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An enhanced dung beetle optimization algorithm based-on multi-strategies for solving global optimization problems

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A B S T R A C T

The Dung Beetle Optimization (DBO) algorithm exhibits rapid convergence and robust search capabilities, yet its performance is constrained by excessive reliance on global best and worst solutions. To resolve these weaknesses, this paper introduces an enhanced DBO that incorporates multiple strategies, named DCWDBO. The dynamic opposition-based learning mechanism improves the quality of the initial population. Horizontal and vertical crossover strategies are incorporated to strengthen search capabilities. To preserve high population diversity throughout iterations, the original boundary-control mechanism is replaced with rules from the Wave Search Algorithm. To evaluate DCWDBO's effectiveness, it was compared with PSO, SCA, SCSO, and standard DBO using benchmark functions from CEC 2017, 2020, and 2022. Results indicate that DCWDBO achieves reliable performance, demonstrating robust global exploration, stable convergence, and superior large-scale optimization capability.

1. Introduction

Different optimization algorithms adopt distinct search mechanisms (Shehab et al., 2020). Among them, metaheuristic algorithms have garnered considerable interest. This is due to their remarkable self-organization and self-learning capabilities in optimizing large-scale nonlinear challenges in reality. Mainstream metaheuristic algorithms primarily fall into two types: swarm intelligence (SI) methods and evolutionary algorithms (EA). EA draw inspiration from biological evolution theory (Daoud et al., 2023). They seek optimal solutions by simulating genetic processes such as inheritance. Within evolutionary algorithms, the genetic algorithm (GA) (Holland, 1975) stands as the classic representative. Additionally, differential evolution (DE) and cooperative co-evolutionary algorithms (CCEAs) also belong to this category (Xu et al., 2014). SI algorithms emulate collective behaviors observed in animal groups (e.g., social insects, fish schools) to solve optimization problems (Abu-Hashem et al., 2024). Representative SI algorithms encompass particle swarm optimization (PSO) (Kennedy & Eberhart, 1995), multi-verse optimizer (MVO) (Mirjalili et al., 2016), whale optimization algorithm (WOA) (Mirjalili & Lewis, 2016), grey wolf optimization (GWO) (Mirjalili et al., 2014), sand cat swarm optimization (SCSO) (Seyyedabbasi & Kiani, 2023), sine cosine algorithm (SCA) (Mirjalili, 2016), shuffled frog leaping algorithm (SFLA) (Eusuff et al., 2006), and dung beetle optimizer (DBO) (Xue & Shen, 2022), all of which demonstrating successful applications across domains, such as the job shop scheduling problem (Meng et al., 2023; Rodríguez-Molina et al., 2022).

DBO is a novel SI algorithm introduced in December 2022, which constructs its search framework by simulating four natural behaviors of dung beetle populations. Benefiting from diversified position update mechanisms, DBO exhibits outstanding optimization capabilities. It has been successfully utilized in classical domains including unmanned aerial vehicles' (UAVs) path planning (Liu et al., 2023) and wireless sensor networks (WSNs) (Sangeetha et al., 2024), while also extending to practical optimization in medicine, energy, agriculture, and so on. However, limitations remain in real-world complex optimization problems. The classical DBO exhibits three primary deficiencies:(1) Random initialization risks uneven solution quality; (2) Excessive reliance on global optima and global worst solutions during iterations risks overlooking potential

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optimal directions; (3) Declining population diversity in later stages increases susceptibility to premature convergence. The No Free Lunch (NFL) (Wolpert & Macready, 1997) theorem asserts that no optimization algorithm can universally solve all practical problems, due to the inherent limitations of such algorithms. Consequently, since its 2022 introduction, researchers have focused on enhancing DBO's performance and expanding its ability. Current enhancement studies mainly focus on these two approaches:

Multi-strategy collaborative enhancement: Zhu et al. (2024) introduced an IDBO algorithm incorporating four strategies. First, good point set initialization was used to ensure uniform population distribution. Then, the convergence factor was improved, and the dynamic allocation between breeding and foraging individuals was implemented to balance exploration-exploitation. Finally, a quantum-based t-distribution mutation was incorporated, aiming to prevent premature convergence in local optima. Ye et al. (2024)'s algorithm combines Latin hypercube sampling initialization, mean differential mutation, lens opposition-based learning, and dimension-wise optimization to enhance the global search ability . Wang et al. (2023) developed a by integrating quantum state updates into quasi-opposition learning for enhanced initialization randomness. Q-learning-based adaptive behavior selection and a variable spiral local search method were also introduced into the algorithm.

Algorithmic mechanism integration: Pan et al. (2023) created a MSADBO algorithm, integrated the Moth Search Algorithm (MSA) with DBO, and employed chaotic mapping initialization and mutation operators to strengthen global exploration and local exploitation. Moreover, DBO research has expanded to address multi-objective problems. Tu and Fan (2023) proposed a multi-objective IMODBO algorithm. It incorporates chaotic mapping, adaptive weighting factors, and variable spiral search for dual optimization of distribution network operational costs and switching operations. Zhu et al. (2023) developed a novel multi-objective DBO with enhanced convergence speed and optimization capability. Their algorithm was successfully applied to tungsten-based heavy alloy cutting parameter optimization, achieving reductions in cutting force, vibration, and surface roughness.

Drawing on analyses of DBO's limitations, this study presents an DCWDBO algorithm with the following enhancements:

(1) Implementing a dynamic opposition-based learning mechanism into population initialization to optimize initial population and enhance search efficiency;
(2) Integrating the horizontal and vertical crossover strategies of the Crisscross Optimization algorithm in the position update mechanisms applied to breeding and foraging individuals;
(3) Replacing the original boundary constraint mechanism with Wave Search Algorithm's rules to enhance population diversity.

The remaining sections are structured as follows: Section 2 describes the core workflow of basic DBO, Section 3 outlines the enhancement strategies in DCWDBO with implementation specifics, Section 4 provides comparative experimental evaluations, and Section 5 summarizes the conclusions." and the final effect should look like this. Please update it accordingly.

2. Dung Beetle Optimization Algorithm

DBO models four behavioral patterns observed in dung beetle populations, dividing the population into four subgroups. Each subgroup employs distinct position update mechanisms to cooperatively search for global optima. The working mechanisms of these subgroups are detailed below.

2.1 Ball-Rolling Individuals

Dung beetles utilize solar navigation to maintain linear dung ball rolling in nature. In the DBO algorithm, 20% of individuals simulate this behavior, with their position update formula given by Eq. (1):

$$\begin{aligned} x_i(t+1) &= x_i(t) + \alpha \times k \times x_i(t-1) + b \times \Delta x \\ \Delta x &= |x_i(t) - X^w| \end{aligned} \tag{1}$$

In this context, t corresponds to the current iteration, while $x_i(t)$ specifies the location of the i-th agent of iteration t. X^w signifies the global worst location. Notably, the trajectory of ball-rolling individuals pushing dung balls is influenced by light intensity. The parameter $\alpha \in \{1, -1\}$ determines whether a rolling individual deviates from its original direction. $\alpha = 1$ denotes maintaining the original trajectory, whereas $\alpha = -1$ signifies deviation. Δx models light intensity variation, where a smaller Δx corresponds to stronger light intensity, and a larger Δx represents weaker light intensity. The deflection coefficient k lies within $(0,0.2]$, and b is constrained to $(0,1)$. Additionally, ball-rolling individuals adjust their direction through dancing when encountering obstacles. The location update mechanism is given by the following formula:

$$x_i(t+1) = x_i(t) + \tan\theta\, |x_i(t) - x_i(t-1)| \tag{2}$$

where the deflection angle θ is bounded within $[0, \pi]$. Notably, when $\theta \in \{0, \frac{\pi}{2}, \pi\}$, $\tan\theta$ is undefined, and the ball-rolling individual will maintain its original direction.

2.2 Oviposition Individuals

Female dung beetles select a safe area for oviposition. The original paper stipulates that 20% of the individuals adopted the oviposition behavior observed in the dung beetle population, while introducing an adaptive boundary selection approach to dynamically determine optimal oviposition regions. The boundaries are defined as Eq. (3):

$$\begin{cases} Lb^* = \max(X^* \times (1-R), Lb) \\ Ub^* = \min(X^* \times (1+R), Ub) \end{cases} \tag{3}$$

Lb and Ub respectively represent the solution space's boundaries. X^* indicates current local optimum, while the current iterations count t governing the convergence factor $R = 1 - t/\mathrm{T}_{\max}$. Each oviposition individual lays only one egg during a single iteration, and its location update mechanism is expressed by the following formula:

$$B_i(t+1) = X^* + b_1 \times (B_i(t) - Lb^*) + b_2 \times (B_i(t) - Ub^*) \tag{4}$$

where b_1 and b_2 are $1 \times d$-dimensional random vectors, while$d$ denotes the problem dimensionality. Notably, eggs must remain within the oviposition area. If boundaries are crossed, corrections follow Eq. (5):

$$B_i = \begin{cases} Lb^*, & B_i < Lb^* \\ Ub^*, & B_i > Ub^* \end{cases} \tag{5}$$

2.3 Larval Individuals

Eggs develop into larvae and initiate foraging behavior. In the DBO algorithm, 25% of individuals simulate larval foraging. The foraging area is also updated dynamically, with its range calculated by Eq.(6):

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

where, X^b denotes the global best solution. After defining the foraging area, the location of larval individuals is updated according to Eq. (7):

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

where C_1 is a vector normally random distributed, and C_2 is a vector uniformly random distributed in $(0,1)$.

2.4 Thieving Individuals

Some dung beetles steal dung balls from conspecifics in nature. Within the DBO framework, 35% of the algorithmic agents simulate this mechanism. The original study specifies that this thieving behavior occurs exclusively near the global best solution X^b. The location update for thieving individuals follows Eq. (8):

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

where S denotes a constant, and g follows a normal distribution as a d-dimensional vector.

2.5 Algorithm Procedure

The flowchart of DBO is provided in Fig. 1, and the pseudocode of DBO is shown in Algorithm 1.

3. The Multi-strategy Enhanced DBO Algorithm

The DBO algorithm has been utilized to complex real-world problems on a large scale due to its exceptional performance. However, limitations such as declining population diversity in later iterations limit its solution accuracy. To solves these issues, this study introduces three kinds of methods to enhance the DBO algorithm.

