Computers, Materials & Continua

Tech Science Press

Doi:10.32604/cmc.2025.066527

ARTICLE

Differential Evolution with Improved Equilibrium Optimizer for Combined Heat and Power Economic Dispatch Problem

Yuanfei Wei[1,2], Panpan Song[3], Qifang Luo[3,4,*] and Yongquan Zhou[1,2,3,4]

[1]Xiangsihu College of Guangxi Minzu University, Nanning, 530006, China
[2]Faculty of Information Science and Technology, National University of Malaysia (UKM), Bangi Selangor, 43600, Malaysia
[3]College of Artificial Intelligence, Guangxi Minzu University, Nanning, 530006, China
[4]Guangxi Key Laboratories of Hybrid Computation and IC Design Analysis, Nanning, 530006, China

*Corresponding Author: Qifang Luo. Email: 20060043@gxmzu.edu.cn

Received: 10 April 2025; Accepted: 24 June 2025; Published: 29 August 2025

ABSTRACT: The combined heat and power economic dispatch (CHPED) problem is a highly intricate energy dispatch challenge that aims to minimize fuel costs while adhering to various constraints. This paper presents a hybrid differential evolution (DE) algorithm combined with an improved equilibrium optimizer (DE-IEO) specifically for the CHPED problem. The DE-IEO incorporates three enhancement strategies: a chaotic mechanism for initializing the population, an improved equilibrium pool strategy, and a quasi-opposite based learning mechanism. These strategies enhance the individual utilization capabilities of the equilibrium optimizer, while differential evolution boosts local exploitation and escape capabilities. The IEO enhances global search to enrich the solution space, and DE focuses on local exploitation for more accurate solutions. The effectiveness of DE-IEO is demonstrated through comparative analysis with other metaheuristic optimization algorithms, including PSO, DE, ABC, GWO, WOA, SCA, and equilibrium optimizer (EO). Additionally, improved algorithms such as the enhanced chaotic gray wolf optimization (ACGWO), improved particle swarm with adaptive strategy (MPSO), and enhanced SCA with elite and dynamic opposite learning (EDOLSCA) were tested on the CEC2017 benchmark suite and four CHPED systems with 24, 84, 96, and 192 units, respectively. The results indicate that the proposed DE-IEO algorithm achieves satisfactory solutions for both the CEC2017 test functions and real-world CHPED optimization problems, offering a viable approach to complex optimization challenges.

KEYWORDS: CHPED; DE; EO; large-scale system; CEC2017 test suite; metaheuristic optimization

1 Introduction

The CHPED problem revolves around optimizing costs to achieve the lowest possible system expenses while adhering to various equations and inequality constraints. Statistics indicate that CHP systems can enhance fuel efficiency by up to 90%, reduce production costs by 10% to 40%, and lower environmental pollution by 13% to 18% [1,2]. These systems consist of three main components: power-only units (POUs), CHP units (CHPUs), and heat-only units (HOUs). The power output of each CHP unit is influenced by the heat produced by the system and *vice versa*, creating a bi-directional relationship [3] known as the feasibility operating region (FOR). Additionally, the valve point effect, power losses, and prohibited operation zones (POZs) contribute to the CHPED problem being a nonlinear, multi-constrained, non-convex optimization challenge. This complexity in bi-directional dependence and constraints significantly complicates the resolution of the CHPED problem.

Numerous researchers have employed a variety of methods to address CHPED issues, including numerical optimization techniques like quadratic programming [4], branch and bound algorithms [5], Bender decomposition [6], and Lagrangian relaxation [7]. These numerical methods can quickly yield exact solutions; however, they face challenges due to the non-convex nature of the problem. As a result, several metaheuristic algorithms have been introduced and are increasingly seen as effective alternatives for tackling CHPED problems, include CS [8], WOA [9,10], DE [11,12], PSO [13], and BCO [14]. These algorithms have been widely utilized in large-scale CHPED systems with over 50 units, owing to their excellent performance [15]. The bi-directional dependence of CHP units causes a significant rise in the number of local minima as the size of the CHPED problem increases, resulting in an exponential growth of candidate solutions. This cascading effect severely impacts the accuracy of solutions for large-scale CHPED. Additionally, the No Free Lunch Theorem (NFL) [16] indicates that no single optimization algorithm can effectively address all optimization problems. Therefore, we introduce a hybrid EO [17] combined with DE [18] to tackle large-scale CHPED problems.

The EO is a metaheuristic algorithm grounded in physical principles and applied in many engineering fields, including multi-objective optimization [19], fuel cells [20], power distribution systems [21], image segmentation [22], engineering design [23], discrete optimization [24], feature selection [25], and quantum optimization [26]. However, the concentration update process of EO primarily relies on equalization among candidate individuals, which limits its utilization of the search space and population data, making it prone to escape local optima—an unfavorable situation for addressing the CHPED. Therefore, we propose three strategies to enhance EO's global search capabilities and help it avoid local minima. Additionally, EO is combined with DE to preserve EO's strong global exploration abilities while enhancing its local exploration capabilities. The main contributions are summarized as follows.

(1) Three enhancement strategies are presented: the chaotic mechanism initialized population strategy, the improved equilibrium pool strategy, and the quasi-opposite based learning mechanism strategy, which are integrated into the EO to boost individual utilization capabilities, while DE enhances local exploitation and escape abilities.

(2) A hybrid DE-IEO algorithm is introduced, where the improved EO enhances global search to enrich the solution space, and DE focuses on local exploitation to find more accurate solutions.

(3) The DE-IEO algorithm is utilized to optimize the CEC2017 test suite and large-scale CHPED problems, with numerical experiment show achieved satisfactory results.

2 Literature Review

To date, numerous metaheuristic algorithms (MHAs) have been developed to address small-scale CHPED. For instance, Subbaraj et al. utilized an enhanced real-valued coded genetic algorithm (SARGA) to tackle a 4-unit CHPED problem, incorporating a parameter-free penalty strategy to manage different constraints and assess the solution's validity [27]. Similarly, Mellal et al. employed an improved cuckoo search with a penalty function to solve small-scale CHPED problem involving 4 units [28].

As industrial technology advances, the medium-scale CHPED problem has arisen. Haghrah et al. proposed an enhancement to the basic genetic algorithm by utilizing Mühlenbein mutation instead of the standard mutation used in real-value coded genetic algorithms, addressing the CHPED problem while considering power loss effects. Additionally, hybrid algorithms are increasingly being applied to this issue [29]. Narang et al. integrated the civilization swarm algorithm with Powell's pattern search method (CSO-PPS), where the civilization swarm algorithm conducts a global search and Powell's method focuses on local search, successfully tackling the CHPED problem involving 48 units while accounting for valve-point effects, POZs, and power loss [30]. Beigvand et al. introduced TVAC-GSA-PSO, which combines an adaptive learning strategy with GSA and PSO to address the CHPED problem with 24 and 48 units, also considering the impacts of power loss and valve-point effects [31]. Zou et al. developed a genetic algorithm featuring innovative mutation and crossover operators (IGA-NCM) to optimize the CHPED problem with 48 units, employing a new approach to create the penalty function [32]. Chen et al. merged the biogeography algorithm with the PSO (BLPSO) to solve the medium-scale CHPED problem, utilizing repair techniques to manage constraints and direct particles toward feasible areas [33]. Lastly, Nasir et al. combined the firefly algorithm with a self-regulating PSO(FSRPSO), achieving satisfactory results for a medium-scale CHPED problem involving 48 units [34].

Regarding the large-scale CHPED problem, Meng et al. were the first to address it using a crisscross optimization algorithm for a scale of 192 units [35], significantly increasing the complexity of the issue. Liu et al. tackled problems with 84, 96, and 192 units by employing a differential evolution (DE) method enhanced with a mutation strategy and neighborhood and direction-induced strategies [36]. Ramachandran et al. combined an improved crow search algorithm (FRCSA) with ABC (FRSCA-ABC) using an adaptive ranking strategy, further enhancing it with three improvement techniques, which led to impressive results on large-scale CHPED challenges [37]. Additionally, Ramachandran et al. enhanced the GOA and the HHO by incorporating sine-cosine acceleration coefficients (SCAC) and an adaptive search mechanism (MGOA-IHHO), respectively, and successfully applied a hybrid of both to solve the CHPED problem with 84 units [38]. Therefore, creating hybrid algorithms that leverage the strengths of individual methods while minimizing weaknesses is an effective approach to addressing this problem [39].

3 CHPED Problem Model

The CHPED is to find the best combination of all unit production with minimum total production costs. For CHP units, their power and heat production must also meet the restrictions of the FOR as shown in Fig. 1, and solutions not in this restricted region are considered invalid, and the two types of output of CHP units are mutually constrained.

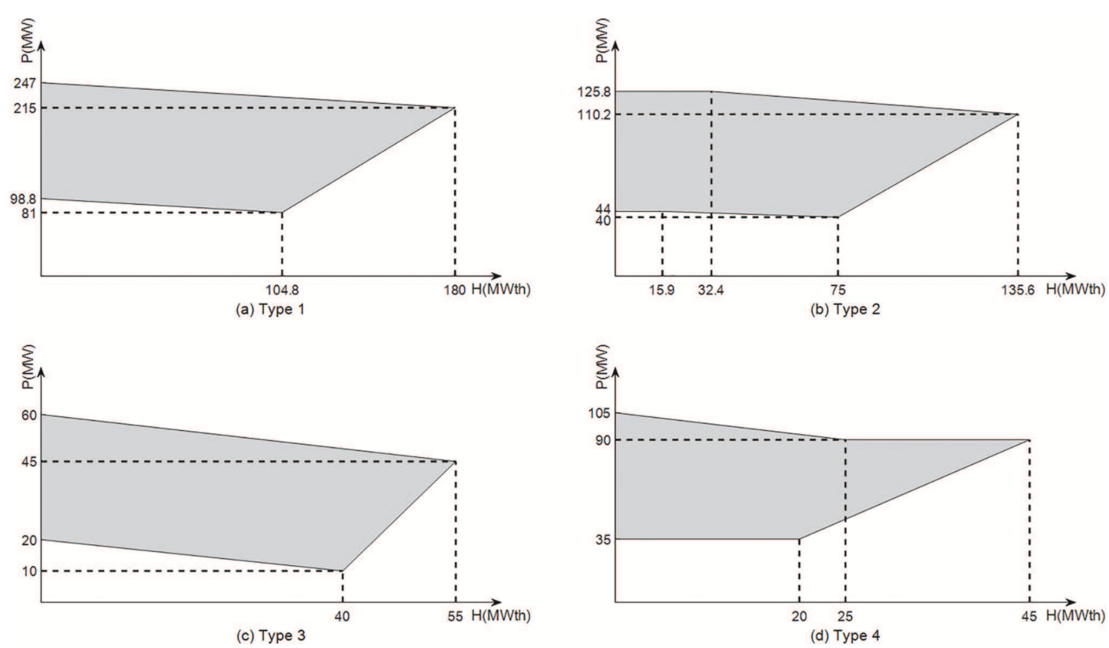

Figure 1: CHP unit feasible operating region

3.1 Objective Function

The objective function of the CHPED is the sum of the fuel costs of each unit, which is modeled:

$$\min F_{\cos t} = \sum_{i=1}^{N_p} F_i\left(P_i^P\right) + \sum_{j=1}^{N_c} F_j\left(P_j^c, H_j^c\right) + \sum_{k=1}^{N_h} F_k\left(H_k^h\right) (\$/\text{h}) \tag{1}$$

where $F_i\left(P_i^p\right)$ is the cost of the i th POU, $F_j\left(P_j^c, H_j^c\right)$ is the cost of the j th CHPU, and $F_k\left(H_k^h\right)$ is the cost of the k th HOU. N_p, N_c and N_h are the number of POUs, CHPUs, and HOUs, respectively.

3.1.1 Power-Only Units

The power-only unit with the valve-point effect is responsible for converting fuel into electricity only without considering the heat generation.

$$F_i\left(P_i^p\right) = \alpha_i\left(P_i^p\right)^2 + \beta_i\left(P_i^p\right) + \gamma_i + \left|\lambda_i \sin\left(\rho_i\left(P_i^{P_{\min}} - P_i^P\right)\right)\right| \tag{2}$$

where $\alpha_i, \beta_i, \gamma_i, \lambda_i$ and ρ_i are coefficient constants, P_i^p and $P_i^{p_{\min}}$ denote the power production and minimum power production, respectively.

Fig. 2 shows the relationship between power generation and cost of the unit after considering the valve-point effect. It can see that the fuel cost of each unit with the valve-point effects is higher than that of the conventional unit for the same power generation.

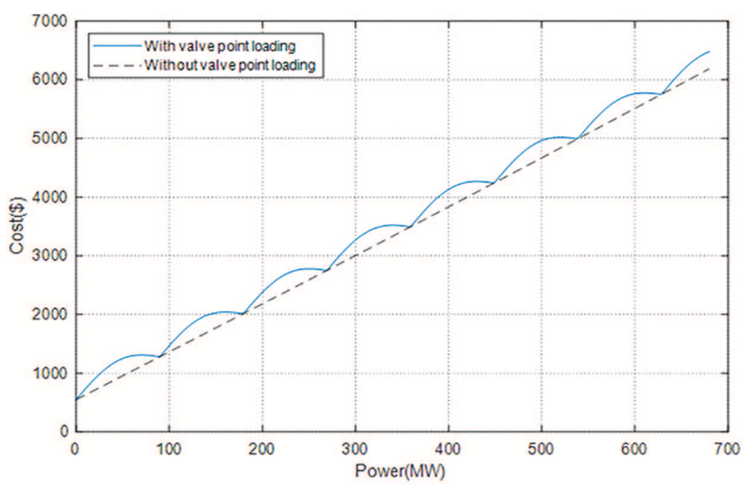

Figure 2: Value-point effects

3.1.2 CHP Units

The CHP unit converts fuel into electricity and available heat with a convex cost function consisting of a quadratic polynomial as follows.

$$F_j\left(P_j^c, H_j^c\right) = a_j\left(P_j^c\right)^2 + b_j P_j^c + c_j + d_j\left(H_j^c\right)^2 + e_j\left(H_j^c\right) + f_j P_j^c H_j^c \tag{3}$$

where *a*, *b*, *c*, *d*, *e* and *f* are cost factor.

3.1.3 Heat-Only Units

The heat-only unit generates only heat, and its cost function is also a convex function consisting of a quadratic polynomial, expressed as follows.

$$F_k\left(H_k^h\right) = a_k\left(H_k^h\right)^2 + b_k H_k^h + c_k \tag{4}$$

where *a, b* and *c* are cost factor.

3.2 System Constraints

3.2.1 Equality Constraints

(1) *Power balance:* the power production of the POU and CHPU must meet the power demand (P_d) and the power losses (P_L). Power loss is calculated using the B-coefficient method [40].

$$\sum_{i=1}^{N_p} P_i^p + \sum_{j=1}^{N_c} P_j^c = P_d + P_L \tag{5}$$

$$P_L = \sum_{i=1}^{N_p+N_c}\sum_{j=1}^{N_p+N_c} P_i^{p,c} B_{ij} P_j^{p,c} + \sum_{i=1}^{N_p+N_c} B_{0i} P_i^{p,c} + B_{00} \tag{6}$$

Here B_{ij}, B_{0i} and B_{00} denote the B matrix coefficients. $P_i^{p,c} = \left(P_1^p, P_2^p, \ldots, P_{N_p}^p, P_1^c, P_2^c, \ldots, P_{N_c}^c\right)$ denotes the power vectors generated by all units

(2) *Heat balance:* The heat generated by the CHPU and the HOU must meet the heat demand (H_d), with the following constraint after neglecting heat losses.

$$\sum_{k=1}^{N_h} H_k^h + \sum_{j=1}^{N_c} H_j^c = H_d \tag{7}$$

3.2.2 Equality Constraints

The prohibited operating zones (POZs) effect means that the power generation is suspended due to machine bearing vibration and other failures, so the POZs effect should be avoided in the actual power generation process.

$$P_i^{\min} \le P_i \le P_i^{\max} \tag{8}$$

$$P_j^{c,\min}\left(H_j^c\right) \le P_j^c \le P_j^{c,\max}\left(H_j^c\right) \tag{9}$$

$$H_j^{c,\min}\left(P_j^c\right) \le H_j^c \le H_j^{c,\max}\left(P_j^c\right) \tag{10}$$

$$H_k^{\min} \le H_k \le H_k^{\max} \tag{11}$$

where $P_j^{c,\min}\left(H_j^c\right)$, $P_j^{c,\max}\left(H_j^c\right)$ are the lower and upper limits of power production of the CHP unit, respectively. $H_j^{c,\min}\left(P_j^c\right)$, $H_j^{c,\max}\left(P_j^c\right)$ are the lower and upper limits of heat production of the CHP unit, respectively.

4 Equilibrium Optimizer and Differential Evolution Algorithm

4.1 Equilibrium Optimizer

Equilibrium optimizer (EO) as a physics-based optimization algorithm is by Afshin Faramarzi et al. proposed in 2020 [17], and is widely used in complex function optimization, engineering optimization, intelligent control and other fields. The EO include four components, which are initialization, equilibrium pool (C_{eq}), exponential term (F), and generation rate (G).

