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Economic and Emission Dispatch Using Ensemble Multi-Objective Differential Evolution Algorithm

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Abstract: In the past two decades, China's manufacturing industry has achieved great success. However, pollution and environmental impacts have become more serious while this industry has grown. The economic and emission dispatch (EED) problem is a typical multi-objective optimization problem with conflicting fuel costs and pollution emission objectives. An ensemble multi-objective differential evolution (EMODE) is proposed to tackle the EED problem. First, the equality constraints of the problem have been transformed into inequality constraints. Next, two mutation strategies DE/rand/1 and DE/current-to-rand/1 have been implemented to improve the conventional DE. The performance of the proposed algorithm is evaluated on six test functions and the numerical results have indicated that the proposed algorithm is effective. The proposed algorithm EMODE is used to solve a series of six generators and eleven generators in the EED problem. The experimental results obtained are compared with those reported using single optimization algorithms and multi-objective evolutionary algorithms (MOEAs). The results have revealed that the proposed algorithm EMODE either matches or outperforms those algorithms. The proposed algorithm is an effective candidate to optimize the manufacturing industry of China.

Keywords: economic and emission dispatch; differential evolution; mutation strategy; multi-objective; manufacturing industry

1. Introduction

Currently, every country has enacted strict regulations and laws to protect the environment from pollution [1]. For example, the US Clean Air act was implemented in 1990. This act mandates that power companies should reduce NO_X by 2 million ton/year and SO_2 emission by 10 million ton/year from 1980 levels [2,3]. In the past decades, China's government has also enacted related laws and regulations to protect the environment [1,3–7]. However, when power companies generate electricity, they produce harmful pollutants. Thus, these companies have to reduce the emissions of these harmful pollutants, such as CO_2, CO and NOx [8]. Therefore, the economic and emission dispatch (EED) problem is a highly critical problem for power companies. The problem consists of two objectives, including minimization costs and emissions with the constraints. It is a typical non-linear constrained multi-objective optimization problem (CMOP).

This problem has to deal with linear/nonlinear, equality/inequality constraints, concave feasible region, et al. Consequently, many traditional optimization approaches may not be attractive since they are computationally expensive or easily get stuck at local optima. In the past decade, evolutionary algorithms have been obtained increasingly attention for solving the problem due to their adaptability and flexibility to the task [9]. Currently, there are many approaches proposed to handle the economic and emission dispatch (EED) problem. These approaches can be classified into two categories.

The first one is to transform the problem into a single optimization problem [10]. Generally, different objectives are combined by the relative weights among these objectives. This category generally applies the following method to form a new objective function:

$$\min \sum_{i=1}^{N_G} [wF_i + (1-w) \cdot \lambda \cdot E_i] \tag{1}$$

where w is the relative weight between fuel costs F_i (\$/h) and emissions E_i (ton/h), λ is a scaling factor and Ng is the number of generators [8,11–21]. The EED problem is converted into single objective function using the penalty factor. The main advantage of the method is that it is easy to implement. However, it is highly difficult to identify suitable weights among different objectives. Multiple runs are often required for the sake of obtaining non-dominated solutions. In the past decades, multi-objective evolutionary algorithms (MOEAs) have made considerable progress. These algorithms are widely applied to solve the EED problem.

The second category addresses the EED problem of MOEAs. These population-based optimization algorithms can obtain multiple non-dominated solutions in a single run. This approach can overcome the main disadvantage of the first category. As the performances of MOEAs are attractive, they have been widely employed to solve the EED problem. A multi-strategy ensemble biogeography-based optimization algorithm is proposed to solve the EED problem [22]. A new MOEA based on an enhanced firefly algorithm is proposed to acquire a set of non-dominated solutions and to solve various EED problems [23]. The differential evolution (DE) algorithm and PSO (particle swarm optimization) algorithm are combined to form a new hybrid algorithm called DEPSO. The proposed hybrid algorithm is used to address the EED problem [24]. A trust region algorithm based on the MOEA is presented to cope with the problem [25]. A time varying acceleration PSO is proposed to improve the solutions of the EED problem [26]. A quantum-behaved PSO algorithm is introduced to address the EED problem [27]. A new bare-bones multi-objective PSO algorithm is designed to solve the EED problem [28]. An extended NSGA-II algorithm is presented for the EED problem [2]. A new two-archive multi-objective grey wolf algorithm is presented to solve reactive power dispatch problems [29].

From the above discussion, it is noticed that MOEAs are widely used in the field of EEDs. In the recent years, the DE as one EA has attracted increasing attention due to its attractive performance. It is a simple powerful optimization algorithm created by Storn and Price [30]. Many multi-objective differential evolution (MODE) algorithms have been proposed and achieved remarkable performances compared to other MOEAs when solving the EED problem. A modified version of MODE is used to tackle the extended dynamic EED problem. In MODE, an ensemble of selection method is implemented [31]. A new extended adaptive MODE algorithm is adopted by double selection and adaptive random restart operators to solve the EED problem. The efforts can avoid premature. Moreover, a new constraint handling technique is also implemented [32]. A DE algorithm based on the orthogonal design method and e-domination is implemented to solve the EED problem for the purpose of saving energy and protecting environment [33]. A summation based on the multi-objective differential evolution (SMODE) algorithm is used to optimize the EED problem with stochastic wind power [34]. An extended multi-objective binary DE algorithm is presented to solve the EED problem. A marginal correction is used to handle various constraints [35]. An enhanced multi-objective DE algorithm is presented to solve the EED problem to realize the aim of the minimization of fuel costs and emission effects. The operators of DE are modified and an elitist archive technique is used to retain the non-dominated solutions during the evolution [36]. The MODE algorithm is proposed to solve the EED problem, which uses an external elitist archive to retain non-dominated solutions during the evolution [37]. The modified differential evolution (MDE) uses five differential solutions instead of three like the conventional DE to solve the EED problem [38]. An improved multi-objective differential evolution algorithm contains the chaos initialization strategy, the parameter adaptive strategy and the dynamic non-dominated sorting strategy to address the EED problem [39]. A DE combined with Gaussian mutation (DEGM) is implemented to handle the EED problem [40].