3.1 Dynamic Opposition-Based Learning

The Opposition-Based Learning (OBL) mechanism, serves as an initialization strategy to generate opposite solutions of current candidates and retain superior ones for enhance global search capability (Tizhoosh, 2005). However, traditional OBL generates opposite solutions at fixed distances from current solutions, which limits its ability to enhance population diversity due to insufficient randomness. Xu et al. (2020) developed Dynamic Opposition-Based Learning (DOL) specifically to overcome this limitation.

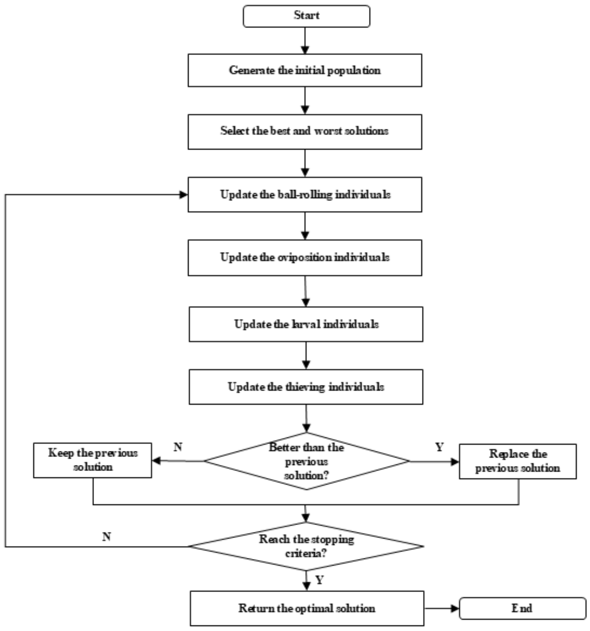

Fig. 1. The flowchart of the DBO.

Algorithm 1. Dung Beetle Optimization (DBO) Procedure

Require: Maximum iteration $\boldsymbol{T_{max}}$, Population scale $\boldsymbol{N}$.
Output: Global optimum $\boldsymbol{X^b}$ with fitness value $\boldsymbol{f_b}$.

```
Generate population {X_i}_{i=1}^N and set parameters
while t < T_max:
  Ball-rolling Phase (20% agents):
  for each agent:
  Generate α ~ U(0,1)
  if α ≤ 0.9:
   Update via Eq.(1)
  Else:
   Update via Eq.(2)
Calculate convergence factor R = 1 − t/T_max.
Spawning Phase (20% agents):
for each agent:
  Update via Eq.(3) and Eq.(4)
    if B_ij > Ub*||B_ij < Lb*
    Apply boundary constraint via Eq. (5)
    Apply boundary constraint via Eq.(5)
Foraging Phase (25% agents):
for each agent:
  Update via Eq.(6) and Eq.(7)
Thieving Phase (35% agents):
for each agent:
  Update via Eq.(8)
t ← t + 1
Return X^b, f_b
```

In the DOL strategy, the Dynamic Opposite Number X^{DO} of a real number $X \epsilon [lb, ub]$ is defined by Eq. (9):

$$X^{DO} = (lb + ub) * rand - X \tag{9}$$

in the equation, $rand$ denotes a randomly generated value within the interval (0,1), while lb (lower bound) and ub (upper bound) represent the corresponding boundaries. For a D-dimensional individual $X = (X_1, X_2, \ldots, X_D)$ in the search space, its dynamic opposite solution $X_d^{DO} = (X_1^{DO}, X_2^{DO}, \ldots, X_D^{DO})$ is defined by Eq.(10):

$$X_d^{DO} = (lb_d + ub_d) * R - X_d \; j = 1:D \quad (10)$$

notably, R in this context represents a D-dimensional random vector within $(0,1)$, and X_d^{DO} remains strictly confined to the boundaries $[lb_d, ub_d]$ for each dimension. During population initialization, the algorithm first randomly generates $Popsize$ solutions, then sequentially produces their corresponding dynamic opposite solutions. Subsequently, it merges both populations and selects the top $Popsize$ individuals based on fitness ranking to form the initial population. This approach effectively expands the initial search scope through stochastic mechanisms. Notably, this expansion maintains randomness rather than restricting exploration near the current global optimum, thereby enhancing the initial population quality.

3.2 Horizontal and Vertical Crossover

The horizontal crossover and vertical crossover mechanisms of the Crisscross Optimization Algorithm(CSO) endow it with robust global search capabilities (Meng et al., 2014). As described above, DBO balances global and local search across the solution space by updating the positions of oviposition and larval individuals. However, since these two search mechanisms focus solely on the global best and worst solutions, they may overlook potential directions for obtaining optimal solutions, leading to premature convergence. To enhance the performance of the algorithm, the mentioned dual crossover strategies are respectively incorporated into the oviposition and foraging phases. The specific implementations are as follows.

3.2.1 Horizontal Crossover

The horizontal crossover generates offspring via full-dimensional arithmetic crossover between a pair of distinct parent individuals. If parents are represented by X_i and X_j, their offspring $X_{i,d}^C$ and $X_{j,d}^C$ in the d-th dimension are defined by Eq. (11) and Eq. (12):

$$X_{i,d}^C = r_1 \times X_{i,d} + (1 - r_1) \times X_{j,d} + c_1 \times \left(X_{i,d} - X_{j,d}\right) \quad (11)$$
$$X_{j,d}^C = r_2 \times X_{j,d} + (1 - r_2) \times X_{i,d} + c_2 \times \left(X_{j,d} - X_{i,d}\right) \quad (12)$$

where, $r_{1,} r_2 \sim \mathrm{U}(0,1)$, while c_1 and c_2 are two random values uniformly distributed between -1 and 1. Oviposition individuals are randomly paired to perform horizontal crossover during iteration. The resulting offspring individuals are compared with the parent individuals. Those with superior fitness are retained. This mechanism expands the search scope to a cubic space with parents as diagonal vertices, reducing search blind spots thereby boosting the algorithm's global exploration. Consequently, the talent of DCWDBO to escape local optima is also strengthened.

3.2.2 Vertical Crossover

Vertical crossover generates offspring through arithmetic crossover applied to two distinct dimensions of the same individual. For an individual X_i, if vertical crossover is applied to its a-th and b-th dimensions, the offspring's a-th dimension $X_{i,a}^C$ is generated by Eq. (13):

$$X_{i,a}^C = r \times X_{i,a} + (1 - r) \quad (13)$$

where r is a random value uniformly distributed in (0,1). Vertical crossover occurs during the foraging process. After updating the position of a larval individual, two dimensions are randomly selected for vertical crossover. By integrating vertical crossover, the algorithm was provided an approach to escape local optima the algorithm avoids local optima traps while effectively avoiding disrupting dimensions that are already in the global optimum state. Subsequently, the offspring is compared with the parent individual, and the superior one is retained. By facilitating information exchange between dimensions, this strategy enhances exploratory efficacy while preventing premature convergence.

3.3 Boundary Constraint Rule of the Wave Search Algorithm

Wave Search Algorithm (WSA) serve as a novel metaheuristic approach, with inspiration is drawn from radar technology (Zhang et al., 2024). WSA introduces an innovative boundary constraint rule. Most conventional boundary constraint rules directly set out-of-bounds dimensions to boundary values. The original DBO algorithm also adopts this traditional mechanism. However, this approach risks causing population aggregation near boundaries, thereby reducing population diversity, particularly during later iterations. To address this limitation, DBO's original boundary constraint rule is replaced with WSA's boundary constraint rule. The core idea is to randomly reset dimensions that exceed boundaries. Specifically, when the i-th individual's d-th dimension exceeds the boundary, this dimension is adjusted according to Eq. (14):

$$X_{i,d} = (ub_d - lb_d) \times r + lb_d, if X_{i,d} > ub_d \; or \; X_{i,d} < lb_d \quad (14)$$

where ub_d and lb_d represent the boundaries. And $r \sim U(0,1)$ denotes an independently generated random number uniformly distributed. By stochastically resetting out-of-bounds dimensions, this strategy perturbs problematic dimensions in a targeted manner. It balances the algorithm's global and local search while preserving solution variety, thereby improving optimization efficacy.

3.4 The Enhanced Algorithm Procedure

The flowchart of the proposed DCWDBO is provided in Fig. 2, and the pseudocode of it is shown in Algorithm 2.

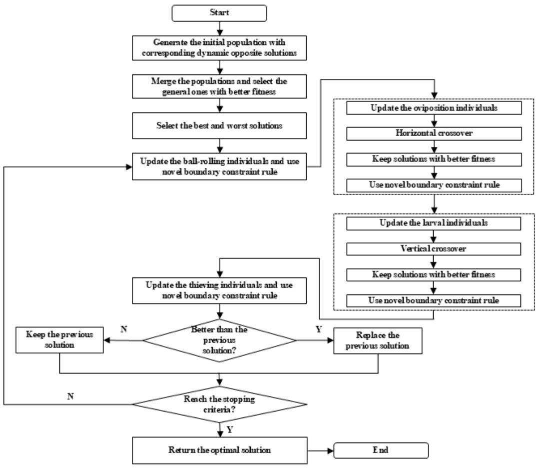

Fig. 2. The flowchart of the proposed DCWDBO.