4.1.1 Equilibrium Pool

The EO equilibrium pool consists of five candidate particles, of which the first four are the best particles in terms of fitness, and the fifth is generated by the average of the first four particles.

$$X_{eq} = \{\vec{X}_1, \vec{X}_2, \vec{X}_3, \vec{X}_4, \vec{X}_{ave}\} \tag{12}$$

where $\vec{X}_1$, $\vec{X}_2$, $\vec{X}_3$ and $\vec{X}_4$ denote the top four particles after ranking the search particles by fitness values, and $\vec{X}_{ave}$ denotes the mean value of the top four particles.

4.1.2 Concentration Update Mechanism

In the concentration update step, the update mechanism has two components, the exponent term that balances the exploration and exploitation phases and affects the concentration update rule, and the generation rate that controls the exploitation phase. It is defined:

$$\vec{F} = a_1 \text{sign}\left(\vec{r} - 0.5\right)\left[e^{-\vec{\lambda} t} - 1\right] \tag{13}$$

where a_1 is a constant value 2, $\vec{r}$ and $\vec{\lambda}$ are random vectors, t is an iterative function expressed.

$$t = (1 - \frac{Iter}{MaxIter})^{(a_2 \frac{Iter}{MaxIter})} \tag{14}$$

where a_2 is a constant value 1.

The generation rate is defined:

$$G = G\overrightarrow{CP}\left(X_{eq} - \vec{\lambda}\vec{X}\right)\vec{F} \tag{15}$$

$$G\vec{C}P = \begin{cases} 0.5r_1 & r_2 \geq GP \\ 0 & r_2 < GP \end{cases} \tag{16}$$

where $\vec{X}_{eq}$ and $\vec{X}$ are randomly selected candidate solution and the current candidate solution, respectively, GP is a constant value 0.5, r_1 and r_2 are random numbers.

In summary, the update mechanism of EO can be defined as

$$\vec{X} = \vec{X}_{eq} + \left(\vec{X} - \vec{X}_{eq}\right) \cdot \vec{F} + \frac{\vec{G}}{\vec{\lambda} V}\left(1 - \vec{F}\right) \tag{17}$$

where V is a unit.

4.2 Differential Evolution

DE is proposed by Storn and Price [18] in 1997, it have two important parameters, namely mutation factor F and crossover rate CR, and the cores are mutation, crossover and selection.

4.2.1 Mutation

In DE, each target vector x_i^g uses the mutation operator of DE/rand/1 to generate the mutation vectors v_i^g, v_i^g is generated as follows.

$$v_i^g = x_{r_1}^g + F \cdot \left(x_{r_2}^g - x_{r_3}^g\right) \tag{18}$$

Among them, $x_{r_1}^g$, $x_{r_2}^g$ and $x_{r_3}^g$ are all randomly selected particles, and $r_1 \neq r_2 \neq r_3 \neq i$. Among these three particles, one particle is the base vector and the other two particles are the interference vectors.

4.2.2 Crossover

In crossover operation, v_i^g and x_i^g are crossed to produce the experimental vectoru_i^g. The most common crossover strategy is binomial crossover.

$$u_{i,j}^g = \begin{cases} v_{i,j}^g & if\ rand \leq\ CR\ or\ j = j_{rand} \\ x_{i,j}^g & otherwise \end{cases} \tag{19}$$

where j_{rand} is random integer in interval [1, m].

4.2.3 Selection

The fitness values of u_i^g and x_i^g are compared, and the better one is greedily selected.

$$x_i^{g+1} = \begin{cases} u_i^g & if\ f\left(u_i^g\right) \leq f\left(x_{i.}^g\right) \\ x_i^g & otherwise \end{cases} \tag{20}$$

where $f\left(u_i^g\right)$ and $f\left(x_i^g\right)$ are fitness values of u_i^g and x_i^g, respectively.

5 Proposed Hybrid DE-IEO Algorithm

Recently, many kinds of efficient hybrid metaheuristic optimization algorithms are proposed and successfully applied to solving complex optimization problems, such as, Broad sparse fine-grained image classification model [41], QDE [42], and so on.

This section proposed a hybrid DE-IEO algorithm, detailing the three improvement strategies and hybrid mechanisms utilized by the proposed algorithm. To overcome drawbacks of EO, three improvement strategies are integrated into EO, and the improved EO is hybrid with DE, as shown in Algorithm 1. The three improvement strategies are as follows.

(1) Initialized search agents using chaotic mechanism.

(2) Candidate particle selection mechanism for equilibrium pool.

(3) Quasi-opposite based learning (QOBL) mechanism for EO update mechanism.

Algorithm 1: DE-IEO pseudo code

Input: objective function $f(x)$

1 Initialization: N: population size, D: problem dimension, $MaxIter$: maximum iteration number, CR: crossover rate, F: scaling factor, a_1,a_2,V,GP: constants

2 Population initialization: initialization of the population using the chaotic mechanism of Eq. (22)

3 Iterations:

4 **while** $Iter < MaxIter$ **do**

5 Initialize the equilibrium pool using Eq. (23)

6 Calculate the iterative function t according to Eq. (14)

7 **for** $i = 1$ to N **do**

8 Random selection of one candidate from the equilibrium pool

9 According to Eq. (13) calculate the exponential term F

10 According to Eq. (15) calculate the generation rate G

11 According to Eq. (17) update of individual position $x_{i,j}^{g}$

12 Mutation operation of the particle individual position obtained in Step 11 according to Eq. (18) to obtain the mutated individual $v_{i,j}^{g}$

13 Calculate the quasi-opposite point $x_{i,j}^{best,q}$ of the individual position $x_{i,j}^{g}$ according to Eq. (26)

14 **if** $fitness\left(v_{i,j}^{g}\right) < fitness\left(x_{i,j}^{best,q}\right)$

15 Crossing $v_{i,j}^{g}$ and $x_{i,j}^{g}$ gives $u_{i,j}^{g}$

16 **else**

17 Crossing $x_{i,j}^{best,q}$ and $x_{i,j}^{g}$ gives $u_{i,j}^{g}$

18 **end if**

19 $u_{i,j}^{g}$ and $x_{i,j}^{g}$ for the selection operation

20 Get the best individual so far

21 $Iter = Iter + 1$

22 **end while**

Output: $gbest$

5.1 Chaotic Mechanism Initialized Population Strategy

Random initialization is the primary step of all MHAs. However, the distribution of population individual generated using random initialization alone is likely to be inhomogeneous, leading to difficulties for EO to find the global optimal or a significant increase in the time to find the global optimal solution. In order to combat this drawback, this paper uses the chaotic system (CS) mechanism to initialize the algorithm instead of just random initialization. The common chaotic mappings are Logistic mapping, Cubic mapping, Tent mapping, etc., while Tent mapping has good distributivitiy and randomness. To make the generated chaotic sequence more uniform [43], the Tent mapping is used in this paper for the generation of random sequences with the following expression.

$$y_i^{j+1} = \begin{cases} \dfrac{y_i^j}{\alpha} & 0 \le y_i^j \le \alpha \\ \dfrac{1 - y_i^j}{1 - \alpha} & \alpha < y_i^j \le 1 \end{cases} \tag{21}$$

Here $\alpha \in [0, 1]$, y_i^j is chaotic variable.

Then the initialization of the proposed algorithm is shown below.

$$X_i^{initial} = X_{\min} + y_i \left(X_{\max} - X_{\min}\right) i = 1, 2, \ldots, n \tag{22}$$

Here y_i denotes the i th chaotic sequence vector generated by Eq. (22)

5.2 *Equilibrium Pool Improved Strategy*

EO has a unique equilibrium pool mechanism to better balance exploration capability and exploitation capability, the selection strategy leads to a high concentration and similarity of the candidate particles, which is the fundamental reason for the weak information utilization among the candidates in the equilibrium pool, and the removal of $\vec{X}_4$ only has a very weak effect on the experimental results. So, the selection mechanism of the equilibrium pool is improved. The source of inspiration for the new selection mechanism of the equilibrium pool is the same as the crossover operation in DE. As shown in Fig. 3, for each dimension in the particles other than $\vec{X}_1$, $\vec{X}_2$ and $\vec{X}_3$, a value is randomly selected to form a new candidate particle $\vec{X}_1'$.

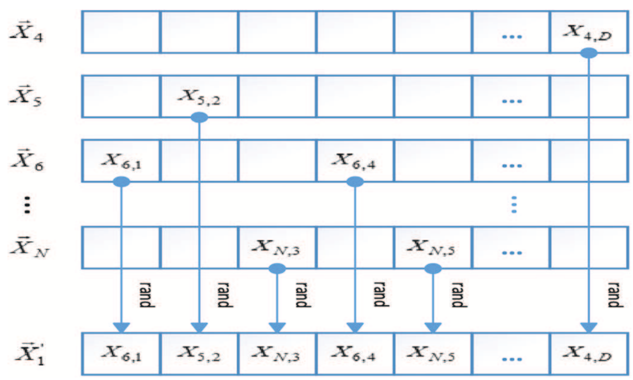

Figure 3: The equilibrium pool particle generation process

Similarly, the operation of Fig. 3 is performed again for $\vec{X}_1$, $\vec{X}_2$, $\vec{X}_3$ and $\vec{X}_1'$ to obtain $\vec{X}_2'$, and the final improved equilibrium pool is obtained as

$$X_{eq} = \left\{\vec{X}_1, \vec{X}_2, \vec{X}_3, \vec{X}_1', \vec{X}_2'\right\} \tag{23}$$

The EO uses random selection the best candidate particles, but this will lead to the same selection probability of $\vec{X}_1$, $\vec{X}_2$, $\vec{X}_3$, $\vec{X}_2'$ and $\vec{X}_1'$. In other words, the candidate particle $\vec{X}_1'$ is selected with the highest probability and the worst candidate particle $\vec{X}_1'$ is selected with the lowest probability, which can ensure the accuracy of the convergence and also reduce falling into a local optimum.

5.3 *Quasi-Opposite Based Learning Mechanism Strategy*

The QOBL [44] is an improvement on the OBL [45], it can be applied in MHAs, one is in population initialization to obtain better quality initial candidate solutions, and is applied in the update mechanism of MHAs. The QOBL is calculated:

Calculate the opposite of the original point.

$$x_{i,j}^{opp,best} = X_{i,j}^{\min} + X_{i,j}^{\max} - x_{i,j}^{best} \tag{24}$$

Next, calculate the center the interval $|X_{i,j}^{\min}, X_{i,j}^{\max}|$.

$$opp_{i,j} = \frac{X_{i,j}^{\min} + X_{i,j}^{\max}}{2} \tag{25}$$

Final calculation of the quasi-opposite point in Eq. (26).

$$x_{i,j}^{best,q} = rand\left(x_{i,j}^{opp,best}, opp_{i,j}\right) \tag{26}$$

6 Simulation Results and Discussions

To verify the superiority of DE-IEO, two parts of experiments, CEC2017 test suite [46] and CHPED problem are designed. The overall performance of DE-IEO is then analyzed in detail based on the experimental results.

6.1 Performance of DE-IEO on CEC2017

In the experiments, the performance of DE-IEO is using 29 CEC2017 benchmark functions (F2 is removed due to its instability in high-dimensional). We use the average value (AVG) and standard deviation (SD) to scientifically compare the optimization results, Friedman test [47,48] is used to rank the algorithms. The population size N and dimension D were set to 30, the experiment repeated 30 times.

The experiment compared algorithms include basic algorithms and improved algorithms. The classical algorithms include PSO, DE, ABC, GWO, WOA, SCA, and EO. Improved algorithms include improved ACGWO, improved MPSO, enhanced sine cosine algorithm with elite and dynamic opposite learning (EDOLSCA). The comparison results are shown in Table 1. Figs. 4–6 represent the convergence curves, where F1 is the unimodal function, F5, F6 are multimodal functions, F11, F13, F15, F17 and F19 are hybrid functions, and F20, F22, F26 and F30 are composition functions.

Table 1: Performance of each algorithm at CEC2017

Algorithm	AVG	SD	AVG	SD	AVG	SD
	F1		F3		F4	
PSO [49]	5.6507E + 04	1.6988E + 04	**7.4279E + 02**	4.2226E + 02	**4.9090E + 02**	3.0262E + 01
DE [18]	6.6944E + 06	2.9273E + 07	1.1239E + 05	1.9305E + 04	5.1126E + 02	**1.1703E + 01**
ABC [50]	1.4740E + 07	1.5601E + 07	3.5509E + 05	1.1426E + 05	5.0357E + 02	4.7829E + 01
GWO [51]	1.6418E + 09	1.0483E + 09	4.4546E + 04	1.1014E + 04	5.8878E + 02	5.0476E + 01
WOA [52]	4.0612E + 08	2.3940E + 08	2.6143E + 05	5.4249E + 04	6.8751E + 02	1.2687E + 02
SCA [53]	1.6416E + 10	2.0797E + 09	6.0388E + 04	1.0114E + 04	2.2259E + 03	5.1317E + 02
EO [17]	4.8305E + 03	6.3288E + 03	1.3482E + 04	4.6006E + 03	4.9721E + 02	2.3784E + 01
ACGWO [54]	5.0637E + 09	9.7224E + 08	4.0946E + 04	7.5327E + 03	7.2869E + 02	6.2437E + 01
MPSO [55]	1.2938E + 08	2.8922E + 08	1.0720E + 04	4.9281E + 03	5.0141E + 02	1.7253E + 01
EDOLSCA [56]	1.6967E + 10	6.3184E + 09	1.6541E + 05	4.7240E + 04	3.1102E + 03	1.7881E + 03
DE-IEO	**4.5271E + 03**	**5.3624E + 03**	8.9776E + 03	3.1399E + 03	4.9147E + 02	1.3295E + 01
	F5		F6		F7	
DE	6.4377E + 02	9.8865E + 00	6.0000E + 02	3.8183E − 12	8.7920E + 02	1.2606E + 01
ABC	7.4028E + 02	1.5285E + 01	6.0490E + 02	1.1965E + 00	9.7944E + 02	1.6706E + 01
GWO	6.0144E + 02	3.2976E + 01	6.0852E + 02	4.0745E + 00	8.7238E + 02	4.1426E + 01
WOA	8.4008E + 02	6.3363E + 01	6.7534E + 02	1.0121E + 01	1.2463E + 03	8.3149E + 01
SCA	8.0470E + 02	2.2306E + 01	6.5807E + 02	5.9941E + 00	1.1811E + 03	4.4255E + 01
EO	5.6959E + 02	2.0867E + 01	6.0019E + 02	3.0479E − 01	8.0378E + 02	2.1368E + 01
ACGWO	7.3217E + 02	1.8116E + 01	6.3113E + 02	3.7628E + 00	1.0053E + 03	2.3847E + 01
MPSO	5.6952E + 02	1.6494E + 01	6.0554E + 02	3.9612E + 00	8.0806E + 02	2.1148E + 01

(Continued)

Table 1 (continued)

