Enhanced Dung Beetle Optimization Algorithm with Chaotic Initialization and Adaptive Perturbation Strategies for Robust Global Search

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***Abstract*— This paper proposes an Enhanced Dung Beetle Optimization (EDBO) algorithm to address the limitations of the original DBO, such as premature convergence, weak global exploration, and low convergence precision. The EDBO integrates three improvement mechanisms: a Cubic Chaotic Map for population initialization, an improved global search strategy, and an adaptive *t*-distribution perturbation operator. These mechanisms jointly enhance population diversity, strengthen global search capability, and accelerate convergence in later iterations. Extensive experiments conducted on the CEC2017 benchmark suite demonstrate that EDBO achieves superior optimization performance compared to several well-known algorithms, including GWO, WOA, DMO, SO, and the original DBO. Statistical analyses confirm its robustness, stability, and adaptability across diverse optimization scenarios. Furthermore, ablation experiments reveal that each enhancement contributes significantly to performance improvement, while their synergistic integration yields the best overall results. The proposed EDBO algorithm thus provides a reliable and efficient optimization framework, offering promising potential for real-world applications such as control parameter tuning, intelligent robotics, and industrial process optimization.**

Keywords—Metaheuristic algorithm; Chaotic Initialization; Adaptive t-Distribution; Enhanced Dung Beetle Optimizer

I. INTRODUCTION

Metaheuristic algorithms, which draw inspiration from biological and natural systems, represent a powerful class of optimization techniques for addressing complex, nonlinear, and multimodal problems [1][2]. Their stochastic, population-based mechanisms facilitate escape from local optima and enable efficient handling of high-dimensional optimization tasks that often challenge deterministic or gradient-based methods. Owing to their robustness, simplicity, and strong global search capabilities, metaheuristics have found widespread application across diverse scientific and engineering disciplines.

In the last decade, numerous metaheuristic algorithms have emerged, such as Particle Swarm Optimization (PSO)[3], Grey Wolf Optimizer (GWO) [4], Whale Optimization Algorithm (WOA) [5], Dwarf Mongoose Optimization (DMO) [6], and Snake Optimizer (SO) [7]. These swarm-based approaches mimic natural foraging and cooperative behaviors to achieve adaptive search and convergence. Thanks to their straightforward structure, broad applicability, and ease of implementation, they have been successfully deployed in various domains, including agricultural monitoring [8], image segmentation [9], path planning [10], and engineering design [11][12]. Nevertheless, many existing methods continue to grapple with challenges like premature convergence, insufficient exploration in high-dimensional spaces, and inadequate balancing between global and local search phases. These limitations frequently lead to stagnation and suboptimal performance when tackling complex optimization landscapes.

The Dung Beetle Optimization (DBO) algorithm, inspired by the distinctive foraging and navigation activities of dung beetles, has recently emerged as a promising metaheuristic characterized by high adaptability and minimal parameter dependency [13]. DBO's structural simplicity, parameter efficiency, and robust search performance have positioned it as a valuable tool for addressing complex optimization challenges, including high-dimensional feature selection and data clustering applications [14]. Despite its efficacy, the original DBO algorithm may still experience early stagnation and limited convergence accuracy, particularly in problems featuring multiple local minima or irregular search surfaces. To address these shortcomings, this study introduces an Enhanced Dung Beetle Optimization (EDBO) algorithm.

The EDBO algorithm incorporates several innovative mechanisms to bolster both global exploration and local exploitation capabilities while preserving low computational complexity. The principal contributions are outlined below:

1. Cubic Chaotic Map for Population Initialization: A cubic chaotic mapping technique is employed to enhance the diversity and distribution of the initial population. This improves search space coverage, mitigates premature convergence, and strengthens global exploration.

2. Improved Global Search Mechanism: A dynamic exploration strategy incorporating stochastic detection and directional reconstruction is introduced during the global search phase. This mechanism adaptively modifies search directions, effectively balancing exploration and exploitation while enhancing robustness in complex landscapes.

3. Adaptive t-Distribution Perturbation Strategy: An adaptive perturbation operator based on the t-distribution is integrated to dynamically control step sizes throughout the iterative process. This promotes vigorous global exploration in early stages and refined local exploitation in later phases, resulting in accelerated convergence with improved precision.

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To comprehensively evaluate the effectiveness of the proposed Enhanced Dung Beetle Optimization (EDBO) algorithm, a series of experiments were conducted on the CEC2017 benchmark set, which includes 30 well-recognized test functions covering different levels of complexity. The EDBO's performance was compared with several representative metaheuristic algorithms—GWO, WOA, DMO, SO, and the original DBO—under uniform experimental settings. The comparative results demonstrate that EDBO consistently achieves superior outcomes in terms of mean fitness value, convergence stability, and optimization speed, confirming its strong capability in solving both unimodal and multimodal optimization problems.

