IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received March 29, 2020, accepted April 29, 2020, date of publication May 11, 2020, date of current version May 26, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2993580

Research on New Adaptive Whale Algorithm

XUAN CHEN
Zhejiang Industry Polytechnic College, Shaoxing 312000, China
e-mail: chenxuan197927@sina.com

ABSTRACT Bionic algorithms have always played an important role in industrial, agricultural, and scientific research. The optimization of bionics algorithms has always been the focus of scholars in various countries. A whale algorithm based on optimization based on adaptive convergence and Levy features (IWOA) is proposed to overcome the disadvantages, such as low precision, slow convergence speed and tending to involve the local optimum of the whale algorithm. The improved Bernouilli Shift map is used to initialize the population to maintain diversity of the population. Optimizing the adaptive convergence factor is able to balance the local and global optimization ability. The Levy flight mechanism is introduced to optimize foraging behavior and improve global searching ability. In addition, the trigger rule is applied to screen individuals after each iteration to maintain individual vitality and enhance overall performance of the algorithm. In the simulation, IWOA, Ant Colony Optimization, Particle Swarm Optimization, Whale Optimization Algorithm and the optimized whale algorithms CWOA, LWOA are compared using the 20 classical test functions. The simulation results demonstrate that the IWOA algorithm possesses good global and local searching ability, especially in solving multi-peak and high-dimensional functions.

INDEX TERMS Whale optimization algorithm, convergence factor, Levy behavior, triggering rule.

I. INTRODUCTION

A large number of practices have demonstrated that bionic algorithms, such as Genetic Algorithm [1], Particle Swarm Optimization Algorithm [2], Differential Evolution Algorithm [3], Ant Colony Algorithm [4], Fruit Fly Algorithm [5], Artificial Fish Swarm Algorithm [6], Artificial Bee Colony Algorithm [7], Chicken Swarm Optimization Algorithm [8], Monkey Algorithm [9], Bat Algorithm [10], Cuckoo Search Algorithm [11], Whale Optimization Algorithm [12], etc., show prospective and excellent capability in solving various kinds of optimization issues. In recently years, there are also many other new Optimization Algorithms have been proposed, such as adaptive guided differential evolution Algorithm [41], differential Evolution Algorithm [42], Naked Mole Rat Algorithm [43] and Improved Versions of Whale Optimization Algorithm [44], Spherical search algorithm [45] and Gaining-sharing knowledge based algorithm [46], real-parameter optimization JSO algorithm [47], LSHADE algorithm with semi-parameter adaptation hybrid with CMA-ES [48], butterfly optimizer (BO) optimization algorithm [49], EBLSHADE Algorithms for Global Numerical Optimization [50], Real-Parameter Unconstrained Optimization Based on Enhanced AGDE Algorithm [51]. These new methods can not only solve many kinds of optimization problems, but also have low algorithm complexity compared with traditional optimization algorithms. Among them, Whale Optimization Algorithm (WOA) is a swarm intelligence algorithm proposed by Mirjalili and Lewis [12], named after the behavior of whales preying in the sea. It exhibits the remarkable advantages of simple principle, simple operation and easy realization. It has been widely used in economic scheduling, photovoltaic MPP system, capacitance location and image segmentation. It has a remarkable effect in dealing with multi-peak and low-dimensional complex functions. In the whale optimization algorithm, humpback whale in search space is a candidate solution in optimization problem, also known as "search agent". WOA uses a set of search agents to determine the global optimal solution of the optimization problem. For a given problem, the search process begins with a set of random solutions, and the candidate solution is updated through optimization rules until the end condition is satisfied. However, the WOA has four problems:

Problem 1: The population lacks effective initialization. The initialization of the intelligent population algorithm can ensure that the solution generated in the population can be uniformly distributed in the search space to a certain extent, so that a better solution can be obtained in the later iterative calculation for the algorithm, however in Whale optimization

The associate editor coordinating the review of this manuscript and approving it for publication was M. Saif Islam.

algorithm, the spatial position of whale individuals is initialized by random method, which reduces the population diversity of the algorithm to a certain extent, which is not conducive to the generation of the optimal solution of the algorithm.

For this problem, the improved Bernouilli Shift mapping is proposed to initialize the population to maintain the diversity of the population.

Problem 2: In the Whale optimization algorithm, parameters is the key to adjusting the local and global search capabilities of the algorithm, and is the important composition of calculating. In the basic WOA algorithm, the convergence factor decreases linearly from 2 to 0 with the number of iterations, yet, the convergence factor's linear decrement strategy makes the algorithm have good global search ability but slow convergence speed in the early stage, speed up the convergence speed in the later stage, but it is easy to fall into the local optimization, and the effect is not good in solving the multi-peak function problem, which shows that the linear decreasing strategy with iterative times of the convergence factor can not fully reflect the actual optimization search process.

For this problem, the improved local and global optimization capability of the adaptive convergence factor balancing algorithm is proposed in this paper.

Problem 3: The individual foraging mode of whales needs to improved. In Whale optimization algorithm, because the reference whale is randomly selected, humpback whales may travel back and forth in a short distance in the process of moving to the position of the reference whale, so it will increase the extra time of the algorithm and lead to the weak global optimization ability of the algorithm.

For this problem, Levy behavior is employed to deal with whale foraging behavior to improve the global search ability.

Problem 4: The individual screening after iteration is lacking. Whale individuals in the Whale optimization algorithm lack the screening of the individual before entering the next iteration through the surrounding, attack, and search steps, which can easily result in a large number of redundant individuals, which affect the performance of the algorithm as a whole.

For this problem, the trigger rules are used to screen the individuals after each iteration, and the individual activity of the algorithm is maintained, and the overall capability of the algorithm is improved.

The main work of this paper is as follows:

1). Improved Whale Optimization Algorithm is proposed, which improves the local and global search ability of the algorithm through priority strategy. The IWOA methods is analyzed and proved theoretically in this paper.
2). In the simulation experiment, the IWOA algorithm is compared with ACO, PSO, WOA, CWOA, LWOA, AGDE [41] and EFADE [42] in 18 classical test functions in detail. The experimental results show that the performance of the IWOA algorithm has been obviously improved, the convergence of the algorithm has improved, and the advantages in solving multi-peak and high-dimensional problems are obvious. Section 2 of this paper describes the research status of the WOA algorithm. Section 3 briefly describes the principle of the WOA algorithm. Because of the current problems of the WOA algorithm, this paper proposes a IWOA algorithm in Section 4 and expounds it from four aspects. In order to illustrate the performance of IWOA algorithm, the IWOA algorithm is compared with other algorithms in section 5 of this paper, and the related simulation experiments are carried out. Finally, the full text is summarized in section 6.

II. RELATED RESEARCH

At present, the research on the WOA algorithm is mainly from three aspects: the improvement of its algorithm performance, the fusion of WOA algorithm and other intelligent algorithms, and the solution of practical problems by the WOA algorithm.

Jangir *et al.* [13] introduced adaptive strategy into the whale optimization algorithm. Through the optimization of 10 classical function problems, the simulation results show that the proposed optimization Whale optimization algorithm is superior to the basic Whale optimization algorithm both in convergence speed and accuracy. Kaveh and Ghazaan [14] proposed an enhanced whale optimization algorithm for position updating in the Whale optimization algorithm. Simulation results show that the performance of the algorithm is better than that of the basic Whale optimization algorithm; Kaur and Arora [15] proposed a whale optimization algorithm-CWOA based on chaotic mapping. The simulation experiment is improved; Abdel-Basset *et al.* [16] proposed a hybrid Whale optimization algorithm-LWOA based on local search optimization, the simulation experiment shows that the performance of the algorithm is better than that of the basic Whale optimization algorithm; Sayed *et al.* [17] proposed a chaotic mapping whale optimization algorithm based on feature selection. The simulation results show that the performance of the chaotic mapping whale optimization algorithm is obviously improved compared with Whale optimization algorithm; Ling *et al.* [18] proposed an improved WOA algorithm (LWOA) based on Levy behavior. The performance of this algorithm is much better than that of the Whale optimization algorithm.

Mirjalili [19] introduced the idea of simulated annealing into the whale optimization algorithm and proposed a hybrid whale optimization algorithm (WOA-SA). The simulation results show that the algorithm has good performance. Trivedi *et al.* [20] proposed a new hybrid PSO-WOA algorithm for global numerical function optimization. Simulation experiments show that the hybrid algorithm has better convergence. Kaveh and Moghaddam [21] proposed a hybrid algorithm of CBO-WOA, which was applied to the layout of construction engineering and achieved good results. Masadeh *et al.* [22] proposed a hybrid algorithm based on

GWO-WOA, which is applied to task priority scheduling in software engineering with good results.

Touma [23] apply the whale optimization algorithm to the economic scheduling problems. The effectiveness of WOA algorithm is verified by using the IEEE-30 bus system, which shows that WOA algorithm has a good effect on economic scheduling. Cherukuri and Rayapudi [24] used the whale optimization algorithm in the tracking system of the global MPP photovoltaic system to achieve the use of energy. The effectiveness of the WOA algorithm in solving this problem is verified by photovoltaic arrays under different conditions. Prakash and Lakshminarayana [25] applied the whale optimization algorithm to capacitance location in the network. Experiments show that the WOA algorithm is superior to other comparative algorithms in maintaining voltage stability and optimization cost. Aljarah *et al.* [26] apply the Whale optimization algorithm to the weight optimization of neural networks. Compared with the basic swarm intelligence algorithm, the optimization effect of Whale optimization algorithm is better. Mostafa *et al.* [27] used the whale optimization algorithm to medical nuclear magnetic resonance image segmentation. Experiments show that Whale optimization algorithm has achieved good segmentation results. Reddy *et al.* [28] used Whale optimization algorithm to optimize distributed renewable resources. Experiments were carried out through different distributed systems. The experiments show that the Whale optimization algorithm has good performance. El Aziz *et al.* [29] used the Whale optimization algorithm in the multi-threshold image segmentation problem. The experimental results show that the performance of the Whale optimization algorithm is better than that of other contrast algorithms. Hassan and Hassanien [30] applied the whale optimization algorithm to retinal image segmentation to improve the accuracy of image segmentation. Oliva and El Aziz [31] used the whale optimization algorithm to predict panel parameters of solar cells and photovoltaic modules. The experimental results show that the improved algorithm can solve the prediction accuracy of the problem. Mafarja and Mirjalili [32] proposed that the Whale optimization algorithm has a better selection effect in feature selection of data sets, especially in searching for optimal feature subsets. Mehne and Mirjalili [33] proposed that Whale optimization algorithm be used for parallel processing in the optimal control problem. The experimental results show that the processing effect of using the Whale optimization algorithm is better. Nasiri and Khiyabani [34] proposed to solve the problem of using Whale optimization algorithm for clustering analysis. It is found in the simulation experiment that compared with ACO, PSO, ABC and other algorithms, it can improve the clustering effect.

From the above research results, the application of the Whale optimization algorithm to solve practical problems has achieved good results, which shows that the performance of Whale optimization algorithm is worthy of affirmation. Thus, it is of great significance to further improve the Whale optimization algorithm. Based on this consideration, an improved Whale optimization algorithm is proposed in this paper to improve the performance of the algorithm.

III. THE BASIC IDEA OF WOA ALGORITHM

WOA is a meta heuristic optimization algorithm. The main difference between the current work and other swarm optimization algorithms is that they use random or optimal search agents to simulate hunting behavior, and use spiral to simulate the bubble net attack mechanism of humpback whales. The most interesting thing about humpback whales is their special hunting methods. This foraging behavior is called bubble net foraging. Humpback whales like to hunt krill or small fish near the sea. It is worth mentioning that the bubble net predation is a unique behavior, which can only be observed in humpback whales.

The Whale optimization algorithm mainly consists of three stages: encircle predation, bubble attack, and prey search. In the WOA algorithm, the whale population size is set to N, the search space is d dimensions, and the position of the i whale in the d dimensional space is represented as $X_i = (X_i^1, X_i^2, \cdots X_i^D)$, $i = 1, 2, \cdots N$. The position of prey corresponds to the global optimal solution of the problem.

A. ENCIRCLE PREDATION

At the beginning of the algorithm, whales can identify the location of their prey and surround it. Because there is no priority in the global optimal position of the algorithm, it is assumed that the optimal position in the current population is the prey, and the optimal individual is surrounded by other whale individuals in the population. Use formula (1) to update the location:

$$X(t+1) = X_p(t) - A \times |C \times X_p(t) - X(t)| \tag{1}$$

where, t is the current number of iterations, $X_p(t) = (X_p^1, X_p^2, \cdots X_p^D)$is the local optimal solution, $A \times |C \times X_p(t) - X(t)|$ is the step of surrounding, The expressions of $A$and C are as follows:

$$A = 2a \times rand_1 - a \tag{2}$$

$$C = 2 \times rand_2 \tag{3}$$

where, $rand_1$ and $rand_2$ represent the random number between (0, 1), a is a convergence factor, and as the number of iterations increases, it decreases linearly from 2 to 0. The expression is as follows

$$a = 2 - 2t \big/ t_{\max} \tag{4}$$

where, $t_{\max}$ is the maximum number of iterations.

B. BUBBLE ATTACK

In the process of whale predation, bubbles are used to attack, and the behavior of whale predation bubbles is simulated by shrinking encirclement and spiral renewal position, to achieve the purpose of whale local optimization.

1) CONTRACTION ENCIRCLING MECHANISM

According to formula (1), get the whale population to shrink and surround. When $|A| < 1$, the whale individual gets close to the whale individual in the current optimal position, the larger the value of $|A|$, the greater the pace of whale swimming, on the contrary, the smaller the pace of whale swimming.

2) SPIRAL UPDATE POSITION

Whale individuals first calculate the distance from their current prey and then search the prey in a spiral mode. The mathematical model of the spiral walk mode is as follows:

$$X(t+1) = D' \times e^{lb} \times \cos(2\pi l) + X_p(t) \tag{5}$$

where $D' = |X_p(t) - X(t)|$indicates the distance between the i whale and its prey, b is a constant used to define the shape of a logarithmic spiral, l is a random number between-1 and 1.In the optimization process, the probability of selecting the shrinkage encirclement mechanism and spiral position update is the same, which is 0.5 [12].

C. HUNTING STAGE

Whales can also look for food at random. In fact, individual whales search randomly according to each other's position, and the expression is as follows:

$$X(t+1) = X_{rand}(t) - A|C \times X_{rand}(t) - X(t)| \tag{6}$$

where, $X_{rand}(t)$ is the randomly selected individual position of whales in the current population.

IV. IMPROVED WHALE OPTIMIZATION LGORITHM–IWOA

Given the shortcomings of the WOA algorithm, it is easy to fall into local optimization and thus slow convergence speed. This paper proposed an Improved Whale Optimization Algorithm (IWOA), It has been improved in the following four areas. First, chaotic mapping is used to initialize the population, so that the diversity of the population can kept and the algorithm can be avoided from falling into "precocious". Secondly, the local and global optimization ability of the optimization adaptive convergence factor balance algorithm is used. Third, the Levy flight mechanism is used to optimize foraging behavior and improve the global searching ability. Fourth, the trigger rule is used to update the individual after each iteration to maintain the development ability of the algorithm.

A. POPULATION INITIALIZTTION

The diversity of the initialization population will affect the convergence speed and accuracy of the swarm intelligence algorithm to a great extent, but the basic Whale optimization algorithm can't guarantee the population diversity by initializing the population randomly. Chaotic maps are widely used in the optimization of intelligent algorithms because of their randomness, ergodicity and regularity. In order to make better use of the space of solution, in this paper, an improved Bernouilli Shift map with the best chaotic effect in one-dimensional space [35] is introduced to initialize the population

$$x_{n+1} = 2(x_n + 0.1 \times rand(0, 1)) \bmod 1 \tag{7}$$

The concrete steps of generating the initial population using improved Bernouilli Shift chaos are shown in algorithm 1.

Algorithm 1 Population Initialization Method Based on Bernouilli Shift Chaos

Set population size N, dimension D and the maximum number of chaotic iterative step K

for $i = 1$ *to* N *do*
  for $j = 1$ *to* D *do*
    for $k = 1$ *to* K *do*
      $x_{k,j} = 2(x_{k-1,j} + 0.1 \times rand(0, 1)) \bmod 1$
    endfor
    $x_{i,j} = x_{\min,j} + x_{k,j} \times (x_{\max,j} - x_{\min,j})$
  endfor
endfor

Where, $x_{k-1,j}$ represents j dimensional individual in the $k-1$ iteration, $x_{k,j}$ represents the j dimensional individual in the k iteration after Bernouilli Shif chaotic mapping is used, $x_{i,j}$ represents the i individual in dimension j, $x_{\max,j}$ and $x_{\min,j}$ respectively represent the upper and lower bounds in j dimensional space.

According to the above principles, the Bernouilli Shift mapping of the population initialization can make better using of the space of solution through the equation of $x_{k,j} = 2\left(x_{k-1,j} + 0.1 \times rand\ (0, 1)\right) \bmod 1$.

B. ADAPTIVE CONVERGENCE FACTOR

In the basic WOA algorithm, A is used to adjust the local and global search ability of the algorithm. When A is larger than 1, the algorithm will expand the search range to find a better candidate solution, whereas the algorithm will narrow the range and carry out a fine search in the local range. From formula (2), it can be seen that the value of A is affected by a to a great extent. When the value of a is large, the algorithm has better global search ability and is not easy to fall into local optimization. On the contrary, the algorithm has strong local searching ability and fast convergence speed. Thus, the dynamic adjustment of a and the balance of the search ability of the algorithm are helpful to improve the optimization performance of the algorithm as a whole, which is expressed as follows:

$$a = a_1 + a_2 \times (\cos(\frac{2\pi t}{t_{\max}}) + \frac{t}{t_{\max}} \times \frac{1}{f_{obj}^{\max}(x_i^t) - f_{obj}^{\min}(x_i^t) + \zeta}) \tag{8}$$

where, $t_{\max}$ is the maximum number of iterations, t is the current number of iterations, $f_{obj}^{\max}(x_i^t)$ and $f_{obj}^{\min}(x_i)$ epresents the maximum and minimum values of the fitness value of the current individual i under the current number of iterations, respectively, ζ is a random number between [1], [2], Figure 1 shows the fluctuation range of the convergence factor. Through a large number of experiments, it is found that when a_1 and a_2 are 0.6 and 0.4, respectively, the effect is better. On the whole, in the early stage of the algorithm, the a value is larger, which makes the algorithm pay more attention to the global optimal search, but with the iterative operation of the algorithm, the a value decreases gradually, which is convenient for fine search in the later stage, and improves the convergence accuracy of the algorithm. In the later iteration stage of the algorithm, the a value increases gradually in order to jump out of the local optimal.

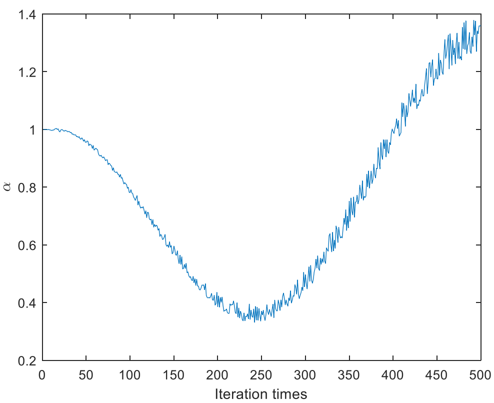

FIGURE 1. Fluctuation range of convergence factor.

According to the above principles, the adaptive convergence factor balancing algorithm based on the equation 8 can solve the problem of local optimization.

C. INTRODUCING LEVY TO OPTIMIZE FORAGING BEHAVIRO

Edwards *et al.* [36] studies the activity characteristics of specific animals and draws the conclusion that it accords with the flight characteristics of Levy. That is to say, this flight feature can not only satisfy the local search in a small range, but also satisfy the global search in a large range, and effectively balance the relationship between the local and the global. The distribution density function of the Levy flight step size change can be approximately expressed as follows:

$$Levy(s) = |s|^{-1-\beta}, \quad 0 < \beta \leq 2 \tag{9}$$

Formula (9) shows that s is the random motion step of the Levy flight behavior. According to reference [37], the expression of s is as follows:

$$s = \mu / |v|^{1/\beta} \tag{10}$$

Parameter μ, v obey normal distribution.

$$\mu = N(0, \sigma_u^2), \quad v = N(0, \sigma_v^2) \tag{11}$$

where

$$\sigma_\mu = \left\{ \frac{\Gamma(1+\beta)\sin(\pi\beta/2)}{\Gamma[(1+\beta)/2]\beta 2^{(\beta-1)/2}} \right\}^{1/\beta}, \quad \sigma_v = 1$$

Whale optimization algorithm has similar Levy flight characteristics like other population intelligent algorithms. In the foraging stage, because the whale position as the reference object is random, it is easy for whales to fall into local optimization when they are getting close to their position. Therefore, Levy - based flight mechanism is introduced into foraging individual renewal behavior. The formula is as following:

$$X(t+1) = X_{rand}(t) - A|C \times X_{rand}(t) - X(t)| + a(t) \times sign(rand) \oplus s, \tag{12}$$

where $rand$ is the random number between $[-1, 1]$. $sign(rand)$ is the Levy flight direction as shown in formula (13), $a(t)$ is the scale coefficient, as shown in formula (14).

$$sign(rand) = \begin{cases} 1 & rand \geq 0 \\ -1 & rand < 0 \end{cases}; \quad -1 \leq rand \leq 1 \tag{13}$$

$$a(t) = a_{init} \times \exp(-t \Big/ f_{obj}^{best}(x_i^t) - f_{obj}(x_i^t)) \tag{14}$$

where, $f_{obj}(x_i^t)$ and $f_{obj}^{best}(x_i^t)$ represent the current individual fitness value and the optimal adaptation value, respectively. t is the current iterations number, a_{init} is the initial scale coefficient.

