3.256E+03	4.888E+03	3.321E+03	5.125E+03	**3.251E+03**
	Median	3.258E+03	3.408E+03	3.446E+03	3.258E+03	4.970E+03	3.305E+03	5.107E+03	**3.258E+03**
	Worse	3.322E+03	3.808E+03	3.611E+03	3.304E+03	6.153E+03	3.456E+03	5.712E+03	**3.277E+03**
	Min	3.782E+03	3.487E+03	4.403E+03	3.623E+03	4.424E+03	3.729E+03	4.317E+03	**3.429E+03**
	Std	2.784E+02	3.550E+02	3.089E+02	5.892E+02	3.553E+02	1.949E+02	4.795E+02	**1.166E+02**
F29	Avg	4.225E+03	3.883E+03	4.861E+03	4.499E+03	4.991E+03	4.084E+03	5.148E+03	**3.586E+03**
	Median	4.243E+03	3.825E+03	4.825E+03	4.323E+03	4.978E+03	4.151E+03	5.096E+03	**3.570E+03**
	Worse	4.727E+03	5.194E+03	5.468E+03	6.080E+03	5.763E+03	4.383E+03	6.439E+03	**3.922E+03**
	Min	8.846E+03	3.259E+06	2.715E+06	1.034E+04	2.850E+05	1.430E+04	5.224E+07	**7.604E+03**
	Std	1.281E+04	4.865E+06	7.715E+06	4.206E+04	1.901E+07	9.148E+04	1.921E+08	**6.192E+03**
F30	Avg	2.046E+04	8.079E+06	1.005E+07	4.697E+04	1.473E+07	8.713E+04	1.781E+08	**1.502E+04**
	Median	1.557E+04	6.722E+06	8.978E+06	2.859E+04	9.583E+06	3.818E+04	1.338E+08	**1.358E+04**
	Worse	4.753E+04	2.348E+07	3.788E+07	1.726E+05	8.651E+07	2.828E+05	9.452E+08	**3.439E+04**

Note: The performance metrics of the best-performing algorithm are presented in bold to indicate superior performance.

Table 4. The results of algorithm optimization (Dim=50).

Functions	Statistic	SSA	GWO	HHO	HBA	GA	PSO	DBO	IDBO
	Min	3.027E+06	2.360E+09	1.431E+09	2.690E+07	3.002E+10	2.218E+08	6.284E+10	**1.138E+06**
	Std	3.267E+06	4.296E+09	1.216E+09	2.402E+09	2.415E+10	2.965E+09	6.067E+09	**4.821E+05**
F1	Avg	7.375E+06	7.512E+09	3.020E+09	1.057E+09	7.811E+10	3.773E+09	7.279E+10	**1.905E+06**
	Median	6.846E+06	6.913E+09	2.707E+09	8.661E+07	7.798E+10	3.008E+09	7.214E+10	**1.960E+06**
	Worse	1.886E+07	2.221E+10	6.160E+09	9.928E+09	1.299E+11	1.288E+10	8.760E+10	**3.404E+06**
	Min	1.575E+05	9.882E+04	**9.345E+04**	9.983E+04	2.329E+05	9.744E+04	1.523E+05	1.571E+05
	Std	5.700E+04	2.124E+04	1.922E+04	**1.724E+04**	1.034E+05	5.047E+04	3.553E+04	3.815E+04
F3	Avg	2.637E+05	1.354E+05	1.432E+05	**1.289E+05**	4.272E+05	1.770E+05	2.177E+05	2.167E+05
	Median	2.766E+05	1.354E+05	1.439E+05	**1.295E+05**	3.989E+05	1.688E+05	2.146E+05	2.177E+05
	Worse	4.031E+05	1.797E+05	1.799E+05	**1.679E+05**	7.152E+05	3.257E+05	3.058E+05	2.934E+05
	Min	5.353E+02	7.593E+02	1.050E+03	5.410E+02	3.993E+03	6.699E+02	1.314E+04	**5.023E+02**
	Std	4.507E+01	3.841E+02	3.683E+02	6.728E+01	4.900E+03	3.635E+02	1.799E+03	**3.502E+01**
F4	Avg	6.226E+02	1.176E+03	1.535E+03	6.557E+02	1.121E+04	9.446E+02	1.570E+04	**5.699E+02**
	Median	6.258E+02	1.146E+03	1.417E+03	6.635E+02	1.053E+04	8.338E+02	1.543E+04	**5.696E+02**
	Worse	6.949E+02	2.685E+03	2.492E+03	8.245E+02	2.245E+04	2.469E+03	1.998E+04	**6.341E+02**
	Min	8.354E+02	6.424E+02	8.508E+02	6.973E+02	1.142E+03	6.918E+02	1.037E+03	**5.976E+02**
	Std	2.098E+01	5.333E+01	3.426E+01	3.777E+01	8.304E+01	5.046E+01	3.437E+01	**2.794E+01**
F5	Avg	8.771E+02	7.343E+02	9.172E+02	7.559E+02	1.285E+03	7.819E+02	1.097E+03	**6.434E+02**
	Median	8.767E+02	7.265E+02	9.171E+02	7.513E+02	1.274E+03	7.764E+02	1.101E+03	**6.500E+02**
	Worse	9.459E+02	9.474E+02	9.855E+02	8.362E+02	1.527E+03	9.310E+02	1.153E+03	**6.961E+02**

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Functions	Statistic	SSA	GWO	HHO	HBA	GA	PSO	DBO	IDBO
	Min	6.468E+02	6.112E+02	6.670E+02	6.172E+02	7.088E+02	6.328E+02	6.723E+02	**6.006E+02**
	Std	6.127E+00	4.058E+00	4.353E+00	7.696E+00	9.926E+00	6.591E+00	5.762E+00	**4.651E-01**
F6	Avg	6.627E+02	6.196E+02	6.779E+02	6.311E+02	7.295E+02	6.463E+02	6.857E+02	**6.012E+02**
	Median	6.630E+02	6.193E+02	6.784E+02	6.310E+02	7.292E+02	6.465E+02	6.852E+02	**6.012E+02**
	Worse	6.719E+02	6.295E+02	6.857E+02	6.519E+02	7.478E+02	6.618E+02	6.958E+02	**6.024E+02**
	Min	1.114E+03	9.757E+02	1.149E+03	9.968E+02	1.398E+03	9.677E+02	1.347E+03	**8.827E+02**
	Std	2.981E+01	6.541E+01	3.355E+01	4.388E+01	8.494E+01	5.321E+01	2.505E+01	**2.334E+01**
F7	Avg	1.203E+03	1.044E+03	1.209E+03	1.066E+03	1.528E+03	1.087E+03	1.397E+03	**9.402E+02**
	Median	1.217E+03	1.032E+03	1.209E+03	1.064E+03	1.537E+03	1.096E+03	1.396E+03	**9.455E+02**
	Worse	1.244E+03	1.352E+03	1.271E+03	1.180E+03	1.788E+03	1.180E+03	1.445E+03	**9.784E+02**
	Min	1.114E+03	9.757E+02	1.149E+03	9.968E+02	1.398E+03	9.677E+02	1.347E+03	**8.827E+02**
	Std	2.981E+01	6.541E+01	3.355E+01	4.388E+01	8.494E+01	5.321E+01	2.505E+01	**2.334E+01**
F8	Avg	1.203E+03	1.044E+03	1.209E+03	1.066E+03	1.528E+03	1.087E+03	1.397E+03	**9.402E+02**
	Median	1.217E+03	1.032E+03	1.209E+03	1.064E+03	1.537E+03	1.096E+03	1.396E+03	**9.455E+02**
	Worse	1.244E+03	1.352E+03	1.271E+03	1.180E+03	1.788E+03	1.180E+03	1.445E+03	**9.784E+02**
	Min	1.099E+04	2.975E+03	2.442E+04	4.903E+03	1.356E+04	5.240E+03	1.949E+04	**2.407E+03**
	Std	2.008E+03	4.335E+03	2.983E+03	4.016E+03	7.080E+03	2.428E+03	4.396E+03	**1.332E+03**
F9	Avg	1.377E+04	8.291E+03	3.035E+04	9.801E+03	2.734E+04	1.007E+04	3.280E+04	**5.602E+03**
	Median	1.360E+04	7.857E+03	3.017E+04	8.353E+03	2.658E+04	1.004E+04	3.276E+04	**5.590E+03**
	Worse	1.979E+04	1.772E+04	3.783E+04	2.308E+04	3.980E+04	1.579E+04	3.966E+04	**1.171E+04**
	Min	6.569E+03	6.678E+03	8.593E+03	5.339E+03	1.158E+04	5.249E+03	1.191E+04	**4.315E+03**
	Std	8.497E+02	2.210E+03	7.644E+02	1.962E+03	8.773E+02	9.411E+02	8.664E+02	**5.399E+02**
F10	Avg	8.531E+03	8.560E+03	1.003E+04	8.636E+03	1.391E+04	7.765E+03	1.432E+04	**5.898E+03**
	Median	8.548E+03	7.788E+03	9.998E+03	8.708E+03	1.404E+04	7.717E+03	1.457E+04	**5.976E+03**
	Worse	1.009E+04	1.542E+04	1.261E+04	1.356E+04	1.593E+04	9.579E+03	1.564E+04	**6.775E+03**
	Min	1.366E+03	1.968E+03	1.765E+03	1.325E+03	1.598E+04	1.229E+03	8.349E+03	**1.265E+03**
	Std	**8.821E+01**	1.964E+03	4.226E+02	3.319E+02	1.393E+04	1.232E+02	2.228E+03	7.662E+02
F11	Avg	**1.493E+03**	4.778E+03	2.364E+03	1.587E+03	4.067E+04	1.504E+03	1.263E+04	1.834E+03
	Median	1.494E+03	4.404E+03	2.266E+03	1.515E+03	4.166E+04	**1.482E+03**	1.265E+04	1.484E+03
	Worse	**1.719E+03**	9.528E+03	3.729E+03	3.209E+03	6.762E+04	1.790E+03	1.626E+04	3.955E+03
	Min	4.245E+06	2.769E+07	1.153E+08	3.984E+06	2.371E+09	2.861E+07	2.321E+10	**2.566E+06**
	Std	8.707E+06	5.755E+08	3.060E+08	1.254E+07	5.109E+09	2.255E+09	6.060E+09	**5.064E+06**
F12	Avg	1.681E+07	7.363E+08	5.291E+08	1.547E+07	8.425E+09	1.304E+09	3.513E+10	**9.520E+06**
	Median	1.631E+07	6.081E+08	4.178E+08	1.119E+07	7.677E+09	2.681E+08	3.469E+10	**8.300E+06**
	Worse	5.074E+07	1.965E+09	1.224E+09	5.320E+07	2.153E+10	1.035E+10	5.067E+10	**2.610E+07**
	Min	4.245E+06	2.769E+07	1.153E+08	3.984E+06	2.371E+09	2.861E+07	2.321E+10	**2.566E+06**
	Std	8.707E+06	5.755E+08	3.060E+08	1.254E+07	5.109E+09	2.255E+09	6.060E+09	**5.064E+06**
F13	Avg	1.681E+07	7.363E+08	5.291E+08	1.547E+07	8.425E+09	1.304E+09	3.513E+10	**9.520E+06**
	Median	1.631E+07	6.081E+08	4.178E+08	1.119E+07	7.677E+09	2.681E+08	3.469E+10	**8.300E+06**
	Worse	5.074E+07	1.965E+09	1.224E+09	5.320E+07	2.153E+10	1.035E+10	5.067E+10	**2.610E+07**
F14	Min	1.602E+05	1.189E+05	3.316E+05	5.209E+04	2.617E+06	**1.072E+04**	1.441E+06	1.263E+05
	Std	4.319E+05	1.551E+06	1.982E+06	**1.959E+05**	3.140E+07	2.935E+05	7.357E+06	7.619E+05