The structure of this paper is organized as follows: Section II reviews the fundamental principles of the original DBO algorithm. Section III elaborates on the enhancement mechanisms and structural improvements introduced in EDBO. Section IV presents the experimental configuration and performance analysis. Finally, Section V concludes the study and discusses prospective directions for future research.

II. Original Dung Beetle Optimization Algorithm

The Dung Beetle Optimization (DBO) algorithm constitutes a nature-inspired metaheuristic framework that emulates the complex behavioral repertoire of dung beetles, encompassing ball rolling, dancing, foraging, stealing, and reproduction.

A. Ball-rolling dung beetle

Dung beetles exhibit remarkable navigational capabilities by forming fecal spheres and utilizing celestial cues for directional orientation. When confronted with impediments, these insects perform a distinctive postural dance to recalibrate their trajectory. The positional update mechanism is mathematically represented as:

$$x_i(t+1) = x_i(t) + \alpha \times k \times x_i(t-1) + b \times \Delta x \tag{1}$$

$$\Delta x = |x_i(t) - X^w| \tag{2}$$

Within this formulation, t signifies the current algorithmic iteration, while $x_i(t)$ corresponds to the spatial coordinates of the ith beetle at that iteration. The deflection coefficient k, constrained within the interval (0, 0.2], governs directional modulation, whereas b, a parameter bounded by (0,1), contributes to positional computation. The stochastic coefficient α, assuming values of ±1, introduces probabilistic variability. The global least favorable position is denoted by X^w , with Δx characterizing luminous intensity variations.

Upon obstacle detection, the beetle's reorientation behavior is computationally modeled through a trigonometric function:

$$x_i(t+1) = x_i(t) + \tan(\theta)\,|x_i(t) - x_i(t-1)| \tag{3}$$

Here, θ represents the angular deflection measured in radians, confined to the domain $[0, \pi]$.

B. Brood ball

The collected fecal matter undergoes bifurcated allocation: one portion serves nutritional purposes, while the remainder is translocated to secure oviposition sites, forming reproductive structures termed brood balls. The spatial confines for brood ball deposition are rigorously delineated:

$$\begin{aligned} Lb^* &= \max\,(X^* \times (1-R), Lb) \\ Ub^* &= \min\,(X^* \times (1-R), Ub) \end{aligned} \tag{4}$$

In this configuration, X^* epitomizes the contemporary local optimum position, analogous to the beetle's preferential nesting location. The parameters Lb and Ub demarcate the inferior and superior boundaries of the oviposition region, respectively, simulating the constrained selection domain available to the insects. The temporal modulation factor $R=1-t/T_{\max}$ progressively contracts these boundaries throughout the iterative process, where t indicates the current cycle and $T_{\max}$ signifies the maximum iteration count. This dynamic adjustment mirrors the beetle's diminishing exploratory range as environmental conditions evolve. The comprehensive search domain remains bounded by the global parameters Lb and Ub.

Following brood ball deposition, female beetles engage in singular oviposition per iterative cycle. The brood ball's positional coordinates undergo updating according to:

$$B_i(t+1) = X^* + b_1 \times (B_i(t) - Lb^*) + b_2 \times (B_i(t) - Ub^*) \tag{5}$$

Within this computational framework, $Bi(t)$ symbolizes the spatial position of the ith ovoid structure at iteration t. To incorporate stochasticity and emulate natural unpredictability, two autonomous random vectors b_1 and b_2 are implemented, each possessing dimensionality $1\times D$, where D corresponds to the problem's dimensional complexity.

C. Small dung beetle

Post-emergence maturation triggers the juvenile beetles' foraging activities, necessitating the establishment of an optimal nutritional acquisition zone to facilitate spatial exploration. The boundaries of this foraging territory are formally defined:

$$\begin{aligned} Lb^b &= \max\,(X^b \times (1-R), Lb) \\ ub^b &= \min\,(X^b \times (1-R), Ub) \end{aligned} \tag{6}$$

where, X^b embodies the global optimum position, while Lb and Ub represent the inferior and superior demarcations of the nutritional acquisition domain. Consequently, the positional update for juvenile beetles follows:

$$x_i(t+1) = x_i(t) + C_1 \times (x_i(t) - Lb^b) + C_2 \times (x_i(t) - Ub^b) \tag{7}$$

In this formulation, $x_i(t)$ designates the spatial coordinates of the ith beetle at iteration t. The coefficient C_1 is derived from a normal distribution, while C_2 constitutes a stochastic vector with elements sampled from the uniform distribution (0,1).

D. Thief Dung Beetle location update

A subset of beetles exhibits kleptoparasitic behavior, appropriating fecal spheres from conspecifics. Presuming the global optimum represents the most favorable pilfering location, the positional update for thief beetles is formalized:

$$x_i(t+1) = X^b + S \times g \times (|x_i(t) - X^*| + |x_i(t) - X^b|) \quad (8)$$

where $x_i(t)$ characterizes the position of the ith thief agent at iteration t. The variable g represents a normally distributed random vector with dimensionality $1\times D$, where D indicates the problem's complexity. The scalar S functions as an algorithmic constant.

