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ABSTRACT

The invasive weed algorithm (IWO) is a meta-heuristic algorithm, which is an effective and promising optimiser to address the optimisation problems. In this study, a hybrid algorithm based on the self-adaptive invasive weed algorithm (IWO) and differential evolution algorithm (DE), named SIWODE, is proposed to address the continuous optimisation problems. In the proposed SIWODE, first, the two parameters are adaptively proposed to improve the convergence speed of the algorithm. Second, the crossover and mutation operations are introduced in SIWODE to improve the population diversity and increase the exploration capability during the iterative process. Furthermore, a local perturbation strategy is presented to improve exploitation ability during the late process. The exploration and exploitation ability of the algorithm is effectively balanced by cooperative mechanisms. The experiment results of SIWODE show that the SIWODE has the superior searching quality and stability than other mentioned approaches.

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1. Introduction

Various real-world applications are transformed into continuous optimisation problems, which are complex with the aggrandising of the problem scales and are challenging to be addressed by the traditional optimisation algorithms (Chen & Pi, 2019; Liu, Han, et al., 2020). The current researches focus on the feasible and efficient optimisation algorithms for addressing the continuous optimisation problems with the increasing of the problem scales (Yu, Gao, Wang, Lei, et al., 2019; Wang et al., 2021). A continuous optimisation problem is defined as $\min f(x), x = [x_1, x_2, \ldots, x_D]$, where the objective is to seek out the maximal or minimum value of $f(x)$, and output the solution x. To solve the continuous optimisation problems directly, researchers have proposed various optimisation algorithms (Abdullah et al., 2018; Liu, Li, et al., 2020; Nagra et al., 2020). The mathematical methods are utilised by initial researchers to solve the problems. With the increase in the scale of

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the problems, the limitations of traditional mathematical methods in the continuous optimisation problems are difficult to be solved effectively (Cao et al., 2019; Yu, Gao, Wang, Todo, et al., 2019). Therefore, the evolutionary algorithms are applied by researchers for solving the continuous optimisation problems (Zhao et al., 2020). The evolutionary algorithms are the randomly search algorithms, which are inspired by the processes of natural evolution, including particle swarm optimisation (PSO) (Zhao, Liu, et al., 2015), differential evolution (DE) (Zhang, 2016; Zhao, Liu, et al., 2015), water wave optimisation (WWO) (Zhao et al., 2017), gravitational search algorithm (GSA) (Zhao et al., 2018) and other evolutionary algorithms (Zhao, Liu, et al., 2015; Zhao, Zhang, et al., 2015; Zhao et al., 2019). The efficiency of the evolutionary algorithms is significantly better than the traditional methods for continuous optimisation problems (Lei et al., 2020).

The invasive weed algorithm (IWO) (Mehrabian & Lucas, 2006) is a new meta-heuristic and promising algorithm inspired by the behaviour of the invasive weed. For the continuous optimisation problems, each weed represents a candidate solution, and new seeds are generated by each weed based on its own merits. The mechanism that determines the number of offspring individuals based on the quality of the parents is the most promising operating mechanism in IWO. That is different from other swarm intelligence algorithms and is also unique to the IWO. In that theory, based on the simple mechanism of IWO, the IWO is applied to various continuous optimisation problems and other discrete optimisation problems. For instance, the travelling salesman problem (Zhou et al., 2015), the multi-objective blocking flow-shop scheduling problem (Shao et al., 2018), the inventory routing problem with an incremental delivery (Jahangir et al., 2019) and others (Giri et al., 2010; Shao et al., 2017; Yahyatabar & Najafi, 2017). Therefore, the researches of IWO in the continuous optimisation problems have crucial academic and engineering significance.

In recent decades, various research has been studied to improve the search performance of IWO. The adaptive dispersion operations were introduced to the standard deviations in the IWO algorithm by Zaharis et al. (2013). That was applied to a novel antenna array beamformer based on neural networks. Envelope and periodic variations were proposed to the standard deviation by Roy et al. (2011), which helped to quickly explore desirable solutions when the standard deviation is relatively large. That was applied to design non-uniform, planar and circular antenna arrays. A taboo table was proposed in the IWO algorithm by Ren et al. (2013). The stagnant weeds were introduced to the taboo table to avoid repetitive search around them, named EIWO. EIWO allowed a random generation of new weeds during the iteration to add new search areas. According to the experimental results of 16 functions in each dimension, EIWO avoided premature convergence and produced competitive results. IIWO was proposed by Ouyang et al. (2014) to modify the seed number and standard deviation. IIWO set the number of seeds to a fixed value and set the initial and final standard deviations to be adaptive, which was utilised to address the problem that the complex high-dimensional function converges slowly and easily enters the local optimum. A binary-continuous invasive weed optimisation algorithm (BCIWO) was designed by Niknamfar and Niaki (2018) to apply it to the supplier selection problem. BCIWO was performed binary coding of spatial diffusion operations. DIWO was proposed by Basak et al. (2013) to add DE's difference vector-based variability scheme to IWO. In DIWO, the authors utilised the variation of the difference vector and the binomial crossover operation for a part of the population in the IWO, which aimed to improve the searchability of the IWO. Furthermore, DIWO was compared to other comparison algorithms on benchmark functions. The experimental results showed that DIWO performance was superior to other compared algorithms.

A new multi-objective discrete intrusive weed optimisation algorithm for multi-objective blocking flow-shop scheduling problem was presented by Shao et al. (2018), named MODIWO. Two local search algorithms were introduced in the MODIWO, which increased the local search ability of the algorithm. Furthermore, a new competitive exclusion strategy was proposed to produce various populations. The oppositional invasive weed optimisation (OIWO) was presented by Barisal and Prusty (2015) to address the large-scale economic load dispatch (ELD) problem. The opposition-based learning (OBL) was introduced in the OIWO. After the seeds were generated, the set of the quasi opposite seeds was calculated based on the newly generated seeds and the standard deviation. The optimal individual was selected in the set of the old seeds and the set of the quasi opposite seeds. A hybrid algorithm (HS-IWO) based on HS and IWO was proposed by Ouyang et al. (2018). HS-IWO was useful for solving problems with low convergence accuracy and easily falling into local optimum. Tan and Du (2018) combined IWO and BFGS to make an algorithm to utilise the exploitation ability of BFGS algorithm and the exploration ability of IWO, which accelerated the convergence speed effectively. HIWO/BBO was designed by Khademi et al. (2017) to combine IWO with BBO and was proposed a gradient descent operation. HIWO/BBO was introduced to the migration operation in BBO to the diffusion operation of seeds, which increased the quality of the distributed seeds, and activated the mutation operation under certain conditions to increase the diversity of the population and aimed to avoid local optimum. IWFO was proposed by Panda et al. (2018) to combine IWO with FA. And the IWFO was applied to autonomous mobile robot motion planning. Firefly optimisation (FA) was introduced to the IWO to improve the location of the current weed population. Due to the spatial diffusion operation of IWO and the motion characteristics of fireflies, IWFO maintained a balance between exploration and exploitation, the balance enhanced the performance of the algorithm. HCMOIWO was presented by Naidu and Ojha (2018) to combine IWO and spatial exchange search for multi-objective optimisation and stores candidate solutions. HCMOIWO was exchanged information between multiple subgroups to explore new search areas. A chaotic IWO (CIWO) was proposed by Ghasemi et al. (2014) to solve the OPF problem. CIWO was added chaotic mapping to the spatial diffusion operation and changed the original normal distribution. The non-repetitiveness of chaotic maps and the searchability of periodic enhancement algorithms were utilised to reduce the convergence speed.