Algorithm	AVG	SD	AVG	SD	AVG	SD
EDOLSCA	8.5021E + 02	6.0360E + 01	6.7154E + 02	1.4086E + 01	1.3720E + 03	1.1982E + 02
DE-IEO	**5.6037E + 02**	2.9249E + 01	**6.0000E + 02**	3.0158E − 04	9.2247E + 02	1.3133E + 02
	F8		F9		F10	
PSO	9.2852E + 02	1.9836E + 01	4.2130E + 03	1.0504E + 03	5.7033E + 03	1.1528E + 03
DE	9.4237E + 02	**9.7475E + 00**	**9.0000E + 02**	**6.9054E − 03**	7.0591E + 03	3.2967E + 02
ABC	1.0413E + 03	1.0103E + 01	3.7197E + 03	7.8364E + 02	9.1362E + 03	3.0581E + 02
GWO	8.9839E + 02	3.2041E + 01	1.7727E + 03	6.3261E + 02	4.4480E + 03	8.8222E + 02
WOA	1.0371E + 03	5.3071E + 01	9.1541E + 03	2.7315E + 03	6.9559E + 03	7.3687E + 02
SCA	1.0766E + 03	1.7943E + 01	6.8194E + 03	1.2469E + 03	8.5840E + 03	3.5430E + 02
EO	8.7257E + 02	2.0153E + 01	9.3807E + 02	7.2210E + 01	4.5598E + 03	6.6571E + 02
ACGWO	1.0113E + 03	1.8884E + 01	3.0565E + 03	6.5282E + 02	7.8872E + 03	5.0003E + 02
MPSO	8.6072E + 02	1.8152E + 01	1.0353E + 03	1.2421E + 02	**4.1893E + 03**	7.5753E + 02
EDOLSCA	1.1012E + 03	4.1586E + 01	1.2362E + 04	3.6097E + 03	8.7149E + 03	6.4118E + 02
DE-IEO	**8.5729E + 02**	2.1521E + 01	9.0027E + 02	7.8899E − 01	4.9685E + 03	**1.0848E + 02**
	F11		F12		F13	
PSO	1.2289E + 03	3.5417E + 01	1.6757E + 06	1.4034E + 06	4.7022E + 04	2.5456E + 04
DE	1.2330E + 03	**2.3272E + 01**	2.2395E + 06	1.5536E + 06	7.6016E + 04	6.2949E + 04
ABC	1.0176E + 04	2.9743E + 03	3.9931E + 08	1.2272E + 08	1.2168E + 06	2.1003E + 06
GWO	2.1495E + 03	1.1236E + 03	6.0973E + 07	7.6399E + 07	1.8520E + 07	6.0857E + 07
WOA	4.8197E + 03	1.8827E + 03	1.6235E + 08	1.1187E + 08	5.6037E + 05	3.3708E + 05
SCA	2.8254E + 03	6.7623E + 02	1.8906E + 09	3.5801E + 08	6.6369E + 08	2.8786E + 08
EO	1.1669E + 03	4.7026E + 01	5.5934E + 05	3.4609E + 05	1.7126E + 04	1.7103E + 04
ACGWO	1.9312E + 03	4.4061E + 02	4.1462E + 08	1.2974E + 08	1.6805E + 08	8.4036E + 07
MPSO	1.2145E + 03	4.0601E + 01	1.6355E + 06	1.6344E + 06	1.6670E + 04	1.2662E + 04
EDOLSCA	7.2945E + 03	3.2468E + 03	2.0402E + 09	1.9456E + 09	6.1034E + 08	1.0736E + 09
DE-IEO	**1.1537E + 03**	3.4647E + 01	**7.4240E + 04**	**6.5393E + 04**	**2.0078E + 03**	**1.4061E + 03**
	F14		F15		F16	
PSO	1.9564E + 04	4.4649E + 04	1.8349E + 04	8.1292E + 03	3.0133E + 03	3.6200E + 02
DE	1.2988E + 05	8.3263E + 04	3.3152E + 04	1.7804E + 04	2.5499E + 03	**1.6237E + 02**
ABC	2.9737E + 05	1.8896E + 05	1.1034E + 06	6.8054E + 05	3.8417E + 03	2.3777E + 02
GWO	3.1481E + 05	3.9711E + 05	3.7411E + 05	1.0247E + 06	2.4529E + 03	2.8443E + 02
WOA	1.1061E + 06	1.3248E + 06	8.1266E + 05	1.7754E + 06	3.8676E + 03	4.3521E + 02
SCA	3.2324E + 05	1.4809E + 05	3.0112E + 07	2.6813E + 07	3.8927E + 03	2.6867E + 02
EO	3.5409E + 04	3.0629E + 04	7.8752E + 03	9.7234E + 03	**2.3446E + 03**	3.5713E + 02
ACGWO	2.4896E + 05	2.8778E + 05	3.9591E + 06	4.5307E + 06	3.2320E + 03	3.1058E + 02
MPSO	5.3083E + 03	3.9342E + 03	3.1888E + 03	1.7994E + 03	2.4817E + 03	2.7043E + 02
EDOLSCA	1.8706E + 06	1.5235E + 06	4.0066E + 07	8.8148E + 07	4.0692E + 03	5.7382E + 02
DE-IEO	**1.4897E + 03**	**1.9238E + 01**	**1.5935E + 03**	**2.9990E + 01**	2.3558E + 03	4.5044E + 02
	F17		F18		F19	
PSO	2.4141E + 03	2.1608E + 02	2.8449E + 05	9.5175E + 05	1.9739E + 04	1.0530E + 04
DE	1.9446E + 03	**6.6374E + 01**	9.3892E + 05	5.0966E + 05	2.7463E + 04	1.9323E + 04
ABC	2.8276E + 03	1.5068E + 02	1.3186E + 07	5.6606E + 06	6.4657E + 04	9.8911E + 04
GWO	2.0268E + 03	1.7749E + 02	1.0766E + 06	8.6731E + 05	2.1210E + 06	6.3629E + 06
WOA	2.6337E + 03	2.6736E + 02	6.9909E + 06	7.0893E + 06	8.0166E + 06	5.9095E + 06
SCA	2.5947E + 03	1.8798E + 02	8.2868E + 06	6.9180E + 06	5.6326E + 07	3.2303E + 07
EO	2.0067E + 03	2.0109E + 02	3.3971E + 05	2.1384E + 05	6.9410E + 03	4.9743E + 03
ACGWO	2.2106E + 03	1.8420E + 02	2.2934E + 06	3.5945E + 06	1.0836E + 07	7.4465E + 06
MPSO	1.9663E + 03	1.5069E + 02	1.1179E + 05	6.3157E + 04	5.7925E + 03	4.1859E + 03
EDOLSCA	2.6774E + 03	3.0268E + 02	1.9111E + 07	2.8808E + 07	5.0024E + 07	1.1955E + 08
DE-IEO	**1.8363E + 03**	1.1881E + 02	**1.1891E + 04**	**9.7402E + 03**	**1.9635E + 03**	**1.0044E + 02**
	F20		F21		F22	
PSO	2.6808E + 03	1.8280E + 02	2.5022E + 03	3.8208E + 01	6.1197E + 03	1.9687E + 03
DE	2.3130E + 03	**8.6889E + 01**	2.4449E + 03	**1.2174E + 01**	2.6749E + 03	5.1322E + 02
ABC	3.0164E + 03	9.7303E + 01	2.5453E + 03	1.3674E + 01	1.0276E + 04	3.9381E + 02

(Continued)

Table 1 (continued)

Algorithm	AVG	SD	AVG	SD	AVG	SD
GWO	2.4034E + 03	2.3143E + 02	2.3864E + 03	2.5027E + 01	4.2035E + 03	1.4849E + 03
WOA	2.8042E + 03	2.0938E + 02	2.5879E + 03	6.1933E + 01	8.1108E + 03	1.2444E + 03
SCA	2.7558E + 03	1.5559E + 02	2.5858E + 03	2.0171E + 01	9.0169E + 03	2.0837E + 03
EO	2.2776E + 03	1.3863E + 02	**2.3585E + 03**	1.8195E + 01	4.4448E + 03	2.1324E + 03
ACGWO	2.5529E + 03	1.4956E + 02	2.5015E + 03	2.1172E + 01	5.8960E + 03	3.1225E + 03
MPSO	2.2880E + 03	2.1216E + 02	2.3618E + 03	1.3938E + 01	2.4360E + 03	6.0476E + 02
EDOLSCA	2.8749E + 03	2.3622E + 02	2.6172E + 03	4.7432E + 01	7.7308E + 03	2.4051E + 03
DE-IEO	**2.1046E + 03**	9.0501E + 01	2.3609E + 03	3.0045E + 01	**2.3000E + 03**	**1.3889E − 05**
	F23		F24		F25	
PSO	3.3559E + 03	1.0168E + 02	3.4737E + 03	1.0748E + 02	2.9112E + 03	2.0247E + 01
DE	2.7918E + 03	**1.0818E + 01**	2.9980E + 03	**8.5731E + 00**	2.8936E + 03	**7.3111E + 00**
ABC	2.8983E + 03	1.8027E + 01	3.0808E + 03	1.3236E + 01	2.9180E + 03	9.6088E + 00
GWO	2.7563E + 03	3.7741E + 01	2.9477E + 03	5.6838E + 01	2.9768E + 03	3.1378E + 01
WOA	3.0572E + 03	8.6150E + 01	3.2134E + 03	9.7118E + 01	3.0588E + 03	4.8500E + 01
SCA	3.0395E + 03	4.2185E + 01	3.2111E + 03	3.0401E + 01	3.3825E + 03	1.4275E + 02
EO	2.7117E + 03	1.8293E + 01	**2.8782E + 03**	1.7609E + 01	**2.8904E + 03**	1.2470E + 01
ACGWO	2.8970E + 03	1.9696E + 01	3.0610E + 03	2.1732E + 01	3.0458E + 03	5.0402E + 01
MPSO	2.7386E + 03	3.5275E + 01	2.9034E + 03	3.6976E + 01	2.9646E + 03	4.4770E + 01
EDOLSCA	3.1919E + 03	1.2033E + 02	3.3746E + 03	1.0961E + 02	3.7786E + 03	3.9323E + 02
DE-IEO	**2.7062E + 03**	2.3793E + 01	2.8796E + 03	2.8831E + 01	2.8911E + 03	1.3402E + 01
	F26		F27		F28	
PSO	7.5247E + 03	1.9587E + 03	4.0974E + 03	3.2890E + 02	**3.1958E + 03**	4.8021E + 01
DE	5.0512E + 03	**1.0519E + 02**	3.2142E + 03	4.9883E + 00	3.3103E + 03	4.5717E + 01
ABC	5.6654E + 03	1.4585E + 02	**3.2000E + 03**	**6.3694E − 05**	3.3000E + 03	**8.1680E − 02**
GWO	4.6739E + 03	4.1258E + 02	3.2529E + 03	2.2804E + 01	3.4060E + 03	6.9354E + 01
WOA	7.8991E + 03	1.4177E + 03	3.3892E + 03	9.1116E + 01	3.4776E + 03	7.3526E + 01
SCA	7.3875E + 03	3.9930E + 02	3.4810E + 03	5.7986E + 01	4.1376E + 03	2.3249E + 02
EO	4.1911E + 03	4.0027E + 02	3.2194E + 03	1.2025E + 01	3.2134E + 03	1.4188E + 01
ACGWO	5.8382E + 03	5.0373E + 02	3.2893E + 03	2.9995E + 01	3.5022E + 03	5.1210E + 01
MPSO	4.3379E + 03	9.6331E + 02	3.2463E + 03	2.2263E + 01	3.3376E + 03	5.5521E + 01
EDOLSCA	8.0827E + 03	9.3241E + 02	3.7574E + 03	1.4465E + 02	4.5880E + 03	5.8630E + 02
DE-IEO	**3.8256E + 03**	5.3896E + 02	3.2065E + 03	8.6238E + 00	3.2145E + 03	1.4364E + 01
	F29		F30		Average	Friedman rank
PSO	4.5337E + 03	2.9227E + 02	3.6549E + 05	1.7956E + 05	7.41	8
DE	3.7875E + 03	8.4147E + 01	8.8056E + 04	1.3337E + 05	4.48	4
ABC	4.9040E + 03	2.0846E + 02	3.4191E + 05	2.2643E + 05	2.59	2
GWO	3.8024E + 03	1.7058E + 02	8.0901E + 06	6.0035E + 06	5.45	5
WOA	5.2088E + 03	4.8787E + 02	3.2066E + 07	2.6078E + 07	5.69	6
SCA	4.9525E + 03	2.1100E + 02	1.2230E + 08	4.1842E + 07	8.72	9
EO	3.5517E + 03	1.5576E + 02	1.0242E + 04	5.1659E + 03	9.24	10
ACGWO	4.2316E + 03	1.7250E + 02	3.3971E + 07	1.3429E + 07	3.17	3
MPSO	3.6274E + 03	2.3293E + 02	1.0558E + 04	3.8546E + 03	10.41	11
EDOLSCA	5.1138E + 03	5.3530E + 02	6.9355E + 07	1.4589E + 08	7.21	7
DE-IEO	**3.5231E + 03**	**1.9578E + 01**	**6.6125E + 03**	**1.1118E + 03**	1.62	1

Note: The bold font indicate the best value.

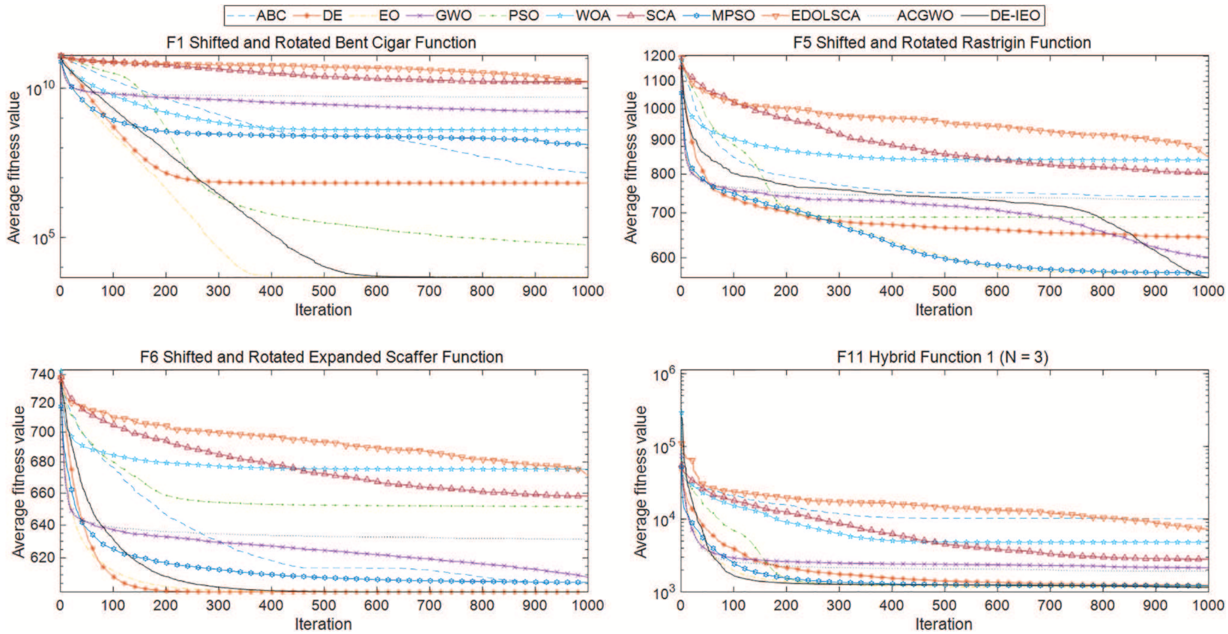

Figure 4: Eleven algorithms convergence curves of functions F1, F5, F6, F11

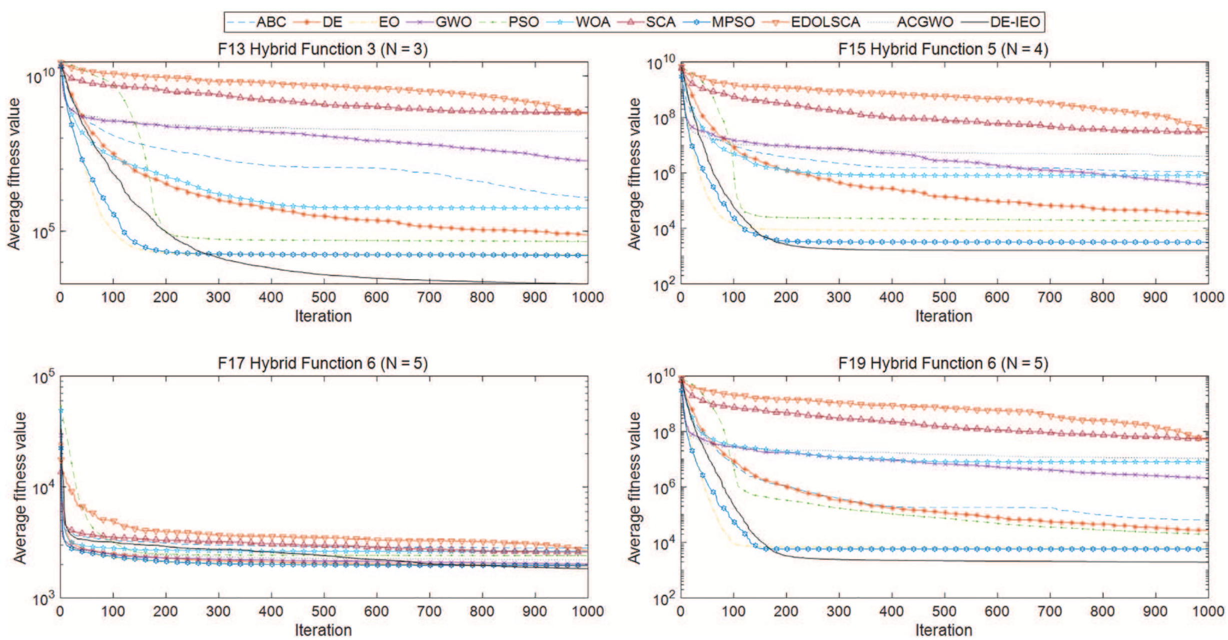

Figure 5: Eleven algorithms convergence curves of functions F13, F15, F17, F19

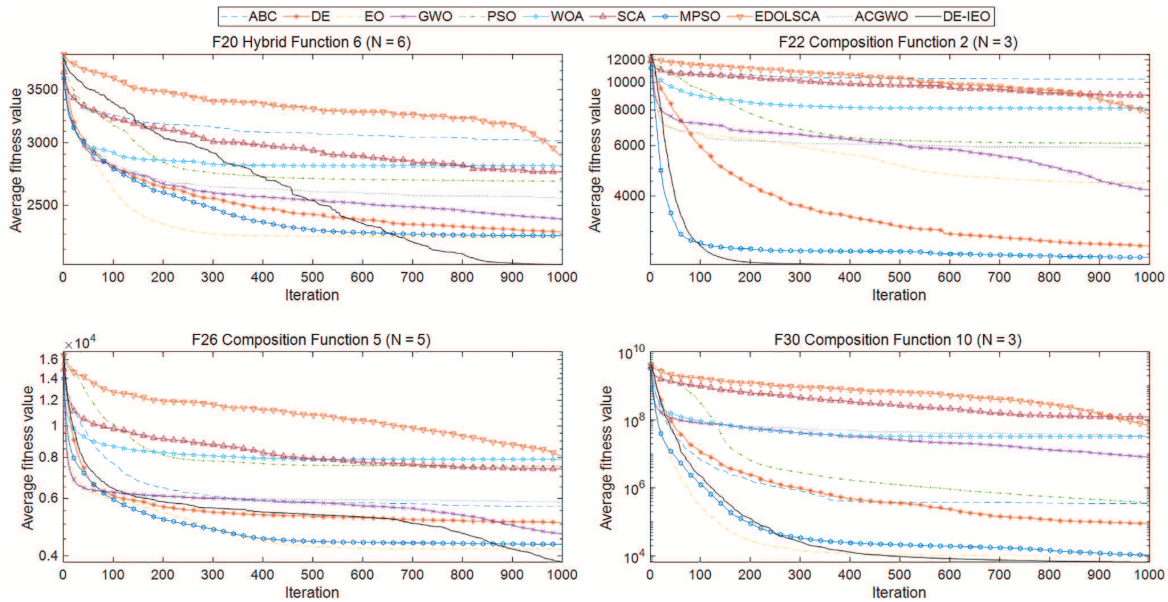

Figure 6: Each algorithms convergence curves of functions F20, F22, F26, F30

Figs. 7–9 show the boxplots of the algorithm for each function. It is important to know that the narrower the boxplot means that the algorithm is more concentrated in the data obtained in 30 runs, which means is more stable; the lower the median of the boxplots, the closer the algorithm is to the theoretical values. So it is clear from the boxplots that the stability and accuracy of DE-IEO is the best among most functions.