III. Enhanced Dung Beetle Optimization Algorithm

A. Improved population initialization with Cubic chaotic map

A well-structured and diverse initial population provides the DBO algorithm with valuable exploratory potential, establishing a solid foundation for intelligent search within heuristic optimization frameworks. In many existing approaches, the initialization of candidate solutions typically depends on pseudorandom number generation, which enhances the global search ability to some extent. However, excessive reliance on randomness often prevents the algorithm from achieving consistent optimization accuracy. Moreover, pseudorandom initialization can result in limited population coverage, reducing overall diversity and leading to premature convergence.

To address these limitations and improve both exploration performance and population diversity [15], chaotic mapping is introduced for population initialization. A chaotic map is a mathematical transformation that exhibits complex, nonlinear, and highly sensitive dynamics, making it suitable for generating diverse search distributions. Among various chaotic systems, the Cubic Chaotic Map is widely applied due to its strong ergodicity and unpredictability [16][17]. This map is mathematically expressed by the following recurrence relation:

$$x_{n+1} = \mu \cdot x_n \cdot (1 - {x_n}^2) \quad (9)$$

In this formulation, x_n represents the system's state at the n-th iteration, taking values between 0 and 1, while μ is a constant coefficient that defines the intensity of the cubic mapping. When μ is set to 1.0, the map retains its original scale without amplification or reduction. The cubic chaotic system is notable for its extreme sensitivity to initial conditions, generating behavior that appears random yet deterministic in nature.

During the population initialization stage, a matrix named *Cubic* is created, where each element is assigned a random value between 0 and 1 for every population member (N) and across all problem dimensions (dim). The cubic chaos function is then iteratively applied to each dimension of every individual. The chaos coefficient μ—maintained at 1.0 in this study—governs the system's nonlinear dynamic evolution. Through successive iterations, each dimension's value is updated based on the previous one, forming a series of chaotic sequences within the search space.

The resulting *Cubic* matrix, filled with these dynamically generated chaotic values, serves as the initial population for the DBO algorithm. Because of the inherent irregularity and ergodicity of the cubic map, this initialization method produces a population with significantly enhanced diversity. Consequently, the initial solutions are more evenly distributed across the search space, mitigating premature convergence and enabling the algorithm to explore a wider range of candidate regions.

Overall, incorporating cubic chaos mapping in the initialization phase effectively broadens the search scope of the Dung Beetle Optimizer (DBO), thereby increasing its ability to identify the global optimum while maintaining stronger population diversity and stability.

B. New global search strategy

For optimization scenarios involving low-dimensional benchmark problems, the integration of the proposed strategy significantly improves the equilibrium between global exploration and local exploitation. Nevertheless, when the Dung Beetle Optimization (DBO) algorithm is applied to large-scale or complex optimization tasks, its relatively uniform search behavior often leads the population to become trapped in local minima. Hence, enhancing the stochastic search dynamics of individual agents is essential to strengthen the algorithm's global exploration ability and prevent premature convergence.

To address the inherent limitations of the ball-rolling behavior in traditional DBO—where the movement depends primarily on the global worst solution and lacks interaction among beetles—along with the challenge of complex parameter tuning [18], a novel global search strategy is introduced. In the proposed method, a random dung beetle is selected to explore and roll toward the position of a randomly chosen dung ball, thereby expanding the diversity of search trajectories. The first-stage formulation of this global exploration mechanism is expressed as follows:

$$x_{i,j}^{P1} = (1 - r_{i,j}) \cdot x_{i,j} + r_{i,j} \cdot (SF_{i,j} - I_{i,j} \cdot x_{i,j}) \quad (10)$$

Here, $x_{i,j}^{P1}$ represents the position vector of the i-th dung beetle at the current iteration, while $x_{i,j}^{P0}$ (from the previous iteration) denotes its earlier position. The term $r_{i,j}$ is a random number uniformly distributed in the range [0,1]. $SF_{i,j}$ corresponds to a superior candidate solution selected from the existing population according to fitness evaluation. If no individual outperforms the current beetle, $SF_{i,j}$ is assigned as the global best position. Conversely, when at least one better solution exists, $SF_{i,j}$ is determined with equal probability: either directly adopting the global best solution or randomly choosing from the superior candidates. The parameter $I_{i,j}$ is a randomly generated integer (1 or 2) that determines the search direction — moving closer to $SF_{i,j}$ if $I_{i,j} = 1$, or moving farther away if $I_{i,j} = 2$.

The new global exploration mechanism introduced in the first stage substitutes the traditional position update rule of the original DBO during the rolling phase. By integrating random exploration and adaptive global guidance, this approach enables dung beetles to update their positions not solely in response to the global worst solution but by probing potentially superior regions across the search space. Such a modification effectively mitigates premature convergence and significantly enhances the algorithm's ability to conduct comprehensive spatial exploration, thereby increasing the likelihood of reaching the true global optimum.