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Functions	Statistic	SSA	GWO	HHO	HBA	GA	PSO	DBO	IDBO
	Avg	6.654E+05	1.379E+06	2.757E+06	2.347E+05	3.168E+07	**1.917E+05**	9.495E+06	1.124E+06
F14	Median	5.570E+05	8.633E+05	1.974E+06	1.467E+05	2.089E+07	**1.152E+05**	8.832E+06	8.490E+05
	Worse	1.950E+06	5.220E+06	8.725E+06	**7.702E+05**	1.533E+08	1.541E+06	3.621E+07	2.685E+06
	Min	3.382E+03	4.537E+04	1.995E+05	3.778E+03	6.977E+05	4.218E+03	2.385E+08	**1.750E+03**
	Std	7.003E+03	1.776E+07	3.826E+05	2.236E+04	8.053E+08	9.076E+03	7.541E+08	**7.001E+03**
F15	Avg	1.543E+04	1.408E+07	9.763E+05	3.469E+04	2.635E+08	1.619E+04	1.670E+09	**8.725E+03**
	Median	1.761E+04	9.597E+06	9.267E+05	2.680E+04	3.221E+07	1.363E+04	1.738E+09	**4.740E+03**
	Worse	2.840E+04	6.145E+07	1.933E+06	1.060E+05	4.303E+09	3.961E+04	3.846E+09	**1.968E+04**
	Min	2.621E+03	2.718E+03	3.127E+03	2.638E+03	3.792E+03	2.747E+03	4.181E+03	**2.485E+03**
	Std	5.052E+02	4.585E+02	7.365E+02	4.841E+02	7.097E+02	4.521E+02	6.207E+02	**2.738E+02**
F16	Avg	3.875E+03	3.345E+03	4.531E+03	3.371E+03	5.476E+03	3.560E+03	5.658E+03	**3.006E+03**
	Median	3.972E+03	3.247E+03	4.483E+03	3.443E+03	5.563E+03	3.569E+03	5.607E+03	**3.042E+03**
	Worse	4.733E+03	4.861E+03	6.318E+03	4.393E+03	6.776E+03	4.543E+03	7.320E+03	**3.557E+03**
	Min	2.661E+03	2.389E+03	3.012E+03	2.552E+03	3.420E+03	2.556E+03	4.148E+03	**2.319E+03**
	Std	4.452E+02	3.460E+02	4.338E+02	3.687E+02	6.432E+02	3.556E+02	4.789E+02	**2.276E+02**
F17	Avg	3.499E+03	3.002E+03	3.822E+03	3.228E+03	4.445E+03	3.294E+03	4.851E+03	**2.774E+03**
	Median	3.460E+03	2.962E+03	3.800E+03	3.265E+03	4.378E+03	3.282E+03	4.796E+03	**2.773E+03**
	Worse	4.692E+03	4.199E+03	4.838E+03	3.816E+03	5.881E+03	3.890E+03	5.826E+03	**3.303E+03**
	Min	4.175E+05	7.331E+05	1.802E+06	1.570E+05	1.478E+06	1.069E+05	1.570E+06	**1.880E+05**
	Std	2.318E+06	5.368E+06	7.078E+06	2.397E+06	5.477E+07	1.565E+06	1.834E+07	**1.471E+06**
F18	Avg	3.670E+06	6.049E+06	7.756E+06	1.875E+06	5.725E+07	**1.157E+06**	2.449E+07	2.150E+06
	Median	3.583E+06	4.511E+06	6.410E+06	1.222E+06	3.633E+07	**6.488E+05**	1.904E+07	1.774E+06
	Worse	8.364E+06	2.615E+07	3.877E+07	1.077E+07	2.282E+08	7.591E+06	6.319E+07	**5.452E+06**
	Min	3.489E+03	1.264E+05	1.798E+05	2.530E+03	4.652E+06	2.269E+03	1.257E+08	**2.108E+03**
	Std	1.329E+04	9.524E+06	1.529E+06	1.442E+04	4.603E+07	1.623E+05	4.945E+08	**6.146E+03**
F19	Avg	2.074E+04	6.194E+06	1.669E+06	1.937E+04	3.685E+07	5.125E+04	9.719E+08	**8.325E+03**
	Median	1.700E+04	1.313E+06	1.166E+06	1.912E+04	2.064E+07	1.552E+04	1.049E+09	**6.274E+03**
	Worse	4.442E+04	3.748E+07	5.856E+06	4.976E+04	2.288E+08	9.059E+05	2.448E+09	**2.270E+04**
	Min	2.281E+03	2.233E+03	2.310E+03	2.218E+03	2.586E+03	2.300E+03	2.473E+03	**2.044E+03**
	Std	2.473E+02	1.522E+02	2.136E+02	1.946E+02	2.669E+02	1.830E+02	1.864E+02	**1.395E+02**
F20	Avg	2.715E+03	2.388E+03	2.800E+03	2.502E+03	3.012E+03	2.599E+03	2.837E+03	**2.298E+03**
	Median	2.767E+03	2.337E+03	2.867E+03	2.474E+03	3.008E+03	2.614E+03	2.842E+03	**2.312E+03**
	Worse	3.136E+03	2.660E+03	3.107E+03	2.955E+03	3.490E+03	2.939E+03	3.124E+03	**2.573E+03**
	Min	2.597E+03	2.447E+03	2.782E+03	2.439E+03	3.045E+03	2.499E+03	2.888E+03	**2.417E+03**
	Std	9.609E+01	3.662E+01	7.586E+01	5.027E+01	1.027E+02	5.657E+01	4.565E+01	**1.910E+01**
F21	Avg	2.759E+03	2.523E+03	2.923E+03	2.520E+03	3.225E+03	2.606E+03	2.977E+03	**2.452E+03**
	Median	2.761E+03	2.524E+03	2.926E+03	2.517E+03	3.231E+03	2.610E+03	2.969E+03	**2.451E+03**
	Worse	3.058E+03	2.586E+03	3.048E+03	2.621E+03	3.427E+03	2.702E+03	3.061E+03	**2.499E+03**
	Min	2.302E+03	2.462E+03	2.745E+03	2.303E+03	3.521E+03	2.417E+03	4.610E+03	**2.300E+03**
	Std	2.037E+03	1.635E+03	1.514E+03	2.769E+03	2.124E+03	2.000E+03	6.438E+02	**2.847E+02**
F22	Avg	5.932E+03	4.353E+03	6.866E+03	5.270E+03	8.088E+03	4.554E+03	5.865E+03	**3.895E+03**
	Median	6.372E+03	4.934E+03	7.341E+03	6.455E+03	8.862E+03	4.295E+03	5.944E+03	**2.304E+03**
	Worse	8.467E+03	9.164E+03	8.849E+03	8.648E+03	1.052E+04	7.488E+03	6.762E+03	**6.555E+03**