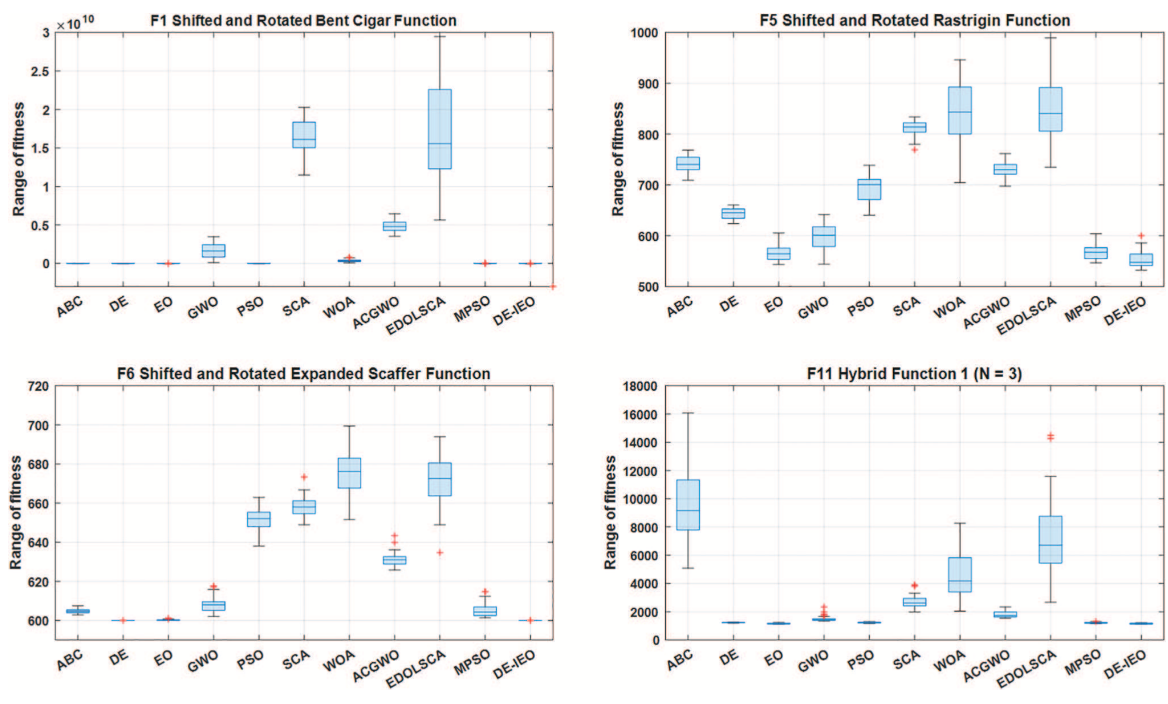

Figure 7: Boxplots obtained by each algorithm on F1, F5, F6, F11

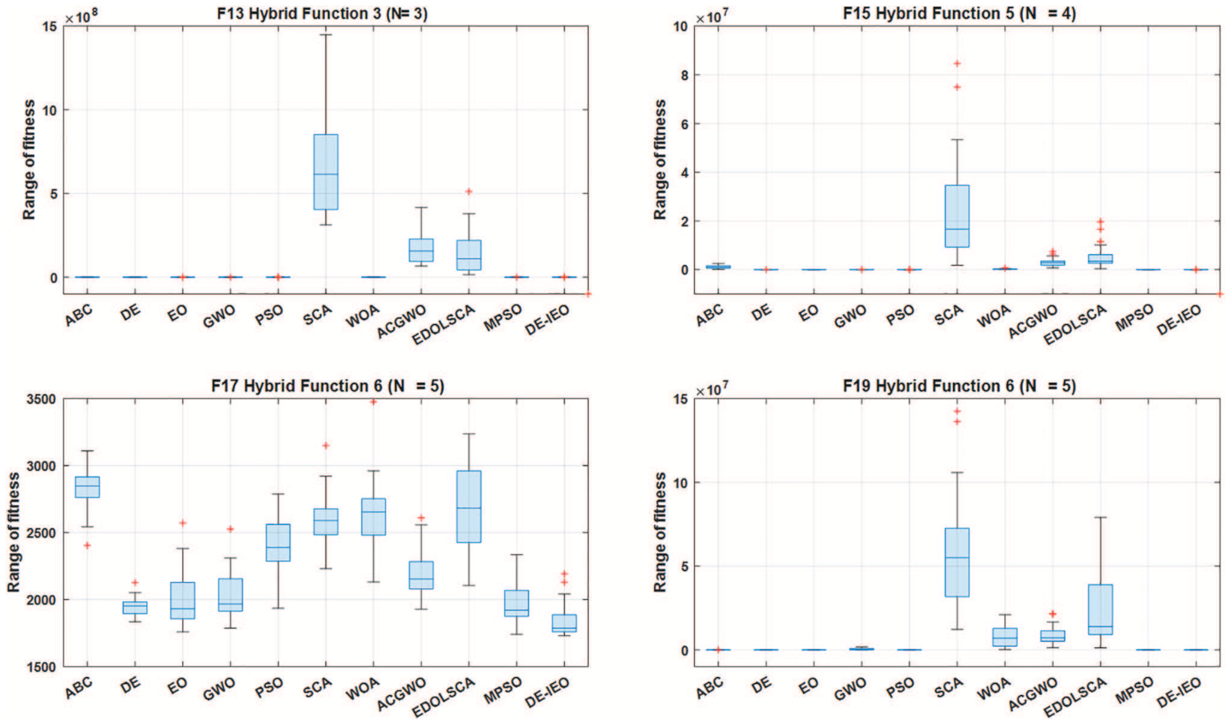

Figure 8: Boxplots obtained by each algorithm on F13, F15, F17, F19

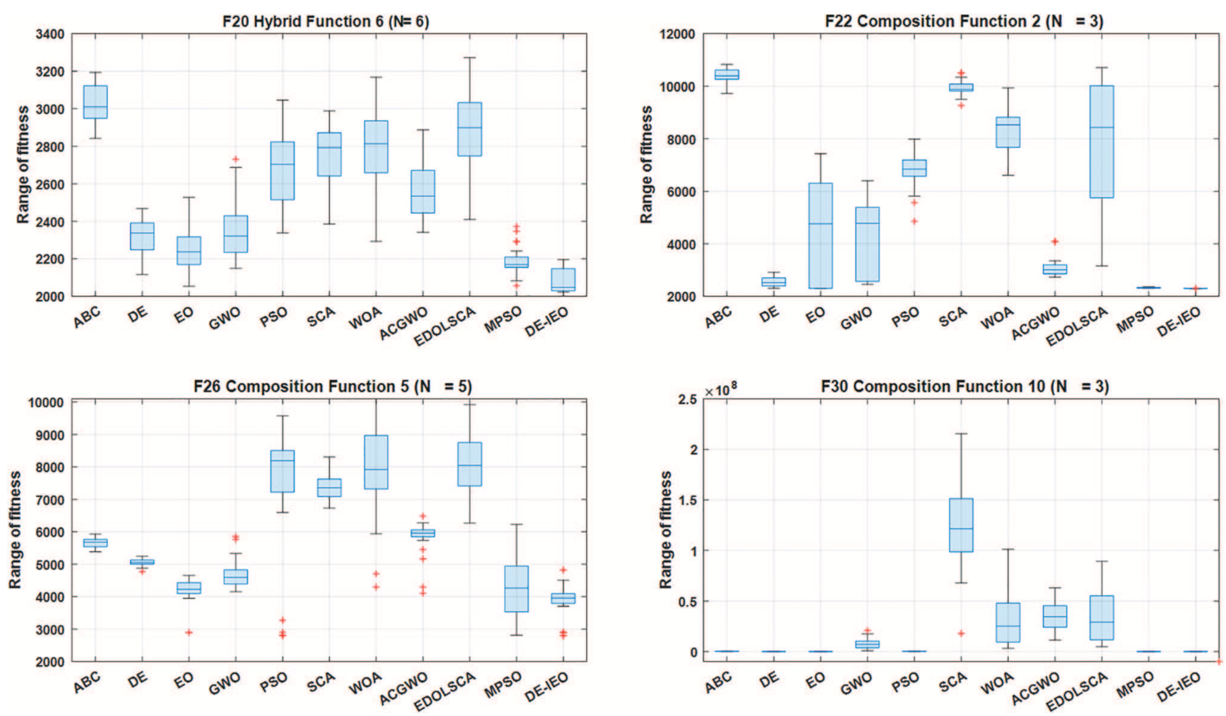

Figure 9: Boxplots obtained by each algorithm on F20, F22, F26, F30

6.2 *Performance of DE-IEO for CHPED Problem*

In this subsection, we first conduct a comprehensive performance test of DE-IEO using 4 cases in the CHPED problem, which contain one small and four large CHPED systems. Secondly, the obtained compared experimental results to verify the effectiveness of DE-IEO. The relevant data for large-scale CHPED systems above 84 units are obtained by scaling up to 24 units [15]. The 24-unit system is divided into two cases depending on whether POZs are considered or not. The penalty factor should be as large as possible, and is set to 10^{10} in [37]. To exclude the effect of rounding on the results, the error of V_{CHP} are set to 10^{-4}, i.e., this result is considered reasonable when V_{CHP} less than 10^{-4}. The population size N was set to 100, and to ensure the reliability of the experimental data, each experiment was run 30 times independently to find its cost maximum $C_{\max}$, cost minimum $C_{\min}$ and cost average C_{mean} for overall comparison.

6.2.1 CHPED System 1 with 24 Units

This test system contains 24 units, of which 1–13 are POUs, 14–19 are CHP units, and 20–24 are HOUs, and the total demand for power is 2350 MW and the total demand for heat is 1250 MWth.

Case 1: POZs are not considered

Considering only the valve-point effects, the three types of costs obtained by DE-IEO are compared with other algorithms, including NDE [15], RCGA-IMM [29], CSO-PPS [30], TVAC-GSA-PSO [31], IGA-NCM [32], BLPSO [33] and OGSO [57]. Table 2 that IDE-EO obtained the best results among all the compared algorithms in terms of minimum and average cost, and the cost savings of DE-IEO compared with other algorithms can be visually found in Fig. 10. And overall IDE-EO is very competitive in this case compared to other algorithms.

Table 2: Case 1 obtained the best dispatch results by different algorithms for the 24-unit test system

Output	NDE [15]	OGSO [57]	RCGA-IMM [29]	CSO-PPS [30]	TVAC-GSA-PSO [31]	IGA-NCM [32]	BLPSO [33]	DE-IEO
P1	628.3186	538.5524	448.8000	538.5238	538.5587	628.3188	628.3185	538.1853
P2	299.1995	298.6687	299.9568	299.1331	299.1993	299.1982	299.1993	299.1483
P3	224.4008	298.9085	299.2108	224.2457	299.2008	299.1665	299.1993	297.2354
P4	109.8665	110.2920	109.8694	109.7563	109.8669	109.8673	109.8666	109.8660
P5	109.8669	110.2545	109.8679	159.6343	109.8667	109.8662	60.0000	109.8666
P6	109.8667	110.3381	159.7353	159.6758	109.8668	60.0000	109.8666	109.7331
P7	159.7333	110.2745	109.8684	109.8585	109.8670	109.8608	109.8666	109.0000
P8	109.8670	110.2452	60.6545	159.7112	109.8666	109.8237	109.8666	109.7331
P9	109.8663	110.1592	159.7354	109.8512	109.8668	109.8523	109.8666	109.0000
P10	40.0002	77.3992	75.8146	40.0000	77.4000	40.0001	40.0000	77.3999
P11	40.0004	77.8364	40.1672	40.0000	77.4000	77.0316	76.9501	77.3999
P12	55.0003	55.0023	92.6079	55.0000	55.0002	55.0098	55.0000	55.3999
P13	55.0002	55.0109	92.4056	55.0000	55.0027	55.0000	55.0000	55.0009
P14	90.6728	81.0524	83.0376	82.8455	81.1710	81.0035	81.0000	81.4947
P15	40.0021	40.0015	40.0071	40.0000	41.7808	40.0003	40.0000	41.0542
P16	83.2701	81.0030	81.4577	81.7652	81.0537	81.0003	81.0000	81.4692
P17	40.0388	40.0009	41.6937	40.0000	40.0225	40.0001	40.0000	40.0083
P18	10.0003	10.0002	10.0042	10.0000	10.0000	10.0002	10.0000	10.0016
P19	35.0293	35.0001	35.1058	35.0000	35.0096	35.0003	35.0000	35.0001
H14	110.2282	105.2219	105.9431	105.8357	104.8861	104.8013	104.8000	104.8689
H15	75.0018	76.5205	75.0059	75.0000	76.5211	75.0001	75.0000	75.0043
H16	106.0736	105.5142	105.0550	105.2294	104.8202	104.7995	104.8000	104.5529
H17	75.0335	75.4833	76.4619	75.0000	75.0040	74.9988	75.0000	75.0004

(Continued)

Table 2 (continued)

Output	NDE [15]	OGSO [57]	RCGA-IMM [29]	CSO-PPS [30]	TVAC-GSA-PSO [31]	IGA-NCM [32]	BLPSO [33]	DE-IEO
H18	40.0000	39.9999	40.0007	40.0000	40.0000	39.9993	40.0000	40.0007
H19	20.0132	18.3944	20.0477	20.0000	20.0043	20.0001	20.0000	18.0000
H20	463.6496	468.9042	467.4871	468.9380	468.7643	470.4096	470.4000	468.9166
H21	60.0000	59.9995	59.9999	60.0000	60.0000	60.0000	60.0000	60.0000
H22	60.0000	59.9999	59.9997	60.0000	60.0000	60.0000	60.0000	60.0000
H23	120.0000	119.9854	119.9991	120.0000	120.0000	120.0000	120.0000	120.0000
H24	120.0000	119.9768	119.9998	120.0000	119.9999	119.9913	120.0000	119.9999
Min cost	57,828.1885	57,829.2456	58,066.6354	57,835.0000	57,842.8749	57,826.0902	57,825.4365	**57,824.7186**
Mean cost	57,951.4517	57,841.4753	58,066.6354	57,838.0000	57,846.3913	57,875.3621	57,835.3869	**57,833.9806**
Max cost	58,182.2503	57,854.9879	58,301.9013	**57,844.0000**	57,848.0421	57,846.5845	57,876.2639	57,854.5418

Note: The bold font indicate the best values.

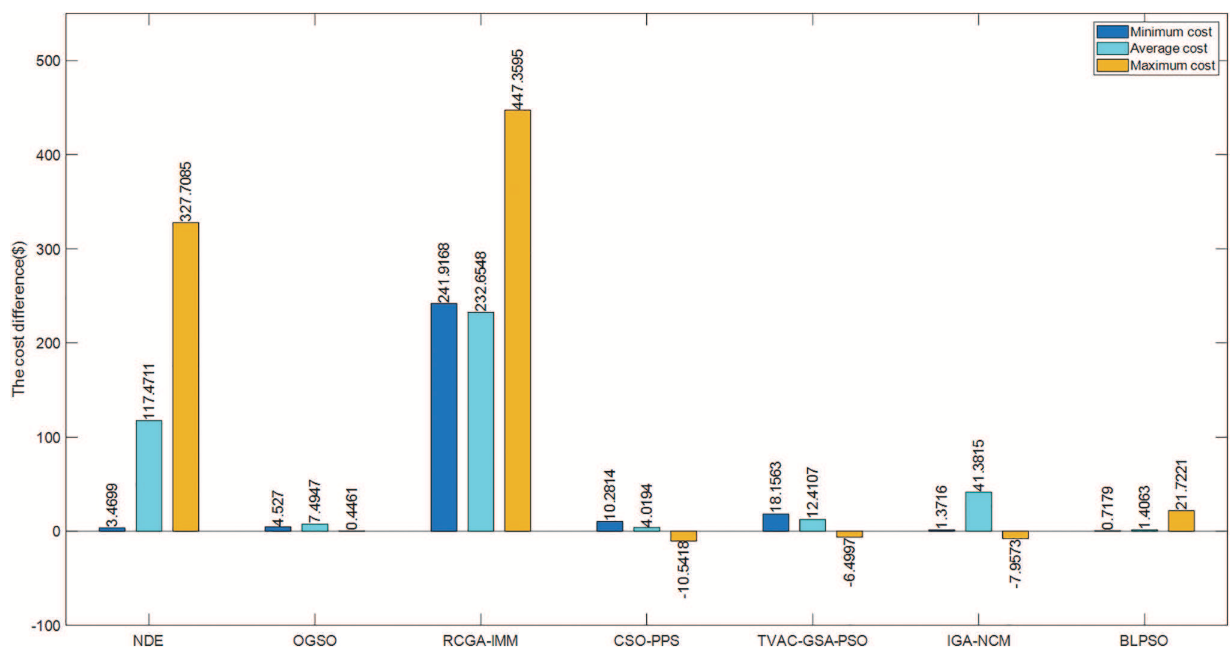

Figure 10: Cost savings of IDE-EO compared to other algorithms for case 1 of the 24-unit system

Case 2: Consider POZs

This case is based on case 1 and introduces the prohibited operating zones constraint. In Table 3, DE-IEO is compared with the results of some literature, such as NDE [15], CSO-PPS [30], IGA-NCM [32], BLPSO [33], OGSO [58] and HTS [59]. From Fig. 11, it can be found that some of the cost savings of DE-IEO compared to the other comparison algorithms are negative, which indicates that the results obtained by DE-IEO are inferior to these comparison algorithms in general. Although the results obtained by DE-IEO are not the best, they are better than half of the other algorithms in terms of minimum and average cost.

