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Improved Slime Mould Algorithm Hybridizing Chaotic Maps and Differential Evolution Strategy for Global Optimization

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ABSTRACT Slime Mould Algorithm (SMA) is a new meta-heuristics algorithm that is inspired by the behaviors of slime mould from nature. Due to its effective performance, SMA has shown its competitive performance among other meta-heuristics algorithms and has been used in many mathematical optimization and real-world problems. However, SMA tends to sink into local optimality and lacks the diversity of the population. Therefore, to cope with the drawbacks of the classical SMA, this paper proposes an improved SMA algorithm named CHDESMA. First of all, the chaotic maps methods have the characteristics of ergodicity and randomness, and we used chaotic maps methods to replace the original random initialization to improve the diversity of the algorithm, which is more suitable for exploring the potential areas in the early stage. Then, based on the superior searching ability of the differential evolution algorithm (DE), the crossover and selection operations of DE are applied to CHDESMA, and the position is updated by the combination of the original SMA operator and the mutation strategy of DE, which effectively avoids the algorithm falling into local optimum. CHDESMA was evaluated using CEC2014 and CEC2017 test suits and four real-world engineering problems. CHDESMA was compared with advanced algorithms and DE variants. The experimental results and statistical analysis indicate that CHDESMA has competitive performance compared with the state-of-the-art algorithms.

INDEX TERMS Slime mould algorithm, differential evolution, chaotic maps, function optimization, engineering design problem.

I. INTRODUCTION

The swarm intelligence algorithms are mainly inspired by the hunting, foraging, and survival processes based on evolution and population in the natural environment [1]. In recent years, these meta-heuristics algorithms have been widely developed in various fields because of their outstanding advantages in many large-scale and real-life problems, such as engineering problems [2], feature selection [3], biological information processing [4], and cost-effective scheduling problems [5]. The most popular optimizers include Evolution Strategies (ES) [6], Grey Wolf Optimizer (GWO) [7], Bat Algorithm (BA) [8], Differential Evolution (DE) [9], Genetic Algorithms (GA) [10] and Salp Swarm Algorithm (SSA) [11], etc.

Li *et al.* [12] introduced a new optimizer which is a random method based on viscous oscillation mode called Slime Mould Algorithm. Many experiments have proved that the algorithm is effective in solving global optimization problems. For example, Djekidel *et al.* [13] employed SMA to affect the magnetic coupling between high-voltage lines and metal pipes. Mostafa *et al.* [14] applied SMA to extract photovoltaic panel model parameters. Gush *et al.* [15] utilized SMA to enhance the photovoltaic capacity on the issue of distribution networks. Tiacht *et al.* [16] applied SMA for damage detection, location, and quantification. Deb *et al.* [17] adopted SMA to alleviate the transmission congestion of generators. Chen *et al.* [18] proposed a chaotic mud model algorithm (CSMA) to predict accuracy and computational complexity. Kumar *et al.* [19] applied SMA to estimate photovoltaic cell parameters. Kadry *et al.* [20] designed a multi-scale matched filter using SMA. Agarwal *et al.* [21] improved SMA to generate the best collision-free path for a mobile robot.

There have been many improvement mechanisms to be proposed to boost the performance of SMA. For instance, Houssein *et al.* [22] proposed to combine

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SMA with an adaptive guided differential evolution algorithm [23]. In [24], the author Yousri proposed a hybrid of SMA and Marine Predator Algorithm (MPA) [25] to simulate photovoltaic systems. Premkumar *et al.* [26] proposed a multi-objective slime mould algorithm (MOSMA). Abdel-Basset *et al.* [27] mixed SMA with Whale Optimization Algorithm (WOA) [28] to resolve the image segmentation issue of COVID-19 [29].

Although the performance of SMA has been improved in some areas, it still has certain limitations when dealing with complex problems. Table 1 summarizes the SMA variants in recent years and illustrates their features, merits, and limitations. For this reason, an enhanced SMA algorithm called CHDESMA has been proposed in this paper, which presents Chaotic Maps [30] and DE strategy into SMA simultaneously. First, Logistic Map [31] is used to initialize the population, which is beneficial to accelerate the convergency at the initial stage of the iteration. Then use the Differential Evolution strategy to improve the local search ability of the group agent, increase the diversity of slime mold populations, and prevent the premature maturity of the entire iterative process. The chaotic maps strategy and DE operator have been successfully applied to deal with various algorithm optimization problems. These successful literature are presented in Table 2 and Table 3, respectively. Chaotic initialization has been shown to improve the quality of the solution. However, the drawbacks are that it lacks robustness in dealing with various problems and the performance of the algorithm combined with the chaotic maps approach is not competitive when dealing with discrete problems. The DE algorithm shows good exploration capabilities, but individuals can easily fall into local optimization as the iterations proceed. The proposed CHDESMA was compared with seven advanced algorithms and seven well-known DE variants. The performance test was carried out on CEC2014 [32] and CEC2017 [33] benchmark functions. CHDESMA was then used to solve four engineering design problems, such as tension/compression spring design problem (TCSD), welded beam design problem (WBD), pressure vessel design problem (PVD), and three-bar truss design problem (TBTD). The experimental results and statistical analysis show that CHDESMA can achieve satisfactory results in the population iteration's convergence speed and quality of optimization problems.

The following shows the main contributions of this research:

a) In the early stage, CHDESMA applies Logistic Map initialization to improve the diversity of the population and find a promising area.
b) The DE algorithm is used to enhance the searching ability and prevent the algorithm from stagnation.
c) The proposed CHDESMA was evaluated by CEC2014 and CEC2017 test suits and four real-world engineering problems. Experimental results and statistical analysis indicate that CHDESMA is more effective than other state-of-the-art algorithms.
d) This study is promising for the study, analysis, improvement, and expansion of SMA, and the study of the evolutionary optimizer is of great significance.

The main components of the paper are distributed as follows: the basic versions of SMA, Differential Evolution, and Chaotic Maps are explained in Section 2. Section 3 describes in detail the proposed variant CHDESMA. In Section 4, the experimental simulation results are studied and discussed. In the end, Section 5 summarizes the article and analyzes possible future work.

II. BACKGROUND

A. THE BASIC VERSION OF SMA

SMA is a new optimizer based on the natural slime moulds oscillation mode. SMA uses weights as the positive and negative feedback generated by simulating the foraging process of slime moulds, composed of the following three different forms: approaching food, wrapping food, and oscillating.

1) APPROACH FOOD

Slime moulds rely on the smell of the air to get close to the desired food. Its approach to food is simulated as follows:

$$x(t+1)=\begin{cases} x_b(t)+vb\times(W\times x_A(t)-x_B(t)) & r<p \\ vc\times x(t) & r\geq p \end{cases} \tag{1}$$

where W is the weight of slime moulds. $x_b(t)$ is the global optimal position, and $x(t)$ is the position of each slime mould. vb oscillates between $[-a, a]$. $x_A(t)$ and $x_B(t)$ are random positions. The formulation of vb, vc, and W are shown in Eq. (3), Eq. (4), and Eq. (5).

Where p is shown as follows:

$$p=\tanh|Fit(i)-BF| \tag{2}$$

where *Fit(i)* is the fitness of each slime mould, *BF* is the best fitness of slime mould in the current iteration.

The value of vb and vc are shown as follows:

$$vb=[-a,a],\quad a=arctanh\left(-\frac{t}{maxiter}\right) \tag{3}$$

$$vc=[-b,b],\quad b=1-\frac{t}{maxiter} \tag{4}$$

Among them, t indicates the current iteration number, and *maxiter* is the maximum iterations.

The W is expressed as follows:

$$W(SmellIndex(i))=\begin{cases} 1+r\times log\left(\frac{BF-Fit(i)}{BF-WF}+1\right) \\ \quad condition \\ 1-r\times log\left(\frac{BF-Fit(i)}{BF-WF}+1\right) \\ \quad others \end{cases} \tag{5}$$

$$SmellIndex=sort(Fit) \tag{6}$$

SmellIndex is the sequence of fitness values after sorting. r is a random number in the range of [0, 1], *condition* indicates that *Fit(i)* is ranked in the first half.

TABLE 1. Summary of the research papers on SMA algorithm variants.

Author	Methods	Features	Merits	Limitations
[18]	CMBSA(2019)	This method mixes the K-means clustering method (KMCM) and the chaotic SMA algorithm and proposes a new SVR-based prediction method.	The proposed method has an excellent performance in accuracy and complexity.	The stability of the algorithm is not very good.
[24]	HMPA(2021)	The developed algorithm is based on the mixture of the MPA algorithm and SMA algorithm, which is used to adjust the optimal parameters of photovoltaic units based on the diode model (TDM).	It enhances the development ability of the MPA algorithm, and can effectively identify TDM parameters.	The algorithms compared in the performance testing phase are not novel enough.
[28]	HSMA_WOA(2020)	The WOA algorithm is employed to further balance the exploration and exploitation ability of the original SMA algorithm to escape from the local optimum.	Few parameters and efficient exploration and exploitation capabilities.	It is easy to fall into the local optimum when dealing with complex problems.
[34]	CSMA(2022)	The proposed algorithm applied the sinusoidal map to further improve the performance of the original SMA algorithm.	The CSMA method is easy to implement, with small mathematical complexity.	The accuracy of the solution is not high enough.

TABLE 2. Summary of the research papers on chaotic maps.

Author	Methods	Features
[35]	CLCA(2016)	Apply the chaotic map to the LCA algorithm and replace the random array with the chaotic map. Chaotic maps can improve convergence speed and accuracy.
[36]	CMBSA(2020)	Taking different chaotic systems instead of random number sequences as BSA parameters, different chaotic map-based bird swarm algorithms (CMBSA) are proposed, and a new field of chaotic dynamics is also introduced. Using chaotic maps in standard BSA is often more useful than using random numbers.
[37]	CABC(2010)	Parameter adaptation is performed by using a chaotic number generator in the classical ABC algorithm. The proposed method effectively improves the quality of the original algorithm solution.
[38]	CHS(2010)	Seven chaotic maps are incorporated into the harmony search algorithm to adapt the parameters. The chaotic maps strategy is utilized to change music rhythm parameters. From the existing results, the chaotic map strategies can improve the global searchability and avoid local optimum.
[39]	CEPSO(2009)	Twelve algorithms based on eight chaotic map methods are proposed in this paper. Chaotic maps are used to update the position of each particle, which can improve the solution quality and help individuals escape from the local optimum.

TABLE 3. Summary of the research papers on DE variants.

Author	Methods	Features
[22]	SMA-AGDE(2021)	The SMA operator is employed in the binomial crossover phase of AGDE. The mutation strategy of AGDE is used to improve the local search ability of the population, increase the diversity of the population, and help to avoid convergence to the local extreme value.
[40]	MBADE(2020)	MBADE algorithm hybridized the DE algorithm with the modified BA algorithm. MBADE selected an appropriate operator based on a probability value. From the existing results, the proposed MBADE algorithm can improve the exploration and exploitation ability.
[41]	DEPSO(2019)	The improved DE/rand/1 mutation strategy is effectively utilized in the PSO algorithm to enhance the global exploration ability.
[42]	HDS(2021)	The proposed algorithm hybridized DE/rand/1 mutation strategy and SOS operators to further enhance exploitation, while DE/best/1 and DE/best/2 mutation strategies are employed to enhance the exploration ability.

2) WRAP FOOD

This part uses a mathematical model to simulate the shrinkage of slime mold mathematically. The positive and negative feedback between food concentration is simulated by Eq. (5). When the food concentration of the area is high, the weight nearby is greater, and when food concentration near the area is low, the weight nearby decreases to explore other areas.

The formula of each slime mould is calculated as follows:

$$x(t+1)=\begin{cases} rand \times (UB-LB)+LB & rand<z \\ x_b(t)+vb\times(W\times x_A(t)-x_B(t)) & r<p \\ vc\times x(t) & r\geq p \end{cases} \tag{7}$$

where UB and LB represent the upper and lower bounds of the total space. z is usually taken as a tiny number, such as 0.03 [12]. The definitions of vb, vc, W, p, x_b, x_A, and x_B are shown in Eq. (1).

3) OSCILLATION

The slime moulds for the most part change the flow of cytoplasm in the vein by the propagation wave generated by the biological vibrator so that it can be placed in a better food concentration position. In order to simulate the changes in the pulse width of slime bacteria, W, vb, and vc are used by us to achieve these changes.

Mathematical methods are used to simulate the vibrational frequencies of different food concentrations. vb is generated in the range of $[-a, a]$ randomly and approaches zero by degrees with the increase of the number of iterations. vc is in the range of [-1, 1] and finally reaches zero.

Algorithm 1 is the pseudo-code of SMA.

B. THE BASIC VERSION OF DE

DE based on genetic algorithms and other evolutionary thoughts was proposed by Storn *et al.* [43] in 1997. The primary process of DE consists of three steps, mutation, crossover, and selection.

Algorithm 1 Pseudo-Code of SMA

Initialization: *maxiter*, *Dim,* slime mould population *N,* and each slime mould position x_i
While (t ≤ *maxiter*)
  Calculate the fitness value of each slime mould.
  Calculate and update *BF* and *WF.*
  Update the global optimal position x_{best}.
  Use Eq. **(5)** to update the value of weight *W.*
  For each individual
    Use Eq. **(2)** to update parameter *p.*
    Use Eq. **(3)** to update parameter *vb.*
    Use Eq. **(4)** to update parameter *vc.*
    Use Eq. **(7)** to update the positions of the slime mould.
  End for
  t + = 1
End while
Return *BF*, x_{best}

1) INITIALIZATION

We initialize the main population randomly in the search space. For example, the j^{th} individual in the i^{th} dimension is generated at first-generation ($G = 0$) and is obtained as follows:

$$x_{j,i}^{0} = LB_j + rand\,(0, 1) \times \left(UB_j - LB_j\right) \tag{8}$$

where *UB* and *LB* represent the upper and lower bounds of the total space.

2) MUTATION OPERATION

The mutation vector of each generation is generated with the following formula:

$$v_i^G = x_{r_1}^G + F \times \left(x_{r_2}^G - x_{r_3}^G\right) \tag{9}$$

where indicators r_1, r_2, and r_3 are randomly chosen from the main population $[1, 2, \ldots, N]$, which are not equal to i. Storn *et al.* [43] mentioned that the range of F is within [0, 2]. F is the control parameter of the proportional vector. The following formulas are the other most commonly used mutation strategies:

$$DE/best/1: \; v_i^G = x_{best}^G + F \times \left(x_{r_1}^G - x_{r_2}^G\right) \tag{10}$$

$$DE/best/2: \; v_i^G = x_{best}^G + F \times \left(x_{r_1}^G - x_{r_2}^G\right) + F \times \left(x_{r_3}^G - x_{r_4}^G\right) \tag{11}$$

$$DE/rand/2: \; v_i^G = x_{r_1}^G + F \times \left(x_{r_2}^G - x_{r_3}^G\right) + F \times \left(x_{r_4}^G - x_{r_5}^G\right) \tag{12}$$

$$DE/current-to-best/1: \; v_i^G = x_i^G + F \times \left(x_{best}^G - x_i^G\right) + F \times \left(x_{r_1}^G - x_{r_2}^G\right) \tag{13}$$

$$DE/current-to-rand/1: \; v_i^G = x_i^G + F \times \left(x_{r_1}^G - x_i^G\right) + F \times \left(x_{r_2}^G - x_{r_3}^G\right) \tag{14}$$

where r_1, r_2, r_3, r_4, and r_5 are randomly chosen from the main population $[1, 2, \ldots, N]$, which are not similar to index i. x_{best}^G is the best fitness value, and F is the control parameter of the proportional vector.

3) CROSSOVER OPERATION

In this part, the target vector and the mutation vector are mixed, and the following scheme is used to obtain the test vector:

$$u_{j,i}^G = \begin{cases} v_{j,i}^G & if \; \left(rand_{j,i} \leq CR \; or \; j = j_{rand}\right) \\ x_{j,i}^G & otherwise \end{cases} \tag{15}$$

where CR is the control crossing number, which controls the probability of generating parameters from the mutation vector.

4) SELECTION OPERATION

In this part, the greedy strategy is used to discuss whether to choose u_i^G or x_i^G. If the fitness value of u_i^G is better, it will be retained; otherwise, it will be replaced by x_i^G. The options are as follows:

$$x_i^{G+1} = \begin{cases} u_i^G & Fit\left(u_i^G\right) \leq Fit\left(x_i^G\right) \\ x_i^G & otherwise \end{cases} \tag{16}$$

C. CHAOTIC MAPS

Chaotic methods have various characteristics, such as ergodicity, randomness, and irregularity. Moreover, they are efficacious initial dependency criteria [38], [39]. Due to the different characteristics mentioned above, a chaotic mapping method composed of different equations is constructed to change random variables in optimization methods. Wang *et al.* [44] called this process the Chaos Optimization Algorithm (COA) [45]. The optimization type gives the intensity traversal of the chaos theory. The optimization method can effectively help the algorithm avoid premature maturity, and at the same time, can speed up the convergence.

III. THE PROPOSED CHDESMA

This section mainly introduces the composition and structure of CHDESMA. In the traditional SMA algorithm, the algorithm tends to fall into local optimization and cannot maintain the balance between exploration and exploitation. We hybridized the original SMA algorithm with a differential evolution algorithm and introduced chaotic mapping to solve these problems. In the early steps of the algorithm, we used Logistic Map to initialize the population. In the whole optimization process of the algorithm, we use the operators of DE instead of the operators of the original SMA to improve the local search capabilities of slime mould, increase the diversity of the population and prevent CHDESMA from stagnating prematurely.