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Functions	Statistic	SSA	GWO	HHO	HBA	GA	PSO	DBO	IDBO
	Min	8.547E+03	7.593E+03	1.033E+04	7.255E+03	1.491E+04	7.558E+03	1.261E+04	**5.839E+03**
	Std	1.026E+03	1.464E+03	8.249E+02	2.616E+03	7.094E+02	9.408E+02	1.198E+03	**7.360E+02**
F23	Avg	1.040E+04	9.411E+03	1.199E+04	1.086E+04	1.645E+04	9.761E+03	1.571E+04	**7.670E+03**
	Median	1.057E+04	9.092E+03	1.210E+04	1.033E+04	1.660E+04	9.972E+03	1.600E+04	**7.808E+03**
	Worse	1.209E+04	1.532E+04	1.331E+04	1.880E+04	1.805E+04	1.125E+04	1.731E+04	**8.824E+03**
	Min	3.335E+03	3.062E+03	3.796E+03	3.091E+03	3.938E+03	3.184E+03	3.798E+03	**3.043E+03**
	Std	1.397E+02	9.309E+01	2.199E+02	1.219E+02	2.081E+02	1.424E+02	1.849E+02	**4.510E+01**
F24	Avg	3.530E+03	3.147E+03	4.207E+03	3.236E+03	4.348E+03	3.526E+03	4.123E+03	**3.106E+03**
	Median	3.512E+03	3.120E+03	4.228E+03	3.206E+03	4.344E+03	3.531E+03	4.089E+03	**3.105E+03**
	Worse	3.757E+03	3.409E+03	4.653E+03	3.591E+03	4.863E+03	3.854E+03	4.541E+03	**3.249E+03**
	Min	3.049E+03	3.158E+03	3.335E+03	3.055E+03	7.731E+03	3.124E+03	8.798E+03	**3.005E+03**
	Std	4.033E+01	3.397E+02	1.242E+02	9.160E+01	4.098E+03	3.471E+02	8.641E+02	**2.249E+01**
F25	Avg	3.137E+03	3.693E+03	3.586E+03	3.220E+03	1.335E+04	3.372E+03	1.071E+04	**3.067E+03**
	Median	3.132E+03	3.660E+03	3.584E+03	3.201E+03	1.371E+04	3.296E+03	1.089E+04	**3.071E+03**
	Worse	3.230E+03	4.820E+03	3.784E+03	3.526E+03	2.365E+04	5.028E+03	1.239E+04	**3.116E+03**
	Min	3.615E+03	5.637E+03	1.023E+04	3.940E+03	1.101E+04	4.818E+03	1.161E+04	**3.218E+03**
	Std	2.651E+03	9.453E+02	8.059E+02	1.113E+03	1.526E+03	1.592E+03	9.196E+02	**3.856E+02**
F26	Avg	9.407E+03	6.673E+03	1.202E+04	6.557E+03	1.402E+04	8.535E+03	1.385E+04	**5.163E+03**
	Median	1.041E+04	6.497E+03	1.208E+04	6.600E+03	1.415E+04	8.762E+03	1.388E+04	**5.168E+03**
	Worse	1.245E+04	9.320E+03	1.340E+04	9.447E+03	1.795E+04	1.143E+04	1.530E+04	**6.008E+03**
	Min	3.226E+03	3.221E+03	3.303E+03	3.226E+03	3.581E+03	3.247E+03	3.355E+03	**3.201E+03**
	Std	3.936E+01	2.787E+01	1.890E+02	1.245E+02	2.133E+02	3.145E+01	1.534E+02	**4.734E+00**
F27	Avg	3.280E+03	3.254E+03	3.537E+03	3.310E+03	3.852E+03	3.298E+03	3.627E+03	**3.213E+03**
	Median	3.277E+03	3.254E+03	3.519E+03	3.270E+03	3.787E+03	3.299E+03	3.617E+03	**3.215E+03**
	Worse	3.373E+03	3.339E+03	3.949E+03	3.722E+03	4.302E+03	3.361E+03	3.907E+03	**3.218E+03**
	Min	3.355E+03	3.663E+03	3.769E+03	3.365E+03	6.876E+03	3.579E+03	6.692E+03	**3.292E+03**
	Std	5.547E+01	3.640E+02	3.951E+02	1.491E+02	1.323E+03	5.384E+02	6.312E+02	**1.714E+01**
F28	Avg	3.458E+03	4.354E+03	4.546E+03	3.530E+03	9.429E+03	4.076E+03	8.356E+03	**3.345E+03**
	Median	3.445E+03	4.297E+03	4.567E+03	3.497E+03	9.697E+03	3.889E+03	8.327E+03	**3.346E+03**
	Worse	3.589E+03	5.042E+03	5.480E+03	3.914E+03	1.157E+04	5.478E+03	9.544E+03	**3.376E+03**
	Min	4.055E+03	4.164E+03	5.777E+03	4.112E+03	5.997E+03	4.095E+03	7.514E+03	**3.370E+03**
	Std	4.154E+02	3.077E+02	7.046E+02	1.024E+03	9.280E+02	5.912E+02	1.831E+03	**2.262E+02**
F29	Avg	5.161E+03	4.759E+03	6.813E+03	5.049E+03	7.591E+03	5.288E+03	1.036E+04	**3.901E+03**
	Median	5.168E+03	4.754E+03	6.721E+03	4.737E+03	7.439E+03	5.257E+03	1.040E+04	**3.920E+03**
	Worse	5.824E+03	5.382E+03	8.889E+03	9.153E+03	9.591E+03	6.791E+03	1.493E+04	**4.332E+03**
	Min	4.055E+03	4.164E+03	5.777E+03	4.112E+03	5.997E+03	4.095E+03	7.514E+03	**3.370E+03**
	Std	4.154E+02	3.077E+02	7.046E+02	1.024E+03	9.280E+02	5.912E+02	1.831E+03	**2.262E+02**
F30	Avg	5.161E+03	4.759E+03	6.813E+03	5.049E+03	7.591E+03	5.288E+03	1.036E+04	**3.901E+03**
	Median	5.168E+03	4.754E+03	6.721E+03	4.737E+03	7.439E+03	5.257E+03	1.040E+04	**3.920E+03**
	Worse	5.824E+03	5.382E+03	8.889E+03	9.153E+03	9.591E+03	6.791E+03	1.493E+04	**4.332E+03**

Note: The performance metrics of the best-performing algorithm are presented in bold to indicate superior performance.

As presented in Table 3, when the dimension is 30, the IDBO algorithm demonstrates superior performance compared with its counterparts. For unimodal functions, the IDBO algorithm outperforms most comparative methods, with the exception of F3. The IDBO algorithm demonstrates superior performance in optimizing multimodal functions, with the exception of its performance on F8 and F10. Moreover, for hybrid and composite functions, the IDBO algorithm outperforms other algorithms, except for F12, F14, F18, F19, F21, and F24.

As presented in Table 4, when the dimension is 50, the performance of the IDBO algorithm was exceptional across F1 to F30. Its various evaluation criteria consistently ranked first in most functions, exhibiting only minor deficiencies in F3, F11, F14, and F18.

3.7.3. Analysis of the algorithm's convergence capability

In addition to assessing the algorithm's optimization capability, its convergence capability is also a crucial factor in evaluating its overall performance. Therefore, to further assess the convergence capability of the IDBO algorithm, this paper comparatively analyzes the convergence trends of eight optimization algorithms using the CEC2017 benchmark test set. As shown in Figures 7–26, the obtained results are graphically demonstrated.

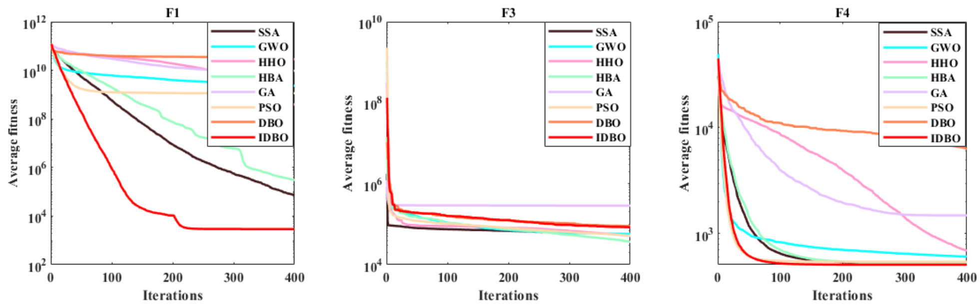

Figure 7. Convergence curves of F1–F4 (Dim=30).

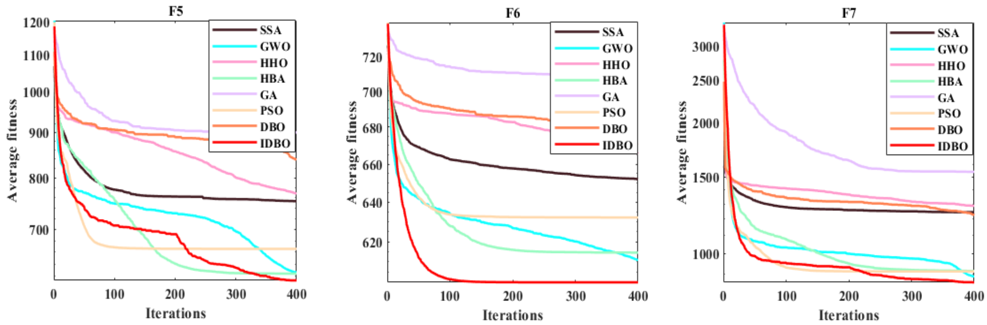

Figure 8 Convergence curves of F5–F7 (Dim=30).