Table 3: Case 2 obtained the best dispatch results by different algorithms for the 24-unit test system

Output	NDE [15]	OGSO [57]	CSO-PPS [30]	IGA-NCM [32]	BLPSO [33]	HTS [58]	DE-IEO
P1	628.3175	628.3261	539.0370	628.3188	628.3185	628.3185	359.0406
P2	224.3968	299.2015	301.6721	299.0346	299.1981	298.9051	299.5543
P3	224.3970	224.4017	222.0012	298.7415	299.1981	224.4078	300.4204
P4	159.7326	60.0008	110.7853	109.8229	60.0000	60.0000	159.7339
P5	60.0000	159.7331	159.0094	60.0000	109.8665	159.1331	109.8677
P6	159.7278	60.0016	159.0085	109.8636	109.8665	60.0000	159.7381
P7	159.7283	159.7352	109.0078	109.8482	109.8665	159.1331	159.7664
P8	159.7326	60.0004	159.8675	109.8429	109.8665	60.0000	159.7377
P9	60.0000	159.7333	109.6085	109.8016	109.8665	159.1331	159.7367
P10	40.0000	40.0002	40.0031	77.3128	40.0000	40.0000	40.0000
P11	40.0000	40.0001	40.9085	40.0000	76.9527	40.0000	40.0624
P12	91.9661	55.0000	55.0032	55.0057	55.0001	55.0000	55.0422
P13	55.0001	92.3988	57.0878	55.0000	55.0000	92.3999	55.0012
P14	81.0002	89.3165	81.0000	81.0010	81.0000	89.3203	81.5455
P15	40.0002	44.8852	40.0000	40.0048	40.0000	44.8825	40.3846
P16	81.0003	86.3341	81.0000	81.0006	81.0000	86.3330	82.2500
P17	40.0004	45.9303	40.0000	40.3997	40.0000	45.9300	43.0414
P18	10.0002	10.0000	10.0000	10.0013	10.0000	10.0000	10.0768
P19	35.0000	35.0012	35.0000	35.0000	35.0001	35.0020	35.0001
H14	104.7996	109.4658	104.8000	104.7975	104.8000	109.4702	105.1059
H15	75.0002	79.2448	75.0000	75.0041	75.0000	79.2433	75.3317
H16	104.8002	107.7917	104.8000	104.7979	104.8000	107.7938	105.5008
H17	75.0003	80.1479	75.0000	75.3439	75.0000	80.1432	77.6253
H18	40.0001	40.0005	40.0000	39.9964	40.0000	40.0006	40.0327
H19	19.9998	20.0003	20.0000	20.0000	20.0000	20.0013	19.9935
H20	470.4001	453.3496	470.4000	470.0659	470.3999	453.3426	466.4196
H21	60.0000	60.0000	60.0000	60.0000	60.0000	60.0000	59.9905
H22	59.9999	59.9996	60.0000	59.9997	60.0000	60.0000	59.9999
H23	120.0000	120.0000	120.0000	119.9962	120.0000	120.0000	119.9999
H24	120.0000	119.9997	120.0000	119.9984	120.0000	120.0000	120.0000
Min cost	57,877.7231	57,942.5577	57,935.0000	57,831.3033	**57,825.4430**	57,959.4100	57,888.5661
Mean cost	57,995.0317	57,946.0934	57,940.0000	57,852.0847	**57,849.0613**	57,959.9200	57,903.3218
Max cost	58,147.1711	57,953.3522	57,945.0000	**57,887.5972**	57,918.7750	57,960.7300	57,955.1651

Note: The bold font indicate the best value.

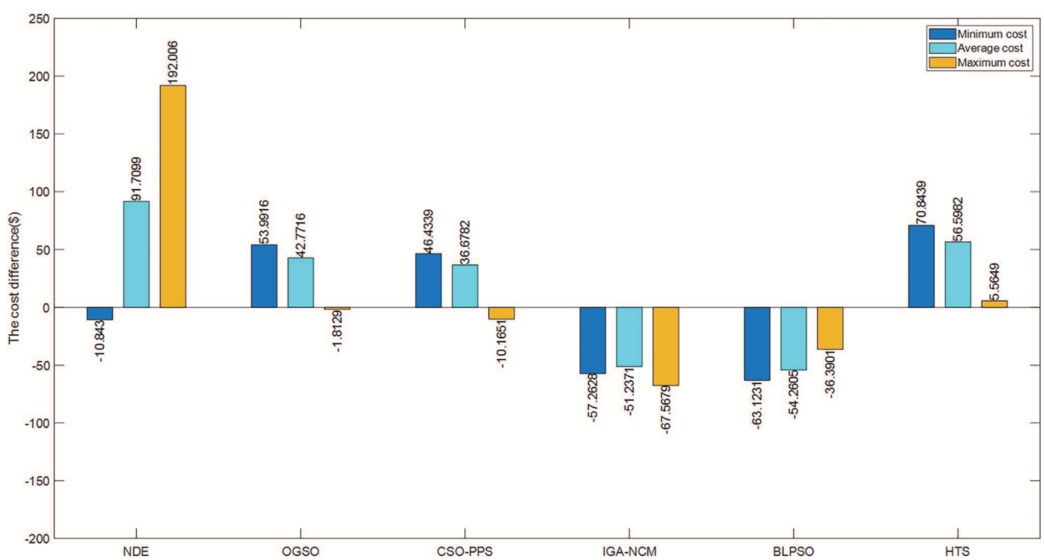

Figure 11: Cost savings of IDE-EO compared to other algorithms for case 2 of the 24-unit system

6.2.2 CHPED System 2 with 84 Units

This test contains 84 units, of which 1–40 are POUs, 41–64 are CHP units, and 65–84 are HOUs, and the total demand for power is 12,700 MW and the total demand for heat is 5000 MWth. Table 4 provides the compared results of DE-IEO, from which it can be seen that all three indexes are the best without violating the FOR constraint. Fig. 12 shows the position of the CHP unit results on FOR obtained by WOA at unit 84, and it can be seen that the solutions obtained by WOA are outside their regional range, which further proves that although WOA obtains the minimum cost, its solution is invalid; for MPHS, similar to WOA, Fig. 13 is showing that the solution it obtains is invalid. Fig. 14 depicts the cost savings of DE-IEO compared to other algorithms in terms of minimum cost, it can be seen DE-IEO is the best in terms of minimum cost.

Table 4: The 84-unit test system obtained the best dispatch results by different algorithms

Output	WOA [9]	NDE [15]	NDIDE [36]	MGOA-IHHO [38]	MPHS [59]	DE-IEO
P1	110.8794	110.9707	113.9236	113.9639	113.9557	113.9984
P2	112.2931	110.9661	113.8767	45.0939	113.2521	113.9980
P3	98.1159	120.0000	98.4608	60.3977	98.8762	97.3997
P4	129.8682	179.7429	179.7476	189.9998	179.7497	179.5850
P5	88.6586	96.9863	96.9905	96.9994	95.8030	90.9996
P6	139.9998	139.9999	139.9944	82.2871	140.0000	139.9999
P7	196.1145	259.8043	272.3862	287.9319	268.7403	300.0000
P8	295.0226	284.7824	286.2030	299.9846	285.4014	300.0000
P9	284.6146	284.6009	287.1768	299.5260	286.4166	299.9977
P10	279.6016	204.8187	204.8137	299.9578	205.0934	204.8007
P11	318.4002	318.4047	318.4028	178.4450	168.8124	318.4014
P12	318.4004	243.6017	243.6041	374.7148	168.8851	243.6021
P13	394.2803	304.5403	394.2916	499.5367	394.2240	304.5206
P14	484.2888	394.2830	394.3059	499.9994	484.0350	394.2797
P15	484.0382	394.2814	394.2887	496.8895	394.2865	394.2806
P16	304.6382	394.2788	394.2848	499.9580	394.2512	394.2792
P17	489.6014	489.2845	489.3710	499.9989	489.3601	489.4827
P18	489.2782	489.3036	489.3234	499.8636	489.3589	489.3515
P19	511.9256	511.2869	511.3071	549.9999	511.9201	511.4482
P20	511.3778	511.3094	511.3503	506.0962	511.3400	511.5581
P21	433.5245	523.2839	523.3430	547.4043	525.5076	523.3371
P22	433.5316	523.2929	523.4627	550.0000	523.5785	523.3069
P23	523.2806	523.3151	523.3649	540.9894	523.4343	523.0553
P24	523.2888	523.3107	523.3476	549.9992	523.7584	523.3565
P25	523.2889	523.2899	523.4283	549.7193	523.7573	526.4715
P26	524.0590	523.2916	524.1057	254.0004	523.8777	527.3658
P27	10.0000	10.0073	10.0252	10.1934	10.0039	10.0002
P28	10.0000	10.0000	10.0325	10.0393	10.0903	10.0014
P29	11.2485	10.0214	10.0359	10.2201	10.0012	10.0049
P30	91.0437	96.9726	96.9874	54.5123	96.9912	96.9996
P31	189.9732	190.0000	189.9914	190.0000	189.9995	190.0000
P32	189.9997	189.9996	189.9831	184.9351	189.9932	189.9999
P33	163.6655	189.9993	189.9836	189.7688	189.9954	190.0000
P34	165.1037	199.9853	199.9958	199.9549	169.3255	200.0000
P35	166.7651	199.9996	199.9954	182.4441	199.9967	199.9999
P36	165.8941	199.9985	199.9829	197.7731	189.6863	199.9999
P37	89.7967	109.9997	109.9856	109.9944	110.0000	110.0000
P38	109.9979	109.9940	109.9846	109.9839	109.9998	110.0000
P39	109.9994	110.0000	109.9888	109.8221	109.9919	109.9999
P40	516.5065	511.2860	511.2890	549.7720	511.4807	511.4836
P41	112.3421	88.6116	88.6480	81.0008	97.1804	88.6158

(Continued)

Table 4 (continued)

Output	WOA [9]	NDE [15]	NDIDE [36]	MGOA-IHHO [38]	MPHS [59]	DE-IEO
P42	50.4459	88.6183	88.6558	81.0360	43.3970	88.6125
P43	131.6591	88.6410	88.6753	81.0009	89.6268	88.6160
P44	57.3384	88.6321	88.6309	81.0004	45.1847	88.6318
P45	10.0991	74.7489	65.3087	40.0574	21.2282	61.2941
P46	44.2424	74.7537	63.7969	40.0004	48.3113	71.4713
P47	103.2198	74.7364	69.7281	40.0077	128.4079	70.9264
P48	40.2287	66.5573	62.1486	40.0160	59.2361	48.5486
P49	127.0797	88.6191	88.6938	81.4912	96.9275	88.6268
P50	65.5205	88.6257	88.6214	81.0055	56.1951	88.6181
P51	20.6157	88.6278	88.6584	81.0009	19.4934	88.6270
P52	56.4012	88.6139	88.6214	81.0008	58.3874	88.6118
P53	168.9969	74.7596	71.2078	40.0207	137.1533	64.4439
P54	40.4449	71.4724	53.9736	40.9298	54.4494	60.8882
P55	101.1777	74.5525	66.4895	40.1157	135.4933	67.8100
P56	55.7835	70.0378	62.8506	40.0219	73.2057	60.6902
P57	10.0560	14.8769	10.0581	10.0001	22.5826	12.6005
P58	64.4182	10.9314	12.1706	10.0000	48.4507	11.2701
P59	152.2648	10.0338	10.0624	10.1697	114.4764	12.8446
P60	56.1164	14.4111	11.3126	10.1295	61.8714	24.8054
P61	123.1718	57.6794	46.0399	35.1355	134.5865	53.9351
P62	46.9576	49.9320	60.0857	66.7188	58.7020	38.0400
P63	11.9343	69.9609	48.2139	66.6428	14.2665	70.6061
P64	57.1203	60.2725	63.9320	38.3275	45.9687	55.1003
H41	122.3890	60.0000	59.9967	104.8001	113.7627	59.9998
H42	84.0170	59.9981	59.9982	104.7793	77.8321	59.9999
H43	133.2295	59.9999	59.9931	104.7973	109.4936	60.0000
H44	89.9664	60.0000	59.9984	104.7997	79.4565	60.0000
H45	40.0414	104.9943	96.8438	74.5404	44.7352	93.3821
H46	24.2001	104.9991	95.5396	74.9988	26.0250	102.1675
H47	115.7242	104.9846	100.6608	74.9062	131.1739	101.6971
H48	75.1974	97.9215	94.1123	74.9903	91.5396	82.3795
H49	130.6574	59.9999	59.9954	104.2382	113.4407	59.9999
H50	97.0303	59.9930	59.9987	104.7756	88.9429	60.0000
H51	44.5495	59.9991	59.9890	104.8000	44.0508	59.9998
H52	29.7277	59.9999	59.9992	104.7965	30.6049	59.9999
H53	154.1830	105.0000	12.1706	74.7035	136.0749	96.1011
H54	75.3759	102.1656	10.0624	72.6757	87.4415	93.0316
H55	116.1224	104.8266	11.3126	73.8865	135.2714	99.0069
H56	88.6239	100.9294	46.0399	74.8688	103.6541	92.8607
H57	39.7995	42.0901	60.0857	40.0000	45.3681	41.1145
H58	33.3716	40.3991	48.2139	40.0000	25.9449	40.5443
H59	144.7767	40.0134	63.9320	39.5006	123.3418	41.2191
H60	88.9117	41.8880	59.9967	39.8988	93.8406	46.3452
H61	128.4364	30.3031	59.9982	10.0286	134.6699	28.6068
H62	81.0055	26.7855	59.9931	34.3092	91.1235	21.3817
H63	40.8289	35.8866	59.9984	26.7368	41.6933	36.1845
H64	30.0546	31.4840	96.8438	17.1219	24.7914	29.1365
H65	383.1144	474.7555	95.5396	563.1890	389.4986	511.1468
H66	59.9997	492.6328	100.6608	710.7487	59.9997	514.8792
H67	60.0000	501.3137	94.1123	444.7412	59.9980	512.5061
H68	119.9855	496.6532	59.9954	419.1562	119.9399	496.3316
H69	119.9990	60.0000	59.9987	49.8212	119.9995	59.9998
H70	402.6530	60.0000	59.9890	56.7435	388.5823	59.9996

(Continued)

Table 4 (continued)

Output	WOA [9]	NDE [15]	NDIDE [36]	MGOA-IHHO [38]	MPHS [59]	DE-IEO
H71	59.8978	59.9994	59.9992	55.2654	59.9997	59.9999
H72	59.9998	60.0000	59.9961	56.1039	59.9890	60.0000
H73	119.9996	59.9999	59.9973	52.0895	119.8977	60.0000
H74	119.9999	59.9981	59.9966	35.2498	119.9265	60.0000
H75	385.5340	59.9997	59.9962	42.0358	385.8941	59.9998
H76	58.9464	59.9999	59.9935	51.5522	59.9999	59.9999
H77	59.9995	119.9996	119.9915	110.0105	59.9967	119.9987
H78	119.7982	119.9998	119.9986	48.2282	119.9970	119.9990
H79	119.9988	119.9965	119.9675	110.6309	119.8126	119.9953
H80	381.8642	119.9976	119.9690	99.1204	402.4022	119.9996
H81	59.9999	119.9954	119.9914	95.6548	59.9995	119.9900
H82	59.9991	119.9996	119.9870	114.8333	59.9995	120.0000
H83	119.9980	119.9988	119.9904	119.6124	120.0000	119.9962
H84	119.9982	119.9998	119.9855	84.2604	119.8582	120.0000
Min cost	290,123.97424	297,398.3793	297,510.0000	303,840.6880	288,157.4297	297,338.9698
Mean cost	290,947.9406	297,558.9311	297,978.0000	–	–	297,520.8086
Max cost	291,347.9406	297,793.9152	298,779.0000	–	–	297,693.3681