Algorithm 2. **The Enhanced Dung Beetle Algorithm (DCWDBO) Procedure**

Require: Maximum iteration $\boldsymbol{T_{max}}$, Population scale $\boldsymbol{N}$.
Output: Global optimum $\boldsymbol{X^b}$ with fitness value $\boldsymbol{f_b}$.
Generate population $\{\boldsymbol{X_i}\}_{i=1}^{N}$ and set parameters.
Create Dynamic opposite solution $\boldsymbol{X_d^{DO}}$ via Eq.(10).
Merge populations and select better $\boldsymbol{N}$ solutions by fitness sorting.
while $\boldsymbol{t < T_{max}}$:
  Ball-rolling Phase (20% agents):
  for each agent:
  Generate $\boldsymbol{\alpha \sim U(0,1)}$
   if $\boldsymbol{\alpha \leq 0.9}$:
    Update via Eq.(1)
   else:
    Update via Eq.(2)
  Apply WSA's boundary constraint via Eq.(14).
  Calculate convergence factor $\boldsymbol{R = 1 - t/T_{max}}$.
  Oviposition Phase (20% agents):
for each agent:
  update via Eq.(3) and Eq.(4)
  Apply **horizontal crossover operation**:
  Select parent pairs and generate offsprings via Eq.(11) and Eq.(12).
  Select better solutions between parents and offsprings.
  Apply WSA's boundary constraint via Eq.(14).
 Larval Phase (25% agents):
 for each agent:
  Update via Eq.(6) and Eq.(7)
  Apply **vertical crossover operation**:
   Randomly select dimensions and generate offsprings via Eq.(13).
   Select better solutions between parents and offsprings.
  Apply WSA's boundary constraint via Eq.(14).
 Thieving Phase (35% agents):
 for each agent:
  Update via by Eq.(8)
  Apply WSA's boundary constraint via Eq.(14).
 $\boldsymbol{t \leftarrow t + 1}$
Return $\boldsymbol{X^b, f_b}$

4. Experimental Results and Discussion

The research assesses DCWDBO's efficacy employing four comparative algorithms: PSO, SCA, SCSO and the typical DBO. The tests cover benchmark function sets CEC 2017 (Wu et al., 2016), 2020 (Yue et al., 2019), and 2022 (Ahrari et al., 2022). CEC2017 is a classical suite for assessing optimization methods, which includes 30 single-objective benchmark functions. In this set, F1–F3 are Unimodal functions, F4–F10 are Simple multimodal functions, F11–F20 serve as Hybrid functions, while F21–F30 are Composition functions. Due to stability issues with F2 in the original test suite, this function was excluded from testing, leaving 29 functions for evaluation. CEC2020 benchmark set has also become a common standard for evaluating optimization algorithms. It includes 10 single-objective benchmark functions, with F1 is a unimodal function, F2–F4 are simple multimodal functions, F5–F7 serve as hybrid functions, and F8–F10 are composite functions. CEC2022 benchmark suite introduces 12 novel single-objective functions, where F1 is a unimodal function, F2–F4 are multimodal functions, F5–F7 are hybrid functions, and F8–F10 are composition functions. The configuration details of all five algorithms are summarized in Table 1. All experiments employed a population size of 30 with 500 maximum iterations. To mitigate random fluctuations, DCWDBO and comparison algorithms underwent 30 separate runs per benchmark function, with results recorded as mean, optimal, worst fitness values, and standard deviations. Furthermore, DCWDBO's performance was statistically compared against four algorithms mentioned above using Wilcoxon rank-sum tests in paired comparisons. When the obtained p-value is below the significance level ($\alpha = 0.05$), a statistically significant difference exists between two algorithms.

Table 1
Parameter setting

Algorithm	Popularity Scale	Iteration number	Parameters
PSO	30	500	c_1=c_2=1.49445,$V_{max} = 1$,$V_{min} = -1$
SCA	30	500	a=2
SCSO	30	500	S=2
DBO	30	500	BRI=6,OI=6,LI=7,TI=11
DCWDBO	30	500	BRI=6,OI=6,LI=7,TI=11

In Table 1, parameters c_1 and c_2 respectively denote the individual learning factor and social learning factor for PSO. For DBO and DCWDBO, BRI refers to ball-rolling individuals, while OI, LI, and TI respectively represent oviposition individuals, larval individuals, and thieving individuals. Additionally, all comparative experiments were conducted on the following hardware platform: Intel Core i7-13700F processor, 16GB RAM, Windows 11 64-bit operating system, and MATLAB 2018b software environment. This setup ensures a stable computational foundation for algorithm performance evaluation.

4.1 Results and Analysis on CEC2017 Benchmark Functions

Tables 2–5 summarize the comparative test results for CEC2017, CEC2020, and CEC2022, incorporating statistical analysis via Wilcoxon rank-sum. The assessment of DCWDBO against four comparative algorithms on 29 functions on 30 D (Table 2) and 100 D (Table 3) is presented below.

Table 2
CEC2017 test results on 30-dimension

Fun	Index	PSO	SCA	SCSO	DBO	DCWDBO
F1	mean	8.6563E+08	2.1331E+10	1.3642E+10	1.8472E+10	**8.4685E+06**
	best	3.7199E+07	1.6943E+10	4.9263E+09	1.1848E+09	**6.7634E+03**
	worst	3.4539E+09	2.9722E+10	2.5078E+10	4.9246E+10	**2.1629E+08**
	std	9.8856E+08	3.0081E+09	5.0110E+09	1.0716E+10	**3.8628E+07**
	p-value	4.9600E-11	1.5100E-11	1.5100E-11	1.5100E-11	
F3	mean	**4.8593E+04**	5.7852E+04	6.5893E+04	8.9198E+04	7.1346E+04
	best	**2.2670E+04**	5.7852E+04	4.3437E+04	6.5940E+04	5.3692E+04
	worst	**8.8231E+04**	1.4576E+05	8.9200E+04	1.2191E+05	8.9446E+04
	std	1.4044E+04	8.6447E+04	1.2264E+04	1.3011E+04	**9.4360E+03**
	p-value	1.0000E+00	6.5100E-04	9.6494E-01	1.5100E-11	
F4	mean	7.6818E+02	8.6474E+02	2.2190E+03	2.0330E+03	**5.2232E+02**
	best	5.3682E+02	1.8451E+03	6.7123E+02	6.3081E+02	**4.4193E+02**
	worst	1.4153E+03	4.9024E+03	4.5484E+03	7.0709E+03	**6.4816E+02**
	std	2.4042E+02	2.9298E+03	1.0590E+03	1.5637E+03	**4.3573E+01**
	p-value	9.3327E-01	1.1100E-09	1.5100E-11	1.5100E-11	
F5	mean	7.2576E+02	8.3144E+02	8.0239E+02	7.6503E+02	**6.2697E+02**
	best	6.4915E+02	7.7446E+02	7.1024E+02	6.4984E+02	**5.6181E+02**
	worst	8.5290E+02	8.8960E+02	8.7350E+02	9.1024E+02	**7.2826E+02**
	std	4.1661E+01	**3.0747E+01**	4.8011E+01	7.6002E+01	3.9445E+01
	p-value	9.2800E-10	1.5100E-11	2.0400E-11	4.0500E-10	
F6	mean	6.6219E+02	6.6643E+02	6.6634E+02	6.5199E+02	**6.2375E+02**
	best	6.4931E+02	6.5228E+02	6.4349E+02	6.2341E+02	**6.1358E+02**
	worst	6.9618E+02	6.8050E+02	6.9332E+02	6.9357E+02	**6.3849E+02**
	std	9.2328E+00	7.7515E+00	1.0533E+01	1.6126E+01	**6.9085E+00**
	p-value	1.5100E-11	1.5100E-11	1.5100E-11	3.6900E-10	

Table 2
CEC2017 test results on 30-dimension (continued)

