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An Improved Transient Search Optimization with Neighborhood Dimensional Learning for Global Optimization Problems

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Abstract: The transient search algorithm (TSO) is a new physics-based metaheuristic algorithm that simulates the transient behavior of switching circuits, such as inductors and capacitors, but the algorithm suffers from slow convergence and has a poor ability to circumvent local optima when solving high-dimensional complex problems. To address these drawbacks, an improved transient search algorithm (ITSO) is proposed. Three strategies are introduced to the TSO. First, a chaotic opposition learning strategy is used to generate high-quality initial populations; second, an adaptive inertia weighting strategy is used to improve the exploration ability, exploitation ability, and convergence speed; finally, a neighborhood dimensional learning strategy is used to maintain population diversity with each iteration of merit seeking. The Friedman test and Wilcoxon's rank sum test were also used by comparing the experiments with recently popular algorithms on 18 benchmark test functions of various types. Statistical results, nonparametric sign tests, and convergence curves all indicate that ITSO develops, explores, and converges significantly better than other popular algorithms, and is a promising intelligent optimization algorithm for applications.

Keywords: transient search algorithm; chaotic opposition learning; adaptive inertia weights; neighbor dimension learning

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1. Introduction

Due to the rapid development of engineering technology, global optimization problems are widely found in the fields of economic scheduling [1,2], portfolio investment [3], image processing [4], mechanical design [5], neural networks [6,7], data mining [8,9], etc., whereas traditional algorithms can only effectively handle those optimization problems with typical mathematical characteristics [10]. However, a large number of global optimization problems in practical applications are high-latitude, large-scale, and without typical mathematical features. Thus, scholars have proposed metaheuristic algorithms [11], which have shown significant superiority in practical applications and promoted the development of science and technology and engineering applications [12,13].

Most of the common metaheuristic algorithms are classified as evolutionary algorithms, swarm intelligence algorithms, and physics-based algorithms [14]. Evolutionary algorithms are inspired by biological evolutionary processes [15]. The widely used evolutionary algorithm is the genetic algorithm (GA) [16], which simulates Darwinian evolutionary theory by simulating the iterative update of the biological evolutionary process, updating the optimal individual each time to obtain a better solution. Differential evolution (DE) [17], genetic planning (GP) [18], evolutionary strategies (ES) [19], the biogeography-based optimizer (BBO) [20], fast evolutionary planning (FEP) [21], and their improved variants, have also been widely used. Swarm intelligence algorithms simulate the group behavior of animals and hunt according to group cooperation [22]. More commonly, this is done by mimicking the natural behavior of flocks of birds, whales, bee colonies, and

other group organisms [23]. The classical approach is the particle swarm algorithm (PSO), which simulates the predatory and cooperative behaviors of bird groups and individuals, and performs well in solving complex optimization problems [24]. Other common swarm intelligence algorithms are ant colony optimization (ACO), which mimics the search for food and group cooperation behavior of ant colonies [25]; the whale optimization algorithm (WOA), which is inspired by the spiral bubble feeding and group collaboration of whales [26]; and the marine predator algorithm (MPA), which simulates hunting behaviors such as Brownian motion and Lévy flight of marine organisms [27]. In addition, the bat algorithm (BA) [28], cuckoo search (CS) [29], artificial bee colony (ABC) [30], the gray wolf optimization algorithm (GWO) [31], the seagull optimization algorithm (SOA) [32], the coyote optimization algorithm (COA) [33], the tern bird optimization algorithm (STOA) [34], the dolphin echolocation algorithm (DEA) [35], the krill swarm algorithm (KHA) [36], the emperor penguin optimization algorithm (EPO) [37], and the parasitic predation algorithm (PPA) [38] are some of the algorithms that have received a large amount of attention. Physics-based algorithms mainly model physical rules, more commonly using physical concepts and laws, such as the law of refraction of light, gravity, gravity and electrical circuits [39]. The common gravitational search algorithm (GSA) arises from Newton's law of gravity [40]; the charged-system search algorithm (CSS) charged-system-search is inspired by Newton's rules of motion and Coulomb's rule [41]; and the ray optimization algorithm (RO) [42] simulates Snell's law of refraction of light. The big bang big crunch (BB-BC) [43], atomic search optimization (ASO) [44], and Henry gas solubility optimization (HGSO) [45] have also been widely used in solving optimization problems.

According to the theory of no free lunch [46], it is known that no optimization algorithm is guaranteed to solve all optimization problems efficiently. Therefore, in 2020, Mohammed et al. proposed a novel physics-based transient search algorithm (TSO) [47], which simulates the transient behavior of storage circuits, such as capacitor–inductors, with simple mathematical models and flowcharts and small computational complexity. Applying it to the optimization problem of the three-diode model (TDM) of Photovoltaic (PV) modules, TSO shows better superiority compared to other algorithms [48]. To address the problem that traditional sentiment analysis methods based on word co-occurrence frequencies perform poorly in most practical situations, Dashtipour et al. [49] proposed a new hybrid framework for concept-level sentiment analysis in Persian, which optimizes polarity detection using deep learning and linguistic rules.

Like most metaheuristic algorithms, TSO shows good performance when dealing with low-dimensional small-scale optimization problems [50]. However, when dealing with high-dimensional complex problems, TSO faces the challenges of being prone to local optima and slow convergence. The problems of TSO are as follows: the exploitation capability tends to local extrema on high-dimensional multi-peaked functions; the exploration capability is not fine-grained enough to solve well for the global optimum; the inertia weights of constant values cannot balance the exploitation and exploration behaviors, which also leads to slow convergence; and the diversity of populations is gradually missing with the increase in iterations.

In this paper, we propose an improved transient search algorithm (ITSO) to address the above problems. First, the randomized generation of the initial population can easily generate the population with concentrated distribution, which will lead to premature convergence of the algorithm. Thus, this paper adopts a chaotic logistic contrastive learning strategy for generating a high-quality initial population. Furthermore, to balance the global extensive search and local fine search, adaptive inertia weights are introduced that can effectively enhance the exploration and exploitation ability of the algorithm, in addition to accelerating the convergence speed. Finally, due to the increase in the number of iterations, the diversity of the population decreases, which leads the algorithm to fall into a local optimum, and the introduction of the neighbor dimensional learning strategy ensures that the population has diversity throughout the iterative process.

To verify the effectiveness of the ITSO, 18 internationally recognized benchmark test functions were selected and compared experimentally with nine recognized metaheuristics and seven improved optimization algorithms. These nine recognized metaheuristics are TSO, GA, DE, PSO, GWO, WOA, PPA, SOA, and STOA. The other seven improved optimization algorithms are Autonomous Groups Particle Swarm Optimization (AGPSO) [51], Modified Particle Swarm Optimization (MPSO) [52], the Opposition-Based Sine Cosine Algorithm (OBSCA) [53], the hybrid algorithm of the Particle Swarm Optimization and Gravitational Search Algorithm (PSOGSA) [54], the Chaotic Grey Wolf Optimization algorithm (CGWO) [55], the hybrid algorithm based on Grey Wolf Optimizer and Cuckoo Search (GWOCS) [56], and Improved Grey Wolf Optimizer (IGWO) [12]. For all experimental data, the Friedman test and Wilcoxon's rank sum test were also used to verify the superiority and significant competitiveness of the ITSO. Experimental results show that these three strategies can effectively improve the performance of TSO, and ITSO shows significant superiority in solving global optimization problems.

This paper is structured as follows. Section 2 briefly describes the TSO. Section 3 elaborates the proposed ITSO. The application of ITSO to parameter selection and benchmark function testing is presented in Section 4. Section 5 concludes and provides an outlook for the paper.

2. Transient Search Algorithm

2.1. Background Information

Circuits containing a single storage element capacitor or inductor are called first-order circuits. The switching of these circuits cannot instantaneously change the process to the next steady state, when the capacitor or inductor needs time to charge or discharge until it reaches its steady-state value. The transient response of a first-order circuit can be calculated from the differential equation, as shown in Equation (1):

$$\begin{gathered} \frac{d}{dt}x(t) + \frac{x(t)}{\tau} = K \\ \text{where } \tau = RC \text{ or } \tau = \frac{L}{R} \end{gathered} \tag{1}$$

where t is the current moment, $x(t)$ is the capacitive voltage of the RC circuit or the inductive current of the RL circuit, τ is the circuit time constant, and K is a constant.

Solving Equation (1) yields the solution of its differential equation in the form shown in Equation (2):

$$x(t) = x(\infty) + (x(0) - x(\infty))e^{\frac{t}{\tau}} \tag{2}$$

where $x(0)$ denotes the initial response value and $x(\infty)$ denotes the final response.

The responses of the second-order circuits are all underdamped responses, and the mathematical expressions of the differential equations for their transient responses are shown below:

$$\frac{d^2}{dt^2}x(t) + 2\alpha\frac{d}{dt}x(t) + w_0^2 x(t) = f(t) \tag{3}$$

where α is the damping factor and w_0 is the resonant frequency.

The expression for the solution of the differential equation of Equation (3) is given in the following equation:

$$x(t) = e^{-\alpha t}(B_1\cos(2\pi f_d t) + B_2\sin(2\pi f_d t)) + x(\infty) \tag{4}$$

where B_1 and B_2 are constants and f_d denotes the damped resonant frequency. When $\alpha < \omega_0$, an underdamped response occurs at this point, resulting in a damped oscillation in the transient response of the RLC circuit.

2.2. Mathematical Models

Firstly, for the generation of the initial population, a randomization inside the search boundary is taken to generate the location of each search agent with the following mathematical expression:

$$X_{ij} = lb + \ r \times (ub - lb)\ i = 0 \ldots N,\ j = 0 \ldots d \tag{5}$$

where X_{ij} represents the coordinates of the j-th dimension of the i-th population, N is the number of search agents, d is the dimensionality of the problem to be optimized, r is a random number conforming to a uniform distribution, and ub and lb are the upper and lower boundaries of the search space, respectively.

The search for the optimal solution is exploration and it is inspired by the oscillation of the second-order Resistance, Inductance, Capacitance (RLC) circuit near the zero point and by the mathematical expression of Equation (4), which is as follows:

$$X(t+1) = X^*(t) + e^{-T}[\cos(2\pi T) + \sin(2\pi T)]\left|X(t) - C_1 X^*(t)\right| \tag{6}$$

where $X(t+1)$ denotes the position of the current agent at the next moment, $X^*(t)$ represents the position of the current best agent, $X(t)$ denotes the current position, and T and C_1 are random coefficients.

The mathematical expressions for T and C_1 are shown below:

$$T = 2 \times z \times r_1 - z \tag{7}$$

$$C_1 = k \times z \times r_2 + 1 \tag{8}$$

where both r_1 and r_2 are random numbers that conform to a uniform distribution between [0, 1] and z is a variable that decreases linearly from 2 to 0.

The mathematical expression for z is as follows:

$$z = 2 - 2\frac{t}{Max_iter} \tag{9}$$

where *Max_iter* represents the maximum number of iterations.

Exploitation is the process of algorithmic local fine search, and TSO exploitation is the process of simulating the exponential decay of the primary discharge. The mathematical expression for exploitation behavior, inspired by Equation (2), is as follows:

$$X(t+1) = X^*(t) + [X(t) - C_1 \cdot X^*(t)] \cdot e^{-T} \tag{10}$$

To balance the exploration and exploitation phases, a random selection rule was used, with p being a random number in [0, 1] that conforms to a uniform distribution, and the search agent performed the exploration behavior when $p > 0.5$, and when $p \leq 0.5$, at which point the search agent undertook the development behavior.

The pseudo-code for TSO is shown in Algorithm 1.

Algorithm 1: TSO

Input: Number of Search Agents: N;
Dimension: d;
Maximum number of iterations: *Max_iter*
Output: The global optimum
Generate initial populations by the Equation (5)
Calculating the fitness value of the population
Filter the best search agent's fitness value and location
While $t <$ *Max_iter*
Calculating the value of T and C_1 by the Equations (7) and (8)
If $p > 0.5$
Update the location of the search agent by the Equation (6)
Else if $p \leq 0.5$
Update the location of the search agent by the Equation (10)
End if
Calculating the fitness value of the population
Update optimal search agent position and fitness
$t = t + 1$
End while

3. Improved Transient Search Algorithm

3.1. Chaotic Opposition Learning

Using the random, ergodic, and regular characteristics of chaotic variables for optimization search allows the algorithm to step out of the local optimum, maintain the population diversity, and improve the global search ability, but different chaotic mappings have a significant influence on the chaotic optimization process [57]. The diversity of the initial population can significantly affect the convergence speed and accuracy of the population intelligence algorithm, but the basic TSO is prone to generating poor quality populations by randomly initializing the population, which affects the convergence speed and merit-seeking accuracy of the algorithm.

To generate high-quality initial populations, the information in the solution space is fully extracted and captured by chaotic mapping in this paper. One of the widely used mapping mechanisms in chaos theory research is logistic chaos mapping [58] with the following mathematical iterative equation:

$$\lambda_{t+1} = \mu \times \lambda_t(1 - \lambda_t), t = 0, 1, 2, \cdots, T \tag{11}$$

where λ_t is a uniformly distributed random number in the interval [0, 1] and requires $\lambda_0 \notin \{0, 0.25, 0.5, 0.75, 1\}$, T is the predetermined maximum number of chaos iterations, and μ is the chaos control parameter. When $\mu = 4$, the system will be in a completely chaotic state.

Using the generated set of chaotic variables λ, the chaotic sequence is then applied to map the position vectors X of all d-dimensional search agents in turn into the upper and lower boundaries of the search space according to Equation (12), with the following mathematical expressions:

$$X_i^j = lb + \lambda_j \times (ub - lb) \tag{12}$$

where X_i^j is the coordinate of the j-th dimension of the i-th search agent and λ_j is the coordinate of the j-th dimension of λ after internal random ordering.

Opposition-based learning, which considers that a better solution may exist on the opposite side of the problem, has been successfully applied to many algorithms, either for initial population generation or for iterative updating of search agents [59].

Although chaotic sequences can produce populations that are rich in diversity and reasonably well distributed, it is undeniable that there may be better search agents on the

opposite side of the search space; then, the same number of opposing populations are produced again, as follows:

$$X_{op_i} = X_{\max} + X_{\min} - X_i \tag{13}$$

where X_{op_i} is the opposing position of the i-th agent, $X_{\max}$ represents the position of the largest boundary, $X_{\min}$ represents the position of the smallest boundary, and X_i is the position of the i-th individual.

Finally, these are combined into $2N$ alternative populations of search agents, i.e., the population is $\{X, X_{op}\}$ at this point, and the N populations with the best fitness are selected as the initial populations by calculating the fitness of the alternative populations.

3.2. Adaptive Inertia Weights

Inertia weights, which are inspired by particle swarm algorithms, play a decisive role in the algorithm's merit-seeking ability and convergence speed, and it has been shown in many algorithms that the performance of the algorithm can be improved by introducing adaptive inertia weights [60]. In the original TSO algorithm, the inertia weights are constant values, which limits the algorithm's merit-seeking ability and convergence speed. For the early iteration, large inertia weights can enhance the global search ability; in the late iteration, small inertia weights can enhance the local fine search ability and accelerate the convergence speed. The choice of inertia weighting strategy is crucial in the TSO search process, so a strategy for adaptively changing the inertia weights according to the number of iterations is proposed with the following expression:

$$w(t) = a\cos^b(\ln(1 + e^{\frac{t}{T_{\max}}}) + c \tag{14}$$

where a, b, and c are optional parameters.

After extensive experiments, it was found that the best results were obtained when a, b, and c were 21, 15, and 0.4, respectively. The graph is shown in Figure 1.

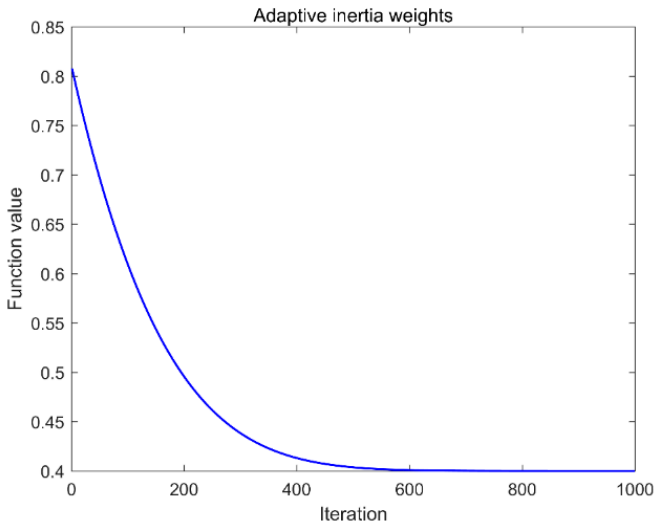


Figure 1. Curve of adaptive weights.

As can be seen from Figure 1, in the early iteration, the inertia weight is large and decreases rapidly, which is focused on the global search; in the late iteration, the inertia weight is small and decreases slowly, which is to be more detailed in the local fine search. With the introduction of adaptive inertia weights, the distribution of exploration and

exploitation behavior of ITSO proceeds according to Equations (15) and (16), with the following mathematical expressions:

$$X(t+1) = w(t)\cdot X^*(t) + e^{-T}[\cos(2\pi T) + \sin(2\pi T)]\left|X(t) - C_1 X^*(t)\right| \tag{15}$$

$$X(t+1) = w(t)\cdot X^*(t) + [X(t) - C_1\cdot X^*(t)]\cdot e^{-T} \tag{16}$$

3.3. Neighborhood Dimensional Learning

Dimension learning-based hunting (DLH), first proposed by Mohammad et al. [12], was first used to improve the performance of GWO, which balances global and local search and maintains population diversity by sharing information among search agents. On this basis, the diversity of positions among populations is ensured by first forming an alternative population, which is used to avoid search agents from aggregating in one piece to make DLH fail. Neighbors are then found within a given distance by constructing a domain space, which is used to share dimensional information among neighbors, so the strategy is called neighbor dimensional learning (NDL).

The population diversity plays a key role in the convergence speed and accuracy of the algorithm. The population diversity of the original TSO gradually decreases with the iterations of the algorithm, which often leads to high-dimensional complex problems easily solving to a local optimum and failure to find the global optimum solution. Therefore, to ensure that the populations remain rich in diversity during each iteration, a neighbor dimension learning strategy is used.

First, at the end of each iteration of the original TSO, candidate populations of the same size are generated for the original population, and the new population is repositioned using either the optimal individual information or its own information, according to the following equation:

$$\overrightarrow{X_{CAND_i}}(t) = \begin{cases} w * \overrightarrow{X}^*(t) + 2 \times (r - 0.5) \times (ub - lb \cdot r + lb) & p > 0.5 \\ w * \overrightarrow{X}_i(t) + 2 \times (r - 0.5) \times (ub - lb \cdot r + lb) & p < 0.5 \end{cases} \tag{17}$$

where $\overrightarrow{X}_i(t)$ denotes the position vector of the i-th search agent, $\overrightarrow{X_{CAND_i}}(t+1)$ denotes the position vector of the i-th candidate population individual, $\overrightarrow{X}^*(t)$ is the position vector of the elite individual, and p is the random probability.

Next, a neighborhood radius is calculated based on the Euclidean distance between the current position of $\overrightarrow{X}_i(t)$ and the candidate position $\overrightarrow{X_{CAND}}(t+1)$, which is calculated by the following equation:

$$R_i(t) = \left\| \overrightarrow{X}_i(t) - \overrightarrow{X_{CAND_i}}(t+1) \right\| \tag{18}$$

Then, according to $R_i(t)$, the Euclidean distance less than the radius search agent is sequentially filtered from the population, and these individuals are saved as neighbors of the i-th individual. The mathematical expression is shown as follows:

$$N_i(t) = \left\{ X_j(t) \mid D_i\left(X_i(t), X_j(t)\right) \le R_i(t), X_j(t) \in X \right\} \tag{19}$$

where $N_i(t)$ denotes the set of neighboring individuals and D_i denotes the Euclidean distance operation performed.

The next step performs dimensional learning among neighbors, updating the dimensional coordinates of the current individual using some dimensional information of neighboring individuals and the dimensional information of an individual randomly selected from the entire population, with the following mathematical expression:

$$X_{NDL_i,d}(t+1) = X_{i,d}(t) + \text{sign}(r-0.5) \times (X_{n,d}(t) - X_{r,d}(t)) \tag{20}$$

where $X_{i,d}(t)$ represents the d-dimensional information of the i-th search agent, $X_{NDL_i,d}(t+1)$ represents the new d-dimensional information, $X_{n,d}(t)$ represents the d-dimensional information of neighboring individuals, and $X_{r,d}(t)$ represents the d-dimensional information of a randomly selected individual.

Finally, the fitness of the candidate and NDL populations is calculated to select the updated information of the individuals of the populations, and the mathematical expression is shown as follows:

$$X_i(t+1) = \begin{cases} X_{CAND_i}(t+1) & \text{if } f(X_{CAND_i}(t+1)) < f(X_{NDL_i}(t+1)) \\ X_{NDL_i}(t+1) & \text{if } f(X_{CAND_i}(t+1)) < f(X_{NDL_i}(t+1)) \end{cases} \tag{21}$$

The pseudo-code for ITSO is shown in Algorithm 2. The block diagram of the ITSO is shown in Figure 2.

Algorithm 2: ITSO

Input: Number of Search Agents: N;
Dimension: d;
Maximum number of iterations: *Max_iter*
Output: The global optimum
Generate chaotic tent mapping sequences by the Equation (11)
Initialized populations by the Equation (12)
Generation of Opposing Populations by the Equation (13)
Calculate the fitness values of the alternative populations.
The first N with good fitness values are selected as the initial populations
While $t <$ *Max_iter*
Calculating Adaptive Inertia Weights by the Equation (14)
Calculating the value of T and C_1 by the Equations (7) and (8)
If $p > 0.5$
  Update the location of the search agent by the Equation (15)
Else if $p \leq 0.5$
  Update the location of the search agent by the Equation (16)
End if
Generation of candidate populations by the Equation (17)
Calculating Neighborhood Radius by the Equation (18)
Finding Neighborhood Populations by the Equation (19)
Calculation of NDL populations by the Equation (20)
Calculate fitness values to update population position by the Equation (21)
Update optimal search agent position and fitness
$t = t + 1$
End while

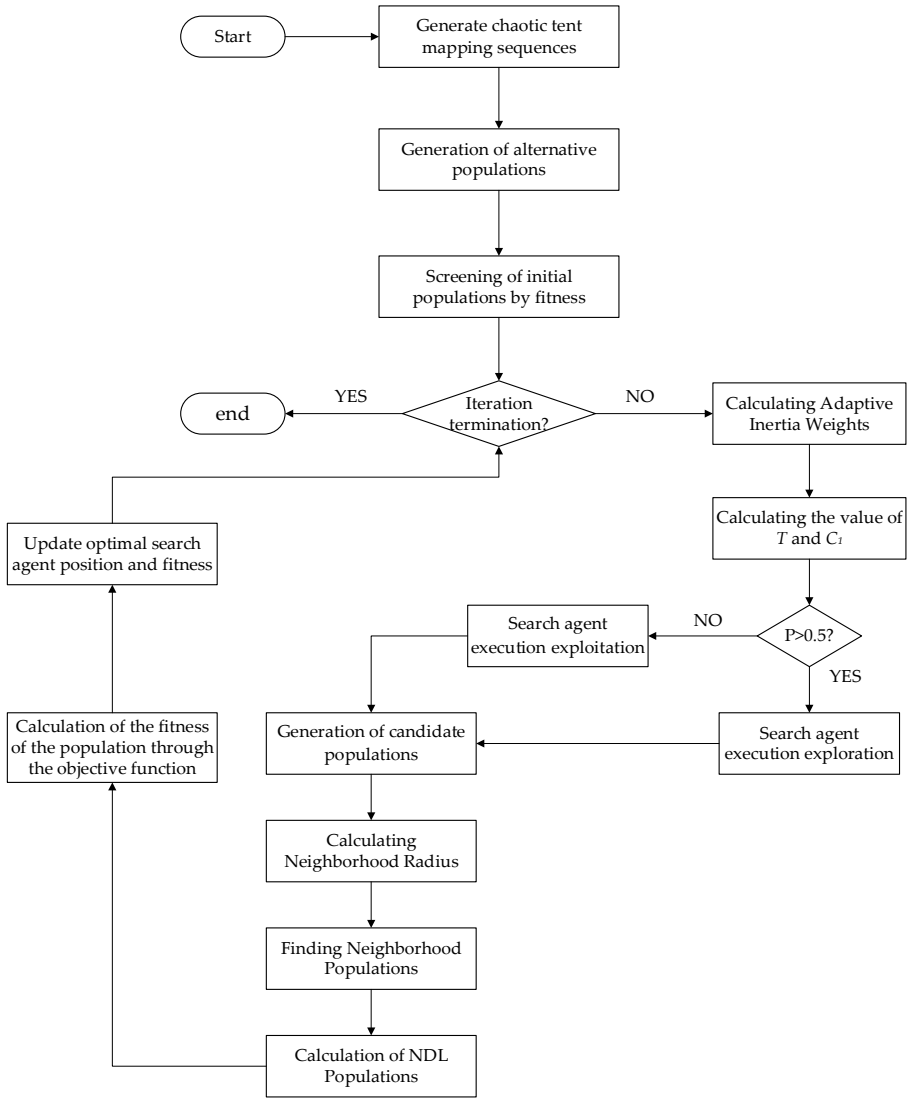


Figure 2. Block diagram of the improved transient search algorithm (ITSO).

4. Simulation Experiments and Comparative Analysis

4.1. Experimental Settings

To verify that the proposed ITSO shows significant superiority in solving global optimization problems, 18 internationally recognized benchmark test functions [26,61] are used for comparison experiments with nine intelligence algorithms (TSO, GA, DE, PSO, GWO, WOA, PPA, SOA, STOA) and seven improved swarm intelligence algorithms (AGPSO, MPSO, OBSCA, PSOGSA, CGWO, GWOCS, IGWO). Each algorithm was run 30 times independently on each benchmark test function, and the evaluation metrics selected for this experiment were the mean (Ave), standard deviation (Std), maximum (Max), and minimum (Min) values. The population size was 30 and the maximum number of iterations was 1000. To more clearly represent the differences in algorithm performance, the popular non-parametric Friedman test [62] was also used, which is able to rank the average performance of the experimental results for each algorithm on all tested functions; its final average ranking is shown at the end of the statistical table of experimental results. Wilcoxon's rank sum test analysis was also performed for the results of each independent experiment. The experimental environment was Windows 10 64 bit, MATLAB R2016A, Intel(R) Core CPU (i5-10210U 2.1 GHz), 16 G RAM. For the sake of fairness, the parameters in each algorithm were set with reference to the original document, and the specific parameters were set as shown in Table 1.

Table 1. Parameter settings of each algorithm.