Compared with the formula (6), formula (12) for foraging behavior has the possibility of random large step search after small step search, so that Whale optimization algorithm can search in different ranges and jump out of local optimality. At the same time, the construction of scale coefficient can ensure that in the early stage of the Whale optimization algorithm, the Levy range is large, the search range is expanded, and the approximate global optimal solution is found. When the Levy flight search range tends to be stable in the later stage, the Levy flight search range can be reduced, the algorithm can be prevented from oscillating near the optimal value, and the optimal solution can be approximated as soon as possible.

According to the above principles, Levy behavior can improve the global search ability through the equation 12.

D. INTRODUCTION OF TRIGGER RULES FOR INDIVIDUAL SCREENING

In each iteration, the basic Whale optimization algorithm lacks the screening of effective individuals in the existing population before moving directly to the next iteration through the steps of encirclement, attack, and search. Therefore, in this paper, the whale individuals are re-screened after each local update, and the trigger rules as described perviously [38], [39] are used to update the individual. By adding the operator and deleting the operator to update the individual, the overall performance of the algorithm can be improved.

Rule 1: If the optimal individual is continuously updated in the 2 GP generation and $ps > PS_{\min}$, the delete operator is executed, delete n_{dec} individual;

Rule 2: If the optimal individual is not updated continuously in the GP generation and $ps = PS_{\max}$, the delete operator is executed, delete n_{dec} individual;

Rule 3: If the optimal individual continuous GP generation is not updated and $ps < PS_{\max}$, the addition operator is executed, add n_{inc} individual.

Where, $PS_{\min}$ and $PS_{\max}$ is the maximum and minimum of population size, ps represents the number of individuals in the current population, GP is the rising period.

1) ADDITION OPERATOR DESIGN

The function of addition operator is that after each local optimal solution is obtained, the individual of the whole population can be updated again, the information of the excellent individual can be shared, and the lack of diversity of the population can be avoided. The steps are as follows:

a: Determine the increase i the number of individuals

$$n_{inc} = \frac{ps \times (PS_{\max} - ps)^2}{PS_{\max}} \tag{15}$$

First, a set S of individuals of size n_{inc} is generated, And then randomly select two individuals x_1 and x_2 from S. According to formula (16) [40], a new individual is cross-generated, of which α is the random number between 0 and 1.

$$x_{new} = \alpha^{0.5} \times x_1 + (1 - \alpha^{0.5}) \times x_2 \tag{16}$$

b: The ways to generate individual S are as follows:

a) Generates a random number n_1 between $[1, n_{inc}]$, the current population is randomly divided into n_1 group, and the optimal individuals in each group are made up of S_1
b) $n_2 \leftarrow n_{inc} - n_1$, Randomly generate n_2 individuals, to compose S_2
c) $S \leftarrow S_1 \cup S_2$

The new individuals generated according to the above methods have the following three possibilities:

① If $x_1, x_2 \in S_1$, then the new individual focuses on the learning of the current population.
② If $x_1, x_2 \in S_2$, then the focus of the new individual will enhance the diversity of the population.
③ If x_1, x_2 belong to S_1 and S_2, then the new individual may be located in other areas that have not yet been explored.

Even if the current whale population falls into local optimization, it can bring new information to the population by adding operators, thus improving the efficiency of the effective operation of the algorithm and the ability to explore other extreme regions. Grouping optimal rather than directly selecting the optimal n1 individual to compose S_1 is beneficial to inhibit the premature convergence of the Whale optimization algorithm.

2) DELETION OPERATOR DESIGN

The population inevitably produces useless individuals in the process of evolution, if these individuals cannot be removed. It will certainly reduce the efficiency of the algorithm, so using the delete operator to remove redundant individuals, the design steps are as follows:

a: Determine the number of deleted individuals

$$n_{dec} = \frac{ps \times (PS_{\max} - ps)}{PS_{\max}} \tag{17}$$

b: According to Algorithm 2, divide into n_{dec} class, the worst individuals in these classes are deleted so that the remaining individuals can be evenly distributed in the population, which is beneficial to preserve the diversity of the population.

Algorithm 2

Step 1: Generate a reference point R within the search range
Step 2: Select a point P closest to R from the current population individual X'
Step 3: Find the nearest point of $P \backslash \{X'\}$ and $M - 1$ from X' to form a subpopulation
Step 4: Delete these P individuals in the M
Step 5: Repeat Step 2- Step 4 until the population is divided into $N_p \backslash M$ classes.

In the process of iteration, it is possible that the algorithm has reached the upper limit of scale when the algorithm has not yet found the optimal solution, so it is necessary to improve the population by adding new individuals. Therefore, the deletion operator is used to remove the worst fitness individual n_{dec}, to save space for resulting new individuals.

According to the above principles, the trigger rules are used to screen the individuals after each iteration. The individuals can maintain activity through the equation 18.

E. ALGORITHM COMPLEXITY ANALYSIS

Time complexity refers to the computational workload required in the execution of the algorithm, which mainly depends on the number of repeated execution of the problem. In the basic Whale optimization algorithm, the time complexity mainly receives the influence from the population size N, the iterations number T and the search dimension D. Since the time complexity of the basic WOA algorithm is O(N*T*D). On the basis of WOA, the IWOA algorithm proposed in this paper, the complexity has been increased as follows, The improved Bernouilli Shift mapping in the initialization increases the complexity of O(D). The adjustment of adaptive convergence factor increases the complexity of O(T). Addition operators and deleting parts increases the complexity of O(T*D). The global optimization of Levy behavior increases the complexity of O(N*T). Therefore, the total complexity of IWOA is O(N*T*D) + O(D) + O(T) + O(T*D) + O(N*T). The overall time complexity is higher than that of the WOA algorithm.

F. ALGORITHM FLOW CHART

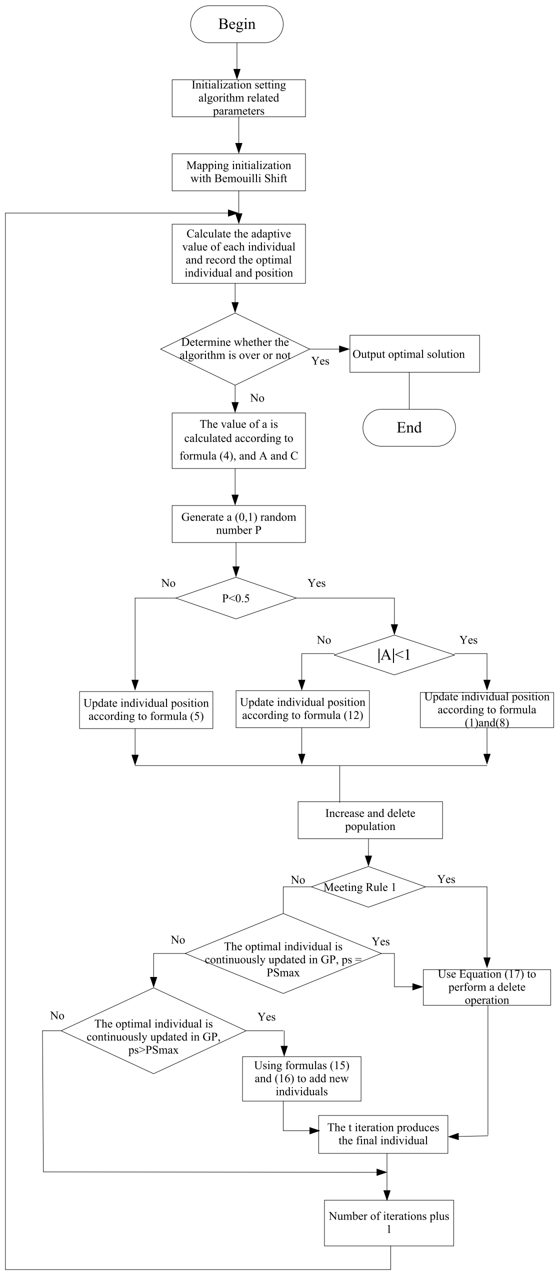

FIGURE 2. Algorithm flow chart in this paper.

V. SIMULATION EXPERIMENT

A. BASIC SETTING OF ALGORITHM

In order to further illustrate the advantages of the algorithm in this paper, the I7 CPU processor, 16GHz memory is, Win7 64-bit operating system, and the simulation software of Matlab2013b were selected. The proposed algorithm (IWOA) is compared with the basic ant colony algorithm (ACO), particle swarm optimization algorithm (PSO), Whale optimization algorithm (WOA) and two improved Whale optimization algorithm (CWOA algorithm in reference [15], LWOA algorithm in reference [16], AGDE algorithm in reference [41], EFADE algorithm in reference [42], EBLSHADE algorithm in reference [50] and EAGDE algorithm in reference [51]). The optimal solutions for each test problem and the obtained best, median, mean, worst values and the standard deviations of error from optimum solution of the proposed algorithms over 50 runs for all 20 benchmark functions. The main parameters required for the algorithm are shown in Table 1.

TABLE 1. Main parameters of five algorithms.

Parameter name	Note
ACO	The population size is 100, the pheromone value of ant colony algorithm is 0.005, the volatilization coefficient of pheromone is 0.01, and the probability of path selection is 0.5.
PSO	The population size is 100, the inertia weight is 0.5, the two learning factors are 0.5, and the random number weight is 0.5.
WOA	The population size is 50, the number of iterations is 200, a decreases linearly from 2 to 0
CWOA	The population size is 50, the number of iterations is 200, a decreases linearly from 2 to 0, and the initial value of the chaotic map is 0.7.
LWOA	The population size is 50, the number of iterations is 200, a decreases linearly from 2 to 0, β is 1.5
IWOA	The population size is 50, the number of iterations is 200, the chaotic step size is 40, a_1 and a_2 are 0.6 and 0.4, ζ is 1.5, β is 1.5
AGDE	The population size is 100, number of iterations is 200, CR1 $\in$ [0.05,0.15] ,CR2 $\in$ [0.9,1]
EFADE	The population size is 100, number of iterations is 200, CR1 $\in$ [0.05,0.15] ,CR2 $\in$ [0.9,1]
EAGDE	The population size is 100, number of iterations is 200, Partition size is 0.1, Nmin is set to 12.51
EBLSHADE	The population size is 100, number of iterations is 200

TABLE 2. Test functions.

NO.	Function
F1	Bent Cigar Function
F2	Sum of Different Power Function
F3	Zakharov Function
F4	Rosenbrock Function
F5	Rastrigin Function
F6	Expanded Schaffer Function
F7	Lunacek bi-Rastrigin Function
F8	Non-continuous Rotated Rastrigin's Function
F9	Levy Function
F10	Modified Schwefel's Function
F11	High Conditioned Elliptic Function
F12	Discus Function
F13	Ackley Function
F14	Weierstrass Function
F15	Griewank Function
F16	Katsuura Function
F17	HappyCat Function
F18	HGBat Function
F19	Expanded Griewank's plus Rosenbrock'
F20	Schaffer's F7 Function

B. CLASSICAL TEST FUNCTION

In this paper, 10 representative classical test functions and the all basic Functions from CEC2017 [52] (Table 2 shows Basic function of CEC2017) are selected to evaluate the performance of the proposed algorithm. These test

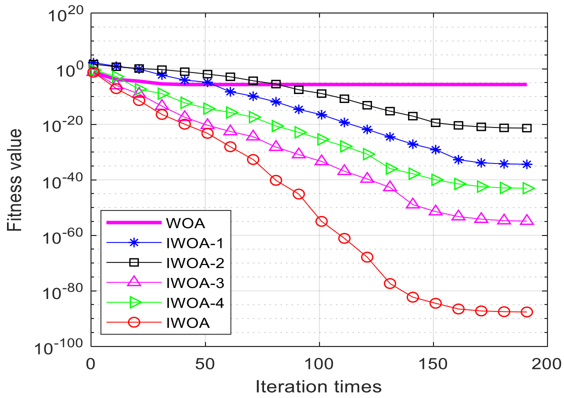

FIGURE 3. The influence of different improvements.

TABLE 3. Wilcoxon's test between IWOA and other 4 improvements.

Algorithm	R+	R-	P value
IWOA-1 versus WOA	172	152	0.1277
IWOA-2 versus WOA	145	121	0.4528
IWOA-3 versus WOA	225	187	0.0542
IWOA-4 versus WOA	208	175	0.0778
IWOA versus WOA	281	192	0.0123

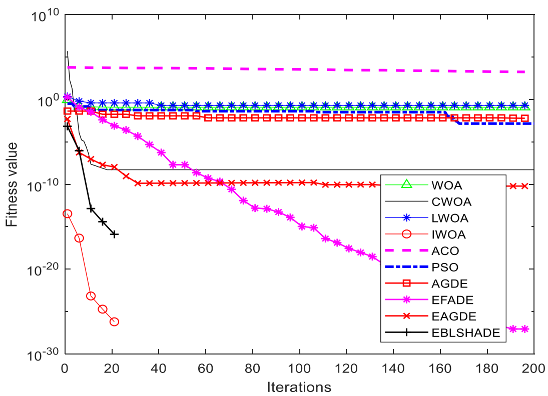

FIGURE 4. Iteration curve of F1.

functions have both high dimensions (30,50,100) and low dimensions(2,5,10), which can be compared with the other five algorithms in all aspects.

The average value, the minimum value, the maximum value and the standard deviation are selected as the evaluation indexes, in which the maximum and the minimum value reflect the quality of the solution, the average value reflects the accuracy that the algorithm can achieve under a given number of iterations, and the standard deviation reflects the convergence speed of the algorithm.

C. PERFORMANCE COMPARISON OF FOUR IMPROVEMENTS

First of all, we take the Sphere function as an example to compare the improvement of traditional WOA optimization

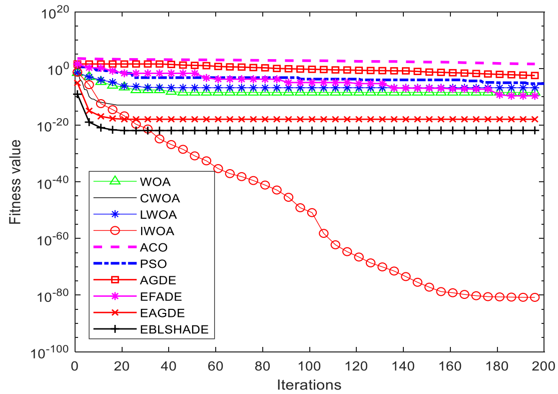

FIGURE 5. Iteration curve of F2.

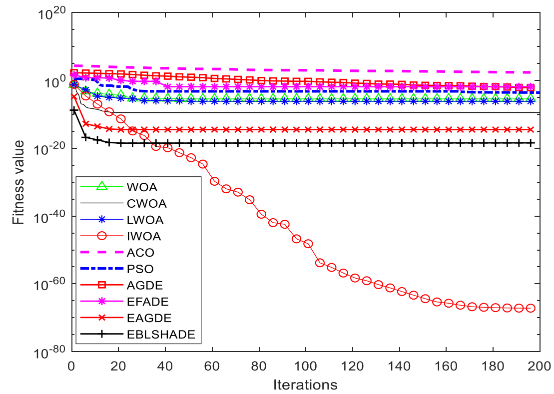

FIGURE 6. Iteration curve of F3.

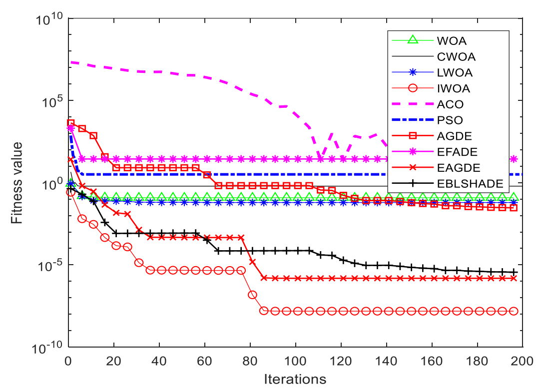

FIGURE 7. Iteration curve of F4.

algorithm by four improvement points. The comparison simulation results are shown in Figure 3.3. The fitness values of WOA and four different improvements are 2.1080e-06, 3.5333e-35, 3.9907e-22, 1.2915e-55, 8.1057e-44, 2.2664e-88 respectively. The improvement 3 has the greatest impact on WOA algorithm, while improvement 2 has the least impact on WOA algorithm.

Due to the importance of multiple-problem statistical analysis, Table 3 also gives the statistical analysis results of Wilcoxon's test between IWOA and the other 4 improvements. The parameters of Wilcoxon's test are $\alpha = 0.01$ and 0.05.

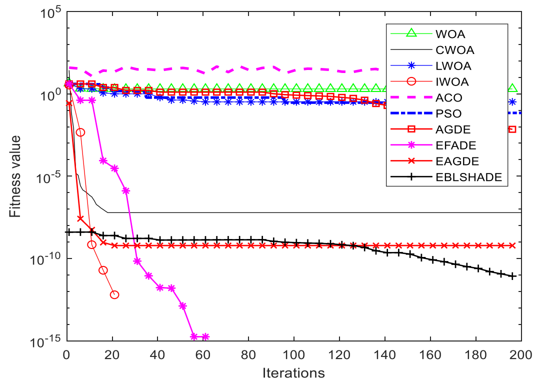

FIGURE 8. Iteration curve of F5.

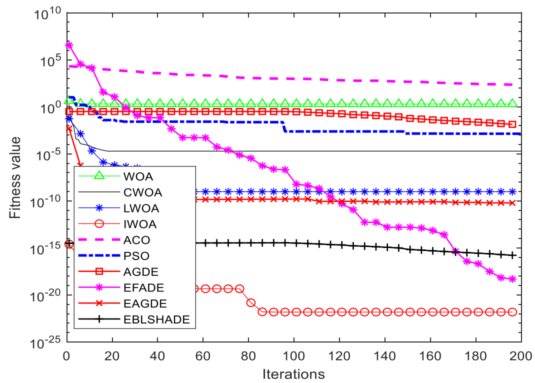

FIGURE 9. Iteration curve of F6.

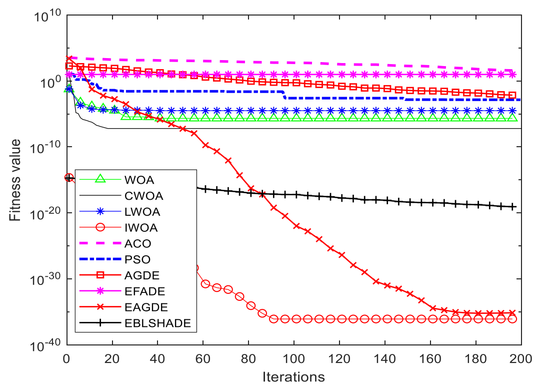

FIGURE 10. Iteration curve of F7.

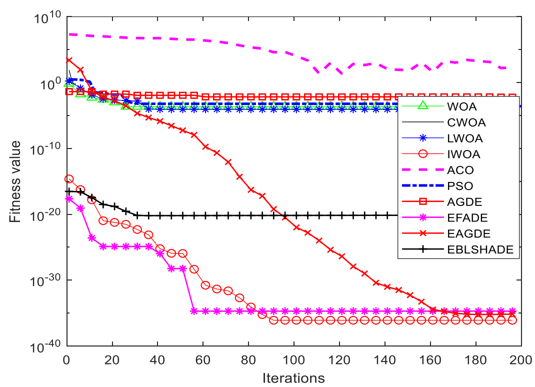

FIGURE 11. Iteration curve of F8.

From the results shown in Table 3, we can see that the IWOA provides higher R+ values and R- values than other 4 single improvements.

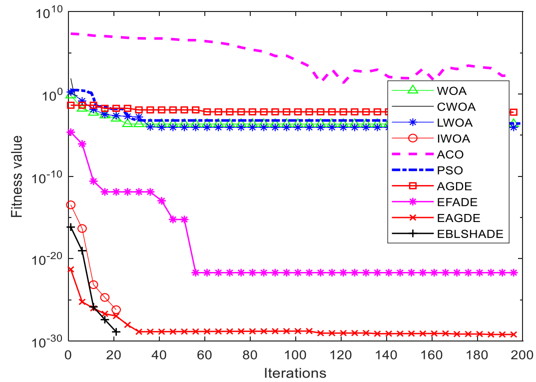

FIGURE 12. Iteration curve of F9.

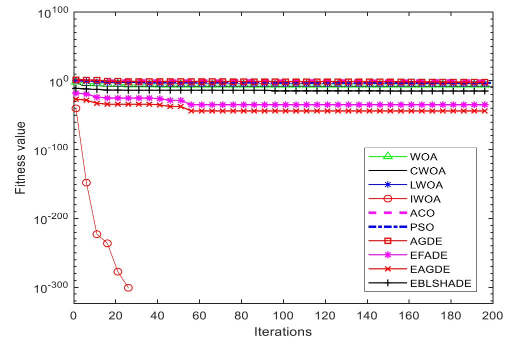

FIGURE 13. Iteration curve of F10.

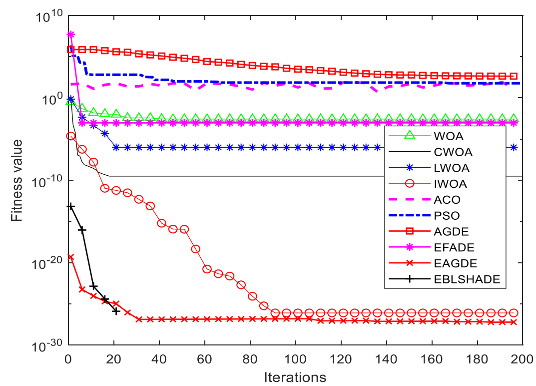

FIGURE 14. Iteration curve of F11.