A. CHAOTIC INITIALIZATION

Among the current chaotic search methods, logistic chaotic mapping is widely used [46]. Due to its simple operation and good optimization performance, CHDESMA uses Logistic Map to initialize the population to achieve acceleration in the early steps of the algorithm. The formulation of the Logistic Map is calculated by Eq. (17), and the pseudo-code of chaotic initialization is shown in Algorithm 2.

$$x^{k+1} = a \times x^k \left(1 - x^k\right) \tag{17}$$

where a is a real number ($a = 4$), k indicates the current iteration, and x^k represents the k^{th} chaotic number.

Algorithm 2 Pseudo-Code of Chaotic Initialization

Generate variable x^k according to the Logistic map shown in Eq. **(17)**
For i = 0 to N
    For j = 0 to Dim
        $X_{i,j} = LB_j + x^k_{i,j} \times (UB_j - LB_j)$
    End for
End for

B. USE THE OPERATORS OF DE TO UPDATE THE POPULATION

The component mark *CR* controls the direction of exploration and exploitation. We mixed the DE strategy in the optimization process to enhance the local search ability of slime mould. Each position of the slime mould is calculated based on the following formula:

$$u^G_{j,i} = \begin{cases} v^G_{j,i} \\ \quad if \left(rand_{j,i} \le CR \; or \; j = j_{rand}\right) \\ x^G_{j,i} + vb \times \left(W \times x^G_{j,A} - x^G_{j,B}\right) \\ \quad otherwise \end{cases} \tag{18}$$

where $rand_{j,i}$ is a random number in the range of [0,1], *CR* is the crossover probability, and parameter W is calculated as follows:

$$W = \begin{cases} 1 + r \times log\left(\frac{BF - Fit\,(i)}{BF - WF} + 1\right) \\ \quad if \; rand < m \\ 1 - r \times log\left(\frac{BF - Fit\,(i)}{BF - WF} + 1\right) \\ \quad otherwise \end{cases} \tag{19}$$

$$m = \frac{t}{maxiter} \tag{20}$$

where *maxiter* is the maximum number of iterations and t is the current iteration. The parameters *BF* and *WF* are the best and worst solutions in the current iteration, respectively, and *Fit(i)* represents the fitness of a current individual.

The formulation of parameter v is defined as follows:

$$v^G_i = x^G_{r_1} + vb \times \left(x^G_{r_2} - x^G_{r_3}\right) \tag{21}$$

where r_1, r_2, and r_3 are randomly chosen from the main population $[1, 2, \ldots, N]$, which are not similar to index i. The variable vb gradually tends to 0 with the algorithm proceeded, and vb oscillates between $[-a, a]$. The values of vb and a are shown in Eq. (3) and Eq. (4).

The main steps of the CHDESMA are shown in Algorithm 3, and Figure 1 shows the flowchart of CHDESMA.

Algorithm 3 Pseudo-Code of CHDESMA

Initialization: *MAXFES*, *Dim*, slime mould population *N*, and the crossover probability *CR*.
Chaotic initialize each slime mould position x_i by algorithm 2.
While ($FES \le MAXFES$)
    Calculate the fitness value of each slime mould.
    Calculate and update *BF* and *WF*.
    Update the global optimal position x_{best}.
    Use Eq. **(19)** to update the parameter weight *W*.
    For each individual
        Use Eq. **(4)** to update the parameter *vb*.
        if rand $\le CR$ **or** rand $= j$ // Update slime moulds
            Use Eq. **(21)** to generate mutant vector *v*.
        else
            Use Eq. **(18)** to generate mutant vector *u*.
        end if
        if $Fit(u) <= Fit(x_i)$
            Use Eq. **(18)** to set x_i to mutant vector *u*.
        end if
    End for
    $FES += N$
End while
Return *BF*, x_{best}

C. COMPUTATIONAL COMPLEXITY OF CHDESMA

This section will analyze the computational complexity of the newly proposed CHDESMA The computational complexity of CHDESMA mainly depends on chaotic maps, DE, and SMA. Among them, the number of slime molds populations is N, the dimension is D, and the maximum number of iterations is T. The computational complexity of SMA is $O(D + T \times N \times (\log N + D))$, the computational complexity of DE is $O(D + T \times N \times D)$, and the computational complexity of chaotic maps is $O(T \times N \times D)$. Therefore, the computational complexity of CHDESMA is $O(D + T \times N(3D + \log N))$, which is equal to $O(T \times N \times D)$.

IV. EXPERIMENTS AND DISCUSSION

The performance of CHDESMA under different functions is evaluated, and the data are analyzed. We set up three sets of experimental schemes. The first experimental scheme was carried out on 29 CEC2017 benchmark functions to verify the effectiveness of the chaotic maps and DE strategy used. The second experiment was to test the performance of CHDESMA on 30 CEC2014 benchmark functions. The experiment compared CHDESMA with published DE variants, which were composed of the latest DE variants and recognized DE variants with better performance. In the third experiment, in order to test the scalability of CHDESMA, CHDESMA was compared with the advanced algorithms in different dimensions. In addition, Wilcoxon rank-sum test was used in each experiment to study the statistical significance of the results. To further analyze the results, the box diagram was used to show the dispersion of data.

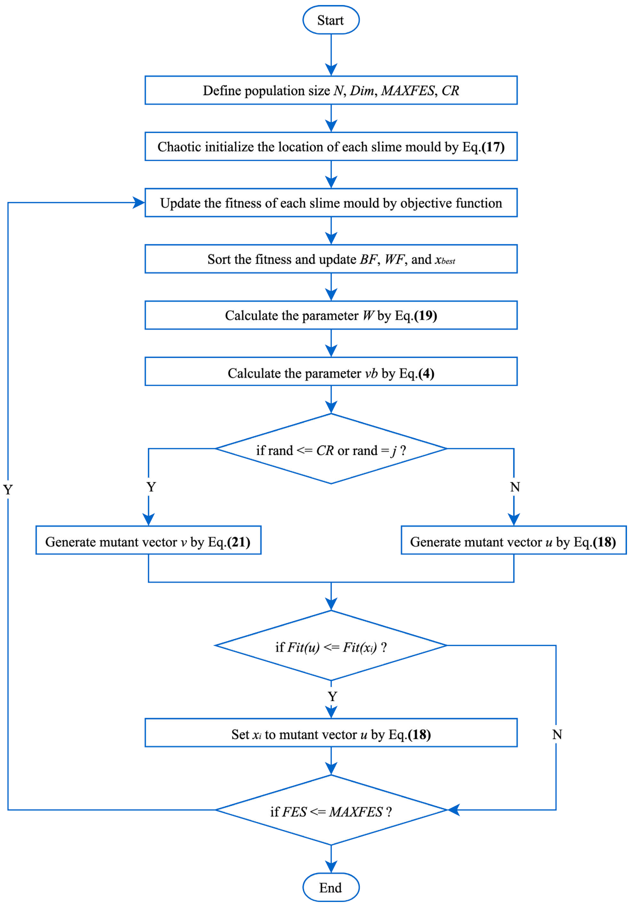

FIGURE 1. Flowchart of CHDESMA.

CHDESMA was used to solve four practical engineering problems. For the sake of fairness, referring to [47], algorithmic hyper parameters of all algorithms must be tuned in the same manner on the selected problems. Therefore, the parameters of the competition optimizer in all experiments were based on the most appropriate parameter settings in the published articles, as shown in Table 4. In this paper, the maximum number of fitness evaluations (*MAXFES*) was set to $10000 \times D$.

A. SYSTEM DETAILS

In this study, all the involved algorithms were tested using python 3.9 under MacOS10.15, with Intel (R) Core (TM) i5 CPU @ 3.8 GHz, and with 16 GB of RAM.

B. VALIDITY OF CHAOTIC MAPS AND DE STRATEGIES

CHDESMA algorithm is mainly composed of chaotic maps, DE strategy, and the original SMA algorithm. This section aims to verify the effectiveness of the use of chaotic maps and DE strategy. CHDESMA was compared with DESMA (SMA algorithm with DE operator), CHSMA (SMA algorithm with chaotic initialization), and SMA in Table 5. The experiment was carried out on the 30-dimensional CEC2017 test suite. The population number was set to 30. For the sake of fairness, each test function was run 30 times independently,

TABLE 4. Parameter settings of the involved algorithms.

Algorithm	Parameter setting
MGFPA	$\gamma = 0.01$; $p = 0.8$; population size = 50
PPSO	$c_1 = 2$; $c_2 = 2$; $wMax = 0.9$; $wMin = 0.2$; $\theta \in [0, 2\pi]$; population size = 60
OBWOA	$a_1 = [2,0]$; $a_2 = [-2,1]$; $b = 1$; population size = 30
TVBSSA	$c_1 \in [0,1]$; $c_2 \in [0,1]$; population size = 50
mSCA	Sr = 0.1; population size = 30
mGWO	$\mu CR = 0.5$; $a \in [2, 0]$; $k \in [1, 0]$; population size = 30
CMAES	$alphamu = 2$; population size = $4 + (3 \times \log(D))$
SMA-AGDE	$CR1 \in [0.05,0.15]$; $CR2 \in [0.9,1.0]$; population size = 30
MBADE	$rend = 0.7$; $a = 0.7$; $rfirst = 0.1$; $afirst = 0.9$; $aend = 0.6$; population size = 100
AGDE	$CR1 \in [0.05,0.15]$; $CR2 \in [0.9,1.0]$; population size = 50
LSHADE_cnEpSi	$ps = 0.5$; $pc = 0.4$; $H = 5$; $freq = 0.5$; $\mu F = 0.5$; $\mu CR = 0.5$; population size = $18D \sim 4$
SADE	$\mu F = 0.5$; $F \sim C\ (\mu F,\ 0.3)$; $\mu Cr = 0.5$; $Cr \sim N\ (\mu Cr,\ 0.1)$; population size = $10D$
CoDE	$\mu F \in [0.4, 0.9]$; $\mu CR \in [0.1, 0.9]$; population size = 30
JSO	$pmax = 0.25$; $pmin = pmax/2$; $H=5$; $\mu F = 0.3$; $\mu CR = 0.9$; population size = $12D \sim 4$

and the average (Mean) and standard deviation (Std) were taken. In addition, Table 5 shows the statistical results (S.R.) obtained at the 5% significance level by Wilcoxon rank-sum test. "−", "≈", and "+" respectively indicate that the performance of competitors is poor, similar, and better than CHDESMA.

As can be seen from the SMA variants in Table 5, CHDESMA ranks first overall. The overall performance of the CHSMA algorithm is better than the original SMA algorithm, which shows that the chaotic maps method can effectively increase the diversity of slime mold populations and improve the performance of the original SMA algorithm. The DESMA algorithm is better than the SMA algorithm, which means that using the DE strategy can prevent SMA from falling into the local optimal value and enable SMA to find the global optimal solution. Wilcoxon rank-sum tests also show that this improvement is statistically significant.

C. COMPARISON WITH DE VARIANTS ON CEC2014

In order to test the performance of the proposed CHDESMA, CHDESMA was compared with DE variants in Table 6, including adaptive guided DE (AGDE) [23], ensemble sinusoidal differential covariance matrix adaptation with Euclidean neighborhood (LSHADE_cnEpSi) (named as LS_cnEpSi) [48], DE with strategy adaptation (SADE) [49], composite differential evolution (CoDE) [50], hybrid SMA with AGDE (SMA-AGDE) [22], modified BA hybridizing by DE (MBADE) [40], and JSO algorithm for solving single-objective real-parameter optimization problems (JSO) [51]. The experiment was carried out on the 30-dimensional CEC2014 test suites. For the sake of fairness, each test function was run 30 times independently. In addition, Table 6 shows the S.R. obtained at the 5% significance level by the Wilcoxon rank-sum test.

It can be seen from Table 6 that among these DE variants, CHDESMA ranks first. The results show that the CHDESMA has reached the global optimum value on the F2, F3, F7, F8,

TABLE 5. Experimental and statistical results of SMA variants on the 30-dimensional CEC2017 benchmark.

F		DESMA	CHSMA	SMA	CHDESMA
F1	Mean	1.00E+04	5.27E+04	5.72E+04	**2.62E+03**
	Std	2.34E+03	9.44E+03	7.21E+03	**1.20E+03**
	Rank/S.R.	2 / -	3 / -	4 / -	**1**
F3	Mean	2.40E+04	4.41E+03	2.55E+04	**3.71E+03**
	Std	2.02E+03	4.47E+02	4.73E+03	**1.76E+02**
	Rank/S.R.	3 / -	2 / -	4 / -	**1**
F4	Mean	4.91E+02	4.91E+02	4.93E+02	**4.89E+02**
	Std	2.52E+00	1.58E+00	4.63E+00	**6.82E-01**
	Rank/S.R.	2 / -	3 / -	4 / -	**1**
F5	Mean	5.41E+02	6.09E+02	6.14E+02	**5.33E+02**
	Std	5.40E+00	1.23E+01	1.80E+01	**1.79E+00**
	Rank/S.R.	2 / -	3 / -	4 / -	**1**
F6	Mean	6.01E+02	6.33E+02	6.38E+02	**6.01E+02**
	Std	3.50E-01	4.22E+00	8.43E+00	**1.21E-01**
	Rank/S.R.	2 / -	3 / -	4 / -	**1**
F7	Mean	7.69E+02	8.41E+02	8.55E+02	**7.61E+02**
	Std	4.91E+00	8.52E+00	1.42E+01	**2.59E+00**
	Rank/S.R.	2 / -	3 / -	4 / -	**1**
F8	Mean	8.42E+02	9.05E+02	9.13E+02	**8.40E+02**
	Std	7.36E+00	8.36E+00	1.95E+01	**3.66E+00**
	Rank/S.R.	2 / ≈	3 / -	4 / -	**1**
F9	Mean	9.10E+02	3.49E+03	4.03E+03	**9.04E+02**
	Std	3.65E+00	5.67E+02	1.31E+03	**3.49E-01**
	Rank/S.R.	2 / -	3 / -	4 / -	**1**
F10	Mean	**3.34E+03**	4.30E+03	4.60E+03	3.48E+03
	Std	2.07E+02	**1.13E+02**	4.60E+02	2.68E+02
	Rank/S.R.	**1** / +	3 / -	4 / -	2
F11	Mean	1.27E+03	1.20E+03	1.28E+03	**1.18E+03**
	Std	3.12E+01	2.70E+01	**1.86E+01**	1.93E+01
	Rank/S.R.	3 / -	2 / -	4 / -	**1**
F12	Mean	1.74E+06	4.51E+06	4.90E+06	**1.46E+06**
	Std	9.79E+05	1.48E+06	3.09E+06	**5.46E+05**
	Rank/S.R.	2 / ≈	3 / -	4 / -	**1**
F13	Mean	6.13E+03	6.43E+04	5.04E+04	**5.90E+03**
	Std	**1.42E+03**	1.84E+04	1.83E+04	1.70E+03
	Rank/S.R.	2 / ≈	4 / -	3 / -	**1**
F14	Mean	6.38E+04	6.04E+04	7.06E+04	**4.28E+04**
	Std	2.27E+04	**1.92E+04**	3.84E+04	2.03E+04
	Rank/S.R.	3 / -	2 / -	4 / -	**1**
F15	Mean	1.30E+04	1.32E+04	2.11E+04	**8.47E+03**
	Std	8.55E+03	5.86E+03	8.00E+03	**4.02E+03**
	Rank/S.R.	2 / -	3 / -	4 / -	**1**
F16	Mean	2.06E+03	2.27E+03	2.42E+03	**1.89E+03**
	Std	1.18E+02	9.35E+01	1.53E+02	**9.11E+01**
	Rank/S.R.	2 / -	3 / -	4 / -	**1**
F17	Mean	1.87E+03	2.22E+03	2.25E+03	**1.87E+03**
	Std	8.64E+01	8.65E+01	9.70E+01	**4.99E+01**
	Rank/S.R.	2 / ≈	3 / ≈	4 / -	**1**
F18	Mean	6.91E+05	7.28E+05	7.76E+05	**6.43E+05**
	Std	2.68E+05	**1.72E+05**	2.73E+05	2.18E+05
	Rank/S.R.	2 / ≈	3 / -	4 / -	**1**
F19	Mean	1.48E+04	1.53E+04	2.20E+04	**9.46E+03**
	Std	7.11E+03	**3.97E+03**	1.68E+04	4.15E+03
	Rank/S.R.	2 / -	3 / -	4 / -	**1**
F20	Mean	2.30E+03	2.47E+03	2.48E+03	**2.17E+03**
	Std	1.54E+02	1.21E+02	1.27E+02	**6.19E+01**
	Rank/S.R.	2 / -	3 / -	4 / -	**1**
F21	Mean	2.35E+03	2.41E+03	2.43E+03	**2.34E+03**
	Std	8.82E+00	1.88E+01	2.04E+01	**3.47E+00**
	Rank/S.R.	2 / -	3 / -	4 / -	**1**
F22	Mean	3.78E+03	4.34E+03	5.26E+03	**2.49E+03**
	Std	9.00E+02	1.34E+03	1.05E+03	**3.60E+01**
	Rank/S.R.	2 / -	3 / -	4 / -	**1**
F23	Mean	2.70E+03	2.75E+03	2.75E+03	**2.69E+03**
	Std	8.20E+00	8.30E+00	1.94E+01	**5.55E+00**
	Rank/S.R.	2 / -	3 / -	4 / -	**1**
F24	Mean	2.87E+03	2.93E+03	2.93E+03	**2.86E+03**
	Std	**6.57E+00**	1.21E+01	1.32E+01	7.01E+00
	Rank/S.R.	2 / -	3 / -	4 / -	**1**
F25	Mean	2.89E+03	2.89E+03	2.89E+03	**2.89E+03**
	Std	9.36E-01	1.17E+00	8.59E-01	**6.01E-01**
	Rank/S.R.	4 / -	3 / -	2 / ≈	**1**
F26	Mean	4.06E+03	4.94E+03	4.81E+03	**4.05E+03**
	Std	**3.20E+01**	2.06E+02	1.72E+02	5.44E+01
	Rank/S.R.	2 / ≈	4 / -	3 / -	**1**
F27	Mean	**3.20E+03**	3.22E+03	3.22E+03	3.21E+03
	Std	**2.60E+00**	3.09E+00	5.90E+00	3.63E+00
	Rank/S.R.	**1** / ≈	3 / -	4 / -	2
F28	Mean	3.25E+03	3.26E+03	3.25E+03	**3.22E+03**
	Std	2.10E+01	1.88E+01	2.78E+01	**1.82E+00**
	Rank/S.R.	2 / -	4 / -	3 / -	**1**
F29	Mean	3.49E+03	3.83E+03	3.90E+03	**3.39E+03**
	Std	4.51E+01	6.89E+01	1.51E+02	**1.94E+01**
	Rank/S.R.	2 / -	3 / -	4 / -	**1**
F30	Mean	1.33E+04	7.88E+04	8.08E+04	**1.13E+04**
	Std	2.08E+03	1.77E+04	3.05E+04	**1.32E+03**
	Rank/S.R.	2 / -	3 / -	4 / -	**1**
Sum of ranks		61	87	111	**31**
Average rank		2.10	3.00	3.83	**1.07**
Overall rank		2	3	4	**1**
- / ≈ / +		21 / 7 / 1	28 / 1 / 0	28 / 1 / 0	

TABLE 6. Experimental and statistical results of DE variants on the 30-dimensional CEC2014 benchmark functions.