The original IWO was improved by the above researchers. However, the issue of balancing the exploration and exploitation of the IWO remains unresolved. On the other hand, the performance of IWO was easily influenced by the parameters. There are few existing studies on parameter adaptation. Research on IWO needs to be further strengthened. Therefore, a new improved algorithm SIWODE was proposed in this study to improve the performance of the algorithm to effectively balance the exploration and exploitation. The search performance of IWO depends on the values of the control parameters. Therefore, the two parameters of SIWODE were set as adaptive parameters. According to the fitness value and the number of evaluation times, the values of parameters were adeptly tuned to increase the convergence speed of the algorithm and reduce the dependence of parameters for the algorithm. Afterwards, IWO was combined with various algorithms to increase population diversity and enhance exploration capabilities. In this study, the crossover and mutation operations of DE were utilised by SIWODE to improve the exploration ability of the algorithm in the global search stage. The crossover and mutation operations of DE were proposed to the breeding stage of the SIWODE, and were mainly utilised to generate parental weeds with better fitness values. The diversity of the population was increased by the mutation operation. In addition, the local perturbation strategy was employed in the spatial diffusion operation of the IWO to improve the exploitation capability of the algorithm in the local search phase. In general, the purpose of this study is to provide the SIWODE in which exploration and exploitation in the iteration process of the algorithm are balanced effectively. Experimental results tested on the CEC-2017 benchmark demonstrated the effectiveness of the proposed SIWODE to balance exploration and exploitation. The results showed that the adaptive strategy of parameters was promising. The main contributions of this study are summarised as follows:

- The exploration and exploitation ability of the algorithm were balanced by the proposed cooperative mechanisms.
- The self-adaptive strategy of parameters σ and W was proposed in the SIWODE algorithm to enhance the adaptive ability.
- During the iterative process of the algorithm, the operations of crossover and mutation were introduced to the breeding phase of the SIWODE. The operation of the crossover was proposed to the algorithm to obtain parental weeds with better fitness values. The diversity of the population was increased by the mutation operation.
- The local perturbation strategy was proposed for the spatial diffusion of the IWO algorithm. The progeny weeds were optimised around the newly generated progeny weeds by the local perturbation strategy, and the exploitation capability of the algorithm was increased by the local perturbation strategy in the local search phase.

The remainder of this study was organised as follows. A detailed introduction and convergence analysis of the proposed SIWODE were introduced in Section 2. Section 3 revealed the experiment environment and the parameters analysis. The experimental analysis was presented in Section 4. The conclusions were given in Section 5.

2. The original IWO and proposed SIWODE

2.1. IWO

In this study, the symbol is described as follows:

W_i	the weed of the *t*th agent
D	the dimension of the search space
N	the number of the population
W_i^d	the weed of the *t*th agent in the *d*th dimension
W_{maxg}	the maximum number of the weed in the current agent
W_{ini}	the initial maximum number of the weeds
W_{final}	the final maximum number of the weeds
T	the maximum number of fitness evaluations

t	the current number of fitness evaluations
n	nonlinear modulation index
σ_{cur}	the standard deviation of the current agent
σ_{init}	the initial standard deviation
σ_{final}	the final standard deviation
S_{max}	the maximum number of the seeds
S_{min}	the minimum number of the seeds
S_{maxg}	the maximum number of the seeds
S_{num}	the number seeds of the weed
σ_{w_i}	the standard deviation of the *i*th weed
PAR_g	the probability of disturbance
bw_{max}	the maximum length of the disturbance
bw_{min}	the minimum length of the disturbance
bw_g	the length of the disturbance in the current agent
$W_{new,j}$	the weed after disturbance

The original IWO is inspired by weed ecology to simulate the invasive process of weeds, which is a meta-heuristic algorithm. In the IWO, each weed represents a candidate solution to the problem. The IWO mainly has the following process.

Step 1. Initialisation
The initial solution of the problem is distributed in a D dimensional problem space in a random manner. Each weed represents an initial candidate solution to the problem.

Step 2. Reproduction
The seeds are produced by the weed according to their maximum and minimum fitness, and the more seeds are produced by the excellent weeds with greater fitness. The numbers of seeds are produced by each weed, which are between $S_{\min}$ and $S_{\max}$. The formula is presented as follows:

$$S_{num} = (S_{\max} - S_{\min}) \times \frac{f - f_{\min}}{f_{\max} - f_{\min}} + S_{\min} \tag{1}$$

Step 3. Spatial dispersal
The generated seeds are distributed randomly in the D dimensional space based on the normal distribution. The means of the seeds is equal to 0, but the variances of the seeds are different. That theory ensures that the seeds are randomly distributed and close to the parent plant. Meanwhile, the standard deviation decreases between the initial value (σ_{init}) to the final value (σ_{final}), which are given as follows:

$$\sigma_{cur} = \left(\frac{T - t}{T}\right)^n \times (\sigma_{init} - \sigma_{final}) + \sigma_{final} \tag{2}$$

Generally, n is set to 3.

$$S_g = W_g + nomrnd(0, \sigma_{cur}) \tag{3}$$

According Equation (3), the new seeds are normally distributed around the parent weed.

Step 4. Competitive exclusion
The maximum number of populations ($P_{\max}$) is set initially. When the population reaches the maximum population, the elimination operation is performed. When all the seeds find

their place in the search space, they are sorted together with their parents (as a group of weeds). Afterwards, weeds with poor fitness are eliminated to reach the maximum allowable population. Such a mechanism is always applied to each generation until the end of the run, which achieves competitive exclusion.

2.2. Parameter self-adaptation strategy

In the IWO, the diffusion distance is affected by the standard deviation in the spatial diffusion operation. Based on Equation (2), the standard deviation is related to t, σ_{init}, σ_{final} and n. Meanwhile, the standard deviation of each weed is identical.

In the SIWODE, the generation of the standard deviation is changed from the original Equation (2) to proposed Equation (5), the standard deviation of each seed is changed from the original gradient drop to the linear decline mode (Sang et al., 2015). The reason is that the standard deviation is dropped too fast in the IWO, leading to the algorithm easily fall into the local optimum at the later iteration. The speed of standard deviation is reduced by the improved generated formula of standard deviation, which ensures that the algorithm is not fallen into local optimum as the standard deviation is too small in the later of the iteration.

$$W_i = (W_i^1, W_i^2, \ldots, W_i^D), \quad i = 1, 2, \ldots, N \tag{4}$$

where W_i is ith weed in the current generation.

$$\sigma_{cur} = \tan\left(0.875 \times \frac{T-t}{T}\right) \times (\sigma_{init} - \sigma_{final}) + \sigma_{final} \tag{5}$$

An adaptive mechanism is proposed to improve the performance of the algorithm in this study. Each weed has a standard deviation corresponding to its own fitness. In SIWODE, the standard deviation of each parent is between $0.5\sigma_{cur}$ and $1.5\sigma_{cur}$ (Basak et al., 2013).

$$\sigma_{W_i} = 1.5 \times \sigma_{cur} - \frac{f - f_{\min}}{f_{\max} - f_{\min}} \times \sigma_{cur} \tag{6}$$

The maximum population ($P_{\max}$) is optimised in this study. In the original algorithm, the maximum number of populations per generation remains unchanged. In the SIWODE, the change in the maximum population number is a process of gradient descent, as shown in the following formula:

$$W_{maxg} = \left(\frac{T-t}{T}\right)^n \times (W_{ini} - W_{final}) + W_{final} \tag{7}$$

Meanwhile, the maximum number of seeds is changed. In the improved algorithm, the maximum number of seeds also shows a trend of decreasing gradient with the number of iterations. The reproduction and diffusion of seeds are shown as the following formula:

$$S_{\max g} = \frac{T-t}{T} \times (S_{\max} - S_{\min}) + S_{\min} \tag{8}$$

The seed number is generated in the same way as Equation (1), but the $S_{\max}$ in Equation (1) is changed to $S_{\max g}$. This operation ensures that the number of seeds is reduced, which increases the number of iterations in the later stage of operation that is beneficial to the local search of the algorithm.

$$S_{num} = (S_{\max g} - S_{\min}) \times \frac{f - f_{\min}}{f_{\max} - f_{\min}} - f_{\min} \tag{9}$$

The following equation indicates that the seed is normally distributed with a new standard deviation σ_{w_i}.

$$S_i = W_i + nomrnd(0, \sigma_{w_i}) \tag{10}$$

2.3. The strategy with DE

DE is a simple and effective global search algorithm (Zhao, Liu, et al., 2015). The combination of DE and other algorithms improved the exploration ability of the algorithm and ensured the diversity of the population. Adding the cross and mutation mechanism of DE to IWO enabled the population to update the parent weed individuals in the early iterations and find the parent weeds with better fitness values, which is beneficial to global search and accelerates the convergence speed of the algorithm. In the later stages of the iteration, the mutation mechanism of DE ensures the diversity of the population. Therefore, in this study, SIWODE based on the "current-to-pbest/1" and "rand/1" mutation and crossover mechanisms is introduced. The mutation model is described as follows:

$$v_i(t) = W_i(t) + sf(i) \times (W_{best} - W_i(t) + W_{r1}(t) - W_{r2}(t)) \tag{11}$$

W_{best} is the best individual in the current iteration. $W_{r1}(t)$ and $W_{r2}(t)$ are different weed in the tth iteration. $sf(i)$ is the mutation factor. The traditional DE generated variable formula is shown as follows:

$$v_i(t) = rand_i \times (X_{max} - X_{min}) + X_{min} \tag{12}$$

where, $rand_i$ is a random number between 0 and 1, X_{max} is the maximum value of the boundary and X_{min} is the minimum value of the boundary.