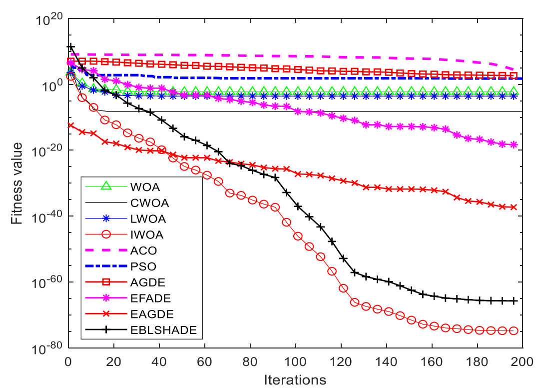

FIGURE 15. Iteration curve of F12.

D. ANALYSIS OF CONVERGENCE BEHAVIOR

Figure 4-23 shows the comparison of fitness values of eight algorithms in 20 test functions. The comparative results of the 10 diagrams are analyzed as follows:

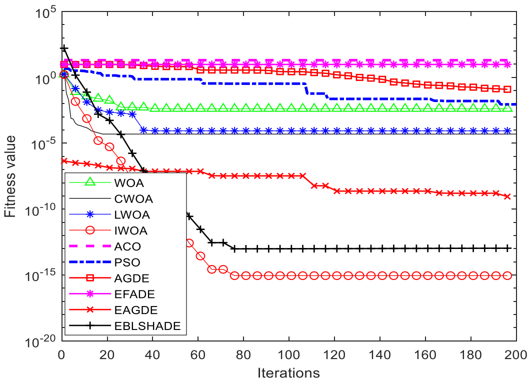

FIGURE 16. Iteration curve of F13.

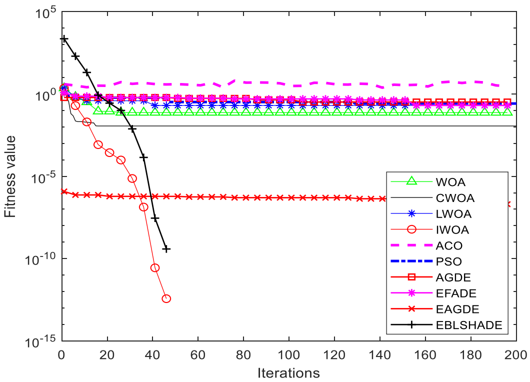

FIGURE 17. Iteration curve of F14.

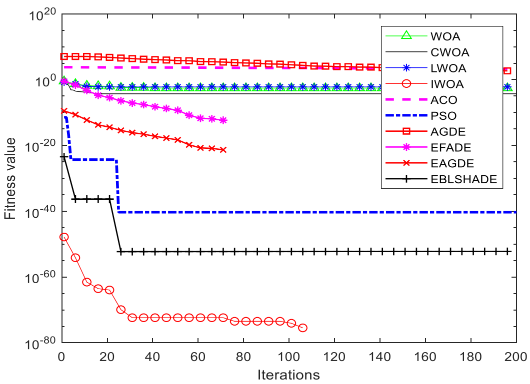

FIGURE 18. Iteration curve of F15.

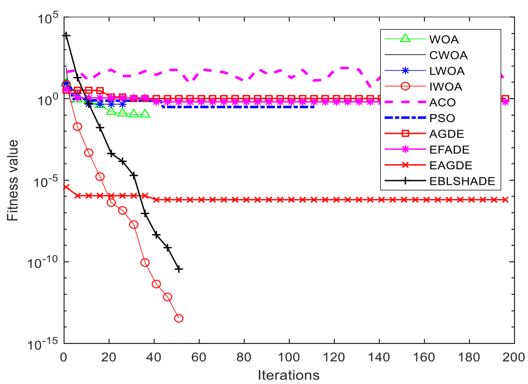

FIGURE 19. Iteration curve of F16.

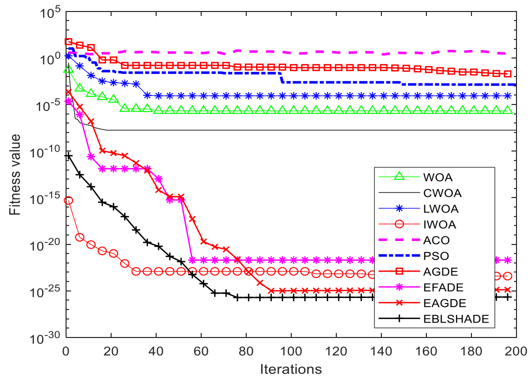

FIGURE 20. Iteration curve of F17.

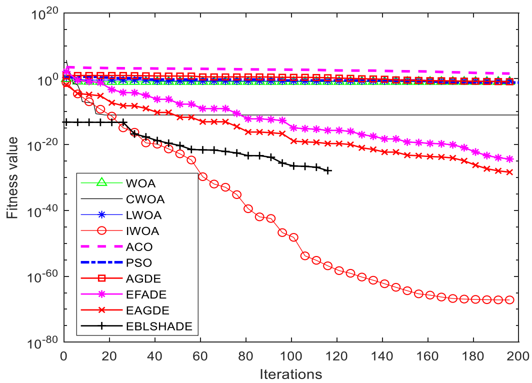

FIGURE 21. Iteration curve of F18.

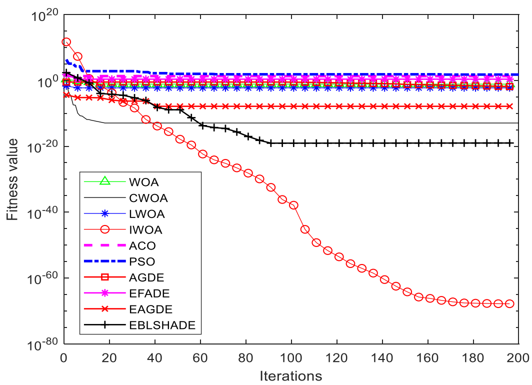

FIGURE 22. Iteration curve of F19.

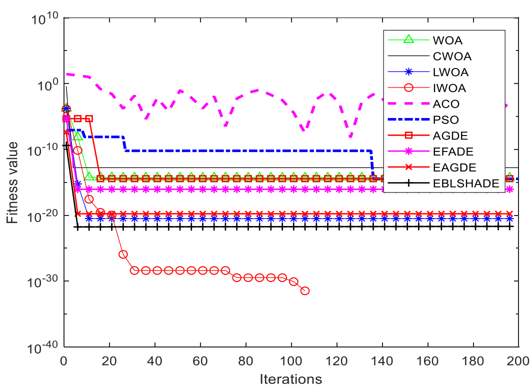

FIGURE 23. Iteration curve of F20.

(a) With the increase of the number of iterations, in the optimization process of 20 test functions, the ACO, PSO, WOA, LWOA, CWOA, AGDE,EFADE,EAGDE and EBLSHADE algorithm will fall into local optimization earlier and difficult to jump out, and can't find the theoretical optimal value and the optimization

TABLE 4. Comparison results of different dimensions in F1 functions.

Algorithm	Dimension	Minimum Value	Maximum Value	Average Value	Variance
ACO	2	1.32E-07	0.124559	0.034336	0.034498
	5	0.014625	0.228675	0.076616	0.05986
	10	0.063953	0.556309	0.248478	0.125398
	30	0.533033	0.762289	0.60982	0.230854
	50	1.114322	1.50605	1.344394	0.314633
	100	1.808369	2.789466	1.779915	0.520567
PSO	2	1.62E-11	1.01E-06	1.65E-07	1.71E-07
	5	5.47E-07	0.000767	5.31E-05	7.72E-05
	10	0.000428	0.016647	0.002361	0.004703
	30	0.014661	0.052832	0.033821	0.009654
	50	0.066586	0.254039	0.095965	0.019109
	100	0.146561	0.316726	0.27347	0.054354
WOA	2	1.12E-19	2.68E-10	1.03E-11	2.23E-11
	5	1.64E-12	3.19E-07	5.21E-08	1.06E-07
	10	1.01E-09	7.37E-06	5.93E-07	1.75E-06
	30	2.63E-08	8.92E-05	1.28E-05	1.32E-05
	50	1.55E-08	9.46E-05	3.10E-05	3.83E-05
	100	1.04E-06	0.000615	0.000121	5.10E-05
CWOA	2	8.48E-23	2.46E-12	7.82E-14	2.73E-13
	5	2.32E-23	2.43E-09	7.75E-11	5.11E-10
	10	4.91E-21	3.03E-09	1.08E-10	5.28E-10
	30	3.73E-18	3.91E-08	1.17E-09	6.67E-09
	50	6.59E-20	4.41E-08	2.08E-09	7.18E-09
	100	6.18E-18	5.10E-07	2.57E-08	8.61E-08
LWOA	2	7.59E-21	2.18E-09	4.88E-11	1.80E-10
	5	6.27E-13	7.01E-07	8.33E-08	1.59E-07
	10	8.58E-11	5.02E-06	9.99E-07	1.44E-06
	30	5.06E-08	7.18E-05	1.52E-05	1.63E-05
	50	1.21E-06	0.000133	3.99E-05	3.93E-05
	100	1.78E-06	0.000274	7.34E-05	5.39E-05
IWOA	2	8.73E-07	7.16E-73	1.50E-74	1.86E-73
	5	3.70E-60	8.10E-46	1.23E-47	1.44E-46
	10	9.24E-55	4.56E-40	1.14E-41	4.84E-41
	30	5.68E-48	2.04E-36	3.57E-38	2.22E-37
	50	2.44E-49	1.41E-36	2.90E-38	2.75E-37
	100	4.64E-45	6.88E-36	3.34E-37	1.07E-36
AGDE	2	8.62E-09	2.02E-07	6.80E-08	2.10E-08
	5	2.32E-07	0.000243	2.66E-05	3.45E-05
	10	8.68E-05	0.004244	0.000602	0.000718
	30	0.006084	0.009465	0.017055	0.003624
	50	0.021695	0.068528	0.030135	0.012798
	100	0.048655	0.125336	0.042603	0.022986
EFADE	2	4.36E-38	5.10E-27	9.75E-29	9.08E-28
	5	7.44E-36	1.74E-26	8.68E-28	3.87E-27
	10	3.14E-37	1.42E-22	2.48E-24	1.79E-23
	30	3.48E-34	2.77E-24	1.65E-25	5.31E-25
	50	8.72E-33	4.83E-25	4.09E-26	9.47E-26
	100	1.24E-32	2.52E-22	8.61E-24	4.46E-23
EAGDE	2	1.39E-66	1.15E-66	1.64E-68	1.53E-67
	5	2.64E-54	7.16E-40	1.33E-41	5.84E-41
	10	7.25E-49	5.51E-34	1.13E-35	7.00E-35
	30	1.59E-42	8.66E-31	3.53E-32	1.80E-31
	50	3.17E-43	7.90E-31	1.42E-32	1.60E-31
	100	5.93E-39	3.39E-30	2.76E-31	6.60E-31
EBLSHADE	2	1.76E-66	2.18E-69	4.18E-71	2.36E-70
	5	5.75E-57	1.50E-42	2.12E-44	1.20E-43
	10	1.50E-51	7.84E-37	1.07E-38	1.26E-37
	30	4.68E-45	2.51E-33	6.22E-35	1.91E-34
	50	1.26E-45	2.78E-33	6.29E-35	4.77E-34
	100	9.37E-42	7.04E-33	2.58E-34	1.08E-33

TABLE 5. Comparison results of different dimensions in F2 functions.

Algorithm	Dimension	Minimum Value	Maximum Value	Average Value	Variance
ACO	2	2.25E-04	1.09E+05	2.49E+03	1.54E+04
	5	1.03E+02	1.43E+10	7.85E+08	3.14E+09
	10	1.94E+07	3.09E+18	1.21E+17	6.00E+17
	30	4.38E+33	1.05E+44	3.96E+42	1.59E+43
	50	6.16E+58	3.73E+75	7.51E+73	5.28E+74
	100	3.03E+128	1.53E+171	4.98E+169	5.77E+245
PSO	2	1.47E-07	2.05E-02	1.35E-03	3.96E-03
	5	6.38E-02	9.57E+02	1.18E+02	2.02E+02
	10	2.36E+03	6.13E+07	3.65E+06	1.05E+07
	30	3.87E+19	2.46E+31	5.49E+29	3.49E+30
	50	4.13E+40	4.16E+54	9.69E+52	5.92E+53
	100	4.12E+90	4.03E+115	8.27E+113	5.69E+114
WOA	2	1.466E-12	8.280E-06	2.403E-07	1.176E-06
	5	1.222E-09	1.609E-02	5.161E-04	2.302E-03
	10	2.879E-06	5.203E-01	3.870E-02	9.670E-02
	30	1.670E-02	1.719E+03	9.584E+01	3.238E+02
	50	8.344E-02	3.227E+06	2.564E+05	5.944E+05
	100	2.312E-02	5.246E+21	1.575E+20	7.966E+20
CWOA	2	4.24E-20	1.83E-08	1.32E-09	3.89E-09
	5	4.93E-19	1.77E-05	4.19E-07	2.51E-06
	10	4.98E-17	2.98E-06	1.89E-07	6.28E-07
	30	5.31E-20	0.0011385	2.77E-05	0.000162
	50	8.06E-17	0.000417	1.22E-05	6.16E-05
	100	2.42E-17	0.0005058	1.49E-05	7.43E-05
LWOA	2	8.40E-16	8.03E-07	4.91E-08	1.44E-07
	5	1.20E-09	2.73E-02	1.11E-03	3.98E-03
	10	1.04E-06	6.08E-01	5.38E-02	1.22E-01
	30	1.29E-03	1.03E+03	6.20E+01	1.68E+02
	50	5.76E-01	1.85E+07	9.63E+05	3.30E+06
	100	3.97E-03	4.85E+21	1.01E+20	6.85E+20
IWOA	2	0	2.11E-72	4.23E-74	2.99E-73
	5	3.50E-75	1.45E-51	2.93E-53	2.05E-52
	10	1.29E-73	1.55E-47	3.10E-49	2.19E-48
	30	1.96E-69	1.63E-48	3.29E-50	2.30E-49
	50	1.55E-72	1.75E-47	4.77E-49	2.58E-48
	100	9.19E-72	1.61E-46	3.41E-48	2.28E-47
AGDE	2	9.00E-06	4.04E-03	7.75E-04	7.49E-04
	5	1.51E-02	3.11E+03	4.30E+02	6.89E+02
	10	1.57E+02	5.57E+07	2.22E+06	8.15E+06
	30	1.64E+17	1.68E+26	3.51E+24	2.38E+25
	50	2.45E+30	3.99E+44	1.32E+43	6.28E+43
	100	3.17E+75	1.39E+101	2.79E+99	1.97E+100
EFADE	2	4.14E-30	1.92E-08	4.07E-10	2.72E-09
	5	3.01E-02	1.65E+06	1.60E+05	3.05E+05
	10	1.53E+07	3.55E+13	1.71E+12	5.19E+12
	30	1.39E+32	7.85E+42	4.46E+41	1.29E+42
	50	3.77E+48	2.23E+74	7.18E+72	3.32E+73
	100	5.71E+140	1.24E+154	2.59E+152	1.75E+153
EAGDE	2	1.02E-11	4.04E-07	1.27E-08	4.97E-08
	5	3.34E-12	2.24E-08	3.29E-09	4.47E-09
	10	2.51E-12	7.76E-09	1.22E-09	1.87E-09
	30	1.67E-13	1.35E-09	1.26E-10	2.21E-10
	50	1.49E-14	5.50E-10	2.11E-10	1.63E-10
	100	3.89E-13	1.36E-09	9.76E-11	2.25E-10
EBLSHADE	2	1.34E-12	5.27E-08	2.01E-09	6.84E-09
	5	4.76E-13	2.62E-09	3.70E-10	5.39E-10
	10	3.34E-13	1.44E-09	1.42E-10	2.91E-10
	30	1.77E-14	1.47E-10	1.76E-11	3.24E-11
	50	1.60E-15	1.76E-10	2.42E-11	4.66E-11
	100	5.41E-14	1.68E-10	8.26E-12	1.44E-11

TABLE 6. Comparison results of different dimensions in F3 functions.

Algorithm	Dimension	Minimum Value	Maximum Value	Average Value	Variance
	2	1.89E-02	4.14E+06	1.31E+05	6.66E+05
	5	8.24E+00	3.65E+07	1.14E+06	5.68E+06
ACO	10	1.71E+03	6.04E+08	1.44E+07	8.65E+07
	30	1.16E+04	3.06E+07	6.60E+05	4.33E+06
	50	2.34E+04	3.00E+07	9.74E+05	4.47E+06
	100	5.88E+04	8.87E+09	1.86E+08	1.25E+09
	2	8.71E-08	6.34E-01	1.62E-02	8.97E-02
	5	1.04E-01	5.76E+01	8.01E+00	1.26E+01
PSO	10	8.06E+00	6.71E+02	2.66E+02	1.62E+02
	30	9.72E+02	6.19E+03	2.51E+03	8.75E+02
	50	3.10E+03	1.04E+04	5.24E+03	1.54E+03
	100	7.51E+03	2.24E+04	1.26E+04	3.04E+03
	2	1.301E-11	1.124E-04	6.464E-06	2.016E-05
	5	1.072E-04	1.291E-01	2.093E-02	2.638E-02
WOA	10	8.434E-02	2.375E+00	7.851E-01	5.016E-01
	30	4.814E+00	2.089E+01	1.240E+01	3.276E+00
	50	2.164E+01	3.810E+01	2.903E+01	3.658E+00
	100	5.780E+01	9.632E+01	7.448E+01	7.561E+00
	2	1.36E-17	4.96E-06	1.21E-07	7.02E-07
	5	5.55E-18	5.82E-04	2.41E-05	1.07E-04
CWOA	10	1.74E-15	2.79E-03	1.08E-04	4.48E-04
	30	5.73E-13	0.4444612	2.92E-02	0.095309
	50	1.16E-13	10.627627	4.20E-01	1.63E+00
	100	2.28E-11	44.897079	3.75E+00	9.16E+00
	2	2.27E-14	3.48E-04	1.66E-05	6.44E-05
LWOA	5	1.46E-04	1.89E-01	2.85E-02	3.93E-02
	10	4.88E-03	3.51E+00	7.21E-01	7.13E-01
	30	4.47E+00	2.01E+01	1.26E+01	3.46E+00
	50	1.53E+01	3.99E+01	2.88E+01	4.41E+00
IWOA	100	6.18E+01	9.28E+01	7.40E+01	7.38E+00
	2	0.00E+00	2.27E-58	8.43E-60	4.09E-59
	5	3.79E-42	1.60E-32	5.16E-34	2.29E-33
	10	5.30E-30	1.34E-20	2.80E-22	1.89E-21
	30	1.57E-14	1.31E-08	1.14E-09	2.55E-09
	50	2.02E-09	3.89E-04	5.52E-05	9.81E-05
	100	3.24E-02	1.42E+00	3.73E-01	3.16E-01
AGDE	2	4.78E-04	1.33E-02	3.85E-03	2.66E-03
	5	2.85E-02	8.54E+01	8.50E+00	1.61E+01
	10	1.11E+01	8.45E+02	1.70E+02	1.39E+02
	30	4.54E+02	3.26E+03	1.53E+03	5.42E+02
	50	1.92E+03	7.56E+03	3.72E+03	1.31E+03
	100	5.10E+03	1.36E+04	8.21E+03	1.83E+03
	2	2.91E-25	1.33E+00	4.92E-02	2.01E-01
EFADE	5	1.20E-15	3.94E+01	1.64E+00	5.93E+00
	10	1.51E-20	5.51E+02	2.14E+01	8.18E+01
	30	2.79E-15	2.15E+03	8.75E+01	3.19E+02
	50	1.28E-15	3.18E+03	2.11E+02	6.42E+02
	100	8.22E-11	4.39E+04	1.33E+03	6.72E+03
	2	1.32E+00	4.08E-57	1.38E-58	8.48E-58
	5	7.54E-41	1.74E-31	7.28E-33	4.59E-32
EAGDE	10	6.01E-29	2.76E-19	5.21E-21	2.84E-20
	30	2.19E-13	2.91E-07	2.12E-08	3.31E-08
	50	3.69E-08	8.50E-03	8.27E-04	1.96E-03
	100	6.21E-01	2.23E+01	7.82E+00	7.22E+00
	2	1.64E-01	3.80E-58	1.08E-59	9.49E-59
	5	4.68E-42	3.23E-32	1.42E-33	5.41E-33
EBLSHADE	10	1.51E-29	2.47E-20	6.20E-22	3.28E-21
	30	3.43E-14	3.00E-08	2.29E-09	4.82E-09
	50	5.52E-09	1.06E-03	7.07E-05	1.77E-04
	100	8.58E-02	3.18E+00	8.87E-01	9.49E-01

TABLE 7. Comparison results of different dimensions in F4 functions.