Function		SMA-AGDE	MBADE	AGDE	LS_cnEpSi	SADE	CoDE	JSO	CHDESMA
	Mean	1.05E+06	1.14E+06	4.02E+04	3.76E+04	2.55E+04	1.79E+07	**1.06E+03**	3.05E+04
F1	Std	7.82E+05	5.28E+05	9.01E+04	2.26E+04	1.38E+04	4.16E+06	**1.72E+03**	2.23E+03
	Rank/S.R.	6 / -	7 / -	5 / ≈	4 / ≈	2 / ≈	8 / -	**1** / ≈	3
	Mean	**2.00E+02**	**2.00E+02**	**2.00E+02**	**2.00E+02**	2.00E+02	2.00E+02	**2.00E+02**	**2.00E+02**
F2	Std	**0.00E+00**	**0.00E+00**	**0.00E+00**	2.32E-14	2.52E-05	6.98E-04	**0.00E+00**	**0.00E+00**
	Rank/S.R.	**1 / ≈**	**1** / ≈	**1** / ≈	**1** / ≈	7 / -	8 / -	**1** / ≈	**1**
	Mean	**3.00E+02**	**3.00E+02**	**3.00E+02**	**3.00E+02**	3.00E+02	3.00E+02	**3.00E+02**	**3.00E+02**
F3	Std	**0.00E+00**	3.11E-14	**0.00E+00**	2.32E-14	3.53E-04	2.30E-06	**0.00E+00**	**0.00E+00**
	Rank/S.R.	**1 / ≈**	**1** / ≈	**1** / ≈	**1** / ≈	8 / -	7 / -	**1** / ≈	**1**
	Mean	4.71E+02	**4.03E+02**	4.09E+02	4.29E+02	4.34E+02	5.04E+02	4.22E+02	4.19E+02
F4	Std	2.84E+01	**1.19E+01**	2.15E+01	3.22E+01	2.83E+01	1.26E+01	3.07E+01	1.76E+01
	Rank/S.R.	7 / -	**1** / +	2 / +	5 / ≈	6 / -	8 / -	4 / ≈	3
	Mean	5.21E+02	5.21E+02	5.21E+02	**5.20E+02**	5.20E+02	5.20E+02	5.20E+02	5.20E+02
F5	Std	5.55E-02	4.04E-02	9.46E-02	1.83E-02	6.19E-02	3.68E-02	5.91E-02	**1.53E-02**
	Rank/S.R.	7 / -	6 / -	8 / -	**1** / +	4 / ≈	5 / -	2 / +	3
	Mean	**6.00E+02**	6.01E+02	6.06E+02	6.31E+02	6.13E+02	6.20E+02	6.29E+02	6.01E+02
F6	Std	**6.02E-01**	3.79E+00	3.60E+00	2.75E+00	2.22E+00	1.08E+00	2.41E+00	6.20E-01
	Rank/S.R.	**1** / -	3 / ≈	4 / -	8 / -	5 / -	6 / -	7 / -	2
	Mean	7.00E+02	7.00E+02	7.00E+02	**7.00E+02**	7.00E+02	7.00E+02	7.00E+02	**7.00E+02**
F7	Std	3.80E-03	1.33E-03	5.82E-03	8.81E-14	1.33E-03	1.80E-03	0.00E+00	**0.00E+00**
	Rank/S.R.	7 / -	4 / ≈	8 / -	**1** / ≈	5 / ≈	6 / -	1 / ≈	**1**
	Mean	8.47E+02	8.49E+02	8.17E+02	9.66E+02	9.38E+02	8.00E+02	9.63E+02	**8.00E+02**
F8	Std	4.54E+00	4.65E+00	5.11E+00	3.20E+00	1.09E+01	1.18E-12	6.11E+00	**0.00E+00**
	Rank/S.R.	4 / -	5 / -	3 / -	8 / -	6 / -	2 / -	7 / -	**1**
	Mean	1.00E+03	9.86E+02	9.26E+02	1.08E+03	1.09E+03	1.01E+03	1.08E+03	**9.22E+02**
F9	Std	8.59E+00	1.19E+01	6.59E+00	1.19E+00	3.99E+00	9.79E+00	1.22E+00	**2.09E+00**
	Rank/S.R.	4 / -	3 / -	2 / -	7 / -	8 / -	5 / -	6 / -	**1**
	Mean	3.11E+03	3.38E+03	3.05E+03	4.79E+03	3.14E+03	**1.00E+03**	4.53E+03	1.12E+03
F10	Std	3.09E+02	2.74E+02	1.40E+03	2.48E+02	3.94E+02	**1.25E+00**	3.68E+02	7.07E+01
	Rank/S.R.	4 / -	6 / -	3 / -	8 / -	5 / -	**1** / +	7 / -	2
	Mean	6.53E+03	6.25E+03	5.71E+03	5.33E+03	5.03E+03	4.84E+03	5.24E+03	**3.66E+03**
F11	Std	2.95E+02	3.32E+02	2.01E+03	**1.66E+02**	3.66E+02	2.04E+02	1.96E+02	3.71E+02
	Rank/S.R.	8 / -	7 / -	6 / -	5 / -	3 / -	2 / -	4 / -	**1**
	Mean	1.20E+03	1.20E+03	1.20E+03	1.20E+03	1.20E+03	1.20E+03	**1.20E+03**	1.20E+03
F12	Std	2.13E-01	1.43E-01	4.52E-01	1.06E-02	4.06E-02	7.15E-02	**4.18E-03**	1.35E-01
	Rank/S.R.	7 / -	6 / -	8 / -	2 / +	3 / +	5 / -	**1** / +	4
	Mean	**1.30E+03**	1.30E+03	1.30E+03	1.30E+03	1.30E+03	1.30E+03	1.30E+03	1.30E+03
F13	Std	2.61E-02	3.49E-02	4.63E-02	5.86E-02	5.19E-02	4.86E-02	3.75E-02	**2.42E-02**
	Rank/S.R.	**1** / -	5 / -	4 / ≈	6 / -	7 / -	8 / -	2 / ≈	3
	Mean	1.40E+03	1.40E+03	1.40E+03	1.40E+03	1.40E+03	1.40E+03	**1.40E+03**	1.40E+03
F14	Std	3.35E-02	**3.08E-02**	1.29E-01	3.65E-02	3.72E-02	4.16E-02	3.27E-02	4.13E-02
	Rank/S.R.	7 / -	6 / -	8 / -	5 / -	3 / ≈	4 / ≈	**1** / -	2
	Mean	1.51E+03	1.51E+03	1.50E+03	1.50E+03	1.51E+03	1.51E+03	1.50E+03	**1.50E+03**
F15	Std	5.86E-01	1.38E+00	2.17E+00	4.67E-01	1.16E+00	9.02E-01	8.81E-01	**1.43E-01**
	Rank/S.R.	7 / -	6 / -	2 / ≈	4 / -	5 / -	8 / -	3 / ≈	**1**
	Mean	1.61E+03	1.61E+03	1.61E+03	1.61E+03	1.61E+03	1.61E+03	1.61E+03	**1.61E+03**
F16	Std	2.47E-01	2.54E-01	2.87E-01	1.82E-01	3.70E-01	2.71E-01	**4.24E-02**	3.84E-01
	Rank/S.R.	3 / -	5 / -	4 / -	7 / -	6 / -	2 / -	8 / -	**1**
	Mean	3.05E+04	5.08E+04	2.21E+03	2.80E+03	2.96E+03	8.05E+04	**1.97E+03**	8.31E+03
F17	Std	1.98E+04	2.56E+04	1.44E+02	3.89E+02	1.12E+03	3.67E+04	**1.10E+02**	4.41E+03
	Rank/S.R.	6 / -	7 / -	2 / +	3 / +	4 / +	8 / -	**1** / +	5
	Mean	1.97E+03	1.99E+03	8.11E+04	1.86E+03	1.90E+03	1.99E+03	**1.80E+03**	1.97E+03
F18	Std	3.23E+01	3.24E+01	2.93E+05	8.93E+00	3.54E+01	3.20E+01	**1.49E+00**	8.02E+01
	Rank/S.R.	5 / ≈	6 / ≈	8 / ≈	2/ +	3/ +	7 / ≈	**1**/ +	4
	Mean	1.91E+03	1.91E+03	1.90E+03	1.91E+03	1.91E+03	1.91E+03	1.90E+03	**1.90E+03**
F19	Std	9.03E-01	7.71E-01	1.49E+00	1.59E+00	6.67E-01	7.42E-01	8.29E-01	**2.76E-01**
	Rank/S.R.	4 / -	6 / -	3 / -	7 / -	5 / -	8 / -	2 / -	**1**
	Mean	2.04E+03	2.04E+03	2.02E+03	2.02E+03	2.05E+03	2.05E+03	**2.01E+03**	2.04E+03
F20	Std	6.72E+00	4.63E+00	2.23E+01	1.01E+01	1.38E+01	7.28E+00	2.18E+00	**1.67E+00**
	Rank/S.R.	6 / -	5 / -	2 / +	3 / +	8 / -	7 / -	**1** / +	4
	Mean	3.94E+03	4.18E+03	2.30E+03	2.42E+03	3.19E+03	3.51E+03	**2.25E+03**	3.15E+03
F21	Std	5.11E+02	2.63E+02	1.10E+02	9.17E+01	8.93E+02	1.93E+02	**8.63E+01**	1.39E+02
	Rank/S.R.	7 / -	8 / -	2 / +	3 / +	5 / ≈	6 / -	**1** / +	4
	Mean	2.35E+03	2.31E+03	2.29E+03	2.66E+03	2.54E+03	2.30E+03	2.52E+03	**2.25E+03**
F22	Std	5.38E+01	5.00E+01	1.25E+02	1.50E+02	7.20E+01	5.11E+01	8.73E+01	**1.27E+01**
	Rank/S.R.	5 / -	4 / -	2 / ≈	8 / -	7 / -	3 / -	6 / -	**1**
	Mean	2.62E+03	2.62E+03	2.62E+03	**2.50E+03**	**2.50E+03**	2.62E+03	**2.50E+03**	**2.50E+03**
F23	Std	0.00E+00	1.36E-12	1.33E-12	**0.00E+00**	5.81E-12	1.59E-10	**0.00E+00**	**0.00E+00**
	Rank/S.R.	5 / -	6 / -	6 / -	**1** / ≈	**1** / ≈	8 / -	**1** / ≈	**1**
	Mean	2.63E+03	2.62E+03	2.63E+03	2.60E+03	2.60E+03	2.63E+03	2.60E+03	**2.60E+03**
F24	Std	2.99E+00	3.24E+00	6.46E+00	7.23E-04	1.61E-02	7.54E-01	1.64E-03	**0.00E+00**
	Rank/S.R.	6 / -	5 / -	8 / -	2 / -	4 / -	7 / -	3 / -	**1**
	Mean	2.70E+03	2.70E+03	2.70E+03	**2.70E+03**	**2.70E+03**	2.71E+03	**2.70E+03**	**2.70E+03**
F25	Std	6.54E-01	4.45E-01	1.00E+00	0.00E+00	6.43E-13	7.73E-01	**0.00E+00**	**0.00E+00**
	Rank/S.R.	7 / -	5 / -	6 / -	**1** / ≈	**1** / ≈	8 / -	**1** / ≈	**1**
	Mean	2.70E+03	2.70E+03	2.70E+03	2.80E+03	2.80E+03	2.70E+03	2.80E+03	**2.70E+03**
F26	Std	2.87E-02	3.00E-02	8.47E-02	8.30E-14	4.07E-13	5.58E-02	**0.00E+00**	1.27E-02
	Rank/S.R.	2 / -	3 / -	4 / -	6 / -	6 / -	5 / -	6 / -	**1**
	Mean	3.02E+03	3.04E+03	3.20E+03	**2.90E+03**	**2.90E+03**	3.34E+03	**2.90E+03**	**2.90E+03**
F27	Std	2.60E+01	3.85E+01	7.97E+01	0.00E+00	3.77E-12	1.76E+02	**0.00E+00**	**0.00E+00**
	Rank/S.R.	5 / -	6 / -	7 / -	**1** / ≈	**1** / ≈	8 / -	**1** / ≈	**1**
	Mean	3.63E+03	3.61E+03	3.69E+03	**3.00E+03**	3.00E+03	3.64E+03	**3.00E+03**	**3.00E+03**
F28	Std	3.48E+01	2.93E+01	5.53E+01	**0.00E+00**	7.60E-12	1.87E+01	**0.00E+00**	**0.00E+00**
	Rank/S.R.	6 / -	5 / -	8 / -	**1** / ≈	4 / -	7 / -	**1** / ≈	**1**
	Mean	4.27E+03	4.52E+03	2.11E+06	**3.10E+03**	3.10E+03	4.05E+03	**3.10E+03**	**3.10E+03**
F29	Std	3.80E+02	2.23E+02	3.78E+06	**0.00E+00**	2.64E-05	9.58E+01	**0.00E+00**	**0.00E+00**
	Rank/S.R.	6 / -	7 / -	8 / -	**1** / ≈	4 / -	5 / -	**1** / ≈	**1**
	Mean	5.20E+03	5.00E+03	6.18E+03	**3.20E+03**	3.20E+03	5.08E+03	3.20E+03	**3.20E+03**
F30	Std	8.38E+02	9.87E+02	2.12E+03	8.30E-14	2.79E-04	6.12E+02	2.23E-07	**0.00E+00**
	Rank/S.R.	7 / -	5 / -	8 / -	**1** / ≈	4 / -	6 / -	**1** / ≈	**1**
Sum of ranks		152	150	143	113	140	178	83	**57**
Average rank		5.07	5.00	4.77	3.77	4.67	5.93	2.77	**1.90**
Overall rank		7	6	5	3	4	8	2	**1**
- / ≈ / +		27 / 3 / 0	24 / 5 / 1	19 / 7 / 4	13 / 11 / 6	19 / 8 / 3	27 / 2 / 1	11 / 13 / 6	

TABLE 7. Experimental and statistical results of advanced algorithms and CHDESMA on CEC2017 with different dimensions.