In fact, the EED problem is a typical constraint multi-objective problem (MOP). Multi-objectives have to be solved and constraints have to be satisfied. Balancing objective optimization and constraint satisfaction are two equally important goals. In the above proposed algorithms based on the DE, there is only one mutation strategy used. In fact, the mutation strategy plays an important role during evolution. In the light of the no free lunch theorem, no single mutation strategy can outperform all others on every optimization problem [41]. In most DE variants, only mutation strategy is adopted to generate trial vector. Thus, the search ability is limited. In fact, different mutation strategies have different features. Chosen mutation strategies have distinct advantages and they can be effectively cooperated and combined to optimize different kinds of problems. The idea is widely used in single optimize problem [42]. Composite DE (CoDE) uses rand/1/bin, rand/2/bin and current-to-rand/1 to generate trial vectors. Simulation results have shown that CoDE is very competitive on all the CEC2005 test functions [42].Three mutation strategies DE/rand/1, DE/best/2 and DE/current-to-rand/1 are chosen to form a mutation strategy pool. Compared with conventional DE and adaptive DE algorithms, simulation results have proven that the ensemble method has achieved better performance [43]. As classical evolutionary programming (CEP) with Gaussian mutation is better at searching in a local neighborhood while the fast EP (FEP) with the Cauchy mutation performs better over a larger neighborhood, an ensemble approach is proposed by combining adaptive EP, Gaussian and Cauchy mutations, the experimental results have revealed that the ensemble is better than the single mutation-based algorithms [44]. Different mutation and update strategies are implemented in mDE-bES [45]. An ensemble of multiple strategies is realized by a multi-population based approach. Extensive experiments show that the proposed method is competitive [46]. An ensemble DE algorithm is proposed to classify electromagnetic targets in resonance scattering region. Compared with DE variants, the performance of the proposed algorithm is better [47]. Thus, all the above simulation results and evidences have clearly revealed that different strategies can be more appropriate and benefit can be derived from the availability of diverse strategies.

Based on the observation, the ensemble mutation strategies of the DE are implemented. As the multi-objective optimization problems are different from single optimization problems, Pareto theory is used to select best solutions. Thus, mutation strategies chosen are different from the single optimization problems. In addition, in order to cope with the equality constraints in the EED problem, a new mechanism is proposed by transforming the equality constraint into the inequality constraint. Next, the constraint domination principle is adopted to select these solutions to enter the next generation. By these efforts, a novel ensemble MODE (EMODE) is implemented to solve the EED problem. The primary advantage is that the proposed algorithm uses two different mutation operators. They have different features and can cooperate with each other to accelerate the optimization process while retaining the diversity of the population. To validate the performance of the proposed algorithm EMODE, it has been compared with the latest single optimization algorithms and MOEAs. Based on the benchmark test functions (CTP2~CTP7), the proposed algorithm is better than NSGAII [48] and MODE with mutation strategy DE/rand/1 according to the performance indicator Inverted Generational Distance (IGD). Then, the algorithm is used to solve the EED problem. Compared with the latest single optimization, the proposed algorithm is better than the recursive, PSO, DE and improved recursive. Compared with MOEAs, EMODE is better than MODE and SPEA 2. The NSGAII, PDE and EMODE have achieved similar performance. We can get the conclusion that the proposed algorithm is competitive.

The paper is organized as follows. In Section 2, the EED problem is briefly introduced. The conventional DE is presented and the proposed algorithm is developed in Section 3. In Section 4, experiments on the EED problem are performed. The study's conclusions are presented in Section 5.

2. Economic Emission Dispatch (EED) Problem

The major aim of power companies is to schedule the generators' output to satisfy the load requirements with minimum fuel costs without considering emissions. Currently, every country has begun to protect the environment from pollution. These power companies have to make alternative strategies to reduce pollutants such that they can meet the requirements of environmental protection. Otherwise, they will be severely punished. The EED problem is a typical MOP [10]. Addressing this problem requires simultaneously minimizing fuel costs and emission levels. Meanwhile, this approach has to meet certain constraints. First, some notations have to be presented such that the problem can be clearly explained. The notations are as follows [10]:

P_{Gi}: The output power of the ith generator
a_i, b_i, c_i: The fuel cost coefficients of the ith generator
$\alpha_i, \beta_i, \gamma_i$: The emission coefficients of the ith generator
N_G: The number of generators
P_D: The total load demand
P_l: The power losses
P_{Gi}^{min}: The minimum power output of the ith generator
P_{Gi}^{max}: The maximum power output of the ith generator
B_{ij}: The loss coefficient between the ith generator and the jth generator
$F(P_{Gi})$: The total fuel costs function
$E(P_{Gi})$: The total emissions function
FE: The total cost of generators

The total fuel costs function $F(P_{Gi})$ can be presented by the following equation

$$F(P_{Gi}) = \sum_{i=1}^{N_G} [a_i + b_i P_{Gi} + c_i P_{Gi}^2] \tag{2}$$

The emission may be SO_2 or NOx. They are released by fossil fuels in power plants. The total emission function $E(P_{Gi})$ can be defined as

$$E(P_{Gi}) = \sum_{i=1}^{N_G} [\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2] \tag{3}$$