Algorithm	Dimension	Minimum Value	Maximum Value	Average Value	Variance
ACO	2	4.72E-01	8.00E+07	7.49E+06	2.27E+07
	5	7.05E+01	1.68E+08	2.36E+07	5.50E+07
	10	1.45E+04	3.24E+08	4.75E+07	9.87E+07
	30	2.23E+07	7.77E+08	1.97E+08	2.48E+08
	50	8.99E+07	1.08E+09	4.19E+08	3.48E+08
	100	4.23E+08	2.07E+09	1.09E+09	5.71E+08
PSO	2	1.11E-05	2.02E+01	1.34E+00	3.90E+00
	5	5.00E+00	2.77E+03	3.63E+02	6.24E+02
	10	1.17E+03	6.69E+05	5.90E+04	1.16E+05
	30	4.76E+05	4.95E+06	2.18E+06	1.25E+06
	50	1.74E+06	1.55E+07	5.92E+06	2.98E+06
	100	5.42E+06	3.48E+07	1.69E+07	6.08E+06
WOA	2	7.875E-08	2.313E+00	7.706E-02	3.250E-01
	5	8.217E-01	6.539E+00	3.862E+00	1.209E+00
	10	8.975E+00	1.686E+02	2.938E+01	3.268E+01
	30	2.922E+01	9.806E+02	2.946E+02	2.602E+02
	50	4.993E+01	3.422E+03	9.151E+02	9.607E+02
	100	1.278E+02	1.442E+04	2.708E+03	3.214E+03
CWOA	2	6.02E-01	9.89E-01	6.56E-01	9.39E-02
	5	3.60E+00	3.9743151	3.89E+00	1.06E-01
	10	8.50E+00	9.0698388	8.88E+00	9.54E-02
	30	2.85E+01	28.848486	28.70421	0.046578
	50	4.85E+01	48.659548	48.51328	0.026758
	100	9.80E+01	99.845042	98.07396	0.29401
LWOA	2	3.16E-05	1.73E-01	2.13E-02	3.67E-02
	5	1.00E+00	8.45E+00	3.92E+00	1.49E+00
	10	8.94E+00	1.88E+02	2.78E+01	3.52E+01
	30	2.94E+01	1.27E+03	3.64E+02	3.10E+02
	50	5.10E+01	5.00E+03	9.88E+02	1.15E+03
	100	1.32E+02	1.10E+04	2.51E+03	2.62E+03
IWOA	2	1.02E-13	1.29E-04	1.09E-05	2.51E-05
	5	1.71E-03	3.07E+00	9.96E-01	8.41E-01
	10	3.10E-01	8.92E+00	6.95E+00	1.67E+00
	30	2.75E+01	2.88E+01	2.83E+01	4.03E-01
	50	4.76E+01	4.87E+01	4.84E+01	2.73E-01
	100	9.77E+01	9.85E+01	9.83E+01	1.91E-01
AGDE	2	2.86E-03	2.87E+00	1.85E-01	4.95E-01
	5	4.22E+00	1.13E+04	1.01E+03	1.97E+03
	10	1.23E+02	2.12E+04	3.90E+03	4.18E+03
	30	4.46E+04	7.42E+05	2.25E+05	1.45E+05
	50	2.09E+05	2.03E+06	8.68E+05	4.32E+05
	100	9.26E+05	7.21E+06	2.95E+06	1.16E+06
EFADE	2	1.36E-02	8.17E+02	5.69E+01	1.30E+02
	5	3.94E+00	2.86E+05	2.10E+04	6.36E+04
	10	9.00E+00	8.99E+05	6.38E+04	1.54E+05
	30	2.90E+01	1.67E+08	4.93E+06	2.40E+07
	50	4.94E+01	3.45E+07	2.16E+06	7.13E+06
	100	9.90E+01	1.66E+08	9.20E+06	2.88E+07
EAGDE	2	1.70E-13	2.57E-04	1.09E-05	5.82E-05
	5	3.68E-03	6.90E+00	1.81E+00	9.72E-01
	10	4.82E-01	2.43E+01	2.07E+01	2.81E+00
	30	6.23E+01	5.82E+01	5.13E+01	8.97E-01
	50	1.10E+02	9.39E+01	8.60E+01	5.46E-01
	100	2.36E+02	2.67E+02	1.48E+02	4.30E-01
EBLSHADE	2	2.09E-13	2.42E-04	1.37E-05	5.16E-05
	5	3.89E-03	6.94E+00	1.26E+00	1.15E+00
	10	4.60E-01	1.59E+01	1.63E+01	2.66E+00
	30	5.74E+01	6.14E+01	6.12E+01	5.83E-01
	50	6.54E+01	1.18E+02	8.32E+01	6.50E-01
	100	2.26E+02	1.19E+02	2.56E+02	3.36E-01

TABLE 8. Comparison results of different dimensions in F5 functions.

Algorithm	Dimension	Minimum Value	Maximum Value	Average Value	Variance
ACO	2	1.91E+00	5.53E+01	2.78E+01	1.30E+01
	5	2.89E+01	1.42E+02	8.40E+01	2.36E+01
	10	1.12E+02	2.41E+02	1.80E+02	3.01E+01
	30	4.85E+02	6.74E+02	5.45E+02	3.81E+01
	50	8.16E+02	1.03E+03	9.10E+02	6.16E+01
	100	1.62E+03	2.04E+03	1.79E+03	8.78E+01
PSO	2	6.55E-08	2.09E+00	6.03E-01	5.56E-01
	5	2.44E+00	2.51E+01	1.09E+01	5.34E+00
	10	2.56E+01	6.89E+01	4.81E+01	1.06E+01
	30	1.54E+02	2.89E+02	2.30E+02	3.11E+01
	50	3.59E+02	5.20E+02	4.36E+02	3.82E+01
	100	8.28E+02	1.07E+03	9.46E+02	5.83E+01
WOA	2	1.603E-10	1.992E+00	3.064E-01	5.525E-01
	5	1.062E-05	1.009E+01	4.128E+00	2.697E+00
	10	7.033E-01	4.856E+01	2.281E+01	1.020E+01
	30	1.578E-01	2.215E+02	1.238E+02	6.525E+01
	50	4.956E-01	4.005E+02	2.097E+02	1.282E+02
	100	1.499E+00	9.041E+02	4.471E+02	3.023E+02
CWOA	2	3.55E-15	8.09E-05	3.81E-06	1.36E-05
	5	0.00E+00	1.8156575	3.83E-02	2.57E-01
	10	1.07E-13	0.7285271	3.27E-02	1.44E-01
	30	8.34E-11	9.2394732	0.392022	1.563004
	50	1.68E-12	17.283799	0.792534	3.294345
	100	1.74E-10	117.0139	5.127721	18.37939
LWOA	2	1.35E-13	1.99E+00	2.02E-01	4.40E-01
	5	1.37E-03	9.87E+00	4.63E+00	2.53E+00
	10	3.90E-02	4.24E+01	1.93E+01	1.10E+01
	30	2.50E-01	2.24E+02	1.26E+02	7.00E+01
	50	3.87E+00	3.99E+02	2.09E+02	1.26E+02
	100	2.55E+01	9.18E+02	4.65E+02	2.71E+02
IWOA	2	0	0	0	0
	5	0	1.78E-15	3.55E-17	2.51E-16
	10	0	8.10E+00	1.62E-01	1.15E+00
	30	0	1.78E-15	1.42E-16	4.87E-16
	50	0	1.78E-15	3.55E-17	2.51E-16
	100	0	0	0	0
AGDE	2	3.61E-04	1.01E+00	8.56E-02	2.73E-01
	5	5.76E-02	1.11E+01	5.56E+00	2.93E+00
	10	1.00E+01	4.68E+01	3.04E+01	9.82E+00
	30	1.12E+02	2.28E+02	1.77E+02	2.49E+01
	50	2.72E+02	4.13E+02	3.55E+02	3.22E+01
	100	6.68E+02	9.07E+02	7.92E+02	5.59E+01
EFADE	2	0	0	0	0
	5	0	0	0	0
	10	0	0	0	0
	30	0	0	0	0
	50	0	0	0	0
	100	0	0	0	0
EAGDE	2	2.56E-06	9.38E-03	5.98E-04	1.13E-03
	5	4.35E-04	8.71E-02	4.28E-02	1.26E-02
	10	7.77E-02	3.17E-01	2.40E-01	5.34E-02
	30	7.48E-01	1.35E+00	1.32E+00	9.97E-02
	50	1.73E+00	3.03E+00	3.02E+00	1.99E-01
	100	5.03E+00	5.46E+00	7.23E+00	3.48E-01
EBLSHADE	2	2.53E-07	4.89E-04	5.46E-05	1.87E-04
	5	4.06E-05	7.42E-03	3.67E-03	2.15E-03
	10	5.75E-03	3.25E-02	2.21E-02	6.51E-03
	30	6.25E-02	1.40E-01	1.08E-01	1.51E-02
	50	2.10E-01	3.12E-01	1.87E-01	2.40E-02
	100	4.11E-01	6.32E-01	5.12E-01	3.64E-02

TABLE 9. Comparison results of different dimensions in F6 functions.

Algorithm	Dimension	Minimum Value	Maximum Value	Average Value	Variance
ACO	2	1.63E-03	788.6423	281.7818	254.4229
	5	77.25228	1661.063	760.1522	473.5137
	10	467.995	4373.585	1331.224	768.3423
	30	5428.964	4602.567	7727.199	1409.313
	50	7174.425	8823.834	14062.6	2209.776
	100	11018.72	35381	22785.1	2393.227
PSO	2	1.22E-07	9.29E-03	9.95E-04	1.16E-03
	5	2.89E-03	4.429467	0.744545	0.638792
	10	3.038799	248.9718	26.84327	18.91991
	30	134.7023	902.0776	501.4368	138.7205
	50	466.7085	1570.165	421.5457	204.5876
	100	1310.47	3151.364	2492.437	411.304
WOA	2	9.98E-16	1.52E-06	6.74E-08	2.41E-07
	5	1.31E-08	3.29E-03	3.15E-04	7.84E-04
	10	8.23E-06	0.067184	6.62E-03	0.009575
	30	1.24E-04	0.575547	0.123156	0.170671
	50	2.02E-04	0.748919	0.253682	0.292595
	100	7.28E-03	3.991266	0.719782	0.775285
CWOA	2	6.77E-19	1.65E-08	4.92E-10	3.92E-09
	5	1.50E-19	2.31E-05	1.22E-06	3.06E-06
	10	2.57E-17	2.66E-05	1.44E-06	4.38E-06
	30	1.60E-14	3.57E-04	9.88E-06	4.97E-05
	50	6.00E-16	3.76E-04	1.39E-05	5.86E-05
	100	6.52E-14	2.05E-03	1.68E-04	6.80E-04
LWOA	2	3.94E-17	1.97E-05	2.44E-07	2.81E-06
	5	2.87E-09	9.07E-03	6.25E-04	1.22E-03
	10	3.98E-07	0.060846	7.43E-03	8.95E-03
	30	3.82E-04	0.573509	0.065148	0.058895
	50	0.007716	1.178915	0.265083	0.175852
	100	0.016776	1.929042	0.319958	0.452667
IWOA	2	6.64E-03	6.88E-69	2.13E-70	1.10E-69
	5	3.23E-56	3.47E-42	1.38E-43	6.46E-43
	10	1.16E-50	5.62E-36	1.22E-37	3.45E-37
	30	3.80E-44	1.05E-32	2.94E-34	1.53E-33
	50	4.89E-45	1.13E-32	3.26E-34	2.16E-33
	100	4.57E-41	5.88E-32	2.42E-33	8.50E-33
AGDE	2	1.15E-04	2.20E-03	7.70E-04	4.08E-04
	5	3.87E-03	2.117326	0.193247	0.342455
	10	0.93041	35.24047	9.811838	8.341322
	30	55.9375	247.7873	67.37895	36.71156
	50	180.8671	664.5684	372.0386	33.72648
	100	398.094	1422.87	695.1925	130.5984
EFADE	2	2.55E-34	5.62E-23	7.74E-25	7.87E-24
	5	5.16E-32	1.21E-22	4.40E-24	2.44E-23
	10	1.96E-33	4.41E-19	1.63E-20	7.90E-20
	30	5.12E-30	4.78E-20	1.24E-21	5.13E-21
	50	8.71E-29	3.63E-21	4.15E-22	1.03E-21
	100	1.40E-28	3.32E-18	7.73E-20	3.08E-19
EAGDE	2	1.25E-62	1.46E-62	1.31E-64	1.01E-63
	5	2.36E-50	6.57E-36	1.39E-37	6.72E-37
	10	9.25E-45	4.38E-30	6.74E-32	5.26E-31
	30	2.49E-38	7.21E-27	1.70E-28	1.68E-27
	50	2.74E-39	8.15E-27	1.69E-28	1.76E-27
	100	6.74E-35	3.00E-26	1.40E-27	3.94E-27
EBLSHADE	2	1.18E-62	1.24E-65	2.81E-67	1.46E-66
	5	4.28E-53	1.06E-38	1.96E-40	1.27E-39
	10	1.62E-47	8.32E-33	7.99E-35	1.30E-33
	30	5.48E-41	7.96E-30	5.71E-31	1.31E-30
	50	5.60E-42	1.81E-29	4.22E-31	3.46E-30
	100	5.98E-38	8.28E-29	4.07E-30	1.82E-29

TABLE 10. Comparison results of different dimensions in F7 functions.

Algorithm	Dimension	Minimum Value	Maximum Value	Average Value	Variance
ACO	2	3.57E-02	20683.9	5934.031	8890.815
	5	3336.041	45428.41	19118.11	12351.83
	10	19008.67	88217.82	30494.19	21855
	30	105648.1	255686.7	183540	35770.33
	50	193281.5	345574.2	198302.9	45835
	100	460705.5	811306.2	564989.7	54768.15
PSO	2	2.98E-06	1.70E-01	2.58E-02	5.72E-02
	5	1.09E-01	106.0968	16.35276	20.66327
	10	80.17098	5952.551	848.4536	892.3245
	30	4604.844	19594.35	9462.309	3583.782
	50	12568.85	29569.89	30352.19	5009.716
	100	18291.21	73699.2	62680.19	9637.693
WOA	2	2.74E-14	4.00E-05	3.23E-06	5.80E-06
	5	4.26E-07	8.89E-02	1.23E-02	2.04E-02
	10	1.95E-04	1.601186	1.64E-01	0.396284
	30	4.55E-03	21.48424	2.976228	4.844223
	50	5.08E-03	11.92477	5.859419	6.946942
	100	1.75E-01	93.99027	19.21416	20.74752
CWOA	2	1.23E-17	4.22E-07	1.71E-08	6.59E-08
	5	5.60E-18	4.09E-04	2.81E-05	7.85E-05
	10	1.04E-15	7.62E-04	2.45E-05	9.52E-05
	30	9.14E-13	7.93E-03	2.64E-04	9.67E-04
	50	1.21E-14	9.57E-03	2.92E-04	1.24E-03
	100	1.84E-12	4.62E-02	2.62E-03	1.79E-02
LWOA	2	1.43E-15	3.91E-04	7.19E-06	6.55E-05
	5	1.33E-07	2.25E-01	1.36E-02	4.94E-02
	10	1.32E-05	0.527276	1.21E-01	2.48E-01
	30	7.82E-03	13.68269	2.221151	3.86774
	50	0.361432	56.54515	8.518907	3.879175
	100	0.440086	59.29671	11.75067	11.13302
IWOA	2	1.03E-01	2.77E-67	2.41E-69	9.48E-69
	5	6.19E-55	1.57E-40	4.22E-42	2.50E-41
	10	1.71E-49	5.02E-35	2.43E-36	1.18E-35
	30	1.12E-42	2.11E-31	9.67E-33	5.33E-32
	50	6.77E-44	4.02E-31	5.12E-33	5.17E-32
	100	9.41E-40	1.11E-30	5.04E-32	1.73E-31
AGDE	2	2.05E-03	4.14E-02	1.97E-02	1.01E-02
	5	9.84E-02	25.69573	3.270342	7.983586
	10	12.73219	551.7728	239.8516	155.5823
	30	907.9067	4381.409	4009.933	809.815
	50	2712.837	15809.2	5852.075	1835.105
	100	11288.74	35798.98	9583.005	3426.126
EFADE	2	1.95E-32	1.64E-21	1.15E-23	1.20E-22
	5	1.20E-30	4.20E-21	1.84E-22	6.17E-22
	10	3.93E-32	1.59E-17	5.38E-19	2.52E-18
	30	9.81E-29	8.19E-19	2.78E-20	1.18E-19
	50	1.75E-27	1.17E-19	9.02E-21	1.93E-20
	100	3.63E-27	6.76E-17	9.55E-19	7.56E-18
EAGDE	2	2.39E-61	1.83E-61	3.84E-63	2.85E-62
	5	4.65E-49	1.09E-34	2.83E-36	1.82E-35
	10	3.28E-43	8.51E-29	2.22E-30	1.39E-29
	30	6.85E-37	1.67E-25	5.02E-27	3.68E-26
	50	8.69E-38	3.08E-25	6.43E-27	4.42E-26
	100	1.27E-33	9.24E-25	4.07E-26	1.17E-25
EBLSHADE	2	2.54E-61	2.76E-64	3.92E-66	4.16E-65
	5	1.36E-51	3.20E-37	4.19E-39	2.33E-38
	10	2.93E-46	1.47E-31	3.75E-33	3.27E-32
	30	1.40E-39	3.95E-28	1.49E-29	1.80E-29
	50	2.13E-40	6.49E-28	6.59E-30	9.98E-29
	100	1.34E-36	3.44E-27	1.20E-28	4.56E-28

TABLE 11. Comparison results of different dimensions in F8 functions.

Algorithm	Dimension	Minimum Value	Maximum Value	Average Value	Variance
ACO	2	1.10E+00	760052.4	108835.5	215577.4
	5	64112.89	1816810	743438.2	423641
	10	353573.5	2946403	1563387	419487.8
	30	2387848	5933816	4615598	1161148
	50	4723285	11619290	6997328	2090451
	100	12654996	22161438	16756569	2262074
PSO	2	6.59E-05	3.30E+00	8.71E-01	1.66E+00
	5	3.37E+00	2729.843	625.1296	552.4539
	10	2325.005	214394.9	27588.29	25609.51
	30	120129.2	555382.4	225734.8	86771.08
	50	335826.7	915136.8	662792.7	167611.1
	100	573381.7	1821335	1226063	254940.9
WOA	2	7.34E-13	1.71E-03	5.44E-05	2.41E-04
	5	9.05E-06	2.47E+00	1.88E-01	6.07E-01
	10	6.03E-03	61.4487	5.37E+00	7.084089
	30	1.54E-01	507.6228	106.6935	114.2844
	50	1.66E-01	644.5441	94.20501	170.1057
	100	6.52E+00	2529.223	359.7785	657.3216
CWOA	2	4.64E-16	1.22E-05	7.68E-07	2.02E-06
	5	1.32E-16	1.63E-02	7.07E-04	3.30E-03
	10	2.59E-14	2.55E-02	1.15E-03	4.01E-03
	30	2.74E-11	3.16E-01	5.54E-03	4.33E-02
	50	4.39E-13	1.94E-01	1.24E-02	4.55E-02
	100	5.91E-11	2.64E+00	1.04E-01	4.94E-01
LWOA	2	3.41E-14	1.01E-02	2.58E-04	1.31E-03
	5	3.06E-06	4.93E+00	3.68E-01	1.55E+00
	10	3.02E-04	44.07006	3.61E+00	8.67E+00
	30	2.56E-01	351.1864	91.56554	133.2572
	50	6.983881	1262.142	213.1796	152.222
	100	13.03386	2100.476	371.0388	344.7069
IWOA	2	4.18E+00	6.18E-66	1.33E-67	7.76E-67
	5	2.56E-53	4.05E-39	1.29E-40	4.88E-40
	10	1.17E-47	2.89E-33	5.73E-35	5.49E-34
	30	3.05E-41	8.17E-30	1.74E-31	1.36E-30
	50	2.36E-42	7.08E-30	1.85E-31	7.51E-31
	100	3.14E-38	3.76E-29	1.99E-30	6.68E-30
AGDE	2	5.36E-02	2.34E+00	3.59E-01	3.07E-01
	5	3.44E+00	837.0251	139.3368	339.1793
	10	449.7692	28749.54	7739.138	3649.71
	30	32495.03	186018.4	124482.2	25010.07
	50	139857.7	522911.1	228236.7	57612.23
	100	552380.6	1002986	521184.6	88735.93
EFADE	2	4.06E-31	3.64E-20	7.41E-22	5.50E-21
	5	3.68E-29	1.19E-19	5.88E-21	1.55E-20
	10	1.95E-30	4.97E-16	1.68E-17	8.43E-17
	30	1.87E-27	9.44E-18	6.25E-19	5.17E-18
	50	4.91E-26	3.28E-18	3.69E-19	7.92E-19
	100	9.02E-26	1.61E-15	6.42E-17	2.33E-16
EAGDE	2	7.05E-60	9.77E-60	1.30E-61	7.59E-61
	5	1.38E-47	2.61E-33	8.75E-35	6.05E-34
	10	8.49E-42	2.13E-27	6.87E-29	3.43E-28
	30	2.23E-35	5.12E-24	1.16E-25	1.51E-24
	50	1.43E-36	6.79E-24	1.22E-25	1.31E-24
	100	3.62E-32	2.94E-23	1.55E-24	3.00E-24
EBLSHADE	2	7.47E-60	1.21E-62	2.57E-64	1.67E-63
	5	4.69E-50	1.10E-35	1.07E-37	5.57E-37
	10	1.05E-44	4.43E-30	9.60E-32	1.07E-30
	30	3.07E-38	1.22E-26	3.54E-28	1.19E-27
	50	4.93E-39	1.67E-26	2.46E-28	2.49E-27
	100	3.80E-35	6.49E-26	3.32E-27	1.04E-26

TABLE 12. Comparison results of different dimensions in F9 functions.