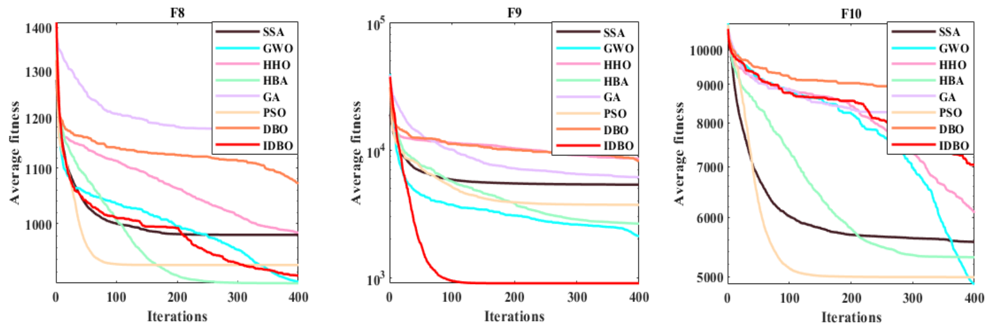

Figure 9. Convergence curves of F8–F10 (Dim=30).

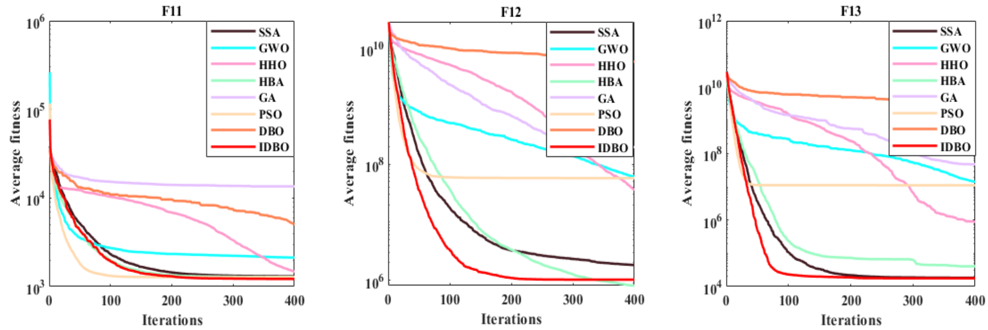

Figure 10. Convergence curves of F11–F13 (Dim=30).

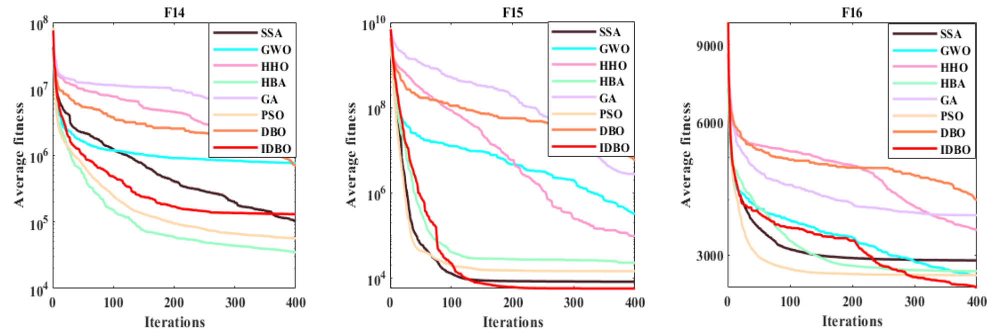

Figure 11. Convergence curves of F14–F16 (Dim=30).

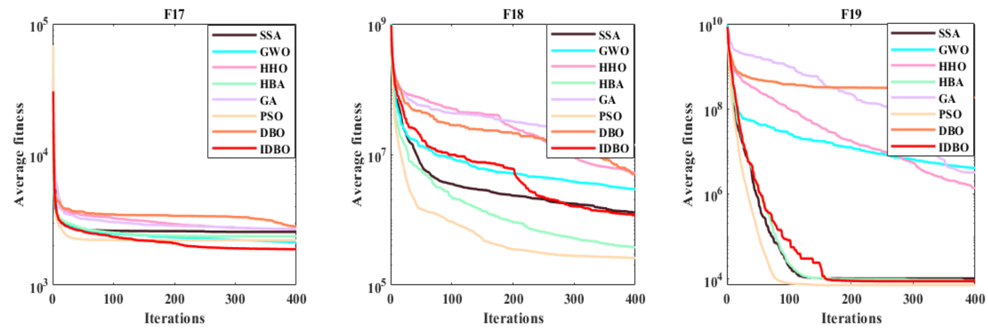

Figure 12. Convergence curves of F17–F19 (Dim=30).

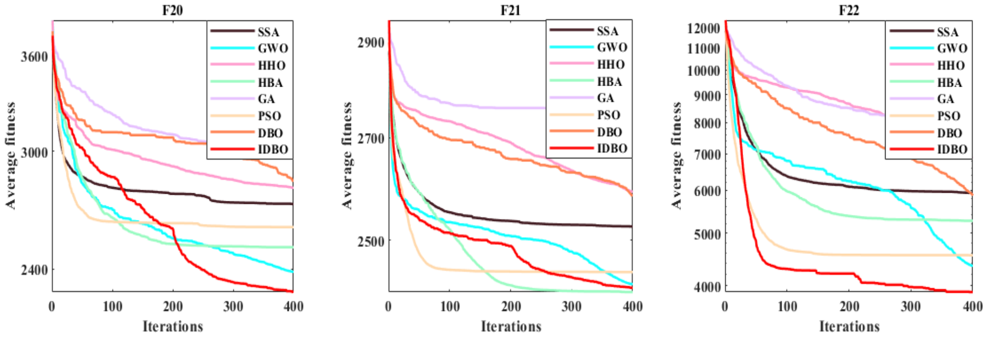

Figure 13. Convergence curves of F20–F22 (Dim=30).

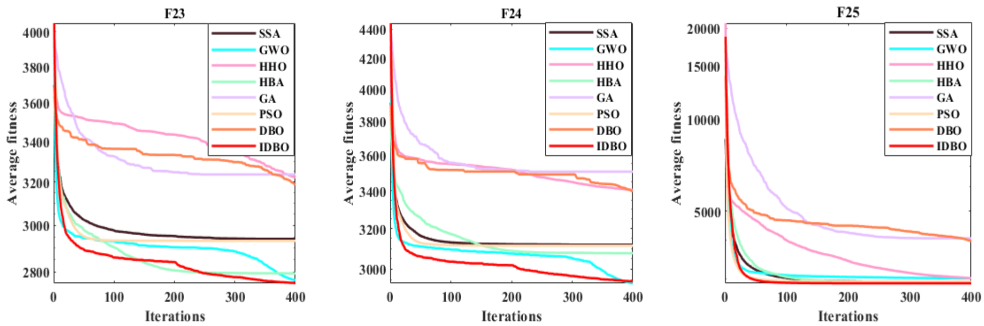

Figure 14. Convergence curves of F23–F25 (Dim=30).

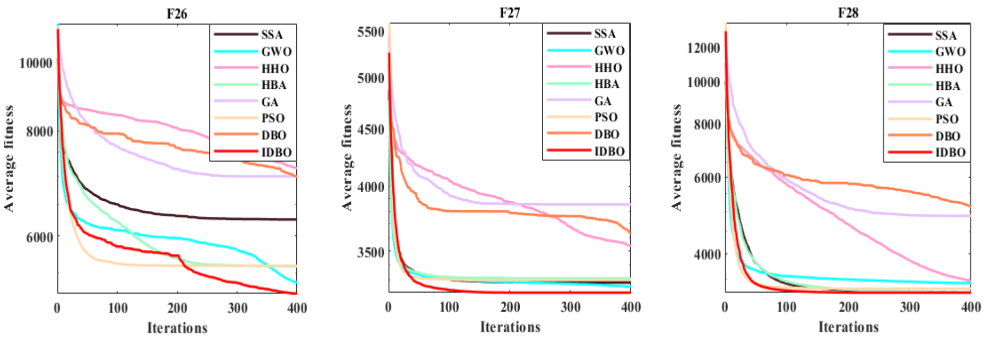

Figure 15. Convergence curves of F26–F28 (Dim=30).

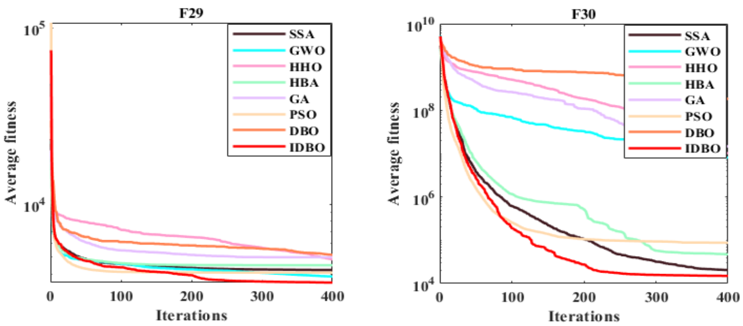

Figure 16. Convergence curves of F29–F30 (Dim=30).