Furthermore, by reducing the number of control parameters, the proposed strategy improves both the stability and applicability of the algorithm. In many optimization scenarios, an excessive number of parameters complicates calibration and decreases algorithmic generalization. Parameter simplification, on the other hand, enhances adaptability and practical usability, making the method more efficient and easier to implement in diverse problem domains.

C. *Adaptive t-distributed perturbation strategy*

The adaptive t-distribution serves as an enhanced probabilistic model frequently utilized in contemporary optimization algorithms to improve both exploration strength and convergence efficiency [19][20]. In the proposed EDBO framework, the foraging dynamics of young dung beetles are perturbed by a mutation mechanism based on the t-distribution, where the degrees of freedom are adaptively modified according to the current iteration index. This adaptive design allows the algorithm to maintain strong global search capability in the initial stages and gradually shift toward refined local exploitation in later iterations, thereby accelerating the convergence rate while preserving accuracy. The corresponding position update formulation is expressed as follows:

$$X_{new}^{j} = X_{best}^{j} + t(C_{iter}) \cdot X_{best}^{j} \tag{11}$$

$$C_{iter} = \frac{1}{exp\left(-4 \times \left(\frac{t}{M}\right)^{2}\right)} \tag{12}$$

In this formulation, X_{new}^{j} denotes the position vector of the i-th dung beetle at the current iteration, while X_{best}^{j} represents the global best position identified during the same iteration. The term C_{iter} serves as the control parameter of the adaptive t-distribution, and $t(C_{iter})$ refers to a random variable drawn from this adaptive distribution.

The adaptive t-distribution mechanism dynamically modifies the degree of randomness in the beetle's movement based on the ongoing iteration number. This adaptive control enhances the algorithm's ability to maintain a balance between exploration in early stages and exploitation in later iterations. By continuously adjusting the perturbation strength, the approach accelerates convergence, prevents stagnation, and substantially improves both the efficiency and accuracy of the DBO when addressing complex optimization tasks.

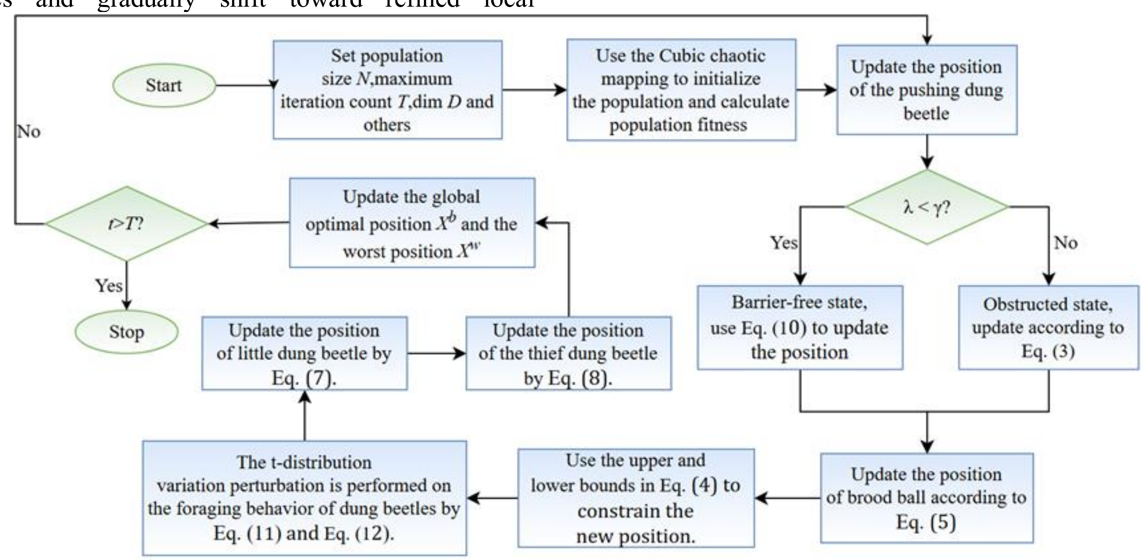


Fig. 1 Flow chart of EDBO

IV. Algorithm Performance Testing and Analysis

A. *Experimental Configuration and Benchmark Suite*

All computational experiments were conducted on a computing system equipped with an AMD Ryzen 7 4800H processor and 16GB RAM, utilizing the MATLAB 2023b programming environment to ensure consistent evaluation conditions across all tested algorithms.

The proposed Enhanced Dung Beetle Optimization (EDBO) algorithm underwent rigorous evaluation using the comprehensive CEC2017 benchmark suite, comprising 30 challenging test functions with dimensionality set to D=30. This diverse collection includes unimodal (F1-F3), multimodal (F4-F10), hybrid (F11-F20), and composite functions (F21-F30), providing a thorough assessment of algorithmic capabilities in handling various optimization landscapes with search boundaries defined as [-100, 100]D.