Algorithm	Dimension	Minimum Value	Maximum Value	Average Value	Variance
ACO	2	3.19E-03	2750.229	540.4198	566.229
	5	203.5671	4197.808	1299.948	1017.533
	10	1090.367	5826.391	3242.308	1375.454
	30	5669.817	20692.78	11272.15	2999.872
	50	17102.71	30638.4	18596.21	5534.26
	100	32580.28	54930.06	29287.09	4532.376
PSO	2	2.02E-07	1.61E-02	1.45E-03	3.37E-03
	5	8.62E-03	5.613008	1.385931	1.720277
	10	4.990086	548.1816	53.56516	58.28749
	30	241.9891	1620.753	723.1229	273.3241
	50	934.9375	3669.045	1674.418	349.8285
	100	1581.086	5353.586	3513.729	553.8368
WOA	2	1.73E-15	3.23E-06	1.43E-07	5.54E-07
	5	3.21E-08	8.24E-03	7.30E-04	8.29E-04
	10	1.26E-05	0.099366	1.52E-02	0.020068
	30	3.24E-04	1.42056	0.241449	0.40173
	50	2.70E-04	1.382634	0.485437	0.426156
	100	1.86E-02	6.768543	1.383984	1.48908
CWOA	2	1.26E-18	3.73E-08	1.65E-09	5.48E-09
	5	2.16E-19	4.94E-05	1.65E-06	8.45E-06
	10	5.15E-17	5.15E-05	3.45E-06	8.81E-06
	30	4.68E-14	6.19E-04	1.53E-05	8.11E-05
	50	5.09E-16	2.83E-04	2.52E-05	1.13E-04
	100	8.17E-14	4.75E-03	2.05E-04	1.13E-03
LWOA	2	7.28E-17	3.89E-05	7.06E-07	4.01E-06
	5	9.08E-09	1.59E-02	1.31E-03	3.09E-03
	10	1.01E-06	0.093469	1.21E-02	1.56E-02
	30	4.40E-04	0.63417	0.219115	0.169436
	50	0.016827	2.951181	0.646701	0.474785
	100	0.033741	2.227238	0.961855	0.938388
IWOA	2	1.22E-02	9.94E-69	1.48E-70	2.51E-69
	5	3.57E-56	7.02E-42	2.27E-43	1.25E-42
	10	4.02E-50	4.65E-36	1.67E-37	7.77E-37
	30	7.44E-44	1.55E-32	6.62E-34	2.52E-33
	50	8.34E-45	1.69E-32	5.04E-34	3.83E-33
	100	1.11E-40	7.53E-32	4.05E-33	1.74E-32
AGDE	2	1.73E-04	5.32E-03	1.17E-03	1.12E-03
	5	6.71E-03	5.739519	0.329327	0.777597
	10	0.87776	49.86511	18.44409	12.24084
	30	56.90568	422.0818	217.3812	60.6454
	50	247.0052	1000.775	627.4237	169.1558
	100	1002.789	1776.423	1310.579	274.8025
EFADE	2	1.34E-33	6.93E-23	2.31E-24	1.87E-23
	5	1.25E-31	1.57E-22	1.17E-23	3.84E-23
	10	5.48E-33	1.73E-18	2.82E-20	2.12E-19
	30	4.69E-30	5.96E-20	1.60E-21	1.01E-20
	50	1.38E-28	9.71E-21	6.23E-22	1.33E-21
	100	3.22E-28	3.79E-18	1.56E-19	4.56E-19
EAGDE	2	1.98E-62	1.81E-62	2.91E-64	2.12E-63
	5	3.39E-50	1.11E-35	1.66E-37	1.08E-36
	10	1.51E-44	6.99E-30	1.57E-31	8.89E-31
	30	5.08E-38	1.66E-26	3.92E-28	2.33E-27
	50	4.33E-39	1.32E-26	2.04E-28	2.79E-27
	100	1.09E-34	8.19E-26	2.83E-27	8.14E-27
EBLSHADE	2	2.42E-62	2.58E-65	7.09E-67	1.91E-66
	5	1.25E-52	2.27E-38	3.46E-40	2.30E-39
	10	2.44E-47	9.96E-33	1.26E-34	1.23E-33
	30	1.43E-40	2.74E-29	1.14E-30	3.34E-30
	50	1.91E-41	4.79E-29	1.26E-30	5.81E-30
	100	9.24E-38	1.45E-28	6.17E-30	3.08E-29

TABLE 13. Comparison results of different dimensions in F10 functions.

Algorithm	Dimension	Minimum Value	Maximum Value	Average Value	Variance
ACO	2	9.33E-03	6580.932	1496.989	2998.117
	5	445.9025	18025.92	4568.638	3922.42
	10	3470.37	27953.28	12205.51	8420.776
	30	20088.34	77469.45	47425.63	10097.89
	50	58072.03	91561.83	54807.1	10714.9
	100	119958.8	203946.7	165283.2	16327.99
PSO	2	1.04E-06	4.53E-02	6.79E-03	1.44E-02
	5	4.29E-02	23.86886	3.334887	5.910636
	10	36.47811	1686.201	115.9882	233.0855
	30	702.7619	5699.05	3288.983	1131.001
	50	3515.305	13572.58	5381.916	1618.038
	100	5616.19	21474	15457.84	2920.145
WOA	2	8.26E-15	1.46E-05	6.62E-07	1.48E-06
	5	9.05E-08	3.05E-02	2.64E-03	4.84E-03
	10	5.09E-05	0.636676	5.55E-02	0.08019
	30	1.17E-03	6.381067	0.990336	1.454341
	50	1.12E-03	8.510968	1.726466	1.99408
	100	6.00E-02	30.98066	5.619023	3.800032
CWOA	2	5.51E-18	1.27E-07	5.97E-09	2.64E-08
	5	1.42E-18	1.22E-04	8.95E-06	3.43E-05
	10	2.54E-16	1.92E-04	7.07E-06	3.48E-05
	30	2.00E-13	2.20E-03	7.65E-05	3.37E-04
	50	1.63E-15	2.02E-03	6.52E-05	5.21E-04
	100	3.83E-13	3.48E-02	1.06E-03	3.57E-03
LWOA	2	3.70E-16	8.98E-05	2.60E-06	2.23E-05
	5	3.54E-08	6.75E-02	4.27E-03	1.06E-02
	10	4.47E-06	0.236605	5.08E-02	5.20E-02
	30	1.79E-03	3.194899	0.868399	0.649149
	50	0.069636	12.63593	1.925627	2.10446
	100	0.100458	13.26807	4.151697	3.316854
IWOA	2	6.20E-02	7.04E-68	1.26E-69	7.67E-69
	5	2.48E-55	3.79E-41	9.38E-43	4.93E-42
	10	1.18E-49	3.76E-35	8.18E-37	4.74E-36
	30	2.76E-43	7.45E-32	2.35E-33	1.07E-32
	50	2.89E-44	6.86E-32	1.71E-33	1.34E-32
	100	2.38E-40	4.01E-31	1.77E-32	5.54E-32
AGDE	2	7.11E-04	2.36E-02	5.27E-03	4.36E-03
	5	3.17E-02	20.7898	1.14907	1.78596
	10	5.490854	287.9711	83.92072	58.70635
	30	370.0134	1802.003	663.5884	186.5698
	50	1074.527	5534.257	1766.613	489.5587
	100	4366.16	11854.61	6588.254	1112.325
EFADE	2	3.39E-33	3.27E-22	3.97E-24	6.62E-23
	5	3.54E-31	1.03E-21	4.15E-23	1.75E-22
	10	1.62E-32	4.86E-18	1.10E-19	8.65E-19
	30	1.83E-29	2.33E-19	1.12E-20	2.81E-20
	50	4.96E-28	3.70E-20	3.65E-21	4.71E-21
	100	8.03E-28	1.93E-17	4.16E-19	3.23E-18
EAGDE	2	9.10E-62	6.29E-62	9.21E-64	9.43E-63
	5	1.08E-49	5.03E-35	8.82E-37	5.02E-36
	10	8.44E-44	3.37E-29	6.80E-31	3.19E-30
	30	1.55E-37	6.36E-26	2.77E-27	8.68E-27
	50	2.36E-38	6.81E-26	1.51E-27	1.01E-26
	100	4.06E-34	3.02E-25	1.48E-26	4.14E-26
EBLSHADE	2	7.67E-62	1.22E-64	1.86E-66	1.33E-65
	5	2.81E-52	1.04E-37	1.06E-39	8.86E-39
	10	7.56E-47	4.33E-32	8.57E-34	8.51E-33
	30	3.68E-40	1.14E-28	4.20E-30	9.31E-30
	50	7.02E-41	1.04E-28	3.05E-30	1.52E-29
	100	4.50E-37	6.73E-28	3.07E-29	1.42E-28

TABLE 14. Comparison results of different dimensions in F11 functions.

Algorithm	Dimension	Minimum Value	Maximum Value	Average Value	Variance
	2	1.28E-05	9.070753	2.449613	3.00958
	5	0.745825	19.61921	7.088849	5.223654
	10	4.033452	32.36331	22.09403	9.196902
	30	38.59611	78.65115	44.65499	17.82993
	50	85.93655	182.2936	81.0087	12.65898
	100	144.4622	366.0115	204.8551	24.00893
	2	1.43E-09	7.50E-05	6.10E-06	1.33E-05
	5	4.75E-05	0.034116	0.007606	0.005848
PSO	10	0.027294	2.248862	0.267402	0.318892
	30	1.270579	7.968303	3.466192	1.130213
	50	3.929362	9.986379	6.965549	1.535413
	100	9.333833	21.94487	25.43411	3.334489
	2	1.00E-17	1.45E-08	7.34E-10	1.95E-09
	5	1.42E-10	3.88E-05	3.95E-06	5.45E-06
WOA	10	6.77E-08	0.00092	5.73E-05	0.000119
	30	1.88E-06	0.006418	0.001172	0.000969
	50	1.46E-06	0.009668	0.002251	0.003333
	100	9.18E-05	0.030558	0.007173	0.005449
	2	3.77E-21	1.60E-10	5.64E-12	2.62E-11
	5	1.60E-21	2.79E-07	9.68E-09	3.56E-08
CWOA	10	3.92E-19	3.07E-07	7.81E-09	4.47E-08
	30	2.89E-16	3.90E-06	8.84E-08	5.38E-07
	50	7.37E-18	3.57E-06	1.58E-07	6.96E-07
	100	5.54E-16	2.83E-05	1.69E-06	7.13E-06
	2	4.79E-19	1.71E-07	2.58E-09	1.89E-08
LWOA	5	3.97E-11	6.73E-05	6.91E-06	1.41E-05
	10	5.32E-09	0.000537	5.54E-05	9.02E-05
	30	3.46E-06	0.005343	0.001007	0.001581
	50	0.000102	0.021752	0.003226	0.003532
	100	0.000109	0.02168	0.003227	0.002944
IWOA	2	6.55E-05	9.00E-71	1.31E-72	9.44E-72
	5	2.85E-58	4.94E-44	1.13E-45	5.94E-45
	10	1.21E-52	2.83E-38	9.69E-40	4.61E-39
	30	3.01E-46	1.03E-34	3.10E-36	1.94E-35
	50	3.56E-47	1.37E-34	2.77E-36	1.53E-35
	100	4.40E-43	4.34E-34	1.90E-35	1.03E-34
AGDE	2	8.87E-07	2.34E-05	8.37E-06	5.70E-06
	5	5.47E-05	0.026563	0.001937	0.003682
	10	0.009696	0.415411	0.069848	0.093184
	30	0.480181	2.093867	1.23536	0.288885
	50	1.61894	4.601559	1.630834	0.844693
	100	6.043936	10.6414	9.377827	1.384355
	2	5.89E-36	6.40E-25	5.30E-27	5.72E-26
EFADE	5	4.25E-34	8.45E-25	8.43E-26	2.64E-25
	10	1.62E-35	8.19E-21	1.06E-22	7.93E-22
	30	3.35E-32	2.99E-22	1.16E-23	5.95E-23
	50	5.39E-31	4.18E-23	2.81E-24	1.28E-23
	100	1.14E-30	1.53E-20	6.96E-22	3.70E-21
	2	9.46E-65	7.44E-65	1.23E-66	6.15E-66
	5	1.77E-52	7.06E-38	9.96E-40	9.27E-39
EAGDE	10	1.32E-46	2.43E-32	1.02E-33	3.53E-33
	30	3.14E-40	8.95E-29	1.95E-30	1.15E-29
	50	3.62E-41	8.00E-29	2.20E-30	1.26E-29
	100	4.88E-37	3.20E-28	1.43E-29	4.02E-29
EBLSHADE	2	6.75E-65	1.36E-67	2.49E-69	1.34E-68
	5	6.20E-55	1.02E-40	2.22E-42	1.71E-41
	10	1.43E-49	6.66E-35	1.22E-36	9.06E-36
	30	5.31E-43	1.53E-31	5.79E-33	1.99E-32
	50	5.56E-44	2.06E-31	5.96E-33	3.51E-32
	100	6.03E-40	1.10E-30	2.93E-32	1.30E-31

TABLE 15. Comparison results of different dimensions in F12 functions.

Algorithm	Dimension	Minimum Value	Maximum Value	Average Value	Variance
ACO	2	6.98E+02	2.44E+09	5.39E+08	9.57E+08
	5	2.36E+03	2.43E+09	5.39E+08	9.65E+08
	10	7.50E+03	2.42E+09	5.37E+08	9.57E+08
	30	2.43E+04	2.42E+09	5.36E+08	9.56E+08
	50	3.82E+04	2.43E+09	5.35E+08	9.58E+08
	100	7.04E+04	2.44E+09	5.34E+08	9.58E+08
PSO	2	1.63E-04	2.25E+03	3.24E+02	5.32E+02
	5	1.65E+02	9.94E+03	2.10E+03	1.95E+03
	10	9.72E+02	1.17E+04	4.42E+03	2.32E+03
	30	3.99E+03	4.10E+04	1.28E+04	6.89E+03
	50	6.60E+03	6.98E+04	2.17E+04	9.76E+03
	100	1.99E+04	7.45E+04	4.10E+04	1.35E+04
WOA	2	4.709E-14	1.549E-02	1.138E-03	2.855E-03
	5	5.173E-11	3.036E+00	2.563E-01	4.893E-01
	10	1.563E-03	4.381E+00	1.051E+00	1.027E+00
	30	7.342E-02	2.903E+01	6.918E+00	6.484E+00
	50	8.786E-02	4.561E+01	1.345E+01	1.131E+01
	100	6.131E-01	1.048E+02	2.910E+01	2.907E+01
CWOA	2	1.17E-13	1.07E+02	2.15E+00	1.52E+01
	5	4.93E-13	3.63E+02	1.63E+01	6.84E+01
	10	4.98E-11	2.13E+02	9.09E+00	3.73E+01
	30	1.25E-10	3155.7994	1.07E+02	450.7412
	50	1.65E-10	2031.8476	1.60E+02	3.73E+02
	100	8.76E-09	2325.7906	1.24E+02	4.13E+02
LWOA	2	2.21E-11	2.18E-02	1.23E-03	3.63E-03
	5	2.57E-04	3.65E+00	4.09E-01	7.45E-01
	10	4.97E-03	1.17E+01	1.11E+00	1.76E+00
	30	7.94E-02	2.89E+01	8.73E+00	7.63E+00
	50	2.24E-02	5.71E+01	1.64E+01	1.56E+01
	100	8.58E-01	9.29E+01	2.82E+01	2.56E+01
IWOA	2	0	5.10E-59	1.02E-60	7.21E-60
	5	8.63E-56	3.13E-39	7.82E-41	4.48E-40
	10	1.77E-48	1.26E-34	2.82E-36	1.78E-35
	30	9.12E-44	1.61E-31	4.92E-33	2.43E-32
	50	8.59E-48	3.96E-33	2.96E-34	8.23E-34
	100	9.91E-44	1.05E-30	3.10E-32	1.54E-31
AGDE	2	4.47E+00	2.21E+03	5.57E+02	5.63E+02
	5	4.55E+01	5.52E+03	2.10E+03	1.15E+03
	10	1.07E+03	9.28E+03	4.91E+03	1.90E+03
	30	6.73E+03	2.76E+04	1.52E+04	4.70E+03
	50	1.26E+04	4.12E+04	2.47E+04	6.97E+03
	100	2.47E+04	8.67E+04	4.83E+04	1.35E+04
EFADE	2	3.38E-28	7.28E-19	5.62E-20	1.61E-19
	5	2.57E-25	1.65E-16	3.45E-18	2.33E-17
	10	3.59E-28	5.89E-17	3.29E-18	1.06E-17
	30	4.21E-26	1.04E-17	9.99E-19	2.26E-18
	50	6.42E-28	4.46E-17	2.15E-18	8.37E-18
	100	1.88E-28	6.69E-17	4.21E-18	1.43E-17
EAGDE	2	2.58E-01	1.10E-55	1.72E-57	1.31E-56
	5	9.27E-53	5.91E-36	1.67E-37	6.16E-37
	10	2.08E-45	2.20E-31	4.49E-33	2.78E-32
	30	1.59E-40	3.45E-28	6.13E-30	3.72E-29
	50	1.61E-44	9.90E-30	5.13E-31	1.74E-30
	100	1.87E-40	1.87E-27	5.76E-29	2.66E-28
EBLSHADE	2	3.75E-02	9.58E-57	1.78E-58	2.52E-57
	5	2.14E-53	6.90E-37	1.48E-38	1.17E-37
	10	3.76E-46	2.54E-32	4.55E-34	4.26E-33
	30	1.22E-41	4.77E-29	1.25E-30	7.43E-30
	50	2.04E-45	8.71E-31	7.34E-32	9.26E-32
	100	2.50E-41	2.42E-28	5.72E-30	3.34E-29

TABLE 16. Comparison results of different dimensions in F13 functions.

Algorithm	Dimension	Minimum Value	Maximum Value	Average Value	Variance
ACO	2	1.98E+00	2.18E+01	1.79E+01	5.57E+00
	5	1.89E+01	2.17E+01	2.06E+01	6.52E-01
	10	1.95E+01	2.16E+01	2.08E+01	3.91E-01
	30	2.07E+01	2.14E+01	2.10E+01	1.61E-01
	50	2.07E+01	2.14E+01	2.11E+01	1.44E-01
	100	2.09E+01	2.13E+01	2.11E+01	1.11E-01
PSO	2	3.09E-03	2.58E+00	1.27E-01	3.66E-01
	5	2.78E-01	6.84E+00	3.32E+00	1.36E+00
	10	4.28E+00	1.52E+01	8.59E+00	2.24E+00
	30	1.06E+01	1.54E+01	1.35E+01	1.03E+00
	50	1.22E+01	1.61E+01	1.42E+01	8.85E-01
	100	1.34E+01	1.68E+01	1.50E+01	6.86E-01
WOA	2	4.535E-06	1.575E-02	1.686E-03	3.003E-03
	5	1.174E-03	8.530E-01	1.258E-01	1.878E-01
	10	2.437E-02	2.924E+00	5.676E-01	6.639E-01
	30	2.069E-02	4.022E+00	1.154E+00	8.945E-01
	50	3.652E-02	3.861E+00	1.384E+00	1.015E+00
	100	4.222E-02	4.659E+00	1.448E+00	9.614E-01
CWOA	2	8.51E-09	1.46E-03	1.32E-04	2.71E-04
	5	2.81E-09	0.0362136	2.54E-03	7.38E-03
	10	2.82E-08	0.0289865	2.22E-03	5.40E-03
	30	4.74E-07	0.0552018	0.003281	0.010387
	50	5.26E-08	0.0429853	0.003091	0.008418
	100	3.74E-07	0.3187847	0.01195	0.046632
LWOA	2	7.44E-08	6.23E-03	7.76E-04	1.30E-03
	5	4.58E-04	1.68E+00	1.55E-01	2.64E-01
	10	1.79E-02	3.12E+00	5.71E-01	6.74E-01
	30	9.00E-02	3.40E+00	1.28E+00	9.68E-01
	50	1.50E-01	4.37E+00	1.61E+00	1.11E+00
	100	1.47E-01	2.75E+00	1.31E+00	6.93E-01
IWOA	2	8.88E-16	2.66E-15	1.07E-15	5.38E-16
	5	8.88E-16	1.33E-14	2.95E-15	2.36E-15
	10	8.88E-16	1.33E-14	4.90E-15	3.90E-15
	30	8.88E-16	2.04E-14	5.12E-15	4.54E-15
	50	8.88E-16	2.04E-14	6.04E-15	4.40E-15
	100	8.88E-16	1.33E-14	4.69E-15	2.71E-15
AGDE	2	4.74E-02	3.35E-01	1.32E-01	6.01E-02
	5	3.77E-01	3.39E+00	1.88E+00	8.20E-01
	10	2.09E+00	7.33E+00	4.95E+00	1.16E+00
	30	7.51E+00	1.04E+01	8.80E+00	7.06E-01
	50	7.75E+00	1.20E+01	1.01E+01	8.50E-01
	100	9.85E+00	1.26E+01	1.14E+01	5.22E-01
EFADE	2	8.88E-16	1.66E+01	9.11E+00	4.67E+00
	5	1.20E+01	2.01E+01	1.75E+01	1.80E+00
	10	1.79E+01	2.06E+01	1.96E+01	5.79E-01
	30	2.02E+01	2.09E+01	2.06E+01	1.61E-01
	50	2.05E+01	2.10E+01	2.08E+01	1.04E-01
	100	2.08E+01	2.11E+01	2.09E+01	6.75E-02
EAGDE	2	1.83E-07	3.80E-07	2.25E-07	9.44E-08
	5	1.54E-07	3.20E-06	3.94E-07	2.88E-07
	10	1.57E-07	2.26E-06	8.11E-07	7.52E-07
	30	1.54E-07	4.29E-06	1.07E-06	6.57E-07
	50	1.28E-07	3.86E-06	1.13E-06	7.87E-07
	100	1.28E-07	3.23E-06	1.21E-06	5.83E-07
EBLSHADE	2	2.09E-12	6.35E-12	1.57E-12	1.25E-12
	5	2.08E-12	3.52E-11	7.55E-12	5.79E-12
	10	1.89E-12	2.18E-11	9.42E-12	9.43E-12
	30	1.91E-12	3.14E-11	1.41E-11	1.04E-11
	50	1.92E-12	5.07E-11	9.91E-12	9.28E-12
	100	8.65E-13	2.05E-11	9.10E-12	5.30E-12

TABLE 17. Comparison results of different dimensions in F14 functions.