F		Dim = 10								Dim = 30							
		CMAES	mGWO	mSCA	TVBSSA	MGFPA	PPSO	OBWOA	CHDESM	CMAES	mGWO	mSCA	TVBSSA	MGFPA	PPSO	OBWOA	CHDESM
F1	Mean	**1.00E+02**	4.08E+06	8.01E+10	3.15E+07	4.99E+08	9.84E+02	5.63E+07	2.50E+03	4.47E+04	7.72E+08	4.86E+11	2.97E+09	3.88E+10	2.48E+05	1.96E+10	**2.62E+03**
	Std	**0.00E+00**	1.47E+06	9.61E+09	6.76E+06	2.45E+08	5.69E+02	2.09E+07	7.54E+02	2.31E+04	1.73E+08	2.96E+10	3.64E+08	5.37E+09	1.17E+05	5.00E+09	**1.20E+03**
	Rank/S.R.	**1 / +**	4 / -	8 / -	5 / -	7 / -	2 / +	6 / -	3	2 / -	4 / -	8 / -	5 / -	7 / -	3 / -	6 / -	**1**
F3	Mean	**3.00E+02**	3.22E+02	1.02E+04	3.28E+02	3.00E+02	3.00E+02	2.32E+03	3.00E+02	3.68E+06	3.55E+04	8.15E+04	3.87E+04	6.67E+03	3.21E+04	1.51E+05	**3.71E+03**
	Std	**0.00E+00**	7.95E+00	1.00E+03	6.04E+00	1.31E-05	2.22E-04	7.85E+02	3.79E-04	5.71E+05	3.26E+03	2.04E+03	2.48E+03	6.55E+02	6.43E+03	2.00E+04	**1.76E+02**
	Rank/S.R.	**1 / +**	5 / -	8 / -	6 / -	2 / +	3 / +	7 / -	4	8 / -	4 / -	6 / -	5 / -	2 / -	3 / -	7 / -	**1**
F4	Mean	**4.00E+02**	4.08E+02	7.69E+02	4.08E+02	4.09E+02	4.04E+02	4.08E+02	4.05E+02	**4.20E+02**	5.22E+02	1.10E+04	5.10E+02	9.79E+02	5.08E+02	8.51E+02	4.89E+02
	Std	**9.92E-01**	3.41E-01	2.66E+01	4.97E+00	1.81E+00	1.17E+01	1.71E+00	1.04E+00	1.31E+00	4.95E+00	8.31E+02	1.00E+01	5.27E+01	1.34E+01	3.57E+01	**6.82E-01**
	Rank/S.R.	**1 / +**	4 / -	8 / -	5 / -	7 / -	2 / ≈	6 / -	3	1 / +	5 / -	8 / -	4 / -	7 / -	3 / -	6 / -	2
F5	Mean	5.09E+02	5.11E+02	5.85E+02	5.23E+02	5.07E+02	5.15E+02	5.35E+02	**5.06E+02**	5.45E+02	6.73E+02	9.33E+02	7.23E+02	6.23E+02	6.33E+02	8.20E+02	**5.33E+02**
	Std	1.60E+00	3.59E+00	6.99E+00	3.82E+00	1.94E+00	3.09E+00	6.58E+00	**1.39E+00**	6.23E+00	2.86E+01	1.26E+01	1.21E+01	1.65E+01	2.29E+01	2.07E+01	**1.79E+00**
	Rank/S.R.	3 / -	4 / -	8 / -	6 / -	2 / -	5 / -	7 / -	**1**	2 / -	5 / -	8 / -	6 / -	3 / -	4 / -	7 / -	**1**
F6	Mean	6.00E+02	6.01E+02	6.59E+02	6.17E+02	6.00E+02	6.06E+02	6.25E+02	**6.00E+02**	**6.00E+02**	6.13E+02	7.12E+02	6.71E+02	6.17E+02	6.55E+02	6.84E+02	6.01E+02
	Std	4.30E-01	1.91E-01	3.57E+00	4.94E+00	1.31E-01	1.77E+00	3.62E+00	**1.85E-04**	1.80E-01	2.20E+00	3.61E+00	6.36E+00	2.06E+00	8.33E+00	5.14E+00	**1.21E-01**
	Rank/S.R.	2 / ≈	4 / -	8 / -	6 / -	3 / -	5 / -	7 / -	**1**	**1 / +**	3 / -	8 / -	6 / -	4 / -	5 / -	7 / -	2
F7	Mean	7.20E+02	7.34E+02	8.31E+02	7.51E+02	7.18E+02	7.40E+02	7.78E+02	**7.14E+02**	7.69E+02	9.38E+02	1.43E+03	1.03E+03	9.11E+02	9.29E+02	1.27E+03	**7.61E+02**
	Std	2.12E+00	5.25E+00	6.82E+00	3.44E+00	2.16E+00	4.72E+00	6.99E+00	**3.17E-01**	5.03E+00	1.06E+01	2.15E+01	2.48E+01	8.97E+00	1.68E+01	3.78E+01	**2.59E+00**
	Rank/S.R.	3 / -	4 / -	8 / -	6 / -	2 / -	5 / -	7 / -	**1**	2 / -	5 / -	8 / -	6 / -	3 / -	4 / -	7 / -	**1**
F8	Mean	8.09E+02	8.14E+02	8.68E+02	8.18E+02	8.05E+02	8.25E+02	8.33E+02	**8.04E+02**	8.48E+02	9.24E+02	1.16E+03	9.87E+02	9.29E+02	1.01E+03	1.03E+03	**8.40E+02**
	Std	7.69E-01	5.07E+00	2.86E+00	3.05E+00	1.03E+00	5.33E+00	4.94E+00	**3.97E-01**	7.00E+00	2.00E+01	8.94E+00	**3.47E+00**	9.06E+00	1.63E+01	1.81E+01	3.66E+00
	Rank/S.R.	3 / -	4 / -	8 / -	5 / -	2 / -	6 / -	7 / -	**1**	2 / -	3 / -	8 / -	5 / -	4 / -	6 / -	7 / -	1
F9	Mean	9.00E+02	9.00E+02	1.52E+03	9.09E+02	9.00E+02	9.08E+02	1.28E+03	**9.00E+02**	**9.00E+02**	1.09E+03	1.15E+04	8.20E+03	1.40E+03	3.36E+03	7.85E+03	9.04E+02
	Std	0.00E+00	4.29E-02	7.74E+01	6.38E+00	1.48E-01	6.53E+00	1.08E+02	**0.00E+00**	**8.94E-02**	2.92E+01	1.55E+02	8.94E+02	1.19E+02	3.33E+02	5.52E+02	3.49E-01
	Rank/S.R.	1 / ≈	3 / -	8 / -	6 / -	4 / -	5 / -	7 / -	**1**	**1 / +**	3 / -	8 / -	7 / -	4 / ≈	5 / -	6 / -	2
F10	Mean	2.07E+03	1.95E+03	2.79E+03	1.88E+03	1.34E+03	1.54E+03	1.99E+03	**1.25E+03**	9.17E+03	8.34E+03	8.82E+03	6.94E+03	7.63E+03	4.68E+03	7.61E+03	**3.48E+03**
	Std	1.09E+02	2.23E+02	1.17E+02	1.30E+02	1.14E+02	1.53E+02	1.27E+02	**7.14E+01**	1.51E+03	**1.29E+02**	2.04E+02	4.99E+02	1.53E+02	3.77E+02	4.36E+02	2.68E+02
	Rank/S.R.	7 / -	5 / -	8 / -	4 / -	2 / -	3 / -	6 / -	**1**	8 / -	6 / -	7 / -	3 / -	5 / -	2 / -	4 / -	**1**
F11	Mean	1.13E+03	1.11E+03	2.71E+03	1.18E+03	**1.10E+03**	1.12E+03	1.18E+03	1.10E+03	2.83E+03	1.37E+03	8.75E+03	1.52E+03	1.22E+03	1.26E+03	4.21E+03	**1.18E+03**
	Std	1.03E+01	3.14E+00	5.32E+02	6.56E+01	**5.83E-01**	4.26E+01	7.00E+01	1.08E+00	9.37E+02	3.33E+01	6.94E+02	6.30E+01	**1.43E+01**	3.37E+01	1.13E+03	1.93E+01
	Rank/S.R.	5 / -	3 / -	8 / -	6 / -	**1 / ≈**	4 / ≈	7 / -	2	6 / -	4 / -	8 / -	5 / -	2 / -	3 / -	7 / -	**1**
F12	Mean	2.11E+03	5.72E+05	1.41E+09	1.69E+06	**2.03E+03**	1.59E+04	1.29E+06	5.70E+03	1.46E+07	1.21E+08	9.10E+10	1.07E+09	7.59E+08	2.70E+06	1.73E+09	**1.46E+06**
	Std	3.53E+02	9.98E+05	6.92E+08	5.51E+05	**2.66E+02**	9.40E+03	7.38E+05	1.81E+03	6.34E+06	3.87E+07	1.24E+10	5.13E+08	4.43E+08	1.37E+06	8.02E+08	**5.46E+05**
	Rank/S.R.	2 / +	5 / -	8 / -	7 / -	**1 / +**	4 / -	6 / -	3	3 / -	4 / -	8 / -	6 / -	5 / -	2 / -	7 / -	**1**
F13	Mean	1.71E+03	7.34E+03	3.55E+07	1.52E+04	**1.32E+03**	1.38E+03	9.11E+03	2.08E+03	1.94E+07	6.15E+06	8.91E+10	3.47E+07	2.49E+07	2.22E+04	1.01E+07	**5.90E+03**
	Std	3.90E+02	5.10E+03	1.52E+07	5.82E+03	**2.13E+00**	2.59E+02	4.08E+03	2.83E+02	1.56E+07	2.25E+06	1.35E+10	1.22E+07	2.08E+07	1.28E+04	4.50E+06	**1.70E+03**
	Rank/S.R.	3 / +	5 / -	8 / -	7 / -	**1 / +**	2 / +	6 / -	4	5 / -	3 / -	8 / -	7 / -	6 / -	2 / -	4 / -	**1**
F14	Mean	2.79E+03	1.63E+03	8.28E+03	1.71E+03	**1.42E+03**	1.44E+03	1.82E+03	1.45E+03	5.50E+04	8.73E+04	3.67E+06	6.55E+04	**1.66E+03**	1.08E+04	8.82E+05	4.28E+04
	Std	5.14E+02	4.20E+02	3.03E+03	9.41E+01	**4.14E+00**	7.83E+00	2.88E+02	1.77E+01	2.62E+04	4.63E+04	1.27E+06	3.45E+04	**1.47E+01**	2.73E+03	5.00E+05	2.03E+04
	Rank/S.R.	7 / -	4 / -	8 / -	5 / -	**1 / +**	2 / +	6 / -	3	4 / ≈	6 / -	8 / -	5 / -	**1 / +**	2 / +	7 / -	3
F15	Mean	1.55E+03	1.87E+03	2.25E+04	7.01E+03	**1.50E+03**	1.57E+03	6.99E+03	1.64E+03	1.10E+07	2.40E+05	3.18E+09	3.51E+06	**3.83E+03**	7.55E+03	2.87E+07	8.47E+03
	Std	9.50E+00	1.16E+02	4.53E+03	2.77E+03	**8.49E-01**	1.29E+02	3.35E+03	7.63E+01	6.47E+06	1.03E+05	7.55E+08	1.34E+06	**1.99E+03**	3.84E+03	2.00E+07	4.02E+03
	Rank/S.R.	2 / +	5 / -	8 / -	7 / -	**1 / +**	3 / +	6 / -	4	6 / -	4 / -	8 / -	5 / -	**1 / ≈**	2 / ≈	7 / -	3
F16	Mean	1.73E+03	1.62E+03	2.09E+03	1.74E+03	**1.60E+03**	1.69E+03	1.89E+03	1.61E+03	2.72E+03	2.98E+03	5.52E+03	3.38E+03	2.66E+03	2.71E+03	3.74E+03	**1.89E+03**
	Std	4.60E+01	4.27E+00	8.98E+01	9.79E+01	**8.77E-01**	7.45E+01	8.56E+01	2.80E+00	2.63E+02	2.27E+02	3.14E+02	2.61E+02	1.40E+02	2.45E+02	2.70E+02	**9.11E+01**
	Rank/S.R.	5 / -	3 / -	8 / -	6 / -	**1 / +**	4 / -	7 / -	2	4 / -	5 / -	8 / -	6 / -	2 / -	3 / -	7 / -	**1**
F17	Mean	1.81E+03	1.74E+03	1.86E+03	1.77E+03	**1.70E+03**	1.74E+03	1.77E+03	1.72E+03	2.55E+03	2.07E+03	4.06E+03	2.35E+03	1.90E+03	2.30E+03	2.59E+03	**1.87E+03**
	Std	1.31E+01	3.26E+00	1.76E+01	3.84E+01	**2.27E+00**	2.62E+01	2.81E+01	2.84E+00	1.72E+02	1.23E+02	1.90E+02	1.29E+02	7.25E+01	8.91E+01	1.59E+02	**4.99E+01**
	Rank/S.R.	7 / -	4 / -	8 / -	6 / -	**1 / +**	3 / -	5 / -	2	6 / -	3 / -	8 / -	5 / -	2 / -	4 / -	7 / -	**1**
F18	Mean	1.83E+03	1.87E+04	9.23E+06	2.37E+04	**1.82E+03**	3.00E+03	8.23E+03	8.45E+03	3.28E+06	8.56E+05	2.77E+07	1.02E+06	**1.07E+04**	1.18E+05	3.03E+06	6.43E+05
	Std	4.00E+00	4.96E+03	4.26E+06	1.10E+04	**2.45E+00**	9.12E+02	3.92E+03	2.10E+03	1.25E+06	2.73E+05	7.34E+06	4.39E+05	**2.28E+03**	3.63E+04	1.61E+06	2.18E+05
	Rank/S.R.	2 / +	6 / -	8 / -	7 / -	**1 / +**	3 / +	4 / ≈	5	7 / -	4 / -	8 / -	5 / -	**1 / +**	2 / +	6 / -	3
F19	Mean	1.93E+03	3.81E+03	3.63E+05	6.98E+03	**1.90E+03**	1.90E+03	1.66E+04	2.57E+03	3.32E+05	4.35E+05	8.39E+09	2.70E+07	**2.52E+03**	4.64E+03	1.08E+08	9.46E+03
	Std	2.48E+01	1.56E+03	2.30E+05	3.07E+03	**2.68E-01**	2.30E+00	9.40E+03	1.61E+02	1.26E+05	1.36E+05	1.56E+09	1.17E+07	**1.77E+02**	1.74E+03	6.77E+07	4.15E+03
	Rank/S.R.	3 / +	5 / -	8 / -	6 / -	**1 / +**	2 / +	7 / -	4	4 / -	5 / -	8 / -	6 / -	**1 / +**	2 / +	7 / -	3
F20	Mean	2.07E+03	2.03E+03	2.26E+03	2.13E+03	2.01E+03	2.01E+03	2.13E+03	**2.00E+03**	2.73E+03	2.43E+03	3.00E+03	2.52E+03	2.37E+03	2.47E+03	2.65E+03	**2.17E+03**
	Std	1.56E+01	3.16E+00	2.87E+01	3.62E+01	6.73E+00	7.34E+00	4.15E+01	**4.86E-01**	2.41E+02	1.25E+02	6.29E+01	9.61E+01	**3.35E+01**	9.12E+01	1.66E+02	6.19E+01
	Rank/S.R.	5 / -	4 / -	8 / -	6 / -	3 / -	2 / -	7 / -	**1**	7 / -	3 / -	8 / -	5 / -	2 / -	4 / -	6 / -	**1**
F21	Mean	2.31E+03	2.20E+03	2.28E+03	2.20E+03	2.28E+03	2.26E+03	2.23E+03	**2.20E+03**	2.35E+03	2.47E+03	2.74E+03	2.53E+03	2.43E+03	2.45E+03	2.58E+03	**2.34E+03**
	Std	**5.17E-01**	7.54E-01	8.92E+00	8.49E-01	3.59E+01	3.84E+01	7.11E+00	5.19E-01	6.53E+00	3.37E+01	1.30E+01	2.18E+01	9.44E+00	1.17E+01	1.57E+01	**3.47E+00**
	Rank/S.R.	8 / -	3 / -	6 / -	2 / -	7 / -	5 / -	4 / -	**1**	2 / -	5 / -	8 / -	6 / -	3 / -	4 / -	7 / -	**1**
F22	Mean	3.43E+03	2.30E+03	2.85E+03	2.31E+03	2.30E+03	2.30E+03	2.32E+03	**2.30E+03**	1.05E+04	2.77E+03	7.66E+03	3.49E+03	2.70E+03	3.89E+03	7.59E+03	**2.49E+03**
	Std	1.19E+02	6.80E-01	7.60E+01	7.40E-01	**5.17E-01**	1.34E+01	1.04E+01	1.80E+01	1.32E+03	6.59E+02	1.71E+03	1.72E+03	**8.64E+00**	1.34E+03	1.28E+03	3.60E+01
	Rank/S.R.	8 / -	4 / -	7 / -	5 / -	3 / ≈	2 / ≈	6 / -	**1**	8 / -	3 / -	7 / -	4 / -	2 / -	5 / -	6 / -	**1**
F23	Mean	2.62E+03	2.62E+03	2.71E+03	2.63E+03	2.61E+03	2.63E+03	2.64E+03	**2.61E+03**	2.70E+03	2.82E+03	3.39E+03	2.95E+03	2.75E+03	2.84E+03	3.07E+03	**2.69E+03**
	Std	1.59E+00	7.29E+00	6.97E+00	8.57E+00	2.88E+00	4.42E+00	1.45E+01	**7.22E-01**	9.30E+00	2.43E+01	5.10E+01	4.41E+01	1.87E+01	2.65E+01	5.21E+01	**5.55E+00**
	Rank/S.R.	4 / -	3 / -	8 / -	6 / -	2 / -	5 / -	7 / -	**1**	2 / -	4 / -	8 / -	6 / -	3 / -	5 / -	7 / -	**1**
F24	Mean	2.74E+03	2.74E+03	2.81E+03	2.67E+03	2.68E+03	2.69E+03	2.74E+03	**2.67E+03**	2.88E+03	3.00E+03	3.56E+03	3.09E+03	2.97E+03	3.06E+03	3.16E+03	**2.86E+03**
	Std	**1.88E+00**	4.48E+01	2.76E+01	8.93E+01	7.12E+01	8.93E+01	5.75E+01	8.27E+01	9.20E+00	2.25E+01	3.84E+01	2.07E+01	1.52E+01	3.30E+01	4.51E+01	**7.01E+00**
	Rank/S.R.	7 / -	6 / -	8 / -	2 / -	3 / -	4 / -	5 / -	**1**	2 / -	4 / -	8 / -	6 / -	3 / -	5 / -	7 / -	**1**
F25	Mean	2.92E+03	2.93E+03	3.25E+03	**2.90E+03**	2.94E+03	2.91E+03	2.94E+03	2.90E+03	**2.88E+03**	2.92E+03	4.98E+03	2.98E+03	3.10E+03	2.89E+03	3.11E+03	2.89E+03
	Std	1.61E+01	1.76E+01	5.34E+01	5.08E+01	1.38E+01	2.43E+01	6.65E+01	**1.40E-01**	**2.97E-02**	6.83E+00	2.25E+02	4.64E+00	3.07E+01	4.13E+00	2.11E+01	6.01E-01
	Rank/S.R.	4 / -	5 / -	8 / -	**1 / ≈**	6 / -	3 / ≈	7 / -	2	**1 / +**	4 / -	8 / -	5 / -	6 / -	3 / -	7 / -	2
F26	Mean	3.09E+03	2.92E+03	3.66E+03	2.97E+03	2.99E+03	2.97E+03	3.27E+03	**2.90E+03**	**3.81E+03**	5.09E+03	1.03E+04	4.85E+03	4.94E+03	5.32E+03	7.71E+03	4.05E+03
	Std	2.80E+01	2.56E+01	2.29E+02	1.46E+02	5.34E+01	1.95E+02	2.40E+02	**9.09E+00**	6.53E+01	1.57E+02	4.84E+02	1.07E+03	2.93E+02	9.00E+02	3.60E+02	**5.44E+01**
	Rank/S.R.	6 / -	2 / -	8 / -	4 / -	5 / -	3 / ≈	7 / -	**1**	**1 / +**	5 / -	8 / -	3 / -	4 / -	6 / -	7 / -	2
F27	Mean	3.20E+03	3.09E+03	3.15E+03	3.09E+03	3.09E+03	3.10E+03	3.12E+03	**3.09E+03**	3.20E+03	3.23E+03	3.35E+03	**3.20E+03**	3.24E+03	3.24E+03	3.33E+03	3.21E+03
	Std	**6.27E-05**	4.44E-01	1.51E+01	2.98E+01	1.34E+00	8.75E+00	8.61E+00	1.48E-01	**1.59E-05**	4.33E+00	1.05E+02	2.91E+00	7.27E+00	9.83E+00	2.29E+01	3.63E+00
	Rank/S.R.	8 / -	2 / -	7 / -	3 / ≈	4 / -	5 / -	6 / -	**1**	2 / +	4 / -	8 / -	**1 / +**	5 / -	6 / -	7 / -	3
F28	Mean	3.29E+03	3.20E+03	3.31E+03	3.27E+03	**3.20E+03**	3.28E+03	3.35E+03	3.27E+03	3.30E+03	3.32E+03	3.30E+03	3.30E+03	3.77E+03	3.25E+03	3.61E+03	**3.22E+03**
	Std	**1.09E+01**	4.21E+01	4.87E+01	3.20E+01	6.21E+01	1.20E+02	9.92E+01	8.72E+01	**5.67E-05**	1.37E+01	2.57E-01	7.31E+00	5.63E+01	7.52E+00	3.59E+01	1.82E+00
	Rank/S.R.	6 / ≈	2 / +	7 / -	4 / ≈	**1 / +**	5 / ≈	8 / -	3	4 / -	6 / -	5 / -	3 / -	8 / -	2 / -	7 / -	**1**
F29	Mean	3.20E+03	3.18E+03	3.45E+03	3.22E+03	3.17E+03	3.21E+03	3.28E+03	**3.14E+03**	4.36E+03	3.89E+03	6.75E+03	4.48E+03	3.67E+03	3.87E+03	4.86E+03	**3.39E+03**
	Std	4.20E+01	1.47E+01	5.89E+01	5.31E+01	8.74E+00	3.65E+01	4.81E+01	**1.52E+00**	1.71E+02	1.25E+02	2.03E+02	1.20E+02	4.79E+01	1.24E+02	1.15E+02	**1.94E+01**
	Rank/S.R.	4 / -	3 / -	8 / -	6 / -	2 / -	5 / -	7 / -	**1**	5 / -	4 / -	8 / -	6 / -	2 / -	3 / -	7 / -	**1**
F30	Mean	**3.28E+03**	2.71E+05	1.11E+07	3.22E+04	4.61E+03	6.78E+03	2.05E+05	6.99E+04	2.36E+05	6.66E+06	1.41E+10	8.17E+07	4.88E+04	1.28E+04	1.59E+08	**1.13E+04**
	Std	**7.73E+01**	1.25E+05	5.07E+06	9.42E+03	3.63E+02	9.58E+02	9.21E+04	3.14E+04	7.18E+04	9.79E+05	2.68E+09	1.61E+07	1.91E+04	1.39E+03	4.46E+07	**1.32E+03**
	Rank/S.R.	**1 / +**	7 / -	8 / -	4 / +	2 / +	3 / +	6 / -	5	4 / -	5 / -	8 / -	6 / -	3 / -	2 / -	7 / -	**1**
Sum of ranks		119	118	227	149	78	105	184	**63**	110	123	225	148	101	102	191	**44**
Average rank		4.10	4.07	7.83	5.14	2.69	3.62	6.34	**2.17**	3.79	4.24	7.76	5.10	3.48	3.52	6.59	**1.52**
Overall rank		5	4	8	6	2	3	7	**1**	4	5	8	6	2	3	7	**1**
- / ≈ / +		17 / 3 / 9	28 / 0 / 1	29 / 0 / 0	25 / 3 / 1	16 / 2 / 11	15 / 6 / 8	28 / 1 / 0		22 / 1 / 6	29 / 0 / 0	29 / 0 / 0	28 / 0 / 1	24 / 2 / 3	25 / 1 / 3	29 / 0 / 0	