Algorithm	Parameter Specific Settings
GA	$crossover = 0.2, mutation = 0.1$
DE	$crossover = 0.2, scaling\ factor = 0.64$
PSO	$c_1 = 2, c_2 = 2$
GWO	$a = 2 * \left(1 - \frac{t}{T_{\max}}\right)$
WOA	$a = 2 * \left(1 - \frac{t}{T_{\max}}\right)$
PPA	$c = 1, r \in [0, 1]$
SOA	$f_c = 2$, Control Parameter (A) $\in [2, 0]$
STOA	$S_A = 2 - \frac{2t}{T_{\max}}$
AGPSO	$c_1 = \frac{-2.05t}{T_{\max}} + 2.55, c_2 = \frac{-t}{T_{\max}} + 1.25$
MPSO	$c_1 = 2, c_2 = 2, w \in [0.4, 0.9]$
OBSCA	$r_1 = a - \frac{t}{T_{\max}}a, r_2 \in [0, 1]$
PSOGSA	$\alpha = 1, \beta = 1, w \in [0.4, 0.9]$
CGWO	$a = 2 * \left(1 - \frac{t}{T_{\max}}\right), \partial = 0.5, \beta = 0.2$
GWOCS	$a = 2 * \left(1 - \frac{t}{T_{\max}}\right), \sigma_v = 1$
IGWO	$a = 2 * \left(1 - \frac{t}{T_{\max}}\right)$
TSO	$k = 2, z \in [0, 2]$
ITSO	$k = 2, z \in [0, 2]$

4.2. Benchmark Function

Details of the 18 benchmarking functions are shown in Table 2. Table 2 includes seven high-dimensional single-peak functions (F1~F7), six high-dimensional multi-peak functions (F8~F13), and five fixed-dimensional multi-peak functions (F14~F18). Because the high-dimensional single-peak function has only one peak, it was used to test the local convergence accuracy and convergence speed of the algorithm; the high-dimensional multi-peak function and the fixed-dimensional multi-peak function have multiple peaks and only one global optimum, so were used to test the global optimum search and the ability to circumvent the local optimum of the algorithm. The 3D plot of the benchmark test function is shown in Figure 3. The shape of each benchmark test function can be seen in Figure 3, in which the darkest blue part represents the global optimum. It can be seen that the high-dimensional multi-peak benchmark test function has multiple local optima, which is meaningful for the performance testing of the algorithm.

Table 2. Description of the 18 classic benchmarking functions.

Type	Function	Dim	Range	Optimum Value
Unimodal	$F_1(x) = \sum_{i=1}^{n} x_i^2$	50	$[-100, 100]$	0
Unimodal	$F_2(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	50	$[-10, 10]$	0
Unimodal	$F_3(x) = \sum_{i=1}^{n} \left(\sum_{j-1}^{i} x_j \right)^2$	50	$[-100, 100]$	0
Unimodal	$F_4(x) = \max_i \{ \lvert x_i \rvert, 1 \le i \le n \}$	50	$[-100, 100]$	0
Unimodal	$F_5(x) = \sum_{i=1}^{n-1} \left[100 \left(x_{i+1} - x_i^2 \right)^2 + (x_i - 1)^2 \right]$	50	$[-30, 30]$	0
Unimodal	$F_6(x) = \sum_{i=1}^{n} (\lvert x_i + 0.5 \rvert)^2$	50	$[-100, 100]$	0
Unimodal	$F_7(x) = \sum_{i=1}^{n} i x_i^4 + \text{random}[0, 1)$	50	$[-1.28, 1.28]$	0
Multimodal	$F_8(x) = \sum_{i=1}^{n} -x_i \sin(\sqrt{\lvert x_i \rvert})$	50	$[-500, 500]$	$-418.9829 \times \mathrm{d}$
Multimodal	$F_9(x) = \sum_{i=1}^{n} \left[x_i^2 - 10 \cos(2\pi x_i) + 10 \right]$	50	$[-5.12, 5.12]$	0
Multimodal	$F_{10}(x) = -20exp(-0.2\sqrt{\frac{1}{n} \sum_{i=1}^{n} x_i^2}) - \exp\left(\frac{1}{n} \sum_{i=1}^{n} \cos(2\pi x_i) \right) + 20 + e$	50	$[-32, 32]$	0
Multimodal	$F_{11}(x) = \frac{1}{4000} \sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos\left(\frac{x_i}{\sqrt{i}} \right) + 1$	50	$[-600, 600]$	0
Multimodal	$F_{12}(x) = \frac{\pi}{n} \left\{ 10 \sin(\pi y_1) + \sum_{i=1}^{n-1} (y_i - 1)^2 \left[1 + 10 \sin^2(\pi y_{i+1}) \right] + (y_n - 1)^2 \right\} + \sum_{i=1}^{n} u(x_i, 10, 100, 4)$ $where\ y_i = 1 + \frac{x_i + 1}{4} \quad u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m x_i > a \\ 0 - a < x_i \le a \\ k(-x_i - a)^m x_i < -a \end{cases}$	50	$[-50, 50]$	0
Multimodal	$F_{13}(x) = 0.1 \left\{ \begin{array}{l} \sin^2(3\pi x_1) + \sum_{i=1}^{n} (x_i - 1)^2 \left[1 + \sin^2(3\pi x_i + 1) \right] + \\ (x_n - 1)^2 \left[1 + \sin^2(2\pi x_n) \right] \end{array} \right\} + \sum_{i=1}^{n} u(x_i, 5, 100, 4)$	50	$[-50, 50]$	0
Fixed Dimension	$F_{14}(x) = \left(\frac{1}{500} + \sum_{j=1}^{25} \frac{1}{j + \sum_{i=1}^{2} (x_i - a_{ij})^6} \right)^{-1}$	2	$[-65, 65]$	1
Fixed Dimension	$F_{15}(x) = \sum_{i=1}^{11} \left[a_i - \frac{x_1 (b_i^2 + b_i x_2)}{b_i^2 + b_i x_3 + x_4} \right]^2$	4	$[-5, 5]$	0.00030
Fixed Dimension	$F_{16}(x) = -\sum_{i=1}^{5} \left[(X - a_i)(X - a_i)^T + c_i \right]^{-1}$	4	$[0, 10]$	-10.1532
Fixed Dimension	$F_{17}(x) = -\sum_{i=1}^{7} \left[(X - a_i)(X - a_i)^T + c_i \right]^{-1}$	4	$[0, 10]$	-10.4028
Fixed Dimension	$F_{18}(x) = -\sum_{i=1}^{10} \left[(X - a_i)(X - a_i)^T + c_i \right]^{-1}$	4	$[0, 10]$	-10.5363

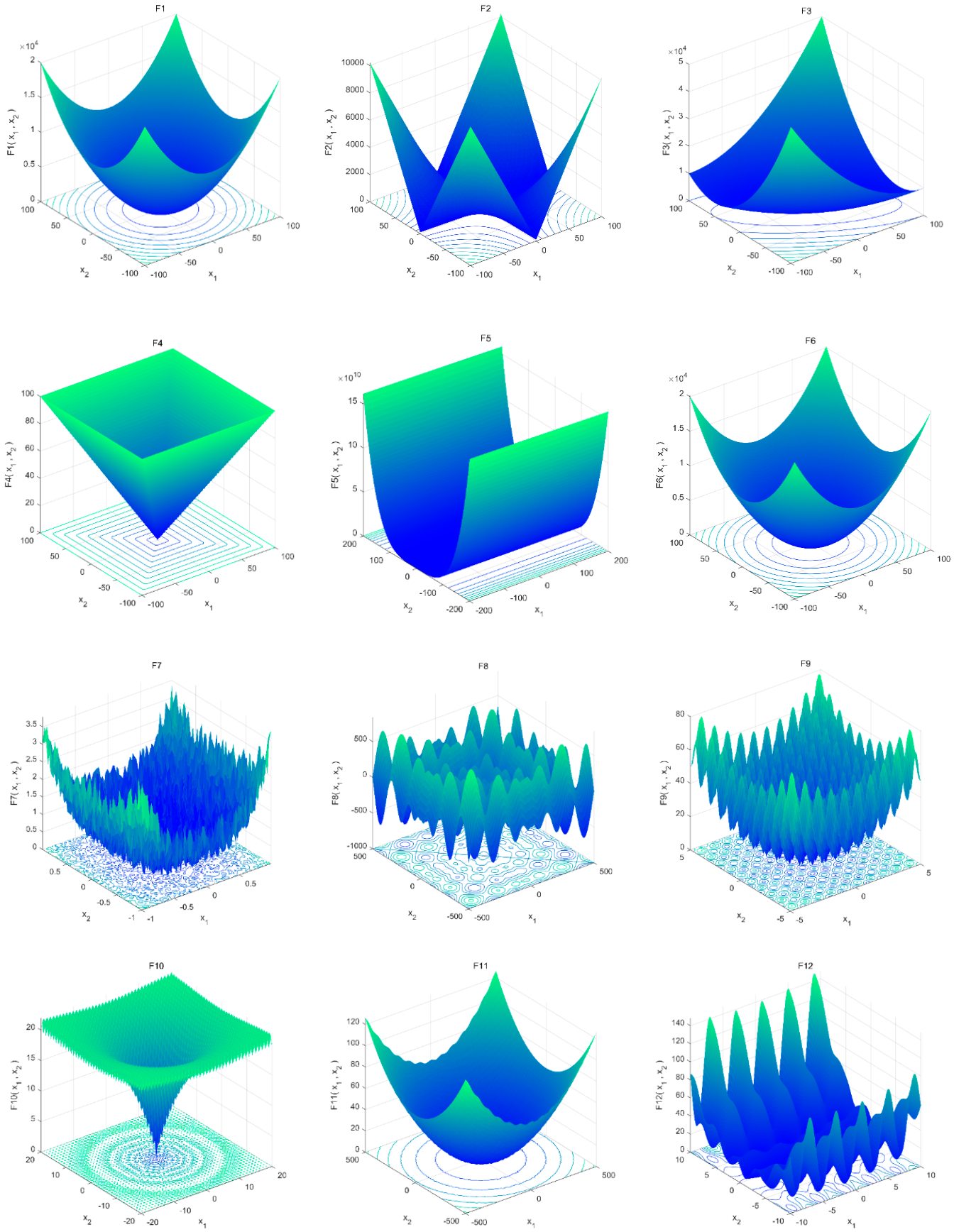


Figure 3. *Cont.*

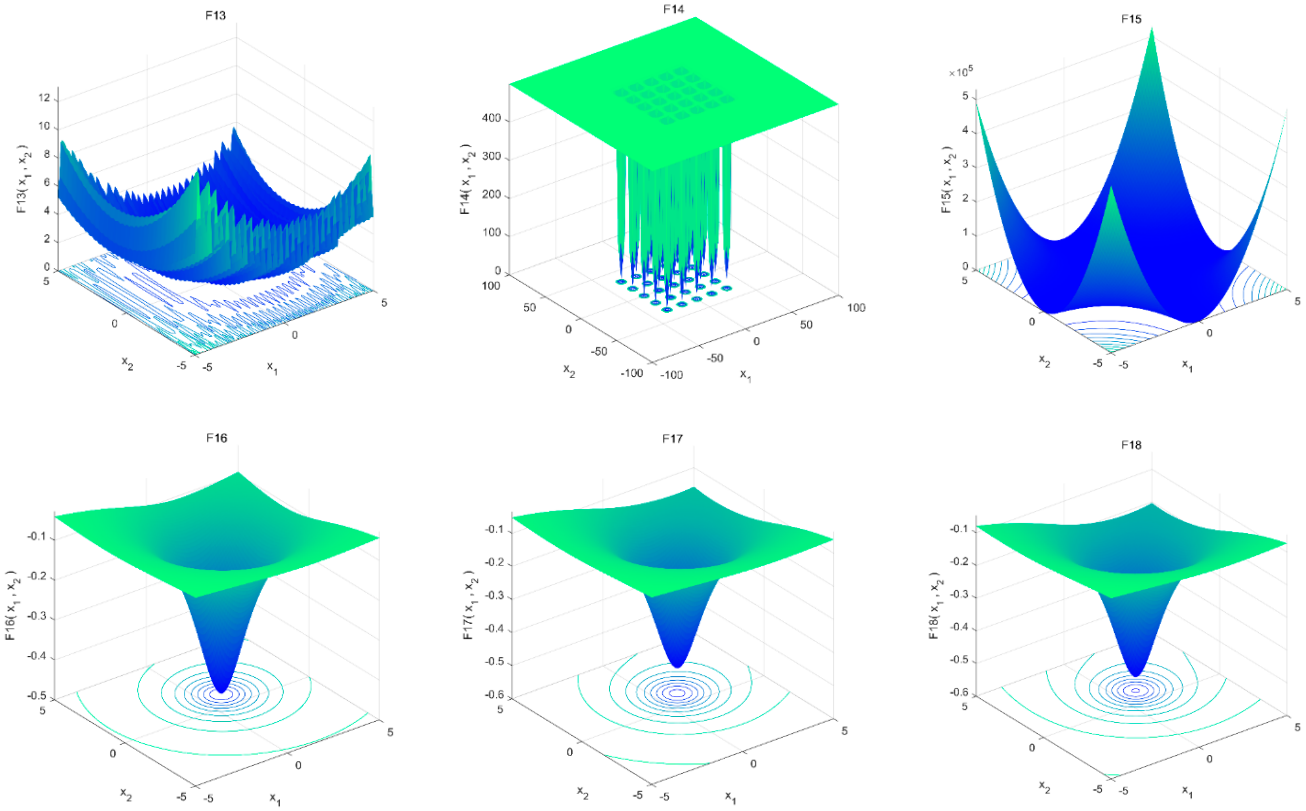


Figure 3. Three-dimensional plot of the benchmark test function.

4.3. Experimental Results and Analysis

The test results of the 18 benchmark functions are shown in Table 3, where the bolded data are the optimal values of performance metrics for all methods under the same function. As can be seen from Table 3, on F1~F6, ITSO is superior to other functions in terms of Ave, Std, Max, and Min; on F7, TSO performs best in terms of Ave, Std, Max, and Min, followed by ITSO; on all high-dimensional multi-peaked functions, all performance metrics of ITSO are optimal; on F14~F16, all performance metrics of ITSO are optimal; on F17 and F18, only the performance indicator of Min is not optimal. It is worth noting that the theoretical optimal values are obtained on F1, F2, F3, F4, F9, F11, F15, and F17. In the Friedman test, the average ranking was 1.9296 and the final ranking was first, the next best was TSO, and the worst performer was GA.

Table 3. Test results of ITSO and standard metaheuristic algorithms on benchmark test functions, The bolded part is the best result.

Function	Criteria	ITSO	TSO	PSO	GWO	WOA	PPA	SOA	STOA	GA	DE
F1	Ave	$\mathbf{0.00 \times 10^{+00}}$	2.44×10^{-201}	3.15×10^{-01}	4.65×10^{-59}	9.93×10^{-149}	$1.22 \times 10^{+00}$	1.24×10^{-27}	1.94×10^{-17}	$5.88 \times 10^{+00}$	7.03×10^{-11}
	Std	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	2.00×10^{-01}	1.02×10^{-58}	5.32×10^{-148}	$2.52 \times 10^{+00}$	2.00×10^{-27}	7.83×10^{-17}	$2.65 \times 10^{+00}$	4.48×10^{-11}
	Max	$\mathbf{0.00 \times 10^{+00}}$	7.32×10^{-200}	9.19×10^{-01}	5.53×10^{-58}	2.96×10^{-147}	$1.39 \times 10^{+01}$	6.91×10^{-27}	4.38×10^{-16}	$1.35 \times 10^{+01}$	1.97×10^{-10}
	Min	$\mathbf{0.00 \times 10^{+00}}$	6.19×10^{-301}	9.08×10^{-02}	1.12×10^{-61}	2.23×10^{-169}	5.42×10^{-02}	1.84×10^{-31}	1.20×10^{-20}	$1.82 \times 10^{+00}$	9.07×10^{-12}
F2	Ave	$\mathbf{0.00 \times 10^{+00}}$	4.22×10^{-102}	$8.74 \times 10^{+00}$	9.87×10^{-35}	6.40×10^{-101}	$3.57 \times 10^{+00}$	6.23×10^{-18}	3.44×10^{-12}	8.63×10^{-01}	2.80×10^{-07}
	Std	$\mathbf{0.00 \times 10^{+00}}$	2.27×10^{-101}	$8.22 \times 10^{+00}$	1.11×10^{-34}	3.45×10^{-100}	$2.60 \times 10^{+00}$	7.38×10^{-18}	7.09×10^{-12}	1.64×10^{-01}	8.12×10^{-08}
	Max	$\mathbf{0.00 \times 10^{+00}}$	1.26×10^{-100}	$3.06 \times 10^{+01}$	5.20×10^{-34}	1.92×10^{-99}	$1.01 \times 10^{+01}$	3.54×10^{-17}	3.91×10^{-11}	$1.21 \times 10^{+00}$	4.65×10^{-07}
	Min	$\mathbf{0.00 \times 10^{+00}}$	4.43×10^{-138}	3.98×10^{-01}	5.18×10^{-36}	1.58×10^{-114}	5.16×10^{-01}	2.27×10^{-19}	2.57×10^{-14}	5.94×10^{-01}	1.39×10^{-07}
F3	Ave	$\mathbf{0.00 \times 10^{+00}}$	4.15×10^{-84}	$7.65 \times 10^{+01}$	2.67×10^{-14}	$2.41 \times 10^{+04}$	$4.61 \times 10^{+02}$	2.03×10^{-12}	1.06×10^{-07}	$1.22 \times 10^{+04}$	$2.73 \times 10^{+04}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	2.24×10^{-83}	$1.59 \times 10^{+01}$	8.37×10^{-14}	$1.20 \times 10^{+04}$	$2.36 \times 10^{+02}$	7.43×10^{-12}	1.94×10^{-07}	$2.64 \times 10^{+03}$	$3.38 \times 10^{+03}$
	Max	$\mathbf{0.00 \times 10^{+00}}$	1.25×10^{-82}	$1.16 \times 10^{+02}$	3.49×10^{-13}	$5.20 \times 10^{+04}$	$1.02 \times 10^{+03}$	3.79×10^{-11}	7.31×10^{-07}	$1.85 \times 10^{+04}$	$3.64 \times 10^{+04}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	3.35×10^{-239}	$3.60 \times 10^{+01}$	2.48×10^{-20}	$3.23 \times 10^{+03}$	$1.15 \times 10^{+02}$	3.02×10^{-18}	2.43×10^{-11}	$8.23 \times 10^{+03}$	$2.12 \times 10^{+04}$
F4	Ave	$\mathbf{0.00 \times 10^{+00}}$	1.57×10^{-100}	$1.53 \times 10^{+00}$	1.02×10^{-14}	$3.79 \times 10^{+01}$	$3.69 \times 10^{+01}$	2.46×10^{-07}	2.22×10^{-05}	$7.65 \times 10^{+00}$	$2.43 \times 10^{+00}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	8.32×10^{-100}	2.31×10^{-01}	1.36×10^{-14}	$3.17 \times 10^{+01}$	$8.45 \times 10^{+00}$	9.90×10^{-07}	2.22×10^{-05}	$1.28 \times 10^{+00}$	3.85×10^{-01}
	Max	$\mathbf{0.00 \times 10^{+00}}$	4.64×10^{-99}	$2.08 \times 10^{+00}$	6.20×10^{-14}	$9.00 \times 10^{+01}$	$5.61 \times 10^{+01}$	5.54×10^{-06}	6.81×10^{-05}	$1.07 \times 10^{+01}$	$3.33 \times 10^{+00}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	1.44×10^{-135}	$1.05 \times 10^{+00}$	7.56×10^{-16}	1.52×10^{-01}	$2.37 \times 10^{+01}$	3.63×10^{-11}	1.26×10^{-06}	$5.27 \times 10^{+00}$	$1.58 \times 10^{+00}$
F5	Ave	$\mathbf{2.18 \times 10^{-04}}$	2.83×10^{-02}	$4.01 \times 10^{+02}$	$2.70 \times 10^{+01}$	$2.72 \times 10^{+01}$	$3.69 \times 10^{+02}$	$2.80 \times 10^{+01}$	$2.79 \times 10^{+01}$	$4.55 \times 10^{+02}$	$5.26 \times 10^{+01}$
	Std	$\mathbf{4.10 \times 10^{-04}}$	3.56×10^{-02}	$5.47 \times 10^{+02}$	7.39×10^{-01}	5.75×10^{-01}	$2.29 \times 10^{+02}$	6.22×10^{-01}	6.48×10^{-01}	$5.53 \times 10^{+02}$	$2.95 \times 10^{+01}$
	Max	$\mathbf{1.98 \times 10^{-03}}$	1.54×10^{-01}	$3.21 \times 10^{+03}$	$2.86 \times 10^{+01}$	$2.87 \times 10^{+01}$	$1.12 \times 10^{+03}$	$2.89 \times 10^{+01}$	$2.88 \times 10^{+01}$	$2.89 \times 10^{+03}$	$1.20 \times 10^{+02}$
	Min	$\mathbf{5.28 \times 10^{-07}}$	1.24×10^{-05}	$1.07 \times 10^{+02}$	$2.52 \times 10^{+01}$	$2.63 \times 10^{+01}$	$5.28 \times 10^{+01}$	$2.69 \times 10^{+01}$	$2.69 \times 10^{+01}$	$1.61 \times 10^{+02}$	$2.56 \times 10^{+01}$
F6	Ave	$\mathbf{5.53 \times 10^{-06}}$	6.77×10^{-04}	2.93×10^{-01}	6.26×10^{-01}	6.37×10^{-02}	8.35×10^{-01}	$3.19 \times 10^{+00}$	$2.60 \times 10^{+00}$	$5.51 \times 10^{+00}$	2.18×10^{-03}
	Std	$\mathbf{7.68 \times 10^{-06}}$	1.07×10^{-03}	1.69×10^{-01}	3.40×10^{-01}	9.28×10^{-02}	9.39×10^{-01}	4.14×10^{-01}	4.72×10^{-01}	$2.13 \times 10^{+00}$	9.02×10^{-04}
	Max	$\mathbf{3.11 \times 10^{-05}}$	5.26×10^{-03}	6.82×10^{-01}	$1.26 \times 10^{+00}$	4.57×10^{-01}	$4.22 \times 10^{+00}$	$3.93 \times 10^{+00}$	$3.49 \times 10^{+00}$	$1.11 \times 10^{+01}$	4.69×10^{-03}
	Min	$\mathbf{4.73 \times 10^{-08}}$	1.08×10^{-07}	7.62×10^{-02}	1.79×10^{-05}	1.03×10^{-02}	3.76×10^{-02}	$2.00 \times 10^{+00}$	$1.29 \times 10^{+00}$	$2.57 \times 10^{+00}$	7.92×10^{-04}
F7	Ave	1.93×10^{-04}	$\mathbf{9.56 \times 10^{-05}}$	$8.19 \times 10^{+00}$	9.88×10^{-04}	1.32×10^{-03}	3.79×10^{-01}	9.09×10^{-04}	1.57×10^{-03}	1.12×10^{-01}	3.00×10^{-02}
	Std	1.41×10^{-04}	$\mathbf{6.44 \times 10^{-05}}$	$7.40 \times 10^{+00}$	5.38×10^{-04}	1.68×10^{-03}	2.24×10^{-01}	6.35×10^{-04}	1.09×10^{-03}	3.38×10^{-02}	6.30×10^{-03}
	Max	6.89×10^{-04}	$\mathbf{2.31 \times 10^{-04}}$	$2.72 \times 10^{+01}$	2.22×10^{-03}	6.59×10^{-03}	$1.18 \times 10^{+00}$	2.87×10^{-03}	5.88×10^{-03}	1.84×10^{-01}	4.08×10^{-02}
	Min	3.33×10^{-05}	$\mathbf{2.28 \times 10^{-06}}$	3.05×10^{-01}	1.82×10^{-04}	5.75×10^{-06}	1.07×10^{-01}	1.63×10^{-04}	4.57×10^{-04}	5.38×10^{-02}	1.82×10^{-02}
F8	Ave	$\mathbf{-1.26 \times 10^{+04}}$	$\mathbf{-1.26 \times 10^{+04}}$	$-6.51 \times 10^{+03}$	$-6.18 \times 10^{+03}$	$-1.12 \times 10^{+04}$	$-8.02 \times 10^{+03}$	$-5.48 \times 10^{+03}$	$-5.59 \times 10^{+03}$	$-1.26 \times 10^{+04}$	$-1.24 \times 10^{+04}$
	Std	1.58×10^{-02}	$\mathbf{7.02 \times 10^{-03}}$	$1.02 \times 10^{+03}$	$6.39 \times 10^{+02}$	$1.55 \times 10^{+03}$	$7.82 \times 10^{+02}$	$7.18 \times 10^{+02}$	$7.09 \times 10^{+02}$	$6.66 \times 10^{+00}$	$1.34 \times 10^{+02}$
	Max	$\mathbf{-1.26 \times 10^{+04}}$	$\mathbf{-1.26 \times 10^{+04}}$	$-3.74 \times 10^{+03}$	$-4.91 \times 10^{+03}$	$-8.12 \times 10^{+03}$	$-6.25 \times 10^{+03}$	$-4.59 \times 10^{+03}$	$-4.43 \times 10^{+03}$	$-1.25 \times 10^{+04}$	$-1.21 \times 10^{+04}$
	Min	$\mathbf{-1.26 \times 10^{+04}}$	$\mathbf{-1.26 \times 10^{+04}}$	$-8.17 \times 10^{+03}$	$-7.22 \times 10^{+03}$	$-1.26 \times 10^{+04}$	$-9.61 \times 10^{+03}$	$-7.10 \times 10^{+03}$	$-8.19 \times 10^{+03}$	$-1.26 \times 10^{+04}$	$-1.26 \times 10^{+04}$
F9	Ave	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$1.71 \times 10^{+02}$	1.71×10^{-14}	$\mathbf{0.00 \times 10^{+00}}$	$6.22 \times 10^{+01}$	$1.77 \times 10^{+00}$	$5.21 \times 10^{+00}$	$2.59 \times 10^{+00}$	$6.28 \times 10^{+01}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$3.82 \times 10^{+01}$	2.60×10^{-14}	$\mathbf{0.00 \times 10^{+00}}$	$1.84 \times 10^{+01}$	$5.44 \times 10^{+00}$	$1.94 \times 10^{+01}$	8.73×10^{-01}	$6.07 \times 10^{+00}$
	Max	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$2.44 \times 10^{+02}$	5.68×10^{-14}	$\mathbf{0.00 \times 10^{+00}}$	$9.75 \times 10^{+01}$	$2.35 \times 10^{+01}$	$1.04 \times 10^{+02}$	$4.85 \times 10^{+00}$	$7.32 \times 10^{+01}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$9.55 \times 10^{+01}$	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$3.68 \times 10^{+01}$	$\mathbf{0.00 \times 10^{+00}}$	5.68×10^{-14}	$1.40 \times 10^{+00}$	$5.25 \times 10^{+01}$