Fun	Index	PSO	SCA	SCSO	DBO	DCWDBO
F7	mean	1.1837E+03	1.2462E+03	1.2727E+03	**6.5199E+02**	9.8790E+02
	best	1.0423E+03	1.1285E+03	1.0967E+03	**6.2341E+02**	8.6606E+02
	worst	1.3374E+03	1.3735E+03	1.4349E+03	**6.9357E+02**	1.1616E+03
	std	7.8924E+01	5.5599E+01	8.2318E+01	**1.6126E+01**	7.6822E+01
	p-value	1.0200E-09	2.2500E-11	4.5000E-11	5.5700E-04	
F8	mean	9.6014E+02	1.0934E+03	1.0481E+03	1.0323E+03	**9.2705E+02**
	best	9.1543E+02	1.0590E+03	9.8902E+02	9.2011E+02	**8.5474E+02**
	worst	**1.0163E+03**	1.1391E+03	1.0940E+03	1.1205E+03	1.0596E+03
	std	2.4914E+01	**2.2407E+01**	2.8765E+01	5.8039E+01	4.1759E+01
	p-value	1.2200E-05	1.8400E-11	2.7900E-10	7.1500E-09	
F9	mean	7.1763E+03	8.6038E+03	7.0153E+03	9.4586E+03	**3.6915E+03**
	best	3.5106E+03	5.6476E+03	5.0550E+03	3.8113E+03	**1.6152E+03**
	worst	1.2928E+04	1.3423E+04	9.3621E+03	1.5808E+04	**6.7144E+03**
	std	2.0667E+03	1.9023E+03	**1.1032E+03**	2.9906E+03	1.4082E+03
	p-value	1.1000E-08	4.0800E-11	3.0600E-10	9.7800E-11	
F10	mean	8.9089E+03	8.7483E+03	7.1238E+03	**6.3479E+03**	7.6064E+03
	best	5.5388E+03	8.0461E+03	5.2467E+03	**4.2283E+03**	4.6492E+03
	worst	9.9842E+03	9.3309E+03	9.2007E+03	9.3549E+03	**8.8258E+03**
	std	8.8791E+02	**3.0357E+02**	8.8304E+02	1.3448E+03	1.1620E+03
	p-value	9.3700E-08	5.5100E-09	9.9800E-01	9.9955E-01	
F11	mean	1.4599E+03	4.0795E+03	3.6312E+03	4.8222E+03	**1.2610E+03**
	best	1.2194E+03	2.6425E+03	1.5649E+03	1.3858E+03	**1.1479E+03**
	worst	2.4040E+03	6.6609E+03	5.8978E+03	1.1003E+04	**1.3802E+03**
	std	2.2548E+02	1.0194E+03	1.2507E+03	3.2395E+03	**5.2750E+01**
	p-value	6.4300E-07	1.5100E-11	1.5100E-11	1.5100E-11	
F12	mean	4.0611E+07	2.6359E+09	1.3043E+09	1.1266E+09	**1.6012E+06**
	best	2.6278E+06	1.6455E+09	8.9076E+07	1.8695E+06	**9.4270E+04**
	worst	1.7398E+08	3.7865E+09	6.5822E+09	6.9256E+09	**4.4732E+06**
	std	4.5511E+07	5.4079E+08	1.3882E+09	1.5504E+09	**1.0825E+06**
	p-value	3.3500E-11	1.5100E-11	1.5100E-11	4.9600E-11	
F13	mean	7.0027E+04	1.4629E+09	7.4592E+07	6.6674E+08	**2.1726E+04**
	best	2.3971E+04	5.1197E+08	5.7180E+04	3.6221E+04	**1.5212E+03**
	worst	1.5487E+05	5.1799E+09	6.7941E+08	4.6591E+09	**5.7879E+04**
	std	3.4421E+04	9.0038E+08	1.4176E+08	1.3427E+09	**1.8193E+04**
	p-value	3.2600E-08	1.5100E-11	1.6700E-11	2.7500E-11	
F14	mean	**9.3086E+04**	7.8685E+05	1.1283E+06	6.4879E+05	1.4111E+05
	best	**1.6697E+03**	1.1475E+05	1.0499E+05	3.0998E+03	9.4054E+03
	worst	9.1279E+05	2.1052E+06	3.5551E+06	3.6301E+06	**8.1017E+05**
	std	**1.6118E+05**	5.2424E+05	9.5404E+05	9.7605E+05	1.6816E+05
	p-value	9.5037E-01	3.5600E-09	7.1500E-09	3.1890E-03	
F15	mean	2.6225E+04	4.2563E+07	3.9332E+06	3.0161E+07	**9.5474E+03**
	best	1.1793E+04	4.6559E+06	3.6395E+04	4.0485E+03	**1.7346E+03**
	worst	6.4172E+04	1.0979E+08	2.1071E+07	9.0293E+08	**4.2409E+04**
	std	1.2553E+04	3.2609E+07	5.3434E+06	1.6207E+08	**9.6006E+03**
	p-value	5.9700E-07	1.5100E-11	1.8400E-11	4.9200E-08	
F16	mean	3.5871E+03	4.1827E+03	3.6881E+03	3.3933E+03	**2.7149E+03**
	best	2.8066E+03	3.5304E+03	2.8298E+03	2.4589E+03	**2.1323E+03**
	worst	5.0143E+03	4.5760E+03	5.1440E+03	4.3486E+03	**3.7843E+03**
	std	6.0807E+02	**2.3654E+02**	5.9214E+02	5.1533E+02	3.6880E+02
	p-value	2.3400E-08	1.8400E-11	1.7500E-09	3.1400E-06	
F17	mean	2.6343E+03	2.8978E+03	2.5536E+03	2.7509E+03	**2.2725E+03**
	best	1.9998E+03	2.4612E+03	1.9729E+03	2.3279E+03	**1.7842E+03**
	worst	3.3028E+03	3.4531E+03	3.3027E+03	3.4660E+03	**2.8737E+03**
	std	2.8580E+02	**1.9584E+02**	3.0186E+02	3.2851E+02	2.7504E+02
	p-value	1.9200E-05	3.3600E-10	4.0600E-04	8.6500E-07	
F18	mean	**8.7113E+05**	1.2743E+07	4.8319E+06	7.1412E+06	1.9945E+06
	best	9.2533E+04	1.1615E+06	**7.3006E+04**	1.1890E+05	8.9278E+04
	worst	**1.1861E+07**	3.2671E+07	2.5763E+07	3.0203E+07	1.4338E+07
	std	**2.0948E+06**	7.4994E+06	6.0667E+06	8.9724E+06	3.0893E+06
	p-value	9.9947E-01	1.3300E-09	7.8190E-03	8.3433E-02	
F19	mean	7.3306E+05	1.1717E+08	1.3041E+07	9.5902E+07	**1.2527E+04**
	best	4.0823E+03	2.4753E+07	3.0476E+04	**2.2906E+03**	2.3409E+03
	worst	2.1754E+06	4.7086E+08	1.0334E+08	1.8097E+09	**5.1318E+04**
	std	6.6533E+05	9.7430E+07	2.1578E+07	3.2265E+08	**1.3952E+04**
	p-value	3.3600E-10	1.5100E-11	2.2500E-11	4.4500E-10	
F20	mean	2.9968E+03	2.8972E+03	2.7773E+03	2.6967E+03	**2.5079E+03**
	best	2.3243E+03	2.5398E+03	2.4098E+03	2.1808E+03	**2.1648E+03**
	worst	3.5766E+03	3.2825E+03	3.1339E+03	3.2061E+03	**3.0212E+03**
	std	3.2678E+02	**1.5616E+02**	1.9138E+02	2.3165E+02	1.9899E+02
	p-value	1.3900E-07	7.1500E-09	6.2500E-06	7.2100E-04	
F21	mean	2.5668E+03	2.6045E+03	2.5737E+03	2.5618E+03	**2.4100E+03**
	best	2.4625E+03	2.5630E+03	2.4782E+03	2.4548E+03	**2.3566E+03**
	worst	2.6940E+03	2.6503E+03	2.6518E+03	2.6851E+03	**2.5372E+03**
	std	5.2441E+01	**2.1922E+01**	4.7155E+01	5.5298E+01	3.4231E+01
	p-value	3.6900E-11	1.5100E-11	2.7500E-11	4.5000E-11	
F22	mean	7.9982E+03	9.6062E+03	7.2873E+03	6.6803E+03	**2.3189E+03**
	best	2.4329E+03	3.9935E+03	3.3960E+03	2.5564E+03	**2.3038E+03**
	worst	1.1312E+04	1.1024E+04	9.6050E+03	9.2117E+03	**2.3521E+03**
	std	2.7703E+03	1.7442E+03	1.8490E+03	2.0915E+03	**1.0486E+01**
	p-value	1.5100E-11	1.5100E-11	1.5100E-11	1.5100E-11	

Table 2
CEC2017 test results on 30-dimension (continued)

Fun	Index	PSO	SCA	SCSO	DBO	DCWDBO
F23	mean	3.5843E+03	3.0818E+03	3.0648E+03	3.0059E+03	**2.8928E+03**
	best	3.2157E+03	2.9797E+03	2.8614E+03	2.8378E+03	**2.7292E+03**
	worst	4.2056E+03	3.1899E+03	3.4185E+03	3.2280E+03	**3.0434E+03**
	std	2.4639E+02	**4.9499E+01**	1.1188E+02	9.6109E+01	9.5193E+01
	p-value	1.5100E-11	8.0700E-11	1.3900E-07	7.0300E-05	
F24	mean	3.4142E+03	3.2549E+03	3.1955E+03	3.2235E+03	**3.1486E+03**
	best	3.1421E+03	3.1615E+03	3.0077E+03	3.0320E+03	**2.9292E+03**
	worst	3.7511E+03	3.3531E+03	3.4301E+03	3.3613E+03	**3.2802E+03**
	std	1.3394E+02	**4.3329E+01**	1.0111E+02	8.9096E+01	9.7066E+01
	p-value	2.0900E-09	2.8000E-07	1.2594E-01	6.1060E-03	
F25	mean	2.9815E+03	3.5827E+03	3.3019E+03	3.3839E+03	**2.9196E+03**
	best	2.9064E+03	3.3446E+03	3.0183E+03	2.9161E+03	**2.8922E+03**
	worst	3.1107E+03	4.2097E+03	3.9285E+03	4.7332E+03	**2.9599E+03**
	std	4.3107E+01	2.0869E+02	2.0650E+02	4.6466E+02	**1.7346E+01**
	p-value	8.4900E-09	1.5100E-11	1.5100E-11	4.8800E-10	
F26	mean	7.9544E+03	7.8031E+03	7.9674E+03	7.4760E+03	**5.1204E+03**
	best	4.1094E+03	6.1107E+03	6.6425E+03	5.9708E+03	**2.8191E+03**
	worst	9.8669E+03	8.5909E+03	1.0147E+04	9.6928E+03	**8.0375E+03**
	std	1.3728E+03	**5.1000E+02**	8.6344E+02	8.0208E+02	1.6211E+03
	p-value	1.9800E-08	5.3500E-10	1.1100E-09	5.7800E-08	
F27	mean	4.2331E+03	3.5758E+03	3.5424E+03	**3.3356E+03**	3.3875E+03
	best	3.6148E+03	3.4321E+03	3.3468E+03	3.2458E+03	**3.2472E+03**
	worst	5.2412E+03	3.7416E+03	3.7812E+03	**3.5045E+03**	3.5744E+03
	std	3.5305E+02	8.2929E+01	1.2046E+02	**7.8815E+01**	9.1893E+01
	p-value	1.5100E-11	7.1500E-09	2.5500E-06	9.8696E-01	
F28	mean	3.4986E+03	4.3505E+03	4.3794E+03	4.8202E+03	**3.2812E+03**
	best	3.3189E+03	3.7961E+03	3.5471E+03	3.3526E+03	**3.2115E+03**
	worst	3.8623E+03	5.1013E+03	5.4167E+03	7.3556E+03	**3.3873E+03**
	std	1.4266E+02	2.9231E+02	4.8249E+02	1.0723E+03	**3.5797E+01**
	p-value	6.0300E-11	1.5100E-11	1.5100E-11	1.8400E-11	
F29	mean	4.8885E+03	5.2835E+03	5.0913E+03	4.5245E+03	**4.0441E+03**
	best	3.8992E+03	4.8607E+03	4.0523E+03	3.8294E+03	**3.5873E+03**
	worst	5.7868E+03	6.0347E+03	6.5716E+03	5.6851E+03	**4.3797E+03**
	std	4.6492E+02	2.9010E+02	5.2667E+02	3.9234E+02	**1.8312E+02**
	p-value	1.6800E-08	1.5100E-11	6.6400E-11	7.9800E-08	
F30	mean	2.7270E+06	6.4665E+09	1.8307E+07	1.4392E+08	**4.1440E+04**
	best	5.6510E+05	7.2901E+07	5.4017E+05	2.1986E+04	**8.4611E+03**
	worst	6.9836E+06	3.6053E+08	9.1185E+07	1.3947E+09	**3.9592E+05**
	std	1.6946E+06	2.9485E+09	2.0268E+07	3.4340E+08	**7.3113E+04**
	p-value	1.5100E-11	1.5100E-11	1.5100E-11	4.8800E-10	