TABLE 7. ***(Continued.)*** **Experimental and statistical results of advanced algorithms and CHDESMA on CEC2017 with different dimensions.**

F		Dim = 50								Dim = 100							
		CMAES	mGWO	mSCA	TVBSSA	MGFPA	PPSO	OBWOA	CHDESM	CMAES	mGWO	mSCA	TVBSSA	MGFPA	PPSO	OBWOA	CHDESM
F1	Mean	2.23E+05	9.96E+09	1.07E+12	2.45E+10	2.06E+11	7.44E+07	1.18E+11	**1.39E+04**	9.88E+09	1.45E+11	2.56E+12	3.08E+11	1.01E+12	9.08E+09	8.75E+11	**4.45E+08**
	Std	1.21E+05	1.89E+09	2.19E+10	3.07E+09	2.28E+10	1.77E+07	1.06E+10	**1.35E+02**	8.44E+07	1.22E+10	1.63E+10	1.67E+10	4.90E+10	1.51E+09	5.24E+10	**4.17E+07**
	Rank/S.R.	2 / -	4 / -	8 / -	5 / -	7 / -	3 / -	6 / -	**1**	3 / -	4 / -	8 / -	5 / -	7 / -	2 / -	6 / -	**1**
F3	Mean	1.12E+07	1.30E+05	1.94E+05	1.41E+05	**6.50E+04**	1.72E+05	1.72E+05	1.28E+05	8.33E+05	3.51E+05	3.57E+05	3.54E+05	2.73E+05	5.96E+05	7.19E+05	**2.62E+05**
	Std	2.60E+06	9.14E+03	1.14E+04	1.93E+04	**8.13E+03**	3.53E+04	1.54E+04	1.10E+04	**2.07E+03**	1.38E+04	6.14E+03	2.63E+04	2.04E+04	6.51E+04	1.11E+05	2.60E+04
	Rank/S.R.	8 / -	3 / ≈	7 / -	4 / -	**1 / ≈**	6 / -	5 / -	2	8 / -	3 / -	5 / -	4 / -	2 / -	6 / -	7 / -	**1**
F4	Mean	**4.50E+02**	7.79E+02	2.82E+04	9.35E+02	3.40E+03	6.64E+02	2.65E+03	5.42E+02	1.01E+03	2.19E+03	8.90E+04	3.47E+03	1.42E+04	1.23E+03	1.25E+04	**7.51E+02**
	Std	1.96E+01	2.92E+01	1.99E+03	7.52E+01	4.23E+02	4.22E+01	2.59E+02	**1.00E+01**	2.99E+02	1.71E+02	5.07E+03	2.92E+02	1.06E+03	1.02E+02	1.23E+03	**2.90E+01**
	Rank/S.R.	**1 / +**	4 / -	8 / -	5 / -	7 / -	3 / -	6 / -	2	2 / -	4 / -	8 / -	5 / -	7 / -	3 / -	6 / -	**1**
F5	Mean	6.24E+02	8.34E+02	1.21E+03	1.01E+03	8.49E+02	8.33E+02	1.05E+03	**5.91E+02**	1.55E+03	1.40E+03	2.14E+03	1.83E+03	1.51E+03	1.39E+03	1.88E+03	**8.18E+02**
	Std	2.79E+01	3.28E+01	1.67E+01	2.52E+01	1.67E+01	3.47E+01	3.22E+01	**1.15E+01**	5.31E+01	4.04E+01	2.12E+01	4.66E+01	3.71E+01	7.02E+01	5.06E+01	**1.86E+01**
	Rank/S.R.	2 / -	4 / -	8 / -	6 / -	5 / -	3 / -	7 / -	**1**	5 / -	3 / -	8 / -	6 / -	4 / ≈	2 / -	7 / -	**1**
F6	Mean	**6.01E+02**	6.33E+02	7.44E+02	7.07E+02	6.40E+02	6.76E+02	7.14E+02	6.06E+02	6.71E+02	6.60E+02	7.31E+02	7.16E+02	6.68E+02	6.83E+02	7.15E+02	**6.29E+02**
	Std	**3.33E-01**	3.25E+00	3.28E+00	6.90E+00	5.06E+00	4.47E+00	6.67E+00	6.79E-01	1.42E+01	5.81E+00	3.12E+00	**2.03E+00**	3.39E+00	4.10E+00	3.74E+00	3.02E+00
	Rank/S.R.	**1 / +**	3 / -	8 / -	6 / -	4 / -	5 / -	7 / -	2	4 / -	2 / -	8 / -	7 / -	3 / -	5 / -	6 / -	**1**
F7	Mean	1.15E+03	1.27E+03	2.01E+03	1.49E+03	1.28E+03	1.33E+03	1.85E+03	**8.55E+02**	1.95E+03	2.38E+03	4.03E+03	2.90E+03	2.61E+03	2.75E+03	3.69E+03	**1.25E+03**
	Std	4.22E+01	1.70E+01	2.16E+01	6.07E+01	6.46E+01	6.97E+01	5.39E+01	**5.14E+00**	3.05E+01	9.00E+01	**1.74E+01**	8.66E+01	1.09E+02	1.10E+02	9.50E+01	3.24E+01
	Rank/S.R.	2 / -	3 / -	8 / -	6 / -	4 / ≈	5 / -	7 / -	**1**	2 / -	3 / -	8 / -	6 / -	4 / -	5 / -	7 / -	**1**
F8	Mean	9.13E+02	1.17E+03	1.56E+03	1.34E+03	1.15E+03	1.32E+03	1.28E+03	**8.96E+02**	1.85E+03	1.71E+03	2.60E+03	2.23E+03	1.82E+03	2.25E+03	2.15E+03	**1.11E+03**
	Std	2.34E+01	4.29E+01	1.21E+01	3.45E+01	3.94E+01	6.14E+01	3.36E+01	**9.61E+00**	**2.04E+01**	4.31E+01	2.23E+01	8.44E+01	9.85E+01	6.24E+01	5.26E+01	2.23E+01
	Rank/S.R.	2 / -	4 / -	8 / -	7 / -	3 / -	6 / -	5 / -	**1**	4 / -	2 / -	8 / -	6 / -	3 / ≈	7 / -	5 / -	**1**
F9	Mean	**9.01E+02**	4.08E+03	4.47E+04	3.46E+04	8.36E+03	1.24E+04	3.05E+04	9.95E+02	3.37E+04	3.00E+04	8.55E+04	8.58E+04	3.75E+04	3.27E+04	6.26E+04	**9.30E+03**
	Std	**8.97E-01**	7.87E+02	1.66E+03	2.53E+03	1.02E+03	1.91E+03	3.80E+03	2.40E+01	1.68E+04	3.28E+03	**2.09E+03**	2.83E+03	2.26E+03	3.32E+03	4.09E+03	2.58E+03
	Rank/S.R.	**1 / +**	3 / -	8 / -	7 / -	4 / -	5 / -	6 / -	2	4 / -	2 / -	7 / -	8 / -	5 / -	3 / -	6 / -	**1**
F10	Mean	1.83E+04	1.47E+04	1.57E+04	1.24E+04	1.37E+04	6.91E+03	1.26E+04	**5.77E+03**	3.74E+04	3.16E+04	3.26E+04	2.82E+04	3.05E+04	1.63E+04	2.93E+04	**1.36E+04**
	Std	1.86E+02	3.68E+02	3.03E+02	2.64E+02	**1.29E+02**	5.04E+02	5.00E+02	5.10E+02	3.75E+02	1.04E+03	**2.30E+02**	5.22E+02	4.22E+02	8.85E+02	6.91E+02	4.63E+02
	Rank/S.R.	8 / -	6 / -	7 / -	3 / -	5 / -	2 / -	4 / -	**1**	8 / -	6 / -	7 / -	3 / -	5 / -	2 / -	4 / -	**1**
F11	Mean	3.80E+06	2.22E+03	2.02E+04	3.00E+03	1.43E+03	1.47E+03	6.39E+03	**1.41E+03**	3.76E+07	8.79E+04	2.25E+05	8.36E+04	1.95E+04	2.77E+04	1.71E+05	**4.49E+03**
	Std	1.26E+06	1.26E+02	1.64E+03	2.67E+02	**2.79E+01**	4.61E+01	5.79E+02	3.79E+01	7.29E+06	1.11E+04	1.72E+04	9.83E+03	2.59E+03	6.61E+03	2.80E+04	**4.31E+02**
	Rank/S.R.	8 / -	4 / -	7 / -	5 / -	2 / -	3 / -	6 / -	**1**	8 / -	5 / -	7 / -	4 / -	2 / -	3 / -	6 / -	**1**
F12	Mean	2.00E+09	1.21E+09	6.07E+11	5.40E+09	2.36E+10	2.79E+07	8.33E+09	**1.22E+07**	1.00E+10	2.25E+10	1.61E+12	3.69E+10	2.05E+11	6.29E+08	8.84E+10	**3.06E+08**
	Std	6.63E+08	3.04E+08	3.11E+10	1.14E+09	5.62E+09	1.07E+07	1.67E+09	**2.18E+06**	0.00E+00	4.75E+09	5.89E+10	3.42E+09	1.80E+10	1.82E+08	7.75E+09	7.17E+07
	Rank/S.R.	4 / -	3 / -	8 / -	5 / -	7 / -	2 / -	6 / -	**1**	3 / -	4 / -	8 / -	5 / -	7 / -	2 / -	6 / -	**1**
F13	Mean	5.58E+08	7.47E+07	3.62E+11	2.50E+08	3.86E+09	2.25E+04	7.06E+08	**1.82E+04**	9.06E+09	8.68E+08	4.22E+11	2.02E+09	3.51E+10	**1.07E+05**	6.78E+09	1.17E+06
	Std	1.71E+08	1.78E+07	3.56E+10	3.33E+07	1.49E+09	5.60E+03	1.80E+08	**5.12E+03**	1.64E+09	2.09E+08	2.75E+10	3.09E+08	7.00E+09	**1.66E+04**	1.70E+09	1.29E+05
	Rank/S.R.	5 / -	3 / -	8 / -	4 / -	7 / -	2 / -	6 / -	**1**	6 / -	3 / -	8 / -	4 / -	7 / -	**1 / +**	5 / -	2
F14	Mean	5.12E+06	4.49E+05	3.57E+07	6.91E+05	**3.41E+03**	6.77E+04	1.52E+06	2.74E+05	7.81E+08	1.60E+07	9.76E+07	7.09E+06	**4.31E+05**	1.97E+06	1.07E+07	1.67E+06
	Std	1.54E+06	1.08E+05	6.81E+06	2.51E+05	**4.25E+02**	1.97E+04	2.36E+05	7.13E+04	1.74E+08	5.25E+06	1.74E+07	1.68E+06	**1.10E+05**	5.86E+05	3.18E+06	2.47E+05
	Rank/S.R.	7 / -	4 / -	8 / -	5 / -	**1 / +**	2 / +	6 / -	3	8 / -	6 / -	7 / -	4 / -	**1 / +**	3 / -	5 / -	2
F15	Mean	6.29E+08	4.61E+06	3.82E+10	4.73E+07	9.46E+07	**7.42E+03**	1.99E+08	1.13E+04	8.54E+09	1.31E+08	2.31E+11	3.32E+08	5.51E+09	1.89E+04	9.04E+08	**1.35E+04**
	Std	2.34E+08	1.49E+06	3.32E+09	9.45E+06	5.42E+07	**1.82E+03**	1.26E+08	3.13E+03	1.80E+09	4.59E+07	1.68E+10	6.28E+07	2.15E+09	5.26E+03	1.85E+08	**2.51E+03**
	Rank/S.R.	7 / -	3 / -	8 / -	4 / -	5 / -	**1 / +**	6 / -	2	7 / -	3 / -	8 / -	4 / -	6 / -	2 / -	5 / -	**1**
F16	Mean	4.79E+03	4.61E+03	8.26E+03	4.51E+03	3.55E+03	3.42E+03	5.37E+03	**2.49E+03**	1.99E+04	9.81E+03	2.16E+04	9.85E+03	8.15E+03	6.04E+03	1.40E+04	**4.69E+03**
	Std	1.88E+02	3.91E+02	2.52E+02	3.65E+02	1.29E+02	1.65E+02	4.52E+02	**3.94E+01**	1.02E+03	7.76E+02	8.54E+02	3.80E+02	5.14E+02	3.98E+02	7.89E+02	**2.54E+02**
	Rank/S.R.	6 / -	5 / -	8 / -	4 / -	3 / -	2 / -	7 / -	**1**	7 / -	4 / -	8 / -	5 / -	3 / -	2 / -	6 / -	**1**
F17	Mean	6.92E+03	3.61E+03	1.04E+04	3.64E+03	3.08E+03	3.24E+03	4.08E+03	**2.29E+03**	2.47E+05	7.90E+03	4.19E+06	8.06E+03	5.73E+03	5.76E+03	1.01E+04	**4.34E+03**
	Std	6.40E+02	1.81E+02	8.49E+02	1.03E+02	1.32E+02	1.33E+02	1.23E+02	**6.08E+01**	6.01E+04	5.09E+02	1.32E+06	4.82E+02	**3.57E+02**	5.61E+02	7.53E+02	4.24E+02
	Rank/S.R.	7 / -	4 / -	8 / -	5 / -	2 / -	3 / -	6 / -	**1**	7 / -	4 / -	8 / -	5 / -	2 / -	3 / -	6 / -	**1**
F18	Mean	3.39E+07	3.33E+06	1.22E+08	4.87E+06	**1.23E+05**	4.35E+05	3.35E+07	1.73E+06	5.94E+08	1.65E+07	2.12E+08	7.59E+06	**1.09E+06**	4.43E+06	9.37E+06	2.44E+06
	Std	8.39E+06	7.13E+05	2.99E+07	1.72E+06	**1.95E+04**	9.60E+04	9.05E+06	5.19E+05	1.57E+08	5.36E+06	3.48E+07	1.50E+06	**2.55E+05**	1.40E+06	2.23E+06	2.73E+05
	Rank/S.R.	7 / -	4 / -	8 / -	5 / -	**1 / +**	2 / +	6 / -	3	8 / -	6 / -	7 / -	4 / -	**1 / ≈**	3 / -	5 / -	2
F19	Mean	1.20E+07	3.63E+06	4.51E+10	4.07E+07	6.91E+05	**1.03E+04**	2.27E+07	1.08E+04	5.22E+09	1.81E+08	2.17E+11	5.34E+08	8.63E+09	3.84E+04	8.08E+08	**7.01E+03**
	Std	2.38E+06	9.22E+05	6.65E+09	1.07E+07	2.60E+05	**4.29E+03**	6.01E+06	1.18E+04	2.37E+09	4.47E+07	2.26E+10	1.62E+08	2.94E+09	2.38E+04	2.36E+08	**3.06E+03**
	Rank/S.R.	5 / -	4 / -	8 / -	7 / -	3 / -	**1 / ≈**	6 / -	2	6 / -	3 / -	8 / -	4 / -	7 / -	2 / -	5 / -	**1**
F20	Mean	4.81E+03	3.78E+03	4.22E+03	3.30E+03	3.36E+03	3.16E+03	3.72E+03	**2.42E+03**	1.05E+04	7.34E+03	7.86E+03	5.94E+03	6.50E+03	5.11E+03	6.86E+03	**4.47E+03**
	Std	1.26E+02	2.60E+02	1.81E+02	1.95E+02	1.22E+02	2.20E+02	1.36E+02	**7.11E+01**	2.84E+02	**1.17E+02**	1.38E+02	2.77E+02	1.73E+02	2.08E+02	2.69E+02	3.58E+02
	Rank/S.R.	8 / -	6 / -	7 / -	3 / -	4 / -	2 / -	5 / -	**1**	8 / -	6 / -	7 / -	3 / -	4 / -	2 / -	5 / -	**1**
F21	Mean	2.48E+03	2.62E+03	3.18E+03	2.82E+03	2.57E+03	2.61E+03	2.96E+03	**2.39E+03**	3.42E+03	3.34E+03	4.40E+03	4.06E+03	3.18E+03	3.31E+03	4.13E+03	**2.63E+03**
	Std	8.21E+01	2.28E+01	2.51E+01	2.38E+01	4.99E+01	2.83E+01	5.24E+01	**6.74E+00**	3.02E+01	3.87E+01	2.49E+02	1.13E+02	1.10E+02	6.28E+01	6.75E+01	**1.21E+01**
	Rank/S.R.	2 / -	5 / -	8 / -	6 / -	3 / -	4 / -	7 / -	**1**	5 / -	4 / -	8 / -	6 / -	2 / -	3 / -	7 / -	**1**
F22	Mean	1.96E+04	1.64E+04	1.74E+04	1.39E+04	1.33E+04	9.19E+03	1.42E+04	**7.53E+03**	3.91E+04	3.48E+04	3.56E+04	3.09E+04	3.30E+04	1.97E+04	3.19E+04	**1.64E+04**
	Std	4.32E+02	**2.00E+02**	3.80E+02	4.60E+02	3.80E+03	4.94E+02	5.09E+02	2.25E+02	**1.53E+02**	4.57E+02	4.66E+02	5.68E+02	2.25E+02	7.63E+02	7.00E+02	7.27E+02
	Rank/S.R.	8 / -	6 / -	7 / -	4 / -	3 / -	2 / -	5 / -	**1**	8 / -	6 / -	7 / -	3 / -	5 / -	2 / -	4 / -	**1**
F23	Mean	2.97E+03	3.11E+03	4.32E+03	3.43E+03	3.00E+03	3.22E+03	3.71E+03	**2.82E+03**	3.96E+03	3.89E+03	6.09E+03	4.74E+03	3.64E+03	3.96E+03	5.08E+03	**3.10E+03**
	Std	1.15E+02	2.30E+01	7.20E+01	8.37E+01	4.58E+01	5.76E+01	8.36E+01	**2.53E+00**	3.68E+01	7.30E+01	1.32E+02	1.35E+02	5.88E+01	9.74E+01	1.66E+02	**1.24E+01**
	Rank/S.R.	2 / -	4 / -	8 / -	6 / -	3 / -	5 / -	7 / -	**1**	5 / -	3 / -	8 / -	6 / -	2 / -	4 / -	7 / -	**1**
F24	Mean	3.02E+03	3.24E+03	4.47E+03	3.56E+03	3.25E+03	3.39E+03	3.73E+03	**2.98E+03**	4.36E+03	4.48E+03	9.37E+03	5.70E+03	4.87E+03	5.04E+03	6.29E+03	**3.58E+03**
	Std	1.52E+01	3.10E+01	5.24E+01	6.96E+01	4.66E+01	7.57E+01	9.76E+01	**7.80E+00**	**1.87E+01**	8.94E+01	2.76E+02	3.68E+02	1.01E+02	3.77E+02	2.84E+02	2.24E+01
	Rank/S.R.	2 / -	3 / -	8 / -	6 / -	4 / -	5 / -	7 / -	**1**	2 / -	3 / -	8 / -	6 / -	4 / -	5 / -	7 / -	**1**
F25	Mean	**2.93E+03**	3.20E+03	1.44E+04	3.39E+03	5.19E+03	3.13E+03	5.16E+03	3.04E+03	4.72E+03	5.94E+03	2.62E+04	5.53E+03	1.08E+04	3.90E+03	1.01E+04	**3.48E+03**
	Std	**3.00E-02**	4.24E+01	5.29E+02	4.42E+01	2.71E+02	1.77E+01	4.97E+02	1.22E+01	1.53E+03	7.49E+02	9.05E+02	2.40E+02	5.38E+02	8.57E+01	7.62E+02	**5.87E+01**
	Rank/S.R.	**1 / +**	4 / -	8 / -	5 / -	7 / -	3 / -	6 / -	2	3 / -	5 / -	8 / -	4 / -	7 / -	2 / -	6 / -	**1**
F26	Mean	4.67E+03	7.42E+03	1.68E+04	6.59E+03	8.07E+03	8.06E+03	1.36E+04	**4.13E+03**	1.71E+04	1.77E+04	5.40E+04	2.38E+04	2.40E+04	1.86E+04	3.52E+04	**9.15E+03**
	Std	5.27E+02	4.32E+02	**3.12E+02**	2.32E+03	4.45E+02	1.07E+03	7.32E+02	8.70E+02	2.76E+02	6.19E+02	8.11E+02	2.42E+03	8.67E+02	9.11E+02	1.60E+03	**2.33E+02**
	Rank/S.R.	2 / -	4 / -	8 / -	3 / -	6 / -	5 / -	7 / -	**1**	2 / -	3 / -	8 / -	5 / -	6 / -	4 / -	7 / -	**1**
F27	Mean	3.20E+03	3.58E+03	4.20E+03	**3.20E+03**	3.43E+03	3.60E+03	4.23E+03	3.31E+03	**3.20E+03**	4.09E+03	6.84E+03	3.22E+03	4.64E+03	3.83E+03	5.59E+03	3.20E+03
	Std	**1.60E-05**	3.48E+01	5.49E+02	7.46E-05	4.05E+01	8.25E+01	1.96E+02	1.90E+01	**2.28E-05**	5.27E+01	3.01E+03	5.84E+01	8.54E+01	8.71E+01	4.37E+02	4.52E-05
	Rank/S.R.	2 / +	5 / -	7 / -	**1 / +**	4 / -	6 / -	8 / -	3	**1 / +**	5 / -	8 / -	3 / ≈	6 / -	4 / -	7 / -	2
F28	Mean	**3.30E+03**	3.89E+03	3.87E+03	3.75E+03	5.81E+03	3.57E+03	4.92E+03	3.32E+03	**3.30E+03**	1.16E+04	4.09E+03	6.85E+03	1.44E+04	4.37E+03	1.22E+04	3.58E+03
	Std	**3.06E-05**	5.06E+02	8.64E+02	2.34E+02	1.75E+02	1.98E+02	3.20E+02	7.90E+00	**2.08E-05**	2.55E+03	8.03E+02	4.83E+02	5.52E+02	2.60E+02	7.70E+02	2.02E+01
	Rank/S.R.	**1 / +**	6 / -	5 / -	4 / -	8 / -	3 / -	7 / -	2	**1 / +**	6 / -	3 / -	5 / -	8 / -	4 / -	7 / -	2
F29	Mean	8.24E+03	4.84E+03	4.45E+04	6.42E+03	4.48E+03	4.66E+03	8.78E+03	**3.78E+03**	1.37E+05	1.07E+04	6.66E+05	1.22E+04	8.76E+03	7.31E+03	1.66E+04	**5.98E+03**
	Std	1.16E+03	3.06E+02	1.36E+04	5.56E+02	1.71E+02	1.92E+02	1.03E+03	**6.34E+01**	3.29E+04	7.26E+02	2.18E+05	7.24E+02	6.15E+02	3.47E+02	1.42E+03	**2.52E+02**
	Rank/S.R.	6 / -	4 / -	8 / -	5 / -	2 / -	3 / -	7 / -	**1**	7 / -	4 / -	8 / -	5 / -	3 / -	2 / -	6 / -	**1**
F30	Mean	2.27E+07	2.33E+08	6.01E+10	4.13E+08	2.49E+08	1.79E+06	4.40E+08	**1.60E+06**	9.03E+09	1.71E+09	3.70E+11	2.83E+09	2.50E+10	2.63E+06	6.26E+09	**4.92E+05**
	Std	4.08E+06	3.02E+07	1.06E+10	1.03E+08	1.15E+08	6.62E+05	1.05E+08	**2.94E+05**	2.04E+09	3.77E+08	4.01E+10	4.13E+08	4.45E+09	1.52E+06	2.65E+09	**6.76E+04**
	Rank/S.R.	3 / -	4 / -	8 / -	6 / -	5 / -	2 / ≈	7 / -	**1**	6 / -	3 / -	8 / -	4 / -	7 / -	2 / -	5 / -	**1**
Sum of ranks		120	119	223	142	120	96	181	**43**	148	115	217	139	130	90	171	**34**
Average rank		4.14	4.10	7.69	4.90	4.14	3.31	6.24	**1.48**	5.10	3.97	7.48	4.79	4.48	3.10	5.90	**1.17**
Overall rank		4	3	8	6	4	2	7	**1**	6	3	8	5	4	2	7	**1**
- / ≈ / +		23 / 0 / 6	28 / 1 / 0	29 / 0 / 0	28 / 0 / 1	25 / 2 / 2	24 / 2 / 3	29 / 0 / 0		27 / 0 / 2	29 / 0 / 0	29 / 0 / 0	28 / 1 / 0	25 / 3 / 1	28 / 0 / 1	29 / 0 / 0	