After the new mutant individual $v_i^d(t)$ is generated, the cross mode is expressed as follows:

$$\begin{cases} u_i^d(t) = v_i^d(t) & \text{if } rand < cr(i) \text{ or } \quad j = jrand \\ u_i^d(t) = W_i^d(t) & \qquad\qquad\qquad\quad \text{otherwise} \end{cases} \tag{13}$$

where, $jrand$ is an index, which is a number randomly selected from [1, D]. $cr(i)$ is the crossover rate in this theory. When all mutant individuals are generated, the required parent value for the next cycle is considered. If the fitness of the mutant individual is less than the fitness of the original individual, the mutant individual is selected. Otherwise, the original individual is selected.

$$W_i(t+1) = \begin{cases} u_i(t) & \text{if } f(u_i(t)) \le f(x_i(t)) \\ W_i(t) & \text{otherwise} \end{cases} \tag{14}$$

2.4. Local perturbation mechanism

The local interference strategies are applied to the search process. This mechanism is utilised to improve the development capabilities of SIWODE (Ouyang et al., 2014). In the iterative process, the local perturbation mechanism perturbs the newly generated progeny weeds under a certain probability and performs optimisation within a certain range. The local perturbation mechanism controls the search range near the optimal solution by controlling the perturbation step size. In the early stage, larger step size is utilised for optimisation, and smaller step size is used for optimisation in the later stage. If a desirable offspring weed is obtained, the current offspring weed is replaced. This strategy is beneficial to the algorithm to optimise in the local scope and make the algorithm jump out of the local optimum.

$$PAR_g = \frac{PAR_{\max} - PAR_{\min}}{T} \times t + PAR_{\min} \tag{15}$$

where, $PAR_{\max}$ is the initial probability of local adjustment. $PAR_{\min}$ is the final probability of local adjustment.

The following equation is used to generate the disturbance distance.

$$bw_g = bw_{\max} \times \exp\left(\frac{\log(bw_{\min}/bw_{\max})}{T} \times t\right) \tag{16}$$

$$W_{new,j} = \begin{cases} W_{rnd,j} & \text{if } rand_i < HMCR \\ X_{\min} + (X_{\max} - X_{\min}) \times rand_i & \text{otherwise} \end{cases}, \quad j = 1, 2, \ldots, D. \tag{17}$$

where, $rand_i$ is the random number between 0 and 1, rnd is the random integers between 1 and N. $HMCR$ was set to 0.95.

$$W_{\text{new},j} = \begin{cases} W_{\text{new},j} \pm rand_i \times bw_g & \text{if } rand_i < PAR_g \\ W_{\text{new},j} & \text{otherwise} \end{cases}, \quad j = 1, 2, \ldots, D. \tag{18}$$

When the random number ($rand_i$) is less than the PAR_g, a new individual would be produced based on Equation (18). In addition, the individual remains unchanged.

2.5. Parameter adaptation scheme based on the historical memory

In this study, the parameter adaptation scheme based on the historical memory is proposed in SIWODE inspired by the SHADE that is a simple and effective global search algorithm. (Tanabe et al., 2013) The SIWODE maintained the historical memory library with H entries for two control parameters M_{sf}, M_{cr}, which is generated by the following formulas:

$$sf_i = rands_i(M_{sf,i}, 0.1) \tag{19}$$

When $sf_i > 1$, sf_i was equal to 1, when $sf_i \leq 0$, again, until a valid value is got. $randc_i$ is the value selected randomly from normal distributions with mean $M_{cr,i}$ and variance 0.1, $rands_i$ is the value selected randomly from Cauchy distributions with mean $M_{sf,i}$ and variance 0.1.

$$cr_i = randc_i(M_{cr,i}, 0.1) \tag{20}$$

When $cr_i > 1$, cr_i is equal to 1, when $cr_i < 0$, cr_i is equal to 0.

In each generation, the values of sf_i and cr_i that succeed in generating a trial vector which is better than the parent iteration are recorded as sf_i and cr_i, and at the end of the generation, $M_{sf,i}$ and $M_{cr,i}$ are updated as follows:

$$M_{sf,i} = (1-c) \times M_{sf,i} + c \times mean_L(S_{sf}) \tag{21}$$

$$M_{cr,i} = (1-c) \times M_{cr,i} + c \times mean_A(S_{cr}) \tag{22}$$

$mean_L(\cdot)$ is computed as follows:

$$mean_L(S_{sf}) = \frac{\sum_{sf \in S_{sf}} sf^2}{\sum_{sf \in S_{sf}} sf} \tag{23}$$

$mean_A(\cdot)$ is computed as follows:

$$mean_A(S_{cr}) = \sum_{k=1}^{|S_{cr}|} \omega_k \times S_{cr,k} \tag{24}$$

$$\omega_k = \frac{\Delta f_k}{\sum_{k=1}^{|S_{cr}|} \Delta f_k} \tag{25}$$

where $\Delta f_k = |f(u_k) - f(x_k)|$.

2.6. The process of SIWODE

The pseudocode of SIWODE is described in Algorithm 1.

Algorithm 1 SIWODE

Initialise the population of N
Initialise the value of parameter
$t = 0$
Evaluate the fitness of population
While ($\boldsymbol{t} < T$)
Update W_{maxg} using Equation (7)
Standard deviation of each generation is calculated according to Equation (5)
Generate sf_i and cr_i using Equations (19) and (20)
for $i = 1 : N$
Using Equation (11)
end for
Crossover operation using Equation (13)
Update the position of the population using Equation (14)
Update $M_{sf,i}$, $M_{cr,i}$ and S_{maxg} Equations (21), (22) and (8)
The number of seeds produced by each individual of parent weed is calculate according to Equation (9)
Calculate the best fitness and the worst fitness
Standard deviation of each weed is calculated according to Equation (6)
Seeds is reproduced according to Equation (10)
Evaluate the fitness of seeds
Arrange the sequence of weed and seeds according to fitness
Weeds with lower fitness are eliminated to reach the maximum allowable population in the colony
Update PAR_g and bw_g using Equations (15) and (16)
if $rand_i < HMCR$
Using Equation (17)
if $rand_i < PAR_g$
Using Equation (18)
end if
else

```
            Using Equation (17)
        end if
    Evaluate the fitness of new weed
        if new fitness < the worst fitness
            Replace the last weed
        end if
End while
Output Result
```

3. The experimental environment and parameters analysis

3.1. The experimental environment

In this study, SIWODE is evaluated on the CEC 2017 benchmark functions. SIWODE is compared with the variation of IWO algorithm, standard IWO algorithm and some state-of-the-art EAs, IWO (Mehrabian & Lucas, 2006), IWO_DE/Ring (Liu et al., 2018), HS-IWO (Ouyang et al., 2014), IWFO (Panda et al., 2018), HIWO/BBO (Khademi et al., 2017), CMA-ES (Hansen et al., 2003), SHADE (Viktorin et al., 2019).

The functions in the CEC2017 problem are set to include four categories, $f_1 - f_3$ are unimodal functions, $f_4 - f_{10}$ are simple multimodal functions, $f_{11} - f_{20}$ are hybrid functions and $f_{21} - f_{30}$ are composition functions. The experiments are run on a PC with 3.4 GHz Intel(R) Core^{TM} i7-6700 CPU, 8GB of RAM and 64-bit OS, the software platform is MATLAB (2016b) which the algorithm runs.

The parameter settings of the compared algorithm are set according to the parameters recommended in the corresponding study. Table 1 shows the parameter sets of the compared algorithm. All algorithms are run independently 51 times for all functions to ensure the reliability of the experimental results.

Table 1. Parameter settings.

Algorithms	Parameter settings
IWO	$P_{ini} = 10, P_{\max} = 15, \sigma_{init} = 3, \sigma_{final} = 0.001, S_{\max} = 5, S_{\min} = 0, n = 3$
IWFO	$P_{ini} = 10, P_{\max} = 15, \sigma_{init} = 0.3, \sigma_{final} = 0.9, S_{\max} = 5, S_{\min} = 0, n = 3,$ $\alpha = 0.2, \gamma = 0.72, \beta_0 = 0.4$
IWO_DE/Ring	$P_{ini} = 20, P_{\max} = 60, \sigma_{init} = 1, \sigma_{final} = 0.001, S_{\max} = 2, S_{\min} = 0, n = 3,$ $F = 0.7, C_r = 0.9$
HS-IWO	$P_{ini} = 10, P_{\max} = 15, \sigma_{init} = 3, \sigma_{final} = 0.001, S_{\max} = 5, S_{\min} = 0, n = 3$
HIWO/BBO	$P_{ini} = 100, P_{\max} = 200, \sigma_{init} = 20, \sigma_{final} = 0.2, S_{\max} = 5, S_{\min} = 0, n = 3,$ $\alpha = 0.6, N_G = 2, \varepsilon = 0.02, G_A = 3, G_{Inc} = 3, \beta = 0.6, M_A = 5, P_M = 0.04,$ $P_{M_{\max}} = 0.08, N_B = 2$

Table 2. Combinations of parameters.