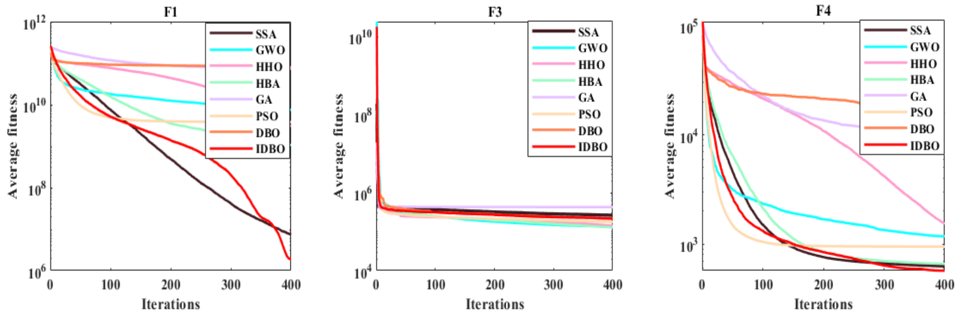

Figure 17. Convergence curves of F1–F4 (Dim=50).

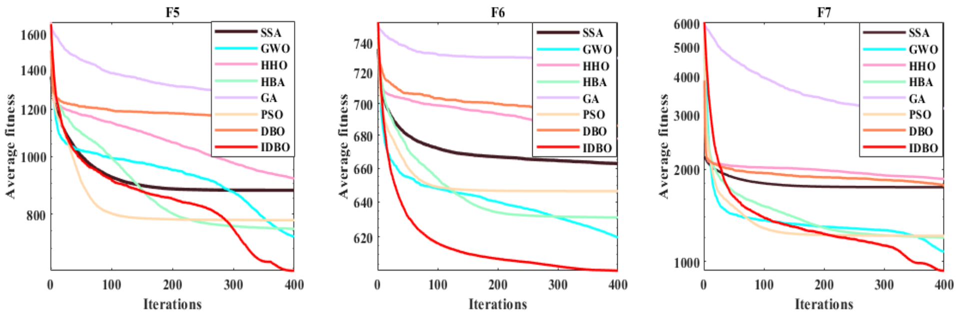

Figure 18. Convergence curves of F5–F7 (Dim=50).

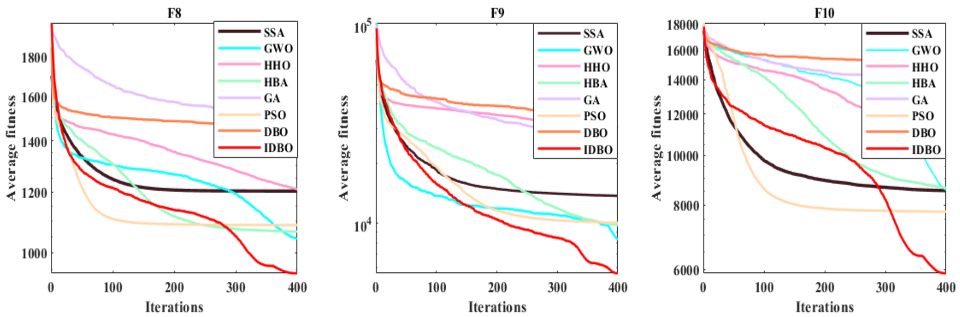

Figure 19. Convergence curves of F8–F10 (Dim=50).

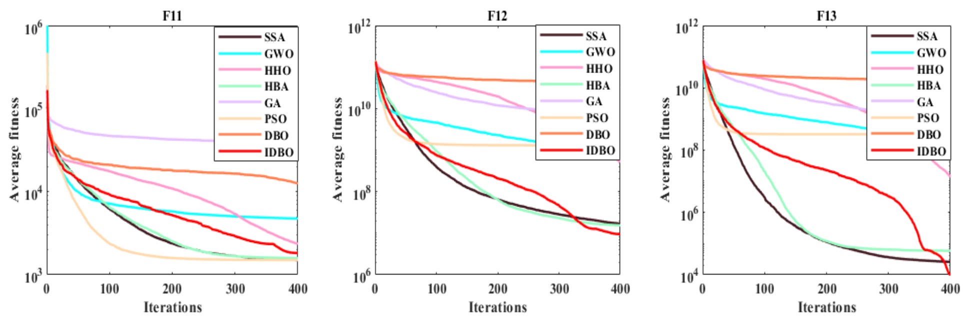

Figure 20. Convergence curves of F11–F13 (Dim=50).

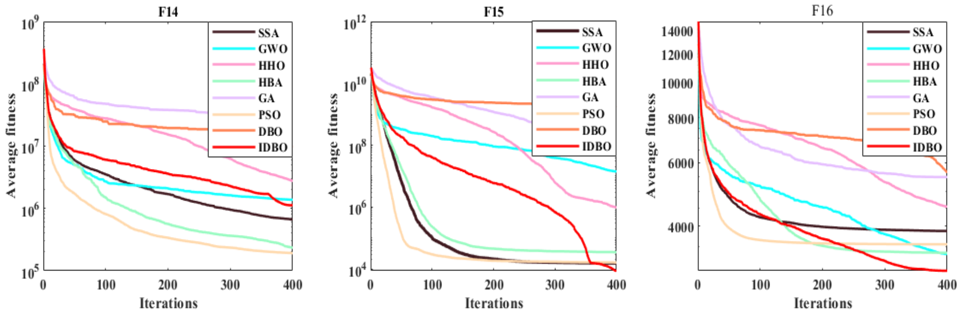

Figure 21. Convergence curves of F14–F16 (Dim=50).

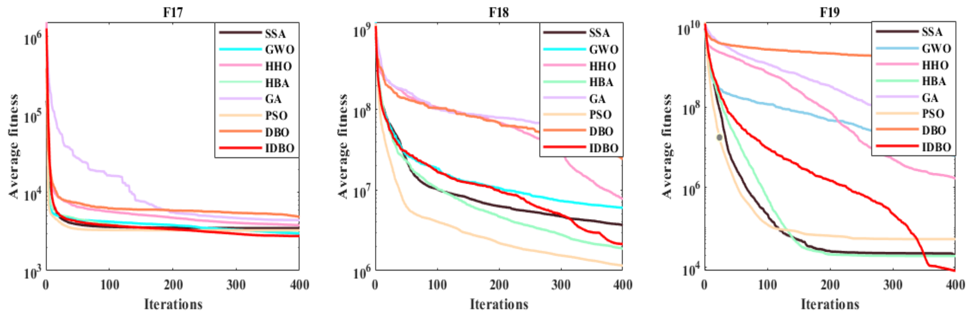

Figure 22. Convergence curves of F17–F19 (Dim=50).

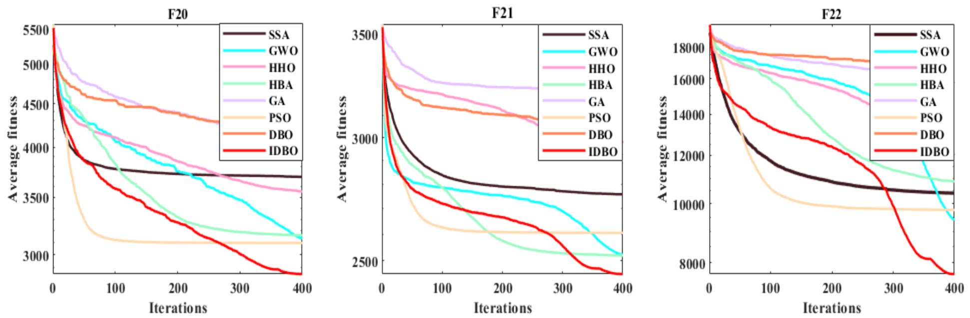

Figure 23. Convergence curves of F20–F22 (Dim=50).

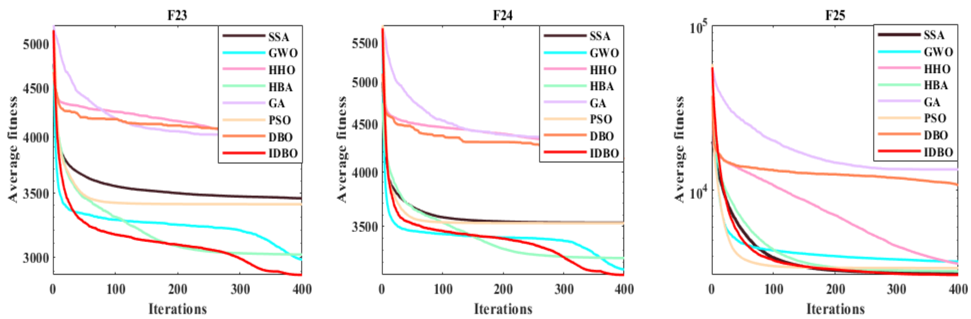

Figure 24. Convergence curves of F23–F25 (Dim=50).