Thus, the multi-objective of the EED problem can be given as follows:

$$FE = (F(P_{Gi}), E(P_{Gi})) \tag{4}$$

When optimizing the EED problem, some constraints have to be met. The first one is power balance. The total power generated has to equal to the total power required and total power lost. It can be expressed as

$$\sum_{i=1}^{N_G} P_{Gi} = P_D + P_l, P_l = \sum_{i=1}^{N_G} \sum_{j=1}^{N_G} P_{Gi} B_{ij} P_{Gj} \tag{5}$$

The second constraint is the capacity constraint. The output power of every generator unit is constrained by the range limits:

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \tag{6}$$

3. Ensemble Multi-Objective Differential Evolution (EMODE)

3.1. Conventional DE

In the conventional DE, mutation, crossover and selection are very critical. The main framework of the DE is similar to the EAs, which is exhibited in Figure 1.

According to the main steps of the DE, $V_i = \{v_i^1, v_i^2, \ldots, v_i^D,\}$ and $U_i = \{u_i^1, u_i^2, \ldots, u_i^D,\}$ are the trial vectors, where D is the dimension of the problem. The former is generated by the mutation strategy in the mutation step. The latter is generated in the crossover step.

The mutation strategy plays an important role during evolution. Price and Storn employed the DE/rand/1/bin that has been widely used. The main strategies used in the DE algorithm are listed as follows [30]:

$$\text{DE/best/1:} \quad V_i = X_{best} + F\cdot(X_{r_1^i} - X_{r_2^i}) \tag{7}$$

$$\text{DE/best/2:} \quad V_i = X_{best} + F\cdot(X_{r_1^i} - X_{r_2^i}) + F\cdot(X_{r_3^i} - X_{r_4^i}) \tag{8}$$

$$\text{DE/current-to-best/1:} \quad V_i = X_i + F\cdot(X_{best} - X_i) + F\cdot(X_{r_1^i} - X_{r_2^i}) \tag{9}$$

$$\text{DE/rand/:} \quad V_i = X_{r_1^i} + F\cdot(X_{r_2^i} - X_{r_3^i}) \tag{10}$$

$$\text{DE/rand/2:} \quad V_i = X_{r_1^i} + F\cdot(X_{r_2^i} - X_{r_3^i}) + F\cdot(X_{r_4^i} - X_{r_5^i}) \tag{11}$$

$$\text{DE/current-to-rand/1:} \quad U_i = X_i + K\cdot(X_{r_1^i} - X_i) + F\cdot(X_{r_2^i} - X_{r_3^i}) \tag{12}$$

The indices r_1^i, r_2^i, r_3^i are mutually exclusive integers. They are randomly generated within the range [0, 1]. The three of them have to be different from the index i. F and K are the mutation scale factors. Both of them are used to control the amplification of the differential variation.

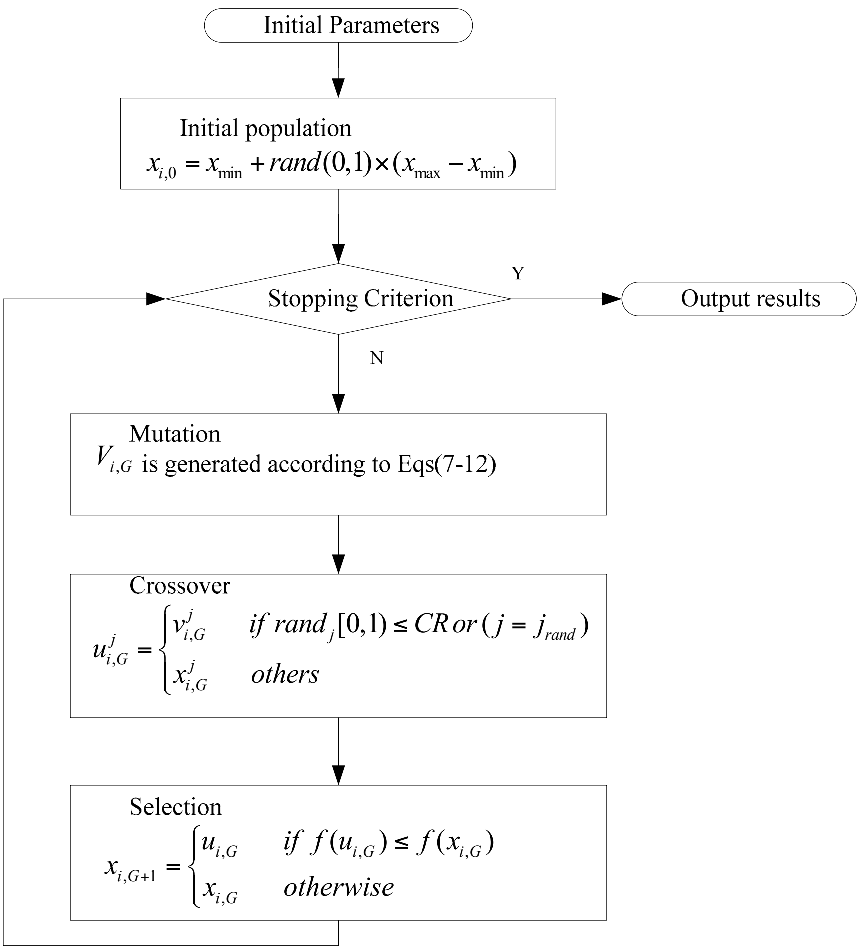

Figure 1. Flowchart of the conventional DE.