Table 3. *Cont.*

Function	Criteria	ITSO	TSO	PSO	GWO	WOA	PPA	SOA	STOA	GA	DE
F10	Ave	**8.88×10^{-16}**	**8.88×10^{-16}**	$1.20 \times 10^{+00}$	1.62×10^{-14}	3.97×10^{-15}	$1.24 \times 10^{+01}$	$2.00 \times 10^{+01}$	$2.00 \times 10^{+01}$	$1.20 \times 10^{+00}$	2.15×10^{-06}
	Std	**$0.00 \times 10^{+00}$**	**$0.00 \times 10^{+00}$**	6.79×10^{-01}	3.57×10^{-15}	2.38×10^{-15}	$1.66 \times 10^{+00}$	1.79×10^{-03}	1.91×10^{-03}	2.86×10^{-01}	5.11×10^{-07}
	Max	**8.88×10^{-16}**	**8.88×10^{-16}**	$2.50 \times 10^{+00}$	2.22×10^{-14}	7.99×10^{-15}	$1.56 \times 10^{+01}$	$2.00 \times 10^{+01}$	$2.00 \times 10^{+01}$	$1.88 \times 10^{+00}$	3.13×10^{-06}
	Min	**8.88×10^{-16}**	**8.88×10^{-16}**	2.98×10^{-01}	7.99×10^{-15}	**8.88×10^{-16}**	$8.68 \times 10^{+00}$	$2.00 \times 10^{+01}$	$2.00 \times 10^{+01}$	7.22×10^{-01}	1.20×10^{-06}
F11	Ave	**$0.00 \times 10^{+00}$**	**$0.00 \times 10^{+00}$**	2.17×10^{-02}	2.85×10^{-03}	3.47×10^{-03}	4.76×10^{-01}	1.01×10^{-03}	2.32×10^{-02}	$1.05 \times 10^{+00}$	1.18×10^{-09}
	Std	**$0.00 \times 10^{+00}$**	**$0.00 \times 10^{+00}$**	1.03×10^{-02}	6.20×10^{-03}	1.31×10^{-02}	2.61×10^{-01}	3.94×10^{-03}	3.64×10^{-02}	1.87×10^{-02}	1.64×10^{-09}
	Max	**$0.00 \times 10^{+00}$**	**$0.00 \times 10^{+00}$**	3.96×10^{-02}	2.36×10^{-02}	5.92×10^{-02}	$1.05 \times 10^{+00}$	1.94×10^{-02}	1.39×10^{-01}	$1.08 \times 10^{+00}$	7.75×10^{-09}
	Min	**$0.00 \times 10^{+00}$**	**$0.00 \times 10^{+00}$**	3.85×10^{-03}	**$0.00 \times 10^{+00}$**	**$0.00 \times 10^{+00}$**	1.74×10^{-01}	**$0.00 \times 10^{+00}$**	**$0.00 \times 10^{+00}$**	9.98×10^{-01}	5.58×10^{-11}
F12	Ave	**1.53×10^{-07}**	1.84×10^{-05}	2.55×10^{-03}	3.22×10^{-02}	6.53×10^{-03}	$1.66 \times 10^{+01}$	3.08×10^{-01}	2.03×10^{-01}	3.33×10^{-02}	3.60×10^{-04}
	Std	**2.74×10^{-07}**	3.22×10^{-05}	2.00×10^{-03}	1.85×10^{-02}	5.54×10^{-03}	$7.62 \times 10^{+00}$	1.35×10^{-01}	1.01×10^{-01}	2.32×10^{-02}	2.97×10^{-04}
	Max	**1.54×10^{-06}**	1.63×10^{-04}	9.35×10^{-03}	7.91×10^{-02}	2.06×10^{-02}	$3.36 \times 10^{+01}$	7.37×10^{-01}	6.41×10^{-01}	1.13×10^{-01}	1.25×10^{-03}
	Min	**1.48×10^{-11}**	2.03×10^{-09}	3.04×10^{-04}	6.51×10^{-03}	6.35×10^{-04}	$3.08 \times 10^{+00}$	1.10×10^{-01}	6.63×10^{-02}	7.97×10^{-03}	1.12×10^{-04}
F13	Ave	**1.25×10^{-06}**	3.41×10^{-04}	8.26×10^{-02}	4.50×10^{-01}	2.03×10^{-01}	$5.44 \times 10^{+01}$	$1.99 \times 10^{+00}$	$1.74 \times 10^{+00}$	2.52×10^{-01}	1.39×10^{-03}
	Std	**1.81×10^{-06}**	4.76×10^{-04}	5.19×10^{-02}	2.12×10^{-01}	1.79×10^{-01}	$1.29 \times 10^{+01}$	1.57×10^{-01}	1.73×10^{-01}	9.96×10^{-02}	5.81×10^{-04}
	Max	**6.58×10^{-06}**	2.10×10^{-03}	2.41×10^{-01}	9.43×10^{-01}	8.84×10^{-01}	$8.20 \times 10^{+01}$	$2.41 \times 10^{+00}$	$2.00 \times 10^{+00}$	5.23×10^{-01}	3.10×10^{-03}
	Min	**3.52×10^{-10}**	3.44×10^{-07}	2.12×10^{-02}	4.13×10^{-05}	2.25×10^{-02}	$2.31 \times 10^{+01}$	$1.68 \times 10^{+00}$	$1.32 \times 10^{+00}$	1.14×10^{-01}	3.11×10^{-04}
F14	Ave	**0.9980**	1.0641	3.2264	4.3297	2.3715	4.0197	1.5271	1.3948	1.0514	0.9980
	Std	**0.0000**	0.3562	3.0592	3.9557	2.8933	2.6425	0.8774	0.7936	0.0747	0.0000
	Max	**0.9980**	2.9821	11.7187	12.6705	10.7632	10.7632	2.9821	2.9821	1.3161	0.9980
	Min	**0.9980**	**0.9980**	**0.9980**	**0.9980**	**0.9980**	**0.9980**	**0.9980**	**0.9980**	0.9980	0.9980
F15	Ave	**0.0003**	0.0004	0.0030	0.0044	0.0006	0.0004	0.0012	0.0011	0.0101	0.0006
	Std	**0.0000**	0.0001	0.0058	0.0080	0.0003	0.0003	0.0002	0.0003	0.0092	0.0001
	Max	**0.0004**	0.0006	0.0204	0.0204	0.0015	0.0016	0.0014	0.0013	0.0381	0.0009
	Min	**0.0003**	**0.0003**	0.0004	**0.0003**	**0.0003**	**0.0003**	**0.0003**	**0.0003**	0.0008	0.0004
F16	Ave	**−10.1531**	−10.1503	−8.2976	−9.9844	−8.1817	−8.3611	−2.6123	−2.8500	−5.4667	−9.7590
	Std	**0.0001**	0.0055	2.4388	0.9070	2.5852	2.8685	3.8453	3.5525	3.3752	1.2401
	Max	**−10.1529**	−10.1272	−5.0552	−5.1002	−2.6305	−2.6295	−0.3507	−0.2731	−2.6219	−4.8213
	Min	**−10.1532**	**−10.1532**	**−10.1532**	**−10.1532**	−10.1531	**−10.1532**	−10.1394	−10.1497	−10.1490	−10.1532
F17	Ave	**−10.4028**	−10.4014	−9.5112	−10.0482	−9.9291	−5.8348	−5.5870	−4.7072	−5.8589	−10.4027
	Std	**0.0002**	0.0032	2.3345	1.3258	1.7790	3.0797	4.4521	4.4994	3.4796	0.0002
	Max	**−10.4017**	−10.3898	−1.8376	−5.0877	−1.8374	−2.7337	−0.5211	−0.3724	−2.7345	−10.4021
	Min	−10.4028	**−10.4029**	**−10.4029**	−10.4028	−10.4028	−10.4003	−10.3867	−10.3926	−10.3960	**−10.4029**
F18	Ave	**−10.5362**	−10.5315	−9.5308	−10.5360	−8.7797	−7.0671	−6.6092	−7.5390	−5.6906	**−10.5360**
	Std	**0.0001**	0.0097	2.3124	0.0002	2.9477	3.6474	3.6848	4.2592	3.6545	3.5575
	Max	**−10.5359**	−10.4888	−1.8595	−10.5353	−1.8595	−2.2820	−0.4046	−0.5585	−2.4128	−10.5354
	Min	−10.5363	**−10.5364**	**−10.5364**	−10.5363	−10.5363	**−10.5364**	−10.5143	−10.5320	−10.5318	**−10.5364**
Friedman Ave Rank		**1.9296**	2.6500	6.4546	4.7259	4.9194	7.8500	6.6407	7.0565	7.8556	4.9176
Rank		**1**	2	6	3	5	9	7	8	10	4

The convergence curves are a visual representation to assess the development capability and convergence speed of the algorithm seeking. The convergence curves of ITSO and the other seven algorithms on the 18 benchmark functions are shown in Figure 4. As can be seen from Figure 4, ITSO converges significantly faster than the other algorithms on the high-dimensional single-peaked function, and the convergence precision is optimal. On high-dimensional multi-peaked functions, the convergence is still faster than other algorithms, and its convergence accuracy performs in line with other algorithms at some moments. On fixed-dimensional multi-peaked functions, ITSO shows superiority in both convergence speed and convergence precision.

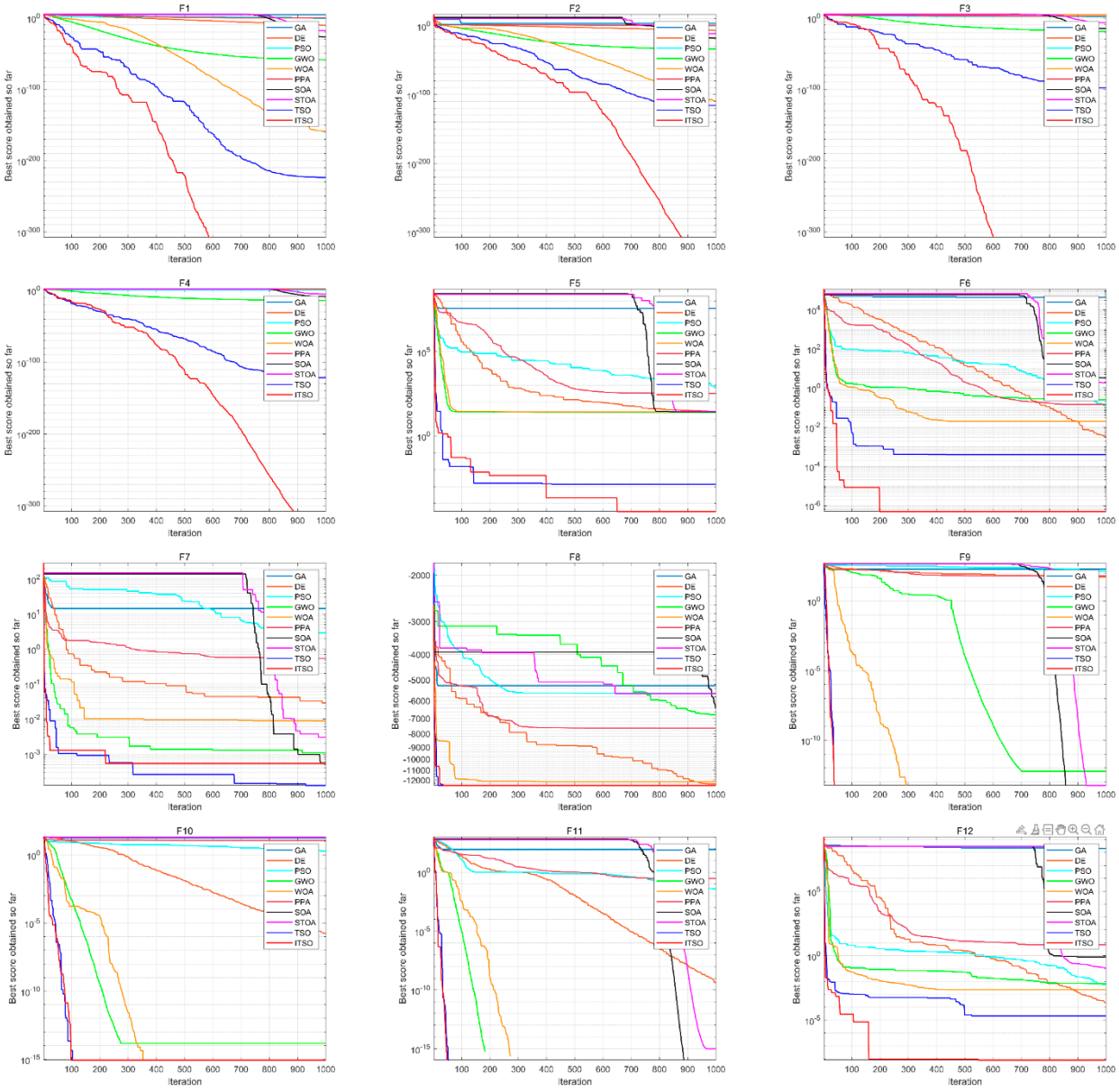


Figure 4. *Cont.*

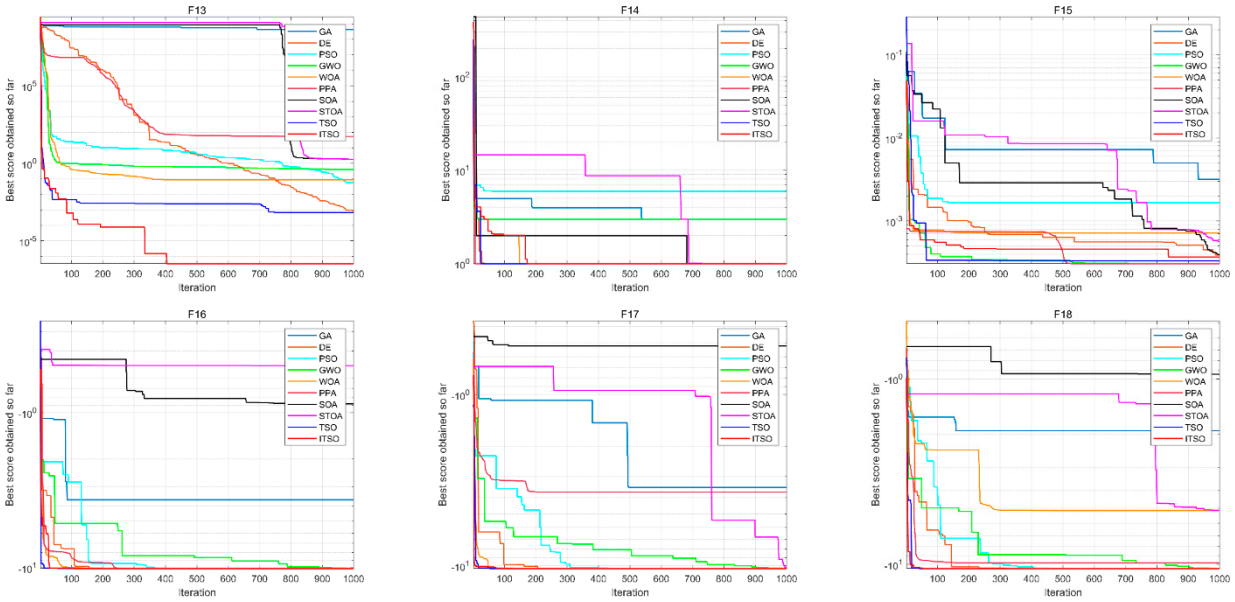


Figure 4. Convergence curve of ITSO with standard metaheuristic calculations.

The test results of ITSO with other improved swarm intelligence algorithms are shown in Table 4, where the bolded font in the table shows the optimal value of the current function under the same evaluation index. From Table 4, it can be concluded that ITSO is still the best-performing algorithm on high-dimensional single peaks, except for STD and MAX on F6, which are suboptimal to IGWO. On the high-dimensional multi-peak functions, ITSO shows superior performance, except for STD and MAX, which are suboptimal to IGWO on F12 only. ITSO performs second best to IGWO on F17 and F18 for fixed dimensional multi-peak functions, and still shows significant advantages on other functions. With an average ranking of 2.1426 in the Friedman test, ITSO still shows the best performance in each, followed by IGWO and the worst performance by PSOGSA.

The convergence curves of ITSO and the improved metaheuristic on the 18 benchmark functions are shown in Figure 5. Figure 5 shows that the convergence speed of ITSO on the high-dimensional single-peaked function F5 is the slowest, but the convergence accuracy is optimal. On the high-dimensional multi-peaked functions, ITSO converges slower than GWOCS and PSOGSA on F13, but they have both fallen into local extrema, which precisely reflects the strong ability of ITSO to circumvent local optima. ITSO exhibits the best convergence rate on fixed-dimensional multi-peaked functions, whereas the convergence curves of the other algorithms exhibit zigzagging, reflecting their poorer global merit-seeking ability.

4.4. Algorithm Stability Analysis

Although the standard deviation of each algorithm on the benchmark test function is given in Tables 3 and 4, it still does not visually represent the distribution of values for each experimental result. To more visually represent the stability of ITSO and other algorithms, this experiment uses box line plots to show the distribution of results for each function after 30 independent tests. The results of ITSO and the standard swarm intelligence algorithm on the benchmark test functions are shown in Figure 6.

Table 4. Test results of ITSO with improved metaheuristic algorithms on benchmark test functions, The bolded part is the best result.

Function	Criteria	ITSO	AGPSO	MPSO	OBSCA	PSOGSA	CGWO	GWOCS	IGWO
F1	Ave	$\mathbf{0.00 \times 10^{+00}}$	$1.91 \times 10{-}03$	1.77×10^{-03}	7.49×10^{-25}	2.06×10^{-04}	7.05×10^{-74}	2.48×10^{-59}	6.21×10^{-61}
	Std	$\mathbf{0.00 \times 10^{+00}}$	3.31×10^{-03}	6.02×10^{-03}	4.02×10^{-24}	6.37×10^{-04}	1.29×10^{-73}	5.24×10^{-59}	8.61×10^{-61}
	Max	$\mathbf{0.00 \times 10^{+00}}$	1.44×10^{-02}	2.94×10^{-02}	2.24×10^{-23}	2.87×10^{-03}	5.88×10^{-73}	2.14×10^{-58}	4.34×10^{-60}
	Min	$\mathbf{0.00 \times 10^{+00}}$	1.75×10^{-06}	5.93×10^{-07}	2.85×10^{-39}	2.03×10^{-19}	1.47×10^{-77}	1.01×10^{-62}	6.50×10^{-63}
F2	Ave	$\mathbf{0.00 \times 10^{+00}}$	$1.42 \times 10^{+00}$	$2.42 \times 10^{+01}$	2.37×10^{-25}	1.15×10^{-06}	1.26×10^{-43}	3.70×10^{-35}	7.80×10^{-37}
	Std	$\mathbf{0.00 \times 10^{+00}}$	$3.36 \times 10^{+00}$	$1.30 \times 10^{+01}$	9.26×10^{-25}	5.65×10^{-06}	3.79×10^{-43}	3.74×10^{-35}	1.08×10^{-36}
	Max	$\mathbf{0.00 \times 10^{+00}}$	$1.00 \times 10^{+01}$	$5.01 \times 10^{+01}$	5.15×10^{-24}	3.14×10^{-05}	2.00×10^{-42}	1.82×10^{-34}	4.72×10^{-36}
	Min	$\mathbf{0.00 \times 10^{+00}}$	3.22×10^{-03}	9.08×10^{-02}	1.05×10^{-31}	1.56×10^{-09}	9.81×10^{-46}	3.19×10^{-36}	1.81×10^{-38}
F3	Ave	$\mathbf{0.00 \times 10^{+00}}$	$1.40 \times 10^{+03}$	$1.17 \times 10^{+04}$	3.01×10^{-03}	$8.81 \times 10^{+03}$	9.47×10^{-18}	8.02×10^{-16}	2.61×10^{-10}
	Std	$\mathbf{0.00 \times 10^{+00}}$	$1.76 \times 10^{+03}$	$7.66 \times 10^{+03}$	1.58×10^{-02}	$8.17 \times 10^{+03}$	2.72×10^{-17}	3.36×10^{-15}	9.44×10^{-10}
	Max	$\mathbf{0.00 \times 10^{+00}}$	$7.59 \times 10^{+03}$	$2.85 \times 10^{+04}$	8.82×10^{-02}	$3.56 \times 10^{+04}$	1.36×10^{-16}	1.88×10^{-14}	5.24×10^{-09}
	Min	$\mathbf{0.00 \times 10^{+00}}$	$1.30 \times 10^{+02}$	$5.04 \times 10^{+02}$	2.30×10^{-13}	$1.07 \times 10^{+03}$	6.58×10^{-23}	1.63×10^{-20}	1.73×10^{-14}
F4	Ave	$\mathbf{0.00 \times 10^{+00}}$	$1.60 \times 10^{+01}$	$1.19 \times 10^{+01}$	2.63×10^{-05}	$5.88 \times 10^{+01}$	2.90×10^{-16}	9.89×10^{-15}	1.63×10^{-11}
	Std	$\mathbf{0.00 \times 10^{+00}}$	$3.73 \times 10^{+00}$	$4.11 \times 10^{+00}$	8.75×10^{-05}	$2.35 \times 10^{+01}$	1.56×10^{-15}	1.30×10^{-14}	2.68×10^{-11}
	Max	$\mathbf{0.00 \times 10^{+00}}$	$2.40 \times 10^{+01}$	$2.39 \times 10^{+01}$	4.73×10^{-04}	$8.75 \times 10^{+01}$	8.68×10^{-15}	6.36×10^{-14}	1.12×10^{-10}
	Min	$\mathbf{0.00 \times 10^{+00}}$	$9.86 \times 10^{+00}$	$4.63 \times 10^{+00}$	1.78×10^{-09}	$2.73 \times 10^{+01}$	9.31×10^{-21}	2.18×10^{-16}	6.47×10^{-13}
F5	Ave	$\mathbf{2.18 \times 10^{-04}}$	$1.43 \times 10^{+02}$	$3.93 \times 10^{+04}$	$2.82 \times 10^{+01}$	$2.67 \times 10^{+06}$	$2.66 \times 10^{+01}$	$2.68 \times 10^{+01}$	$2.28 \times 10^{+01}$
	Std	$\mathbf{4.10 \times 10^{-04}}$	$9.98 \times 10^{+01}$	$4.44 \times 10^{+04}$	3.39×10^{-01}	$1.44 \times 10^{+07}$	6.64×10^{-01}	7.46×10^{-01}	3.30×10^{-01}
	Max	$\mathbf{1.98 \times 10^{-03}}$	$4.46 \times 10^{+02}$	$9.01 \times 10^{+04}$	$2.89 \times 10^{+01}$	$8.00 \times 10^{+07}$	$2.79 \times 10^{+01}$	$2.85 \times 10^{+01}$	$2.35 \times 10^{+01}$
	Min	$\mathbf{5.28 \times 10^{-07}}$	$2.82 \times 10^{+01}$	$2.43 \times 10^{+01}$	$2.77 \times 10^{+01}$	$2.26 \times 10^{+01}$	$2.52 \times 10^{+01}$	$2.60 \times 10^{+01}$	$2.17 \times 10^{+01}$
F6	Ave	$\mathbf{5.53 \times 10^{-06}}$	8.95×10^{-04}	2.80×10^{-04}	$4.36 \times 10^{+00}$	$3.37 \times 10^{+02}$	7.73×10^{-05}	6.89×10^{-01}	5.63×10^{-06}
	Std	7.68×10^{-06}	2.06×10^{-03}	5.93×10^{-04}	2.45×10^{-01}	$1.81 \times 10^{+03}$	1.98×10^{-05}	4.17×10^{-01}	$\mathbf{2.90 \times 10^{-06}}$
	Max	3.11×10^{-05}	1.08×10^{-02}	3.01×10^{-03}	$4.82 \times 10^{+00}$	$1.01 \times 10^{+04}$	1.21×10^{-04}	$1.75 \times 10^{+00}$	$\mathbf{1.42 \times 10^{-05}}$
	Min	4.73×10^{-08}	3.33×10^{-06}	8.66×10^{-08}	$3.96 \times 10^{+00}$	$\mathbf{1.55 \times 10^{-19}}$	3.81×10^{-05}	9.89×10^{-06}	1.98×10^{-06}
F7	Ave	$\mathbf{1.93 \times 10^{-04}}$	5.00×10^{-02}	5.01×10^{-01}	2.09×10^{-03}	7.57×10^{-02}	8.69×10^{-02}	8.27×10^{-04}	1.14×10^{-03}
	Std	$\mathbf{1.41 \times 10^{-04}}$	1.82×10^{-02}	$1.56 \times 10^{+00}$	1.46×10^{-03}	2.52×10^{-02}	4.29×10^{-02}	3.29×10^{-04}	5.01×10^{-04}
	Max	$\mathbf{6.89 \times 10^{-04}}$	8.82×10^{-02}	$8.08 \times 10^{+00}$	6.56×10^{-03}	1.18×10^{-01}	2.13×10^{-01}	1.36×10^{-03}	2.66×10^{-03}
	Min	$\mathbf{3.33 \times 10^{-05}}$	1.67×10^{-02}	1.78×10^{-02}	3.42×10^{-04}	2.16×10^{-02}	2.97×10^{-02}	1.64×10^{-04}	3.07×10^{-04}
F8	Ave	$\mathbf{-1.26 \times 10^{+04}}$	$-9.65 \times 10^{+03}$	$-8.99 \times 10^{+03}$	$-4.07 \times 10^{+03}$	$-7.29 \times 10^{+03}$	$-5.18 \times 10^{+03}$	$-1.10 \times 10^{+04}$	$-9.46 \times 10^{+03}$
	Std	$\mathbf{1.58 \times 10^{-02}}$	$5.74 \times 10^{+02}$	$6.40 \times 10^{+02}$	$2.65 \times 10^{+02}$	$6.50 \times 10^{+02}$	$1.68 \times 10^{+03}$	$1.45 \times 10^{+03}$	$1.10 \times 10^{+03}$
	Max	$\mathbf{-1.26 \times 10^{+04}}$	$-8.66 \times 10^{+03}$	$-7.68 \times 10^{+03}$	$-3.65 \times 10^{+03}$	$-5.22 \times 10^{+03}$	$-3.42 \times 10^{+03}$	$-6.02 \times 10^{+03}$	$-6.57 \times 10^{+03}$
	Min	$\mathbf{-1.26 \times 10^{+04}}$	$-1.09 \times 10^{+04}$	$-1.02 \times 10^{+04}$	$-4.80 \times 10^{+03}$	$-8.62 \times 10^{+03}$	$-9.85 \times 10^{+03}$	$-1.24 \times 10^{+04}$	$-1.14 \times 10^{+04}$