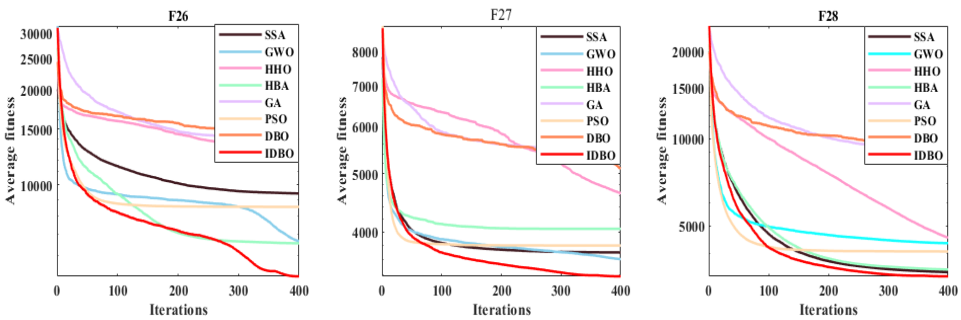

Figure 25. Convergence curves of F26–F28 (Dim=50).

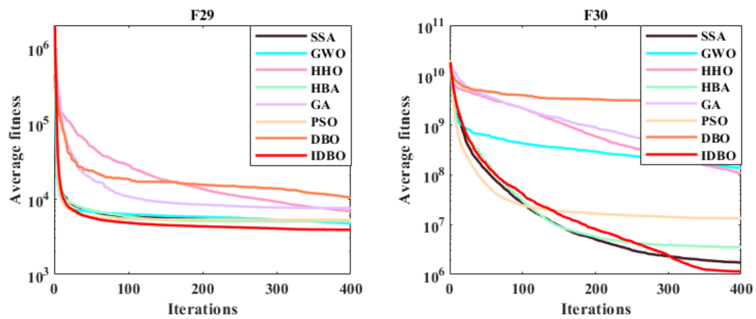

Figure 26. Convergence curves of F29-F30 (Dim=50).

According to the convergence curves of the eight algorithms above, the IDBO algorithm achieves superior convergence speed and achieves a higher degree of accuracy than the other seven algorithms. For unimodal functions, the IDBO algorithm's convergence curve rapidly approaches or reaches the theoretically optimal solution, allowing for the swift identification and localization of the promising region containing the global optimal solution and efficiently converging toward it. For multimodal functions, the proposed enhanced strategy in the IDBO algorithm significantly improves its global exploration performance during the initial iterations, enabling multimodal function optimization to reach comparable precision with fewer computational cycles. The IDBO algorithm demonstrates fluctuations and a gradual decline in optimization values during the late phases in handling hybrid and composite functions, which enhances its ability to overcome local optima stagnation and achieve superior optimization outcomes. The analysis of the algorithm's convergence behavior above confirms that the proposed optimization strategy effectively accelerates the algorithm’s convergence rate while substantially improving its overall performance.

According to the performance evaluation across the CEC2017 benchmark test, the IDBO algorithm demonstrates outstanding convergence efficiency and optimization capability in handling unimodal optimization problems. For multimodal functions, the IDBO algorithm effectively avoids local optima and prevents premature convergence to extreme points. For complex functions, the algorithm maintains a high level of stability while showcasing robust global exploration and local exploitation capabilities. Overall, the proposed improvement strategy enhances the IDBO algorithm’s optimization performance, making it more effective and stable than the other algorithms.

3.7.4. Wilcoxon rank-sum test

To comprehensively validate the superiority of the IDBO algorithm, it is insufficient to merely analyze its optimization and convergence capabilities. Therefore, to statistically evaluate the performance disparities between each algorithm, the Wilcoxon rank-sum test was employed in this paper. When analyzing the differences between two independent datasets, the Wilcoxon rank-sum test is generally used as a nonparametric comparative tool. The fundamental approach involves combining the data from all algorithms, ranking them, and then computing a test statistic based on these ranks to assess whether there is a statistically significant difference between the distributions of the datasets. Each algorithm was independently executed 30 times, each algorithm was independently executed 30 times, and pairwise *p*-values were then calculated between all algorithms. Most notably, as the IDBO algorithm is inherently identical to itself, the *p*-value for the self-comparison of the IDBO algorithm is omitted. The statistical analysis reveals that when *p*-values fall below the 0.05 threshold, they demonstrate a significant distinction between the two algorithmic approaches; conversely, *p*-values reaching or exceeding this critical value suggest no observable difference in performance. The relevant results are presented in Table 5.

Table 5. The results of the Wilcoxon rank-sum test.

Functions	Dim	SSA	GWO	HHO	HBA	GA	PSO	DBO
F1	30	5.896E-05	7.111E-07	7.111E-07	2.218E-07	7.111E-07	7.111E-07	7.111E-07
	50	1.734E-06	1.734E-06	1.734E-06	1.734E-06	1.734E-06	1.734E-06	1.734E-06
F3	30	1.431E-07	1.376E-06	7.111E-07	7.111E-07	7.111E-07	1.803E-06	9.246E-03
	50	2.353E-06	1.734E-06	1.921E-06	2.353E-06	2.603E-06	3.589E-04	5.193E-02
F4	30	**9.461E-01**	1.047E-06	7.111E-07	3.648E-02	7.111E-07	1.444E-04	7.111E-07
	50	1.734E-06	1.734E-06	3.112E-05	1.734E-06	1.734E-06	1.734E-06	2.370E-05
F5	30	1.431E-07	8.604E-04	7.111E-07	1.136E-02	7.111E-07	5.091E-04	7.111E-07
	50	1.734E-06	4.072E-05	1.921E-06	1.734E-06	4.729E-06	1.734E-06	1.734E-06
F6	30	7.111E-07	7.111E-07	7.111E-07	7.111E-07	7.111E-07	7.111E-07	7.111E-07
	50	1.734E-06	1.734E-06	1.734E-06	1.734E-06	1.127E-05	1.734E-06	1.734E-06
F7	30	7.111E-07	1.794E-04	7.111E-07	6.040E-03	7.111E-07	5.629E-04	7.111E-07
	50	1.734E-06	1.360E-05	1.734E-06	1.734E-06	1.734E-06	8.217E-03	1.734E-06
F8	30	7.111E-07	8.355E-03	3.939E-07	7.764E-03	7.111E-07	4.570E-02	7.111E-07
	50	1.921E-06	1.779E-01	1.734E-06	1.734E-06	1.921E-06	1.734E-06	1.734E-06
F9	30	7.111E-07	7.111E-07	7.111E-07	7.111E-07	7.111E-07	7.111E-07	7.111E-07
	50	1.742E-04	1.734E-06	2.585E-03	1.734E-06	2.585E-03	1.734E-06	1.734E-06
F10	30	1.201E-06	1.576E-06	1.794E-04	1.251E-05	4.112E-02	7.898E-08	4.601E-04
	50	3.112E-05	2.831E-04	6.288E-01	1.734E-06	2.163E-05	1.734E-06	1.734E-06
F11	30	2.222E-04	7.111E-07	7.898E-08	1.803E-06	7.111E-07	4.539E-07	7.111E-07
	50	1.921E-06	1.734E-06	**1.414E-01**	1.734E-06	7.271E-03	1.734E-06	1.044E-02
F12	30	8.357E-04	7.111E-07	7.111E-07	**8.103E-02**	7.111E-07	**4.407E-01**	7.111E-07
	50	1.734E-06	1.734E-06	3.709E-01	1.734E-06	2.127E-06	1.734E-06	7.712E-04
F13	30	4.388E-02	7.111E-07	7.111E-07	9.748E-06	7.111E-07	4.540E-06	7.111E-07
	50	1.734E-06	1.734E-06	1.114E-03	1.734E-06	6.984E-06	1.734E-06	1.127E-05