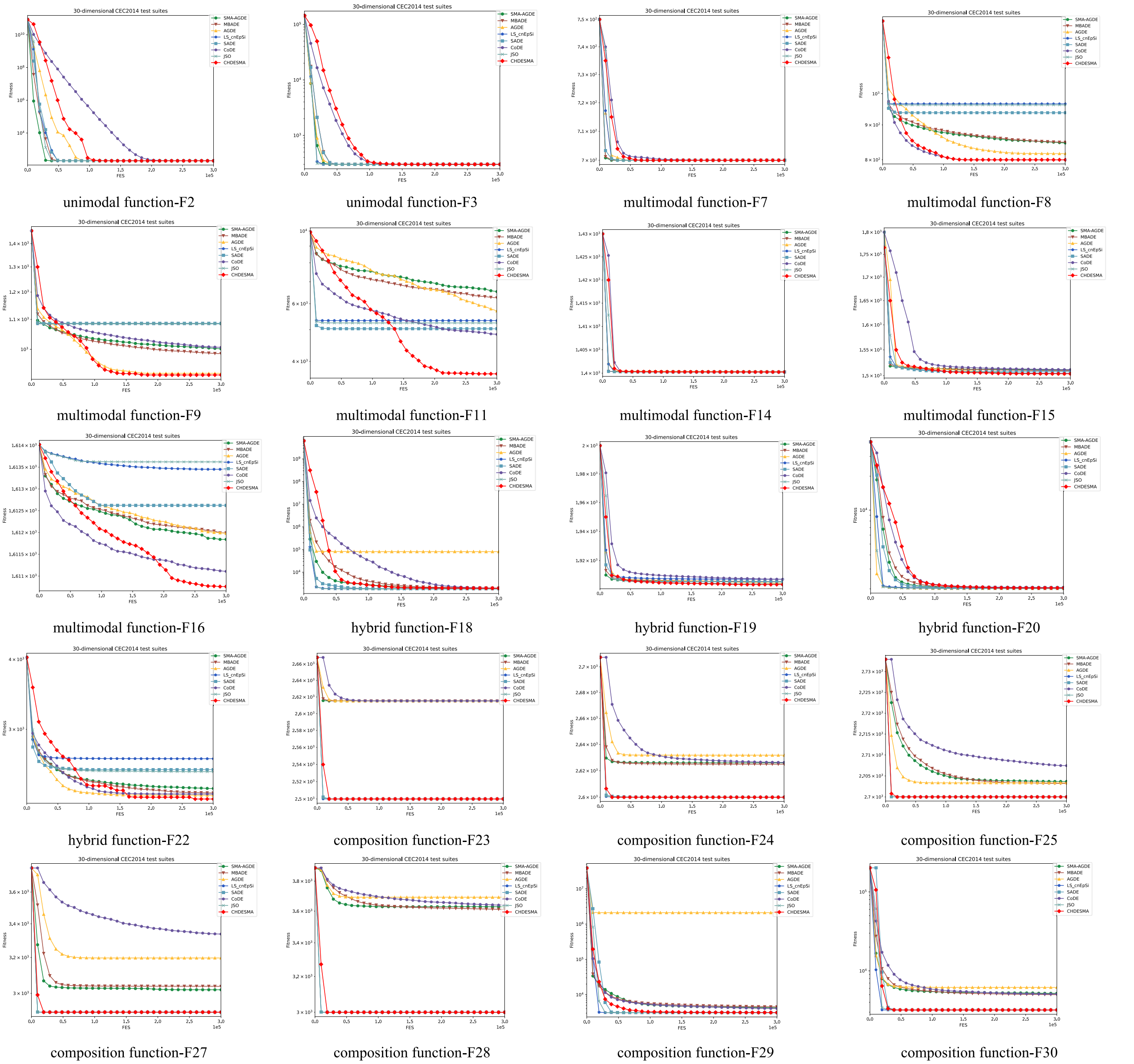

FIGURE 2. **Convergence curves with DE variants on the 30-dimensional CEC2014 benchmark functions.**

F15, F19, and F23 to F30, and the CHDESMA algorithm has achieved minimum optimization on F9, F11, F16, and F22. According to the Wilcoxon rank-sum test in Table 6, the p-value of most functions is ≤ 0.05 (5% significance level), so the experimental results are statistically significant for the CEC2014 test suite, verifying that the performance of CHDESMA is not random.

The convergence of CHDESMA and DE variants on CEC2014 test suites is shown in Figure 2. It can be observed that the CHDESMA converges faster than other advanced algorithms in most cases. On F8, F9, F16, F24, F25, F27, and F28, the convergence rate of CHDESMA is fast, and CHDESMA has reached the global optimum on functions F2, F3, F7, F8, F15, F19, and F23 to F30. On F11 F22 and F29, the convergence rate of CHDESMA is not the fastest, but the final optimization results of CHDESMA are much smaller than other competitors. On F2, F15, F18 to F20, and F22, the convergence speed of CHDESMA is relatively slow at the beginning of the iteration. Still, as the number of iterations increases, the final optimization result of CHDESMA is much smaller than the competition. The chaotic maps method can effectively increase the diversity of slime mold populations and improve the performance of the original SMA algorithm, and the DE strategy can prevent SMA from falling into the local optimal value and enable SMA to find the global optimal solution.