Table 4. *Cont.*

Function	Criteria	ITSO	AGPSO	MPSO	OBSCA	PSOGSA	CGWO	GWOCS	IGWO
F9	Ave	**$0.00 \times 10^{+00}$**	$5.86 \times 10^{+01}$	$1.25 \times 10^{+02}$	**$0.00 \times 10^{+00}$**	$1.48 \times 10^{+02}$	**$0.00 \times 10^{+00}$**	4.80×10^{-01}	$1.99 \times 10^{+01}$
	Std	**$0.00 \times 10^{+00}$**	$2.18 \times 10^{+01}$	$2.62 \times 10^{+01}$	**$0.00 \times 10^{+00}$**	$3.68 \times 10^{+01}$	**$0.00 \times 10^{+00}$**	$1.27 \times 10^{+00}$	$1.68 \times 10^{+01}$
	Max	**$0.00 \times 10^{+00}$**	$1.22 \times 10^{+02}$	$1.75 \times 10^{+02}$	**$0.00 \times 10^{+00}$**	$2.23 \times 10^{+02}$	**$0.00 \times 10^{+00}$**	$4.42 \times 10^{+00}$	$8.78 \times 10^{+01}$
	Min	**$0.00 \times 10^{+00}$**	$2.89 \times 10^{+01}$	$5.37 \times 10^{+01}$	**$0.00 \times 10^{+00}$**	$6.37 \times 10^{+01}$	**$0.00 \times 10^{+00}$**	**$0.00 \times 10^{+00}$**	$2.98 \times 10^{+00}$
F10	Ave	**8.88×10^{-16}**	$2.46 \times 10^{+00}$	$1.53 \times 10^{+00}$	4.47×10^{-02}	$1.54 \times 10^{+01}$	8.11×10^{-15}	1.55×10^{-14}	1.37×10^{-14}
	Std	**$0.00 \times 10^{+00}$**	5.69×10^{-01}	8.25×10^{-01}	1.62×10^{-01}	$4.32 \times 10^{+00}$	6.38×10^{-16}	2.12×10^{-15}	2.53×10^{-15}
	Max	**8.88×10^{-16}**	$4.55 \times 10^{+00}$	$3.10 \times 10^{+00}$	8.12×10^{-01}	$1.91 \times 10^{+01}$	1.15×10^{-14}	2.22×10^{-14}	1.51×10^{-14}
	Min	**8.88×10^{-16}**	$1.50 \times 10^{+00}$	1.35×10^{-03}	4.44×10^{-15}	$1.50 \times 10^{+00}$	7.99×10^{-15}	1.15×10^{-14}	7.99×10^{-15}
F11	Ave	**$0.00 \times 10^{+00}$**	5.81×10^{-02}	$3.05 \times 10^{+00}$	1.29×10^{-12}	$1.21 \times 10^{+01}$	6.32×10^{-04}	1.49×10^{-03}	3.20×10^{-03}
	Std	**$0.00 \times 10^{+00}$**	4.02×10^{-02}	$1.62 \times 10^{+01}$	5.70×10^{-12}	$3.08 \times 10^{+01}$	3.40×10^{-03}	3.79×10^{-03}	5.44×10^{-03}
	Max	**$0.00 \times 10^{+00}$**	1.52×10^{-01}	$9.05 \times 10^{+01}$	3.13×10^{-11}	$9.09 \times 10^{+01}$	1.90×10^{-02}	1.13×10^{-02}	2.22×10^{-02}
	Min	**$0.00 \times 10^{+00}$**	1.47×10^{-03}	1.07×10^{-06}	**$0.00 \times 10^{+00}$**	1.63×10^{-07}	**$0.00 \times 10^{+00}$**	**$0.00 \times 10^{+00}$**	**$0.00 \times 10^{+00}$**
F12	Ave	**1.53×10^{-07}**	$1.80 \times 10^{+00}$	$1.28 \times 10^{+00}$	4.81×10^{-01}	$8.53 \times 10^{+06}$	3.27×10^{-02}	3.60×10^{-02}	2.39×10^{-07}
	Std	2.74×10^{-07}	$1.15 \times 10^{+00}$	$1.33 \times 10^{+00}$	6.87×10^{-02}	$4.60 \times 10^{+07}$	2.00×10^{-02}	1.53×10^{-02}	**1.12×10^{-07}**
	Max	1.54×10^{-06}	$4.14 \times 10^{+00}$	$6.26 \times 10^{+00}$	6.31×10^{-01}	$2.56 \times 10^{+08}$	1.06×10^{-01}	7.96×10^{-02}	**6.07×10^{-07}**
	Min	**1.48×10^{-11}**	2.82×10^{-03}	1.68×10^{-05}	3.12×10^{-01}	5.22×10^{-01}	6.56×10^{-03}	6.47×10^{-03}	1.16×10^{-07}
F13	Ave	**1.25×10^{-06}**	$3.42 \times 10^{+00}$	8.87×10^{-01}	$2.42 \times 10^{+00}$	$1.37 \times 10^{+07}$	8.86×10^{-02}	5.17×10^{-01}	3.25×10^{-03}
	Std	**1.81×10^{-06}**	$4.33 \times 10^{+00}$	$2.10 \times 10^{+00}$	1.52×10^{-01}	$7.36 \times 10^{+07}$	1.54×10^{-01}	2.37×10^{-01}	1.75×10^{-02}
	Max	**6.58×10^{-06}**	$2.01 \times 10^{+01}$	$1.11 \times 10^{+01}$	$2.70 \times 10^{+00}$	$4.10 \times 10^{+08}$	5.87×10^{-01}	$1.05 \times 10^{+00}$	9.74×10^{-02}
	Min	**3.52×10^{-10}**	8.16×10^{-02}	6.67×10^{-04}	$2.08 \times 10^{+00}$	$5.67 \times 10^{+00}$	9.80×10^{-05}	2.00×10^{-01}	1.98×10^{-06}
F14	Ave	**0.9980**	**0.9980**	**0.9980**	1.6612	3.1618	2.7656	5.0058	**0.9980**
	Std	**0.0000**	**0.0000**	0.0000	0.9341	2.9642	3.0361	4.5789	**0.0000**
	Max	**0.9980**	**0.9980**	**0.9980**	2.9821	10.7632	12.6705	12.6705	**0.9980**
	Min	**0.9980**	**0.9980**	**0.9980**	**0.9980**	**0.9980**	**0.9980**	**0.9980**	**0.9980**
F15	Ave	**0.0003**	0.0009	0.0027	0.0008	0.0032	0.0058	**0.0003**	0.0004
	Std	**0.0000**	0.0014	0.0059	0.0001	0.0061	0.0088	**0.0000**	0.0002
	Max	0.0004	0.0083	0.0204	0.0011	0.0204	0.0204	**0.0003**	0.0012
	Min	**0.0003**	**0.0003**	**0.0003**	0.0004	**0.0003**	**0.0003**	**0.0003**	**0.0003**
F16	Ave	**−10.1531**	−7.5403	−7.0458	−9.5456	−5.0697	−7.0971	−9.1031	−9.9210
	Std	**0.0001**	2.6471	3.0215	1.3003	3.3806	2.4947	2.1062	0.9586
	Max	**−10.1529**	−2.6829	−2.6305	−4.5249	−2.6305	−5.0552	−4.0602	−5.1008
	Min	**−10.1532**	**−10.1532**	**−10.1532**	−10.0760	−10.1532	−10.1530	−10.1531	**−10.1532**

Table 4. *Cont.*

Function	Criteria	ITSO	AGPSO	MPSO	OBSCA	PSOGSA	CGWO	GWOCS	IGWO
F17	Ave	−10.4028	−10.0513	−8.7116	−10.1378	−5.7383	−8.6308	−8.9906	**−10.4029**
	Std	0.0002	1.3156	2.8616	0.1446	3.6367	2.5054	2.3413	**0.0000**
	Max	−10.4017	−5.1288	−2.7519	−9.7125	−1.8376	−5.0877	−5.0877	**−10.4029**
	Min	−10.4028	**−10.4029**	**−10.4029**	−10.3963	**−10.4029**	**−10.4029**	−10.4028	**−10.4029**
F18	Ave	−10.5362	−10.3577	−8.9633	−10.2362	−5.5384	−8.8234	−9.6410	**−10.5364**
	Std	0.0001	0.9623	2.9103	0.1678	3.3755	2.6570	2.0015	**0.0000**
	Max	−10.5359	−5.1756	−2.4217	−9.8002	−2.4217	−2.4217	−5.1285	**−10.5364**
	Min	−10.5363	**−10.5364**	**−10.5364**	−10.5022	**−10.5364**	−10.5363	−10.5363	**−10.5364**
Friedman Ave Rank		**2.1426**	5.3398	5.5454	5.4250	6.3713	4.1704	4.0546	2.9509
Rank		**1**	5	7	6	8	4	3	2

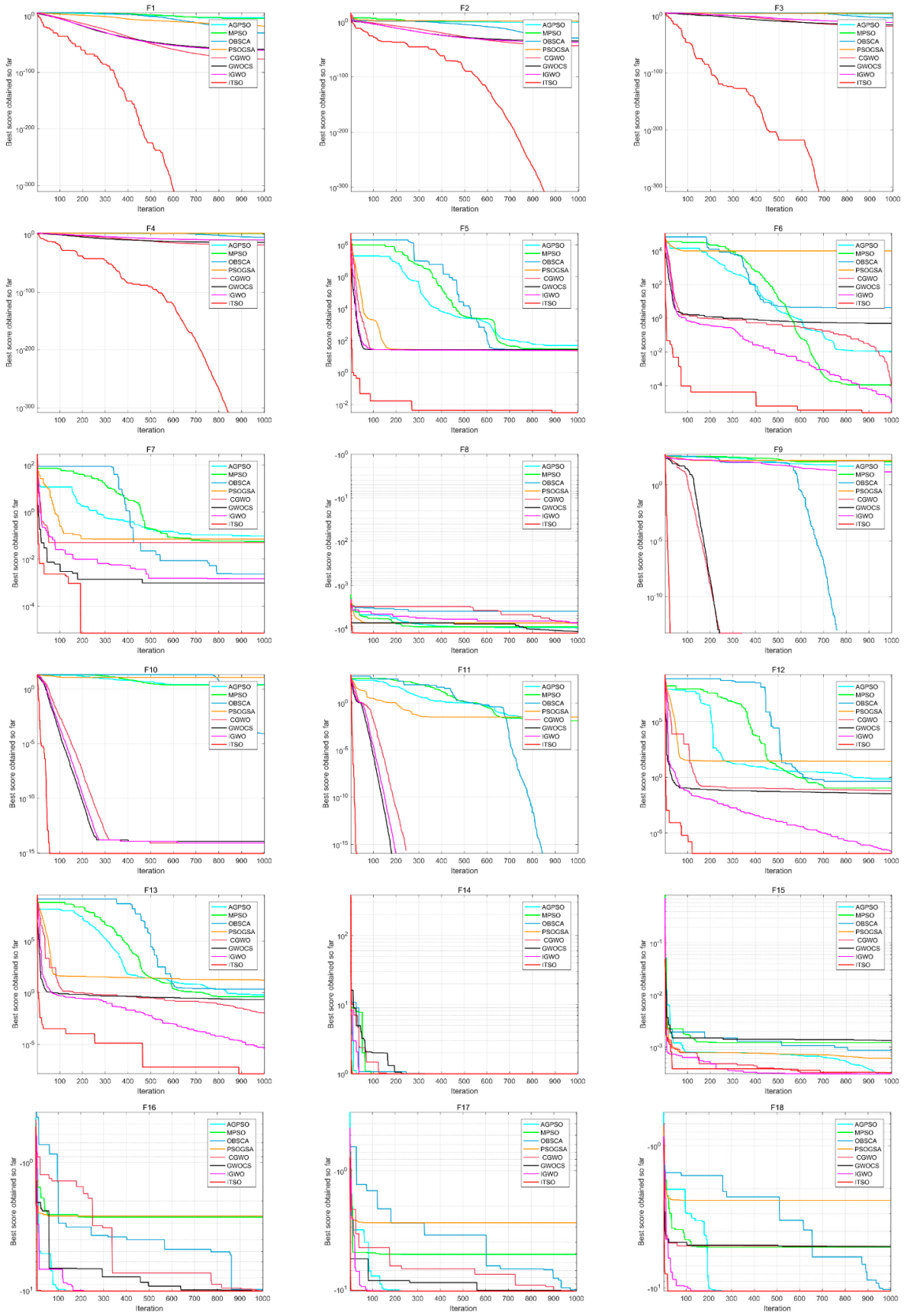


Figure 5. Convergence curve of ITSO with the improved metaheuristic algorithm.

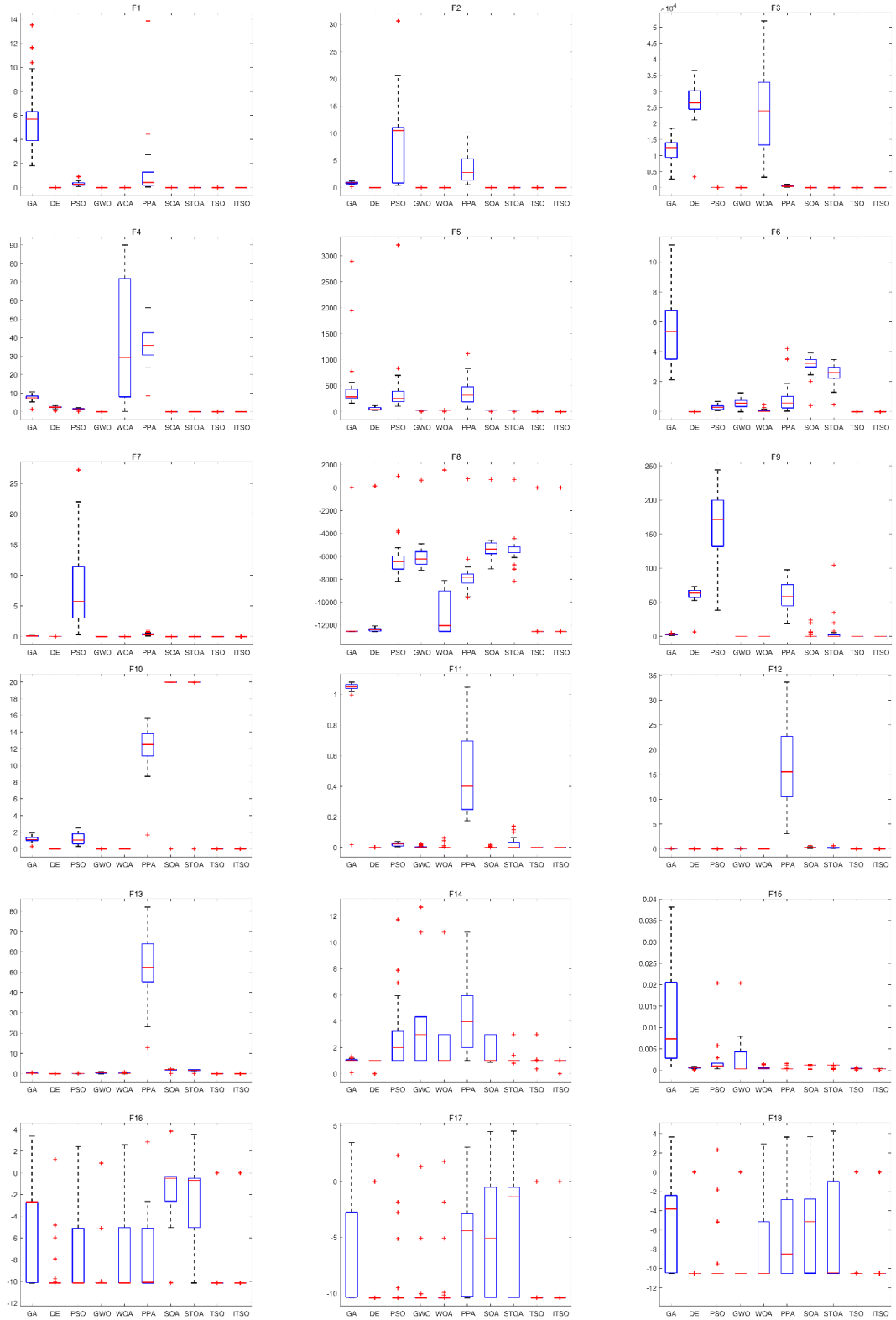


Figure 6. Box line diagram of ITSO with standard metaheuristic algorithms.

As can be seen from Figure 4, on all functions, ITSO compares its value distribution with the standard swarm intelligence optimization algorithm, and ITSO shows significant stability and superior performance, as evidenced by the fact that its lower edge, upper edge, and median are always lower than the other algorithms for the same function.

The distributions of the outcome-seeking values of ITSO and the improved metaheuristic algorithm on the benchmark test functions are shown in Figure 7. It can be seen from Figure 5 that the distribution of the search value of ITSO is the most stable, both on the high-dimensional single-peak, high-dimensional multi-peak and fixed-dimensional multi-peak functions, reflecting the remarkable stability of ITSO.

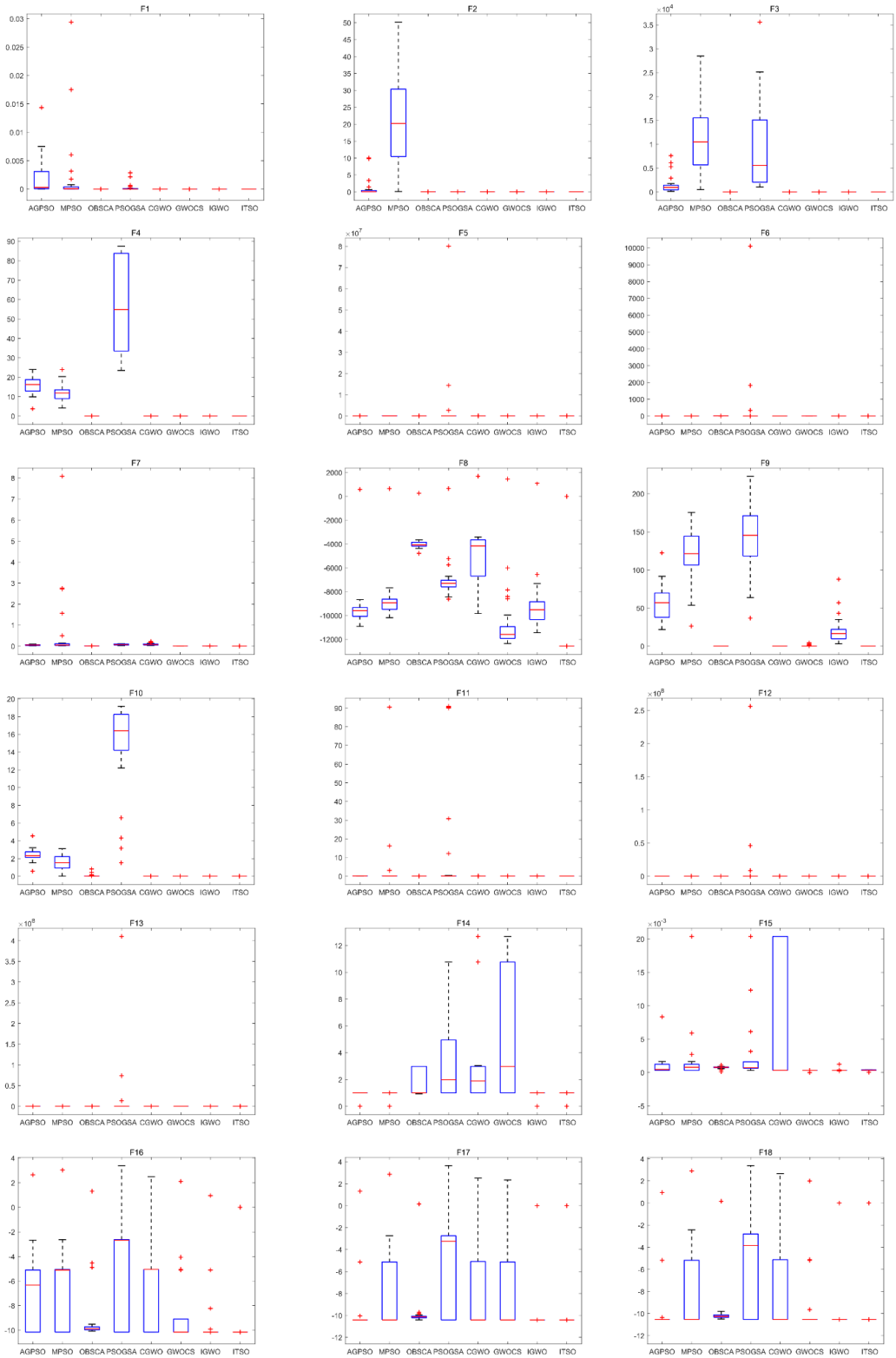


Figure 7. Box line diagram of ITSO with improved metaheuristic algorithm.

4.5. Wilcoxon's Rank Sum Test Analysis

Because too many random factors affect the performance of the algorithm, statistical tests are a suitable means to assess the variability in performance of ITSO and other algorithms. The commonly used Wilcoxon's rank sum test [63] was chosen for this experiment, and the significance evaluation index was set at 5%. For 30 independent experiments, *p*-values were obtained by two-by-two rank sum test analysis of ITSO and other algorithms. When the *p*-value is less than 5%, it means that there is a statistically significant difference between ITSO and this algorithm on the current function. The results of the Wilcoxon's rank sum test for ITSO with the standard metaheuristic algorithm are shown in Table 5, in which the bolded font indicates values greater than 5% or NaN. NaN indicates that both ITSO and the current algorithm converge to the global optimum.

As can be seen from Table 5, there is no statistically significant difference between ITSO and TSO on F9, F10, F11, and F15; no statistically significant difference between ITSO and PSO on F14 and F16; no statistically significant difference with WOA only on F9 and F11; no statistically significant difference between ITSO and SOA on F11; and a statistically significant difference between ITSO and the standard swarm intelligence algorithm in the vast majority of cases.

The results of Wilcoxon's rank sum test of ITSO with the improved metaheuristic algorithm are shown in Table 6. As can be seen from Table 6, on F6, there is no statistically significant difference between ITSO and PSOGSA; on F9, there is no statistically significant difference between ITSO and OBSCA and CGWO; on F11 and F15, there is no significant difference between CGWO and ITSO in the value of merit seeking; on F14 and F17, there is no statistically significant difference between PSOGSA and ITSO; AGPSO and ITSO showed no statistically significant differences on F15 and F16; MPSO and ITSO showed no statistically significant differences on F16; and statistically significant differences in the majority of cases.

4.6. High-Dimensional Performance Analysis

Because TSO tends to converge prematurely to local extrema when dealing with complex high-dimensional optimization problems, to test that the ITSO proposed in this paper can handle high-dimensional complex optimization problems more effectively, the dimensions from F1 to F13 were set to three higher-dimensional types, 100, 200 and 500. The population size and the maximum number of iterations remained the same as for the previous settings. The results of testing ITSO with the standard optimization algorithm for high-dimensional functions in dimensions 100, 200, and 500 are shown in Tables 7–9, respectively.

From Tables 7–9, it can be seen that ITSO performs second best to TSO on F7 in any dimension; ITSO performs second best to TSO on F2 when the dimension is 500; the performance of ITSO is extremely competitive and superior in all other cases; the final result of the average ranking of ITSO by the Friedman test is first. It is worth noting that the ITSO seeking values are theoretical on F1, F2, F3, F4, F9, and F11.

The test results of ITSO with the improved optimization algorithm for high-dimensional functions of dimension 100, 200, and 500 are shown in Tables 10–12, respectively. From these three tables, we can see that ITSO only performs second best to CGWO on F2 with dimension 500, and ITSO performs the best in all other cases; the final result of the average ranking of the Friedman test for ITSO is still first place. These precisely prove the remarkable superiority and stability of ITSO in solving complex high-dimensional problems.

Table 5. Wilcoxon's rank sum test results for ITSO and the standard metaheuristic algorithm, The bolded part is the best result.

Function		ITSO VS.								
		TSO	**PSO**	**GWO**	**WOA**	**PPA**	**SOA**	**STOA**	**GA**	**DE**
F1	*p*-value	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}
F2	*p*-value	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}
F3	*p*-value	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}
F4	*p*-value	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}
F5	*p*-value	1.07×10^{-07}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}
F6	*p*-value	2.19×10^{-08}	3.02×10^{-11}	4.50×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}
F7	*p*-value	3.03×10^{-03}	3.02×10^{-11}	6.72×10^{-10}	2.25×10^{-04}	3.02×10^{-11}	4.18×10^{-09}	4.50×10^{-11}	3.02×10^{-11}	3.02×10^{-11}
F8	*p*-value	1.70×10^{-02}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	7.39×10^{-11}
F9	*p*-value	**NaN**	1.21×10^{-12}	1.31×10^{-03}	**NaN**	1.21×10^{-12}	1.10×10^{-02}	1.15×10^{-12}	1.21×10^{-12}	1.21×10^{-12}
F10	*p*-value	**NaN**	1.21×10^{-12}	5.17×10^{-13}	3.14×10^{-08}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}
F11	*p*-value	**NaN**	1.21×10^{-12}	1.10×10^{-02}	$\mathbf{1.61 \times 10^{-01}}$	1.21×10^{-12}	$\mathbf{1.61 \times 10^{-01}}$	1.92×10^{-10}	1.21×10^{-12}	1.21×10^{-12}
F12	*p*-value	5.00×10^{-09}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}
F13	*p*-value	1.46×10^{-10}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}
F14	*p*-value	1.11×10^{-03}	$\mathbf{7.60 \times 10^{-02}}$	4.44×10^{-07}	1.49×10^{-06}	6.71×10^{-05}	3.02×10^{-11}	3.34×10^{-11}	3.02×10^{-11}	1.21×10^{-12}
F15	*p*-value	$\mathbf{8.77 \times 10^{-02}}$	4.06×10^{-11}	1.95×10^{-03}	3.56×10^{-04}	1.10×10^{-06}	6.12×10^{-10}	4.18×10^{-09}	3.02×10^{-11}	6.70×10^{-11}
F16	*p*-value	4.44×10^{-07}	$\mathbf{7.44 \times 10^{-02}}$	8.10×10^{-10}	1.78×10^{-10}	2.02×10^{-08}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	4.50×10^{-04}
F17	*p*-value	1.49×10^{-04}	6.36×10^{-07}	5.97×10^{-09}	3.50×10^{-09}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	4.41×10^{-09}
F18	*p*-value	3.59×10^{-05}	5.59×10^{-06}	3.09×10^{-06}	2.83×10^{-08}	1.16×10^{-07}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	9.27×10^{-12}

Table 6. Rank sum test results of Wilcoxon for ITSO with improved metaheuristics, The bolded part is the best result.

Function		ITSO VS.						
		AGPSO	**MPSO**	**OBSCA**	**PSOGSA**	**CGWO**	**GWOCS**	**IGWO**
F1	*p*-value	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}
F2	*p*-value	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}
F3	*p*-value	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}
F4	*p*-value	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}	1.21×10^{-12}
F5	*p*-value	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}
F6	*p*-value	1.86×10^{-09}	3.01×10^{-07}	3.02×10^{-11}	$\mathbf{1.33 \times 10^{-01}}$	3.02×10^{-11}	4.98×10^{-11}	4.36×10^{-02}
F7	*p*-value	3.02×10^{-11}	3.02×10^{-11}	1.21×10^{-10}	3.02×10^{-11}	3.02×10^{-11}	1.29×10^{-09}	1.09×10^{-10}
F8	*p*-value	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}
F9	*p*-value	1.21×10^{-12}	1.21×10^{-12}	$\mathbf{3.34 \times 10^{-01}}$	1.21×10^{-12}	**NaN**	2.78×10^{-03}	1.21×10^{-12}
F10	*p*-value	1.21×10^{-12}	1.21×10^{-12}	1.19×10^{-12}	1.21×10^{-12}	6.13×10^{-14}	1.20×10^{-13}	2.57×10^{-13}
F11	*p*-value	1.21×10^{-12}	1.21×10^{-12}	4.19×10^{-02}	1.21×10^{-12}	$\mathbf{3.34 \times 10^{-01}}$	4.19×10^{-02}	1.37×10^{-03}
F12	*p*-value	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	1.61×10^{-06}
F13	*p*-value	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.02×10^{-11}	3.82×10^{-10}
F14	*p*-value	1.21×10^{-12}	1.72×10^{-12}	3.02×10^{-11}	$\mathbf{1.00 \times 10^{+00}}$	7.74×10^{-06}	8.84×10^{-07}	1.72×10^{-12}
F15	*p*-value	$\mathbf{6.31 \times 10^{-01}}$	7.94×10^{-03}	3.02×10^{-11}	8.48×10^{-09}	$\mathbf{5.11 \times 10^{-01}}$	3.02×10^{-11}	8.48×10^{-09}
F16	*p*-value	$\mathbf{6.61 \times 10^{-01}}$	$\mathbf{6.62 \times 10^{-01}}$	3.02×10^{-11}	7.78×10^{-03}	3.69×10^{-11}	2.37×10^{-10}	7.56×10^{-09}
F17	*p*-value	5.12×10^{-05}	1.78×10^{-03}	3.02×10^{-11}	$\mathbf{7.64 \times 10^{-02}}$	2.67×10^{-09}	3.08×10^{-08}	1.10×10^{-11}
F18	*p*-value	4.23×10^{-09}	3.39×10^{-04}	3.02×10^{-11}	7.91×10^{-03}	3.50×10^{-09}	1.75×10^{-05}	4.11×10^{-12}

Table 7. Results of ITSO and standard optimization algorithms for high-dimensional functions with dimension 100, The bolded part is the best result.