3.2. EMODE Algorithm

3.2.1. Mutation Strategies

The performance of the DE relies on parameter values and the mutation strategy. On the basis of the no free lunch theorem, no single mutation strategy can outperform all others on every optimization problem [41]. Different optimization problems have different features. They demand different mutation strategies with different parameter values. Furthermore, to optimize a specific problem, different mutation strategies with different characteristics may be better than the conventional DE with a single mutation strategy [43]. Mutation strategies involved in the conventional DE are analyzed as follows.

The mutation strategies DE/best/1/bin, DE/rand-to-best/1/bin, DE/best/2/bin and DE/rand-to-best/2/bin have the best solution information that we have found so far. They are widely used in the single optimization problem. However, these strategies cannot be directly used to solve the multi-objective optimization problem since there are no best solution concepts. Those solutions with the lowest fronts also cannot dominate each other.

DE/rand/1 and DE/rand/2 have similar exploration capabilities. Nonetheless, DE/rand/1 was first developed for the DE and is one of the most widely and successful employed strategies. Thus, it is chosen as one of mutation strategies for the proposed algorithm.

DE/current-to-rand/1 is a rotational-invariant mutation strategy. This approach does not have crossover, which is significantly different from the above mutation strategies. Therefore, it is also chosen as the second mutation strategy.

3.2.2. Handling the Equality Constraints in EED Problem

In the EED problem, there are N_G equality constraints. Generally, these equality constraints are converted into inequality constraints:

$$|h(P_{Gi})| - \delta \leq 0 \tag{13}$$

$$h(P_{Gi}) = \sum_{i=1}^{N_G} P_{Gi} - P_D - P_l = \sum_{i=1}^{N_G} P_{Gi} - P_D - \sum_{i=1}^{N_G}\sum_{j=1}^{N_G} P_{Gi}B_{ij}P_{Gj} \tag{14}$$

where δ is the tolerance value for the equality constraints. According to [9], δ is a very small positive number, such as 0.0001. The absolute value operator can be removed by transforming Equation (13) into inequality constraints:

$$-\delta \leq h(P_{Gi}) \leq \delta \rightarrow \leq \begin{cases} h(P_{Gi}) \leq \delta \\ -h(P_{Gi}) \leq \delta \end{cases} \tag{15}$$

Thus, the total constraint violation (CV) can be expressed as follows:

$$CV(P_{Gi}) = max(-h(P_{Gi}) - \delta, 0) + max(h(P_{Gi}) - \delta, 0) \tag{16}$$

In the past decades, many techniques have been proposed to solve the constraints. These techniques mainly include the constraint domination principle [48] and penalty function [49].

Deb et al. proposed the constraint domination principle [48]. If two solutions are feasible, the solution that Pareto dominates the other solution is better. If two solutions are infeasible, the solution with the larger constraint violation is worse and the solution with the smaller constraint violation is better. If one solution is infeasible and the other solution is feasible, the feasible solution is better than the infeasible solution. The principle is similar to the feasibility rules that are used to address single objective constraint problems.

The penalty method is one of the simplest and most commonly used techniques to address constraint MOPs [49]. The penalty method introduces a penalty function or a coefficient into the original objective function to penalize those solutions that violate constraints. The main advantage of the penalty method is that the infeasible solutions will also have the opportunity to enter into following generations. The drawback is that when using the penalty method to solve constraint problems, it is still the most difficult method to find appropriate penalty coefficients, which guides the search direction towards the optimum.

However, the constraint domination principle prefers constraints to objectives. It is a greedy mechanism [50].The advantage of the principle is that it has the ability to motivate the population to the feasible regions and accelerate the optimization. In addition, the method does not need any penalty parameters, which makes it attractive. Thus, the approach is adopted to solve the constraints in the EED problem.

3.2.3. Solve the EED Problem by EMODE Algorithm

In the proposed algorithm, evolution can be implemented by the DE algorithm. The offspring population is generated by the DE operator. Then, the parent population and offspring population are combined to form a mating pool. The mating pool is divided into feasible solutions and infeasible solutions. These solutions are sorted in increasing order according to the respective objective function values and constraint violations. If the number of feasible solutions is more than the population size, the population will be directly selected from these solutions to enter in the next generation. Otherwise, some infeasible solutions with lower constraint violations will be chosen to enter the next generation.

According to the discussion above, the main procedure based on the EMODE to solve EED problem is presented as follows:

Step 1 Initialize the parameters that include the mutation scale factor *F*, the crossover rate *CR*, the maximum iteration numbers and number in the population (*NP*).

Step 2 Randomly generate *NP* individuals $p = \{X_{1,G,}, \ldots, X_{NP,G,}\}$ uniformly distributed in the range $[P_G^{min}, P_G^{max}]$, where $P_G^{min} = \{P_{G1}^{min}, P_{G2}^{min}, \ldots, P_{Gi}^{min} \ldots\}$ and $P_G^{max} = \{P_{G1}^{max}, P_{G2}^{max}, \ldots, P_{Gi}^{max} \ldots\}$.

Step 3 Calculate fuel costs and emissions according to Equations (2) and (3) and, total constraint violations *CV* based on Equation (16).

Step 4 while stopping criterion is not met

- **Step 4.1** Generate two vectors $V_{i,G}^1, V_{i,G}^2$ according to Equations (10) and (12).
- **Step 4.2** Generate two vectors $U_{i,G}^1, U_{i,G}^2$ according to the DE crossover.
- **Step 4.3** If the trial vectors $U_{i,G}^1, U_{i,G}^2$ cannot meet the constraints of Equation (6); randomly generate them within the search space
- **Step 4.4** Selection

  Calculate fuel costs and emissions according to Equations (2) and (3) and, the total constraint violations *CV* based on Equation (16) of $U_{i,G}^1, U_{i,G}^2$ respectively.