Factor levels	1	2	3	4
W_{final}	10	20	30	50
W_{ini}	90	100	120	150
σ_{ini}	1	3	5	10
σ_{final}	0.001	0.01	0.1	0.5

3.2. Parameters analysis

The SIWODE has four critical parameters, W_{final}, W_{ini}, σ_{ini}, σ_{final}. In this study, the design of the experimental algorithm (Montgomery, 2001) is used to design a series of parameters for

Table 3. Rank of parameters.

	Parameters			
Levels	W_{final}	W_{ini}	σ_{ini}	σ_{final}
1	8.80E+03	8.34E+03	8.11E+03	8.48E+03
2	8.24E+03	8.84E+03	8.88E+03	9.21E+03
3	8.94E+03	8.41E+03	8.74E+03	8.56E+03
4	8.37E+03	8.78E+03	8.64E+03	8.12E+03
Std.	39.51	22.27	40.06	70.75
Rank	3	4	2	1

Table 4. Orthogonal array.

	Parameters				AVE			
No.	W_{final}	W_{ini}	σ_{ini}	σ_{final}	10D	30D	50D	TAVE
1	1	1	1	1	2.85E+03	3.91E+02	2.07E+04	7.97E+03
2	1	2	2	2	8.29E+03	4.06E+02	2.12E+04	9.98E+03
3	1	3	3	3	2.84E+03	3.47E+02	2.17E+04	8.31E+03
4	1	4	4	4	5.57E+03	3.40E+02	2.10E+04	8.96E+03
5	2	1	2	3	2.84E+03	4.45E+02	2.26E+04	8.64E+03
6	2	2	1	4	3.66E+02	3.66E+02	2.06E+04	7.10E+03
7	2	3	4	1	2.84E+03	3.33E+02	2.09E+04	8.01E+03
8	2	4	3	2	5.56E+03	3.07E+02	2.17E+04	9.21E+03
9	3	1	3	4	2.84E+03	3.72E+02	2.21E+04	8.42E+03
10	3	2	4	3	5.56E+03	5.01E+02	2.17E+04	9.25E+03
11	3	3	1	2	5.56E+03	3.45E+02	2.20E+04	9.30E+03
12	3	4	2	1	5.56E+03	3.06E+02	2.08E+04	8.90E+03
13	4	1	4	2	2.84E+03	5.55E+02	2.16E+04	8.34E+03
14	4	2	3	1	2.83E+03	2.83E+03	2.15E+04	9.05E+03
15	4	3	2	4	2.83E+03	3.16E+02	2.09E+04	8.02E+03
16	4	4	1	3	2.83E+03	3.04E+02	2.10E+04	8.05E+03

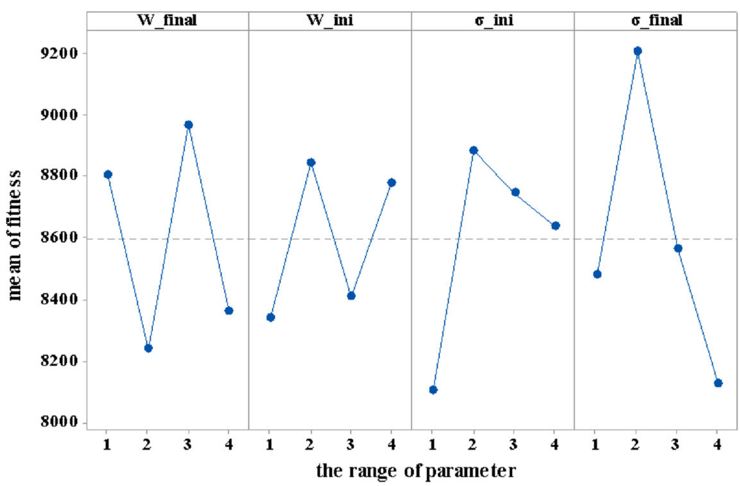

Figure 1. Change tendency of the parameters.

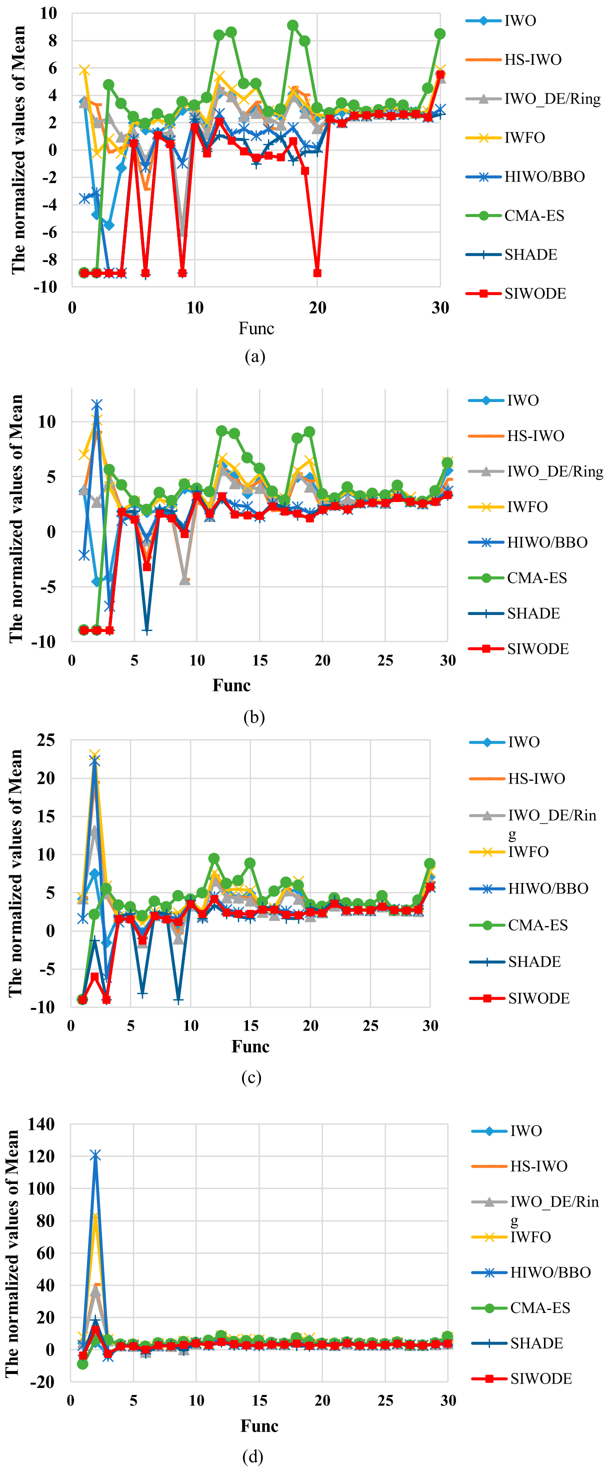

Figure 2. The visualisation of experimental results.

SIOWDE. The CEC2017 benchmark is used in the test set. SIWODE runs 10 times independently for each function in each dimension with each set of parameters. The orthogonal table $L_{16}(4^4)$ is designed based on the number of parameters and factor levels. The different combinations of parameters were shown in Table 2. The levels of each parameter are shown in Table 3. Table 4 shows the average (*AVE*) of each set of parameters in each dimension and the total mean (*TAVE*). The changed tendency of each parameter is shown in Figure 1. The σ_{final} is the most important parameter of the four parameters according to Table 3.

The effect of four parameters on the performance of the algorithm is shown in Table 3. Among the four parameters, σ_{final} has the most significant impact on the algorithm than the other three parameters. The second parameter is σ_{ini}. The two parameters control the range of variation of the standard deviation. The range of seed diffusion is affected by the standard deviation in the early and late stages of the algorithm. The third parameter is W_{final} and the fourth parameter is W_{ini}. The two parameters control the number of seeds. The number of seeds ensure the diversity of the population and effectively improve the performance of SIWODE. According to Table 3, $\sigma_{final} = 0.5$, $\sigma_{ini} = 1$, $W_{ini} = 90$, and $W_{final} = 20$.