Continued on next page

Functions	Dim	SSA	GWO	HHO	HBA	GA	PSO	DBO
F14	30	3.369E-02	1.436E-02	7.948E-07	3.605E-02	1.657E-07	**1.636E-01**	2.356E-06
	50	**1.986E-01**	1.494E-05	3.317E-04	1.734E-06	6.035E-03	1.734E-06	**3.820E-01**
F15	30	4.249E-02	1.065E-07	7.111E-07	2.390E-02	1.065E-07	2.944E-02	7.111E-07
	50	1.734E-06	1.734E-06	2.765E-03	1.734E-06	5.999E-01	1.734E-06	5.792E-05
F16	30	5.166E-06	1.782E-03	9.173E-08	5.629E-04	1.657E-07	5.874E-06	7.111E-07
	50	1.127E-05	1.973E-05	1.484E-03	1.734E-06	9.271E-03	1.734E-06	1.921E-06
F17	30	7.111E-07	4.155E-04	3.939E-07	1.251E-05	9.173E-08	2.690E-06	7.111E-07
	50	7.271E-03	1.605E-04	8.730E-03	3.515E-06	2.895E-02	1.734E-06	1.921E-06
F18	30	2.733E-02	1.333E-02	8.585E-03	4.679E-02	1.803E-06	8.357E-04	8.597E-06
	50	1.852E-02	4.860E-05	5.706E-04	1.921E-06	4.992E-03	1.494E-05	1.319E-02
F19	30	**8.181E-01**	1.235E-07	7.111E-07	7.972E-04	7.898E-08	8.604E-03	7.111E-07
	50	1.734E-06	1.734E-06	**2.059E-01**	1.734E-06	3.872E-02	1.734E-06	3.609E-03
F20	30	1.918E-07	2.596E-05	1.431E-07	5.166E-06	7.111E-07	1.047E-06	7.111E-07
	50	4.196E-04	3.501E-02	1.593E-03	1.238E-05	1.150E-04	8.307E-04	1.734E-06
F21	30	9.173E-08	4.112E-02	7.111E-07	1.404E-04	7.111E-07	9.278E-05	9.209E-04
	50	1.734E-06	5.792E-05	1.734E-06	1.734E-06	1.973E-05	2.603E-06	1.734E-06
F22	30	1.625E-03	1.227E-03	7.579E-04	1.481E-03	1.415E-05	1.227E-03	8.357E-04
	50	1.779E-02	2.127E-06	2.304E-02	1.734E-06	1.752E-02	1.734E-06	2.353E-06
F23	30	9.127E-07	7.643E-03	7.111E-07	1.014E-03	7.111E-07	7.111E-07	7.111E-07
	50	1.734E-06	1.734E-06	1.734E-06	1.921E-06	2.712E-02	2.127E-06	1.734E-06
F24	30	7.111E-07	1.636E-03	7.111E-07	3.336E-03	7.111E-07	1.431E-07	7.111E-07
	50	2.353E-06	1.734E-06	8.944E-04	1.734E-06	**1.470E-01**	1.734E-06	1.734E-06
F25	30	1.667E-02	7.111E-07	7.111E-07	4.166E-05	7.111E-07	1.918E-07	7.111E-07
	50	1.734E-06	1.734E-06	1.639E-05	1.734E-06	1.734E-06	1.734E-06	6.339E-06
F26	30	1.600E-05	7.579E-04	7.111E-07	3.336E-03	7.111E-07	8.357E-04	7.111E-07
	50	4.897E-04	2.585E-03	6.424E-03	1.734E-06	7.499E-02	1.921E-06	2.597E-05
F27	30	1.431E-07	7.948E-07	7.111E-07	1.657E-07	7.111E-07	7.111E-07	7.111E-07
	50	6.564E-03	1.734E-06	5.706E-04	1.734E-06	4.492E-02	1.734E-06	1.734E-06
F28	30	1.636E-02	7.111E-07	7.111E-07	8.817E-04	7.111E-07	9.173E-08	7.111E-07
	50	1.734E-06	1.734E-06	5.307E-05	1.734E-06	2.127E-06	1.734E-06	1.921E-06
F29	30	7.111E-07	1.803E-06	7.111E-07	1.576E-06	7.111E-07	7.111E-07	7.111E-07
	50	1.470E-02	1.734E-06	2.989E-02	1.734E-06	4.897E-04	1.734E-06	1.734E-06
F30	30	1.227E-03	7.111E-07	7.111E-07	1.953E-03	7.111E-07	1.803E-06	7.111E-07
	50	1.734E-06	1.734E-06	3.589E-04	1.734E-06	1.734E-06	1.734E-06	2.585E-03

Note: The test results (p-values) that exceed 0.05 have been marked in bold.

As shown in Table 5, on the one hand, when the dimension is 30, for all test functions except F4, F12, F14, and F19, the optimization results of the IDBO algorithm are significantly different from those of other comparative algorithms. On the other hand, when the dimension is increased to 50, significant differences are observed for all test functions except F11, F14, F19, and F24. Notably, for the majority of the test functions, the p-values between IDBO and the other algorithms are all below 0.05. These results strongly indicate that the IDBO algorithm exhibits a statistically significant performance advantage and possesses theoretical superiority in terms of optimization.

4. Simulation experiment and result analysis

4.1. UAV path planning problem

The UAV path planning problem can fundamentally be characterized as an optimization challenge in a complex environment. The primary objective is to identify an optimal flight path that enables the UAV to safely and efficiently navigate from its origin to a specified target location. To achieve this, this paper formulates a comprehensive objective function that integrates multiple criteria, including the length cost, threat cost, altitude cost and smoothness cost. The specific description is presented below.

4.1.1. Length cost

The shorter the flight path generated by the UAV path planning algorithm, the lower the flight time and energy consumption. Consequently, path length is considered one of the key performance indicators for evaluating the efficiency of path planning. The formula used to calculate the length cost is presented in Eq (19).

$$F_1\left(X_i\right)=\sum_{i=1}^{n}\sqrt{\left(x_{i+1}-x_i\right)^2+\left(y_{i+1}-y_i\right)^2+\left(z_{i+1}-z_i\right)^2}, \tag{19}$$

where n is the number of path points and (x_i, y_i, z_i) denotes the coordinates of the ith path point.

4.1.2. Threat cost

In addition to optimizing for path length, the considerations of flight safety and operational feasibility must also be incorporated. To ensure the safe operation of the UAVs, it is essential to design flight paths rationally and avoid areas that pose potential threats (threat areas). Therefore, the flight threat cost function is introduced to enhance flight safety. The formula is given below.

$$F_2(X_i)=\sum_{i=1}^{n-1}\sum_{t=1}^{K}T_k\left(p_{k,i}\right), \tag{20}$$

$$T_k\left(p_{k,i}\right)=\begin{cases}0, & d_k>S+D+R_t\\ \left(S+D+R_t\right)-d_k, & D+R_t<d_k\le S+D+R_t\\ \infty, & d_k\le D+R_t\end{cases}, \tag{21}$$

where R_t denotes the radius of the obstacle, S denotes the threat influence range, D is defined as the minimum safe flight distance for the UAV, and d_k indicates the perpendicular distance between the UAV's path point and the obstacle.

4.1.3. Altitude cost

The altitude at which the UAV operates is a critical factor affecting both its stability and safety during flight. Consequently, UAVs' flight altitude is typically subject to restrictions. The corresponding calculation formula for calculating altitude cost is presented as follows:

$$H_i == \begin{cases} \left| h_{ij} - \dfrac{h_{\max} - h_{\min}}{2} \right|, & h_{\min} \le h_i \le h_{\max} \\ \infty, & otherwize \end{cases}, \tag{22}$$

$$F_3\left(X_i\right) = \sum_{j=1}^{n} H_i, \tag{23}$$

where H_i denotes the flight altitude.

4.1.4. Smoothness cost

When a UAV performs turning or climbing maneuvers, the complexity of flight control increases, and fuel consumption accelerates accordingly. Meanwhile, the UAV's flight path should minimize sharp turns and abrupt ascents or descents as much as possible. These constraints must align with the UAV's actual angular limitations; otherwise, the path planning model may fail to generate a feasible trajectory. Therefore, ensuring the smoothness of the flight path is essential during the UAV's navigation. The corresponding path smoothness cost function is presented as follows:

$$F_4 = \sum_{i=1}^{n-2} \varphi_i + \sum_{i=1}^{n-1} \left(\varphi_i - \varphi_{i-1} \right), \tag{24}$$

$$\phi_i = \arctan\left(\frac{z_{i+1} - z_i}{\sqrt{\left(x_{i+1} - x_i\right)^2 + \left(y_{i+1} - y_i\right)^2}} \right). \tag{25}$$

4.1.5. Comprehensive path cost

This paper presents a weighted aggregation of the four costs above and establishes a comprehensive objective function, as shown in Eq (26).

$$F = b_1 F_1 + b_2 F_2 + b_3 F_3 + b_4 F_4 \tag{26}$$

where b_1, b_2, b_3, and b_4 denote the weight coefficients corresponding to the length cost, threat cost, altitude cost, and smoothness cost, respectively. A smaller F value indicates a path with higher quality.

4.1.6. Path planning experiment

To assess the performance of the IDBO algorithm in UAV path planning within complex environments, simulation experiments were conducted in 3D space based on the established UAV path planning model. The IDBO algorithm was evaluated in comparison with several algorithms, including the SSA, GWO, HHO, HBA, GA, PSO, and DBO algorithms. The experimental environment was defined as a flight area measuring 1000 m × 1000 m × 400 m, with the starting point located at (100, 50, 180) and the target point at (950, 700, 50), which included 10 mountain peaks as obstacles. The population size was set to 100, and the maximum number of iterations was set to 400. To minimize the impact of randomness, 30 independent runs were conducted. The detailed spatial environment settings of the threat areas are presented in Table 6.

Table 6. The spatial environment settings of the threat areas.

Number	Coordinates	Radius
1	(200,180,150)	70
2	(400,150,125)	70
3	(550,300,150)	80
4	(350,650,150)	90
5	(470,500,150)	70
6	(300,350,150)	80
7	(600,700,100)	70
8	(650,500,130)	80
9	(850,600,130)	90
10	(750,250,150)	90

To more effectively illustrate the actual performance of UAV path planning, the path planning results of each algorithm based on three views, along with their corresponding convergence curve, are presented as follows. The threat areas are represented by a red cylinder.