  $MP = (p, U_{i,G}^1, U_{i,G}^2)$;// combine *p* and $U_{i,G}^1, U_{i,G}^2$ to form a mating pool (*MP*).

  $(p_1, p_2) = split(MP)$;//feasible solutions (p_1) and infeasible solutions (p_2)

  If $(\text{size}(p_1) \geq NP)$

  Select *NP* individuals from p_1 by the non-dominated and crowding distance sorting and store these individuals in the current population *p*

  End

  If $size(p_1) < NP$

  Sort p_2 by *CV*

  $p = p_1 + p_2(NP - szie(p_1))$;

  End

Step 5 End while

Step 6 Select non-dominated solutions from p and output the corresponding results.

To clearly reveal the proposed algorithm, Figure 2 illustrates the main steps.

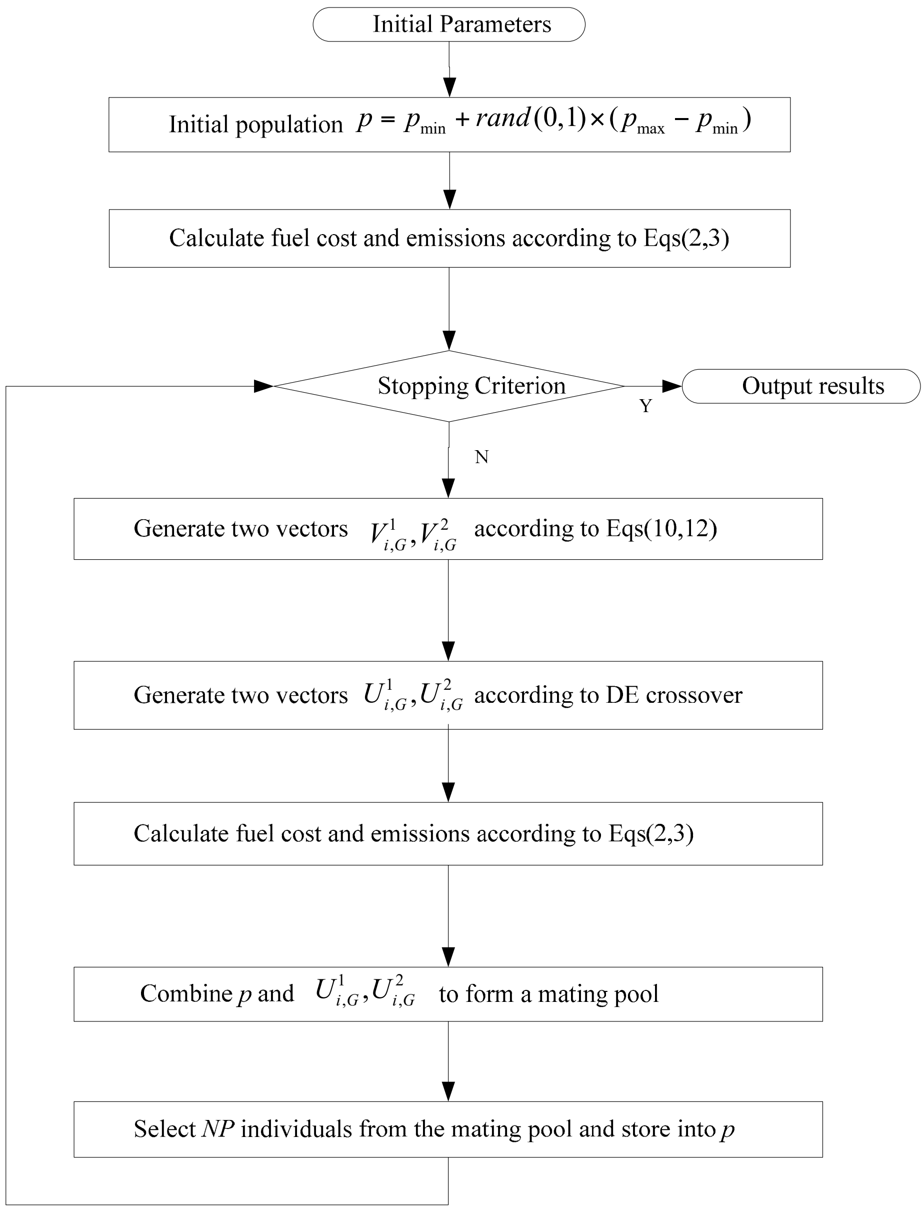

Figure 2. Flowchart of the proposed algorithm.

4. Experiment Results

4.1. Experiments Based on Benchmark Functions

To verify the performance of the proposed algorithm, six benchmark functions (CTP2, CTP3, CTP4, CTP5, CTP6 and CTP7) are adopted [51]. They are presented in Equation (17). The parameters settings are listed in Table 1.

$$
\begin{aligned}
\text{Minimize} \quad & f_1(\vec{x}) = x_1 \\
\text{Minimize} \quad & f_2(\vec{x}) = g(\vec{x})(1 - \tfrac{f_1(\vec{x})}{g(\vec{x})}) \\
\text{subject to} \quad & c(\vec{x}) = \cos(\theta)(f_2(\vec{x}) - e) - \sin(\theta) f_1(\vec{x}) \geq \\
& a|\sin(b\pi(\sin(\theta)(f_2(\vec{x}) - e) + \cos(\theta) f_1(\vec{x}))^c)|^d \\
& g(x) = 1 + \sum_{i=2}^{10} [x_i^2 - 10\cos(2\pi x_i) + 10], x \in [0,1]
\end{aligned}
\tag{17}
$$

The MODE algorithm based on mutation strategies DE/rand/1 is used to make comparisons. In addition, NSGAII with the constraint domination principle is also selected. The Inverted Generational Distance (IGD) is adopted as a performance indicator, which is widely used in MOEAs.

$$
\mathrm{IGD} = \frac{\sum_{v \in P_A} d(v, P_A)}{|P^*|} \tag{18}
$$

where $d(v, P_A)$ is the minimum Euclidean distance between v and the points in P_A [60, 61] depicted in Figure 3 [52].