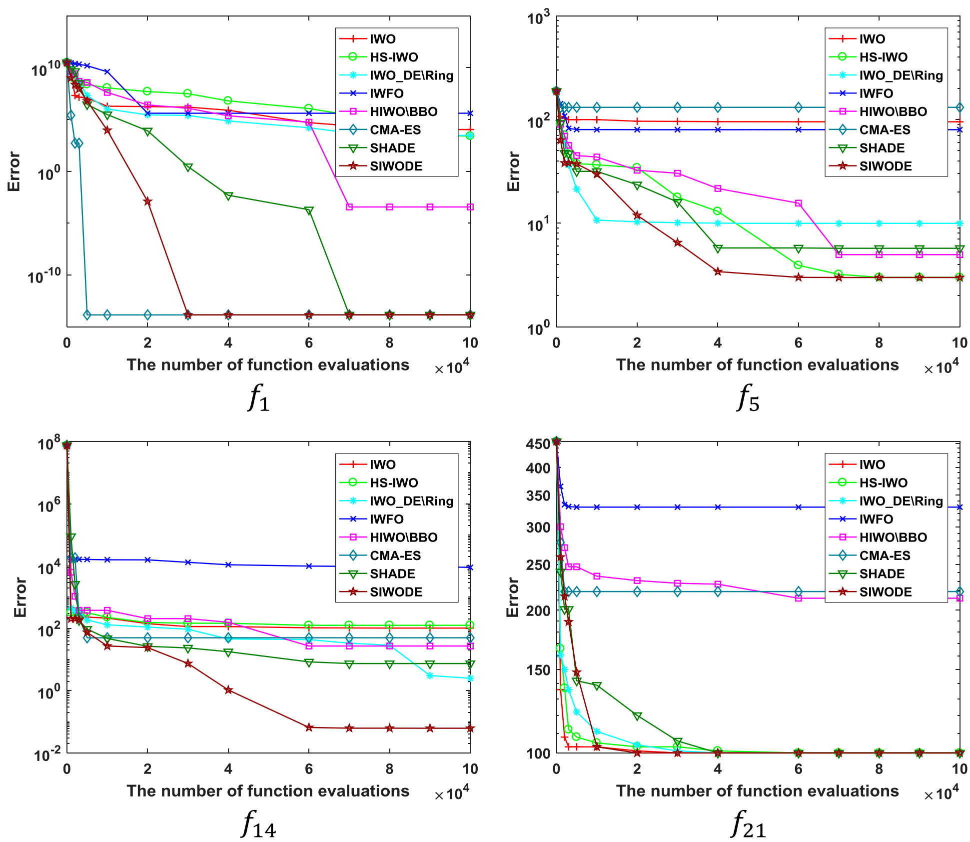

Figure 3. Convergence curves of some typical benchmark functions (10D).

4. The experimental results and analysis

4.1. The experimental results

The mean and standard deviation of SIWODE and compared algorithms are shown in the Tables with $D = 10, 30, 50, 100$ in the electronic supplement. The mean values and standard deviations smaller than 1e-8 are taken as zero. The optimal values of all algorithms are shown in boldface. The mean and standard deviations are derived from the results of 51 independent runs in the table.

The results of SIWODE in 22 functions are superior to those of other compared algorithms in the 10D. For the results of 30 dimensional, the experimental results of SIWODE in 14 function are superior to the results of the other compared algorithms. The benchmark functions are also executed with $D = 50, 100$ to verify the performance of SIWODE in high dimensions. Therefore, SIWODE is significantly better than other comparison algorithms at $D = 30, 50$. And at $D = 10$, the performance of SIWODE is better than the performance of IWO, HS-IWO, IWO_DE/Ring, IWFO, HIWO/BBO and CMA-ES. And at $D = 100$, the performance of SIWODE is better than the performance of IWO, IWO_DE/Ring, IWFO, HIWO/BBO and CMA-ES. In summary, the convergence accuracy of SIWODE is superior

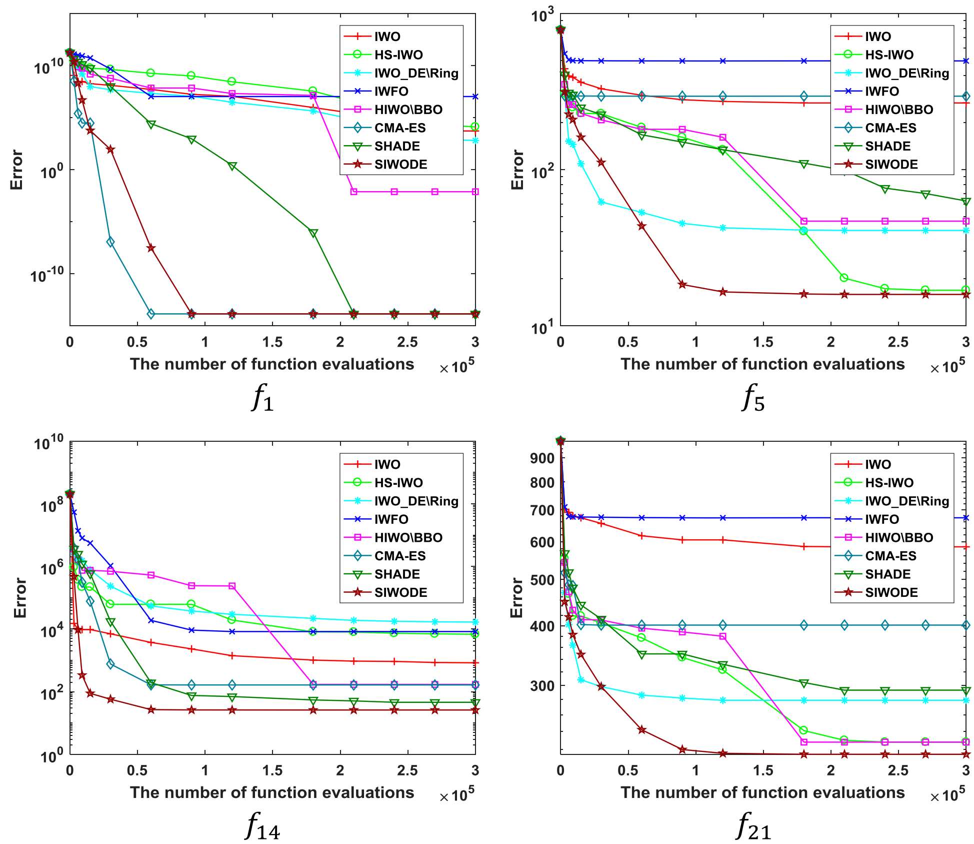

Figure 4. Convergence curves of some typical benchmark functions (30D).

to the convergence accuracy of other compared algorithms in the CEC2017 benchmark functions on $D = 10, 30, 50, 100$.

For a clear comparison of experimental results, the visualisation of the experimental results is made in Figure 2. The horizontal axis is the sequence number of the test function. The vertical axis is the normalised values of the mean. To make the effect clear, the means in the results are normalised as

$$\text{Normalized Value} = \log_{10}(\text{Mean}) \tag{26}$$

where the Mean is the data of mean. If the visualisation line is lower than the others, the performance of the algorithm is better than the compared algorithm. From Figure 2, most of the lines of SIWODE are at the bottom of the graph. That means the results of the SIWODE for most benchmark functions are the best compared with other contrast algorithms. For the functions $f_{11} - f_{30}$, the SIWODE is an excellent algorithm compared with the other experimental algorithms. In general, the visualisation of experimental results shows that the proposed mechanisms in SIWODE are feasible, and the performance of the SIWODE is expectable. Meanwhile, scientific and rigorous analysis is necessary for the experiment.