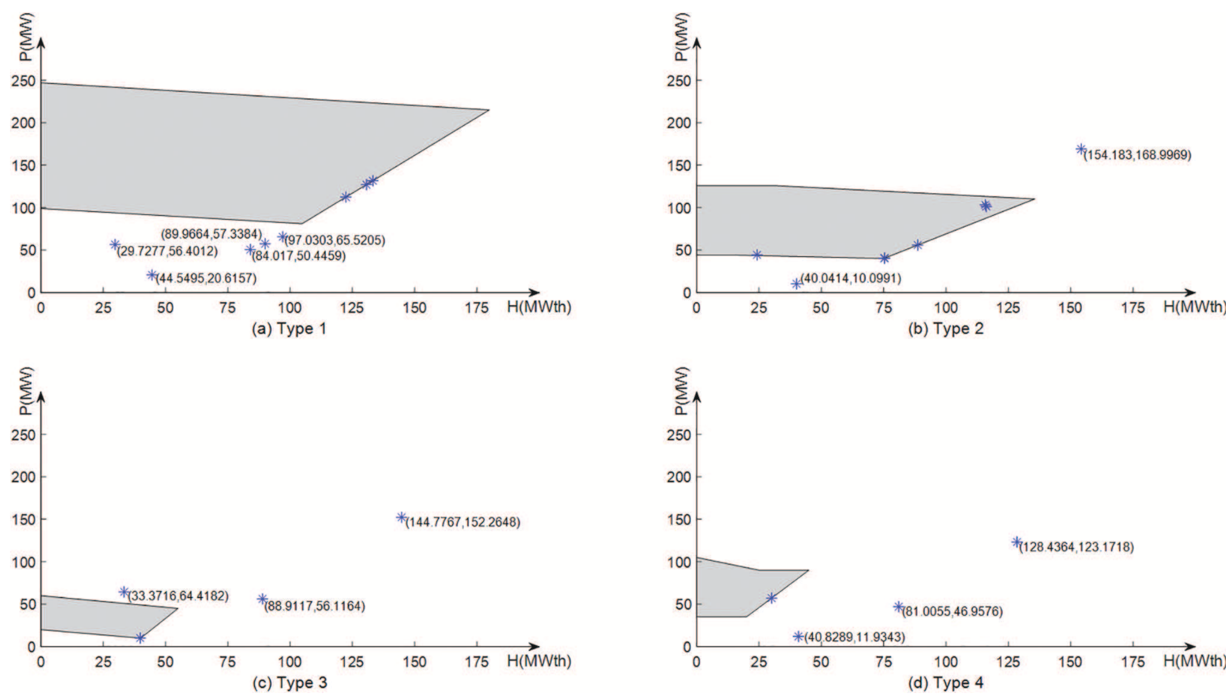

Figure 12: Location of WOA in the FOR of the 84-unit system

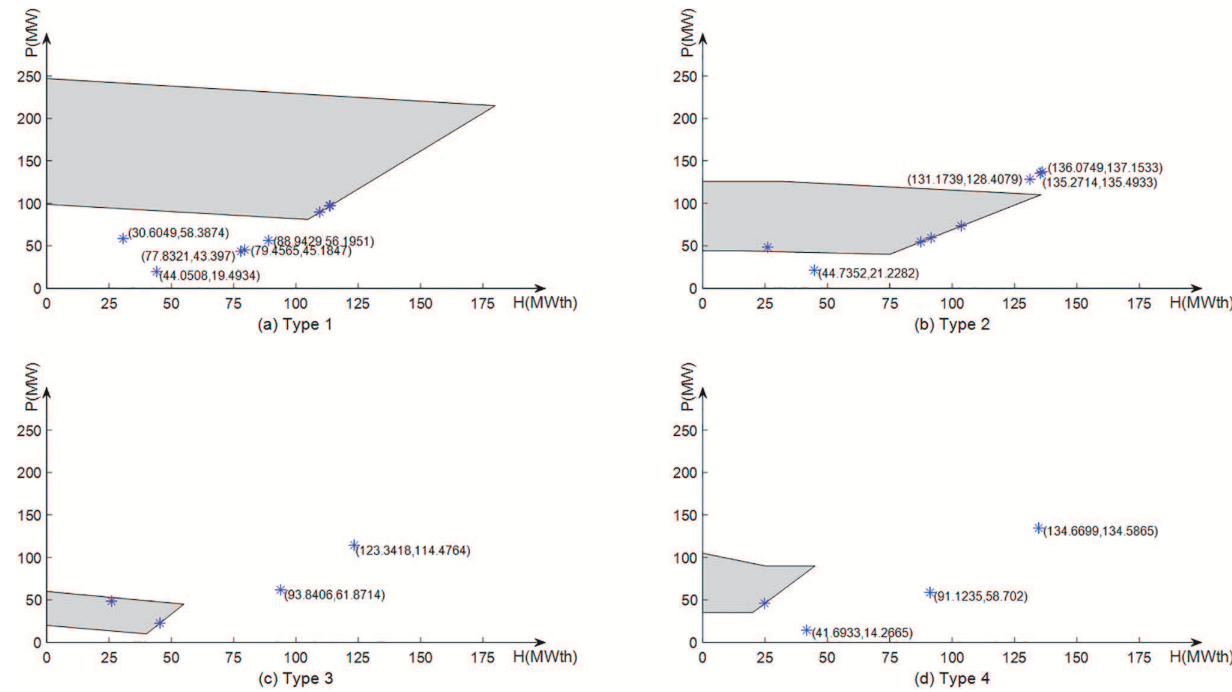

Figure 13: Location of MPHS in the FOR of the 84-unit system

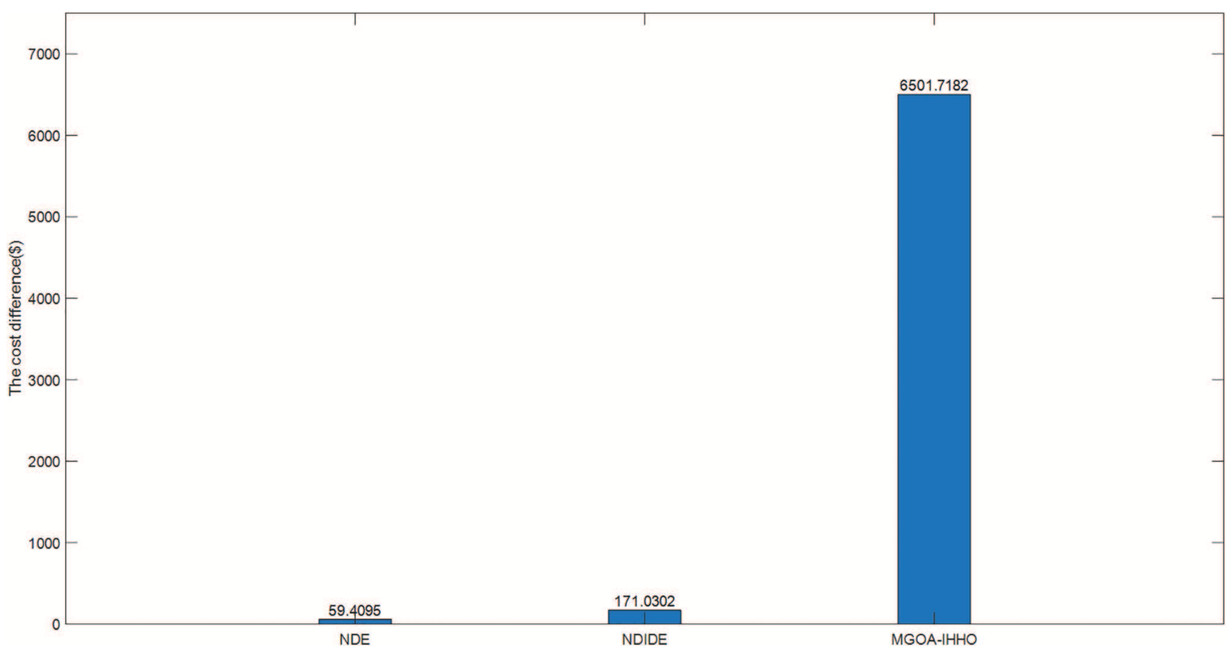

Figure 14: Minimum cost savings of IDE-EO compared to other algorithms in 84 unit system

6.2.3 CHPED System 3 with 96 Units

This test system contains 96 units, of which 1–52 are POUs, 53–76 are CHP units, and 77–96 are HOUs, and the total demand for power is 9400 MW and the total demand for heat is 5000 MWth.

Table 5 shows the results of comparing DE-IEO with other algorithms, which includes WOA, NDE, and NDIDE. Fig. 15 is DE-IEO obtains the minimum cost, which is the best among all the algorithms, and the maximum and average cost also get the best results. Compared with the small-scale CHPED system case with 24 units, DE-IEO is obviously more advantageous for the large-scale problem.

Table 5: The 96-unit test system obtained the best dispatch results by different algorithms

Output	WOA [9]	NDE [15]	NDIDE [36]	DE-IEO	Output	WOA [9]	NDE [15]	NDIDE [36]	DE-IEO
P1	361.6989	448.7989	359.8335	269.2850	P63	33.3173	10.5143	10.1104	11.5681
P2	225.5924	149.6099	149.8092	0.7667	P64	59.7067	49.7249	35.0890	49.4598
P3	224.3946	299.2000	225.0407	225.8237	P65	100.4416	91.2397	81.2344	84.9449
P4	110.8030	159.7331	110.2676	110.0675	P66	74.1967	60.9464	46.7759	48.2344
P5	110.0061	109.8666	110.6198	110.7603	P67	120.2089	112.4783	90.4141	99.5746
P6	159.6156	159.7331	160.3067	109.9098	P68	61.1074	51.0796	47.6527	42.8284
P7	109.8526	159.7332	113.9236	109.9010	P69	11.0113	16.1096	10.1191	10.1007
P8	110.3586	109.8666	110.7848	159.7349	P70	69.0899	39.8839	37.2848	43.2156
P9	160.0915	109.8666	111.4883	159.7448	P71	122.8034	117.0076	88.7498	89.1158
P10	114.8006	77.4001	77.7165	114.0565	P72	49.2350	41.0784	53.4230	49.8041
P11	114.9807	77.3999	78.9346	40.2137	P73	115.1764	102.3438	83.3692	90.9708
P12	92.3721	55.0000	93.1258	92.4343	P74	43.7841	67.0384	46.0345	52.2273
P13	92.4525	55.0001	92.6119	92.2403	P75	10.2339	10.0146	10.0826	10.3678
P14	359.0854	359.0392	448.8556	359.0892	P76	36.5443	35.4658	39.0234	35.2291
P15	225.1433	224.4096	299.2677	360.0000	H53	121.6489	109.0715	112.7052	105.8966
P16	229.5487	230.0986	299.7252	151.9140	H54	99.6187	85.4346	82.7894	76.0687
P17	164.3339	109.8666	160.1781	159.7409	H55	112.9517	111.2016	104.7315	110.9962
P18	160.2151	109.8666	110.1232	111.2855	H56	92.9964	90.5497	83.8238	77.6274
P19	159.9402	159.7331	160.5795	109.8685	H57	45.8595	40.5010	40.1835	47.7112
P20	109.9636	159.7331	160.2275	159.7587	H58	22.7261	20.7560	19.9847	23.7354
P21	146.0127	109.8666	110.0585	109.9504	H59	137.7969	110.2504	113.2290	110.9348
P22	120.0047	109.8666	110.3814	109.8807	H60	80.8243	89.1942	85.0588	86.7822
P23	77.9996	40.0001	111.1386	109.2600	H61	124.6482	114.8399	114.7792	125.9758
P24	77.4223	77.4000	78.6545	77.7314	H62	108.7221	96.3128	77.8401	88.0725
P25	92.4849	55.0000	92.3999	93.4233	H63	49.9249	40.2204	39.9734	40.6720
P26	93.9975	55.0003	93.1683	92.7736	H64	31.1612	26.6931	19.9439	26.5726
P27	359.1802	538.5588	359.8441	269.2955	H65	115.7042	110.5465	104.6872	107.0138
P28	299.9979	149.6223	227.1615	153.8858	H66	104.5144	93.0819	80.7769	82.1083
P29	224.7272	224.3996	227.3378	300.4100	H67	126.7515	122.4654	109.9522	115.2238
P30	159.8239	109.8667	159.9580	109.8822	H68	93.2126	84.5645	81.4566	77.4416
P31	160.1449	109.8666	161.0270	159.8843	H69	40.4142	42.6184	40.0103	40.0431
P32	124.3426	109.8667	160.5617	159.8387	H70	35.4893	22.2200	21.0155	23.7344
P33	159.7681	109.8667	110.1725	109.9305	H71	128.2524	125.0072	109.0655	109.3546
P34	109.9525	159.7332	110.3539	159.7526	H72	82.9501	75.9309	86.5523	83.4634
P35	110.0723	109.8666	160.0424	110.2591	H73	123.9395	116.7780	105.7732	110.3956
P36	78.0018	77.3999	78.4186	114.8816	H74	78.2419	98.3408	80.0655	85.5552
P37	77.4827	40.0000	82.1891	114.9400	H75	39.1403	40.0062	39.9329	40.1576
P38	66.6749	92.4000	94.5274	92.8637	H76	20.4940	20.2117	21.7251	20.1041
P39	92.4487	92.4000	92.5797	120.0000	H77	407.0662	424.9316	461.7811	434.7314
P40	180.3641	628.3186	448.8420	538.5646	H78	59.7975	60.0000	59.8977	60.0000
P41	224.5898	299.1995	224.7125	360.0000	H79	59.9911	60.0000	59.9262	59.9994
P42	224.4866	224.4023	225.0088	360.0000	H80	119.2458	120.0000	119.9210	119.9978
P43	109.6226	109.8666	160.1359	60.8726	H81	119.9549	120.0000	119.9006	119.9950
P44	109.8456	60.0000	160.1469	109.8706	H82	390.1828	432.7141	437.9845	421.2480
P45	65.8336	109.8666	110.6488	159.7454	H83	59.9729	60.0000	59.9791	59.9993
P46	159.6880	159.7331	110.4907	110.1677	H84	59.9805	60.0000	59.9609	60.0000
P47	116.6052	159.7331	110.1052	159.7473	H85	119.9912	120.0000	117.5132	119.9927
P48	159.2737	159.7331	159.7279	109.9183	H86	119.6621	120.0000	119.7310	119.9993

(Continued)

Table 5 (continued)

Output	WOA [9]	NDE [15]	NDIDE [36]	DE-IEO	Output	WOA [9]	NDE [15]	NDIDE [36]	DE-IEO
P49	78.0268	77.4001	78.0201	115.8004	H87	368.0236	410.1485	444.5562	419.6894
P50	77.5176	77.4000	80.9676	77.6272	H88	59.9905	60.0000	59.9736	59.9999
P51	92.8301	92.4000	92.4166	94.0631	H89	59.9849	60.0000	59.8821	59.9965
P52	85.2843	92.4000	93.8317	92.8973	H90	119.9669	120.0000	119.9620	119.9979
P53	111.0331	88.6115	95.3384	82.9541	H91	119.9050	120.0000	119.8456	119.9978
P54	68.5580	52.0876	49.2064	41.2380	H92	378.9529	405.4087	443.9475	468.8073
P55	95.6342	92.4071	81.2095	92.0412	H93	59.5063	60.0000	59.9727	59.9999
P56	60.8717	58.0131	50.2848	43.0437	H94	59.9907	60.0000	59.9575	59.9995
P57	23.7300	11.1690	10.4838	27.9929	H95	119.9904	120.0000	119.5557	119.9091
P58	41.3490	36.6633	35.1457	43.2179	H96	119.8607	120.0000	119.6960	119.9988
P59	139.9448	90.7121	96.3764	91.9317	**Min cost**	236,699.1501	233,246.0000	232,871.0000	**232,862.5238**
P60	46.8012	56.4428	51.6781	53.6487	**Mean cost**	237,431.4678	234,217.3757	233,604.0000	**233,417.3561**
P61	116.4269	98.8903	99.0994	118.7334	**Max cost**	238,877.0492	234,840.4640	234,298.0000	**234,170.6291**
P62	79.0704	64.6891	43.3653	55.1434					

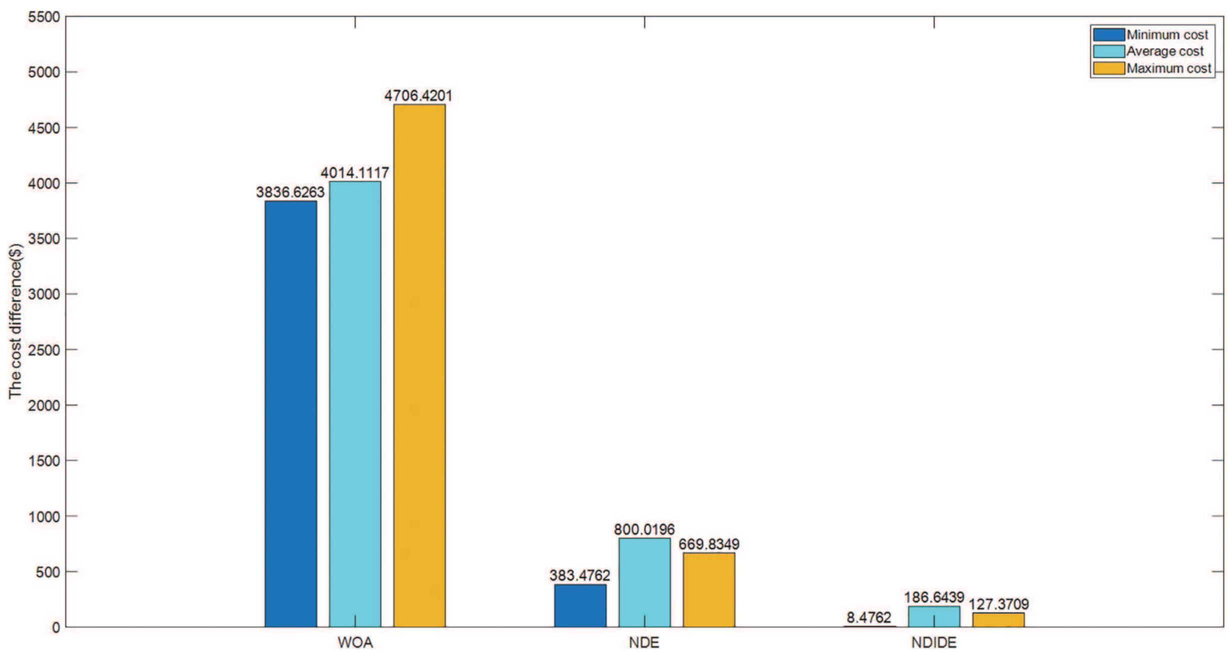

Figure 15: Cost savings of IDE-EO compared to other algorithms for the 96-unit system

6.2.4 CHPED System 4 with 192 Units

This section test systems contain 192 units, of which 1–104 are POUs, 105–152 are CHPUs, and 153–192 are HOUs, and the total demand for power is 18,800 MW and the total demand for heat is 10,000 MWth. Table 6 shows the comparison results, Fig. 16 shows that DE-IEO achieves the best results are superiority of DE-IEO on the large-scale systems.