Function	Criteria	ITSO	TSO	PSO	GWO	WOA	PPA	SOA	STOA	GA	DE
F1	Ave	$\mathbf{0.00 \times 10^{+00}}$	1.02×10^{-176}	$1.06 \times 10^{+02}$	1.90×10^{-29}	2.84×10^{-148}	$4.04 \times 10^{+03}$	2.93×10^{-15}	1.50×10^{-09}	$1.22 \times 10^{+02}$	$5.87 \times 10^{+01}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$2.33 \times 10^{+01}$	1.47×10^{-29}	1.27×10^{-147}	$1.55 \times 10^{+03}$	5.93×10^{-15}	2.60×10^{-09}	$2.47 \times 10^{+01}$	$1.02 \times 10^{+01}$
	Max	$\mathbf{0.00 \times 10^{+00}}$	3.06×10^{-175}	$2.33 \times 10^{+01}$	5.63×10^{-29}	6.95×10^{-147}	$7.69 \times 10^{+03}$	3.17×10^{-14}	9.70×10^{-09}	$1.76 \times 10^{+02}$	$8.38 \times 10^{+01}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	7.89×10^{-276}	$6.26 \times 10^{+01}$	6.50×10^{-31}	7.59×10^{-162}	$1.53 \times 10^{+03}$	3.01×10^{-17}	6.90×10^{-12}	$8.46 \times 10^{+01}$	$3.92 \times 10^{+01}$
F2	Ave	$\mathbf{0.00 \times 10^{+00}}$	9.87×10^{-101}	$2.19 \times 10^{+02}$	5.45×10^{-18}	5.69×10^{-100}	$9.29 \times 10^{+01}$	5.17×10^{-11}	1.35×10^{-07}	$6.59 \times 10^{+00}$	$4.30 \times 10^{+00}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	4.76×10^{-100}	$5.13 \times 10^{+01}$	3.14×10^{-18}	2.04×10^{-99}	$4.06 \times 10^{+01}$	4.82×10^{-11}	2.30×10^{-07}	5.38×10^{-01}	4.12×10^{-01}
	Max	$\mathbf{0.00 \times 10^{+00}}$	2.64×10^{-99}	$5.13 \times 10^{+01}$	1.51×10^{-17}	9.96×10^{-99}	$2.23 \times 10^{+02}$	1.87×10^{-10}	9.83×10^{-07}	$7.80 \times 10^{+00}$	$5.21 \times 10^{+00}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	6.59×10^{-130}	$1.13 \times 10^{+02}$	2.37×10^{-18}	3.92×10^{-112}	$5.75 \times 10^{+01}$	1.70×10^{-12}	4.66×10^{-09}	$4.99 \times 10^{+00}$	$3.49 \times 10^{+00}$
F3	Ave	$\mathbf{0.00 \times 10^{+00}}$	2.13×10^{-66}	$1.41 \times 10^{+04}$	$2.17 \times 10^{+01}$	$9.58 \times 10^{+05}$	$3.31 \times 10^{+04}$	5.73×10^{-02}	$2.23 \times 10^{+01}$	$1.04 \times 10^{+05}$	$4.09 \times 10^{+05}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	7.97×10^{-66}	$2.37 \times 10^{+03}$	$5.44 \times 10^{+01}$	$2.21 \times 10^{+05}$	$1.04 \times 10^{+04}$	2.03×10^{-01}	$6.86 \times 10^{+01}$	$1.36 \times 10^{+04}$	$2.93 \times 10^{+04}$
	Max	$\mathbf{0.00 \times 10^{+00}}$	3.25×10^{-65}	$2.37 \times 10^{+03}$	$2.68 \times 10^{+02}$	$1.45 \times 10^{+06}$	$5.68 \times 10^{+04}$	8.43×10^{-01}	$3.54 \times 10^{+02}$	$1.28 \times 10^{+05}$	$4.83 \times 10^{+05}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	8.37×10^{-200}	$9.91 \times 10^{+03}$	2.99×10^{-03}	$3.86 \times 10^{+05}$	$1.40 \times 10^{+04}$	9.58×10^{-07}	1.79×10^{-02}	$7.97 \times 10^{+04}$	$3.39 \times 10^{+05}$
F4	Ave	$\mathbf{0.00 \times 10^{+00}}$	1.56×10^{-103}	$1.02 \times 10^{+01}$	4.94×10^{-03}	$7.77 \times 10^{+01}$	$5.38 \times 10^{+01}$	$5.70 \times 10^{+01}$	$5.81 \times 10^{+01}$	$3.02 \times 10^{+01}$	$8.62 \times 10^{+01}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	6.84×10^{-103}	$1.28 \times 10^{+00}$	1.23×10^{-02}	$2.27 \times 10^{+01}$	$6.37 \times 10^{+00}$	$2.43 \times 10^{+01}$	$2.25 \times 10^{+01}$	$2.05 \times 10^{+00}$	$2.20 \times 10^{+00}$
	Max	$\mathbf{0.00 \times 10^{+00}}$	3.72×10^{-102}	$1.28 \times 10^{+00}$	6.48×10^{-02}	$9.61 \times 10^{+01}$	$6.53 \times 10^{+01}$	$8.86 \times 10^{+01}$	$8.92 \times 10^{+01}$	$3.46 \times 10^{+01}$	$9.02 \times 10^{+01}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	2.95×10^{-139}	$7.76 \times 10^{+00}$	2.84×10^{-05}	$1.13 \times 10^{+01}$	$4.11 \times 10^{+01}$	$3.56 \times 10^{+00}$	$3.19 \times 10^{+00}$	$2.65 \times 10^{+01}$	$8.14 \times 10^{+01}$
F5	Ave	$\mathbf{6.26 \times 10^{-04}}$	1.22×10^{-01}	$1.06 \times 10^{+05}$	$9.74 \times 10^{+01}$	$9.77 \times 10^{+01}$	$1.14 \times 10^{+06}$	$9.86 \times 10^{+01}$	$9.85 \times 10^{+01}$	$3.68 \times 10^{+03}$	$6.34 \times 10^{+04}$
	Std	$\mathbf{1.04 \times 10^{-03}}$	2.56×10^{-01}	$2.64 \times 10^{+04}$	7.30×10^{-01}	3.89×10^{-01}	$5.27 \times 10^{+05}$	2.61×10^{-01}	2.70×10^{-01}	$7.79 \times 10^{+02}$	$1.46 \times 10^{+04}$
	Max	$\mathbf{4.76 \times 10^{-03}}$	$1.09 \times 10^{+00}$	$2.64 \times 10^{+04}$	$9.84 \times 10^{+01}$	$9.83 \times 10^{+01}$	$2.07 \times 10^{+06}$	$9.88 \times 10^{+01}$	$9.87 \times 10^{+01}$	$5.13 \times 10^{+03}$	$1.11 \times 10^{+05}$
	Min	$\mathbf{4.16 \times 10^{-07}}$	1.11×10^{-04}	$7.14 \times 10^{+04}$	$9.60 \times 10^{+01}$	$9.70 \times 10^{+01}$	$2.15 \times 10^{+05}$	$9.80 \times 10^{+01}$	$9.79 \times 10^{+01}$	$2.51 \times 10^{+03}$	$4.01 \times 10^{+04}$
F6	Ave	$\mathbf{1.96 \times 10^{-05}}$	1.73×10^{-03}	$1.08 \times 10^{+02}$	$8.95 \times 10^{+00}$	$1.93 \times 10^{+00}$	$2.94 \times 10^{+03}$	$1.83 \times 10^{+01}$	$1.68 \times 10^{+01}$	$1.23 \times 10^{+02}$	$3.56 \times 10^{+03}$
	Std	$\mathbf{2.95 \times 10^{-05}}$	2.82×10^{-03}	$1.97 \times 10^{+01}$	8.29×10^{-01}	7.88×10^{-01}	$7.42 \times 10^{+02}$	7.35×10^{-01}	6.93×10^{-01}	$2.72 \times 10^{+01}$	$4.63 \times 10^{+02}$
	Max	$\mathbf{1.18 \times 10^{-04}}$	1.53×10^{-02}	$1.97 \times 10^{+01}$	$1.05 \times 10^{+01}$	$3.89 \times 10^{+00}$	$4.95 \times 10^{+03}$	$2.00 \times 10^{+01}$	$1.85 \times 10^{+01}$	$1.76 \times 10^{+02}$	$4.72 \times 10^{+03}$
	Min	$\mathbf{7.58 \times 10^{-09}}$	1.93×10^{-06}	$7.10 \times 10^{+01}$	$7.35 \times 10^{+00}$	8.22×10^{-01}	$1.87 \times 10^{+03}$	$1.69 \times 10^{+01}$	$1.52 \times 10^{+01}$	$7.22 \times 10^{+01}$	$2.87 \times 10^{+03}$
F7	Ave	1.85×10^{-04}	$\mathbf{1.26 \times 10^{-04}}$	$6.93 \times 10^{+02}$	2.71×10^{-03}	1.71×10^{-03}	$7.00 \times 10^{+00}$	2.36×10^{-03}	7.14×10^{-03}	8.75×10^{-01}	7.61×10^{-01}
	Std	1.73×10^{-04}	$\mathbf{1.30 \times 10^{-04}}$	$1.55 \times 10^{+02}$	1.09×10^{-03}	1.16×10^{-03}	$3.45 \times 10^{+00}$	1.98×10^{-03}	4.30×10^{-03}	1.42×10^{-01}	1.00×10^{-01}
	Max	7.72×10^{-04}	$\mathbf{6.20 \times 10^{-04}}$	$1.55 \times 10^{+02}$	5.46×10^{-03}	4.76×10^{-03}	$1.81 \times 10^{+01}$	7.52×10^{-03}	2.30×10^{-02}	$1.20 \times 10^{+00}$	9.64×10^{-01}
	Min	$\mathbf{7.70 \times 10^{-07}}$	5.87×10^{-06}	$4.30 \times 10^{+02}$	6.00×10^{-04}	2.04×10^{-05}	$3.54 \times 10^{+00}$	8.93×10^{-05}	1.76×10^{-03}	5.66×10^{-01}	5.72×10^{-01}
F8	Ave	$\mathbf{-4.19 \times 10^{+04}}$	$-4.19 \times 10^{+04}$	$-2.08 \times 10^{+04}$	$-1.64 \times 10^{+04}$	$-3.90 \times 10^{+04}$	$-2.19 \times 10^{+04}$	$-1.09 \times 10^{+04}$	$-1.14 \times 10^{+04}$	$-4.16 \times 10^{+04}$	$-1.81 \times 10^{+04}$
	Std	$\mathbf{9.54 \times 10^{-02}}$	$6.38 \times 10^{+01}$	$2.15 \times 10^{+03}$	$2.25 \times 10^{+03}$	$3.99 \times 10^{+03}$	$1.07 \times 10^{+03}$	$1.73 \times 10^{+03}$	$1.83 \times 10^{+03}$	$4.93 \times 10^{+01}$	$5.52 \times 10^{+02}$
	Max	$\mathbf{-4.19 \times 10^{+04}}$	$-4.15 \times 10^{+04}$	$2.15 \times 10^{+03}$	$-6.22 \times 10^{+03}$	$-2.97 \times 10^{+04}$	$-2.01 \times 10^{+04}$	$-8.82 \times 10^{+03}$	$-8.62 \times 10^{+03}$	$-4.15 \times 10^{+04}$	$-1.68 \times 10^{+04}$
	Min	$-4.19 \times 10^{+04}$	$\mathbf{-4.19 \times 10^{+04}}$	$-2.41 \times 10^{+04}$	$-1.92 \times 10^{+04}$	$-4.19 \times 10^{+04}$	$-2.46 \times 10^{+04}$	$-1.49 \times 10^{+04}$	$-1.72 \times 10^{+04}$	$-4.17 \times 10^{+04}$	$-1.91 \times 10^{+04}$
F9	Ave	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$1.13 \times 10^{+03}$	7.16×10^{-01}	$\mathbf{0.00 \times 10^{+00}}$	$2.96 \times 10^{+02}$	8.39×10^{-01}	$3.46 \times 10^{+00}$	$3.06 \times 10^{+01}$	$7.16 \times 10^{+02}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$8.61 \times 10^{+01}$	$2.21 \times 10^{+00}$	$\mathbf{0.00 \times 10^{+00}}$	$6.86 \times 10^{+01}$	$3.06 \times 10^{+00}$	$5.89 \times 10^{+00}$	$2.72 \times 10^{+00}$	$1.78 \times 10^{+01}$
	Max	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$8.61 \times 10^{+01}$	$9.28 \times 10^{+00}$	$\mathbf{0.00 \times 10^{+00}}$	$4.81 \times 10^{+02}$	$1.56 \times 10^{+01}$	$2.98 \times 10^{+01}$	$3.61 \times 10^{+01}$	$7.46 \times 10^{+02}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$9.70 \times 10^{+02}$	1.14×10^{-13}	$\mathbf{0.00 \times 10^{+00}}$	$2.02 \times 10^{+02}$	$\mathbf{0.00 \times 10^{+00}}$	1.82×10^{-12}	$2.65 \times 10^{+01}$	$6.76 \times 10^{+02}$

Table 7. *Cont.*

Function	Criteria	ITSO	TSO	PSO	GWO	WOA	PPA	SOA	STOA	GA	DE
F10	Ave	$\mathbf{8.88 \times 10^{-16}}$	$\mathbf{8.88 \times 10^{-16}}$	$5.56 \times 10^{+00}$	1.11×10^{-13}	4.56×10^{-15}	$1.56 \times 10^{+01}$	$2.00 \times 10^{+01}$	$2.00 \times 10^{+01}$	$2.81 \times 10^{+00}$	$3.04 \times 10^{+00}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	3.84×10^{-01}	8.93×10^{-15}	2.67×10^{-15}	9.42×10^{-01}	2.92×10^{-04}	3.20×10^{-04}	1.77×10^{-01}	2.81×10^{-01}
	Max	$\mathbf{8.88 \times 10^{-16}}$	$\mathbf{8.88 \times 10^{-16}}$	3.84×10^{-01}	1.36×10^{-13}	7.99×10^{-15}	$1.71 \times 10^{+01}$	$2.00 \times 10^{+01}$	$2.00 \times 10^{+01}$	$3.14 \times 10^{+00}$	$3.99 \times 10^{+00}$
	Min	$\mathbf{8.88 \times 10^{-16}}$	$\mathbf{8.88 \times 10^{-16}}$	$4.71 \times 10^{+00}$	9.33×10^{-14}	$\mathbf{8.88 \times 10^{-16}}$	$1.35 \times 10^{+01}$	$2.00 \times 10^{+01}$	$2.00 \times 10^{+01}$	$2.41 \times 10^{+00}$	$2.29 \times 10^{+00}$
F11	Ave	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	7.96×10^{-01}	3.65×10^{-03}	3.70×10^{-18}	$3.14 \times 10^{+01}$	4.21×10^{-03}	1.09×10^{-02}	$2.08 \times 10^{+00}$	$1.52 \times 10^{+00}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	1.11×10^{-01}	7.55×10^{-03}	1.99×10^{-17}	$1.10 \times 10^{+01}$	1.33×10^{-02}	2.26×10^{-02}	1.86×10^{-01}	8.60×10^{-02}
	Max	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	1.11×10^{-01}	2.43×10^{-02}	1.11×10^{-16}	$5.67 \times 10^{+01}$	5.90×10^{-02}	8.66×10^{-02}	$2.60 \times 10^{+00}$	$1.65 \times 10^{+00}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	5.39×10^{-01}	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$1.16 \times 10^{+01}$	$\mathbf{0.00 \times 10^{+00}}$	4.83×10^{-12}	$1.65 \times 10^{+00}$	$1.36 \times 10^{+00}$
F12	Ave	$\mathbf{3.96 \times 10^{-08}}$	9.37×10^{-06}	$5.62 \times 10^{+00}$	2.44×10^{-01}	1.78×10^{-02}	$6.30 \times 10^{+04}$	7.36×10^{-01}	6.39×10^{-01}	2.37×10^{-01}	$6.16 \times 10^{+06}$
	Std	$\mathbf{4.03 \times 10^{-08}}$	9.78×10^{-06}	$2.37 \times 10^{+00}$	5.86×10^{-02}	9.00×10^{-03}	$1.29 \times 10^{+05}$	6.09×10^{-02}	8.33×10^{-02}	6.96×10^{-02}	$2.10 \times 10^{+06}$
	Max	$\mathbf{1.52 \times 10^{-07}}$	3.91×10^{-05}	$2.37 \times 10^{+00}$	4.17×10^{-01}	3.85×10^{-02}	$6.80 \times 10^{+05}$	8.66×10^{-01}	8.63×10^{-01}	3.74×10^{-01}	$1.08 \times 10^{+07}$
	Min	$\mathbf{5.53 \times 10^{-12}}$	1.55×10^{-08}	$1.37 \times 10^{+00}$	1.57×10^{-01}	7.39×10^{-03}	$6.07 \times 10^{+01}$	6.21×10^{-01}	5.17×10^{-01}	1.01×10^{-01}	$2.33 \times 10^{+06}$
F13	Ave	$\mathbf{4.36 \times 10^{-06}}$	7.27×10^{-04}	$1.03 \times 10^{+02}$	$6.21 \times 10^{+00}$	$1.78 \times 10^{+00}$	$4.92 \times 10^{+05}$	$9.02 \times 10^{+00}$	$8.81 \times 10^{+00}$	$6.31 \times 10^{+00}$	$1.56 \times 10^{+07}$
	Std	$\mathbf{1.18 \times 10^{-05}}$	1.05×10^{-03}	$2.36 \times 10^{+01}$	3.32×10^{-01}	6.17×10^{-01}	$6.14 \times 10^{+05}$	1.81×10^{-01}	3.18×10^{-01}	$1.42 \times 10^{+00}$	$5.79 \times 10^{+06}$
	Max	$\mathbf{6.54 \times 10^{-05}}$	3.82×10^{-03}	$2.36 \times 10^{+01}$	$6.98 \times 10^{+00}$	$3.25 \times 10^{+00}$	$2.74 \times 10^{+06}$	$9.32 \times 10^{+00}$	$9.47 \times 10^{+00}$	$9.88 \times 10^{+00}$	$3.41 \times 10^{+07}$
	Min	$\mathbf{4.63 \times 10^{-10}}$	2.84×10^{-07}	$6.38 \times 10^{+01}$	$5.49 \times 10^{+00}$	5.84×10^{-01}	$2.96 \times 10^{+04}$	$8.56 \times 10^{+00}$	$8.13 \times 10^{+00}$	$3.89 \times 10^{+00}$	$7.33 \times 10^{+06}$
Friedman Ave Rank		**1.3731**	1.8859	7.7205	4.3090	4.0141	8.4974	5.9897	6.3359	6.6103	8.2641
Rank		**1**	2	8	4	3	10	5	6	7	9

Table 8. Results of ITSO with standard optimization algorithms for high-dimensional functions of dimension 200, The bolded part is the best result.

Function	Criteria	ITSO	TSO	PSO	GWO	WOA	PPA	SOA	STOA	GA	DE
F1	Ave	$\mathbf{0.00 \times 10^{+00}}$	1.56×10^{-180}	$7.12 \times 10^{+02}$	4.50×10^{-20}	3.29×10^{-145}	$3.25 \times 10^{+04}$	8.09×10^{-12}	4.51×10^{-07}	$1.79 \times 10^{+03}$	$3.13 \times 10^{+04}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$8.69 \times 10^{+01}$	2.89×10^{-20}	1.30×10^{-144}	$9.93 \times 10^{+03}$	1.08×10^{-11}	8.10×10^{-07}	$1.82 \times 10^{+02}$	$2.64 \times 10^{+03}$
	Max	$\mathbf{0.00 \times 10^{+00}}$	4.68×10^{-179}	$8.87 \times 10^{+02}$	1.37×10^{-19}	6.70×10^{-144}	$5.75 \times 10^{+04}$	4.98×10^{-11}	4.55×10^{-06}	$2.19 \times 10^{+03}$	$3.68 \times 10^{+04}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	2.85×10^{-283}	$5.48 \times 10^{+02}$	5.70×10^{-21}	3.32×10^{-161}	$1.22 \times 10^{+04}$	5.60×10^{-13}	5.22×10^{-09}	$1.37 \times 10^{+03}$	$2.70 \times 10^{+04}$
F2	Ave	$\mathbf{0.00 \times 10^{+00}}$	1.19×10^{-103}	$1.08 \times 10^{+30}$	1.69×10^{-12}	1.33×10^{-100}	$3.84 \times 10^{+02}$	4.99×10^{-09}	2.91×10^{-06}	$3.47 \times 10^{+01}$	$3.25 \times 10^{+02}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	6.34×10^{-103}	$3.75 \times 10^{+30}$	6.26×10^{-13}	4.93×10^{-100}	$1.02 \times 10^{+02}$	3.69×10^{-09}	4.74×10^{-06}	$2.23 \times 10^{+00}$	$2.91 \times 10^{+01}$
	Max	$\mathbf{0.00 \times 10^{+00}}$	3.53×10^{-102}	$1.91 \times 10^{+31}$	3.11×10^{-12}	2.21×10^{-99}	$5.51 \times 10^{+02}$	1.80×10^{-08}	2.66×10^{-05}	$3.94 \times 10^{+01}$	$3.82 \times 10^{+02}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{5.23 \times 10^{-141}}$	$6.42 \times 10^{+02}$	7.54×10^{-13}	1.62×10^{-110}	$1.94 \times 10^{+02}$	7.96×10^{-10}	1.17×10^{-07}	$2.99 \times 10^{+01}$	$2.62 \times 10^{+02}$
F3	Ave	$\mathbf{0.00 \times 10^{+00}}$	1.19×10^{-45}	$8.32 \times 10^{+04}$	$3.19 \times 10^{+03}$	$4.26 \times 10^{+06}$	$1.20 \times 10^{+05}$	$7.05 \times 10^{+01}$	$1.15 \times 10^{+03}$	$3.44 \times 10^{+05}$	$1.60 \times 10^{+06}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	6.40×10^{-45}	$1.81 \times 10^{+04}$	$2.92 \times 10^{+03}$	$1.38 \times 10^{+06}$	$3.54 \times 10^{+04}$	$1.78 \times 10^{+02}$	$1.21 \times 10^{+03}$	$2.72 \times 10^{+04}$	$1.09 \times 10^{+05}$
	Max	$\mathbf{0.00 \times 10^{+00}}$	3.56×10^{-44}	$1.34 \times 10^{+05}$	$1.26 \times 10^{+04}$	$6.64 \times 10^{+06}$	$2.43 \times 10^{+05}$	$7.00 \times 10^{+02}$	$4.15 \times 10^{+03}$	$3.88 \times 10^{+05}$	$1.81 \times 10^{+06}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	5.37×10^{-202}	$5.55 \times 10^{+04}$	$1.97 \times 10^{+02}$	$1.76 \times 10^{+06}$	$7.12 \times 10^{+04}$	1.24×10^{-03}	$9.45 \times 10^{+00}$	$3.04 \times 10^{+05}$	$1.40 \times 10^{+06}$
F4	Ave	$\mathbf{0.00 \times 10^{+00}}$	4.58×10^{-96}	$1.91 \times 10^{+01}$	$9.43 \times 10^{+00}$	$7.69 \times 10^{+01}$	$6.38 \times 10^{+01}$	$9.21 \times 10^{+01}$	$9.15 \times 10^{+01}$	$5.06 \times 10^{+01}$	$9.80 \times 10^{+01}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	2.47×10^{-95}	$1.30 \times 10^{+00}$	$5.17 \times 10^{+00}$	$2.16 \times 10^{+01}$	$8.42 \times 10^{+00}$	$3.26 \times 10^{+00}$	$2.66 \times 10^{+00}$	$2.13 \times 10^{+00}$	6.48×10^{-01}
	Max	$\mathbf{0.00 \times 10^{+00}}$	1.38×10^{-94}	$2.14 \times 10^{+01}$	$2.91 \times 10^{+01}$	$9.83 \times 10^{+01}$	$7.63 \times 10^{+01}$	$9.79 \times 10^{+01}$	$9.75 \times 10^{+01}$	$5.48 \times 10^{+01}$	$9.88 \times 10^{+01}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	2.56×10^{-140}	$1.60 \times 10^{+01}$	$2.39 \times 10^{+00}$	$1.68 \times 10^{+01}$	$4.75 \times 10^{+01}$	$8.51 \times 10^{+01}$	$8.36 \times 10^{+01}$	$4.59 \times 10^{+01}$	$9.59 \times 10^{+01}$
F5	Ave	$\mathbf{1.34 \times 10^{-03}}$	1.45×10^{-01}	$1.73 \times 10^{+06}$	$1.98 \times 10^{+02}$	$1.97 \times 10^{+02}$	$1.52 \times 10^{+07}$	$1.99 \times 10^{+02}$	$1.99 \times 10^{+02}$	$1.05 \times 10^{+05}$	$1.22 \times 10^{+08}$
	Std	$\mathbf{2.75 \times 10^{-03}}$	1.90×10^{-01}	$2.93 \times 10^{+05}$	4.90×10^{-01}	3.12×10^{-01}	$9.15 \times 10^{+06}$	1.37×10^{-01}	2.13×10^{-01}	$1.96 \times 10^{+04}$	$1.80 \times 10^{+07}$
	Max	$\mathbf{1.45 \times 10^{-02}}$	8.13×10^{-01}	$2.14 \times 10^{+06}$	$1.98 \times 10^{+02}$	$1.98 \times 10^{+02}$	$4.57 \times 10^{+07}$	$1.99 \times 10^{+02}$	$1.99 \times 10^{+02}$	$1.54 \times 10^{+05}$	$1.55 \times 10^{+08}$
	Min	$\mathbf{4.10 \times 10^{-08}}$	1.14×10^{-05}	$1.17 \times 10^{+06}$	$1.96 \times 10^{+02}$	$1.97 \times 10^{+02}$	$5.47 \times 10^{+06}$	$1.98 \times 10^{+02}$	$1.98 \times 10^{+02}$	$5.78 \times 10^{+04}$	$8.51 \times 10^{+07}$
F6	Ave	$\mathbf{4.60 \times 10^{-05}}$	5.57×10^{-03}	$7.09 \times 10^{+02}$	$2.78 \times 10^{+01}$	$6.28 \times 10^{+00}$	$2.92 \times 10^{+04}$	$4.21 \times 10^{+01}$	$4.06 \times 10^{+01}$	$1.75 \times 10^{+03}$	$1.16 \times 10^{+05}$
	Std	$\mathbf{8.62 \times 10^{-05}}$	7.42×10^{-03}	$6.35 \times 10^{+01}$	$1.24 \times 10^{+00}$	$2.38 \times 10^{+00}$	$7.78 \times 10^{+03}$	6.98×10^{-01}	7.89×10^{-01}	$1.84 \times 10^{+02}$	$8.39 \times 10^{+03}$
	Max	$\mathbf{4.67 \times 10^{-04}}$	3.45×10^{-02}	$8.18 \times 10^{+02}$	$3.14 \times 10^{+01}$	$1.40 \times 10^{+01}$	$4.80 \times 10^{+04}$	$4.33 \times 10^{+01}$	$4.20 \times 10^{+01}$	$2.20 \times 10^{+03}$	$1.35 \times 10^{+05}$
	Min	$\mathbf{1.23 \times 10^{-07}}$	1.27×10^{-06}	$5.81 \times 10^{+02}$	$2.58 \times 10^{+01}$	$2.40 \times 10^{+00}$	$1.78 \times 10^{+04}$	$4.06 \times 10^{+01}$	$3.93 \times 10^{+01}$	$1.36 \times 10^{+03}$	$1.01 \times 10^{+05}$
F7	Ave	2.67×10^{-04}	$\mathbf{1.03 \times 10^{-04}}$	$5.92 \times 10^{+03}$	4.46×10^{-03}	2.18×10^{-03}	$5.04 \times 10^{+01}$	5.35×10^{-03}	1.49×10^{-02}	$4.31 \times 10^{+00}$	$2.49 \times 10^{+02}$
	Std	1.78×10^{-04}	$\mathbf{9.94 \times 10^{-05}}$	$6.37 \times 10^{+02}$	1.52×10^{-03}	2.03×10^{-03}	$2.21 \times 10^{+01}$	3.62×10^{-03}	7.66×10^{-03}	6.40×10^{-01}	$3.87 \times 10^{+01}$
	Max	6.36×10^{-04}	$\mathbf{4.04 \times 10^{-04}}$	$7.11 \times 10^{+03}$	8.74×10^{-03}	7.90×10^{-03}	$1.30 \times 10^{+02}$	1.30×10^{-02}	3.26×10^{-02}	$5.78 \times 10^{+00}$	$3.29 \times 10^{+02}$
	Min	2.88×10^{-05}	$\mathbf{7.08 \times 10^{-06}}$	$4.65 \times 10^{+03}$	1.63×10^{-03}	1.18×10^{-05}	$2.16 \times 10^{+01}$	1.10×10^{-03}	3.76×10^{-03}	$3.37 \times 10^{+00}$	$1.93 \times 10^{+02}$
F8	Ave	$\mathbf{-8.38 \times 10^{+04}}$	$-8.38 \times 10^{+04}$	$-4.27 \times 10^{+04}$	$-2.89 \times 10^{+04}$	$-7.77 \times 10^{+04}$	$-3.48 \times 10^{+04}$	$-1.60 \times 10^{+04}$	$-1.63 \times 10^{+04}$	$-8.1 \times 10^{+04}$	$-2.6 \times 10^{+04}$
	Std	$\mathbf{9.39 \times 10^{-02}}$	$1.60 \times 10^{+02}$	$3.34 \times 10^{+03}$	$4.53 \times 10^{+03}$	$1.07 \times 10^{+04}$	$2.32 \times 10^{+03}$	$3.74 \times 10^{+03}$	$2.39 \times 10^{+03}$	$3.68 \times 10^{+02}$	$6.52 \times 10^{+02}$
	Max	$\mathbf{-8.38 \times 10^{+04}}$	$-8.29 \times 10^{+04}$	$-3.59 \times 10^{+04}$	$-8.54 \times 10^{+03}$	$-3.93 \times 10^{+04}$	$-2.79 \times 10^{+04}$	$-1.21 \times 10^{+04}$	$-1.30 \times 10^{+04}$	$-8.0 \times 10^{+04}$	$-2.4 \times 10^{+04}$
	Min	$-8.38 \times 10^{+04}$	$\mathbf{-8.38 \times 10^{+04}}$	$-4.97 \times 10^{+04}$	$-3.52 \times 10^{+04}$	$-8.38 \times 10^{+04}$	$-3.77 \times 10^{+04}$	$-2.53 \times 10^{+04}$	$-2.06 \times 10^{+04}$	$-8.1 \times 10^{+04}$	$-2.7 \times 10^{+04}$
F9	Ave	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$2.67 \times 10^{+03}$	$1.58 \times 10^{+00}$	7.58×10^{-15}	$9.83 \times 10^{+02}$	4.36×10^{-01}	$4.64 \times 10^{+00}$	$1.71 \times 10^{+02}$	$2.09 \times 10^{+03}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$1.28 \times 10^{+02}$	$3.91 \times 10^{+00}$	4.08×10^{-14}	$1.15 \times 10^{+02}$	$1.77 \times 10^{+00}$	$7.60 \times 10^{+00}$	$7.82 \times 10^{+00}$	$3.92 \times 10^{+01}$
	Max	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$3.02 \times 10^{+03}$	$1.76 \times 10^{+01}$	2.27×10^{-13}	$1.19 \times 10^{+03}$	$9.16 \times 10^{+00}$	$3.12 \times 10^{+01}$	$1.90 \times 10^{+02}$	$2.16 \times 10^{+03}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$2.40 \times 10^{+03}$	1.14×10^{-12}	$\mathbf{0.00 \times 10^{+00}}$	$7.31 \times 10^{+02}$	4.55×10^{-13}	3.96×10^{-11}	$1.59 \times 10^{+02}$	$2.00 \times 10^{+03}$