Table 1. Parameters of the second group test functions.

Functions	Parameters
CT2	$\theta = -0.2\pi, a = 0.20, b = 10.0, c = 1, d = 6.0, e = 1$
CT3	$\theta = -0.2\pi, a = 0.10, b = 10.0, c = 1, d = 0.5, e = 1$
CT4	$\theta = -0.2\pi, a = 0.75, b = 10.0, c = 1, d = 0.5, e = 1$
CT5	$\theta = -0.2\pi, a = 0.75, b = 10.0, c = 2, d = 0.5, e = 1$
CT6	$\theta = 0.1\pi, a = 40.00, b = 0.5, c = 1, d = 2.0, e = -2$
CT7	$\theta = -0.05\pi, a = 40.00, b = 5.0, c = 1, d = 6.0, e = 0$

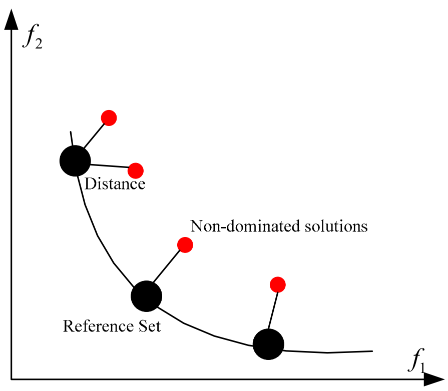

Figure 3. Generational distance measurement.

Each algorithm runs 25 times. The NSGAII is implemented based on the GA. All the parameters are the same, including the crossover probability 0.9, the mutation probability 0.1, the mutation distribution index 20 and the population size 100. For the proposed method, the population size is set to 100, F linearly decreases from 1.0 to 0.7 and CR linearly increases from 0.4 to 0.8. The stopping criterion is set at 500 generations for the above four methods.

Results and Discussion

The results of IGD are presented in Table 2. The complexities of constrained search space are controlled. The complexity of the test functions can be further increased by using a multi-modal function $g(x)$. It is difficult to find and maintain correlated decision variables to fall on the constrained boundaries. In addition, there could be other difficulties near the real Pareto front. The constraints can make the real Pareto front become a set of discrete regions. At the extreme, the real Pareto front can become a collection of discrete solutions. It can be observed that the proposed algorithm has achieved the best IGD on CTP2, CTP4, CTP5, CTP6 and CTP7. The NSGAII obtained superior results on CTP3. Since NSGAII and DE algorithm with rand/1 mutation strategy get trapped in the local feasible regions in some runs, the performance of the two methods is bad. The reason is that the constrained complexities make the two methods unable to overcome a series of infeasible regions before coming to inland with the Pareto front. However, the proposed algorithm can accelerate the whole process with the help of ensemble mutation strategies. The non-dominated solutions obtained by the proposed algorithm and the Pareto front are presented in Figure 4. These non-dominated solutions are uniformly distributed along the Pareto front of each test functions. By the comparisons and experimental results, it can be concluded that ensemble mutation strategies are effective and the proposed algorithm is competitive.

Table 2. The IGD metric of three algorithms.

IGD	NSGAII	DE/rand/1	EMODE
CTP2	4.63×10^{-3} (6.76×10^{-6})	2.78×10^{-3} (4.27×10^{-8})	$\mathbf{2.35 \times 10^{-3}}$ **($\mathbf{3.04 \times 10^{-8}}$)**
CTP3	$\mathbf{1.18 \times 10^{-2}}$ **($\mathbf{2.10 \times 10^{-4}}$)**	4.13×10^{-2} (1.36×10^{-3})	1.92×10^{-2} (4.21×10^{-6})
CTP4	1.20×10^{-1} (1.53×10^{-3})	8.4×10^{-2} (5.13×10^{-5})	$\mathbf{8.81 \times 10^{-2}}$ **($\mathbf{1.18 \times 10^{-4}}$)**
CTP5	1.35×10^{-1} (1.62×10^{-3})	1.054×10^{-1} (4.53×10^{-4})	$\mathbf{9.90 \times 10^{-2}}$ **($\mathbf{1.26 \times 10^{-5}}$)**
CTP6	1.03×10^{-2} (2.41×10^{-5})	1.16×10^{-1} (7.70×10^{-2})	$\mathbf{9.62 \times 10^{-3}}$ **($\mathbf{1.43 \times 10^{-7}}$)**
CTP7	2.10×10^{-3} (7.16×10^{-6})	6.73×10^{-2} (5.24×10^{-3})	$\mathbf{1.04 \times 10^{-3}}$ **($\mathbf{3.10 \times 10^{-9}}$)**