The comparative analysis encompassed five established metaheuristics: Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), Dwarf Mongoose Optimization Algorithm (DMO), Snake Optimizer (SO), and the original Dung Beetle Optimizer (DBO). To ensure equitable comparison, uniform experimental parameters were maintained throughout: population size N=30, maximum iteration count T=500, with each algorithm executing 30 independent runs to establish statistical significance.

TABLE I. PARAMETER CONFIGURATIONS FOR COMPETING ALGORITHMS.

Algorithms	Parameter	Value
GWO	*a*	[0,2]
WOA	*a, a2, b*	[0,2], [-1,-2], 1
DMO	*α, β, τ, phi*	1, 1, 0.1, [-1,1]
SO	*c1, c2, c3*	0.5, 0.05, 2
DBO	*K, b, θ, α*	(0, 0.2], (0,1), [0,π], 1 or -1
EDBO	*K, b, θ, α*	(0, 0.2], (0,1), [0,π], 1 or -1

B. Comparative Analysis of EDBO and Other Algorithms

This research conducted comparative evaluations of the proposed methodology against five established optimization techniques: GWO, WOA, DMO, SO, and DBO. Experimental consistency was ensured through standardized parameter configurations, including execution count, population size, problem dimensionality, and maximum iteration count, as detailed in Section IV-A.

Through thirty independent experimental trials, optimal fitness values were systematically recorded during each iterative process. Table III comprehensively presents the average best fitness (Ave) and corresponding standard deviations (Std) obtained from these trials across all evaluated algorithms, including GWO, WOA, DMO, SO, DBO, and EDBO.

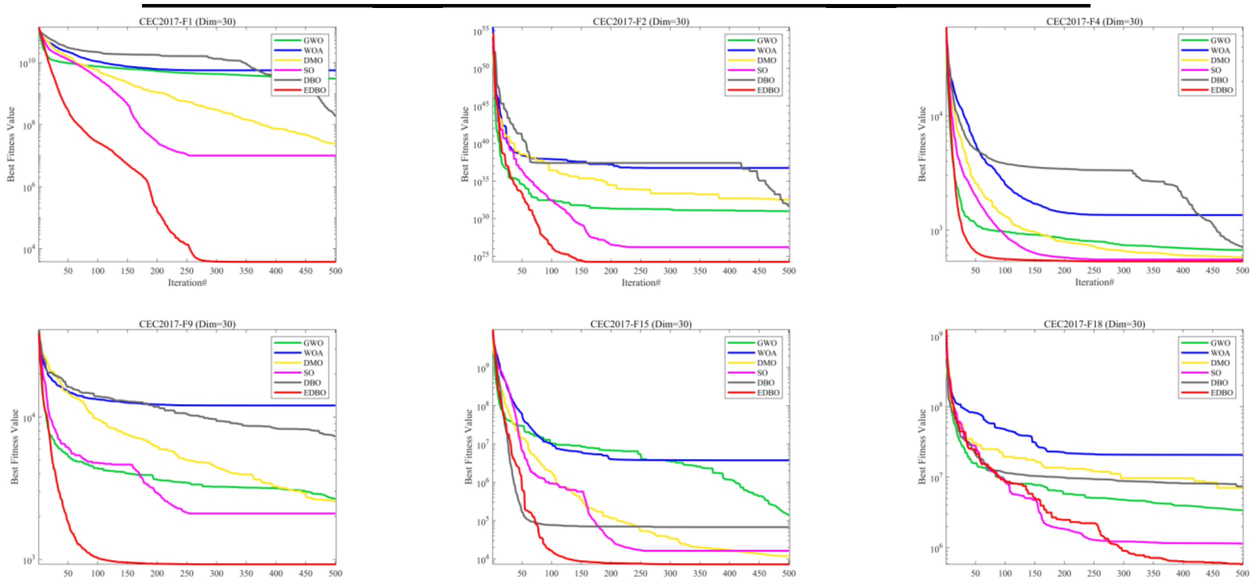
Statistical evaluation conclusively demonstrates EDBO's competitive advantage. The Friedman test results, displayed in the table's concluding rows, provide both mean values and comprehensive rankings. The tabulated results employ bold formatting to distinguish the most competitive values, highlighting algorithmic superiority in specific test scenarios.

When evaluated against five prominent optimization techniques using the CEC2017 benchmark suite, the Enhanced Dung Beetle Optimization (EDBO) method demonstrated dominant performance characteristics. The algorithm secured top rankings in 22 of the 30 test functions while maintaining competitive performance across all remaining functions, never falling to last position in any evaluation metric.