Table 8. *Cont.*

Function	Criteria	ITSO	TSO	PSO	GWO	WOA	PPA	SOA	STOA	GA	DE
F10	Ave	$\mathbf{8.88 \times 10^{-16}}$	$\mathbf{8.88 \times 10^{-16}}$	$8.31 \times 10^{+00}$	1.28×10^{-11}	3.38×10^{-15}	$1.64 \times 10^{+01}$	$2.00 \times 10^{+01}$	$2.00 \times 10^{+01}$	$5.12 \times 10^{+00}$	$1.52 \times 10^{+01}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	6.02×10^{-01}	4.38×10^{-12}	2.08×10^{-15}	8.28×10^{-01}	1.41×10^{-04}	1.85×10^{-04}	1.59×10^{-01}	7.30×10^{-01}
	Max	$\mathbf{8.88 \times 10^{-16}}$	$\mathbf{8.88 \times 10^{-16}}$	$1.10 \times 10^{+01}$	2.86×10^{-11}	7.99×10^{-15}	$1.89 \times 10^{+01}$	$2.00 \times 10^{+01}$	$2.00 \times 10^{+01}$	$5.40 \times 10^{+00}$	$1.67 \times 10^{+01}$
	Min	$\mathbf{8.88 \times 10^{-16}}$	$\mathbf{8.88 \times 10^{-16}}$	$7.17 \times 10^{+00}$	6.41×10^{-12}	$\mathbf{8.88 \times 10^{-16}}$	$1.50 \times 10^{+01}$	$2.00 \times 10^{+01}$	$2.00 \times 10^{+01}$	$4.80 \times 10^{+00}$	$1.38 \times 10^{+01}$
F11	Ave	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$1.18 \times 10^{+00}$	4.35×10^{-03}	6.31×10^{-03}	$2.75 \times 10^{+02}$	6.84×10^{-03}	1.50×10^{-02}	$1.72 \times 10^{+01}$	$2.84 \times 10^{+02}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	2.00×10^{-02}	9.29×10^{-03}	3.40×10^{-02}	$9.17 \times 10^{+01}$	2.17×10^{-02}	2.76×10^{-02}	$2.26 \times 10^{+00}$	$2.33 \times 10^{+01}$
	Max	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$1.24 \times 10^{+00}$	3.26×10^{-02}	1.89×10^{-01}	$5.56 \times 10^{+02}$	9.38×10^{-02}	8.34×10^{-02}	$2.26 \times 10^{+01}$	$3.31 \times 10^{+02}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$1.15 \times 10^{+00}$	1.11×10^{-16}	$\mathbf{0.00 \times 10^{+00}}$	$1.65 \times 10^{+02}$	5.12×10^{-14}	2.03×10^{-09}	$1.18 \times 10^{+01}$	$2.30 \times 10^{+02}$
F12	Ave	$\mathbf{4.30 \times 10^{-08}}$	6.28×10^{-06}	$2.00 \times 10^{+02}$	4.63×10^{-01}	2.52×10^{-02}	$2.06 \times 10^{+06}$	8.82×10^{-01}	8.19×10^{-01}	$3.12 \times 10^{+00}$	$1.07 \times 10^{+09}$
	Std	$\mathbf{8.22 \times 10^{-08}}$	8.59×10^{-06}	$2.91 \times 10^{+02}$	5.48×10^{-02}	9.63×10^{-03}	$1.85 \times 10^{+06}$	3.99×10^{-02}	4.23×10^{-02}	3.51×10^{-01}	$1.25 \times 10^{+08}$
	Max	$\mathbf{3.29 \times 10^{-07}}$	3.70×10^{-05}	$1.55 \times 10^{+03}$	5.90×10^{-01}	4.25×10^{-02}	$7.34 \times 10^{+06}$	9.81×10^{-01}	9.14×10^{-01}	$4.08 \times 10^{+00}$	$1.30 \times 10^{+09}$
	Min	$\mathbf{1.92 \times 10^{-10}}$	6.80×10^{-09}	$3.34 \times 10^{+01}$	3.63×10^{-01}	1.27×10^{-02}	$1.16 \times 10^{+05}$	8.11×10^{-01}	7.35×10^{-01}	$2.35 \times 10^{+00}$	$8.45 \times 10^{+08}$
F13	Ave	$\mathbf{4.36 \times 10^{-06}}$	4.79×10^{-04}	$2.36 \times 10^{+04}$	$1.60 \times 10^{+01}$	$3.64 \times 10^{+00}$	$2.15 \times 10^{+07}$	$1.90 \times 10^{+01}$	$1.92 \times 10^{+01}$	$4.32 \times 10^{+02}$	$1.96 \times 10^{+09}$
	Std	$\mathbf{9.08 \times 10^{-06}}$	5.83×10^{-04}	$1.16 \times 10^{+04}$	4.82×10^{-01}	$1.31 \times 10^{+00}$	$1.71 \times 10^{+07}$	1.85×10^{-01}	3.65×10^{-01}	$1.40 \times 10^{+03}$	$2.67 \times 10^{+08}$
	Max	$\mathbf{4.68 \times 10^{-05}}$	2.16×10^{-03}	$5.84 \times 10^{+04}$	$1.68 \times 10^{+01}$	$7.31 \times 10^{+00}$	$9.24 \times 10^{+07}$	$1.94 \times 10^{+01}$	$2.01 \times 10^{+01}$	$7.95 \times 10^{+03}$	$2.47 \times 10^{+09}$
	Min	$\mathbf{5.48 \times 10^{-10}}$	6.50×10^{-08}	$6.35 \times 10^{+03}$	$1.49 \times 10^{+01}$	$2.02 \times 10^{+00}$	$4.89 \times 10^{+06}$	$1.87 \times 10^{+01}$	$1.84 \times 10^{+01}$	$9.45 \times 10^{+01}$	$1.37 \times 10^{+09}$
Friedman Ave Rank		**1.3423**	1.8526	7.3949	4.3128	3.7615	8.1846	5.9692	6.2205	6.7590	9.2026
Rank		**1**	2	8	4	3	9	5	6	7	10

Table 9. Results of ITSO with standard optimization algorithms for high-dimensional functions of dimension 500, The bolded part is the best result.

Function	Criteria	ITSO	TSO	PSO	GWO	WOA	PPA	SOA	STOA	GA	DE
F1	Ave	$\mathbf{0.00 \times 10^{+00}}$	4.57×10^{-208}	$7.47 \times 10^{+03}$	1.59×10^{-12}	2.86×10^{-145}	$1.77 \times 10^{+05}$	6.04×10^{-09}	9.97×10^{-05}	$7.40 \times 10^{+04}$	$7.60 \times 10^{+05}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$3.83 \times 10^{+02}$	8.49×10^{-13}	1.54×10^{-144}	$3.26 \times 10^{+04}$	5.95×10^{-09}	1.43×10^{-04}	$4.38 \times 10^{+03}$	$2.34 \times 10^{+04}$
	Max	$\mathbf{0.00 \times 10^{+00}}$	1.37×10^{-206}	$8.26 \times 10^{+03}$	3.88×10^{-12}	8.56×10^{-144}	$2.42 \times 10^{+05}$	2.73×10^{-08}	7.78×10^{-04}	$8.40 \times 10^{+04}$	$8.07 \times 10^{+05}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	2.31×10^{-263}	$6.84 \times 10^{+03}$	3.99×10^{-13}	6.02×10^{-162}	$1.18 \times 10^{+05}$	6.46×10^{-11}	1.73×10^{-06}	$6.49 \times 10^{+04}$	$7.07 \times 10^{+05}$
F2	Ave	1.70×10^{-05}	5.73×10^{-98}	$1.97 \times 10^{+144}$	5.84×10^{-08}	$\mathbf{8.89 \times 10^{-101}}$	$1.82 \times 10^{+47}$	2.03×10^{-07}	3.57×10^{-05}	$3.59 \times 10^{+02}$	$8.25 \times 10^{+146}$
	Std	5.20×10^{-05}	3.08×10^{-97}	$1.06 \times 10^{+145}$	1.24×10^{-08}	$\mathbf{4.69 \times 10^{-100}}$	$9.37 \times 10^{+47}$	1.87×10^{-07}	3.28×10^{-05}	$1.01 \times 10^{+01}$	$3.38 \times 10^{+147}$
	Max	2.86×10^{-04}	1.72×10^{-96}	$5.91 \times 10^{+145}$	8.26×10^{-08}	$\mathbf{2.61 \times 10^{-99}}$	$5.22 \times 10^{+48}$	7.59×10^{-07}	1.30×10^{-04}	$3.75 \times 10^{+02}$	$1.80 \times 10^{+148}$
	Min	3.16×10^{-14}	$\mathbf{1.64 \times 10^{-140}}$	$6.19 \times 10^{+43}$	2.96×10^{-08}	3.00×10^{-109}	$6.19 \times 10^{+02}$	9.46×10^{-09}	4.49×10^{-06}	$3.39 \times 10^{+02}$	$5.42 \times 10^{+131}$
F3	Ave	$\mathbf{4.31 \times 10^{-227}}$	1.40×10^{-40}	$5.79 \times 10^{+05}$	$1.34 \times 10^{+05}$	$3.17 \times 10^{+07}$	$7.73 \times 10^{+05}$	$1.15 \times 10^{+04}$	$1.23 \times 10^{+05}$	$1.97 \times 10^{+06}$	$9.98 \times 10^{+06}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	6.65×10^{-40}	$1.45 \times 10^{+05}$	$4.79 \times 10^{+04}$	$1.09 \times 10^{+07}$	$2.25 \times 10^{+05}$	$2.15 \times 10^{+04}$	$1.47 \times 10^{+05}$	$1.94 \times 10^{+05}$	$8.67 \times 10^{+05}$
	Max	$\mathbf{1.29 \times 10^{-225}}$	3.69×10^{-39}	$9.47 \times 10^{+05}$	$2.90 \times 10^{+05}$	$6.04 \times 10^{+07}$	$1.28 \times 10^{+06}$	$1.03 \times 10^{+05}$	$7.64 \times 10^{+05}$	$2.35 \times 10^{+06}$	$1.21 \times 10^{+07}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	2.46×10^{-138}	$3.97 \times 10^{+05}$	$5.98 \times 10^{+04}$	$1.12 \times 10^{+07}$	$4.10 \times 10^{+05}$	8.23×10^{-01}	$1.37 \times 10^{+04}$	$1.56 \times 10^{+06}$	$8.21 \times 10^{+06}$
F4	Ave	$\mathbf{0.00 \times 10^{+00}}$	1.12×10^{-96}	$2.80 \times 10^{+01}$	$5.87 \times 10^{+01}$	$8.38 \times 10^{+01}$	$6.75 \times 10^{+01}$	$9.80 \times 10^{+01}$	$9.82 \times 10^{+01}$	$7.49 \times 10^{+01}$	$9.92 \times 10^{+01}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	6.00×10^{-96}	$1.29 \times 10^{+00}$	$7.52 \times 10^{+00}$	$1.52 \times 10^{+01}$	$6.81 \times 10^{+00}$	5.65×10^{-01}	6.74×10^{-01}	$1.18 \times 10^{+00}$	2.56×10^{-01}
	Max	$\mathbf{0.00 \times 10^{+00}}$	3.34×10^{-95}	$3.20 \times 10^{+01}$	$7.99 \times 10^{+01}$	$9.80 \times 10^{+01}$	$8.37 \times 10^{+01}$	$9.90 \times 10^{+01}$	$9.93 \times 10^{+01}$	$7.67 \times 10^{+01}$	$9.96 \times 10^{+01}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	1.55×10^{-142}	$2.59 \times 10^{+01}$	$4.74 \times 10^{+01}$	$4.46 \times 10^{+01}$	$5.36 \times 10^{+01}$	$9.68 \times 10^{+01}$	$9.64 \times 10^{+01}$	$7.23 \times 10^{+01}$	$9.85 \times 10^{+01}$
F5	Ave	$\mathbf{2.26 \times 10^{-03}}$	3.07×10^{-01}	$5.44 \times 10^{+07}$	$4.98 \times 10^{+02}$	$4.96 \times 10^{+02}$	$1.71 \times 10^{+08}$	$4.99 \times 10^{+02}$	$4.99 \times 10^{+02}$	$3.59 \times 10^{+07}$	$3.89 \times 10^{+09}$
	Std	$\mathbf{5.22 \times 10^{-03}}$	3.60×10^{-01}	$7.04 \times 10^{+06}$	1.33×10^{-01}	4.49×10^{-01}	$9.10 \times 10^{+07}$	1.42×10^{-01}	6.13×10^{-01}	$3.85 \times 10^{+06}$	$1.46 \times 10^{+08}$
	Max	$\mathbf{2.81 \times 10^{-02}}$	$1.21 \times 10^{+00}$	$7.25 \times 10^{+07}$	$4.98 \times 10^{+02}$	$4.97 \times 10^{+02}$	$5.55 \times 10^{+08}$	$4.99 \times 10^{+02}$	$5.01 \times 10^{+02}$	$4.20 \times 10^{+07}$	$4.15 \times 10^{+09}$
	Min	$\mathbf{2.34 \times 10^{-06}}$	2.81×10^{-03}	$4.17 \times 10^{+07}$	$4.97 \times 10^{+02}$	$4.95 \times 10^{+02}$	$6.68 \times 10^{+07}$	$4.98 \times 10^{+02}$	$4.99 \times 10^{+02}$	$2.83 \times 10^{+07}$	$3.47 \times 10^{+09}$
F6	Ave	$\mathbf{7.59 \times 10^{-05}}$	1.80×10^{-02}	$7.51 \times 10^{+03}$	$9.33 \times 10^{+01}$	$1.99 \times 10^{+01}$	$1.79 \times 10^{+05}$	$1.16 \times 10^{+02}$	$1.14 \times 10^{+02}$	$7.31 \times 10^{+04}$	$1.00 \times 10^{+06}$
	Std	$\mathbf{1.15 \times 10^{-04}}$	3.10×10^{-02}	$2.86 \times 10^{+02}$	$1.92 \times 10^{+00}$	$5.53 \times 10^{+00}$	$4.08 \times 10^{+04}$	9.92×10^{-01}	8.83×10^{-01}	$3.92 \times 10^{+03}$	$2.37 \times 10^{+04}$
	Max	$\mathbf{5.85 \times 10^{-04}}$	1.59×10^{-01}	$8.19 \times 10^{+03}$	$9.94 \times 10^{+01}$	$3.29 \times 10^{+01}$	$2.75 \times 10^{+05}$	$1.18 \times 10^{+02}$	$1.15 \times 10^{+02}$	$8.23 \times 10^{+04}$	$1.05 \times 10^{+06}$
	Min	$\mathbf{1.17 \times 10^{-09}}$	6.36×10^{-06}	$7.07 \times 10^{+03}$	$8.84 \times 10^{+01}$	$9.99 \times 10^{+00}$	$1.26 \times 10^{+05}$	$1.14 \times 10^{+02}$	$1.12 \times 10^{+02}$	$6.71 \times 10^{+04}$	$9.33 \times 10^{+05}$
F7	Ave	2.87×10^{-04}	$\mathbf{1.03 \times 10^{-04}}$	$5.70 \times 10^{+04}$	1.07×10^{-02}	2.57×10^{-03}	$1.49 \times 10^{+03}$	8.93×10^{-03}	2.93×10^{-02}	$2.31 \times 10^{+02}$	$2.32 \times 10^{+04}$
	Std	3.05×10^{-04}	$\mathbf{1.02 \times 10^{-04}}$	$2.06 \times 10^{+03}$	2.93×10^{-03}	3.24×10^{-03}	$7.92 \times 10^{+02}$	4.49×10^{-03}	1.42×10^{-02}	$2.58 \times 10^{+01}$	$1.11 \times 10^{+03}$
	Max	1.66×10^{-03}	$\mathbf{4.17 \times 10^{-04}}$	$6.19 \times 10^{+04}$	1.69×10^{-02}	1.58×10^{-02}	$5.00 \times 10^{+03}$	1.83×10^{-02}	6.23×10^{-02}	$2.95 \times 10^{+02}$	$2.52 \times 10^{+04}$
	Min	3.02×10^{-05}	$\mathbf{3.13 \times 10^{-06}}$	$5.30 \times 10^{+04}$	5.49×10^{-03}	2.86×10^{-05}	$5.42 \times 10^{+02}$	1.52×10^{-03}	1.29×10^{-02}	$1.77 \times 10^{+02}$	$2.05 \times 10^{+04}$
F8	Ave	$\mathbf{-2.09 \times 10^{+05}}$	$-2.09 \times 10^{+05}$	$-9.76 \times 10^{+04}$	$-5.91 \times 10^{+04}$	$-1.89 \times 10^{+05}$	$-5.67 \times 10^{+04}$	$-2.72 \times 10^{+04}$	$-2.69 \times 10^{+04}$	$-1.63 \times 10^{+05}$	$-3.97 \times 10^{+04}$
	Std	$\mathbf{3.56 \times 10^{-01}}$	$2.61 \times 10^{+02}$	$1.77 \times 10^{+04}$	$8.89 \times 10^{+03}$	$2.38 \times 10^{+04}$	$3.27 \times 10^{+03}$	$6.44 \times 10^{+03}$	$4.64 \times 10^{+03}$	$1.84 \times 10^{+03}$	$1.17 \times 10^{+03}$
	Max	$\mathbf{-2.09 \times 10^{+05}}$	$-2.08 \times 10^{+05}$	$-1.29 \times 10^{+04}$	$-1.61 \times 10^{+04}$	$-1.39 \times 10^{+05}$	$-4.74 \times 10^{+04}$	$-1.94 \times 10^{+04}$	$-1.88 \times 10^{+04}$	$-1.60 \times 10^{+05}$	$-3.76 \times 10^{+04}$
	Min	$-2.09 \times 10^{+05}$	$\mathbf{-2.09 \times 10^{+05}}$	$-1.12 \times 10^{+05}$	$-6.62 \times 10^{+04}$	$-2.09 \times 10^{+05}$	$-6.21 \times 10^{+04}$	$-4.45 \times 10^{+04}$	$-3.80 \times 10^{+04}$	$-1.68 \times 10^{+05}$	$-4.36 \times 10^{+04}$
F9	Ave	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$7.64 \times 10^{+03}$	$7.02 \times 10^{+00}$	$\mathbf{0.00 \times 10^{+00}}$	$3.71 \times 10^{+03}$	$1.08 \times 10^{+00}$	$5.09 \times 10^{+00}$	$1.71 \times 10^{+03}$	$7.03 \times 10^{+03}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$1.73 \times 10^{+02}$	$6.57 \times 10^{+00}$	$\mathbf{0.00 \times 10^{+00}}$	$2.20 \times 10^{+02}$	$3.20 \times 10^{+00}$	$1.20 \times 10^{+01}$	$5.64 \times 10^{+01}$	$7.48 \times 10^{+01}$
	Max	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$7.94 \times 10^{+03}$	$2.07 \times 10^{+01}$	$\mathbf{0.00 \times 10^{+00}}$	$4.15 \times 10^{+03}$	$1.73 \times 10^{+01}$	$6.64 \times 10^{+01}$	$1.87 \times 10^{+03}$	$7.13 \times 10^{+03}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$7.27 \times 10^{+03}$	8.55×10^{-11}	$\mathbf{0.00 \times 10^{+00}}$	$3.26 \times 10^{+03}$	7.28×10^{-12}	1.91×10^{-08}	$1.58 \times 10^{+03}$	$6.87 \times 10^{+03}$

Table 9. *Cont.*

Function	Criteria	ITSO	TSO	PSO	GWO	WOA	PPA	SOA	STOA	GA	DE
F10	Ave	$\mathbf{8.88 \times 10^{-16}}$	$\mathbf{8.88 \times 10^{-16}}$	$1.29 \times 10^{+01}$	5.36×10^{-08}	3.49×10^{-15}	$1.73 \times 10^{+01}$	$2.00 \times 10^{+01}$	$2.00 \times 10^{+01}$	$1.26 \times 10^{+01}$	$2.08 \times 10^{+01}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	2.42×10^{-01}	1.36×10^{-08}	2.58×10^{-15}	8.43×10^{-01}	8.72×10^{-05}	5.84×10^{-05}	1.78×10^{-01}	1.43×10^{-02}
	Max	$\mathbf{8.88 \times 10^{-16}}$	$\mathbf{8.88 \times 10^{-16}}$	$1.36 \times 10^{+01}$	8.09×10^{-08}	7.99×10^{-15}	$1.90 \times 10^{+01}$	$2.00 \times 10^{+01}$	$2.00 \times 10^{+01}$	$1.29 \times 10^{+01}$	$2.08 \times 10^{+01}$
	Min	$\mathbf{8.88 \times 10^{-16}}$	$\mathbf{8.88 \times 10^{-16}}$	$1.24 \times 10^{+01}$	2.62×10^{-08}	$\mathbf{8.88 \times 10^{-16}}$	$1.58 \times 10^{+01}$	$2.00 \times 10^{+01}$	$2.00 \times 10^{+01}$	$1.22 \times 10^{+01}$	$2.08 \times 10^{+01}$
F11	Ave	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$3.52 \times 10^{+00}$	2.88×10^{-03}	$\mathbf{0.00 \times 10^{+00}}$	$1.58 \times 10^{+03}$	1.93×10^{-03}	2.22×10^{-02}	$6.55 \times 10^{+02}$	$6.81 \times 10^{+03}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	1.17×10^{-01}	9.11×10^{-03}	$\mathbf{0.00 \times 10^{+00}}$	$2.82 \times 10^{+02}$	8.56×10^{-03}	4.44×10^{-02}	$4.36 \times 10^{+01}$	$2.10 \times 10^{+02}$
	Max	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$3.80 \times 10^{+00}$	4.18×10^{-02}	$\mathbf{0.00 \times 10^{+00}}$	$2.15 \times 10^{+03}$	4.68×10^{-02}	1.35×10^{-01}	$7.56 \times 10^{+02}$	$7.10 \times 10^{+03}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$3.25 \times 10^{+00}$	6.75×10^{-14}	$\mathbf{0.00 \times 10^{+00}}$	$1.03 \times 10^{+03}$	3.65×10^{-11}	5.55×10^{-07}	$5.71 \times 10^{+02}$	$6.32 \times 10^{+03}$
F12	Ave	$\mathbf{4.62 \times 10^{-08}}$	4.32×10^{-06}	$8.10 \times 10^{+05}$	7.44×10^{-01}	3.70×10^{-02}	$1.03 \times 10^{+08}$	$1.03 \times 10^{+00}$	9.96×10^{-01}	$3.14 \times 10^{+06}$	$1.61 \times 10^{+10}$
	Std	$\mathbf{8.70 \times 10^{-08}}$	6.17×10^{-06}	$2.51 \times 10^{+05}$	2.82×10^{-02}	1.18×10^{-02}	$1.32 \times 10^{+08}$	1.80×10^{-02}	2.15×10^{-02}	$8.38 \times 10^{+05}$	$5.59 \times 10^{+08}$
	Max	$\mathbf{4.34 \times 10^{-07}}$	2.90×10^{-05}	$1.56 \times 10^{+06}$	8.06×10^{-01}	6.68×10^{-02}	$7.49 \times 10^{+08}$	$1.07 \times 10^{+00}$	$1.04 \times 10^{+00}$	$4.74 \times 10^{+06}$	$1.68 \times 10^{+10}$
	Min	$\mathbf{4.10 \times 10^{-13}}$	1.27×10^{-08}	$3.93 \times 10^{+05}$	6.91×10^{-01}	1.71×10^{-02}	$5.17 \times 10^{+06}$	9.94×10^{-01}	9.51×10^{-01}	$1.81 \times 10^{+06}$	$1.49 \times 10^{+10}$
F13	Ave	$\mathbf{6.74 \times 10^{-06}}$	1.61×10^{-03}	$8.39 \times 10^{+06}$	$4.58 \times 10^{+01}$	$9.61 \times 10^{+00}$	$3.46 \times 10^{+08}$	$4.94 \times 10^{+01}$	$5.14 \times 10^{+01}$	$4.25 \times 10^{+07}$	$2.68 \times 10^{+10}$
	Std	$\mathbf{1.27 \times 10^{-05}}$	2.32×10^{-03}	$1.62 \times 10^{+06}$	5.23×10^{-01}	$3.25 \times 10^{+00}$	$2.13 \times 10^{+08}$	3.82×10^{-01}	$1.26 \times 10^{+00}$	$6.53 \times 10^{+06}$	$1.38 \times 10^{+09}$
	Max	$\mathbf{6.00 \times 10^{-05}}$	9.63×10^{-03}	$1.18 \times 10^{+07}$	$4.67 \times 10^{+01}$	$1.76 \times 10^{+01}$	$1.08 \times 10^{+09}$	$5.05 \times 10^{+01}$	$5.41 \times 10^{+01}$	$5.62 \times 10^{+07}$	$3.00 \times 10^{+10}$
	Min	$\mathbf{7.33 \times 10^{-11}}$	3.63×10^{-06}	$5.16 \times 10^{+06}$	$4.46 \times 10^{+01}$	$4.08 \times 10^{+00}$	$8.56 \times 10^{+07}$	$4.87 \times 10^{+01}$	$4.98 \times 10^{+01}$	$3.06 \times 10^{+07}$	$2.29 \times 10^{+10}$
Friedman Ave Rank		**1.6244**	1.7936	7.0923	4.3692	3.5590	7.9769	5.7231	6.2615	6.9949	9.6051
Rank		**1**	2	8	4	3	9	5	6	7	10

Table 10. Results of ITSO with improved optimization algorithms for 100-dimensional high-dimensional functions, The bolded part is the best result.