Algorithm	Dimension	Minimum Value	Maximum Value	Average Value	Variance
ACO	2	1.46E+00	6.01E+00	4.02E+00	1.33E+00
	5	6.19E+00	1.45E+01	1.01E+01	1.78E+00
	10	1.60E+01	2.54E+01	1.93E+01	2.32E+00
	30	4.73E+01	7.07E+01	5.47E+01	4.45E+00
	50	8.19E+01	1.01E+02	9.08E+01	4.74E+00
	100	1.71E+02	1.97E+02	1.85E+02	7.04E+00
PSO	2	5.29E-02	5.35E-01	2.20E-01	1.11E-01
	5	5.82E-02	3.65E+00	1.28E+00	8.42E-01
	10	2.24E-02	1.08E+01	3.82E+00	2.86E+00
	30	1.17E+00	2.65E+01	1.04E+01	5.27E+00
	50	2.77E+00	3.52E+01	1.79E+01	7.23E+00
	100	1.09E+01	8.58E+01	3.86E+01	1.61E+01
WOA	2	5.334E-04	4.797E-01	1.423E-01	1.224E-01
	5	3.502E-01	3.884E+00	2.206E+00	8.790E-01
	10	3.182E+00	1.138E+01	8.431E+00	1.687E+00
	30	2.550E+00	4.400E+01	3.455E+01	9.581E+00
	50	9.337E+00	8.031E+01	6.009E+01	1.925E+01
	100	1.636E+01	1.721E+02	1.269E+02	4.403E+01
CWOA	2	1.11E-04	5.81E-01	5.89E-02	1.31E-01
	5	8.58E-05	1.20E+00	1.92E-01	2.91E-01
	10	1.43E-04	6.22E+00	8.63E-01	1.24E+00
	30	4.41E-03	1.24E+01	2.09E+00	3.17E+00
	50	2.28E-02	3.06E+01	5.61E+00	7.14E+00
	100	4.76E-02	6.49E+01	1.34E+01	1.70E+01
LWOA	2	4.75E-03	5.06E-01	1.62E-01	1.34E-01
	5	8.52E-01	3.64E+00	2.48E+00	7.53E-01
	10	4.77E+00	1.14E+01	8.37E+00	1.68E+00
	30	7.36E+00	4.37E+01	3.52E+01	7.06E+00
	50	1.83E+01	7.87E+01	6.14E+01	1.74E+01
	100	1.17E+01	1.69E+02	1.30E+02	4.45E+01
IWOA	2	0	1.44E-01	2.02E-02	3.34E-02
	5	0	2.07E+00	3.17E-01	5.63E-01
	10	0	7.58E+00	7.27E-01	1.82E+00
	30	0	2.96E+00	6.75E-02	4.22E-01
	50	0	3.63E-01	7.26E-03	5.14E-02
	100	0	2.06E-10	4.12E-12	2.91E-11
AGDE	2	8.59E-02	6.84E-01	3.34E-01	1.33E-01
	5	1.64E+00	4.30E+00	3.51E+00	5.02E-01
	10	8.91E+00	1.18E+01	1.05E+01	7.61E-01
	30	3.99E+01	4.58E+01	4.37E+01	1.15E+00
	50	7.48E+01	8.16E+01	7.85E+01	1.63E+00
	100	1.64E+02	1.75E+02	1.69E+02	2.48E+00
EFADE	2	0.00E+00	5.44E-01	2.58E-01	1.27E-01
	5	1.62E+00	4.14E+00	3.26E+00	5.79E-01
	10	6.76E+00	1.15E+01	1.02E+01	8.84E-01
	30	3.86E+01	4.52E+01	4.27E+01	1.52E+00
	50	6.00E+01	8.05E+01	7.65E+01	3.97E+00
	100	1.37E+02	1.73E+02	1.67E+02	5.46E+00
EAGDE	2	0.00E+00	2.10E-02	1.51E-02	7.41E-03
	5	1.17E-01	2.46E-01	2.43E-01	2.94E-02
	10	3.31E-01	7.81E-01	5.16E-01	3.68E-02
	30	2.63E+00	2.99E+00	3.16E+00	9.27E-02
	50	2.68E+00	7.39E+00	5.36E+00	3.06E-01
	100	1.12E+01	1.17E+01	1.03E+01	3.12E-01
EBLSHADE	2	0.00E+00	4.52E-03	1.13E-03	8.53E-04
	5	8.88E-03	2.34E-02	1.24E-02	4.48E-03
	10	6.44E-02	8.80E-02	6.72E-02	7.04E-03
	30	2.22E-01	2.34E-01	3.64E-01	1.33E-02
	50	4.08E-01	3.54E-01	6.34E-01	3.49E-02
	100	1.18E+00	1.31E+00	7.80E-01	4.26E-02

TABLE 18. **Comparison results of different dimensions in F15 functions.**

Algorithm	Dimension	Minimum Value	Maximum Value	Average Value	Variance
ACO	2	0.014055	0.001079	0.506922	0.380185
	5	0.023451	0.170559	0.629853	0.51226
	10	0.082592	0.313585	0.565461	0.574986
	30	0.194754	0.42136	0.398352	0.725278
	50	0.36107	0.556783	0.484582	0.715396
	100	0.845663	0.538259	0.660128	1.069996
PSO	2	1.02E-02	1.58E-06	0.003294	0.000397
	5	0.03619	0.001324	0.057063	0.020453
	10	0.048942	0.027729	0.163947	0.111342
	30	0.123083	0.170612	0.300547	0.244035
	50	0.419335	0.196803	0.499029	0.259633
	100	0.676875	0.09729	0.328548	0.330641
WOA	2	1.45E-02	5.51E-09	1.31E-03	5.60E-05
	5	2.66E-02	0.000238	0.005393	0.002106
	10	7.14E-02	0.00147	0.007393	0.00458
	30	0.16846	0.0061	0.011237	0.010554
	50	0.365588	0.003858	0.012646	0.009737
	100	0.551507	0.009789	0.012305	0.01295
CWOA	2	1.43E-02	5.11E-12	4.05E-06	2.01E-07
	5	5.15E-02	1.10E-12	2.65E-05	8.70E-07
	10	7.78E-02	2.40E-11	1.23E-04	4.40E-06
	30	1.81E-01	1.59E-12	1.11E-04	2.05E-06
	50	3.18E-01	1.23E-10	3.05E-05	1.92E-06
	100	4.64E-01	5.53E-10	2.71E-05	1.55E-06
LWOA	2	1.36E-02	1.72E-08	1.26E-03	9.65E-05
	5	4.04E-02	5.67E-05	0.004438	0.001874
	10	8.21E-02	0.00163	0.006865	0.002621
	30	0.174578	0.006269	0.011926	0.011649
	50	0.357839	0.004328	0.008286	0.009001
	100	0.707518	0.009628	0.018514	0.009152
IWOA	2	0.013483	0.00E+00	2.38E-17	9.64E-19
	5	2.86E-02	2.24E-14	2.77E-04	1.05E-05
	10	5.70E-02	2.57E-08	3.14E-03	5.90E-04
	30	2.00E-01	1.40E-04	4.76E-03	1.26E-03
	50	3.05E-01	6.82E-04	4.60E-03	4.29E-03
	100	6.10E-01	1.85E-03	4.50E-03	3.62E-03
AGDE	2	0.014752	0.000147	0.001657	0.000688
	5	0.038096	0.001694	0.023093	0.009248
	10	0.065926	0.010761	0.068243	0.050828
	30	0.212423	0.069427	0.205652	0.118917
	50	0.416545	0.102331	0.167428	0.178307
	100	0.588769	0.128679	0.199968	0.11978
EFADE	2	1.43E-02	2.33E-33	3.45E-28	1.07E-29
	5	3.67E-02	4.00E-30	4.88E-24	8.81E-26
	10	6.34E-02	1.67E-31	7.06E-25	3.98E-26
	30	1.91E-01	9.53E-31	3.12E-24	1.01E-25
	50	3.32E-01	5.21E-30	1.60E-24	1.91E-25
	100	5.66E-01	9.31E-32	2.04E-24	1.68E-25
EAGDE	2	1.73E-02	0.00E+00	1.20E-19	7.53E-21
	5	3.34E-02	2.54E-16	1.46E-06	8.59E-08
	10	5.65E-02	8.11E-11	1.00E-05	6.28E-06
	30	1.87E-01	1.22E-06	1.89E-05	2.25E-05
	50	4.31E-01	3.83E-06	2.92E-05	1.51E-05
	100	4.29E-01	1.25E-05	1.93E-05	2.44E-05
EBLSHADE	2	1.47E-02	0.00E+00	1.40E-20	1.17E-21
	5	3.90E-02	2.27E-17	1.73E-07	7.72E-09
	10	7.66E-02	2.09E-11	1.56E-06	3.97E-07
	30	1.45E-01	4.55E-08	2.10E-06	1.94E-06
	50	4.53E-01	4.62E-07	5.75E-06	1.99E-06
	100	6.26E-01	1.33E-06	1.83E-06	1.86E-06

TABLE 19. Comparison results of different dimensions in F16 functions.

Algorithm	Dimension	Minimum Value	Maximum Value	Average Value	Variance
ACO	2	4.13E+00	7.44E+01	3.75E+01	1.91E+01
	5	7.25E+00	4.53E+01	2.12E+01	9.37E+00
	10	4.64E+00	3.10E+01	1.58E+01	6.12E+00
	30	8.20E+00	2.93E+01	1.50E+01	5.04E+00
	50	8.41E+00	2.66E+01	1.38E+01	3.71E+00
	100	7.93E+00	1.69E+01	1.07E+01	2.09E+00
PSO	2	1.55E-21	9.99E-21	4.03E-21	8.63E-21
	5	1.61E-18	1.68E-18	1.07E-18	5.91E-19
	10	1.88E-12	3.11E-12	1.85E-12	3.34E-12
	30	1.17E-01	9.45E-02	6.55E-02	1.51E-01
	50	3.75E+14	8.87E+13	3.13E+14	1.56E+14
	100	9.03E+35	2.10E+35	1.10E+34	5.83E+35
WOA	2	1.47E-04	1.78E-04	1.06E-04	1.59E-04
	5	1.82E-04	5.06E-05	2.58E-04	1.93E-04
	10	1.44E-05	4.05E-04	3.05E-04	6.18E-05
	30	1.28E-03	1.53E-03	5.12E-04	1.23E-03
	50	3.17E-03	2.14E-03	1.09E-03	2.10E-03
	100	5.42E-03	2.64E-03	5.28E-03	1.16E-03
CWOA	2	8.94E-06	9.61E-07	9.35E-06	2.58E-06
	5	4.79E-06	1.22E-05	9.89E-07	2.81E-05
	10	4.95E-05	6.54E-05	1.28E-04	6.67E-05
	30	4.08E-04	1.34E-03	1.09E-03	2.25E-03
	50	3.98E-03	2.12E-02	1.48E-02	2.51E-02
	100	2.58E-01	3.01E-01	3.74E-01	1.94E-01
LWOA	2	7.91E-05	7.30E-05	2.24E-05	4.04E-05
	5	7.98E-05	1.00E-04	2.47E-04	2.26E-04
	10	7.36E-04	2.37E-03	2.02E-03	8.94E-05
	30	1.77E-02	1.33E-02	5.58E-03	2.46E-02
	50	2.55E-01	2.48E-01	1.37E-01	1.44E-01
	100	2.02E+00	2.81E+00	2.66E+00	1.30E+00
IWOA	2	3.22E-101	2.47E-102	6.43E-101	9.07E-101
	5	2.41E-98	4.37E-99	1.95E-98	3.78E-99
	10	2.28E-92	2.17E-92	3.57E-92	9.13E-93
	30	1.09E-81	6.35E-82	9.21E-82	9.92E-82
	50	6.69E-66	7.83E-66	8.25E-66	2.77E-67
	100	1.84E-45	9.34E-46	5.52E-45	4.04E-45
AGDE	2	7.67E-02	1.00E+00	5.06E-01	2.24E-01
	5	4.94E-01	2.01E+00	1.21E+00	2.96E-01
	10	1.30E+00	2.64E+00	1.78E+00	3.25E-01
	30	2.53E+00	4.56E+00	3.71E+00	4.85E-01
	50	3.60E+00	5.68E+00	4.76E+00	4.42E-01
	100	4.23E+00	5.89E+00	5.27E+00	3.66E-01
EFADE	2	0	9.03E-01	3.74E-01	0.213979661
	5	0	1.73E+00	8.90E-01	0.480149801
	10	0	2.24E+00	1.42E+00	0.658873511
	30	0	4.17E+00	2.84E+00	1.40E+00
	50	0	3.73E+00	7.46E-02	5.28E-01
	100	0	9.03E-01	3.74E-01	0.213979661
EAGDE	2	5.55E-03	4.71E-02	2.19E-02	1.52E-02
	5	3.16E-02	1.37E-01	8.79E-02	1.81E-02
	10	5.91E-02	1.95E-01	1.42E-01	1.45E-02
	30	1.31E-01	2.33E-01	1.59E-01	3.63E-02
	50	2.70E-01	3.03E-01	3.09E-01	3.30E-02
	100	3.13E-01	4.86E-01	2.69E-01	2.14E-02
EBLSHADE	2	5.65E-04	9.22E-03	4.21E-03	1.85E-03
	5	2.41E-03	1.32E-02	6.19E-03	2.65E-03
	10	6.53E-03	1.96E-02	1.57E-02	1.98E-03
	30	1.30E-02	3.39E-02	2.81E-02	4.29E-03
	50	2.35E-02	4.07E-02	2.44E-02	3.10E-03
	100	2.52E-02	4.08E-02	4.29E-02	1.73E-03

TABLE 20. Comparison results of different dimensions in F17 functions.

Algorithm	Dimension	Minimum Value	Maximum Value	Average Value	Variance
ACO	2	0.283061	0.010912	23.11427	8.274136
	5	1.3254	8.09981	21.95869	16.48445
	10	2.264175	8.93236	19.94027	18.02957
	30	7.700525	18.75431	23.46226	18.8462
	50	9.493539	16.38239	17.79018	23.59319
	100	21.80169	19.84205	26.26258	20.22334
PSO	2	5.04E-01	4.74E-05	0.100209	0.019433
	5	0.941337	0.036743	0.950059	0.521929
	10	2.227686	0.750503	4.325305	2.238894
	30	4.313176	3.350848	7.755728	4.912028
	50	9.413729	5.249648	8.839472	9.274833
	100	19.52182	6.797718	13.06509	8.086244
WOA	2	3.44E-01	1.76E-07	3.56E-02	4.15E-03
	5	6.85E-01	0.007711	0.146914	0.054489
	10	2.12E+00	0.059032	0.194651	0.114413
	30	6.288243	0.111198	0.286887	0.291155
	50	11.24489	0.112206	0.386225	0.260265
	100	23.87408	0.182825	0.367336	0.454205
CWOA	2	3.30E-01	1.19E-10	1.34E-04	7.71E-06
	5	1.05E+00	2.82E-11	5.33E-04	5.05E-05
	10	2.06E+00	7.23E-10	3.37E-03	1.13E-04
	30	7.44E+00	4.52E-11	2.45E-03	0.000123
	50	1.18E+01	2.60E-09	7.68E-04	6.62E-05
	100	1.69E+01	2.38E-08	0.000908	4.38E-05
LWOA	2	2.55E-01	1.17E-06	3.65E-02	2.46E-03
	5	8.38E-01	0.001814	0.155648	0.060044
	10	2.40E+00	0.067441	0.246262	0.107225
	30	5.991141	0.187791	0.38898	0.261753
	50	9.592562	0.252868	0.317861	0.227916
	100	17.21303	0.235444	0.321899	0.36575
IWOA	2	0.349998	0.00E+00	6.03E-16	3.58E-17
	5	1.09E+00	9.93E-13	8.04E-03	3.01E-04
	10	2.30E+00	7.42E-07	7.56E-02	2.16E-02
	30	6.61E+00	4.68E-03	1.23E-01	1.02E-01
	50	1.04E+01	2.10E-02	7.81E-02	9.55E-02
	100	2.47E+01	4.64E-02	1.15E-01	1.39E-01
AGDE	2	0.385568	0.004818	0.044882	0.020784
	5	0.996743	0.04989	0.816632	0.220845
	10	1.608192	0.528726	3.348842	1.426928
	30	6.24073	2.286892	6.005239	4.136596
	50	9.705048	1.301871	6.369169	4.105034
	100	15.92049	3.278996	5.501703	4.307429
EFADE	2	4.44E-01	7.36E-32	7.02E-27	3.31E-28
	5	1.05E+00	1.24E-28	1.44E-22	3.10E-24
	10	2.82E+00	2.97E-30	2.28E-23	1.03E-24
	30	6.62E+00	4.38E-29	1.31E-22	5.39E-24
	50	1.10E+01	1.52E-28	5.79E-23	2.64E-24
	100	1.93E+01	1.79E-30	4.98E-23	4.79E-24
EAGDE	2	3.13E-01	0.00E+00	4.56E-18	2.09E-19
	5	7.63E-01	6.20E-15	5.79E-05	2.39E-06
	10	2.14E+00	4.02E-09	4.96E-04	1.35E-04
	30	7.84E+00	1.83E-05	6.54E-04	5.40E-04
	50	1.08E+01	1.07E-04	8.69E-04	5.60E-04
	100	2.38E+01	4.18E-04	1.03E-03	7.48E-04
EBLSHADE	2	3.61E-01	0.00E+00	5.71E-19	3.59E-20
	5	1.06E+00	4.67E-16	6.92E-06	2.06E-07
	10	1.89E+00	7.51E-10	3.38E-05	1.24E-05
	30	5.05E+00	1.94E-06	8.24E-05	5.49E-05
	50	1.15E+01	9.69E-06	5.70E-05	5.65E-05
	100	1.89E+01	2.81E-05	5.66E-05	7.25E-05

TABLE 21. Comparison results of different dimensions in F18 functions.

Algorithm	Dimension	Minimum Value	Maximum Value	Average Value	Variance
ACO	2	0.004742	5298.108	1046.677	2207.938
	5	457.6908	10600.68	3563.705	1647.238
	10	2660.607	24665.49	7938.802	6302.021
	30	25776.32	68445.5	41921.88	9833.351
	50	35082.17	108647	40215.4	16110.9
	100	136296.5	294145.6	155757	19139.62
PSO	2	3.88E-07	0.059482	0.005338	0.007439
	5	0.045095	14.24501	3.832187	3.631064
	10	24.32091	2140.079	131.0352	102.5497
	30	265.0948	2803.297	1640.833	818.8519
	50	3517.242	6832.285	3732.719	1526.478
	100	1590.113	20713.96	7720.163	1823.417
WOA	2	6.54E-15	1.21E-05	3.91E-07	1.63E-06
	5	1.47E-07	0.022214	0.001905	0.003606
	10	4.50E-05	0.448659	0.019201	0.018249
	30	0.001256	2.349666	0.290271	0.524622
	50	0.001375	3.013598	-0.05863	1.349697
	100	0.046211	9.682709	4.518649	5.015365
CWOA	2	4.70E-18	1.34E-07	3.06E-09	1.16E-08
	5	8.81E-19	9.54E-05	6.83E-06	1.52E-05
	10	2.63E-16	7.62E-05	6.52E-06	1.79E-05
	30	1.15E-13	0.002489	6.57E-05	0.000385
	50	3.61E-15	0.001698	9.19E-05	0.000374
	100	3.23E-13	0.012429	0.001431	0.003674
LWOA	2	2.09E-16	9.84E-05	2.04E-06	1.59E-05
	5	2.75E-08	0.055642	0.004522	0.011536
	10	1.75E-06	0.320509	0.033103	0.041636
	30	0.000843	2.209188	0.442216	0.30902
	50	0.029856	9.244219	0.764803	0.941265
	100	0.070171	10.43725	1.589698	3.483843
IWOA	2	0.052235	5.03E-68	1.55E-69	7.83E-69
	5	1.61E-55	3.87E-41	4.30E-43	2.51E-42
	10	1.16E-49	3.80E-35	6.59E-37	2.99E-36
	30	3.07E-43	5.58E-32	2.03E-33	1.01E-32
	50	1.75E-44	5.80E-32	2.15E-33	1.08E-32
	100	1.29E-40	2.75E-31	1.19E-32	4.67E-32
AGDE	2	0.000457	0.019346	0.003406	0.002279
	5	0.019793	11.59951	1.347139	2.895087
	10	6.833144	253.1197	47.41811	33.47606
	30	202.4088	981.9189	753.528	131.0106
	50	1357.114	2413.198	2563.771	166.6191
	100	3446.087	12169.58	5854.41	433.6431
EFADE	2	3.71E-33	3.66E-22	4.58E-24	7.71E-23
	5	2.10E-31	9.75E-22	4.18E-23	1.25E-22
	10	1.01E-32	4.82E-18	1.43E-19	1.01E-18
	30	1.92E-29	1.57E-19	3.01E-21	2.49E-20
	50	4.72E-28	3.63E-20	2.58E-21	7.60E-21
	100	3.72E-28	2.00E-17	6.17E-19	1.71E-18
EAGDE	2	6.68E-62	2.66E-62	8.72E-64	5.10E-63
	5	8.34E-50	2.02E-35	7.13E-37	4.61E-36
	10	6.98E-44	2.01E-29	6.15E-31	3.05E-30
	30	2.05E-37	6.28E-26	2.64E-27	1.16E-26
	50	5.86E-39	5.90E-26	1.52E-27	7.73E-27
	100	2.47E-34	2.96E-25	8.40E-27	3.09E-26
EBLSHADE	2	5.86E-62	7.28E-65	1.66E-66	8.72E-66
	5	7.52E-53	8.84E-38	8.34E-40	8.27E-39
	10	1.08E-47	2.83E-32	6.84E-34	8.32E-33
	30	1.37E-40	3.76E-29	6.09E-31	1.14E-29
	50	5.93E-41	1.29E-28	1.97E-30	1.22E-29
	100	5.59E-37	5.70E-28	2.41E-29	4.31E-29

TABLE 22. Comparison results of different dimensions in F19 functions.