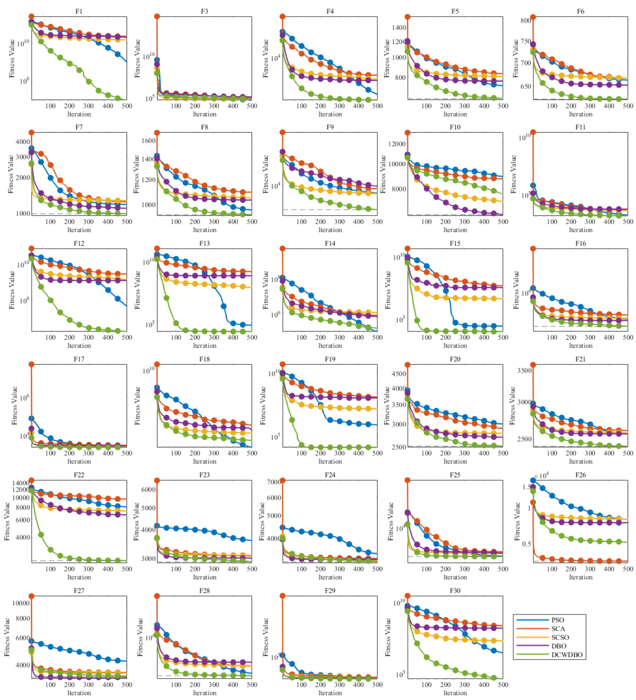

Fig. 3. CEC2017 Convergence Curves 30-dimension

In the 30-dimensional tests, the proposed DCWDBO achieved overall best performance in 12 out of 29 functions. On the unimodal function F1, it demonstrated exceptional search ability. Its absolute advantage on multimodal functions F4 and F6 confirmed excellent global exploration capability to escape local optima. The proposed DCWDBO performs well on hybrid benchmark F11-F13/F15 and composite benchmark F22/F25/F28-F30, demonstrating its strong adaptability to large-scale complex optimization problems. Moreover, DCWDBO delivered competitive results on 9 other functions. For multimodal functions F5 and F9, it achieved optimal average, best, and worst fitness values, showing superiority and stability in multimodal problems. While slightly trailing SCA in standard deviation on hybrid functions F16-F17, DCWDBO maintained leading performance in other evaluation metrics against all other compared algorithms. On composite functions F20-F21/F23-F24/F26, it secured optimal average/best/worst fitness values. Among the 23 benchmarks where DCWDBO achieved the overall best mean values, DCWDBO showed no significant difference from PSO only on F4. On F10 and F27, although DCWDBO's mean fitness was slightly inferior to DBO, the degree of difference between them was not significant. Similarly, on F14 and F18, DCWDBO's mean fitness was marginally higher than that of PSO, but no obvious disparity existed between the two algorithms, which indirectly proves the algorithm's superior search capability. Convergence analysis showed DCWDBO reached overall best fitness among all competitors in 19 functions, with rapid and stable convergence trends observed throughout all benchmarks.

Table 3

CEC2017 test results on 100-dimension

Fun	Index	PSO	SCA	SCSO	DBO	DCWDBO
F1	mean	8.9776E+10	2.5487E+11	1.4102E+11	1.1613E+11	**3.2968E+10**
	best	5.9238E+10	2.0751E+11	1.0428E+11	3.6678E+10	**1.7643E+10**
	worst	1.2509E+11	3.0413E+11	1.8088E+11	2.2599E+11	**5.7385E+10**
	std	1.5606E+10	2.4662E+10	1.9498E+10	5.8081E+10	**9.1548E+09**
	p-value	1.5100E-11	1.5100E-11	1.5100E-11	1.1100E-09	
F3	mean	4.1341E+05	8.5724E+05	**3.6518E+05**	7.1446E+05	4.5026E+05
	best	2.9604E+05	6.6236E+05	**2.8807E+05**	3.5980E+05	3.4037E+05
	worst	**5.4198E+05**	1.0776E+06	6.9178E+05	1.4124E+06	6.2449E+05
	std	**5.8388E+04**	1.1494E+05	6.9838E+04	3.1311E+05	8.1792E+04
	p-value	9.4232E-01	1.5100E-11	1.0000E+00	1.5000E-04	
F4	mean	1.8724E+04	7.2087E+04	2.9413E+04	3.3616E+04	**4.7309E+03**
	best	1.0853E+04	5.4764E+04	1.7580E+04	3.6654E+03	**2.5008E+03**
	worst	2.8677E+04	1.1667E+05	5.4729E+04	8.1630E+04	**9.7701E+03**
	std	5.3703E+03	1.3975E+04	9.0143E+03	1.9254E+04	**1.5971E+03**
	p-value	1.5100E-11	1.5100E-11	1.5100E-11	1.6000E-09	
F5	mean	1.5442E+03	2.2331E+03	1.7897E+03	1.8449E+03	**1.4517E+03**
	best	1.3036E+03	2.0794E+03	1.6402E+03	1.3607E+03	**1.2152E+03**
	worst	1.9649E+03	2.4104E+03	**1.9035E+03**	2.2115E+03	1.9452E+03
	std	1.4279E+02	9.1668E+01	**6.3838E+01**	2.5714E+02	1.8318E+02
	p-value	4.9420E-03	1.5100E-11	8.4900E-09	3.0200E-07	
F6	mean	6.8820E+02	7.1974E+02	6.9601E+02	6.7686E+02	**6.5467E+02**
	best	6.7353E+02	7.0763E+02	6.8055E+02	6.5645E+02	**6.4074E+02**
	worst	7.0538E+02	7.6206E+02	7.0712E+02	7.1831E+02	**6.7024E+02**
	std	7.9710E+00	9.9165E+00	**5.8884E+00**	1.4692E+01	6.5906E+00
	p-value	1.5100E-11	1.5100E-11	1.5100E-11	2.2900E-09	
F7	mean	3.4225E+03	4.7783E+03	3.6847E+03	2.9068E+03	**2.9105E+03**
	best	2.8786E+03	3.8872E+03	3.2712E+03	2.4776E+03	**2.4699E+03**
	worst	3.9000E+03	5.9661E+03	3.8705E+03	**3.3994E+03**	3.6668E+03
	std	2.1238E+02	5.0946E+02	**1.3186E+02**	2.0955E+02	2.7754E+02
	p-value	2.1600E-08	1.5100E-11	6.6400E-11	4.7348E-01	
F8	mean	1.9248E+03	2.5991E+03	2.2528E+03	2.2378E+03	**1.8040E+03**
	best	1.7668E+03	2.4897E+03	2.0676E+03	1.7807E+03	**1.6088E+03**
	worst	**2.1462E+03**	2.8016E+03	2.4335E+03	2.6811E+03	2.3363E+03
	std	9.6321E+01	**7.4775E+01**	8.4843E+01	2.5337E+02	1.6769E+02
	p-value	7.0300E-05	1.5100E-11	2.7900E-10	2.3400E-08	
F9	mean	6.9102E+04	1.2454E+05	**5.7769E+04**	8.1997E+04	7.5919E+04
	best	4.6111E+04	8.7806E+04	4.4134E+04	**3.1970E+04**	5.2904E+04
	worst	1.0866E+05	1.6085E+05	**7.6669E+04**	9.8615E+04	9.0598E+04
	std	1.3901E+04	1.6483E+04	**8.4783E+03**	1.5425E+04	1.0368E+04
	p-value	9.9527E-01	1.8400E-11	1.0000E+00	1.3120E-03	
F12	mean	3.1141E+10	1.2561E+11	5.8928E+10	5.5450E+10	**4.4411E+09**
	best	1.4376E+10	9.5353E+10	1.8484E+10	5.3893E+09	**1.1538E+09**
	worst	5.5478E+10	1.6407E+11	1.2311E+11	1.3752E+11	**1.4207E+10**
	std	1.2455E+10	1.6010E+10	2.4917E+10	3.2230E+10	**3.4984E+09**
	p-value	1.5100E-11	1.5100E-11	1.5100E-11	6.0300E-11	
F13	mean	1.6375E+09	2.2798E+10	1.0979E+10	9.2798E+09	**3.6357E+06**
	best	1.8084E+07	1.4682E+10	3.5923E+09	7.9327E+05	**3.0780E+04**
	worst	6.0547E+09	2.8149E+10	2.1671E+10	3.2955E+10	**3.6378E+07**
	std	1.3335E+09	3.1344E+09	4.5911E+09	9.2162E+09	**8.0426E+06**
	p-value	2.0400E-11	1.5100E-11	1.5100E-11	6.6400E-11	
F14	mean	**2.5950E+06**	1.0765E+08	1.4694E+07	2.0475E+07	4.6879E+06
	best	**4.7185E+05**	2.2574E+07	4.7506E+06	2.6293E+06	8.9450E+05
	worst	1.4878E+07	2.0270E+08	3.8807E+07	8.8152E+07	**1.2181E+07**
	std	2.5661E+06	3.8810E+07	8.0370E+06	1.8547E+07	**2.3599E+06**
	p-value	9.9997E-01	1.5100E-11	1.0200E-09	5.7800E-08	

Table 3
CEC2017 test results on 100-dimension (Continued)