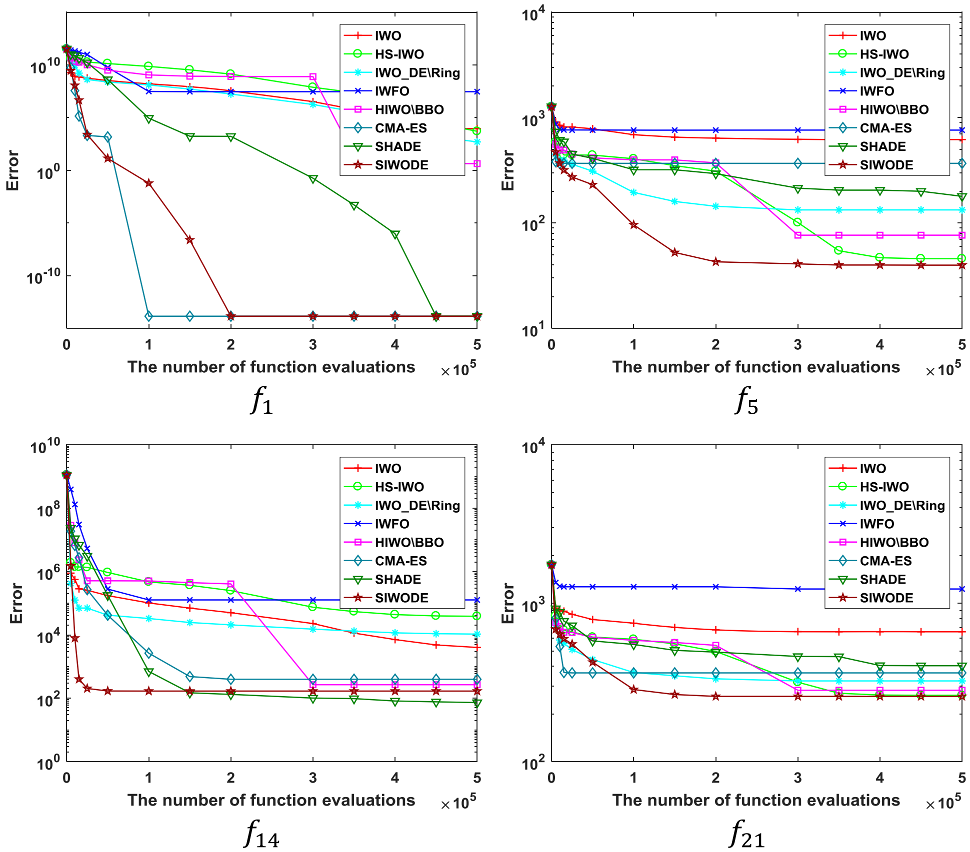

Figure 5. Convergence curves of some typical benchmark functions (50D).

4.2. The experimental analysis

The convergence curves of SIWODE and the compared algorithm are shown in Figures 3–6 on f_1, f_5, f_{14} and f_{21}, with $D = 10, 30, 50, 100$. The four types of functions of the CEC2017 benchmark set are represented by the four functions. From Figures 3–6, the accuracies of SIWODE are best than the accuracies of other compared algorithms on f_5 and f_{21} with $D = 10, 30, 50, 100$. The SIWODE is excellent in the simple multimodal functions and the composition functions. The reason is that the convergence speed and convergence accuracy of SIWODE are balanced during the iterative process. SIWODE is avoided prematurely falling into the local optimum. Figures 3–6 show that the SIWODE get the comparative solutions on f_1 with $D = 10, 30, 50, 100$ compared with the CMA-ES and SHADE. And the SIWODE get the best solution on the f_{14} with $D = 10, 30, 50$. In general, the SIWODE is effective for unimodal functions and hybrid functions.

The convergence speed of the algorithm is ensured by the adaptive parameter operation. The crossover operation is used by SIWODE to update the parent weeds in the population, which enhances the utilisation of the algorithm, and the diversity of the population is increased by the mutation operation. Meanwhile, the local perturbation strategy ensures that the algorithm updates the offspring weeds in the later iterations, and finds the

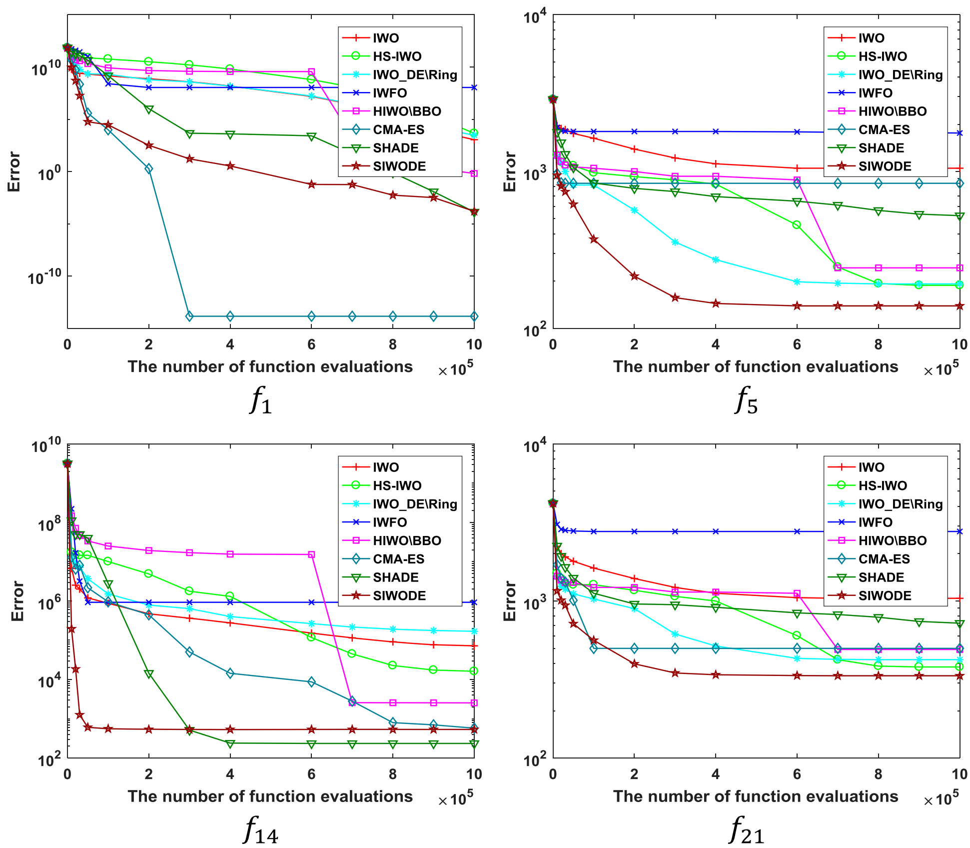

Figure 6. Convergence curves of some typical benchmark functions (100D).

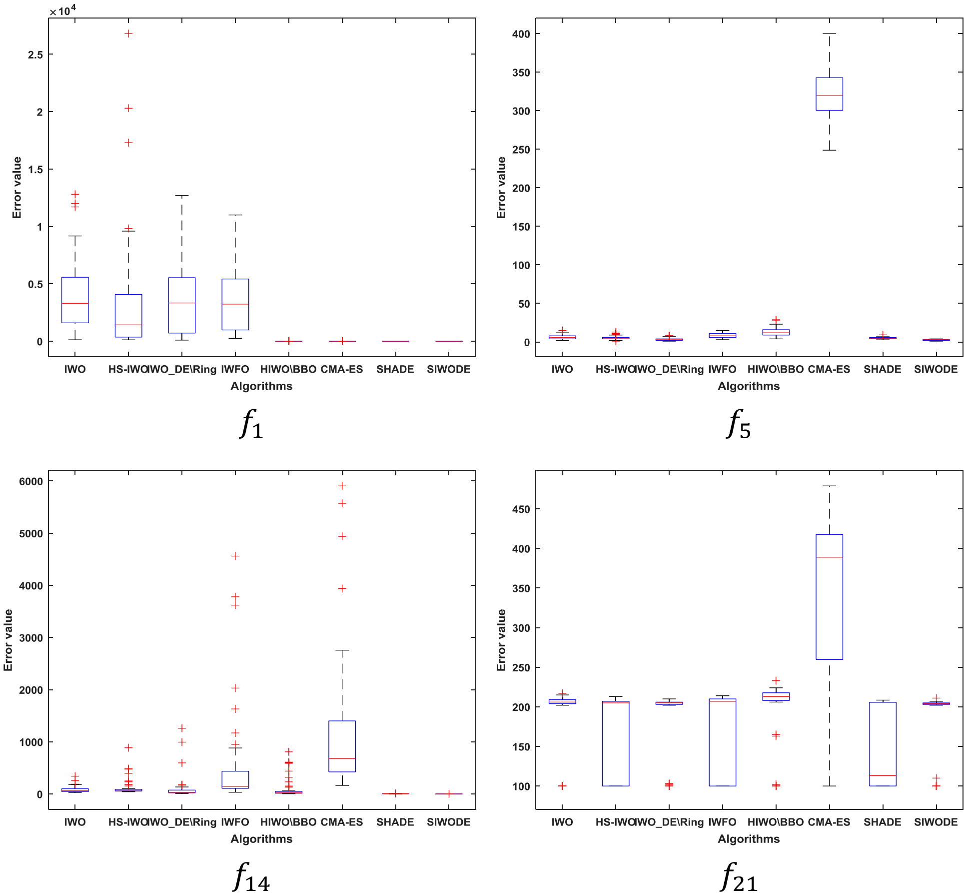

Figure 7. Boxplots of some typical benchmark functions (10D).

Table 5. p-Value of Wilcoxon's rank-sum test for $D = 10$.