TABLE II TEST RESULTS FOR CEC2017

ID	Metric	GWO	WOA	DMO	SO	DBO	EDBO
CEC2017-F1	Ave	3.053E+09	5.616E+09	2.459E+07	1.009E+07	1.815E+08	**3.790E+03**
	Std	1.891E+09	2.073E+09	5.926E+06	1.263E+07	9.576E+07	**3.597E+03**
CEC2017-F2	Ave	9.986E+30	5.544E+36	3.453E+32	1.648E+26	4.598E+31	**1.835E+24**
	Std	2.861E+31	1.710E+37	8.788E+32	5.149E+26	1.436E+32	**5.798E+24**
CEC2017-F3	Ave	5.756E+04	3.117E+05	1.582E+05	**7.065E+04**	8.257E+04	8.120E+04
	Std	1.317E+04	7.813E+04	3.140E+04	**7.235E+03**	1.430E+04	1.927E+04
CEC2017-F4	Ave	6.698E+02	1.355E+03	5.774E+02	5.531E+02	7.156E+02	**5.331E+02**
	Std	1.283E+02	3.712E+02	4.004E+01	4.089E+01	2.177E+02	**3.131E+01**
CEC2017-F5	Ave	6.370E+02	9.086E+02	7.361E+02	**5.961E+02**	7.741E+02	6.037E+02
	Std	6.238E+01	7.957E+01	**1.332E+01**	2.104E+01	5.699E+01	2.422E+01
CEC2017-F6	Ave	6.120E+02	6.778E+02	6.047E+02	6.193E+02	6.484E+02	**6.001E+02**
	Std	4.309E+00	1.387E+01	**1.216E+00**	5.875E+00	8.513E+00	1.523E-01
CEC2017-F7	Ave	8.839E+02	1.323E+03	9.950E+02	9.261E+02	1.040E+03	**8.400E+02**
	Std	3.734E+01	8.231E+01	**1.270E+01**	5.114E+01	9.710E+01	2.311E+01
CEC2017-F8	Ave	8.927E+02	1.095E+03	1.040E+03	**8.892E+02**	1.037E+03	9.000E+02
	Std	2.094E+01	4.555E+01	**8.966E+00**	2.029E+01	4.958E+01	1.939E+01
CEC2017-F9	Ave	2.666E+03	1.208E+04	2.553E+03	2.101E+03	7.346E+03	**9.228E+02**
	Std	9.813E+02	4.164E+03	5.909E+02	4.682E+02	2.839E+03	**3.115E+01**
CEC2017-F10	Ave	5.448E+03	7.592E+03	8.427E+03	**4.017E+03**	6.665E+03	7.020E+03
	Std	1.682E+03	6.110E+02	**2.573E+02**	6.010E+02	1.037E+03	4.223E+02
CEC2017-F11	Ave	2.550E+03	1.118E+04	1.648E+03	1.463E+03	2.650E+03	**1.283E+03**
	Std	1.359E+03	5.192E+03	5.997E+01	1.901E+02	2.358E+03	**5.035E+01**
CEC2017-F12	Ave	1.631E+08	6.018E+08	2.493E+07	5.067E+06	2.727E+07	**1.453E+06**
	Std	1.320E+08	3.316E+08	1.346E+07	4.450E+06	1.994E+07	**1.281E+06**
CEC2017-F13	Ave	6.953E+06	1.366E+07	**1.865E+04**	7.776E+04	4.501E+06	2.496E+04
	Std	1.097E+07	1.498E+07	1.651E+04	5.555E+04	8.258E+06	**1.350E+04**
CEC2017-F14	Ave	4.038E+05	1.769E+06	**1.926E+05**	6.077E+04	2.392E+05	3.147E+05
	Std	4.211E+05	2.503E+06	1.015E+05	**4.033E+04**	2.232E+05	3.416E+05
CEC2017-F15	Ave	1.365E+05	3.763E+06	1.184E+04	1.626E+04	6.753E+04	**7.197E+03**
	Std	1.844E+05	4.378E+06	1.049E+04	1.169E+04	5.256E+04	**6.898E+03**
CEC2017-F16	Ave	2.685E+03	4.557E+03	3.498E+03	2.762E+03	3.214E+03	**2.502E+03**
	Std	3.051E+02	6.389E+02	1.954E+02	1.909E+02	3.441E+02	2.063E+02