Table 6: The 192-unit test system obtained best dispatch results by different algorithms

Output	NDE [15]	NDIDE [36]	DE-IEO	Output	NDE [15]	NDIDE [36]	DE-IEO
P1	448.7991	359.8190	359.0439	P123	114.8009	106.5853	83.1355
P2	299.1994	300.2693	150.1586	P124	56.3723	40.6537	64.5295
P3	224.3995	300.1580	226.2082	P125	87.9206	94.5047	94.9296
P4	109.8673	110.5775	159.7901	P126	43.0774	51.0150	42.3901
P5	159.7331	110.6040	159.7330	P127	12.1350	10.8847	10.4361
P6	159.7334	110.2757	109.8982	P128	52.8768	37.9711	40.0966
P7	109.8667	110.3442	109.7605	P129	105.0870	106.0862	89.3204
P8	159.7331	160.5056	109.8831	P130	45.2073	49.8803	73.5536
P9	109.8666	160.0503	109.9181	P131	110.8268	83.6626	108.1283
P10	77.4001	78.5900	77.4945	P132	58.4036	42.1933	62.0202
P11	40.0001	77.8194	77.7325	P133	18.2300	10.2333	10.1025
P12	92.4000	93.3934	92.4760	P134	49.4442	38.5382	48.2080
P13	92.4006	92.5907	55.4122	P135	94.0965	83.9268	107.3109
P14	89.7607	449.0304	269.2831	P136	54.8961	45.7243	47.3068
P15	224.3994	226.6429	77.8307	P137	106.3187	93.4599	98.9137
P16	299.1994	300.2088	228.7587	P138	67.6949	48.3688	48.4636
P17	109.8666	110.3179	159.7423	P139	19.1281	10.3802	10.2862
P18	159.7334	162.2735	109.7447	P140	38.0917	50.9006	52.1772
P19	109.8668	159.9375	109.9347	P141	98.6561	101.3751	82.5672
P20	109.8666	110.1202	159.7973	P142	58.3583	52.1310	80.7201
P21	159.7332	123.1314	159.7455	P143	93.7549	94.3336	106.6918
P22	109.8666	111.6709	109.9961	P144	52.6396	50.0807	78.3109
P23	77.4006	78.9207	77.7811	P145	22.7250	11.5578	12.4278
P24	40.0001	116.5739	114.8206	P146	50.2207	41.2990	49.7997
P25	92.4000	92.7614	92.4304	P147	95.7770	100.8876	88.3636
P26	92.4001	93.3612	92.4179	P148	75.4567	60.7994	41.6690
P27	628.3195	449.6826	359.0418	P149	112.4619	90.4803	102.5957
P28	0.0015	300.5840	225.2349	P150	50.3767	52.7240	44.5102
P29	224.3995	150.8773	151.5253	P151	10.5137	10.2001	10.4093
P30	60.0003	110.0028	159.7468	P152	54.7299	44.2285	50.6006
P31	159.7332	110.6543	109.8890	H105	126.8681	108.0110	108.0688
P32	109.8666	159.9055	159.7422	H106	100.4397	92.0469	96.7033
P33	159.7331	110.5652	159.7629	H107	121.6008	119.1387	118.3001
P34	60.0003	160.3906	109.8941	H108	93.2388	92.4412	107.8583
P35	109.8668	110.1470	159.7420	H109	42.2528	40.0184	40.1495
P36	77.4001	79.2549	114.9689	H110	21.0775	20.1508	23.7345
P37	77.3999	114.5574	77.8105	H111	118.5522	111.7146	123.9821
P38	92.3999	93.2638	92.5113	H112	100.4417	78.7793	90.9924
P39	92.4000	93.0990	92.4834	H113	109.2960	105.7310	127.5820
P40	628.3185	449.0728	448.8057	H114	105.5847	98.4330	83.1796
P41	224.3997	226.5377	225.9281	H115	40.7587	40.0930	40.0317
P42	299.1997	226.4568	80.5254	H116	27.3102	25.3100	21.2119
P43	109.8666	111.0785	109.9000	H117	118.7924	105.8894	110.6765
P44	159.7334	111.4555	109.9010	H118	99.5006	83.4289	96.0639
P45	159.7331	159.8342	109.9271	H119	123.8145	110.0348	108.7315
P46	159.7332	110.7954	109.9522	H120	101.8217	87.9038	92.5208
P47	159.7333	160.1631	109.8882	H121	40.2040	40.2430	40.1797
P48	159.7331	110.5514	109.8947	H122	33.1114	20.1301	26.6605
P49	77.4001	115.1942	77.4576	H123	123.7687	119.1292	105.9982
P50	77.4000	79.2575	78.3565	H124	89.1333	75.5551	96.1749
P51	55.0009	93.3634	92.5368	H125	108.6838	112.1128	112.6168
P52	92.3999	92.8283	92.4775	H126	77.6565	84.3889	77.0631
P53	448.7990	359.6493	538.5641	H127	40.9149	40.3304	40.1869

(Continued)

Table 6 (continued)

Output	NDE [15]	NDIDE [36]	DE-IEO	Output	NDE [15]	NDIDE [36]	DE-IEO
P54	299.1999	226.1268	301.4999	H128	28.1258	21.2665	22.3164
P55	299.1994	225.5070	301.7183	H129	118.3173	118.5414	109.4689
P56	159.7332	110.6638	159.7447	H130	79.4952	83.3564	103.9645
P57	109.8669	160.9112	159.7469	H131	121.5386	106.1234	120.0240
P58	109.8666	160.4427	109.8789	H132	90.8869	76.7697	94.0086
P59	109.8668	110.6853	159.7441	H133	43.5271	39.9439	40.0437
P60	109.8666	109.9517	109.8741	H134	26.5655	21.5402	26.0033
P61	109.8665	111.2179	159.7384	H135	112.1496	106.2641	119.5652
P62	77.3999	78.1848	114.8119	H136	87.8590	79.8917	81.3075
P63	114.8004	116.0606	114.8263	H137	119.0086	111.6262	114.8522
P64	92.4005	57.9754	92.4860	H138	98.9075	82.1655	82.3062
P65	92.4001	93.4726	119.9995	H139	43.9121	40.0858	40.1226
P66	359.0395	449.7110	448.8080	H140	21.4053	27.1023	27.8077
P67	275.1901	300.3172	152.4077	H141	114.7083	116.1379	105.6785
P68	224.3997	225.3556	227.4233	H142	90.8477	85.4249	110.1514
P69	109.8666	159.8383	109.9572	H143	111.9579	112.1387	119.2174
P70	60.0000	110.4954	159.7574	H144	85.9111	83.6943	108.0716
P71	159.7333	160.5701	60.0140	H145	45.4535	40.6103	41.0404
P72	159.7332	111.0250	109.9013	H146	26.9185	22.8268	26.7271
P73	159.7332	160.1128	109.8947	H147	113.0927	115.7804	108.9323
P74	109.8665	160.1580	159.7376	H148	105.6079	92.8750	76.4407
P75	77.4000	77.7016	77.5430	H149	122.4562	110.1027	111.3191
P76	40.0008	78.0129	77.9274	H150	83.9576	85.8987	78.8932
P77	92.3999	93.5273	92.4935	H151	40.2201	39.9246	40.1754
P78	92.4000	93.3458	92.4976	H152	28.9681	24.1304	20.0911
P79	269.2795	270.6223	359.0414	H153	405.7596	430.1251	417.4177
P80	299.1993	156.5600	231.8119	H154	60.0000	59.9937	59.9987
P81	224.3995	224.8400	300.0463	H155	60.0000	59.9128	59.9934
P82	109.8670	160.4733	109.8842	H156	119.9999	119.5797	119.9989
P83	109.8667	110.3437	109.8727	H157	120.0000	119.8573	119.9979
P84	159.7330	160.1064	109.8977	H158	429.6657	391.8788	436.9916
P85	109.8666	160.6580	159.7690	H159	59.9999	59.9295	59.9960
P86	109.8671	110.7468	109.8679	H160	59.9999	59.9753	59.9979
P87	109.8667	110.5070	109.8848	H161	120.0000	119.8566	119.9974
P88	114.8000	77.8310	77.4313	H162	120.0000	119.0570	119.9880
P89	77.4002	78.1304	77.5022	H163	400.5420	407.9893	438.3980
P90	92.3999	92.7103	92.4108	H164	60.0000	59.9223	59.9992
P91	92.4003	94.5945	93.3295	H165	60.0000	59.9598	59.9999
P92	448.7991	359.6790	538.5590	H166	120.0000	119.8682	119.9984
P93	224.3999	150.4347	224.9692	H167	119.9998	119.7763	119.9516
P94	74.7998	151.2860	227.6759	H168	405.2696	434.8725	399.8958
P95	159.7332	110.6891	109.8967	H169	60.0000	59.9171	59.9992
P96	60.0004	110.3779	159.7393	H170	60.0000	59.9752	59.9990
P97	159.7336	161.9415	109.9582	H171	119.9999	119.8325	119.9807
P98	159.7336	160.2018	109.8915	H172	120.0000	119.8479	119.9792
P99	109.8671	110.4313	159.7474	H173	362.5547	450.9202	396.5107
P100	109.8665	161.3671	109.9802	H174	60.0000	59.9609	59.9991
P101	40.0003	115.5733	77.7198	H175	60.0000	59.9699	59.9991
P102	77.4000	77.9125	114.8778	H176	119.9999	119.8981	119.9543
P103	55.0000	92.9338	92.6127	H177	119.9998	119.9432	119.9875
P104	55.0005	93.6971	92.5366	H178	386.8036	443.6538	377.8577
P105	120.3236	87.0167	86.8253	H179	60.0000	59.9828	59.9998
P106	69.4698	59.7920	65.1416	H180	60.0000	59.9943	59.9941

(Continued)

Table 6 (continued)

Output	NDE [15]	NDIDE [36]	DE-IEO	Output	NDE [15]	NDIDE [36]	DE-IEO
P107	110.9377	106.5770	105.0565	H181	120.0000	119.7978	119.9855
P108	61.1282	60.3208	78.0637	H182	120.0000	119.8313	119.9969
P109	15.2566	10.1058	10.3490	H183	382.2037	479.0853	401.9777
P110	37.3705	35.5932	43.2159	H184	60.0000	59.9313	59.9972
P111	105.5059	93.5223	115.1811	H185	60.0000	59.9317	59.9998
P112	69.4722	44.5167	58.5261	H186	120.0000	119.9242	119.9789
P113	89.0118	83.0336	121.5961	H187	119.9999	119.8605	119.9545
P114	75.4298	67.3508	49.4758	H188	420.5815	430.2805	421.4568
P115	11.7704	10.3745	10.0740	H189	60.0000	59.9725	59.9995
P116	51.0824	46.8361	37.6663	H190	59.9999	59.9793	59.9966
P117	105.9335	83.3263	91.4718	H191	120.0000	119.8694	119.9943
P118	68.3819	49.7926	64.4010	H192	120.0000	119.8503	119.9856
P119	114.8823	90.4210	88.0062	**Min cost**	469,242.9695	466,910.0000	466,858.6147
P120	71.0706	55.0573	60.2964	**Mean cost**	470,541.6368	468,316.0000	468,069.3054
P121	10.4761	10.7142	10.4193	**Max cost**	472,200.6389	469,983.0000	469,183.9489
P122	63.8450	35.3932	49.6532				

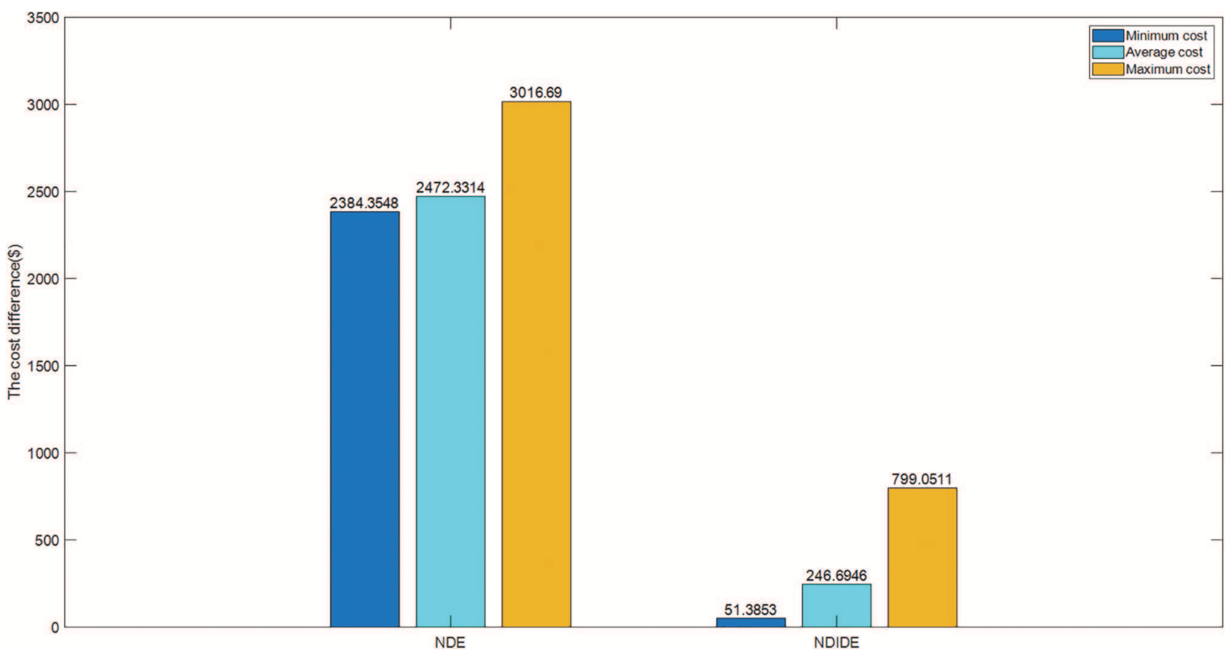

Figure 16: Cost savings of IDE-EO compared to other algorithms for the 24-unit system

6.3 Results and Discussion

The performance of DE-IEO are evaluated on the CEC2017 test suite and the CHPED. For the first part of the experiments, 29 standard test functions in the CEC2017 test suites are selected to benchmark the performance of DE-IEO in this paper. In Table 1, DE-IEO ranks first among all algorithms. Among the 29 test functions, DE-IEO achieves the optimal mean 18 times. Among the four types of functions, DE-IEO can reach the optimum, which shows that DE-IEO has more comprehensive performance, especially in multimodal and hybrid functions DE-IEO has more advantages, which is also more conducive to the solution of the CHPED problem to be discussed. Compared with EO and DE, the hybrid algorithm achieves optimality on more than half of the functions, which fully indicates that DE-IEO, which is made by combining EO and DE, is very successful. Specifically, from Figs. 4–6, the convergence speed of DE-IEO is not the fastest, but the final result achieved is the best. From the convergence curve, we can also find that EO tends to stop converging earlier than DE-IEO, which is the characteristic of falling into local optimum, while DE can keep converging slowly, so mixing the two can achieve a better convergence effect. It is evident from Figs. 7–9 that DE-IEO has narrower boxplots for most functions, indicating that it is more stable compared to other algorithms; it is also evident that DE-IEO has relatively lower boxplots, indicating that the results obtained are closer to the theoretical optimum. In addition, the mutation and crossover steps in DE can well help EO to jump out of local optimum and avoid premature maturity of the algorithm, while the selection steps in DE can ensure better individuals are inherited to the next generation, which can ensure the excellent performance of DE-IEO in test functions and real-world problems. Although DE-IEO performs well on the test function, it is not enough to prove that DE-IEO has excellent performance on real problems, because the constraints in real problems are much more complex than the test function, such as the CHPED problem. Based on this, a second part of experiments is also designed in this paper to demonstrate the excellent performance of DE-IEO in solving real-world problems.