SIWODE VS	$R+$	$R-$	p-value	$+$	$\approx$	$-$	$\alpha = 0.05$
IWO	460	5	2.88E-06	29	0	1	Yes
HS-IWO	402	63	4.90E-04	26	0	4	Yes
IWO_DE/Ring	423.5	41.5	8.50E-05	28	0	2	Yes
IWFO	461	4	2.60E-06	29	0	1	Yes
HIWO/BBO	339	67	1.96E-03	25	2	3	Yes
CMA-ES	406	0	3.79E-06	28	2	0	Yes
SHADE	145	131	8.31E-01	15	7	8	No

self-generation weeds with better fitness through a certain range of optimisation, thereby improving the exploitation ability of the algorithm. The stability and precision of SIWODE are better than that of other algorithms. The box plots of the SIWODE and the compared algorithms for f_1, f_5, f_{14} and f_{21} are shown in Figures 7–10 to demonstrate the stability of SIWODE. According to Figures 7–10, SIWODE is the excellent algorithm in the compared algorithms. The two non-parametric tests are chosen to compare the performance of the algorithm, named Friedman's sign rank test and Wilcoxon's sign rank test (García et al.,

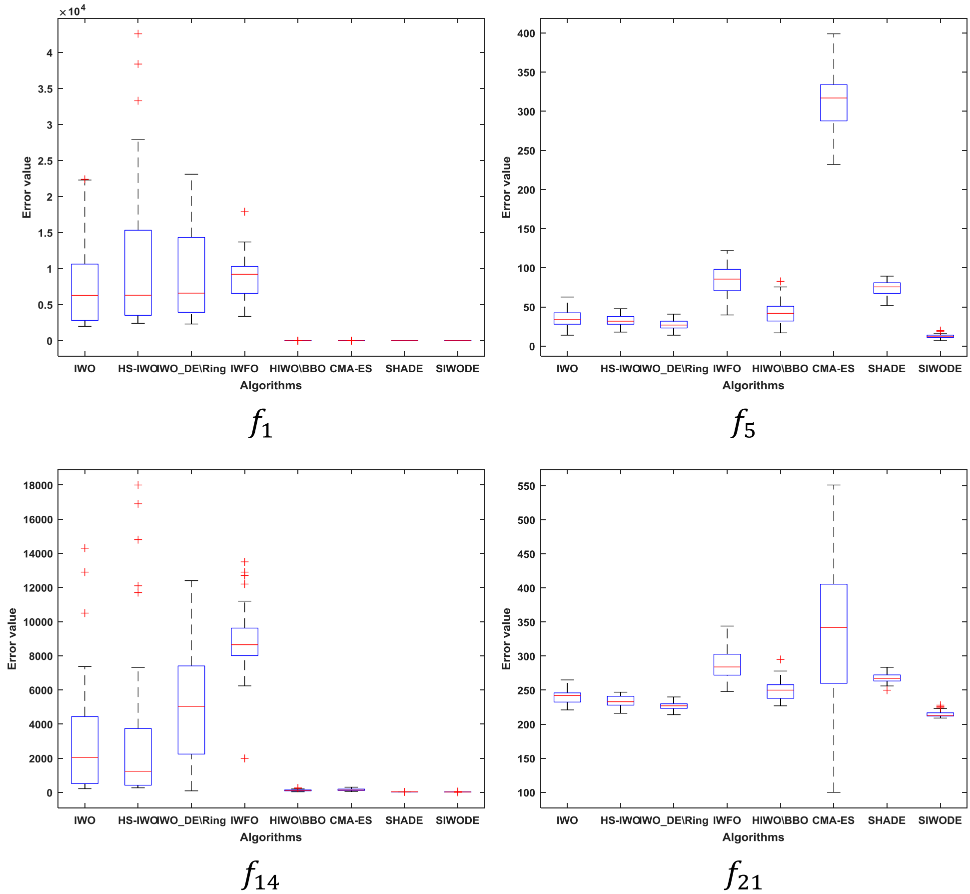

Figure 8. Boxplots of some typical benchmark functions (30D).

Table 6. p-Value of Wilcoxon's rank-sum test for $D = 30$.

SIWODE VS	$R+$	$R-$	p-value	$+$	$\approx$	$-$	$\alpha = 0.05$
IWO	460	5	2.88E-06	29	0	1	Yes
HS-IWO	336	99	1.04E-02	21	1	8	Yes
IWO_DE/Ring	426	9	6.53E-06	27	1	2	Yes
IWFO	465	0	1.73E-06	30	0	0	Yes
HIWO/BBO	369.5	95.5	4.83E-03	23	0	7	Yes
CMA-ES	405	1	4.23E-06	27	2	1	Yes
SHADE	236	89	4.80E-02	15	5	10	Yes

Table 7. p-Value of Wilcoxon's rank-sum test for $D = 50$.

SIWODE VS	$R+$	$R-$	p-value	$+$	$\approx$	$-$	$\alpha = 0.05$
IWO	423	42	8.92E-05	25	0	5	Yes
HS-IWO	378	87	2.76E-03	22	0	8	Yes
IWO_DE/Ring	315.5	149.5	8.78E-02	18	0	12	Yes
IWFO	459.5	5.5	3.02E-06	28	0	2	Yes
HIWO/BBO	363.5	101.5	7.05E-03	23	0	7	Yes
CMA-ES	433	2	3.17E-06	28	1	1	Yes
SHADE	294	112	3.82E-02	16	2	12	Yes

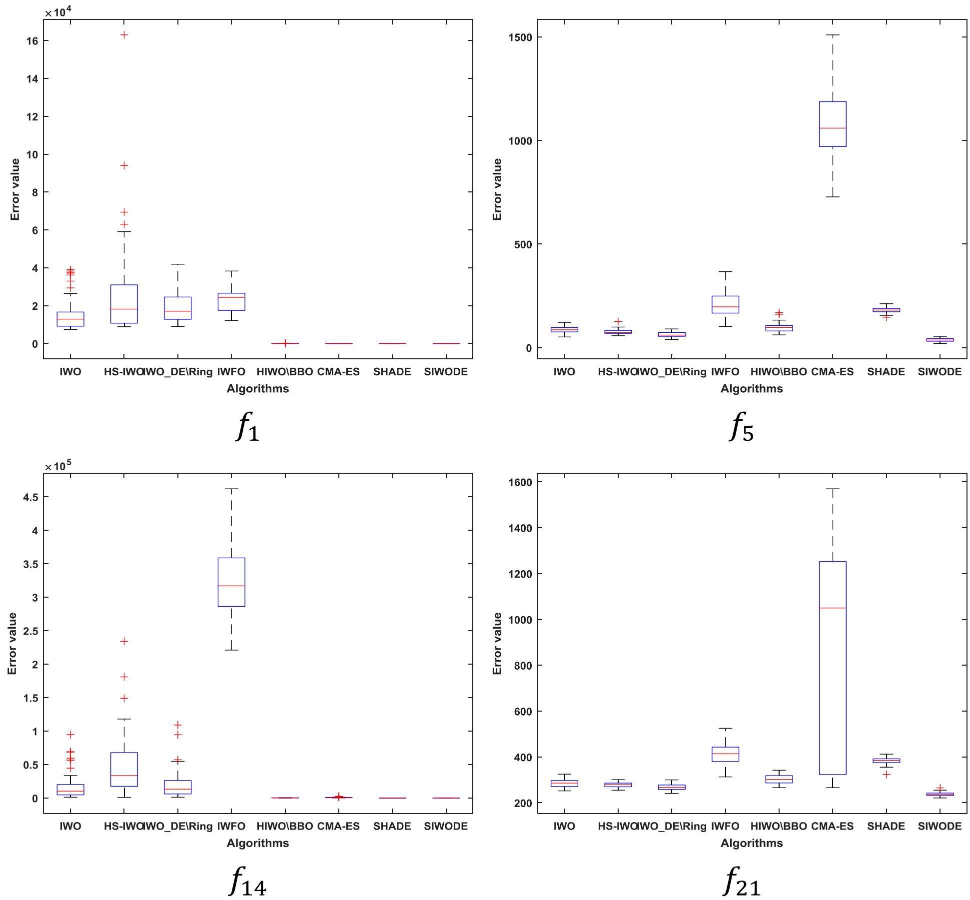

Figure 9. Boxplots of some typical benchmark functions (50D).

Table 8. *p*-Value of Wilcoxon's rank-sum test for $D = 100$.