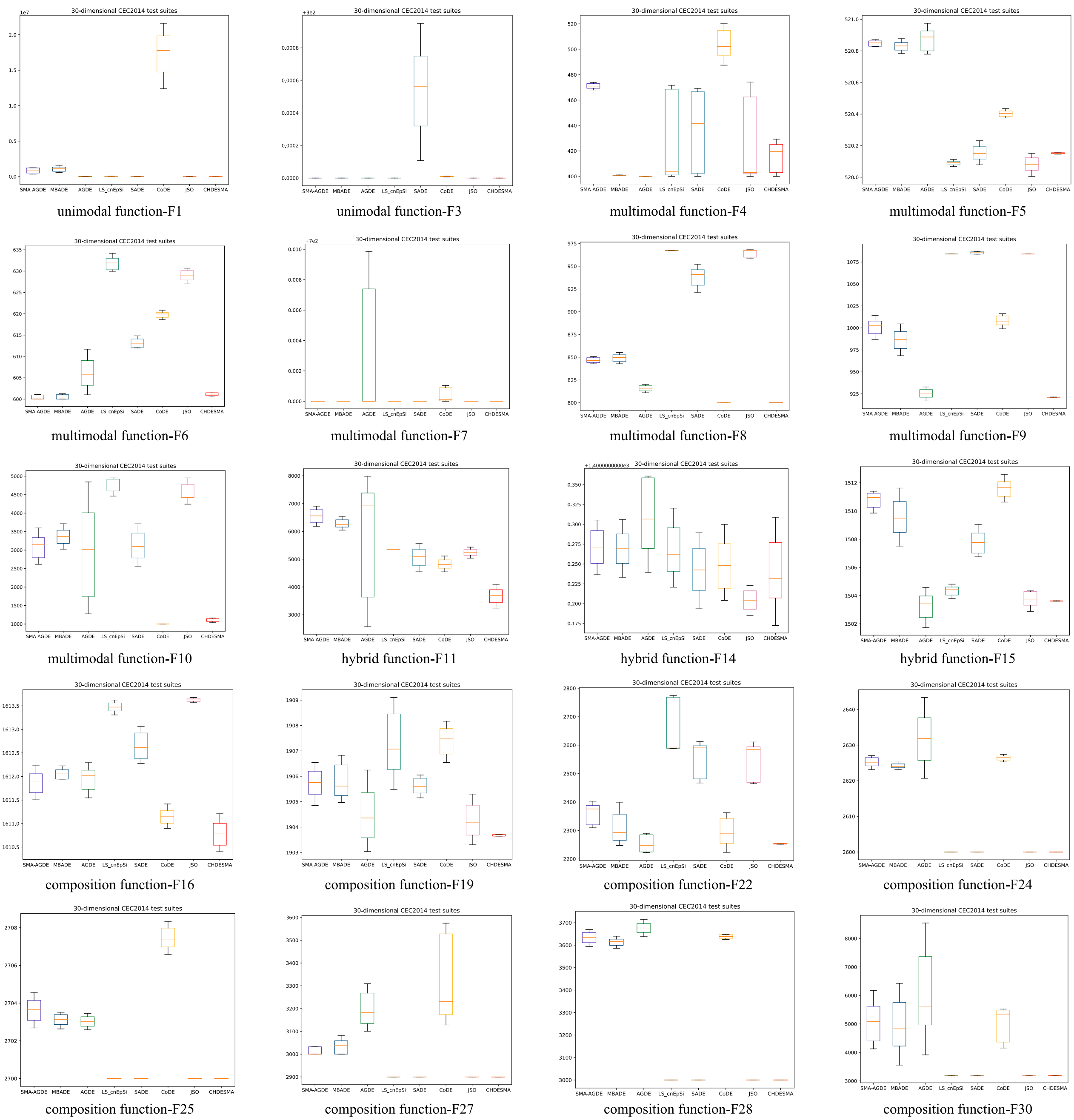

FIGURE 3. Boxplots of CHDESMA and DE variants on the 30-dimensional CEC2014 benchmark functions.

The boxplots of the CHDESMA and DE variants are shown in Figure 3. It can be seen from the distribution of the data that in most functions, the line shape of CHDESMA is narrow, and the distribution of the data is relatively concentrated. Only on F11, F14, and F16 the data of this algorithm is relatively scattered.

D. SCALABILITY OF CHDESMA AND ADVANCED ALGORITHMS

In this part, different dimensions (dim = 10, 30, 50, and 100) are used to test the ductility of the proposed CHDESMA. The test results are used to compare with the advanced algorithms proposed on the CEC2017 test functions in Table 7, including the CMA Evolution Strategy (CMAES) [52], memory-based grey wolf optimizer (mGWO) [53], modified Sine Cosine Algorithm (mSCA) [54], time-varying hierarchical salp swarm algorithm (TVBSSA) [55], modified global flower pollination algorithm (MGFPA) [56], phasor particle swarm optimization (PPSO) [57] and improved opposition-based whale optimization algorithm (OBWOA) [58]. For the sake of fairness, each test function was run 30 times independently. In addition, Table 7 shows the S.R. obtained at the 5% significance level by Wilcoxon rank-sum test.

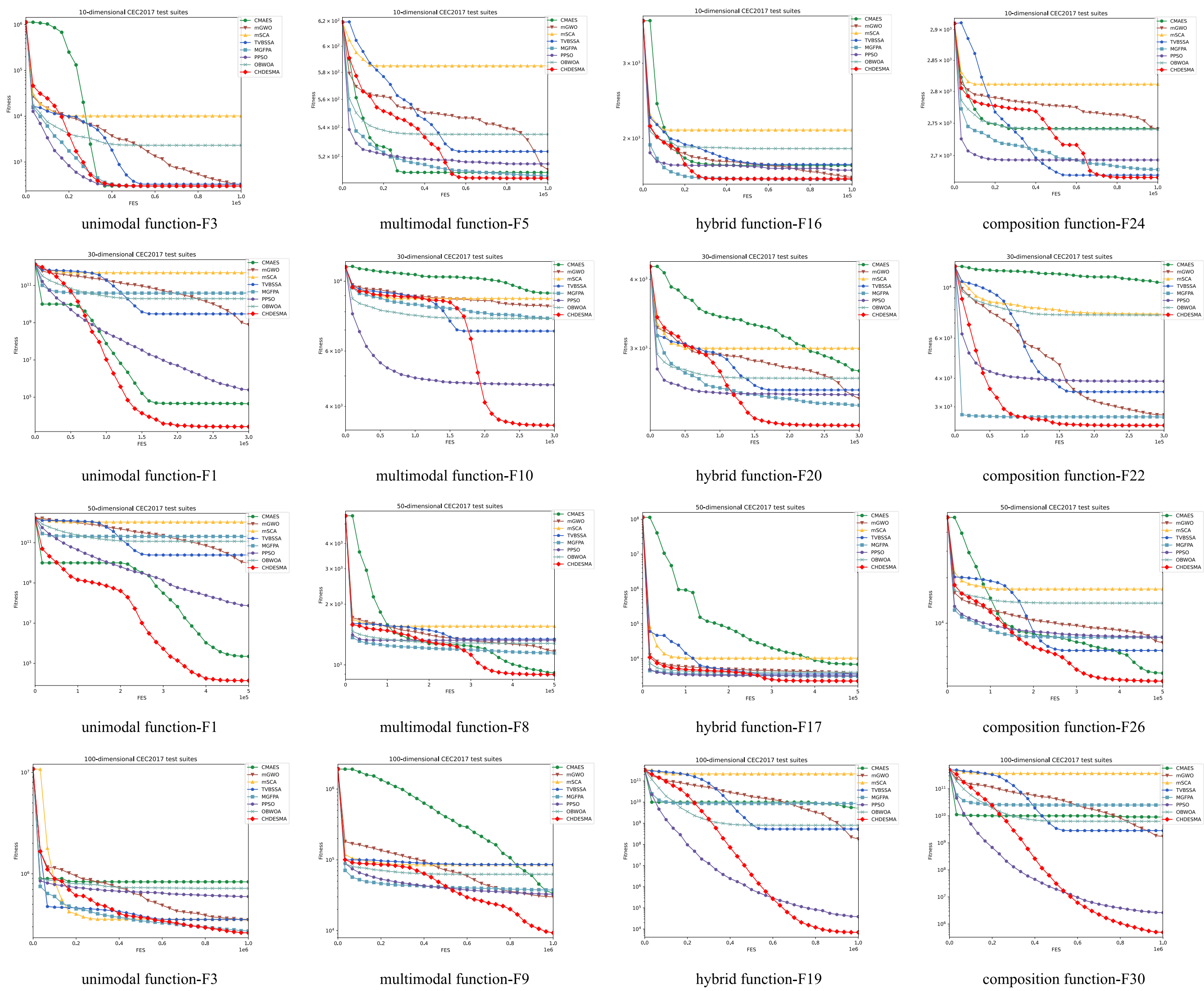

FIGURE 4. **Convergence curves of CHDESMA and advanced algorithms on CEC2017 with different dimensions.**

Table 7 shows the comparison and statistical results between CHDESMA and the advanced algorithms with different dimensions. As shown in Table 7, CHDESMA ranks first across different dimensions. For unimodal functions (F1 and F3), CHDESMA converges very quickly, and the quality of its solution is very high. For multi-modal functions, CHDESMA performs better at higher dimensions. It is worth noting that for composition functions (F21 to F30), the performance of CHDESMA did not deteriorate seriously as the dimension increased. These results indicate that the search-ability of CHDESMA is effective. Moreover, CHDESMA can avoid falling into local optimum, and the optimization performance of solving high dimensional functions is strong. The results of p-values in Table 7 show that the p-values of CHDESMA on most functions are less than 0.05, which suggests that the proposed algorithm has obvious advantages over the other algorithms.

The convergence curves of CHDESMA and other algorithms on CEC2017 test suites are shown in Figure 4. In Figure 4, F1 and F3 are unimodal functions, F5, F8, F9, and F10 are multi-modal functions, F16, F17, F19, and F20 are hybrid functions, and F22, F24, F26, and F30 are composition functions. The first row of the figure shows the results of the involved algorithms on a 10-dimensional test set. The second row displays the results of the 30-dimensional test set. The third row represents the results of 50-dimensional benchmark functions. The graph in the fourth row shows the results of the 100-dimensional test set.

It is not difficult to see from Figure 4 that of these advanced algorithms, CHDESMA has the best optimization effect. As shown in Figure 4, CHDESMA converges fast and outperforms the other algorithms on most benchmark functions. There is close competition among all algorithms in dealing with hybrid functions (F16, F17, F19, and F20), but

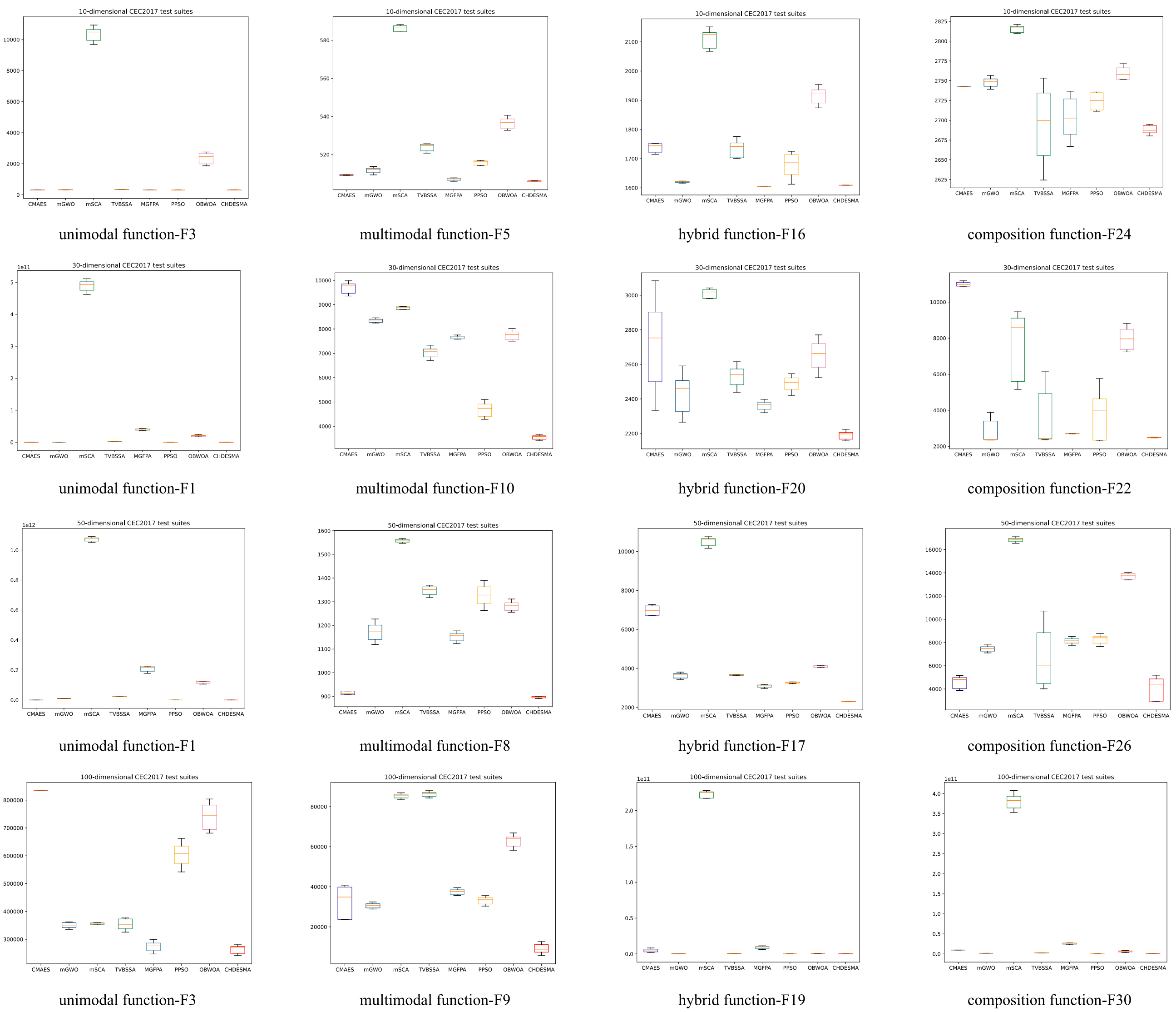

FIGURE 5. Boxplots of CHDESMA and advanced algorithms on CEC2017 with different dimensions.

CHDESMA can find a better solution during the overall steps. It is because the chaotic map method in CHDESMA can increase the diversity of the population, and the DE strategy can prevent SMA from falling into the local optimal value and accelerate the algorithm's convergence rate. All in all, the experimental results of CHDESMA are superior to other advanced algorithms.

The boxplots of the CHDESMA and DE variants are shown in Figure 5. It can be seen from the distribution of the data that in most functions, the line shape of CHDESMA is narrow, and the distribution of the data is relatively concentrated.

E. CHDESMA FOR ENGINEERING DESIGN PROBLEMS

The performance tested by the optimizer on engineering constraint problems shows the potential efficiency in other types of problems. Therefore, engineering constraint problems are often used to verify the algorithm's performance [59]. This article uses the proposed CHDESMA to solve four classic engineering design problems: TCSD, WBD, PVD, and TBTD. The CHDESMA's results were compared to results obtained with SMA [12], ILSHADE [60], JADE [61], JSO [51], LSHADE_cnEpSi [48], LSHADE [62], SADE [49], SHADE [63], MPEDE [64], and mGWO [53]. The constrained optimization problem in the real world can be represented by the following mathematical formulation [65].

$$\begin{aligned} &Minimize, f\left(\bar{x}\right), \bar{x} = (x_1, x_2, \ldots, x_n) \\ &Subject\ to: \ g_i\left(\bar{x}\right) \leq 0, \quad i = 1, \ldots, n \\ &\qquad\qquad\quad h_j\left(\bar{x}\right) = 0, \quad j = n+1, \ldots, n \end{aligned} \tag{22}$$

In general, one equation constraint can be transformed into two-equation constraints, as follows:

$$\left|h_j\left(\bar{x}\right)\right| - \varepsilon \leq 0, \quad j = n+1, \ldots, m \tag{23}$$

where ε is a small value (close to zero).

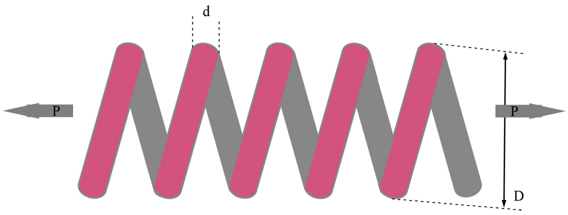

FIGURE 6. Schematic of the TCSD problem.

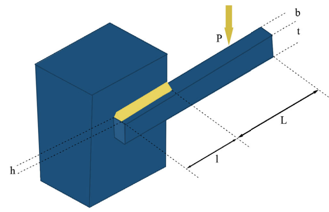

FIGURE 7. Schematic of the WBD problem.

The ranking of algorithms in the table is based on the best value. The penalty function method is as follows [66], [67]:

$$min\phi\left(X\right)=f\left(x\right)+\lambda\sum_{c\in N_c}\left(\max\left(0,g_c\left(x\right)\right)\right)^2 \tag{24}$$

where $f(x)$ represents the objective function, and $g_c(x)$ represents its constraints. λ is the penalty coefficient, and N_c is the number of constraints.

1) ENGINEERING PROBLEM 1 (TCSD)

The primary purpose of the TCSD problem is to obtain the value of the minimum spring weight [68]. Therefore, the following three parameters must be optimized in modeling: average coil diameter (D), wire diameter (d), and effective coil number (N), as shown in Figure 6. The detailed description of the TCSD is shown in Appendix A.

Table 8 shows the best design solution for the TCSD problem, and Table 9 summarizes the comparison results between CHDESMA and other algorithms. CHDESMA has the smallest value for the best solution to the TCSD problem and ranks first for the worst solution and average value. Therefore, the CHDESMA algorithm has good performance and stability in solving the TCSD problem.

2) ENGINEERING PROBLEM (WBD)

The primary purpose of the WBD problem is to minimize the economic cost [69]. There are the following four optimization constraints parameters: the buckling load on the rod (P_c), the end deflection of the beam (δ), the shear stress (τ), and the bending stress in the beam (θ). Reducing costs requires controlling the following four variables: connecting steel bar length (l), weld thickness (h), steel bar thickness (b), and steel bar height (t), as shown in Figure 7. The detailed descriptions of the WBD are shown in Appendix B.