ID	Metric	GWO	WOA	DMO	SO	DBO	EDBO
CEC2017-F17	Ave	2.124E+03	2.705E+03	2.501E+03	2.230E+03	2.852E+03	**1.855E+03**
	Std	1.896E+02	4.225E+02	7.971E+01	2.406E+02	3.181E+02	9.315E+01
CEC2017-F18	Ave	3.401E+06	2.072E+07	7.065E+06	1.147E+06	7.373E+06	**5.817E+05**
	Std	2.827E+06	1.467E+07	3.746E+06	7.440E+05	6.778E+06	4.702E+05
CEC2017-F19	Ave	5.242E+05	2.129E+07	1.688E+04	2.277E+04	2.544E+06	**8.173E+03**
	Std	3.068E+05	2.088E+07	1.977E+04	2.699E+04	5.362E+06	9.915E+03
CEC2017-F20	Ave	2.410E+03	2.824E+03	2.825E+03	2.499E+03	2.789E+03	**2.354E+03**
	Std	1.488E+02	2.589E+02	1.098E+02	1.035E+02	2.394E+02	1.190E+02
CEC2017-F21	Ave	2.429E+03	2.639E+03	2.536E+03	**2.399E+03**	2.539E+03	2.405E+03
	Std	3.731E+01	6.275E+01	1.475E+01	1.349E+01	8.199E+01	1.889E+01
CEC2017-F22	Ave	4.721E+03	8.227E+03	6.762E+03	**3.064E+03**	4.740E+03	4.068E+03
	Std	1.676E+03	1.525E+03	2.963E+03	1.474E+03	2.523E+03	2.798E+03
CEC2017-F23	Ave	2.791E+03	3.171E+03	2.881E+03	2.793E+03	2.988E+03	**2.727E+03**
	Std	5.848E+01	1.374E+02	1.340E+01	2.930E+01	6.196E+01	3.014E+01
CEC2017-F24	Ave	2.946E+03	3.248E+03	3.046E+03	2.964E+03	3.157E+03	**2.944E+03**
	Std	5.974E+01	5.557E+01	1.220E+01	3.409E+01	5.978E+01	1.505E+01
CEC2017-F25	Ave	3.016E+03	3.237E+03	2.930E+03	2.978E+03	3.020E+03	**2.913E+03**
	Std	3.672E+01	1.279E+02	1.598E+01	4.874E+01	1.167E+02	2.076E+01
CEC2017-F26	Ave	4.843E+03	7.959E+03	5.884E+03	5.515E+03	6.841E+03	**4.517E+03**
	Std	5.353E+02	1.188E+03	2.278E+02	5.944E+02	5.591E+02	3.100E+02
CEC2017-F27	Ave	3.262E+03	3.508E+03	3.237E+03	3.288E+03	3.346E+03	**3.226E+03**
	Std	2.117E+01	1.332E+02	7.604E+00	2.654E+01	8.667E+01	1.373E+01
CEC2017-F28	Ave	3.486E+03	4.016E+03	3.345E+03	3.349E+03	3.728E+03	**3.341E+03**
	Std	6.939E+01	1.543E+02	3.169E+01	6.131E+01	1.109E+03	3.976E+01
CEC2017-F29	Ave	4.254E+03	5.358E+03	4.550E+03	3.945E+03	4.360E+03	**3.661E+03**
	Std	2.343E+02	6.626E+02	2.326E+02	1.899E+02	3.777E+02	1.854E+02
CEC2017-F30	Ave	1.019E+07	8.884E+07	3.001E+05	2.743E+05	4.127E+06	**2.432E+04**
	Std	7.163E+06	7.093E+07	2.956E+05	2.730E+05	3.085E+06	8.464E+03
Friedman Mean		3.157E+00	5.707E+00	3.663E+00	2.417E+00	4.240E+00	1.650E+00
Rank		3	6	4	2	5	1



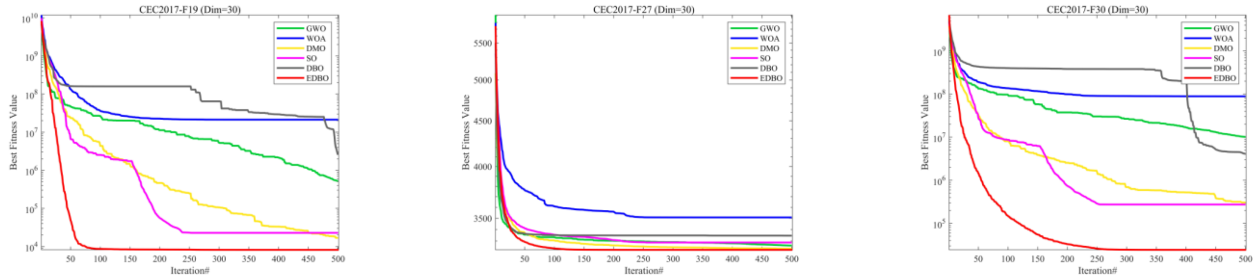


Fig. 2 Convergence curve comparison.

Statistical assessment through Friedman ranking positioned EDBO at the premier level with a ranking of 1, indicating its consistent dominance across diverse problem domains. This performance pattern confirms the algorithm's enhanced capabilities and adaptability to varying optimization challenges. The collective experimental evidence substantiates EDBO's exceptional performance through both individual function results and comprehensive statistical analysis, establishing it as a reliable and efficient optimization methodology for diverse application scenarios.

Further investigation into convergence characteristics utilized selectively chosen test functions for detailed comparative assessment. Figure 2 clearly illustrate EDBO's consistent advantage over competing algorithms, exhibiting both accelerated convergence velocity and enhanced solution accuracy, thereby validating its effectiveness as an advanced optimization approach.