For the second part of the experiment, 4 test cases of the CHPED problem are selected for analysis and discussion to demonstrate the superior performance of DE-IEO. Figs. 10–11 and Figs. 14–16 show that DE-IEO did not obtain the best results for all three metrics for the 24-unit system, but the best results were obtained for the 84-, 96-, and 192-unit CHPED systems. This indicates that DE-IEO has obvious advantages in solving large-scale CHPED problems.

7 Conclusion and Future Work

The main contributions of this paper are outlined: (1) A novel hybrid DE-IEO algorithm is introduced. (2) The DE-IEO is utilized to optimize the CEC2017 test suite, with detailed experimental results confirming its validity while discarding any invalid outcomes. (3) The DE-IEO has been effectively employed to tackle large-scale CHPED problems, where it is compared against ten other high-performing algorithms. The results indicate that DE-IEO achieves superior outcomes on most of the tested functions. Additionally, DE-IEO is tested on six CHPED cases, including systems with 24, 84, 96, and 192 units, with numerous figures and tables demonstrating its significant advantages in large-scale CHPED scenarios. DE-IEO proves to be competitive in both test functions and practical applications. Future research will explore: (1) Integrating wind, tidal, and other power generation methods with the CHPED problem, while also addressing environmental pollution to create a multi-objective problem. (2) Investigating the multi-region CHPED problem as a potential research avenue. (3) Applying DE-IEO to other optimization challenges, such as microgrid energy management, image threshold segmentation, and data clustering.

Acknowledgement: This work was supported by the National Natural Science Foundation of China. Thanks.

Funding Statement: This work was supported by the Scientific Research Project of Xiangsihu College of Guangxi Minzu University, Grant No. 2024XJKY06, and the National Natural Science Foundation of China under Grant No. U21A20464.

Author Contributions: Yuanfei Wei: writing—draft; Panpan Song: Investigation, experiment; Qifang Luo: Algorithm design, writing—review; Yongquan Zhou: Supervision, writing—review and editing. All authors reviewed the results and approved the final version of the manuscript.

Availability of Data and Materials: Not applicable.

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest to report regarding the present study.

References

1. Ghorbani N. Combined heat and power economic dispatch using exchange market algorithm. Int J Electr Power Energy Syst. 2016;82(1):58–66. doi:10.1016/j.ijepes.2016.03.004.
2. Davoodi E, Zare K, Babaei E. A GSO-based algorithm for combined heat and power dispatch problem with modified scrounger and ranger operators. Appl Therm Eng. 2017;120(4):36–48. doi:10.1016/j.applthermaleng.2017.03.114.
3. Niknam T, Azizipanah-Abarghooee R, Roosta A, Amiri B. A new multi-objective reserve constrained combined heat and power dynamic economic emission dispatch. Energy. 2012;42(1):530–45. doi:10.1016/j.energy.2012.02.041.
4. Rooijers FJ, van Amerongen RAM. Static economic dispatch for co-generation systems. IEEE Trans Power Syst. 1994;9(3):1392–8. doi:10.1109/59.336125.
5. Rong A, Lahdelma R. An efficient envelope-based Branch and Bound algorithm for non-convex combined heat and power production planning. Eur J Oper Res. 2007;183(1):412–31. doi:10.1016/j.ejor.2006.09.072.
6. Abdolmohammadi HR, Kazemi A. A Benders decomposition approach for a combined heat and power economic dispatch. Energy Convers Manag. 2013;71(1):21–31. doi:10.1016/j.enconman.2013.03.013.
7. Sashirekha A, Pasupuleti J, Moin NH, Tan CS. Combined heat and power (CHP) economic dispatch solved using Lagrangian relaxation with surrogate subgradient multiplier updates. Int J Electr Power Energy Syst. 2013;44(1):421–30. doi:10.1016/j.ijepes.2012.07.038.
8. Mehdinejad M, Mohammadi-Ivatloo B, Dadashzadeh-Bonab R. Energy production cost minimization in a combined heat and power generation systems using cuckoo optimization algorithm. Energy Effic. 2017;10(1):81–96. doi:10.1007/s12053-016-9439-6.
9. Nazari-Heris M, Mehdinejad M, Mohammadi-Ivatloo B, Babamalek-Gharehpetian G. Combined heat and power economic dispatch problem solution by implementation of whale optimization method. Neural Comput Appl. 2019;31(2):421–36. doi:10.1007/s00521-017-3074-9.
10. Paul C, Roy PK, Mukherjee V. Optimal solution of combined heat and power dispatch problem using whale optimization algorithm. Int J Appl Metaheuristic Comput (IJAMC). 2022;13(1):1–26. doi:10.4018/ijamc.290532.
11. Zou D, Gong D. Differential evolution based on migrating variables for the combined heat and power dynamic economic dispatch. Energy. 2022;238(1):121664. doi:10.1016/j.energy.2021.121664.
12. Yang Q, Liu P, Zhang J, Dong N. Combined heat and power economic dispatch using an adaptive cuckoo search with differential evolution mutation. Appl Energy. 2022;307(1):118057. doi:10.1016/j.apenergy.2021.118057.
13. Mohammadi-Ivatloo B, Moradi-Dalvand M, Rabiee A. Combined heat and power economic dispatch problem solution using particle swarm optimization with time varying acceleration coefficients. Electr Power Syst Res. 2013;95(3):9–18. doi:10.1016/j.epsr.2012.08.005.
14. Basu M. Bee colony optimization for combined heat and power economic dispatch. Expert Syst Appl. 2011;38(11):13527–31. doi:10.1016/j.eswa.2011.03.067.
15. Liu D, Hu Z, Su Q, Liu M. A niching differential evolution algorithm for the large-scale combined heat and power economic dispatch problem. Appl Soft Comput. 2021;113(9):108017. doi:10.1016/j.asoc.2021.108017.
16. Wolpert DH, Macready WG. No free lunch theorems for optimization. IEEE Trans Evol Comput. 1997;1(1):67–82. doi:10.1109/4235.585893.
17. Faramarzi A, Heidarinejad M, Stephens B, Mirjalili S. Equilibrium optimizer: a novel optimization algorithm. Knowl Based Syst. 2020;191:105190. doi:10.1016/j.knosys.2019.105190.
18. Storn R, Price K. Differential evolution—a simple and efficient heuristic for global optimization over continuous spaces. J Glob Optim. 1997;11(4):341. doi:10.1023/A:1008202821328.
19. Abdel-Basset M, Mohamed R, Mirjalili S, Chakrabortty RK, Ryan MJ. MOEO-EED: a multi-objective equilibrium optimizer with exploration-exploitation dominance strategy. Knowl Based Syst. 2021;214(6):106717. doi:10.1016/j.knosys.2020.106717.

20. Wang J, Yang B, Li D, Zeng C, Chen Y, Guo Z, et al. Photovoltaic cell parameter estimation based on improved equilibrium optimizer algorithm. Energy Convers Manag. 2021;236(3):114051. doi:10.1016/j.enconman.2021.114051.
21. Ali Shaik M, Mareddy PL, Visali N. Enhancement of voltage profile in the distribution system by reconfiguring with DG placement using equilibrium optimizer. Alex Eng J. 2022;61(5):4081–93. doi:10.1016/j.aej.2021.09.063.
22. Houssein EH, Helmy BE, Oliva D, Jangir P, Premkumar M, Elngar AA, et al. An efficient multi-thresholding based COVID-19 CT images segmentation approach using an improved equilibrium optimizer. Biomed Signal Process Control. 2022;73(4):103401. doi:10.1016/j.bspc.2021.103401.
23. Liu J, Li W, Li Y. LWMEO: an efficient equilibrium optimizer for complex functions and engineering design problems. Expert Syst Appl. 2022;198(9):116828. doi:10.1016/j.eswa.2022.116828.
24. Faramarzi A, Mirjalili S, Heidarinejad M. Binary equilibrium optimizer: theory and application in building optimal control problems. Energy Build. 2022;277:112503. doi:10.1016/j.enbuild.2022.112503.
25. Guha R, Ghosh KK, Bera SK, Sarkar R, Mirjalili S. Discrete equilibrium optimizer combined with simulated annealing for feature selection. J Comput Sci. 2023;67(1):101942. doi:10.1016/j.jocs.2023.101942.
26. Zhong C, Li G, Meng Z, Li H, He W. A self-adaptive quantum equilibrium optimizer with artificial bee colony for feature selection. Comput Biol Med. 2023;153(10):106520. doi:10.1016/j.compbiomed.2022.106520.
27. Subbaraj P, Rengaraj R, Salivahanan S. Enhancement of combined heat and power economic dispatch using self adaptive real-coded genetic algorithm. Appl Energy. 2009;86(6):915–21. doi:10.1016/j.apenergy.2008.10.002.
28. Mellal MA, Williams EJ. Cuckoo optimization algorithm with penalty function for combined heat and power economic dispatch problem. Energy. 2015;93(1):1711–8. doi:10.1016/j.energy.2015.10.006.
29. Haghrah A, Nazari-Heris M, Mohammadi-ivatloo B. Solving combined heat and power economic dispatch problem using real coded genetic algorithm with improved Mühlenbein mutation. Appl Therm Eng. 2016;99(10):465–75. doi:10.1016/j.applthermaleng.2015.12.136.
30. Narang N, Sharma E, Dhillon JS. Combined heat and power economic dispatch using integrated civilized swarm optimization and Powell's pattern search method. Appl Soft Comput. 2017;52:190–202. doi:10.1016/j.asoc.2016.12.046.
31. Beigvand SD, Abdi H, La Scala M. Hybrid gravitational search algorithm-particle swarm optimization with time varying acceleration coefficients for large scale CHPED problem. Energy. 2017;126:841–53. doi:10.1016/j.energy.2017.03.054.
32. Zou D, Li S, Kong X, Ouyang H, Li Z. Solving the combined heat and power economic dispatch problems by an improved genetic algorithm and a new constraint handling strategy. Appl Energy. 2019;237(10):646–70. doi:10.1016/j.apenergy.2019.01.056.
33. Chen X, Li K, Xu B, Yang Z. Biogeography-based learning particle swarm optimization for combined heat and power economic dispatch problem. Knowl Based Syst. 2020;208(1):106463. doi:10.1016/j.knosys.2020.106463.
34. Nasir M, Sadollah A, Aydilek İ.B, Lashkar Ara A, Ali Nabavi-Niaki S. A combination of FA and SRPSO algorithm for combined heat and power economic dispatch. Appl Soft Comput. 2021;102(5):107088. doi:10.1016/j.asoc.2021.107088.
35. Meng A, Mei P, Yin H, Peng X, Guo Z. Crisscross optimization algorithm for solving combined heat and power economic dispatch problem. Energy Convers Manag. 2015;105(3):1303–17. doi:10.1016/j.enconman.2015.09.003.
36. Liu D, Hu Z, Su Q. Neighborhood-based differential evolution algorithm with direction induced strategy for the large-scale combined heat and power economic dispatch problem. Inf Sci. 2022;613(3):469–93. doi:10.1016/j.ins.2022.09.025.
37. Ramachandran M, Mirjalili S, Malli Ramalingam M, Charles Gnanakkan CAR, Parvathysankar DS, Sundaram A. A ranking-based fuzzy adaptive hybrid crow search algorithm for combined heat and power economic dispatch. Expert Syst Appl. 2022;197(3):116625. doi:10.1016/j.eswa.2022.116625.
38. Ramachandran M, Mirjalili S, Nazari-Heris M, Parvathysankar DS, Sundaram A, Charles Gnanakkan CAR. A hybrid grasshopper optimization algorithm and Harris Hawks optimizer for combined heat and power economic dispatch problem. Eng Appl Artif Intell. 2022;111:104753. doi:10.1016/j.engappai.2022.104753.
39. Thymianis M, Tzanetos A. Is integration of mechanisms a way to enhance a nature-inspired algorithm? Nat Comput. 2024;23(3):567–87. doi:10.1007/s11047-022-09920-3.

40. Victoire TAA, Jeyakumar AE. Reserve constrained dynamic dispatch of units with valve-point effects. IEEE Trans Power Syst. 2005;20(3):1273–82. doi:10.1109/TPWRS.2005.851958.
41. Zheng J, Liang P, Zhao H, Deng W. A broad sparse fine-grained image classification model based on dictionary selection strategy. IEEE Trans Reliab. 2024;73(1):576–88. doi:10.1109/tr.2023.3309278.
42. Deng W, Wang J, Guo A, Zhao H. Quantum differential evolutionary algorithm with quantum-adaptive mutation strategy and population state evaluation framework for high-dimensional problems. Inf Sci. 2024;676(6):120787. doi:10.1016/j.ins.2024.120787.
43. Li M, Yang S, Zhang M. Power supply system scheduling and clean energy application based on adaptive chaotic particle swarm optimization. Alex Eng J. 2022;61(3):2074–87. doi:10.1016/j.aej.2021.08.008.
44. Rahnamayan S, Tizhoosh HR, Salama MMA. Quasi-oppositional differential evolution. In: 2007 IEEE Congress on Evolutionary Computation; 2007 Sep 25–28; Singapore. p. 2229–36. doi:10.1109/CEC.2007.4424748.
45. Tizhoosh HR. Opposition-based learning: a new scheme for machine intelligence. In: International Conference on Computational Intelligence for Modelling, Control and Automation and International Conference on Intelligent Agents, Web Technologies and Internet Commerce (CIMCA-IAWTIC'06); 2005 Nov 28–30; Vienna, Austria. p. 695–701. doi:10.1109/CIMCA.2005.1631345.
46. Awad NH, Ali MZ, Liang JJ, Qu BY, Suganthan PN. Problem definitions and evaluation criteria for the CEC 2017 special session and competition on single objective bound constrained real-parameter numerical optimization. Technical report. Singapore: Nanyang Technological University; 2016 [Internet]. [cited 2025 Jun 23]. Available from: https://www.researchgate.net/publication/317228117.
47. Demšar J. Statistical comparisons of classifiers over multiple data sets. J Mach Learn Res. 2006;7:1–30.
48. García S, Fernández A, Luengo J, Herrera F. Advanced nonparametric tests for multiple comparisons in the design of experiments in computational intelligence and data mining: experimental analysis of power. Inf Sci. 2010;180(10):2044–64. doi:10.1016/j.ins.2009.12.010.
49. Kennedy J, Eberhart R. Particle swarm optimization. In: Proceedings of ICNN'95—International Conference on Neural Networks; 1995 Nov 27–Dec 1; Perth, WA, Australia. p. 1942–8. doi:10.1109/ICNN.1995.488968.
50. Karaboga D. An idea based on honey bee swarm for numerical optimization. Technical report-tr06, Erciyes university, engineering faculty, computer engineering department, 2005 [Internet]. [cited 2025 Jun 23]. Available from: http://www.lia.deis.unibo.it/Courses/SistInt/articoli/bee-colony1.pdf.
51. Mirjalili S, Mirjalili SM, Lewis A. Grey wolf optimizer. Adv Eng Softw. 2014;69:46–61. doi:10.1016/j.advengsoft.2013.12.007.
52. Mirjalili S, Lewis A. The whale optimization algorithm. Adv Eng Softw. 2016;95(12):51–67. doi:10.1016/j.advengsoft.2016.01.008.
53. Mirjalili S. SCA: a Sine Cosine Algorithm for solving optimization problems. Knowl Based Syst. 2016;96(63):120–33. doi:10.1016/j.knosys.2015.12.022.
54. He M, Hong L, Yang ZY, Yang TB, Zeng J. Bioactive assay and hyphenated chromatography detection for complex supercritical CO_2 extract from Chaihu Shugan San using an experimental design approach. Microchem J. 2018;142:394–402. doi:10.1016/j.microc.2018.07.016.
55. Liu H, Zhang XW, Tu LP. A modified particle swarm optimization using adaptive strategy. Expert Syst Appl. 2020;152(3):113353. doi:10.1016/j.eswa.2020.113353.
56. Zhang L, Hu T, Yang Z, Yang D, Zhang J. Elite and dynamic opposite learning enhanced sine cosine algorithm for application to plat-fin heat exchangers design problem. Neural Comput Appl. 2023;35(17):12401–14. doi:10.1007/s00521-021-05963-2.
57. Basu M. Combined heat and power economic dispatch using opposition-based group search optimization. Int J Electr Power Energy Syst. 2015;73(3):819–29. doi:10.1016/j.ijepes.2015.06.023.
58. Pattanaik JK, Basu M, Dash DP. Heat transfer search algorithm for combined heat and power economic dispatch. Iran J Sci Technol Trans Electr Eng. 2020;44(2):963–78. doi:10.1007/s40998-019-00280-w.
59. Nazari-Heris M, Mohammadi-Ivatloo B, Asadi S, Geem ZW. Large-scale combined heat and power economic dispatch using a novel multi-player harmony search method. Appl Therm Eng. 2019;154:493–504. doi:10.1016/j.applthermaleng.2019.03.095.