Function	Criteria	ITSO	AGPSO	MPSO	OBSCA	PSOGSA	CGWO	GWOCS	IGWO
F1	Ave	$\mathbf{0.00 \times 10^{+00}}$	$2.86 \times 10^{+03}$	$2.43 \times 10^{+04}$	2.53×10^{-09}	$2.47 \times 10^{+04}$	7.26×10^{-36}	3.83×10^{-30}	7.27×10^{-29}
	Std	$\mathbf{0.00 \times 10^{+00}}$	$3.31 \times 10^{+03}$	$1.33 \times 10^{+04}$	7.40×10^{-09}	$1.10 \times 10^{+04}$	6.11×10^{-36}	3.32×10^{-30}	6.79×10^{-29}
	Max	$\mathbf{0.00 \times 10^{+00}}$	$1.40 \times 10^{+04}$	$5.44 \times 10^{+04}$	4.06×10^{-08}	$5.01 \times 10^{+04}$	2.17×10^{-35}	1.43×10^{-29}	2.59×10^{-28}
	Min	$\mathbf{0.00 \times 10^{+00}}$	$7.69 \times 10^{+02}$	$2.08 \times 10^{+03}$	1.11×10^{-16}	$8.07 \times 10^{+02}$	3.08×10^{-37}	1.47×10^{-31}	3.82×10^{-30}
F2	Ave	$\mathbf{0.00 \times 10^{+00}}$	$1.07 \times 10^{+02}$	$2.40 \times 10^{+02}$	2.82×10^{-13}	$4.14 \times 10^{+17}$	6.79×10^{-22}	2.69×10^{-18}	8.04×10^{-19}
	Std	$\mathbf{0.00 \times 10^{+00}}$	$2.83 \times 10^{+01}$	$3.15 \times 10^{+01}$	9.22×10^{-13}	$2.23 \times 10^{+18}$	7.45×10^{-22}	1.80×10^{-18}	3.93×10^{-19}
	Max	$\mathbf{0.00 \times 10^{+00}}$	$1.74 \times 10^{+02}$	$2.98 \times 10^{+02}$	4.94×10^{-12}	$1.24 \times 10^{+19}$	4.02×10^{-21}	7.07×10^{-18}	1.98×10^{-18}
	Min	$\mathbf{0.00 \times 10^{+00}}$	$6.05 \times 10^{+01}$	$1.87 \times 10^{+02}$	6.79×10^{-18}	$7.05 \times 10^{+01}$	9.28×10^{-23}	5.13×10^{-19}	3.24×10^{-19}
F3	Ave	$\mathbf{0.00 \times 10^{+00}}$	$1.01 \times 10^{+05}$	$1.97 \times 10^{+05}$	$7.96 \times 10^{+03}$	$1.50 \times 10^{+05}$	$2.75 \times 10^{+01}$	$1.20 \times 10^{+00}$	$1.15 \times 10^{+03}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	$2.53 \times 10^{+04}$	$5.13 \times 10^{+04}$	$1.01 \times 10^{+04}$	$3.30 \times 10^{+04}$	$8.39 \times 10^{+01}$	$1.24 \times 10^{+00}$	$8.08 \times 10^{+02}$
	Max	$\mathbf{0.00 \times 10^{+00}}$	$1.43 \times 10^{+05}$	$2.84 \times 10^{+05}$	$5.42 \times 10^{+04}$	$2.37 \times 10^{+05}$	$4.62 \times 10^{+02}$	$4.97 \times 10^{+00}$	$2.96 \times 10^{+03}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	$5.64 \times 10^{+04}$	$9.99 \times 10^{+04}$	$1.47 \times 10^{+02}$	$9.02 \times 10^{+04}$	9.70×10^{-05}	7.22×10^{-03}	$1.76 \times 10^{+02}$
F4	Ave	$\mathbf{0.00 \times 10^{+00}}$	$5.14 \times 10^{+01}$	$6.57 \times 10^{+01}$	$3.72 \times 10^{+01}$	$8.60 \times 10^{+01}$	$2.50 \times 10^{+01}$	1.57×10^{-05}	$1.57 \times 10^{+00}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	$4.19 \times 10^{+00}$	$5.27 \times 10^{+00}$	$1.25 \times 10^{+01}$	$1.05 \times 10^{+01}$	$2.84 \times 10^{+01}$	2.20×10^{-05}	$1.90 \times 10^{+00}$
	Max	$\mathbf{0.00 \times 10^{+00}}$	$6.30 \times 10^{+01}$	$7.42 \times 10^{+01}$	$6.07 \times 10^{+01}$	$9.79 \times 10^{+01}$	$8.14 \times 10^{+01}$	1.17×10^{-04}	$7.36 \times 10^{+00}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	$4.26 \times 10^{+01}$	$5.69 \times 10^{+01}$	$1.46 \times 10^{+01}$	$7.09 \times 10^{+01}$	6.67×10^{-06}	7.86×10^{-07}	3.45×10^{-02}
F5	Ave	$\mathbf{6.26 \times 10^{-04}}$	$3.03 \times 10^{+05}$	$1.91 \times 10^{+07}$	$9.99 \times 10^{+01}$	$6.13 \times 10^{+07}$	$9.75 \times 10^{+01}$	$9.76 \times 10^{+01}$	$9.58 \times 10^{+01}$
	Std	$\mathbf{1.04 \times 10^{-03}}$	$1.93 \times 10^{+05}$	$3.23 \times 10^{+07}$	$3.38 \times 10^{+00}$	$6.42 \times 10^{+07}$	7.43×10^{-01}	7.34×10^{-01}	$1.82 \times 10^{+00}$
	Max	$\mathbf{4.76 \times 10^{-03}}$	$9.65 \times 10^{+05}$	$8.71 \times 10^{+07}$	$1.17 \times 10^{+02}$	$1.60 \times 10^{+08}$	$9.83 \times 10^{+01}$	$9.84 \times 10^{+01}$	$9.83 \times 10^{+01}$
	Min	$\mathbf{4.16 \times 10^{-07}}$	$2.47 \times 10^{+04}$	$4.21 \times 10^{+05}$	$9.89 \times 10^{+01}$	$8.17 \times 10^{+03}$	$9.56 \times 10^{+01}$	$9.60 \times 10^{+01}$	$9.36 \times 10^{+01}$
F6	Ave	$\mathbf{1.96 \times 10^{-05}}$	$2.78 \times 10^{+03}$	$1.98 \times 10^{+04}$	$2.23 \times 10^{+01}$	$2.01 \times 10^{+04}$	$2.27 \times 10^{+00}$	$9.36 \times 10^{+00}$	$5.19 \times 10^{+00}$
	Std	$\mathbf{2.95 \times 10^{-05}}$	$2.27 \times 10^{+03}$	$1.14 \times 10^{+04}$	5.76×10^{-01}	$1.28 \times 10^{+04}$	8.92×10^{-01}	8.84×10^{-01}	8.84×10^{-01}
	Max	$\mathbf{1.18 \times 10^{-04}}$	$1.10 \times 10^{+04}$	$4.57 \times 10^{+04}$	$2.34 \times 10^{+01}$	$5.02 \times 10^{+04}$	$4.48 \times 10^{+00}$	$1.14 \times 10^{+01}$	$6.71 \times 10^{+00}$
	Min	$\mathbf{7.58 \times 10^{-09}}$	$4.61 \times 10^{+02}$	$1.69 \times 10^{+03}$	$2.13 \times 10^{+01}$	$5.56 \times 10^{+02}$	4.60×10^{-01}	$7.84 \times 10^{+00}$	$3.58 \times 10^{+00}$
F7	Ave	$\mathbf{1.85 \times 10^{-04}}$	$1.09 \times 10^{+01}$	$9.61 \times 10^{+01}$	1.03×10^{-02}	$1.56 \times 10^{+00}$	1.66×10^{-01}	2.29×10^{-03}	6.54×10^{-03}
	Std	$\mathbf{1.73 \times 10^{-04}}$	$1.54 \times 10^{+01}$	$4.45 \times 10^{+01}$	5.79×10^{-03}	2.61×10^{-01}	5.12×10^{-02}	1.27×10^{-03}	1.55×10^{-03}
	Max	$\mathbf{7.72 \times 10^{-04}}$	$6.45 \times 10^{+01}$	$1.89 \times 10^{+02}$	2.34×10^{-02}	$1.98 \times 10^{+00}$	2.85×10^{-01}	6.83×10^{-03}	9.65×10^{-03}
	Min	$\mathbf{7.70 \times 10^{-07}}$	$2.01 \times 10^{+00}$	$2.40 \times 10^{+01}$	2.03×10^{-03}	9.95×10^{-01}	8.43×10^{-02}	3.88×10^{-04}	3.68×10^{-03}
F8	Ave	$\mathbf{-4.19 \times 10^{+04}}$	$-2.63 \times 10^{+04}$	$-2.26 \times 10^{+04}$	$-7.30 \times 10^{+03}$	$-2.00 \times 10^{+04}$	$-9.35 \times 10^{+03}$	$-3.96 \times 10^{+04}$	$-2.09 \times 10^{+04}$
	Std	$\mathbf{9.54 \times 10^{-02}}$	$2.04 \times 10^{+03}$	$1.78 \times 10^{+03}$	$4.77 \times 10^{+02}$	$1.78 \times 10^{+03}$	$3.86 \times 10^{+03}$	$9.03 \times 10^{+02}$	$6.19 \times 10^{+03}$
	Max	$\mathbf{-4.19 \times 10^{+04}}$	$-2.16 \times 10^{+04}$	$-1.93 \times 10^{+04}$	$-6.55 \times 10^{+03}$	$-1.71 \times 10^{+04}$	$-6.23 \times 10^{+03}$	$-3.77 \times 10^{+04}$	$-1.14 \times 10^{+04}$
	Min	$\mathbf{-4.19 \times 10^{+04}}$	$-3.02 \times 10^{+04}$	$-2.72 \times 10^{+04}$	$-8.53 \times 10^{+03}$	$-2.42 \times 10^{+04}$	$-1.87 \times 10^{+04}$	$-4.11 \times 10^{+04}$	$-2.93 \times 10^{+04}$

Table 10. *Cont.*

Function	Criteria	ITSO	AGPSO	MPSO	OBSCA	PSOGSA	CGWO	GWOCS	IGWO
F9	Ave	$\mathbf{0.00 \times 10^{+00}}$	$4.39 \times 10^{+02}$	$7.13 \times 10^{+02}$	1.71×10^{-08}	$5.69 \times 10^{+02}$	2.65×10^{-14}	1.84×10^{-01}	$1.06 \times 10^{+02}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	$4.38 \times 10^{+01}$	$7.98 \times 10^{+01}$	9.18×10^{-08}	$7.50 \times 10^{+01}$	4.81×10^{-14}	9.89×10^{-01}	$4.83 \times 10^{+01}$
	Max	$\mathbf{0.00 \times 10^{+00}}$	$5.42 \times 10^{+02}$	$8.85 \times 10^{+02}$	5.12×10^{-07}	$7.61 \times 10^{+02}$	1.14×10^{-13}	$5.51 \times 10^{+00}$	$1.77 \times 10^{+02}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	$3.41 \times 10^{+02}$	$5.77 \times 10^{+02}$	$\mathbf{0.00 \times 10^{+00}}$	$4.29 \times 10^{+02}$	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$2.46 \times 10^{+01}$
F10	Ave	$\mathbf{8.88 \times 10^{-16}}$	$1.37 \times 10^{+01}$	$1.80 \times 10^{+01}$	$5.01 \times 10^{+00}$	$1.92 \times 10^{+01}$	3.85×10^{-14}	1.03×10^{-13}	1.02×10^{-13}
	Std	$\mathbf{0.00 \times 10^{+00}}$	$1.27 \times 10^{+00}$	$1.33 \times 10^{+00}$	$3.86 \times 10^{+00}$	4.85×10^{-01}	3.26×10^{-15}	8.35×10^{-15}	9.73×10^{-15}
	Max	$\mathbf{8.88 \times 10^{-16}}$	$1.56 \times 10^{+01}$	$1.95 \times 10^{+01}$	$1.50 \times 10^{+01}$	$2.00 \times 10^{+01}$	4.35×10^{-14}	1.22×10^{-13}	1.29×10^{-13}
	Min	$\mathbf{8.88 \times 10^{-16}}$	$1.10 \times 10^{+01}$	$1.42 \times 10^{+01}$	1.67×10^{-07}	$1.81 \times 10^{+01}$	3.29×10^{-14}	8.62×10^{-14}	7.90×10^{-14}
F11	Ave	$\mathbf{0.00 \times 10^{+00}}$	$1.85 \times 10^{+01}$	$1.71 \times 10^{+02}$	1.71×10^{-06}	$3.16 \times 10^{+02}$	$\mathbf{0.00 \times 10^{+00}}$	3.22×10^{-03}	1.09×10^{-03}
	Std	$\mathbf{0.00 \times 10^{+00}}$	$8.60 \times 10^{+00}$	$8.61 \times 10^{+01}$	4.10×10^{-06}	$1.43 \times 10^{+02}$	$\mathbf{0.00 \times 10^{+00}}$	8.40×10^{-03}	4.18×10^{-03}
	Max	$\mathbf{0.00 \times 10^{+00}}$	$4.32 \times 10^{+01}$	$3.93 \times 10^{+02}$	1.68×10^{-05}	$6.29 \times 10^{+02}$	$\mathbf{0.00 \times 10^{+00}}$	3.18×10^{-02}	2.00×10^{-02}
	Min	$\mathbf{0.00 \times 10^{+00}}$	$6.56 \times 10^{+00}$	$2.66 \times 10^{+01}$	1.08×10^{-13}	$1.20 \times 10^{+02}$	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$	$\mathbf{0.00 \times 10^{+00}}$
F12	Ave	$\mathbf{3.96 \times 10^{-08}}$	$2.17 \times 10^{+02}$	$1.02 \times 10^{+05}$	$1.16 \times 10^{+00}$	$2.47 \times 10^{+08}$	1.26×10^{-01}	2.24×10^{-01}	8.95×10^{-02}
	Std	$\mathbf{4.03 \times 10^{-08}}$	$5.59 \times 10^{+02}$	$1.52 \times 10^{+05}$	1.42×10^{-01}	$2.68 \times 10^{+08}$	5.36×10^{-02}	5.43×10^{-02}	2.81×10^{-02}
	Max	$\mathbf{1.52 \times 10^{-07}}$	$3.13 \times 10^{+03}$	$6.10 \times 10^{+05}$	$1.71 \times 10^{+00}$	$1.02 \times 10^{+09}$	3.67×10^{-01}	4.05×10^{-01}	1.60×10^{-01}
	Min	$\mathbf{5.53 \times 10^{-12}}$	$2.55 \times 10^{+01}$	$2.32 \times 10^{+02}$	9.83×10^{-01}	$4.07 \times 10^{+02}$	6.62×10^{-02}	1.62×10^{-01}	4.44×10^{-02}
F13	Ave	$\mathbf{4.36 \times 10^{-06}}$	$5.66 \times 10^{+04}$	$3.14 \times 10^{+07}$	$1.15 \times 10^{+01}$	$4.51 \times 10^{+08}$	$6.19 \times 10^{+00}$	$6.08 \times 10^{+00}$	$4.56 \times 10^{+00}$
	Std	$\mathbf{1.18 \times 10^{-05}}$	$9.38 \times 10^{+04}$	$1.02 \times 10^{+08}$	$1.40 \times 10^{+00}$	$4.28 \times 10^{+08}$	5.01×10^{-01}	4.03×10^{-01}	5.58×10^{-01}
	Max	$\mathbf{6.54 \times 10^{-05}}$	$5.01 \times 10^{+05}$	$4.13 \times 10^{+08}$	$1.59 \times 10^{+01}$	$1.64 \times 10^{+09}$	$7.26 \times 10^{+00}$	$6.66 \times 10^{+00}$	$5.74 \times 10^{+00}$
	Min	$\mathbf{4.63 \times 10^{-10}}$	$1.88 \times 10^{+03}$	$6.23 \times 10^{+04}$	$1.01 \times 10^{+01}$	$1.48 \times 10^{+04}$	$5.17 \times 10^{+00}$	$5.21 \times 10^{+00}$	$3.21 \times 10^{+00}$
Friedman Ave Rank		**1.1513**	5.9282	7.1949	4.9333	7.2385	3.1628	3.0551	3.3359
Rank		**1**	6	7	5	8	3	2	4

Table 11. Results of ITSO with improved optimization algorithms for 200-dimensional high-dimensional functions, The bolded part is the best result.

Function	Criteria	ITSO	AGPSO	MPSO	OBSCA	PSOGSA	CGWO	GWOCS	IGWO
F1	Ave	$\mathbf{0.00 \times 10^{+00}}$	$3.67 \times 10^{+04}$	$1.18 \times 10^{+05}$	1.93×10^{-04}	$8.52 \times 10^{+04}$	2.38×10^{-24}	7.40×10^{-21}	6.90×10^{-19}
	Std	$\mathbf{0.00 \times 10^{+00}}$	$6.31 \times 10^{+03}$	$1.72 \times 10^{+04}$	3.60×10^{-04}	$1.41 \times 10^{+04}$	2.24×10^{-24}	7.08×10^{-21}	5.66×10^{-19}
	Max	$\mathbf{0.00 \times 10^{+00}}$	$5.02 \times 10^{+04}$	$1.60 \times 10^{+05}$	1.32×10^{-03}	$1.22 \times 10^{+05}$	9.31×10^{-24}	3.32×10^{-20}	2.91×10^{-18}
	Min	$\mathbf{0.00 \times 10^{+00}}$	$2.29 \times 10^{+04}$	$8.06 \times 10^{+04}$	2.61×10^{-09}	$5.58 \times 10^{+04}$	3.79×10^{-25}	1.38×10^{-21}	1.34×10^{-19}
F2	Ave	$\mathbf{0.00 \times 10^{+00}}$	$4.26 \times 10^{+02}$	$7.28 \times 10^{+02}$	3.53×10^{-10}	$6.34 \times 10^{+37}$	3.17×10^{-15}	6.16×10^{-13}	5.01×10^{-13}
	Std	$\mathbf{0.00 \times 10^{+00}}$	$8.60 \times 10^{+01}$	$8.24 \times 10^{+01}$	9.07×10^{-10}	$3.41 \times 10^{+38}$	1.37×10^{-15}	2.89×10^{-13}	1.69×10^{-13}
	Max	$\mathbf{0.00 \times 10^{+00}}$	$6.85 \times 10^{+02}$	$8.79 \times 10^{+02}$	4.82×10^{-09}	$1.90 \times 10^{+39}$	7.19×10^{-15}	1.71×10^{-12}	9.37×10^{-13}
	Min	$\mathbf{0.00 \times 10^{+00}}$	$2.81 \times 10^{+02}$	$5.78 \times 10^{+02}$	7.07×10^{-13}	$6.84 \times 10^{+02}$	1.22×10^{-15}	2.45×10^{-13}	2.64×10^{-13}
F3	Ave	$\mathbf{0.00 \times 10^{+00}}$	$4.25 \times 10^{+05}$	$7.64 \times 10^{+05}$	$7.69 \times 10^{+04}$	$5.16 \times 10^{+05}$	$3.99 \times 10^{+03}$	$1.19 \times 10^{+03}$	$4.26 \times 10^{+04}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	$1.03 \times 10^{+05}$	$1.67 \times 10^{+05}$	$5.16 \times 10^{+04}$	$1.07 \times 10^{+05}$	$4.12 \times 10^{+03}$	$8.09 \times 10^{+02}$	$1.01 \times 10^{+04}$
	Max	$\mathbf{0.00 \times 10^{+00}}$	$6.21 \times 10^{+05}$	$1.18 \times 10^{+06}$	$2.02 \times 10^{+05}$	$7.20 \times 10^{+05}$	$1.59 \times 10^{+04}$	$2.90 \times 10^{+03}$	$6.35 \times 10^{+04}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	$2.54 \times 10^{+05}$	$4.67 \times 10^{+05}$	$3.81 \times 10^{+03}$	$3.52 \times 10^{+05}$	$1.55 \times 10^{+02}$	$1.33 \times 10^{+02}$	$2.51 \times 10^{+04}$
F4	Ave	$\mathbf{0.00 \times 10^{+00}}$	$6.32 \times 10^{+01}$	$7.71 \times 10^{+01}$	$8.80 \times 10^{+01}$	$9.73 \times 10^{+01}$	$7.62 \times 10^{+01}$	1.45×10^{-01}	$3.23 \times 10^{+01}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	$3.49 \times 10^{+00}$	$7.00 \times 10^{+00}$	$4.53 \times 10^{+00}$	$1.28 \times 10^{+00}$	$2.98 \times 10^{+01}$	1.85×10^{-01}	$3.65 \times 10^{+00}$
	Max	$\mathbf{0.00 \times 10^{+00}}$	$7.37 \times 10^{+01}$	$9.66 \times 10^{+01}$	$9.47 \times 10^{+01}$	$9.89 \times 10^{+01}$	$1.00 \times 10^{+02}$	7.38×10^{-01}	$4.01 \times 10^{+01}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	$5.62 \times 10^{+01}$	$6.82 \times 10^{+01}$	$7.59 \times 10^{+01}$	$9.25 \times 10^{+01}$	$7.29 \times 10^{+00}$	1.54×10^{-03}	$2.64 \times 10^{+01}$
F5	Ave	$\mathbf{1.34 \times 10^{-03}}$	$2.04 \times 10^{+07}$	$2.59 \times 10^{+08}$	$6.35 \times 10^{+03}$	$1.47 \times 10^{+08}$	$1.98 \times 10^{+02}$	$1.98 \times 10^{+02}$	$1.97 \times 10^{+02}$
	Std	$\mathbf{2.75 \times 10^{-03}}$	$7.46 \times 10^{+06}$	$9.35 \times 10^{+07}$	$1.39 \times 10^{+04}$	$1.17 \times 10^{+08}$	3.23×10^{-01}	5.30×10^{-01}	$1.05 \times 10^{+00}$
	Max	$\mathbf{1.45 \times 10^{-02}}$	$4.81 \times 10^{+07}$	$5.21 \times 10^{+08}$	$6.45 \times 10^{+04}$	$4.83 \times 10^{+08}$	$1.98 \times 10^{+02}$	$1.98 \times 10^{+02}$	$1.98 \times 10^{+02}$
	Min	$\mathbf{4.10 \times 10^{-08}}$	$9.92 \times 10^{+06}$	$9.04 \times 10^{+07}$	$2.01 \times 10^{+02}$	$2.20 \times 10^{+06}$	$1.97 \times 10^{+02}$	$1.96 \times 10^{+02}$	$1.94 \times 10^{+02}$
F6	Ave	$\mathbf{4.60 \times 10^{-05}}$	$3.52 \times 10^{+04}$	$1.21 \times 10^{+05}$	$4.87 \times 10^{+01}$	$8.85 \times 10^{+04}$	$1.73 \times 10^{+01}$	$2.80 \times 10^{+01}$	$2.15 \times 10^{+01}$
	Std	$\mathbf{8.62 \times 10^{-05}}$	$9.21 \times 10^{+03}$	$2.00 \times 10^{+04}$	$3.11 \times 10^{+00}$	$2.24 \times 10^{+04}$	$3.12 \times 10^{+00}$	$1.03 \times 10^{+00}$	$1.33 \times 10^{+00}$
	Max	$\mathbf{4.67 \times 10^{-04}}$	$6.11 \times 10^{+04}$	$1.61 \times 10^{+05}$	$6.51 \times 10^{+01}$	$1.35 \times 10^{+05}$	$2.38 \times 10^{+01}$	$3.02 \times 10^{+01}$	$2.51 \times 10^{+01}$
	Min	$\mathbf{1.23 \times 10^{-07}}$	$2.24 \times 10^{+04}$	$8.38 \times 10^{+04}$	$4.70 \times 10^{+01}$	$4.69 \times 10^{+04}$	$1.20 \times 10^{+01}$	$2.63 \times 10^{+01}$	$1.94 \times 10^{+01}$
F7	Ave	$\mathbf{2.67 \times 10^{-04}}$	$1.68 \times 10^{+02}$	$1.16 \times 10^{+03}$	5.05×10^{-02}	$1.76 \times 10^{+01}$	1.65×10^{-01}	4.69×10^{-03}	1.49×10^{-02}
	Std	$\mathbf{1.78 \times 10^{-04}}$	$1.03 \times 10^{+02}$	$3.88 \times 10^{+02}$	4.49×10^{-02}	$3.15 \times 10^{+00}$	5.30×10^{-02}	1.76×10^{-03}	3.29×10^{-03}
	Max	$\mathbf{6.36 \times 10^{-04}}$	$5.83 \times 10^{+02}$	$2.16 \times 10^{+03}$	2.18×10^{-01}	$2.77 \times 10^{+01}$	3.17×10^{-01}	8.79×10^{-03}	2.42×10^{-02}
	Min	$\mathbf{2.88 \times 10^{-05}}$	$7.03 \times 10^{+01}$	$4.67 \times 10^{+02}$	5.94×10^{-03}	$1.02 \times 10^{+01}$	8.10×10^{-02}	1.25×10^{-03}	8.67×10^{-03}
F8	Ave	$\mathbf{-8.38 \times 10^{+04}}$	$-4.41 \times 10^{+04}$	$-3.58 \times 10^{+04}$	$-1.06 \times 10^{+04}$	$-2.99 \times 10^{+04}$	$-1.31 \times 10^{+04}$	$-7.76 \times 10^{+04}$	$-3.57 \times 10^{+04}$
	Std	$\mathbf{9.39 \times 10^{-02}}$	$2.28 \times 10^{+03}$	$2.53 \times 10^{+03}$	$6.61 \times 10^{+02}$	$2.14 \times 10^{+03}$	$1.76 \times 10^{+03}$	$1.14 \times 10^{+03}$	$1.37 \times 10^{+04}$
	Max	$\mathbf{-8.38 \times 10^{+04}}$	$-3.92 \times 10^{+04}$	$-2.87 \times 10^{+04}$	$-9.30 \times 10^{+03}$	$-2.31 \times 10^{+04}$	$-1.03 \times 10^{+04}$	$-7.53 \times 10^{+04}$	$-1.50 \times 10^{+04}$
	Min	$\mathbf{-8.38 \times 10^{+04}}$	$-4.88 \times 10^{+04}$	$-4.11 \times 10^{+04}$	$-1.17 \times 10^{+04}$	$-3.50 \times 10^{+04}$	$-1.84 \times 10^{+04}$	$-8.00 \times 10^{+04}$	$-5.52 \times 10^{+04}$