Table 10 and Table 11 show the best design for the WBD problem and the statistical results of the comparison algorithms, respectively. It can be seen from these tables that CHDESMA ranks first in the best value among all algorithms. In addition, the worst solution and average value are also the smallest. The SMA algorithm ranks second on the WBD problem. Therefore, the performance of the proposed CHDESMA in solving the WBD problem is better than the original SMA and other competing optimizers.

TABLE 8. The best design for TCSD problems.

	d	D	N	Cost
CHDESMA	0.051815396	0.35981903	11.1069113	0.012663458
SMA	0.051676806	0.356444001	11.30816581	0.012680818
ILSHADE	0.060106319	0.555342376	5.614903217	0.013072726
JADE	0.051685266	0.356680704	11.28856837	0.012663458
JSO	0.052312324	0.316835201	14.10601395	0.012831426
LSHADE_cnEpSi	0.060106319	0.555342376	5.614903217	0.01333175
LSHADE	0.051685266	0.356680704	11.28856837	0.012663458
SADE	0.052657831	0.316232134	12.22932321	0.012675767
SHADE	0.052179413	0.368684458	10.61800087	0.012665855
MPEDE	0.051765343	0.356342344	11.30353425	0.012700565
mGWO	0.051678432	0.356444001	11.30816581	0.012718571

TABLE 9. Comparison of optimization results for TCSD problems.

	Best	Worst	Mean	Std	Rank
CHDESMA	**0.01266345**	**0.012663458**	**0.01266345**	**1.81124E-13**	**1**
SMA	0.01268081	0.060085587	0.01517044	0.009229341	6
ILSHADE	0.01307272	0.017769452	0.01571714	0.001969464	10
JADE	0.01266345	0.017769452	0.01633988	0.002292402	2
JSO	0.01283142	0.017769452	0.01570148	0.002112603	9
LSHADE_cnEpSi	0.01333175	0.018539071	0.01413694	0.001177887	11
LSHADE	0.01266345	0.017769452	0.01453584	0.002460406	2
SADE	0.01267576	39.72679509	1.60415660	7.78175136	5
SHADE	0.01266585	0.017769452	0.01577875	0.002438553	4
MPEDE	0.01270056	39.72679509	7.95776400	15.8845157	7
mGWO	0.01271857	0.013155826	0.01277144	9.19045E-05	8

TABLE 10. The best design for WBD problems.

	H	L	t	b	Cost
CHDESMA	0.20570385	3.25092767	9.03483512	0.20581976	1.68767455
SMA	0.20540955	3.25894975	9.03844643	0.20580188	1.69604092
ILSHADE	0.20576534	3.26896572	9.03844643	0.20580188	1.72485185
JADE	0.20554678	3.25894342	9.03844643	0.20580188	1.72485185
JSO	0.20540955	3.25856462	9.03844643	0.20580188	1.72485185
LSHADE_cnEpSi	0.20178754	3.66900284	8.99945659	0.20812085	1.75743448
LSHADE	0.20504019	3.24655627	9.03844643	0.20580188	1.72485185
SADE	0.20486230	3.24135572	9.03844643	0.20580188	1.72485185
SHADE	0.20468440	3.23615517	9.03844643	0.20580188	1.72485185
MPEDE	0.20573031	3.47047410	9.03662391	0.20572964	1.72485185
mGWO	0.20922455	3.37232663	9.10355140	0.20943986	1.73253837

3) ENGINEERING PROBLEM (PVD)

The PVD problem's primary purpose is to obtain the smallest value of the total cost [70]. Economic cost calculation needs to consider three factors welding, forming, and material. To minimize the financial cost, four design variables need to be constrained: head thickness (T_h), thickness (T_s), container cylindrical section length (L), and inner radius (R), as shown in Figure 8. The detailed description of the PVD is shown in Appendix C.

TABLE 11. Comparison of optimization results for WBD problems.

	Best	Worst	Mean	Std	Rank
CHDESMA	**1.687674556**	**1.696092112**	**1.691041769**	**0.004106817**	**1**
SMA	1.696040923	1.696287812	1.696164188	7.43152E-05	2
ILSHADE	1.72485185	1.995689945	1.76748445	0.065119842	3
JADE	1.72485185	1.767572073	1.726560659	0.00837142	3
JSO	1.72485185	1.746023798	1.726031733	0.004405783	3
LSHADE_cnEpSi	1.757434483	5.31144385	3.936655983	0.958796031	11
LSHADE	1.72485185	1.72485185	1.72485185	5.61733E-15	3
SADE	1.72485185	1.891596521	1.74922385	0.053517655	3
SHADE	1.72485185	1.928623958	1.759570538	0.060116468	3
MPEDE	1.724851851	1.725185584	1.724871336	6.5493E-05	9
mGWO	1.73253837	1.762758751	1.742223711	0.007773855	10

TABLE 12. The best design for PVD problems.

	T_h	T_s	R	L	Cost
CHDESMA	0.77433280	0.38351134	40.3209426	199.99950	5870.123977
SMA	0.80925768	0.40015306	42.1092835	176.50234	5870.124245
ILSHADE	0.77454909	0.38320385	40.3196187	200	5870.123984
JADE	0.77454909	0.38320385	40.3196187	200	5870.123983
JSO	0.77454909	0.38320385	40.3196187	200	5870.123992
LSHADE_cnEpSi	0.77454909	0.38320385	40.3196187	200	5870.123987
LSHADE	0.77454909	0.38320385	40.3196187	200	5870.123989
SADE	0.77454909	0.38320385	40.3196187	200	5870.123981
SHADE	0.77454909	0.38320385	40.3196187	200	5870.123979
MPEDE	0.77454909	0.38320385	40.3196187	200	5870.123978
mGWO	0.80862185	0.39839536	42.0760261	183.23247	5889.821384

TABLE 13. Comparison of optimization results for PVD problems.

	Best	Worst	Mean	Std	Rank
CHDESMA	**5870.123977**	6667.19696	6044.530333	225.6433629	**1**
SMA	5870.124245	13419.37396	8201.247079	2556.485358	10
ILSHADE	5870.123984	6020.368967	5882.048724	38.24651958	6
JADE	5870.123983	6020.368967	5882.048724	38.24651959	5
JSO	5870.123992	6020.368967	5882.048724	38.24651957	9
LSHADE_cnEpSi	5870.123987	6020.368968	5882.048724	38.24651957	7
LSHADE	5870.123989	6020.368968	5882.048724	38.24651957	8
SADE	5870.123981	6020.368969	5882.048724	38.24651956	4
SHADE	5870.123979	6020.368969	5882.048724	38.24651956	3
MPEDE	5870.123978	**6020.368968**	**5882.048724**	**38.24651956**	2
mGWO	5889.821384	7200.603667	6247.061139	313.3915772	11

Table 12 and Table 13 show the best design for the PVD problem and the statistical results of the comparison algorithms, respectively. CHDESMA can find the best optimization solution. But the statistical results show that CHDESMA's worst value and average ranking are both 9th, indicating that CHDESMA does not find the best solution every time.

4) ENGINEERING PROBLEM (TBTD)

The primary purpose of TBTD is to ensure that the volume of the truss should be minimized under static pressure and to meet the stress (σ) constraints on each truss member. This problem can be transformed into an optimal cross-sectional area (x_1, x_2) problem, as shown in Figure 9. The detailed description of the TBTD is shown in Appendix D.

Table 14 and Table 15 show the optimized design and statistical results on the TBTD problem. CHDESMA gets the best function value in this problem. However, ILSHADE, JSO, SADE, and MPEDE rank first in the worst solution and average value. Therefore, CHDESMA has a close competitive relationship with these DE variants.

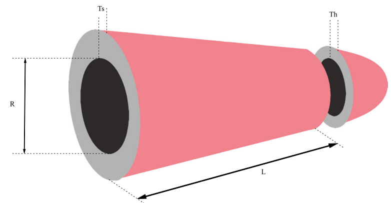

FIGURE 8. Schematic of the PVD problem.

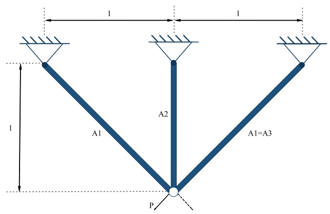

FIGURE 9. Schematic of the TBTD problem.

TABLE 14. The best design for TBTD problems.

	X_1	X_2	Cost
CHDESMA	0.788704746	0.40816358	263.895701
SMA	0.788591506	0.408484013	263.895805
ILSHADE	0.788674876	0.408248148	263.8957998
JADE	0.788674877	0.408248148	263.8957999
JSO	0.788674876	0.408248148	263.8957998
LSHADE_cnEpSi	0.788674878	0.408248148	263.8957999
LSHADE	0.788674777	0.408248148	263.8957999
SADE	0.788674776	0.408248148	263.8957998
SHADE	0.788674877	0.408248148	263.8957999
MPEDE	0.788674877	0.408248148	263.8957998
mGWO	0.787703391	0.411002896	263.8974926

TABLE 15. Comparison of optimization results for TBTD problems.

	Best	Worst	Mean	Std	Rank
CHDESMA	**263.895701**	263.9010924	263.8965835	0.0012859	**1**
SMA	263.895805	263.9742488	263.9031715	0.0147960	10
ILSHADE	263.8957998	**263.8957999**	**263.8957999**	1.97185E-	2
JADE	263.8957999	263.8957999	263.8957999	**0**	6
JSO	263.8957998	**263.8957999**	**263.8957999**	1.97185E-	2
LSHADE_cnEpSi	263.8957999	263.8957999	263.8957999	**0**	6
LSHADE	263.8957999	263.8957999	263.8957999	**0**	6
SADE	263.8957998	**263.8957999**	**263.8957999**	4.50177E-	2
SHADE	263.8957999	263.8957999	263.8957999	**0**	6
MPEDE	263.8957998	**263.8957999**	**263.8957999**	2.75676E-	2
mGWO	263.8974926	263.9486238	263.9115862	0.0125675	11

F. DISCUSSION OF EXPERIMENTAL RESULTS

In the proposed algorithm, we mainly use two methods (chaotic initialization and DE algorithm) to further improve the performance of the original SMA. Chaotic initialization has been shown to improve the quality of the solution. However, it lacks robustness in dealing with various problems, and the performance of the proposed algorithm is not competitive when dealing with discrete problems.

The DE algorithm shows good exploration capabilities, but individuals easily fall into local optima as the iterations proceed. From the effectiveness test of the components (Section IV.B), the effectiveness of the chaotic maps and DE components in CHDESMA can be confirmed. From the statistical results of the CEC2014 and CEC2017 test functions (Sections IV.C and IV.D), the proposed algorithm CHDESMA shows excellent performance in dealing with multimodal and mixed functions. However, the convergence of the algorithm is not fast enough when dealing with unimodal functions. In general, CHDESMA is applicable to multimodal and mixed functions, but not to unimodal functions. It can be seen from the different dimensions (10, 30, 50, and 100) that the higher the dimensionality, the better the performance of CHDESMA compared to other competing algorithms. From the statistical results (Section IV.E) of four real-world engineering problems (TCSD, WBD, PVD, and TBTD), the CHDESMA algorithm exhibits superior performance and can better solve the four engineerings constrained problems.

V. CONCLUSION

This paper proposes a hybrid SMA algorithm based on Chaotic Maps and Differential Evolution. The proposed CHDESMA introduces the Chaotic Maps strategy to accelerate the convergence in the initial iteration process. The operators of differential evolution effectively avoid prematurely, enhance the local searchability, and avoid stagnation in local optima. CHDESMA conducted three sets of test experiments on the CEC2014 and CEC2017 benchmark functions. Experiments compared with DE variants and advanced algorithms verify the effectiveness of the proposed improved strategies, including SMA-AGDE, MBADE, AGDE, LSHADE_cnEpSi, SADE, CoDE, JSO, CMAES, mGWO, mSCA, TVBSSA, MGFPA, PPSO, and OBWOA. In addition, CHDESMA was used to solve four practical engineering design problems. Experimental results and statistical analysis show that CHDESMA algorithm is more suitable for solving multi-model and hybrid function problems, and CHDESMA performs well in high dimensions, which can effectively solve global optimization problems and complex engineering practical problems.

In future work, based on the advantages of CHDESMA, we will apply CHDESMA to large-scale and high-dimensional problems. CHDESMA can also be used for multi-peaked complex optimization problems, such as constraint engineering optimization, photovoltaic design, and other related problems. In addition, the binary version of the variant can be further enhanced and used for feature selection.

APPENDIX A
TENSION/COMPRESSION SPRING DESIGN PROBLEM (TCSD)

The mathematical model of the Tension/compression spring design problem is as follows:

$$
\begin{aligned}
&\min f(x) = \left(2\sqrt{2}\,x_1 + x_2\right) \times l\\
&\textit{subject to}:\ g_1(x) = \frac{\sqrt{2}\,x_1 + x_2}{\sqrt{2}\,x_1^2 + 2x_1x_2} p - \sigma \le 0\\
&\qquad g_2(x) = \frac{x_2}{\sqrt{2}\,x_1^2 + 2x_1x_2} p - \sigma \le 0\\
&\qquad g_3(x) = \frac{1}{\sqrt{2}\,x_2 + x_1} p - \sigma \le 0\\
&\qquad 0 \le x_i \le 1, \quad i = 1, 2\\
&\qquad l = 100cm, \quad p = 2kN/cm^2, \ \sigma = 2kN/cm^2
\end{aligned}
\tag{25}
$$

APPENDIX B
WELDED BEAM DESIGN PROBLEM (WBD)

The mathematical model of the Welded beam design problem is as follows:

$$
\begin{aligned}
&\min f(x) = 1.1047x_1^2x_2 + 0.04811x_3x_4(14.0 + x_2)\\
&\textit{subject to}:\ g_1(x) = \iota(x) - \iota_{\max} \le 0\\
&\qquad g_2 = \sigma(x) - \sigma_{\max} \le 0\\
&\qquad g_3 = x_1 - x_4 \le 0\\
&\qquad g_4(x) = 0.1047x_1^2 + 0.0481x_3x_4\\
&\qquad \times (14 + x_2) - 5 \le 0\\
&\qquad g_5(x) = 0.125 - x_1 \le 0\\
&\qquad g_6(x) = \delta(x) - \delta_{\max} \le 0,\\
&\qquad g_7(x) = P(x) - P_c(x) \le 0\\
&\qquad 0.1 \le x_i \le 2, \quad i = 1, 4, 0.1 \le x_i \le 10,\\
&\qquad i = 2, 3\\
&\qquad \iota(x) = \sqrt{(\iota')^2 + 2\iota'\iota''\frac{x_2}{2R} + (\iota'')^2},\\
&\qquad \iota' = \frac{p}{\sqrt{2}\,x_1x_2}, \quad \iota'' = \frac{MR}{j}\\
&\qquad M = P\left(L + \frac{x_2}{2}\right),\\
&\qquad R = \sqrt{\frac{x_2^2}{4} + \left(\frac{x_1 + x_3}{2}\right)^2}\\
&\qquad P_c(x) = \frac{4.013E\sqrt{\frac{x_3^2x_4^6}{36}}}{L^2}\left(1 - \frac{x^3}{2L}\sqrt{\frac{E}{4G}}\right)\\
&\qquad J = 2\left\{\sqrt{2}\,x_1x_2\left[\frac{x_2^2}{12} + \left(\frac{x_1 + x_3}{2}\right)^2\right]\right\}\\
&\qquad \sigma(x) = \frac{6PL}{x_4x_3^2}, \delta(x) = \frac{4PL^3}{Ex_3^3x_4}\\
&\qquad P = 6000lb, L = 14in, \quad e = 30 \times 10^6 psi,\\
&\qquad G = 12 \times 10^6 psi\\
&\qquad \iota_{\max} = 13,600psi, \quad \sigma_{\max} = 30,000psi,\\
&\qquad \delta_{\max} = 0.25in
\end{aligned}
\tag{26}
$$

APPENDIX C
PRESSURE VESSEL DESIGN PROBLEM (PVD)

The mathematical model of the Pressure vessel design problem is as follows:

$$\begin{aligned}
\min f(x) &= 0.6224x_1x_3x_4 + 1.7781x_2x_3^2 \\
&\quad + 3.1661x_1^2x_4 + 19.84x_1^2x_3 \\
\textit{subject to}: \ & g_1(x) = -x_1 + 0.0193x_3 \leq 0 \\
& g_2(x) = -x_2 + 0.00954x_3 \leq 0 \\
& g_3(x) = -\pi x_3^2 x_4 - \frac{4}{3}\pi x_3^3 + 1296000 \leq 0 \\
& g_4(x) = x_4 - 240 \leq 0 \\
& 0 \leq x_i \leq 99 \ i = 1, 210 \leq x_i \leq 200 \ i = 3, 4
\end{aligned} \tag{27}$$

APPENDIX D
THREE-BAR TRUSS DESIGN PROBLEM (TBTD)

The mathematical model of the Three-bar truss design problem is as follows:

$$\begin{aligned}
\min f(x) &= \left(2\sqrt{2}\,x_1^2 + 2x_1x_2\right) * l \\
\textit{subject to}: \ & g_1(x) = \frac{\sqrt{2}\,x_1 + x_2}{\sqrt{2}\,x_1^2 + 2x_1x_2} P - \sigma \leq 0 \\
& g_2(x) = \frac{x_2}{\sqrt{2}\,x_1^2 + 2x_1x_2} P - \sigma \leq 0 \\
& g_3(x) = \frac{1}{\sqrt{2}\,x_2 + x_1} P - \sigma \leq 0 \\
& 0 \leq x_i \leq 1 \ i = 1, 2
\end{aligned} \tag{28}$$

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