Fun	Index	PSO	SCA	SCSO	DBO	DCWDBO
F15	mean	2.9955E+07	8.1538E+09	3.4584E+09	3.7016E+09	**2.1494E+04**
	best	2.0287E+05	5.9440E+09	1.7240E+08	2.8566E+05	**3.2714E+03**
	worst	5.3956E+08	1.1765E+10	9.2701E+09	1.5951E+10	**1.7462E+05**
	std	9.9922E+07	1.6307E+09	2.5954E+09	3.5261E+09	**3.8696E+04**
	p-value	1.5100E-11	1.5100E-11	1.5100E-11	1.5100E-11	
F16	mean	1.1056E+04	1.6099E+04	1.3093E+04	9.8799E+03	**7.3129E+03**
	best	8.8659E+03	1.4108E+04	8.2792E+03	6.9911E+03	**4.7709E+03**
	worst	1.5310E+04	1.9109E+04	1.9076E+04	**1.3304E+04**	1.3595E+04
	std	1.5594E+03	**1.1574E+03**	2.3479E+03	1.5346E+03	1.7079E+03
	p-value	2.5000E-09	1.5100E-11	2.7900E-10	6.2700E-08	
F17	mean	7.3864E+03	1.3351E+05	2.6856E+04	2.8434E+05	**5.8655E+03**
	best	5.3915E+03	3.0790E+04	7.4450E+03	7.9970E+03	**3.9965E+03**
	worst	2.2591E+04	4.5976E+05	1.3014E+05	3.4556E+06	**8.4173E+03**
	std	2.9567E+03	1.1784E+05	2.7046E+04	6.8353E+05	**9.4570E+02**
	p-value	5.8700E-05	1.5100E-11	2.0400E-11	1.8400E-11	
F18	mean	**6.0692E+06**	2.4987E+08	1.5012E+07	2.6495E+07	1.2539E+07
	best	**3.6760E+05**	7.7589E+07	3.3488E+06	3.7000E+06	2.9914E+06
	worst	7.5975E+07	4.3064E+08	**3.5748E+07**	7.5749E+07	4.6746E+07
	std	1.3286E+07	7.8332E+07	**8.3175E+06**	1.8443E+07	8.8867E+06
	p-value	1.0000E+00	1.5100E-11	7.6834E-02	2.6300E-04	
F19	mean	4.1900E+07	8.1343E+09	2.8415E+09	3.5367E+09	**4.5592E+06**
	best	2.3854E+06	5.6375E+09	3.9890E+08	2.5996E+05	**2.8516E+03**
	worst	3.5448E+08	1.2830E+10	1.0741E+10	1.3579E+10	**1.3590E+08**
	std	6.7072E+07	1.4732E+09	2.3701E+09	3.2275E+09	**2.4389E+07**
	p-value	2.5400E-10	1.5100E-11	1.5100E-11	2.0400E-11	
F20	mean	7.9198E+03	8.3118E+03	**6.4701E+03**	7.4768E+03	7.6544E+03
	best	5.8738E+03	7.2980E+03	5.4061E+03	**5.3073E+03**	5.7927E+03
	worst	9.2825E+03	8.8113E+03	**7.4939E+03**	8.8815E+03	8.3332E+03
	std	7.8556E+02	**3.1547E+02**	5.2262E+02	9.9834E+02	4.8739E+02
	p-value	2.2573E-02	1.5400E-08	1.0000E+00	4.1513E-01	
F21	mean	4.4537E+03	4.3090E+03	4.0069E+03	4.0718E+03	**3.3857E+03**
	best	3.8681E+03	4.0521E+03	3.7359E+03	3.8319E+03	**3.1595E+03**
	worst	5.4113E+03	4.5396E+03	4.6091E+03	4.3895E+03	**4.2303E+03**
	std	3.5793E+02	**1.0610E+02**	1.9202E+02	1.4201E+02	2.4933E+02
	p-value	4.5000E-11	2.7500E-11	1.6000E-09	3.6900E-10	
F22	mean	3.5578E+04	3.5474E+04	2.9399E+04	**2.8798E+04**	3.2677E+04
	best	2.9363E+04	3.4278E+04	2.3364E+04	2.1681E+04	**5.8280E+03**
	worst	3.8438E+04	3.6273E+04	**3.2200E+04**	3.6328E+04	3.5717E+04
	std	2.2810E+03	**4.6604E+02**	1.8685E+03	4.9602E+03	5.8454E+03
	p-value	2.2300E-04	2.3200E-05	1.0000E+00	9.9916E-01	
F23	mean	7.0201E+03	5.1991E+03	5.0880E+03	**4.8530E+03**	5.3073E+03
	best	5.8574E+03	4.8907E+03	**4.3305E+03**	4.3454E+03	5.0466E+03
	worst	8.9727E+03	5.4589E+03	6.0090E+03	**5.2566E+03**	5.6329E+03
	std	5.8812E+02	**1.3304E+02**	2.7866E+02	2.1904E+02	1.4189E+02
	p-value	1.5100E-11	9.9506E-01	9.9999E-01	1.0000E+00	
F24	mean	7.8631E+03	7.1453E+03	6.7373E+03	**6.3379E+03**	7.5842E+03
	best	6.9995E+03	6.5896E+03	5.7771E+03	**5.5838E+03**	6.4726E+03
	worst	8.9996E+03	7.5254E+03	8.8716E+03	**7.3512E+03**	8.5582E+03
	std	5.8595E+02	**2.7262E+02**	6.7946E+02	4.7917E+02	4.9129E+02
	p-value	5.1163E-02	9.9995E-01	1.0000E+00	1.0000E+00	
F25	mean	8.8653E+03	3.1798E+04	1.4074E+04	1.1639E+04	**6.3102E+03**
	best	7.2840E+03	2.2748E+04	1.0628E+04	5.7254E+03	**5.0267E+03**
	worst	1.1112E+04	5.3407E+04	1.8443E+04	3.0250E+04	**8.1695E+03**
	std	1.1032E+03	6.0856E+03	2.1240E+03	6.9208E+03	**8.1708E+02**
	p-value	3.0600E-10	1.5100E-11	1.5100E-11	5.8400E-06	
F26	mean	3.2028E+04	4.2998E+04	3.6001E+04	3.4514E+04	**2.9431E+04**
	best	2.5426E+04	3.5274E+04	2.9042E+04	2.4963E+04	**1.8848E+04**
	worst	**3.7579E+04**	4.7379E+04	4.2683E+04	4.3352E+04	4.3895E+04
	std	2.9099E+03	**2.6337E+03**	3.2544E+03	4.8212E+03	7.2901E+03
	p-value	3.5063E-02	6.4400E-10	3.6500E-04	2.9140E-03	
F27	mean	9.7768E+03	8.6869E+03	7.3190E+03	**4.9528E+03**	7.7325E+03
	best	6.2217E+03	7.1639E+03	5.2006E+03	**3.9840E+03**	4.4392E+03
	worst	1.4569E+04	1.0076E+04	8.9519E+03	**5.9095E+03**	9.3220E+03
	std	2.0091E+03	6.2475E+02	1.0650E+03	**5.2573E+02**	1.0324E+03
	p-value	2.9900E-05	1.2200E-05	8.8000E-01	1.0000E+00	
F28	mean	1.4655E+04	3.5188E+04	1.5675E+04	2.2987E+04	**8.8726E+03**
	best	1.0527E+04	2.8057E+04	1.1969E+04	1.1335E+04	**6.5512E+03**
	worst	1.8591E+04	4.5142E+04	1.9438E+04	2.8690E+04	**1.3966E+04**
	std	1.9605E+03	4.0778E+03	1.9159E+03	4.2208E+03	**1.6028E+03**
	p-value	7.3200E-11	1.5100E-11	2.2500E-11	2.0400E-11	
F29	mean	1.3969E+04	7.2351E+04	2.5819E+04	5.4378E+04	**8.7954E+03**
	best	1.0702E+04	2.4694E+04	1.3195E+04	8.7471E+03	**7.0921E+03**
	worst	1.9228E+04	1.7711E+05	5.6822E+04	5.9874E+05	**1.8221E+04**
	std	2.1282E+03	3.3844E+04	1.0366E+04	1.2283E+05	**2.0590E+03**
	p-value	5.3500E-10	1.5100E-11	3.6900E-11	1.2200E-09	
F30	mean	1.9929E+09	1.5663E+10	9.6080E+09	5.3378E+09	**1.7468E+08**
	best	3.1058E+08	9.7274E+09	2.6263E+09	8.9654E+06	**2.7150E+06**
	worst	5.0722E+09	2.1619E+10	1.8424E+10	1.7766E+10	**1.3008E+09**
	std	1.0711E+09	2.6712E+09	3.9346E+09	4.7380E+09	**3.2176E+08**
	p-value	1.1900E-10	1.5100E-11	1.5100E-11	4.8800E-10	

In 100-dimensional evaluations, DCWDBO attained optimal results on 11 benchmarks. It demonstrated order-of-magnitude superiority on unimodal function F1, confirming significant search efficiency improvements. For multimodal functions, DCWDBO achieved optimal performance on F4 and best mean/best fitness values on F5-F8. The algorithm maintained strong competitiveness in high-dimensional optimization, securing leading positions on hybrid functions F15/F17/F19 and composite function F25, with only marginally higher standard deviation than SCA on F16 and F21. Additionally, among the 18 benchmark functions where DCWDBO achieved the overall best mean fitness, it exhibited no significant difference from the DBO algorithm only on F7. On F3, although DCWDBO's mean fitness was slightly worse than SCSO, the difference between them was not statistically significant. Similarly, on F11 and F14, DCWDBO's mean fitness was moderately higher than PSO, but no significant difference existed between them. On F22-F23 and F27, although DCWDBO slightly underperformed the DBO algorithm, no statistically significant gap was observed, which undoubtedly verifies DCWDBO's outstanding performance.

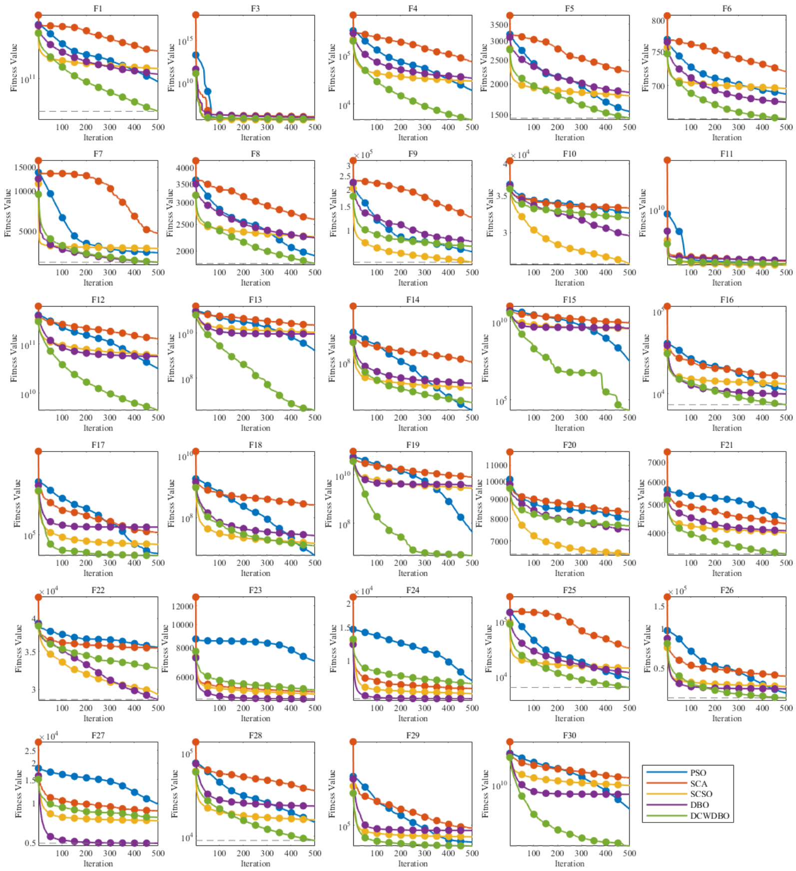

Fig. 4. CEC2017 Convergence Curves 100-dimension

As shown in Fig. 4, DCWDBO exhibited stable and rapid convergence across all benchmark functions, achieving the overall best fitness values among all competitors in 20 benchmarks, demonstrating superior convergence precision.