Algorithm	Dimension	Minimum Value	Maximum Value	Average Value	Variance
	2	0.045564	34296.14	7386.883	11909.42
	5	2955.851	77961.75	24166.93	19845.89
ACO	10	18339.34	116696.6	66108.76	33592.4
	30	83751.72	214746	198443.7	54826.07
	50	242314.7	464408.4	282974.2	74856.18
	100	506102	1060650	490645.3	96216.19
	2	5.06E-06	0.29348	0.028308	0.058381
	5	0.165869	121.8095	16.40702	33.82265
PSO	10	125.3475	5995.754	1149.476	1152.504
	30	3786.734	28559.45	12086.03	3726.548
	50	10896.66	57295.84	16426.8	4136.919
	100	37343.32	78847.7	64797.11	6233.447
	2	2.74E-14	4.55E-05	2.26E-06	6.70E-06
	5	4.33E-07	0.096277	0.016692	0.019145
WOA	10	0.000213	2.590453	0.213253	0.404569
	30	0.006072	17.99347	3.937066	4.15202
	50	0.006367	26.38528	6.235243	8.354866
	100	0.386375	116.124	22.9046	26.34097
	2	2.73E-17	5.05E-07	2.49E-08	6.35E-08
	5	6.62E-18	0.000645	3.60E-05	0.000115
CWOA	10	1.34E-15	0.000936	3.81E-05	0.00013
	30	7.13E-13	0.010366	0.000315	0.001384
	50	2.40E-14	0.007359	0.000227	0.001693
	100	1.57E-12	0.136737	0.00537	0.022011
	2	1.04E-15	0.000397	1.24E-05	6.16E-05
LWOA	5	2.36E-07	0.317689	0.019998	0.055416
	10	1.98E-05	1.386304	0.229234	0.304742
	30	0.008749	14.11409	3.039463	4.088065
IWOA	50	0.314573	71.57203	10.09102	11.86757
	100	0.526946	69.58601	14.02591	20.75145
	2	0	2.38E-67	6.50E-69	4.75E-68
	5	7.35E-55	1.50E-40	4.50E-42	1.74E-41
	10	4.92E-49	1.19E-34	3.89E-36	2.08E-35
	30	1.26E-42	4.11E-31	1.07E-32	4.22E-32
	50	7.56E-44	4.66E-31	9.38E-33	3.36E-32
	100	1.15E-39	1.60E-30	7.40E-32	1.96E-31
AGDE	2	0.002381	0.068186	0.026215	0.009636
	5	0.123403	77.4139	3.151764	8.881991
	10	17.48317	1189.131	191.1204	276.8719
	30	1527.359	6460.611	4740.387	940.4784
	50	6296.246	23599.46	13021.02	4009.213
	100	11741.39	38142.15	25242.43	4411.654
	2	1.89E-32	1.82E-21	3.93E-23	2.62E-22
EFADE	5	1.89E-30	5.31E-21	3.58E-22	8.20E-22
	10	8.90E-32	2.64E-17	5.49E-19	3.47E-18
	30	1.24E-28	1.04E-18	3.66E-20	1.38E-19
	50	2.30E-27	1.66E-19	1.14E-20	3.17E-20
	100	3.79E-27	5.05E-17	2.10E-18	8.14E-18
	2	2.69E-61	3.52E-61	5.46E-63	3.01E-62
	5	5.93E-49	1.80E-34	3.50E-36	1.76E-35
EAGDE	10	2.95E-43	1.33E-28	3.55E-30	1.63E-29
	30	7.30E-37	1.87E-25	7.55E-27	6.66E-26
	50	1.11E-37	2.03E-25	5.34E-27	7.22E-26
	100	1.73E-33	5.28E-25	6.23E-26	9.16E-26
	2	3.93E-61	5.42E-64	9.40E-66	6.60E-65
	5	1.76E-51	5.03E-37	6.40E-39	3.06E-38
EBLSHAD	10	3.46E-46	1.77E-31	2.15E-33	2.89E-32
E	30	1.06E-39	8.03E-28	1.71E-29	5.73E-29
	50	1.77E-40	5.53E-28	1.02E-29	9.27E-29
	100	2.08E-36	2.25E-27	1.14E-28	5.25E-28

TABLE 23. Comparison results of different dimensions in F20 functions.

Algorithm	Dimension	Minimum Value	Maximum Value	Average Value	Variance
ACO	2	1.53E-09	2.36E+02	2.04E+01	6.16E+01
	5	8.10E-04	1.19E+02	7.07E+00	2.69E+01
	10	1.21E-02	8.20E+01	5.45E+00	1.78E+01
	30	7.35E-01	6.40E+01	1.20E+01	1.92E+01
	50	3.13E+00	5.14E+01	1.26E+01	1.53E+01
	100	7.60E+00	4.66E+01	2.02E+01	1.48E+01
PSO	2	8.04E-19	7.81E-08	2.88E-09	1.20E-08
	5	3.64E-07	5.73E-01	5.55E-02	1.04E-01
	10	4.82E-02	6.88E+00	1.57E+00	1.34E+00
	30	1.78E+00	9.90E+00	5.63E+00	1.86E+00
	50	4.96E+00	1.29E+01	7.96E+00	1.90E+00
	100	5.96E+00	1.36E+01	9.48E+00	1.61E+00
WOA	2	2.928E-29	4.066E-11	8.298E-13	5.749E-12
	5	2.158E-08	1.553E-02	8.633E-04	2.633E-03
	10	1.763E-04	6.139E-02	1.803E-02	1.678E-02
	30	2.351E-02	4.546E-01	1.798E-01	7.048E-02
	50	1.655E-03	4.635E-01	2.726E-01	1.077E-01
	100	4.215E-03	7.123E-01	3.845E-01	1.828E-01
CWOA	2	9.00E-19	2.45E-05	8.13E-07	3.79E-06
	5	1.93E-14	1.28E-02	4.94E-04	2.43E-03
	10	3.38E-19	2.01E-02	4.10E-04	2.84E-03
	30	1.23E-16	0.0006435	2.52E-05	0.000107
	50	3.28E-16	0.0008533	4.33E-05	1.69E-04
	100	1.29E-12	0.0008203	2.46E-05	1.18E-04
LWOA	2	2.58E-31	3.01E-11	6.25E-13	4.25E-12
	5	1.08E-08	3.99E-03	3.93E-04	8.95E-04
	10	2.79E-04	9.42E-02	1.87E-02	2.41E-02
	30	4.79E-02	3.42E-01	1.66E-01	6.88E-02
	50	1.54E-02	4.71E-01	2.76E-01	1.18E-01
	100	7.76E-03	6.44E-01	3.95E-01	1.57E-01
IWOA	2	0	5.41E-33	1.08E-34	7.65E-34
	5	5.66E-21	2.99E-04	2.47E-05	6.17E-05
	10	2.30E-13	1.27E-03	1.44E-04	2.57E-04
	30	6.30E-23	2.78E-02	2.44E-03	4.98E-03
	50	7.42E-30	2.76E-02	2.31E-03	5.03E-03
	100	4.27E-33	6.12E-02	2.99E-03	1.24E-02
AGDE	2	7.85E-25	2.80E-11	2.02E-12	5.85E-12
	5	1.35E-05	5.53E-02	4.27E-03	9.05E-03
	10	1.19E-02	1.42E+00	2.92E-01	2.88E-01
	30	8.93E-01	4.50E+00	2.37E+00	1.03E+00
	50	1.59E+00	7.80E+00	3.65E+00	1.24E+00
	100	2.84E+00	9.93E+00	4.47E+00	1.14E+00
EFADE	2	1.64E-20	5.50E-07	1.67E-08	7.87E-08
	5	5.94E-10	1.04E-01	1.71E-02	2.94E-02
	10	4.17E-15	5.30E-01	1.08E-02	7.49E-02
	30	8.72E-12	2.84E-08	1.23E-08	6.99E-09
	50	1.57E-19	3.06E-08	1.69E-08	7.53E-09
	100	2.38E-18	5.07E-08	2.37E-08	1.33E-08
EAGDE	2	2.19E-03	8.35E-30	1.59E-31	1.39E-30
	5	1.01E-17	5.57E-01	3.51E-02	1.14E-01
	10	5.21E-10	2.65E+00	2.54E-01	4.15E-01
	30	7.19E-20	4.10E+01	4.86E+00	6.84E+00
	50	1.40E-26	5.43E+01	4.09E+00	9.68E+00
	100	5.96E-30	1.40E+02	4.43E+00	2.20E+01
EBLSHADE	2	2.46E-06	1.14E-32	2.02E-34	1.13E-33
	5	1.09E-20	4.33E-04	4.64E-05	1.21E-04
	10	4.58E-13	2.53E-03	2.53E-04	6.43E-04
	30	1.15E-22	7.45E-02	6.65E-03	8.19E-03
	50	1.30E-29	5.45E-02	4.52E-03	1.12E-02
	100	1.18E-32	1.83E-01	7.17E-03	3.04E-02

accuracy is limited. Compared with the test functions, the algorithm in this paper has better optimization accuracy. Although it will fall into local optimization in the later stage, however, on the whole, the optimization accuracy and speed have certain advantages. Especially, this algorithm improves the convergence accuracy on the F1∼F4, F6∼F8, F10, F12-F16 F18∼F20 test function.

(b) Compared with ACO, PSO, WOA, LWOA, CWOA, AGDE,EFADE, EAGDE and EBLSHADE algorithm, this algorithm can also improve the convergence accuracy on the F1, F5, F9-F10, F14-F16, F20 test function. This shows that the improvement of the Whale optimization algorithm in this paper has a certain effect, which can effectively improve the convergence accuracy of the algorithm.

(c) From the overall effect, the algorithm in this paper has a good effect on the optimization of F4, F6-F8, F11, F13 both in convergence rate and accuracy. These test functions show that the algorithm has a flat trend in the second half of its value range, which shows that the algorithm has a certain effect in improving the accuracy.

In summary, the proposed algorithm outperforms the other 9 algorithms in 20 classical test functions with faster convergence speed and convergence accuracy.

E. EVALUATION OF EXPLORATION CAPABILITY (F1–F20)

Table 4-Table 23 shows the comparison of statistical results, which includes minimum value, maximum value, average value and standard deviation test index of the 10 algorithms in different dimensions of 20 test functions from CEC 2017.

Let' take the first test function for examples, from low dimension to high dimension, the statistical minimum value of IWOA is from 8.73E-07 to 4.64E-45. The statistical maximum value of IWOA is from 7.16Ee-73 to 6.88E-36. The statistical average value of IWOA is from 1.50E-74 to 3.34E-37. The statistical standard deviation of IWOA is from 1.86E-73 to 1.07E-36. The performance of these four indexes is better than other 9 algorithm. On the other hand, according to the performance of test functions in six different dimensions, it can be concluded that the performance of the IWOA algorithm slightly diminishes and it is still more robust against the curse of dimensionality.

Other test functions can also be made a similar conclusion analysis. Therefore, according to the results of tables 4∼23, it can be clearly seen that IWOA succeeded at solving most of the problems. In F1,F2, F4,F6-F14,F18-20 test functions, under the condition that the dimensions are 2, 5, 10, 30,50,100 the results of the proposed algorithm is optimal and the advantages are obvious, especially when the dimension is 2, the minimum value is 0, which shows that the proposed algorithm has a good quality of solution. While in F3, F5, F15, F17 test functions, the results of the EFADE algorithm is the best.

TABLE 24. Wilcoxon's test between IWOA and other algorithms over all dimensions on 18 test functions.

Algorithm	R+	R-	P value
IWOA versus ACO	352	232	0.0072
IWOA versus PSO	341	233	0.0092
IWOA versus WOA	281	192	0.0123
IWOA versus CWOA	191	123	0.1238
IWOA versus LWOA	224	142	0.0591
IWOA versus AGDE	251	167	0.0182
IWOA versus EFADE	172	92	0.4251
IWOA versus EAGDE	163	85	0.5211
IWOA versus EBLSHADE	145	78	0.5476

Therefore, from the results of the above 20 test functions, the proposed algorithm has some advantages over the other 9 algorithms, especially the convergence speed is obviously improved compared with the basic WOA algorithm, and the quality effect of the solution is further enhanced.

F. WILCOXON'S TEST

According to the result of table 4∼23, the performance of the 10 algorithms can be sorted into the following order: IWOA, EBLSHADE, EAGDE,EFADE, CWOA, LWOA, AGDE, WOA, PSO, ACO. Additionally, due to the importance of the multiple-problem statistical analysis, Table 24 also gives the statistical analysis resultsthroug Wilcoxon's test between IWOA and other 7 compared algorithms. The parameters of Wilcoxon's test are $\alpha = 0.01$ and 0.05.

From the results shown in Table 24, we can see that IWOA provides higher R+ values than R- in all the cases. Therefore, we can obtain the conclusions: IWOA is better than EBLSHADE, EAGDE,EFADE, CWOA, LWOA, AGDE, WOA, PSO, ACO significantly.

G. EVALUATION OF SIMULATION TIMES

Table 25 shows the comparison of the usage time of 10 algorithms in different dimensions under 20 test functions. It is found that the usage time of this algorithm is higher than that of the other 2 algorithms includes CWOA and LWOA in all dimensions. While the usage time of the proposed algorithm is less than that of the algorithms of AGDE, EFADE, EAGDE and EBLSHADE in most dimensions.

VI. DISCUSSION

In this paper, the author presented a new swarm-based optimization algorithm based on the Whale Optimization Algorithm. According to the disadvantages of the WOA, the paper proposed four improvements, which includes population initialization by Bernouilli Shift mapping, adaptive convergence factor, levy optimization and new trigger rules.

TABLE 25. Time comparison of 10 algorithms in Test functions(a).

Algorithm	D	F1	F2	F3	F4	F5	F6	F7	F8	F9
ACO	2	0.17	0.34	0.279	0.236	0.098	13.06	15.11	20.98	5.80
	5	0.52	0.704	0.494	0.441	0.134	22.95	31.50	52.49	22.86
	10	0.79	1.337	0.868	0.853	0.199	42.99	93.67	105.71	28.55
	30	3.32	3.634	2.13	2.219	0.507	113.00	209.56	262.78	110.83
	50	4.73	5.051	2.862	2.802	0.683	201.89	317.02	659.72	153.42
	100	6.24	8.217	4.089	4.189	1.064	413.46	1000.2	1022.28	383.71
PSO	2	0.01	0.070	0.084	0.048	0.042	0.42	1.26	1.81	0.54
	5	0.07	0.209	0.225	0.181	0.114	2.98	5.98	6.36	2.59
	10	0.31	0.544	0.520	0.423	0.263	13.03	15.09	21.74	15.01
	30	2.19	3.122	2.399	2.121	1.202	84.43	172.63	228.73	69.41
	50	5.83	8.250	6.071	4.981	2.711	285.09	477.40	602.14	214.18
	100	26.32	31.326	21.413	19.647	8.953	1247.83	1356.4	3153.80	1333.45
WOA	2	0.01	0.032	0.037	0.017	0.017	0.40	0.52	0.90	0.21
	5	0.04	0.087	0.095	0.072	0.041	1.75	2.32	4.10	1.40
	10	0.10	0.265	0.245	0.189	0.116	3.01	10.13	9.55	3.59
	30	1.04	1.621	1.334	1.159	0.783	41.29	61.95	91.76	46.78
	50	2.65	4.582	3.498	3.124	2.117	151.93	261.26	327.36	114.29
	100	11.57	17.952	12.493	12.967	8.720	545.41	1143.2	1149.72	476.20
CWOA	2	0.00	0.027	0.035	0.026	0.014	0.30	0.46	0.91	0.23
	5	0.04	0.077	0.090	0.078	0.031	1.37	2.10	3.92	1.11
	10	0.11	0.201	0.229	0.191	0.085	5.45	8.17	9.61	4.80
	30	1.15	1.372	1.313	1.184	0.482	37.94	76.10	105.71	16.71
	50	2.87	3.299	3.278	3.066	1.262	85.39	185.28	314.73	56.48
	100	8.70	14.148	13.334	12.176	4.739	376.55	702.75	1016.17	352.57
LWOA	2	0.01	0.032	0.042	0.020	0.018	0.32	0.50	1.07	0.24
	5	0.02	0.107	0.116	0.093	0.061	1.83	2.47	4.60	1.22
	10	0.12	0.323	0.309	0.265	0.196	6.01	10.38	14.14	3.24
	30	1.11	2.293	2.006	1.841	1.456	53.14	106.69	137.60	32.69
	50	3.41	6.112	5.240	4.963	3.991	130.60	235.44	322.12	97.16
	100	9.18	24.452	20.922	19.926	15.929	473.25	645.25	1143.72	363.46
IWOA	2	0.01	0.037	0.043	0.028	0.018	0.32	0.57	0.82	0.22
	5	0.03	0.099	0.106	0.093	0.045	1.49	2.34	3.52	1.09
	10	0.10	0.277	0.264	0.225	0.114	3.69	8.12	11.61	3.47
	30	1.08	1.980	1.659	1.578	0.928	43.61	67.10	139.38	44.50
	50	2.70	5.075	4.109	3.950	1.774	136.94	158.64	294.85	77.23
	100	9.87	20.208	16.166	16.063	7.210	455.59	726.61	1760.62	529.37
AGDE	2	0.02	0.070	0.083	0.045	0.038	0.79	0.85	1.39	0.47
	5	0.07	0.208	0.228	0.181	0.098	3.18	4.41	7.77	1.69
	10	0.22	0.535	0.522	0.419	0.210	9.45	17.59	33.19	7.53
	30	2.00	3.127	2.405	2.125	0.757	82.50	146.82	321.66	84.19
	50	5.37	7.894	5.569	5.331	1.456	224.29	378.53	615.43	239.57

TABLE 25. Time comparison of 10 algorithms in Test functions(b).

	100	21.70	30.865	20.885	20.588	4.138	989.31	1524.9	1942.42	811.70
EFADE	2	0.04	0.139	0.174	0.084	0.068	1.72	2.50	4.23	1.31
	5	0.15	0.424	0.477	0.362	0.170	7.45	14.39	14.23	7.43
	10	0.53	1.078	1.108	0.886	0.357	31.13	59.71	65.89	16.83
	30	5.63	6.516	5.842	5.121	1.208	319.08	442.43	608.70	173.91
	50	19.89	16.461	15.254	13.645	2.280	770.94	1021.0	2061.83	343.33
	100	52.76	63.130	50.021	50.253	6.073	2946.84	4719.8	7960.01	1918.48
EAGDE	2	0.03	0.155	0.175	0.094	0.069	1.33	2.53	3.88	1.58
	5	0.20	0.429	0.493	0.396	0.172	8.39	10.08	27.21	8.95
	10	0.67	1.129	1.252	0.948	0.395	35.14	29.63	76.66	40.71
	30	5.44	6.976	6.697	5.972	1.396	256.88	287.19	725.56	225.75
	50	17.78	19.165	17.230	15.242	2.706	493.27	1160.2	2470.62	346.33
	100	61.17	63.324	54.532	55.778	6.231	1970.27	4126.7	7125.40	3151.07
EBLSHADE	2	0.06	0.298	0.363	0.173	0.145	3.81	4.51	7.27	3.31
	5	0.37	0.874	1.019	0.756	0.344	15.63	30.95	40.53	13.56
	10	0.94	2.481	2.436	1.815	0.743	81.25	83.05	160.39	49.96
	30	9.97	15.160	12.195	10.474	2.466	301.15	789.46	1679.32	522.10
	50	23.87	35.330	33.573	31.244	4.700	1631.99	2800.2	5217.08	1344.01
	100	114.19	128.598	111.901	110.217	12.632	5730.71	11044.	14158.0	5440.02

Algorithm	D	F10	F11	F12	F13	F14	F15	F16	F17	F18
ACO	2	6.55	0.69	0.206	0.112	9.758	3.30	13.937	1.72	2.40
	5	14.37	1.03	0.408	0.154	24.044	7.57	36.413	6.66	6.80
	10	36.65	2.23	0.789	0.215	47.22	12.21	70.488	11.59	12.86
	30	76.34	8.75	2.127	0.549	141.849	51.94	213.99	30.07	39.07
	50	187.40	14.50	2.658	0.768	233.438	73.71	351.30	50.26	62.98
	100	432.78	25.46	3.922	1.16	464.087	209.68	704.87	145.76	173.57
PSO	2	0.60	0.04	0.053	0.050	0.724	0.27	0.683	0.15	0.24
	5	1.72	0.20	0.148	0.128	3.487	1.89	3.901	0.66	1.06
	10	8.99	0.58	0.358	0.297	12.591	6.56	15.817	3.28	2.67
	30	79.60	5.75	1.901	1.350	105.895	43.75	138.11	37.12	21.44
	50	314.27	13.55	5.151	2.930	288.275	108.79	393.66	72.44	52.50
	100	1095.00	47.44	18.502	9.505	1157.05	569.47	1528.9	307.10	527.98
WOA	2	0.29	0.02	0.018	0.020	0.363	0.11	0.332	0.07	0.13
	5	1.70	0.09	0.054	0.048	1.680	0.76	1.939	0.56	0.53
	10	3.86	0.29	0.156	0.139	6.107	2.12	7.654	1.56	1.48
	30	38.49	2.74	1.124	0.835	51.718	19.03	72.845	14.30	11.96
	50	146.74	8.56	2.830	2.157	143.02	49.52	198.14	28.95	47.61
	100	584.36	30.29	11.581	8.721	561.68	250.54	770.93	164.40	221.25
CWOA	2	0.30	0.02	0.019	0.020	0.330	0.11	0.328	0.09	0.07
	5	1.23	0.07	0.056	0.040	1.405	0.44	1.986	0.27	0.38
	10	3.49	0.25	0.154	0.100	4.943	2.20	7.690	1.25	1.46
	30	37.59	1.73	1.145	0.525	40.894	14.97	70.974	9.30	7.38
	50	74.66	6.47	2.918	1.389	111.846	47.97	201.89	28.57	39.20