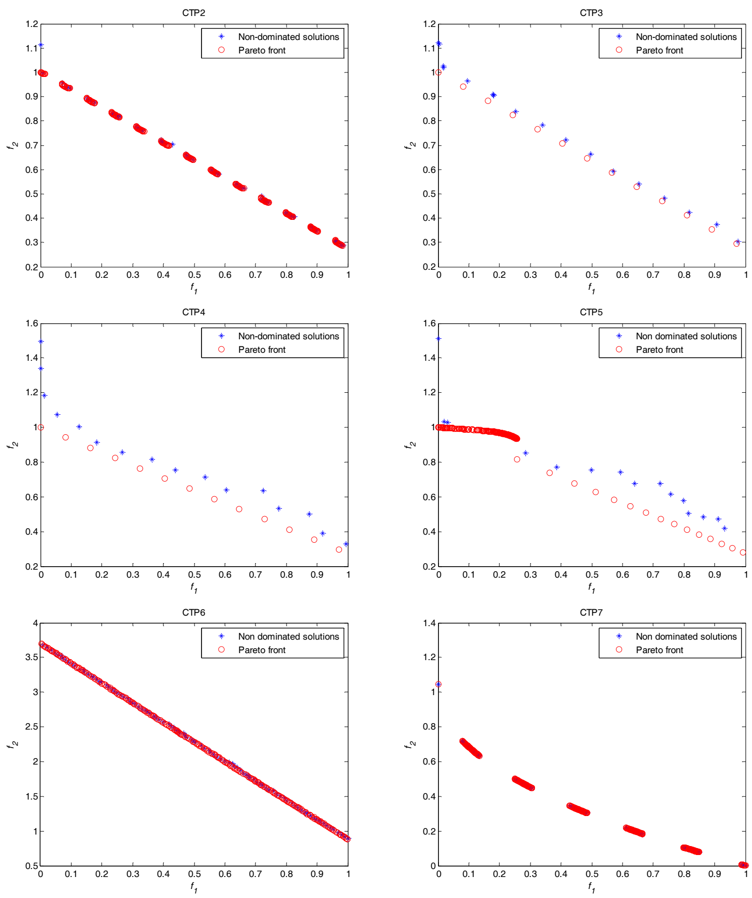

Figure 4. Comparisons between non-dominated solutions and the Pareto front.

4.2. Experiments Based on Typical EED Problems

To evaluate the performance of the proposed algorithm EMODE, it has been used to solve the EED problem by considering the following three test systems. The three test systems have been widely used as benchmark functions. The results from various optimization methods can make fair and faithful comparisons based on the benchmark functions. In the three test systems, the population size of the proposed EMODE is set to 200, F linearly decreases from 1.0 to 0.7 and CR linearly increases from 0.4 to 0.8. The maximum number of iterations is set to 1000.

Results and Discussion

(1) The first test system with six generators

The test system has six generators. It has quadratic cost functions and emission level functions. The power demands range from 500 MW to 1100 MW. They are 500 MW, 600 MW, 700 MW, 800 MW, 900 MW, 1000 MW and 1100 MW. In this test system, the loss coefficients and power loss are not taken into account. The coefficients are listed in Table 3. To make comparisons, the recursive method, PSO, DE and improved recursive method are selected to optimize the test system. The results of the above four methods are directly taken from [11]. The results from the proposed method and the four methods are presented in Table 4. The best results obtained are highlighted in bold.

Table 3. Coefficients of the six-unit generator.

Unit	a_i	b_i	c_i	ff_i	fi_i	fl_i	$P_{Gi}^{\min}$	$P_{Gi}^{\max}$
1	756.800	38.540	0.1525	13.860	0.3300	0.0042	10	125
2	451.325	46.160	0.1060	13.860	0.3300	0.0042	10	150
3	1050.000	40.400	0.0280	40.267	−0.5455	0.0068	35	225
4	1243.530	38.310	0.0355	40.267	−0.5455	0.0068	35	210
5	1658.570	36.328	0.0211	42.900	−0.5112	0.0046	130	325
6	1356.660	38.270	0.0180	42.900	−0.5112	0.0046	125	315

Table 4. Comparison of fuel costs and emission for the six-generator system (Cost: unit $ and Emission: unit kg).

Load	Recursive		PSO		DE		Improved Recursive		EMODE	
	Cost	Emission	Cost	Emission	Cost	Emission	Cost	Emission	Cost	Emission
500	27,093	118.7	27,098	118.9	27,098	118.8	27,093	118.7	**27,073**	**118.5**
600	32,627	153.8	27,098	154.1	31,629	153.8	31,629	153.8	**31,621**	**153.3**
700	36,314	197.0	31,635	197.1	36,314	197.1	36,314	197.0	**36,312**	**196.4**
800	41,148	248.5	36,314	248.5	41,153	248.5	41,148	248.5	**41,144**	**248.1**
900	46,132	308.1	41,160	308.3	46,132	308.1	46,132	308.1	**46,104**	**307.9**
1000	51,265	375.9	51,270	376	51,265	375.9	51,265	375.9	**51,257**	**375.6**
1100	56,546	451.9	56,557	451.8	56,547	451.9	56,546	451.9	**56,518**	**451.3**

It can be observed that the proposed algorithm EMODE has achieved the best results in the six generators test system with different required loads. For example, when the load demand is 1100, the fuel costs are 56,518$ and emissions are 451.3 kg. Meanwhile, the recursive and improved recursive methods have achieved the same performance and can be ranked as the second best. The PSO has the worst performance. Thus, the best compromised results from the proposed method are significantly better than other four methods. The finding has revealed that the proposed method can accelerate optimization while retaining population diversity. The best compromised solutions are given in Table 5.

Table 5. EED solutions of the six-generator system.