4.2 Results and Analysis on CEC2020 Benchmark Functions

The performance comparison between DCWDBO and the four competing algorithms on these 10 CEC2020 functions is presented below.

Table 4

CEC2020 test results on 20-dimension

Fun	Index	PSO	SCA	SCSO	DBO	DCWDBO
F1	mean	2.9010E+07	8.8929E+09	5.6978E+09	2.5229E+07	**3.6414E+03**
	best	3.2849E+05	5.2880E+09	7.9120E+07	1.1967E+04	**1.0043E+02**
	worst	3.9528E+08	1.2471E+10	1.8171E+10	1.1461E+08	**1.1960E+04**
	std	7.9291E+07	1.7405E+09	3.8644E+09	2.6548E+07	**3.0885E+03**
	p-value	1.5100E-11	1.5100E-11	1.5100E-11	6.0300E-11	

Table 4
CEC2020 test results on 20-dimension (continued)

Fun	Index	PSO	SCA	SCSO	DBO	DCWDBO
F2	mean	5.3727E+03	5.3354E+03	3.9866E+03	3.4822E+03	**2.4047E+03**
	best	3.5673E+03	4.5452E+03	2.8372E+03	2.5664E+03	**1.4430E+03**
	worst	6.3332E+03	5.9115E+03	5.7981E+03	4.5035E+03	**4.3242E+03**
	std	7.3973E+02	**3.3318E+02**	6.2935E+02	5.0203E+02	5.9939E+02
	p-value	1.4600E-09	9.7800E-11	8.1800E-06	4.6100E-05	
F3	mean	8.7259E+02	9.5223E+02	9.4959E+02	8.3146E+02	**8.1669E+02**
	best	7.8072E+02	9.0667E+02	8.4818E+02	7.7018E+02	**7.4026E+02**
	worst	9.6821E+02	1.0530E+03	1.0421E+03	9.5786E+02	**8.8892E+02**
	std	3.8965E+01	**3.1412E+01**	4.6782E+01	3.9206E+01	3.2244E+01
	p-value	2.2100E-06	1.5100E-11	4.5000E-11	2.4280E-03	
F4	mean	1.9420E+03	5.3366E+03	3.6440E+03	1.9238E+03	**1.9135E+03**
	best	1.9162E+03	2.3877E+03	1.9347E+03	1.9100E+03	**1.9041E+03**
	worst	1.9755E+03	1.5849E+04	1.1295E+04	1.9948E+03	**1.9590E+03**
	std	1.4508E+01	3.2683E+03	2.1358E+03	1.6936E+01	**1.1593E+01**
	p-value	1.3000E-10	1.5100E-11	1.6700E-11	2.2500E-11	
F5	mean	**1.6861E+05**	2.8985E+06	1.2157E+06	7.8175E+05	4.3533E+05
	best	**2.3931E+04**	4.8198E+05	7.5790E+04	1.3448E+05	5.8875E+04
	worst	**4.0965E+05**	5.0807E+06	2.8569E+06	1.9513E+06	1.4464E+06
	std	**1.1080E+05**	1.3431E+06	6.9227E+05	5.1840E+05	3.2667E+05
	p-value	9.9924E-01	8.8800E-11	9.4600E-05	1.5900E-04	
F6	mean	2.4333E+03	2.5847E+03	2.4354E+03	2.2983E+03	**1.8048E+03**
	best	1.8973E+03	2.0541E+03	1.8790E+03	1.7817E+03	**1.6028E+03**
	worst	3.0395E+03	2.9830E+03	2.9943E+03	2.9235E+03	**2.3271E+03**
	std	3.1735E+02	2.0229E+02	2.7201E+02	2.7660E+02	**1.4717E+02**
	p-value	6.0300E-11	2.4900E-11	2.5400E-10	3.3600E-10	
F7	mean	**1.0806E+05**	8.7041E+05	7.9687E+05	5.9444E+05	1.8391E+05
	best	**7.4366E+03**	2.2473E+05	4.3977E+04	2.5145E+04	1.6228E+04
	worst	**4.1534E+05**	2.3950E+06	3.2588E+06	3.9492E+06	4.9461E+05
	std	**9.2474E+04**	6.3587E+05	9.1842E+05	7.7164E+05	1.0483E+05
	p-value	9.4232E-01	2.3100E-10	4.2800E-04	5.2900E-04	
F8	mean	5.6373E+03	5.2655E+03	4.0070E+03	2.7972E+03	**2.3020E+03**
	best	2.3107E+03	2.9391E+03	2.3488E+03	2.3116E+03	**2.3000E+03**
	worst	8.2523E+03	7.5675E+03	6.5746E+03	6.2510E+03	**2.3065E+03**
	std	2.2254E+03	1.7133E+03	1.3963E+03	1.0214E+03	**1.6697E+00**
	p-value	2.0400E-11	1.5100E-11	1.5100E-11	2.2900E-09	
F9	mean	3.1856E+03	3.0210E+03	3.0087E+03	3.0035E+03	**2.9031E+03**
	best	3.0205E+03	2.9726E+03	2.8812E+03	2.9348E+03	**2.8237E+03**
	worst	3.4006E+03	3.0808E+03	3.1349E+03	3.1550E+03	**3.0393E+03**
	std	9.6394E+01	**2.3635E+01**	6.3144E+01	5.5413E+01	5.5451E+01
	p-value	1.8400E-11	1.5400E-08	2.7300E-06	4.4400E-06	
F10	mean	2.9901E+03	3.2971E+03	3.3067E+03	2.9925E+03	**2.9756E+03**
	best	2.9150E+03	3.1087E+03	3.0411E+03	2.9150E+03	**2.9124E+03**
	worst	3.0205E+03	3.7503E+03	3.9117E+03	3.2584E+03	**3.0279E+03**
	std	**2.1214E+01**	1.5097E+02	2.4031E+02	6.2133E+01	3.2520E+01
	p-value	1.1129E-01	1.5100E-11	1.5100E-11	2.3400E-08	

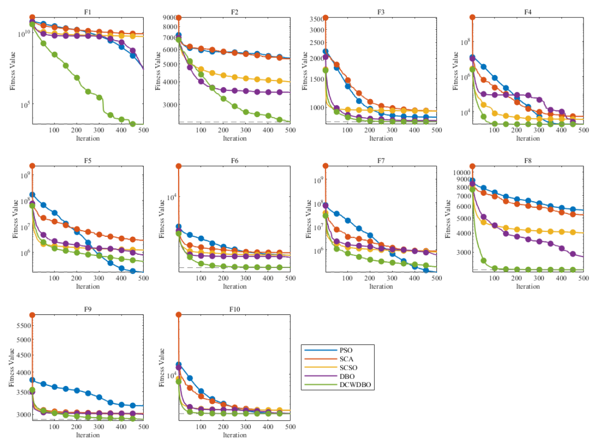

Fig. 5. CEC2020 Convergence Curves 20-dimension

DCWDBO achieved the outright best performance on 4 test functions and performed excellently on another 4. DCWDBO slightly trailed PSO only on benchmark functions F5 and F7. Nevertheless, it demonstrated significant superiority over three other algorithms on both functions, including the original DBO. This performance gap directly testified to the effectiveness of DCWDBO's improvements. On the unimodal function F1, DCWDBO's order-of-magnitude better performance proved its groundbreaking improvement in search ability. On the multimodal function F4, DCWDBO also gained the best performance. On F2 and F3, only its standard deviation was slightly inferior to SCA. DCWDBO outperformed all other algorithms on hybrid function F6 and composite functions F8-F10. Its standard deviation was slightly higher than SCA and PSO only on F9 and F10, respectively. Among the 8 functions where DCWDBO achieved the overall best mean fitness in CEC2020, it failed to establish a clear advantage over PSO only on F10. Although DCWDBO performed significantly worse than PSO on F5 and F7, it still outperformed all other compared algorithms by a large margin. In terms of convergence, DCWDBO's convergence curves showed a stable convergence trend on all functions, highlighting its stability. Moreover, DCWDBO swiftly converged to the overall best fitness values on 8 test functions, which verified its superior convergence accuracy and speed.

4.3 Results and Analysis on CEC2022 Benchmark Functions

The performance comparison between DCWDBO and the other four algorithms on these 12 CEC2022 functions is presented below.