Table 11. *Cont.*

Function	Criteria	ITSO	AGPSO	MPSO	OBSCA	PSOGSA	CGWO	GWOCS	IGWO
F9	Ave	$\mathbf{0.00 \times 10^{+00}}$	$1.20 \times 10^{+03}$	$1.73 \times 10^{+03}$	7.24×10^{-04}	$1.22 \times 10^{+03}$	1.89×10^{-13}	$1.54 \times 10^{+00}$	$1.91 \times 10^{+02}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	$7.91 \times 10^{+01}$	$1.07 \times 10^{+02}$	3.82×10^{-03}	$1.07 \times 10^{+02}$	1.86×10^{-13}	$4.17 \times 10^{+00}$	$1.26 \times 10^{+02}$
	Max	$\mathbf{0.00 \times 10^{+00}}$	$1.33 \times 10^{+03}$	$1.92 \times 10^{+03}$	2.13×10^{-02}	$1.44 \times 10^{+03}$	4.55×10^{-13}	$2.05 \times 10^{+01}$	$5.49 \times 10^{+02}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	$1.04 \times 10^{+03}$	$1.57 \times 10^{+03}$	2.62×10^{-10}	$1.00 \times 10^{+03}$	$\mathbf{0.00 \times 10^{+00}}$	2.27×10^{-13}	$1.22 \times 10^{+01}$
F10	Ave	$\mathbf{8.88 \times 10^{-16}}$	$1.76 \times 10^{+01}$	$1.96 \times 10^{+01}$	$1.11 \times 10^{+01}$	$1.96 \times 10^{+01}$	2.69×10^{-13}	5.80×10^{-12}	5.51×10^{-11}
	Std	$\mathbf{0.00 \times 10^{+00}}$	2.94×10^{-01}	9.58×10^{-02}	$5.35 \times 10^{+00}$	3.38×10^{-01}	6.17×10^{-14}	1.99×10^{-12}	2.37×10^{-11}
	Max	$\mathbf{8.88 \times 10^{-16}}$	$1.82 \times 10^{+01}$	$1.98 \times 10^{+01}$	$1.76 \times 10^{+01}$	$2.00 \times 10^{+01}$	4.59×10^{-13}	1.18×10^{-11}	1.04×10^{-10}
	Min	$\mathbf{8.88 \times 10^{-16}}$	$1.71 \times 10^{+01}$	$1.94 \times 10^{+01}$	8.06×10^{-05}	$1.90 \times 10^{+01}$	1.86×10^{-13}	2.13×10^{-12}	2.51×10^{-11}
F11	Ave	$\mathbf{0.00 \times 10^{+00}}$	$3.06 \times 10^{+02}$	$1.14 \times 10^{+03}$	1.99×10^{-03}	$1.26 \times 10^{+03}$	1.32×10^{-03}	2.29×10^{-03}	9.43×10^{-04}
	Std	$\mathbf{0.00 \times 10^{+00}}$	$7.74 \times 10^{+01}$	$1.70 \times 10^{+02}$	7.71×10^{-03}	$2.22 \times 10^{+02}$	4.94×10^{-03}	5.96×10^{-03}	3.77×10^{-03}
	Max	$\mathbf{0.00 \times 10^{+00}}$	$4.16 \times 10^{+02}$	$1.51 \times 10^{+03}$	4.26×10^{-02}	$1.95 \times 10^{+03}$	2.01×10^{-02}	2.04×10^{-02}	1.93×10^{-02}
	Min	$\mathbf{0.00 \times 10^{+00}}$	$1.72 \times 10^{+02}$	$6.90 \times 10^{+02}$	2.99×10^{-09}	$9.41 \times 10^{+02}$	$\mathbf{0.00 \times 10^{+00}}$	1.11×10^{-16}	1.11×10^{-16}
F12	Ave	$\mathbf{4.30 \times 10^{-08}}$	$3.15 \times 10^{+06}$	$3.55 \times 10^{+08}$	$2.42 \times 10^{+04}$	$6.59 \times 10^{+08}$	2.52×10^{-01}	4.73×10^{-01}	$1.15 \times 10^{+01}$
	Std	$\mathbf{8.22 \times 10^{-08}}$	$2.76 \times 10^{+06}$	$2.41 \times 10^{+08}$	$1.30 \times 10^{+05}$	$4.45 \times 10^{+08}$	1.02×10^{-01}	5.34×10^{-02}	$7.44 \times 10^{+00}$
	Max	$\mathbf{3.29 \times 10^{-07}}$	$1.24 \times 10^{+07}$	$8.80 \times 10^{+08}$	$7.26 \times 10^{+05}$	$1.54 \times 10^{+09}$	6.71×10^{-01}	5.63×10^{-01}	$2.61 \times 10^{+01}$
	Min	$\mathbf{1.92 \times 10^{-10}}$	$6.03 \times 10^{+05}$	$6.82 \times 10^{+07}$	$1.18 \times 10^{+00}$	$7.72 \times 10^{+06}$	1.26×10^{-01}	3.62×10^{-01}	3.80×10^{-01}
F13	Ave	$\mathbf{4.36 \times 10^{-06}}$	$2.29 \times 10^{+07}$	$9.81 \times 10^{+08}$	$2.52 \times 10^{+03}$	$1.21 \times 10^{+09}$	$1.60 \times 10^{+01}$	$1.60 \times 10^{+01}$	$2.08 \times 10^{+01}$
	Std	$\mathbf{9.08 \times 10^{-06}}$	$1.15 \times 10^{+07}$	$4.11 \times 10^{+08}$	$1.30 \times 10^{+04}$	$8.19 \times 10^{+08}$	4.01×10^{-01}	4.37×10^{-01}	$1.65 \times 10^{+01}$
	Max	$\mathbf{4.68 \times 10^{-05}}$	$6.66 \times 10^{+07}$	$1.85 \times 10^{+09}$	$7.24 \times 10^{+04}$	$3.28 \times 10^{+09}$	$1.67 \times 10^{+01}$	$1.72 \times 10^{+01}$	$1.07 \times 10^{+02}$
	Min	$\mathbf{5.48 \times 10^{-10}}$	$8.68 \times 10^{+06}$	$1.33 \times 10^{+08}$	$2.02 \times 10^{+01}$	$2.10 \times 10^{+07}$	$1.53 \times 10^{+01}$	$1.51 \times 10^{+01}$	$1.36 \times 10^{+01}$
Friedman Ave Rank		**1.0500**	5.8128	7.2436	5.0487	7.0872	3.1038	2.9205	3.7333
Rank		**1**	6	8	5	7	3	2	4

Table 12. Results of ITSO with improved optimization algorithms for 500-dimensional high-dimensional functions, The bolded part is the best result.

Function	Criteria	ITSO	AGPSO	MPSO	OBSCA	PSOGSA	CGWO	GWOCS	IGWO
F1	Ave	$\mathbf{0.00 \times 10^{+00}}$	$2.87 \times 10^{+05}$	$6.66 \times 10^{+05}$	$4.67 \times 10^{+01}$	$5.43 \times 10^{+05}$	2.47×10^{-15}	4.98×10^{-13}	1.37×10^{-10}
	Std	$\mathbf{0.00 \times 10^{+00}}$	$1.95 \times 10^{+04}$	$3.56 \times 10^{+04}$	$1.79 \times 10^{+02}$	$5.79 \times 10^{+04}$	1.88×10^{-15}	2.53×10^{-13}	7.70×10^{-11}
	Max	$\mathbf{0.00 \times 10^{+00}}$	$3.16 \times 10^{+05}$	$7.27 \times 10^{+05}$	$9.24 \times 10^{+02}$	$6.41 \times 10^{+05}$	8.44×10^{-15}	1.11×10^{-12}	3.73×10^{-10}
	Min	$\mathbf{0.00 \times 10^{+00}}$	$2.44 \times 10^{+05}$	$5.68 \times 10^{+05}$	5.48×10^{-04}	$4.31 \times 10^{+05}$	6.45×10^{-16}	1.17×10^{-13}	3.88×10^{-11}
F2	Ave	1.70×10^{-05}	$2.19 \times 10^{+27}$	$1.20 \times 10^{+142}$	7.33×10^{-07}	$4.26 \times 10^{+267}$	$\mathbf{9.16 \times 10^{-10}}$	2.59×10^{-08}	$1.46 \times 10^{+270}$
	Std	5.20×10^{-05}	$1.18 \times 10^{+28}$	$6.46 \times 10^{+142}$	1.85×10^{-06}	INF	$\mathbf{3.35 \times 10^{-10}}$	6.73×10^{-09}	INF
	Max	2.86×10^{-04}	$6.56 \times 10^{+28}$	$3.60 \times 10^{+143}$	1.01×10^{-05}	$1.28 \times 10^{+269}$	$\mathbf{1.76 \times 10^{-09}}$	4.51×10^{-08}	$4.37 \times 10^{+271}$
	Min	$\mathbf{3.16 \times 10^{-14}}$	$1.46 \times 10^{+03}$	$1.94 \times 10^{+03}$	1.79×10^{-10}	$2.97 \times 10^{+92}$	4.68×10^{-10}	1.72×10^{-08}	1.55×10^{-03}
F3	Ave	$\mathbf{4.31 \times 10^{-227}}$	$2.44 \times 10^{+06}$	$4.17 \times 10^{+06}$	$8.89 \times 10^{+05}$	$3.01 \times 10^{+06}$	$1.63 \times 10^{+05}$	$5.98 \times 10^{+04}$	$4.89 \times 10^{+05}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	$5.48 \times 10^{+05}$	$6.55 \times 10^{+05}$	$3.61 \times 10^{+05}$	$6.48 \times 10^{+05}$	$6.42 \times 10^{+04}$	$2.61 \times 10^{+04}$	$6.16 \times 10^{+04}$
	Max	$\mathbf{1.29 \times 10^{-225}}$	$3.63 \times 10^{+06}$	$5.57 \times 10^{+06}$	$2.30 \times 10^{+06}$	$4.78 \times 10^{+06}$	$3.49 \times 10^{+05}$	$1.14 \times 10^{+05}$	$6.23 \times 10^{+05}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	$1.27 \times 10^{+06}$	$2.31 \times 10^{+06}$	$4.21 \times 10^{+05}$	$2.03 \times 10^{+06}$	$5.51 \times 10^{+04}$	$1.47 \times 10^{+04}$	$3.77 \times 10^{+05}$
F4	Ave	$\mathbf{0.00 \times 10^{+00}}$	$7.43 \times 10^{+01}$	$9.88 \times 10^{+01}$	$9.83 \times 10^{+01}$	$9.87 \times 10^{+01}$	$9.99 \times 10^{+01}$	$1.91 \times 10^{+01}$	$5.30 \times 10^{+01}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	$2.86 \times 10^{+00}$	3.56×10^{-01}	5.37×10^{-01}	7.42×10^{-01}	4.81×10^{-01}	$4.30 \times 10^{+00}$	$2.79 \times 10^{+00}$
	Max	$\mathbf{0.00 \times 10^{+00}}$	$7.99 \times 10^{+01}$	$9.94 \times 10^{+01}$	$9.90 \times 10^{+01}$	$9.97 \times 10^{+01}$	$1.00 \times 10^{+02}$	$2.93 \times 10^{+01}$	$5.84 \times 10^{+01}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	$6.81 \times 10^{+01}$	$9.79 \times 10^{+01}$	$9.70 \times 10^{+01}$	$9.63 \times 10^{+01}$	$9.74 \times 10^{+01}$	$8.34 \times 10^{+00}$	$4.76 \times 10^{+01}$
F5	Ave	$\mathbf{2.26 \times 10^{-03}}$	$3.39 \times 10^{+08}$	$2.11 \times 10^{+09}$	$1.08 \times 10^{+06}$	$8.30 \times 10^{+08}$	$4.98 \times 10^{+02}$	$4.97 \times 10^{+02}$	$6.58 \times 10^{+02}$
	Std	$\mathbf{5.22 \times 10^{-03}}$	$5.58 \times 10^{+07}$	$1.65 \times 10^{+08}$	$1.91 \times 10^{+06}$	$1.88 \times 10^{+08}$	2.65×10^{-01}	4.49×10^{-01}	$2.28 \times 10^{+02}$
	Max	$\mathbf{2.81 \times 10^{-02}}$	$4.73 \times 10^{+08}$	$2.50 \times 10^{+09}$	$1.03 \times 10^{+07}$	$1.32 \times 10^{+09}$	$4.98 \times 10^{+02}$	$4.98 \times 10^{+02}$	$1.39 \times 10^{+03}$
	Min	$\mathbf{2.34 \times 10^{-06}}$	$2.24 \times 10^{+08}$	$1.80 \times 10^{+09}$	$7.25 \times 10^{+03}$	$3.34 \times 10^{+08}$	$4.97 \times 10^{+02}$	$4.96 \times 10^{+02}$	$4.98 \times 10^{+02}$
F6	Ave	$\mathbf{7.59 \times 10^{-05}}$	$2.82 \times 10^{+05}$	$6.85 \times 10^{+05}$	$1.41 \times 10^{+02}$	$5.79 \times 10^{+05}$	$9.34 \times 10^{+01}$	$9.38 \times 10^{+01}$	$8.35 \times 10^{+01}$
	Std	$\mathbf{1.15 \times 10^{-04}}$	$2.74 \times 10^{+04}$	$2.92 \times 10^{+04}$	$3.21 \times 10^{+01}$	$5.76 \times 10^{+04}$	$2.95 \times 10^{+00}$	$1.73 \times 10^{+00}$	$2.39 \times 10^{+00}$
	Max	$\mathbf{5.85 \times 10^{-04}}$	$3.53 \times 10^{+05}$	$7.31 \times 10^{+05}$	$2.37 \times 10^{+02}$	$6.80 \times 10^{+05}$	$9.81 \times 10^{+01}$	$9.84 \times 10^{+01}$	$8.88 \times 10^{+01}$
	Min	$\mathbf{1.17 \times 10^{-09}}$	$2.27 \times 10^{+05}$	$6.20 \times 10^{+05}$	$1.23 \times 10^{+02}$	$4.47 \times 10^{+05}$	$8.37 \times 10^{+01}$	$9.04 \times 10^{+01}$	$7.88 \times 10^{+01}$
F7	Ave	$\mathbf{2.87 \times 10^{-04}}$	$5.36 \times 10^{+03}$	$1.96 \times 10^{+04}$	$8.80 \times 10^{+00}$	$3.56 \times 10^{+02}$	1.01×10^{-01}	1.38×10^{-02}	2.22×10^{-01}
	Std	$\mathbf{3.05 \times 10^{-04}}$	$1.08 \times 10^{+03}$	$1.83 \times 10^{+03}$	$1.79 \times 10^{+01}$	$7.90 \times 10^{+01}$	3.77×10^{-02}	4.95×10^{-03}	7.10×10^{-02}
	Max	$\mathbf{1.66 \times 10^{-03}}$	$8.63 \times 10^{+03}$	$2.34 \times 10^{+04}$	$8.66 \times 10^{+01}$	$5.33 \times 10^{+02}$	1.90×10^{-01}	2.99×10^{-02}	3.53×10^{-01}
	Min	$\mathbf{3.02 \times 10^{-05}}$	$3.77 \times 10^{+03}$	$1.55 \times 10^{+04}$	5.90×10^{-02}	$2.33 \times 10^{+02}$	1.38×10^{-02}	6.96×10^{-03}	7.80×10^{-02}
F8	Ave	$\mathbf{-2.09 \times 10^{+05}}$	$-7.68 \times 10^{+04}$	$-6.37 \times 10^{+04}$	$-1.70 \times 10^{+04}$	$-4.79 \times 10^{+04}$	$-2.93 \times 10^{+04}$	$-1.67 \times 10^{+05}$	$-7.48 \times 10^{+04}$
	Std	$\mathbf{3.56 \times 10^{-01}}$	$4.74 \times 10^{+03}$	$5.11 \times 10^{+03}$	$1.17 \times 10^{+03}$	$3.83 \times 10^{+03}$	$2.22 \times 10^{+03}$	$3.08 \times 10^{+03}$	$3.14 \times 10^{+04}$
	Max	$\mathbf{-2.09 \times 10^{+05}}$	$-6.81 \times 10^{+04}$	$-5.58 \times 10^{+04}$	$-1.46 \times 10^{+04}$	$-3.95 \times 10^{+04}$	$-2.59 \times 10^{+04}$	$-1.59 \times 10^{+05}$	$-2.39 \times 10^{+04}$
	Min	$\mathbf{-2.09 \times 10^{+05}}$	$-8.50 \times 10^{+04}$	$-7.70 \times 10^{+04}$	$-1.98 \times 10^{+04}$	$-5.69 \times 10^{+04}$	$-3.51 \times 10^{+04}$	$-1.74 \times 10^{+05}$	$-1.13 \times 10^{+05}$

Table 12. *Cont.*

Function	Criteria	ITSO	AGPSO	MPSO	OBSCA	PSOGSA	CGWO	GWOCS	IGWO
F9	Ave	$\mathbf{0.00 \times 10^{+00}}$	$4.12 \times 10^{+03}$	$5.62 \times 10^{+03}$	$2.25 \times 10^{+00}$	$3.61 \times 10^{+03}$	2.66×10^{-09}	$2.36 \times 10^{+00}$	$1.76 \times 10^{+02}$
	Std	$\mathbf{0.00 \times 10^{+00}}$	$1.57 \times 10^{+02}$	$1.60 \times 10^{+02}$	$1.21 \times 10^{+01}$	$3.75 \times 10^{+02}$	1.43×10^{-08}	$3.82 \times 10^{+00}$	$1.02 \times 10^{+02}$
	Max	$\mathbf{0.00 \times 10^{+00}}$	$4.40 \times 10^{+03}$	$5.93 \times 10^{+03}$	$6.75 \times 10^{+01}$	$4.20 \times 10^{+03}$	7.96×10^{-08}	$1.52 \times 10^{+01}$	$4.94 \times 10^{+02}$
	Min	$\mathbf{0.00 \times 10^{+00}}$	$3.73 \times 10^{+03}$	$5.29 \times 10^{+03}$	7.29×10^{-10}	$2.96 \times 10^{+03}$	3.64×10^{-12}	1.73×10^{-11}	$5.60 \times 10^{+01}$
F10	Ave	$\mathbf{8.88 \times 10^{-16}}$	$1.88 \times 10^{+01}$	$2.02 \times 10^{+01}$	$1.69 \times 10^{+01}$	$2.00 \times 10^{+01}$	1.60×10^{-09}	2.86×10^{-08}	4.98×10^{-07}
	Std	$\mathbf{0.00 \times 10^{+00}}$	1.43×10^{-01}	6.81×10^{-02}	$5.75 \times 10^{+00}$	5.50×10^{-02}	4.63×10^{-10}	8.97×10^{-09}	1.52×10^{-07}
	Max	$\mathbf{8.88 \times 10^{-16}}$	$1.92 \times 10^{+01}$	$2.03 \times 10^{+01}$	$2.02 \times 10^{+01}$	$2.01 \times 10^{+01}$	2.63×10^{-09}	5.80×10^{-08}	8.82×10^{-07}
	Min	$\mathbf{8.88 \times 10^{-16}}$	$1.86 \times 10^{+01}$	$2.00 \times 10^{+01}$	2.93×10^{-03}	$1.98 \times 10^{+01}$	7.59×10^{-10}	1.45×10^{-08}	2.51×10^{-07}
F11	Ave	$\mathbf{0.00 \times 10^{+00}}$	$2.56 \times 10^{+03}$	$6.11 \times 10^{+03}$	3.11×10^{-01}	$6.49 \times 10^{+03}$	1.01×10^{-15}	8.37×10^{-04}	3.73×10^{-03}
	Std	$\mathbf{0.00 \times 10^{+00}}$	$1.93 \times 10^{+02}$	$3.17 \times 10^{+02}$	6.01×10^{-01}	$4.82 \times 10^{+02}$	4.94×10^{-16}	4.51×10^{-03}	7.72×10^{-03}
	Max	$\mathbf{0.00 \times 10^{+00}}$	$2.92 \times 10^{+03}$	$6.67 \times 10^{+03}$	$3.24 \times 10^{+00}$	$7.60 \times 10^{+03}$	2.55×10^{-15}	2.51×10^{-02}	2.36×10^{-02}
	Min	$\mathbf{0.00 \times 10^{+00}}$	$2.12 \times 10^{+03}$	$5.46 \times 10^{+03}$	6.89×10^{-05}	$5.75 \times 10^{+03}$	4.44×10^{-16}	2.92×10^{-14}	4.71×10^{-12}
F12	Ave	$\mathbf{4.62 \times 10^{-08}}$	$2.06 \times 10^{+08}$	$4.24 \times 10^{+09}$	$2.55 \times 10^{+06}$	$2.41 \times 10^{+09}$	5.68×10^{-01}	8.38×10^{-01}	$6.43 \times 10^{+01}$
	Std	$\mathbf{8.70 \times 10^{-08}}$	$4.89 \times 10^{+07}$	$5.51 \times 10^{+08}$	$4.10 \times 10^{+06}$	$9.93 \times 10^{+08}$	1.06×10^{-01}	2.68×10^{-01}	$6.67 \times 10^{+00}$
	Max	$\mathbf{4.34 \times 10^{-07}}$	$3.01 \times 10^{+08}$	$5.21 \times 10^{+09}$	$1.39 \times 10^{+07}$	$5.27 \times 10^{+09}$	8.29×10^{-01}	$1.40 \times 10^{+00}$	$8.90 \times 10^{+01}$
	Min	$\mathbf{4.10 \times 10^{-13}}$	$1.29 \times 10^{+08}$	$2.92 \times 10^{+09}$	$4.49 \times 10^{+00}$	$7.28 \times 10^{+08}$	4.12×10^{-01}	5.02×10^{-01}	$5.32 \times 10^{+01}$
F13	Ave	$\mathbf{6.74 \times 10^{-06}}$	$8.39 \times 10^{+08}$	$9.05 \times 10^{+09}$	$1.11 \times 10^{+07}$	$4.81 \times 10^{+09}$	$4.61 \times 10^{+01}$	$4.69 \times 10^{+01}$	$9.74 \times 10^{+02}$
	Std	$\mathbf{1.27 \times 10^{-05}}$	$1.39 \times 10^{+08}$	$7.61 \times 10^{+08}$	$1.64 \times 10^{+07}$	$1.49 \times 10^{+09}$	5.52×10^{-01}	$1.56 \times 10^{+00}$	$8.90 \times 10^{+01}$
	Max	$\mathbf{6.00 \times 10^{-05}}$	$1.16 \times 10^{+09}$	$1.06 \times 10^{+10}$	$6.19 \times 10^{+07}$	$8.87 \times 10^{+09}$	$4.80 \times 10^{+01}$	$5.16 \times 10^{+01}$	$1.17 \times 10^{+03}$
	Min	$\mathbf{7.33 \times 10^{-11}}$	$6.06 \times 10^{+08}$	$7.16 \times 10^{+09}$	$1.32 \times 10^{+02}$	$2.55 \times 10^{+09}$	$4.52 \times 10^{+01}$	$4.33 \times 10^{+01}$	$8.18 \times 10^{+02}$
Friedman Ave Rank		**1.1846**	5.7308	7.3744	5.0231	6.7923	3.1154	2.6487	4.1308
Rank		**1**	6	8	5	7	3	2	4

5. Conclusions

In this paper, an improved TSO is proposed to address the defects of the original TSO, namely, slow convergence speed and ease of falling into a local optimum when solving high-dimensional complex problems. Firstly, a chaotic opposition learning strategy is used to improve the quality of the initial population, then adaptive inertia weights are introduced to improve the global and local search ability of the algorithm and accelerate the convergence speed. Then, a neighbor dimension learning strategy is used to ensure the population diversity of each iteration. In the 18 benchmark test functions, 30 independent comparative experiences were conducted with 16 popular algorithms, and Ave, Std, Max, and Min were chosen to evaluate the mathematical characteristics of the experimental data, in addition to the means of Wilcoxon's rank sum test with a significance evaluation index of 5%. The experimental results show that ITSO not only showed obvious competitiveness in Ave, Std, Max, and Min, but also showed significant statistical advantages in the nonparametric sign test. ITSO consistently maintained the best stability, as shown in box-line plots, for all data. In conclusion, ITSO shows significant superiority and high competitiveness in finding accuracy, convergence speed, and solving complex high-dimensional problems. The main features of ITSO are not only high exploitation and exploration abilities, but also fast convergence. However, we cannot guarantee the best performance in all global optimization problems.

The research prospects for the TSO should not be underestimated. Its development and exploration capability can be improved by introducing other strategies, and by mixing it with other metaheuristics to obtain a more competitive and improved TSO. The TSO can be applied not only to solve global optimization problems, but also to solve optimal parameter combinations in single diode models, neural network parameter optimization, power load scheduling, and unmanned aircraft.

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