TABLE 25. **Time comparison of 10 algorithms in Test functions(c).**

	100	387.12	27.82	12.620	4.860	434.031	161.39	758.47	103.07	119.41
LWOA	2	0.31	0.02	0.022	0.022	0.367	0.15	0.340	0.09	0.15
	5	1.69	0.12	0.075	0.069	1.724	0.34	1.995	0.34	0.48
	10	4.51	0.30	0.236	0.208	6.164	2.70	7.846	1.44	2.00
	30	47.99	2.53	1.745	1.514	53.215	29.18	69.652	15.34	12.32
	50	130.64	5.78	4.757	4.054	140.940	68.09	198.48	47.53	37.00
	100	372.04	23.85	19.882	16.106	566.912	268.08	770.96	108.83	130.32
IWOA	2	0.29	0.01	0.026	0.024	0.347	0.13	0.343	0.13	0.11
	5	1.68	0.09	0.067	0.054	1.590	0.66	2.004	0.52	0.60
	10	4.66	0.38	0.189	0.130	5.694	2.39	7.839	1.47	1.51
	30	35.12	2.59	1.393	0.958	46.782	19.07	69.889	10.99	15.26
	50	112.05	7.51	3.611	2.229	128.342	42.81	199.24	27.60	34.62
	100	391.31	32.83	15.522	7.423	517.620	192.46	779.44	150.96	158.46
AGDE	2	0.59	0.02	0.051	0.046	0.672	0.26	0.691	0.14	0.25
	5	2.47	0.15	0.148	0.115	3.175	1.15	4.039	0.72	0.98
	10	9.13	0.61	0.357	0.245	11.459	5.35	16.021	3.37	2.72
	30	82.64	5.41	1.884	0.862	94.582	57.04	138.42	25.71	23.51
	50	268.47	9.75	4.719	1.691	263.729	77.57	391.70	77.76	76.43
	100	914.75	41.88	18.898	4.772	1048.66	430.23	1560.7	288.63	302.54
EFADE	2	1.76	0.10	0.096	0.097	1.656	0.47	1.602	0.38	0.41
	5	4.18	0.43	0.288	0.266	8.788	4.43	10.150	1.97	2.73
	10	23.07	1.76	0.725	0.656	31.685	16.25	44.928	9.18	11.91
	30	219.84	10.60	4.580	3.363	262.412	70.06	346.83	56.80	74.77
	50	481.17	24.31	11.834	7.963	722.080	401.11	978.34	223.36	207.76
	100	1674.57	161.91	46.641	28.996	2810.40	880.29	3945.4	813.71	471.89
EAGDE	2	1.59	0.11	0.103	0.108	1.772	0.74	1.669	0.47	0.45
	5	9.37	0.69	0.324	0.291	10.438	5.09	10.762	2.61	2.26
	10	31.51	1.29	0.838	0.658	37.236	15.33	49.160	9.99	10.31
	30	251.45	10.67	4.654	3.590	291.286	170.01	362.81	124.19	96.57
	50	536.48	28.63	14.034	8.221	811.975	503.59	1143.5	198.43	317.80
	100	2262.22	155.71	53.877	33.602	3140.36	1290.89	4099.0	540.68	1280.98
EBLSHADE	2	2.75	0.15	0.195	0.207	3.515	0.87	3.257	1.22	1.03
	5	14.12	1.29	0.601	0.536	20.470	7.59	21.186	5.74	5.75
	10	54.40	2.26	1.644	1.509	63.769	21.18	94.878	13.88	22.26
	30	709.71	19.62	9.205	7.785	602.250	204.05	772.24	229.38	198.39
	50	1202.80	86.62	27.332	17.229	1663.98	515.48	2001.2	461.83	575.60
	100	5752.86	394.28	104.636	62.721	6366.66	2586.49	8839.3	1685.32	2207.30

Algorithm	D	F19	F20
ACO	2	4.52	0.507
	5	10.58	0.989
	10	20.83	1.815
	30	83.03	4.812
	50	73.46	7.017

TABLE 25. Time comparison of 10 algorithms in Test functions(c).

TABLE 25. Time comparison of 10 algorithms in Test functions(c).

	100	222.42	12.511
PSO	2	0.38	0.102
	5	1.52	0.336
	10	6.90	0.836
	30	52.19	4.534
	50	117.09	11.575
	100	597.20	41.995
WOA	2	0.17	0.046
	5	0.77	0.158
	10	2.62	0.454
	30	26.18	2.609
	50	45.11	6.633
	100	258.47	24.917
CWOA	2	0.15	0.058
	5	0.57	0.139
	10	2.79	0.330
	30	17.44	1.910
	50	61.97	4.525
	100	259.37	17.356
LWOA	2	0.18	0.049
	5	0.91	0.181
	10	3.48	0.487
	30	26.18	3.218
	50	78.09	8.383
	100	211.88	33.178
IWOA	2	0.21	0.051
	5	0.64	0.176
	10	1.81	0.440
	30	29.87	2.707
	50	63.37	6.725
	100	282.05	26.266
AGDE	2	0.31	0.101
	5	1.26	0.331
	10	2.21	0.828
	30	53.21	4.504
	50	124.30	11.024
	100	503.64	41.731
EFADE	2	0.90	0.220
	5	3.15	0.742
	10	13.53	1.867
	30	161.31	10.662
	50	404.21	27.465
	100	1045.11	100.017
EAGDE	2	0.50	0.244
	5	4.62	0.786
	10	19.41	2.145
	30	173.09	11.065
	50	413.60	31.237
	100	1217.73	103.688
EBLSHADE	2	1.87	0.456
	5	7.84	1.513
	10	25.76	3.919
	30	261.75	22.457
	50	627.42	58.813
	100	3010.82	216.965

In order to prove the performance of the proposed IWOA algorithm, the statistical test index is simulated in different dimensions of 20 test functions from CEC 2017. The simulation results show that the proposed algorithm has the advantages over the other 9 algorithms both in the convergence speed and convergence accuracy.

However, there are still some defects in the algorithm proposed in this paper. Due to the addition of four improvement points, the complexity of the algorithm is far greater than other traditional optimization algorithms. On the other hand, the improved algorithm proposed in this paper has not reached the optimal performance in some test functions, such as F3, F5, F15, F17 test functions.

VII. CONCLUSION

In views of the shortcomings of WOA algorithm, which is slow in convergence speed and easy to fall into local optimization, this paper proposes an improved Whale optimization algorithm-IWOA, to improve the performance of the algorithm as a whole through population initialization, optimizing adaptive convergence factor, adopting Levy behavior and using trigger rules. In the simulation experiment, IWOA and ACO, PSO, WOA, CWOA,LWOA, AGDE,EFADE,EAGDE and EBLSHADE are compared with the minimum, maximum, average, standard deviation and time of different dimension dimensions of 10 test functions. The experimental results show that the IWO algorithm has a better effect on the aspects of the quality of the solution, the accuracy of the solution, the speed of convergence, etc. The accuracy of the convergence of the algorithm is obviously improved.

REFERENCES

[1] D. Whitley, "A genetic algorithm tutorial," *Statist. Comput.*, vol. 4, no. 2, pp. 65–85, Jun. 1994, doi: 10.1007/BF00175354.

[2] I. C. Trelea, "The particle swarm optimization algorithm: Convergence analysis and parameter selection," *Inf. Process. Lett.*, vol. 85, no. 6, pp. 317–325, Mar. 2003, doi: 10.1016/S0020-0190(02)00447-7.

[3] R. Storn and K. Price, "Differential evolution—A simple and efficient heuristic for global optimization over continuous spaces," *J. Gobal Optimizaiton*, vol. 11, no. 4, pp.341–359, Dec. 1997, doi: 10.1023/A:1008202821328.

[4] M. Dorigo, M. Birattari, and T. Stutzle, "Ant colony optimization: A new meta-heuristic," in *Proc. Congr. Evol. Comput. (CEC)*, Washington, DC, USA, Aug. 2002, pp. 6–9, doi: 10.1109/CEC.1999.782657.

[5] W.-T. Pan, "A new fruit fly optimization algorithm: Taking the financial distress model as an example," *Knowl.-Based Syst.*, vol. 26, no. 2, pp. 69–74, Feb. 2012, doi: 10.1016/j.knosys.2011.07.001.

[6] X. L. Li, Z. J. Shao, and J. X. Qian, "An optimizing method based on autonomous animats: Fish-swarm algorithm," *Syst. Eng. Pract.*, vol. 11, pp. 32–38, 2002.

[7] D. Karaboga and B. Basturk, "On the performance of artificial bee colony (ABC) algorithm," *Appl. Soft Comput.*, vol. 8, no. 1, pp. 687–697, Jan. 2008, doi: 10.1016/j.asoc.2007.05.007.

[8] X. B. Meng, Y. Liu, and X. Z. Gao, "A new bio-inspired algorithm: Chicken swarm optimization," in *Proc. Int. Conf. Swarm Intell.*, 2014, pp. 86–94, doi: 10.1007/978-3-319-11857-4_10.

[9] R. Q. Zhao and W. S. Tang, "Monkey algorithm for global numerical optimization," *J. Uncertain Syst.*, vol. 2, no. 3, pp. 164–175, 2008.

[10] X. S. Yang, "A new metaheuristic bat-inspired algorithm," in *Nature Inspired Cooperative Strategies for Optimization—NISCO*. Berlin, Germany: Springer, 2010, pp. 65–74, doi: 10.1007/978-3-642-12538-6_6.

[11] X. S. Yang and D. Suash, "Cuckoo search via Lévy flights," in *Proc. World Congr. Nature Biologically Inspired Comput.*, Coimbatore, India, Jan. 2010, pp. 210–214, doi: 10.1109/NABIC.2009.5393690.

[12] S. Mirjalili and A. Lewis, "The whale optimization algorithm," *Adv. Eng. Softw.*, vol. 95, pp. 51–67, May 2016, doi: 10.1016/j.advengsoft.2016.01.008.

[13] I. N. Trivedi, J. Pradeep, J. Narottam, K. Arvind, and L. Dilip, "Novel adaptive whale optimization algorithm for global optimization," *Indian J. Sci. Technol.*, vol. 9, no. 38, pp. 319–326, Oct. 2016, doi: 10.17485/ijst/2016/v9i38/101939.

[14] A. Kaveh and M. I. Ghazaan, "Enhanced whale optimization algorithm for sizing optimization of skeletal structures," *Mech. Based Design Struct. Mach.*, vol. 45, no. 3, pp. 345–362, Jul. 2017, doi: 10.1080/15397734.2016.1213639.

[15] G. Kaur and S. Arora, "Chaotic whale optimization algorithm," *J. Comput. Des. Eng.*, vol. 5, no. 3, pp. 275–284, Jul. 2018, doi: 10.1016/j.jcde.2017.12.006.

[16] M. Abdel-Basset, G. Manogaran, D. El-Shahat, and S. Mirjalili, "A hybrid whale optimization algorithm based on local search strategy for the permutation flow shop scheduling problem," *Future Gener. Comput. Syst.*, vol. 85, pp. 129–145, Aug. 2018, doi: 10.1016/j.future.2018.03.020.

[17] G. I. Sayed, A. Darwish, and A. E. Hassanien, "A new chaotic whale optimization algorithm for features selection," *J. Classification*, vol. 35, no. 2, pp. 300–344, Jul. 2018, doi: 10.1007/s00357-018-9261-2.

[18] Y. Ling, Y. Zhou, and Q. Luo, "Lévy flight trajectory-based whale optimization algorithm for global optimization," *IEEE Access*, vol. 5, pp. 6168–6186, 2017, doi: 10.1109/ACCESS.2017.2695498.

[19] M. M. Mafarja and S. Mirjalili, "Hybrid whale optimization algorithm with simulated annealing for feature selection," *Neurocomputing*, vol. 260, pp. 302–312, Oct. 2017, doi: 10.1016/j.neucom.2017.04.053.

[20] I. N. Trivedi, P. Jangir, A. Kumar, N. Jangir, and R. Totlani, "A novel hybrid PSO–WOA algorithm for global numerical functions optimization," in *Proc. Adv. Comput. Comput. Sci.*, Sep. 2018, pp. 53–60, doi: 10.1007/978-981-10-3773-3_6.

[21] A. Kaveh and M. Rastegar Moghaddam, "A hybrid WOA-CBO algorithm for construction site layout planning problem," *Scientia Iranica*, vol. 25, no. 3, pp. 1094–1104, Aug. 2017, doi: 10.24200/SCI.2017.4212.

[22] R. Masadeh, A. Hudaib, and A. Alzaqebah, "WGW: A hybrid approach based on whale and grey wolf optimization algorithms for requirements prioritization," *Adv. Syst. Sci. Appl.*, vol. 18, no. 2, pp. 63–83, Aug. 2018, doi: 10.25728/assa.2018.18.2.576.

[23] H. J. Touma, "Study of the economic dispatch problem on IEEE 30-bus system using whale optimization algorithm," *Int. J. Eng. Technol. Sci.*, vol. 5, no. 1, pp. 11–18, Jun. 2016, doi: 10.15282/ijets.5.2016.1.2.1041.

[24] C. S. Kumar and R. S. Rao, "A novel global MPP tracking of photovoltaic system based on whale optimization algorithm," *Int. J. Renew. Energy Develop.*, vol. 5, no. 3, pp. 225–232, Nov. 2016, doi: 10.14710/ijred.5.3.225-232.

[25] D. B. Prakash and C. Lakshminarayana, "Optimal siting of capacitors in radial distribution network using whale optimization algorithm," *Alexandria Eng. J.*, vol. 56, no. 4, pp. 499–509, Dec. 2017, doi: 10.1016/j.aej.2016.10.002.

[26] I. Aljarah, H. Faris, and S. Mirjalili, "Optimizing connection weights in neural networks using the whale optimization algorithm," *Soft Comput.*, vol. 22, no. 1, pp. 1–15, Jan. 2018, doi: 10.1007/s00500-016-2442-1.

[27] A. Mostafa, A. E. Hassanien, M. Houseni, and H. Hefny, "Liver segmentation in MRI images based on whale optimization algorithm," *Multimedia Tools Appl.*, vol. 76, no. 23, pp. 24931–24954, Dec. 2017, doi: 10.1007/s11042-017-4638-5.

[28] P. D. P. Reddy, V. C. V. Reddy, and T. G. Manohar, "Whale optimization algorithm for optimal sizing of renewable resources for loss reduction in distribution systems," *Renewables, Wind, Water, Sol.*, vol. 4, no. 1, pp. 1–16, Dec. 2017, doi: 10.1186/s40807-017-0040-1.

[29] M. A. E. Aziz, A. A. Ewees, and A. E. Hassanien, "Whale optimization algorithm and moth-flame optimization for multilevel thresholding image segmentation," *Expert Syst. Appl.*, vol. 83, pp. 242–256, Oct. 2017, doi: 10.1016/j.eswa.2017.04.023.

[30] G. Hassan and A. E. Hassanien, "Retinal fundus vasculature multilevel segmentation using whale optimization algorithm," *Signal, Image Video Process.*, vol. 12, no. 2, pp. 263–270, Feb. 2018, doi: 10.1007/s11760-017-1154-z.

[31] D. Oliva, M. Abd El Aziz, and A. E. Hassanien, "Parameter estimation of photovoltaic cells using an improved chaotic whale optimization algorithm," *Appl. Energy*, vol. 200, pp. 141–154, Aug. 2017, doi: 10.1016/j.apenergy.2017.05.029.

[32] M. Mafarja and S. Mirjalili, "Whale optimization approaches for wrapper feature selection," *Appl. Soft Comput.*, vol. 62, pp. 441–453, Jan. 2018, doi: 10.1016/j.asoc.2017.11.006.

[33] H. H. Mehne and S. Mirjalili, "A parallel numerical method for solving optimal control problems based on whale optimization algorithm," *Knowl.-Based Syst.*, vol. 151, pp. 114–123, Jul. 2018, doi: 10.1016/j.knosys.2018.03.024.

[34] J. Nasiri and F. M. Khiyabani, "A whale optimization algorithm (WOA) approach for clustering," *Cogent Math. Statist.*, vol. 5, no. 1, Jun. 2018, Art. no. 1483565, doi: 10.1080/25742558.2018.1483565.

[35] X. Zhao, "Research on optimization performance comparison of different one-dimensional chaotic maps," *Appl. Res. Comput.*, vol. 29, no. 3, pp. 913–915, Mar. 2012, doi: 10.3969/j.issn.1001-3695.2012.03.031.

[36] A. M. Edwards, R. A. Phillips, N. W. Watkins, M. P. Freeman, E. J. Murphy, V. Afanasyev, S. V. Buldyrev, M. G. E. da Luz, E. P. Raposo, H. E. Stanley, and G. M. Viswanathan, "Revisiting Lévy flight search patterns of wandering albatrosses, bumblebees and deer," *Nature*, vol. 449, no. 7165, pp. 1044–1048, Oct. 2007, doi: 10.1038/nature06199.

[37] R. N. Mantegna and H. E. Stanley, "Stochastic process with ultraslow convergence to a Gaussian: The truncated Lévy flight," *Phys. Rev. Lett.*, vol. 73, no. 22, pp. 2946–2949, Nov. 1994, doi: 10.1103/PhysRevLett.73.2946.

[38] R.-F. Wang, L.-C. Jiao, F. Liu, and S.-Y. Yang, "Nature computation with self-adaptive dynamic control strategy of population size," *J. Softw.*, vol. 23, no. 7, pp. 1760–1772, Sep. 2012, doi: 10.3724/SP.J.1001.2012.04151.

[39] J. Liu and Y. P. Wang, "Central force optimization with self-adaptive control strategy of population size," *J. Beijing Univ. Posts Telecommun.*, vol. 38, no. 6, pp. 15–19, Jun. 2015, doi: 10.13190/j.jbupt.2015.06.004.

[40] M. S. Arumugam and M. V. C. Rao, "On the improved performances of the particle swarm optimization algorithms with adaptive parameters, crossover operators and root mean square (RMS) variants for computing optimal control of a class of hybrid systems," *Appl. Soft Comput.*, vol. 8, no. 1, pp. 324–336, Jan. 2008, doi: 10.1016/j.asoc.2007.01.010.

[41] A. W. Mohamed and A. K. Mohamed, "Adaptive guided differential evolution algorithm with novel mutation for numerical optimization," *Int. J. Mach. Learn. Cybern.*, vol. 10, no. 2, pp. 253–277, Feb. 2019, doi: 10.1007/s13042-017-0711-7.

[42] A. W. Mohamed and P. N. Suganthan, "Real-parameter unconstrained optimization based on enhanced fitness-adaptive differential evolution algorithm with novel mutation," *Soft Comput.*, vol. 22, no. 10, pp. 3215–3235, May 2018, doi: 10.1007/s00500-017-2777-2.

[43] R. Salgotra and U. Singh, "The naked mole-rat algorithm," *Neural Comput. Appl.*, vol. 31, no. 12, pp. 8837–8857, Dec. 2019, doi: 10.1007/s00521-019-04464-7.

[44] R. Salgotra, U. Singh, and S. Saha, "On some improved versions of whale optimization algorithm," *Arabian J. Sci. Eng.*, vol. 44, no. 11, pp. 9653–9691, Nov. 2019, doi: 10.1007/s13369-019-04016-0.

[45] A. Kumar, R. K. Misra, D. Singh, S. Mishra, and S. Das, "The spherical search algorithm for bound-constrained global optimization problems," *Appl. Soft Comput.*, vol. 85, Dec. 2019, Art. no. 105734, doi: 10.1016/j.asoc.2019.105734.

[46] A. W. Mohamed, A. A. Hadi, and A. K. Mohamed, "Gaining-sharing knowledge based algorithm for solving optimization problems: A novel nature-inspired algorithm," *Int. J. Mach. Learn. Cybern.*, pp. 1–29, Dec. 2019, doi: 10.1007/s13042-019-01053-x.

[47] J. Brest, M. S. Maucec, and B. Boskovic, "Single objective real-parameter optimization: Algorithm jSO," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jun. 2017, pp. 1311–1318, doi: 10.1109/CEC.2017.7969456.

[48] A. W. Mohamed, A. A. Hadi, A. M. Fattouh, and K. M. Jambi, "LSHADE with semi-parameter adaptation hybrid with CMA-ES for solving CEC 2017 benchmark problems," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jun. 2017, pp. 145–152, doi: 10.1109/CEC.2017.7969307.

[49] A. Kumar, R. K. Misra, and D. Singh, "Improving the local search capability of effective butterfly optimizer using covariance matrix adapted retreat phase," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jun. 2017, pp. 1835–1842, doi: 10.1109/CEC.2017.7969524.

[50] A. W. Mohamed, A. A. Hadi, and K. M. Jambi, "Novel mutation strategy for enhancing SHADE and LSHADE algorithms for global numerical optimization," *Swarm Evol. Comput.*, vol. 50, Nov. 2019, Art. no. 100455, doi: 10.1016/j.swevo.2018.10.006.

[51] A. K. Mohamed and A. W. Mohamed, "Real-parameter unconstrained optimization based on enhanced AGDE algorithm," in *Machine Learning Paradigms: Theory and Application*, A. Hassanien, Eds. Cham, Switzerland: Springer, 2019, pp. 431–450.

[52] N. H. Awad, M. Z. Ali, J. J. Liang, B. Y. Qu, and P. N. Suganthan, "Problem definitions and evaluation criteria for the CEC 2017 special session and competition on single objective real-parameter numerical optimization," Nanyang Technol. Univ., Singapore, Tech. Rep., 2016.

XUAN CHEN received the B.S. degree in information management and information system from the Zhengzhou University of Aeronautics, Zhengzhou, China, in 2003, and the M.S. degree in computer science from the University of Electronic Science and Technology of China, Chengdu, China, in 2011. He is currently an Associate Professor of design and art with the Zhejiang Industry Polytechnic College, Shaoxing, China. His research interests include cloud computing and algorithm designs.