SIWODE VS	$R+$	$R-$	*p*-value	$+$	$\approx$	$-$	$\alpha = 0.05$
IWO	427	38	6.32E-05	26	0	4	Yes
HS-IWO	265	170	3.04E-01	15	0	14	No
IWO_DE/Ring	315.5	149.5	8.78E-02	17	0	13	Yes
IWFO	435	0	2.56E-06	29	0	0	Yes
HIWO/BBO	375	60	6.60E-04	23	0	6	Yes
CMA-ES	428	37	5.79E-05	26	0	4	Yes
SHADE	239	226	8.94E-01	13	0	17	No

2009). The results of Friedman's test are shown in Figures 11–14. According to Figures 11–14, SIWODE ranks best with $D = 10, 30, 50, 100$. The results of Wilcoxon's sign rank test are shown in the Tables 5–8. $R+$ represents a positive rank-sum, which means the rank of SIWODE is superior to that of other algorithms. $R-$ is the opposite. According to the Tables 5–8, the performance of SIWODE is better than that of other compared algorithms under the Wilkerson test with $\alpha = 0.05$.

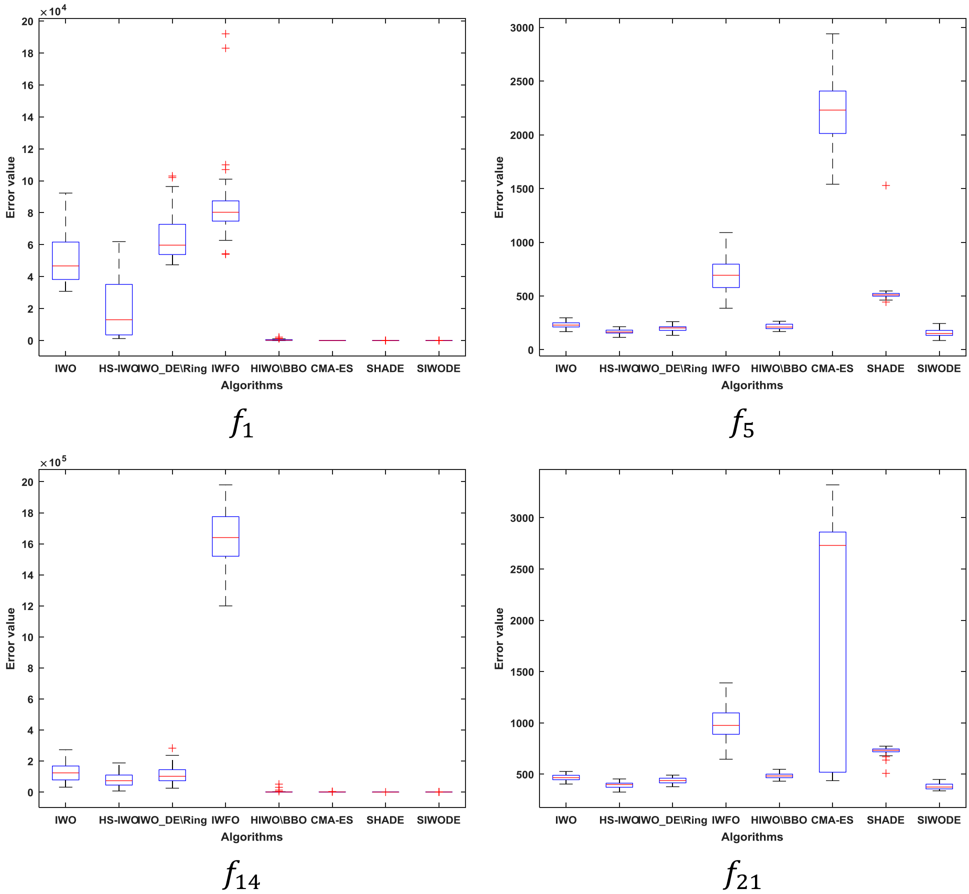

Figure 10. Boxplots of some typical benchmark functions (100D).

Algorithms	Mean Rank
IWO	5.45
HS-IWO	3.95
IWO_DE/Ring	4.80
IWFO	6.72
HIWO/BBO	3.68
CMA-ES	7.53
SHADE	2.05
SIWODE	1.82

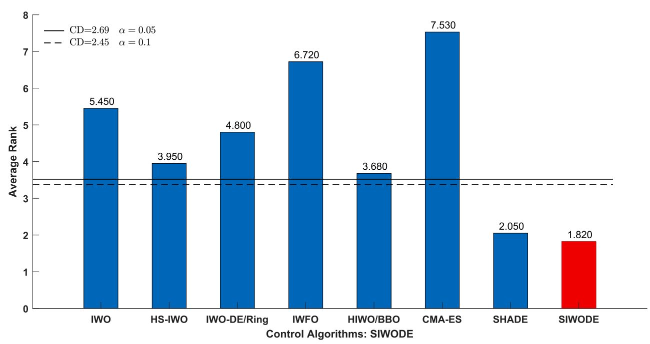

Figure 11. Rankings for $D = 10$.

Algorithms	Mean Rank
IWO	5.60
HS-IWO	3.42
IWO_DE/Ring	4.58
IWFO	7.03
HIWO/BBO	3.13
CMA-ES	7.30
SHADE	2.82
SIWODE	2.12

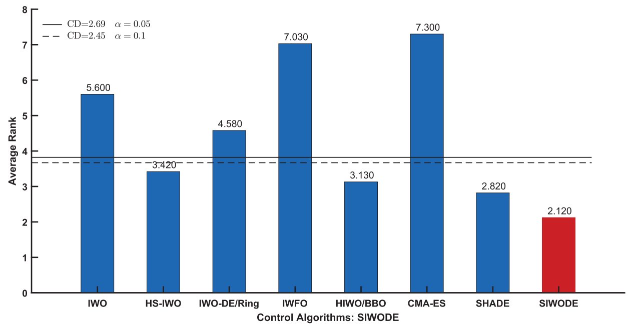

Figure 12. Rankings for $D = 30$.

Algorithms	Mean Rank
IWO	4.68
HS-IWO	3.87
IWO_DE/Ring	2.93
IWFO	6.83
HIWO/BBO	4.03
CMA-ES	7.33
SHADE	3.70
SIWODE	2.62

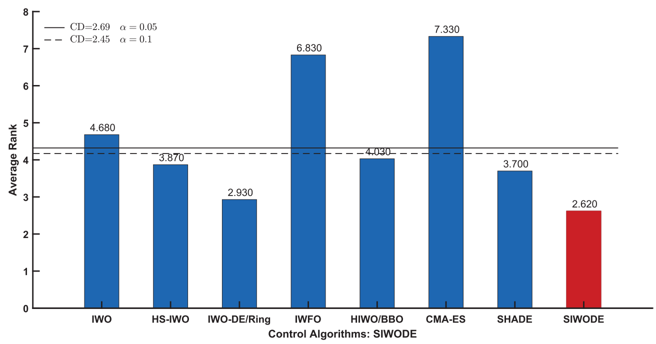

Figure 13. Rankings for $D = 50$.

5. Conclusions

In this study, SIWODE was proposed as a novel variant of IWO. The proposed cooperative mechanisms, including parameter self-adaptation strategy, parameter adaptation scheme based on the historical memory, the strategy with DE and local perturbation mechanism, were introduced in SIWODE. The experiment results demonstrated that the convergence speed of the algorithm was increased by the parameter self-adaptation strategy and parameter adaptation scheme based on the historical memory in the iterative process. Meanwhile, the exploitation of the SIWODE was improved by the strategy with DE. In addition, the local search ability of the SIWODE was enhanced by the local perturbation mechanism. The experiment results revealed that the efficiency and robustness of the SIWODE were raised.

In the future work, SIWODE, which is applied to solve certain actual optimisation problems, is an optional direction. For instance, the flow-shop scheduling problem and the

Algorithms	Mean Rank
IWO	5.33
HS-IWO	3.14
IWO_DE/Ring	3.28
IWFO	7.34
HIWO/BBO	3.98
CMA-ES	6.81
SHADE	3.19
SIWODE	2.93

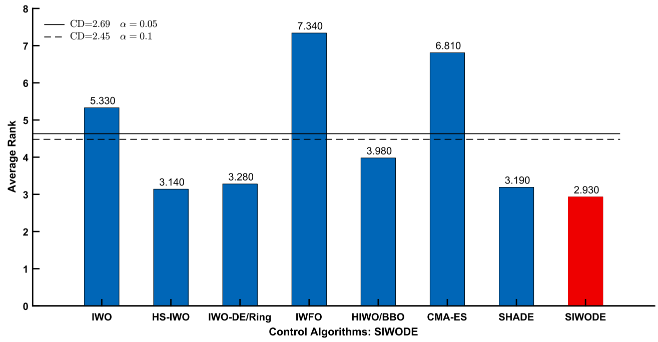

Figure 14. Rankings for $D = 100$.

optimal reactive power dispatch. The SIWODE is also embedded in the machine learning and other research fields.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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