Table 5
CEC2022 test results on 20-dimension

Fun	Index	PSO	SCA	SCSO	DBO	DBOWSA
F1	mean	**1.2491E+04**	2.0921E+04	1.9117E+04	3.5050E+04	1.7296E+04
	best	**1.5024E+03**	9.2170E+03	7.6652E+03	1.9293E+04	6.2222E+03
	worst	3.9132E+04	3.3814E+04	3.9542E+04	6.4002E+04	**2.5536E+04**
	std	7.1624E+03	5.2794E+03	8.3108E+03	1.0594E+04	**5.0399E+03**
	p-value	9.9964E-01	6.1060E-03	4.5585E-01	1.3300E-09	
F2	mean	4.9263E+02	8.2059E+02	7.5467E+02	5.1804E+02	**4.6944E+02**
	best	4.4977E+02	6.2699E+02	5.2624E+02	4.4951E+02	**4.4119E+02**
	worst	**5.5969E+02**	1.0383E+03	1.4126E+03	7.6342E+02	5.6933E+02
	std	3.0236E+01	1.0519E+02	1.8848E+02	8.0177E+01	**2.5165E+01**
	p-value	2.1100E-04	1.5100E-11	1.8400E-11	5.5700E-04	
F3	mean	6.5619E+02	6.4796E+02	6.5942E+02	6.3621E+02	**6.1252E+02**
	best	6.3730E+02	6.3260E+02	6.4395E+02	6.0972E+02	**6.0335E+02**
	worst	6.7398E+02	6.5885E+02	6.8098E+02	6.6338E+02	**6.2948E+02**
	std	8.8020E+00	6.3877E+00	1.0653E+01	1.1743E+01	**5.8040E+00**
	p-value	1.5100E-11	1.5100E-11	1.5100E-11	5.8700E-10	
F4	mean	8.8776E+02	9.5611E+02	9.0980E+02	9.1454E+02	**8.8160E+02**
	best	8.4433E+02	9.2896E+02	8.6806E+02	8.7463E+02	**8.3610E+02**
	worst	9.9984E+02	9.8375E+02	9.7519E+02	9.6838E+02	**9.4083E+02**
	std	3.2759E+01	**1.3968E+01**	2.3070E+01	2.5138E+01	3.0144E+01
	p-value	2.8461E-01	2.7500E-11	1.9900E-04	4.0700E-05	
F5	mean	2.6064E+03	2.6707E+03	2.5595E+03	2.1375E+03	**1.5440E+03**
	best	1.6340E+03	1.7139E+03	1.7076E+03	1.0240E+03	**9.5500E+02**
	worst	4.0927E+03	5.4414E+03	3.3338E+03	3.6698E+03	**3.1445E+03**
	std	5.6275E+02	7.1597E+02	**4.0100E+02**	7.0033E+02	5.0596E+02
	p-value	1.3000E-08	7.1500E-09	7.1500E-09	4.0600E-04	
F6	mean	**5.7819E+03**	1.7329E+08	2.2025E+07	4.4498E+05	6.0066E+03
	best	2.5809E+03	3.3555E+07	2.8059E+05	1.9714E+03	**1.9718E+03**
	worst	**1.2125E+04**	5.8195E+08	2.3917E+08	8.1086E+06	1.7792E+04
	std	**2.7758E+03**	1.3459E+08	4.3789E+07	1.4685E+06	4.2145E+03
	p-value	2.4589E-01	1.5100E-11	1.5100E-11	4.5340E-03	
F7	mean	2.2061E+03	2.1677E+03	2.1824E+03	2.1457E+03	**2.0754E+03**
	best	2.1139E+03	2.0835E+03	2.1243E+03	2.0656E+03	**2.0233E+03**
	worst	2.3673E+03	2.2356E+03	2.3095E+03	2.2331E+03	**2.1371E+03**
	std	6.7558E+01	3.5164E+01	3.6006E+01	4.9697E+01	**2.7062E+01**
	p-value	3.6900E-11	1.3000E-10	1.8400E-11	1.1000E-07	
F9	mean	2.5465E+03	2.6281E+03	2.5794E+03	2.5051E+03	**2.4788E+03**
	best	2.4923E+03	2.5456E+03	2.5092E+03	2.4808E+03	**2.4719E+03**
	worst	2.6836E+03	2.7134E+03	2.7379E+03	2.6196E+03	**2.4944E+03**
	std	4.1785E+01	3.6625E+01	4.8779E+01	2.6527E+01	**4.7344E+00**
	p-value	1.6700E-11	1.5100E-11	1.5100E-11	1.3300E-09	
F10	mean	5.2686E+03	3.4646E+03	4.5554E+03	3.4266E+03	**2.5875E+03**
	best	2.5012E+03	2.5222E+03	2.5009E+03	2.5009E+03	**2.5007E+03**
	worst	7.2992E+03	7.1717E+03	6.3908E+03	6.8505E+03	**3.5444E+03**
	std	1.6392E+03	1.6536E+03	1.1911E+03	1.2504E+03	**2.2768E+02**
	p-value	4.6300E-09	1.1600E-06	5.0500E-09	3.1800E-05	
F11	mean	8.6103E+04	6.8804E+03	5.8864E+03	3.0415E+03	**2.9017E+03**
	best	4.4889E+04	5.1675E+03	4.0761E+03	2.6014E+03	**2.6001E+03**
	worst	1.4332E+05	8.9037E+03	7.9950E+03	5.6751E+03	**2.9664E+03**
	std	1.8241E+04	7.9751E+02	1.0020E+03	5.0480E+02	**5.8737E+01**
	p-value	1.5100E-11	1.5100E-11	1.5100E-11	3.2836E-02	
F12	mean	3.6989E+03	3.0981E+03	3.1203E+03	3.0399E+03	**3.0333E+03**
	best	3.3361E+03	3.0390E+03	3.0093E+03	2.9523E+03	**2.9478E+03**
	worst	4.0382E+03	3.1868E+03	3.2802E+03	3.1620E+03	**3.1297E+03**
	std	1.8284E+02	**3.5351E+01**	7.0328E+01	5.4817E+01	3.8418E+01
	p-value	1.5100E-11	9.3700E-08	2.0600E-07	4.5000E-01	

DCWDBO outperforms all comparison algorithms in 6 functions, with equally prominent advantages in 4 other benchmarks. On unimodal function F1, DCWDBO is only slightly inferior to PSO in average/best fitness, but shows clear superiority over other algorithms. On multimodal function F2, only DCWDBO's worst fitness is slightly inferior to PSO. Its standard deviations ranked second to SCA and SCSO on F4 and F5, respectively. In F3, it comprehensively surpasses all algorithms, verifying enhanced search capabilities. Among hybrid functions F7-F8, DCWDBO achieved the overall best fitness values. In F6, its result was only slightly inferior to PSO. Compared with other algorithms, DCWDBO's advantage reached an order of magnitude, achieving the overall best fitness values. Among composite functions F9-F11, DCWDBO outperformed all algorithms in all aspects, while only its standard deviation slightly trailed SCA in F12. Among the 10 functions where DCWDBO obtained the overall best mean fitness in this benchmark suite, it showed no significant lead only over PSO on F4 and DBO on F12, respectively.

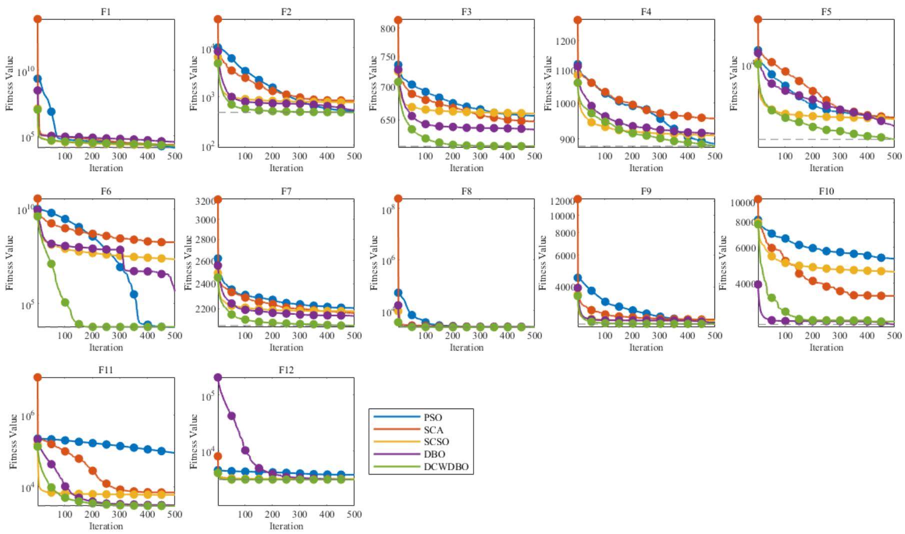

Fig. 6. CEC2022 Convergence Curves 20-dimension

From a convergence perspective, DCWDBO converged smoothly and rapidly to the overall best fitness values on 11 test functions. Its initial population quality markedly outperformed comparative algorithms, validating both enhancement effectiveness and convergence accuracy improvement. The above results show that DCWDBO demonstrates significant advantages in unimodal, multimodal, hybrid, and composite function optimization problems, verifying its comprehensive ability in complex optimization scenarios. The superior performance of DCWDBO on unimodal functions demonstrates that the horizontal and vertical crossover strategies effectively enhance its global and local search capabilities, thus significantly boosting its exploration efficiency in the search space. For multimodal problems, DCWDBO has achieved all-round advantages across multiple benchmark functions and dimensions. Its convergence stability is significantly superior to traditional algorithms, highlighting robustness in avoiding premature convergence. DCWDBO's outstanding performance on hybrid and composite functions demonstrates its groundbreaking improvements in complex optimization scenarios. Remarkably, the optimization accuracy on some functions improved by an order of magnitude, further verifying its core ability to handle nonlinear complex optimization problems. Overall, the DCWDBO algorithm demonstrates advantages in global search and convergence ability, presenting breakthrough improvements for complex optimization. Its performance and convergence stability are markedly superior to traditional methods. These characteristics make it an efficient tool for addressing large-scale complex practical problems, particularly valuable for real-world applications.

5. Conclusion

This study introduces three key improvements to the original DBO: First, a dynamic opposite learning mechanism is incorporated during population initialization to enhance search efficiency by optimizing the initial population. Second, horizontal and vertical crossover strategies from the CSO algorithm are integrated into the position update process of oviposition and larval individuals. The horizontal crossover strengthens global exploration, while the vertical crossover improves local exploitation through dimensional information exchange. Their synergistic interaction effectively broadens the search scope for optimal solutions while enhancing its talent to escape local optima. Finally, boundary constraint rule of WSA replaces the original mechanism to improve population diversity. To validate the effectiveness of DCWDBO, CEC2017, CEC2020, and CEC2022 were used to evaluate its performance. Experimental results demonstrate that DCWDBO exhibits stronger global search capabilities in early iterations, significantly decreasing the risk of premature convergence. It also maintains efficient local search while effectively avoiding local optima traps through sustained population diversity in later iterations. The statistical significance of DCWDBO's improvements compared to DBO was validated through Wilcoxon rank-sum analysis. The job shop scheduling problem is prevalent in practical manufacturing industries and is becoming increasingly critical (Meng et al., 2024). Future investigations will focus on applying DCWDBO to real-world engineering problems, particularly in job shop scheduling contexts.

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