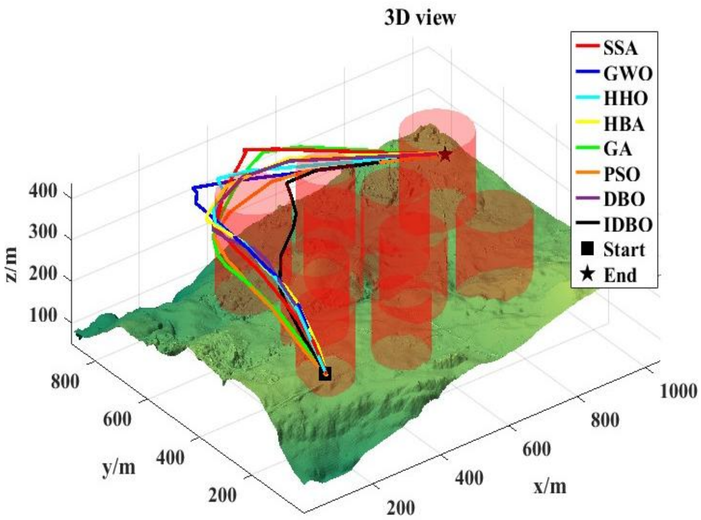

Figure 27. The result of UAV path planning (3D view).

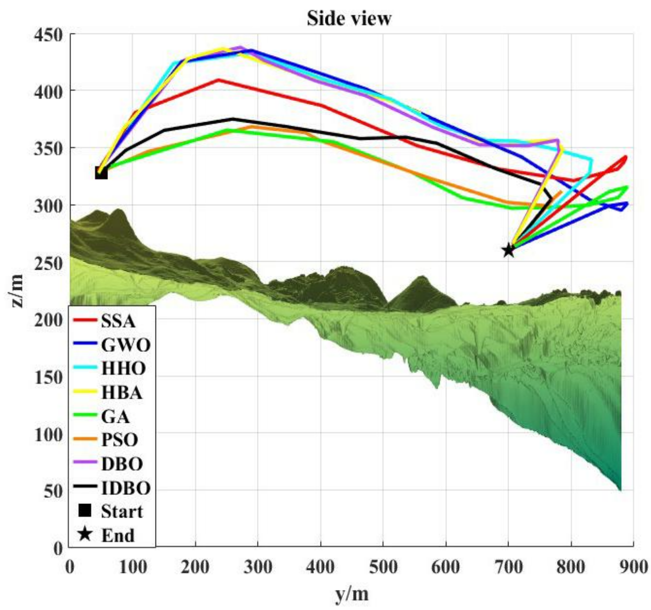

Figure 28. The result of UAV path planning (side view).

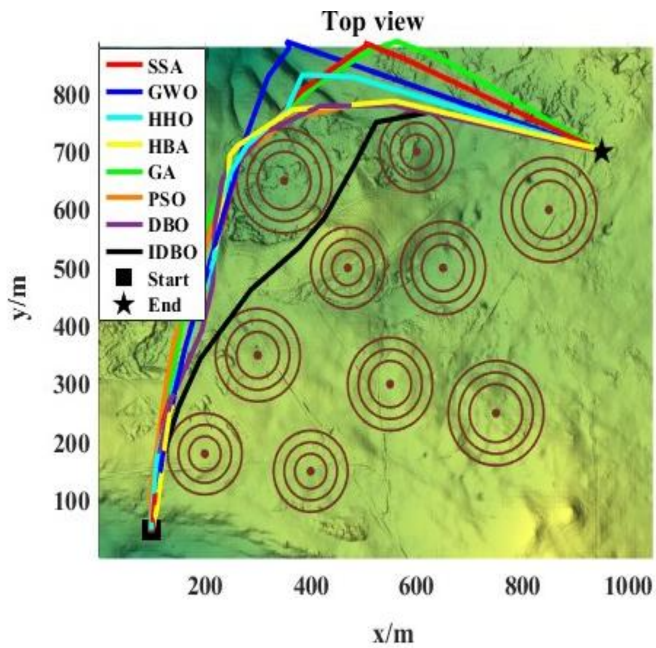

Figure 29. The result of UAV path planning (top view).

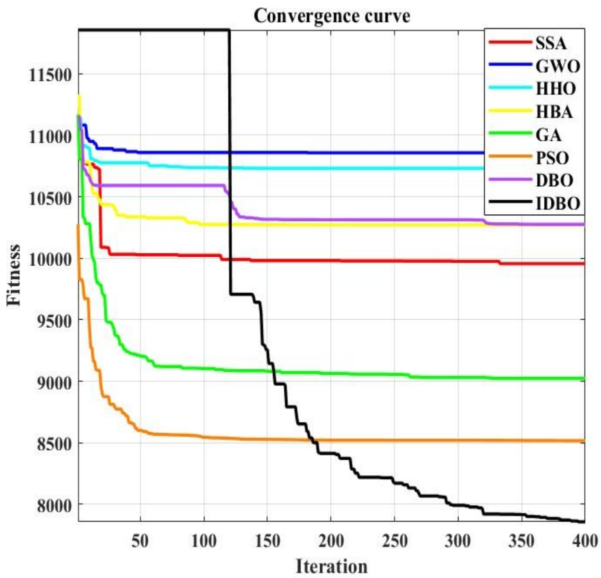

Figure 30. Convergence curve of the UAV path planning problem.

It can be clearly observed from Figures 27–29 that the paths generated by the IDBO algorithm are not only shorter but also smoother compared with those produced by the other seven algorithms, indicating its stable performance in path planning and its ability to avoid mountainous and threatening areas effectively. As illustrated in Figure 30, The IDBO algorithm reaches the optimum solution more rapidly and with greater precision than other algorithms, showcasing superior convergence performance. Furthermore, the proposed IDBO algorithm achieves the optimal result with the minimum cost function value.

4.2. Analysis of optimization results

Combining the optimization results of the four above engineering optimization problems, the IDBO algorithm demonstrates the ability to continue searching even after falling into a local optimal solution, ultimately converging to the global optimal solution with a faster convergence speed and higher accuracy compared with the other algorithms. Moreover, the IDBO algorithm exhibits strong robustness and effectively balances local exploitation and global exploration, indicating that the IDBO algorithm achieves excellent performance in engineering applications.

5. Conclusions

This paper presents an improved dung beetle optimizer algorithm, designed to address the limitations of the original dung beetle optimizer algorithm during the later phases of the iterative process. Multiple enhancement strategies are incorporated to improve the algorithm’s performance. Specifically, the Sobol sequence is introduced to enhance the population’s diversity, while the nonlinear convergence factor is employed to better balance global exploration and local exploitation. To enhance the algorithm’s ability to escape from local optima, Lévy flight is integrated. Additionally, the adaptive Cauchy–Gaussian hybrid mutation and the greedy strategy are introduced to refine the search process, thereby contributing to accelerated convergence toward the global optimum. The efficacy of the proposed IDBO algorithm is thoroughly assessed using the CEC2017 benchmark set. The experimental results indicate that the enhanced method achieves superior convergence speed and improved solution accuracy. Furthermore, the IDBO algorithm is applied to actual engineering optimization problem, where it outperforms the other optimization algorithms, showcasing its superior stability and competitiveness. Subsequent investigations will explore the utilization of the proposed IDBO algorithm to assess its viability in solving practical problems across various engineering disciplines, such as fault diagnosis, energy management, and supply chain optimization, thereby enhancing its applicability in solving complex optimization problems.

6. Discussion

The IDBO algorithm proposed in this paper significantly enhances the efficiency and stability of UAV path planning in complex environments. This technological advancement offers essential support for the development and upgrading of the low-altitude economy industry. The specific contributions and practical applications are reflected in the following three aspects:

6.1. Overcome the challenges associated with operational bottlenecks in complex terrain

Traditional UAVs face significant challenges in meeting the operational demands of industrial and economic activities—such as agricultural, forestry pest control, and emergency rescue—in extreme environments like mountainous areas and canyons. These challenges primarily stem from limitations in their path planning capabilities. The IDBO algorithm addresses these limitations by enhancing both global search and local exploitation performance, thereby substantially reducing path-related costs, including flight time, energy consumption, and risk. This advancement effectively overcomes technical barriers to enabling large-scale operations in complex terrain.

6.2. Drive the improvement of industrial economic efficiency

(1) Reducing operating costs: Efficient path planning reduces unnecessary flight mileage, directly cutting down operating costs in scenarios such as logistics distribution and mapping exploration.

(2) Expanding application scenarios: In areas such as mines, wind power bases, and border patrols, where traditional manned aviation is difficult to cover, UAVs can perform high-risk operations and help create new economic growth points.

(3) Promoting industrial integration: The high reliability of algorithms serves as a solid technical foundation for the "UAV+ industry" (such as "UAV+ logistics" and "UAV+ smart agriculture"), thereby accelerating its collaborative innovation with traditional sectors.

6.3. Enhance the competitiveness of the low-altitude economy

As a core element of autonomous decision-making, UAV path planning directly impacts flight safety and the success rate of missions. The notable advantages of the IDBO algorithm can enhance the reliability of low-altitude aviation services, encourage regulatory authorities to allocate additional airspace resources, and unlock the potential for large-scale industry development, thereby effectively promoting high-quality regional economic growth.

Author contributions

The authors confirm contribution to the paper as follows: Conception and design, Qing Hu; data collection, Qing Hu; software, Qing Hu; analysis and interpretation of results, Fenhua Zhu; draft manuscript preparation, Qing Hu. All authors reviewed the results and approved the final version of the manuscript.

Use of Generative-AI tools declaration

The authors declare that they have not used artificial intelligence (AI) tools in the creation of this article.

Availability of data and materials

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Conflict of interest

The authors declare no conflicts of interest to report regarding the present study.

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