The methodology demonstrates optimal convergence speed coupled with superior solution precision at convergence, reflecting its well-calibrated equilibrium between global exploration and local optimization. These experimental outcomes further substantiate EDBO's position as a powerful optimization tool. In essence, the EDBO algorithm represents an advanced optimization methodology that reliably generates high-quality solutions, characterized by exceptional stability, rapid convergence dynamics, precise solution generation, and outstanding capability to avoid local optima, positioning it as an exemplary choice for addressing diverse optimization challenges.

C. Ablation experiment

Comparative experiments are conducted to assess the contributions of each enhancement mechanism to the EDBO algorithm's performance. Three strategies are integrated into the baseline DBO, with each affecting convergence and solution quality. Ablation experiments using stepwise addition and removal evaluate their impact. In stepwise addition, each strategy is added to the baseline DBO, recording performance changes. In stepwise removal, one strategy is removed at a time from the full EDBO configuration to assess its importance. The configurations of all combinations are shown in TABLE III, with "1" indicating activation and "0" deactivation of a strategy.

Figure 3 presents the Friedman mean rankings of ten strategy combinations on the CEC2017 (Dim = 30) benchmark suite. The QHEEFO algorithm, integrating all four enhancement strategies, achieves the lowest average ranking (mean ≈ 1.76) across most test functions, outperforming all other combinations. In contrast, the original DBO ranks lowest, with an average score near 8, highlighting its limited optimization potential.

Among partial combinations, EDBO13 shows stable and strong performance, with average rankings between 2 and 4, confirming that multiple mechanisms enhance optimization stability and precision. Single-enhancement variants (e.g., EDBO1, EDBO2, EDBO3) provide modest gains over DBO but are less effective than multi-mechanism models, indicating that isolated strategies cannot fully leverage the algorithm's potential.

EDBO excels on functions such as F23, F26, and F27, demonstrating its adaptability and robustness in solving multimodal and combinatorial problems. Overall, the results validate that the combined mechanisms in EDBO offer superior stability, convergence speed, and accuracy across complex optimization tasks.

TABLE III VARIOUS EEFO VARIANTS WITH FOUR STRATEGIES.

Algorithms	Cubic Chaotic Map	Global Search Mechanism	Adaptive t-Distribution Perturbation Strategy
DMO	0	0	0
EDMO1	1	0	0
EDMO2	0	1	0
EDMO3	0	0	1
EDMO12	1	1	0
EDMO13	1	0	1
EDMO23	0	1	0
EDMO	1	1	1

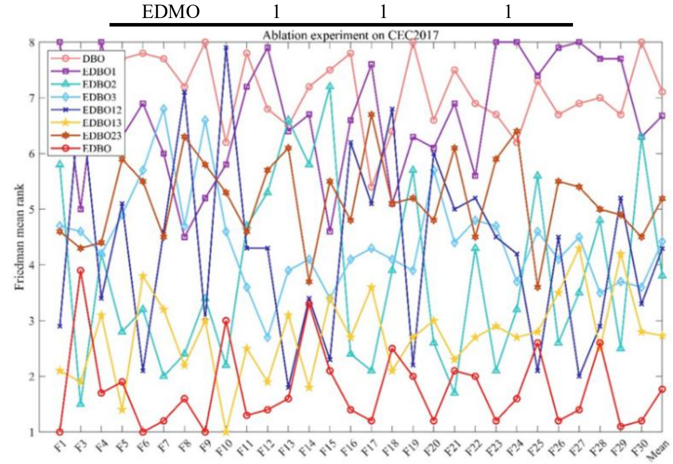


Fig. 3 Ablation experiment on CEC2017 (Dim=30).

V. CONCLUSION

This study presents an EDBO algorithm designed to address the inherent shortcomings of the classical DBO, such as early convergence, insufficient exploration, and limited solution precision. The proposed EDBO incorporates three key mechanisms—Cubic Chaotic Map for population initialization, a refined global exploration strategy, and an adaptive t-distribution–based perturbation scheme—to simultaneously strengthen global search capability and local refinement while maintaining computational efficiency.

The Cubic Chaotic Map improves population diversity at the initialization stage, thereby expanding search coverage and mitigating premature convergence. The enhanced global exploration mechanism enables individuals to flexibly reorient their search trajectories, improving robustness and performance in complex, multimodal environments. In addition, the adaptive t-distribution perturbation dynamically tunes disturbance strength throughout the iteration process, accelerating convergence in the later stages without compromising solution accuracy. Comprehensive evaluations on the CEC2017 benchmark suite demonstrate that EDBO consistently outperforms several established algorithms, including GWO, WOA, DMO, SO, and the baseline DBO, showcasing its superior stability, adaptability, and robustness.

In conclusion, EDBO proves to be a reliable and efficient optimization framework with excellent global exploration, high precision, and fast convergence. Future work will explore its application in areas such as control system parameter optimization, robotic motion planning, and industrial process optimization, further validating its potential as a versatile and high-performance tool for complex engineering and intelligent systems.

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