Load	500	600	700	800	900	1000	1100
P1	25.7573	36.7136	50.1154	60.3290	69.0865	83.5220	92.5939
P2	11.5306	25.9094	37.3288	52.5394	65.8889	78.5015	93.0328
P3	87.2611	103.6695	119.5007	133.4621	150.9331	158.9832	179.3460
P4	90.5584	104.5445	120.1008	131.7089	149.9904	168.0432	182.2870
P5	145.4741	168.0550	188.8845	214.5138	233.1996	257.4707	274.9088
P6	139.4184	161.1081	184.0696	207.4469	230.9015	253.4795	277.8315
Time(s)	5.3	7.6	7.9	8.0	7.8	8.1	7.9

In order to further validate the effectiveness of the proposed method, the set coverage is introduced. The performance index can be used to compare the difference between two algorithms. Let A and B be two non-dominated solutions. $C(A,B)$ is defined as the percentage of the solutions in B that are dominated by at least one solution in A:

$$C(A,B) = \frac{\{u \in B | \exists v \in A v \; dominates \; u\}}{|B|} \tag{19}$$

where $|B|$ is the number of solutions in the B [52]. $C(A,B)$ is not necessarily to $1 - C(B,A)$. If $C(A,B) = 1$ indicates that all solutions in B are dominated by some solutions in A. If $C(A,B) = 0$ implies that no solution in B is dominated by a solution in A. The results of set coverage between EMODE and four algorithms are listed in Table 6. It can be noticed that all set coverage is equal to 1, which indicates that all solutions generated by the four algorithms are dominated by some solutions generated by EMODE. As EMODE is the multi-objective evolutionary algorithm, it can obtain multiple non-dominated solutions in a single run. Thus, we can get the conclusion that EMODE is better than the four algorithms.

Table 6. The results of set coverage between EMODE and four algorithms.

C(EMODE, Algorithm)	Recursive	PSO	DE	Improved Recursive
EMODE	1	1	1	1

(2) Test systems with eleven generators

The second test system has eleven generators. It also has quadratic cost functions and emission level functions. The power demands range from 1000 MW to 2500 MW. They are 1000 MW, 1250 MW, 1500 MW, 1750 MW, 2000 MW, 2250 MW and 2500 MW. The coefficients are listed in Table 7. It is noticed that the loss coefficients and power loss are also not taken into account. The results from above five methods are listed in Table 8. It can be observed that the proposed method outperforms the other four methods that include two recursive methods and two heuristic methods. We take demand = 2500 as an example. In the proposed method, fuel costs are 12,403$ and emissions are 902.2 kg. Therefore, it is better than other four optimization methods. The best compromise solutions are given in Table 9.

Table 7. Coefficients of the eleven-unit generator.

Unit	a_i	b_i	c_i	ff_i	fi_i	fl_i	$P_{Gi}^{\min}$	$P_{Gi}^{\max}$
1	387.85	1.92699	0.00762	33.93	−0.67767	0.00419	20	250
2	441.62	2.11969	0.00838	24.62	−0.69044	0.00461	20	210
3	422.57	2.19196	0.00523	33.93	−0.67767	0.00419	20	250
4	552.50	2.01983	0.00140	27.14	−0.54551	0.00683	60	300

Table 7. *Cont.*

Unit	a_i	b_i	c_i	ff_i	fi_i	fl_i	$P_{Gi}^{\min}$	$P_{Gi}^{\max}$
5	557.75	2.12181	0.00154	24.15	−0.40060	0.00751	20	210
6	562.18	1.91528	0.00177	27.14	−0.54551	0.00683	60	300
7	568.39	2.10681	0.00195	24.15	−0.40006	0.00751	20	215
8	682.93	1.99138	0.00106	30.45	−0.51116	0.00355	100	455
9	741.22	1.99802	0.00117	25.59	−0.56228	0.00417	100	455
10	617.83	2.12352	0.00089	30.45	−0.41116	0.00355	110	460
11	674.61	2.10487	0.00099	25.59	−0.56228	0.00417	110	465

Table 8. Comparison of fuel costs and emissions for the eleven-generator system.

Load		1000	1250	1500	1750	2000	2250	2500
Recursive	Costs	8502.3	9108.4	9733.5	10,378	11,041	11,723	12,424
	Emissions	93.1	154.2	245.2	366.1	517.1	697.9	908.7
PSO	Costs	8508	9114	9737	10,380	11,041	11,725	12,429
	Emissions	94.3	156.8	247.3	368.7	518.1	698.8	911.6
DE	Costs	8506	9118	9736	10,377	11,041	11,723	12,425
	Emissions	93.1	154.2	246.9	366.1	517.1	697.9	908.7
Improved Recursive	Costs	8502.3	9108.4	9733.5	10,377.8	11,041	11,723	12,425
	Emissions	93.1	154.2	245.2	366.1	517.1	697.9	908.9
EMODE	Costs	**8496.7**	**9107**	**9730.1**	**10,369**	**11,020**	**11,718**	**12,403**
	Emissions	**93.1**	**151.8**	**240.9**	**361.9**	**516.6**	**685.8**	**902.2**

Table 9. EED solutions of the eleven-generator system.

Load	1000	1250	1500	1750	2000	2250	2500
P1	86.4143	95.9372	102.9861	108.3956	118.1331	128.3625	128.7609
P2	72.9674	86.5057	86.4853	95.9172	98.7609	101.8583	118.5395
P3	90.4008	96.3682	115.3208	122.5703	124.8677	152.8952	144.9564
P4	82.7058	98.2494	119.8692	139.2933	167.6652	189.9708	203.6015
P5	55.1308	77.6149	94.8632	110.9899	144.2773	155.3846	161.9490
P6	73.4721	99.1753	116.2041	150.2056	165.3362	175.5657	200.9291
P7	49.5901	71.0873	96.0055	106.7755	130.9537	143.0967	172.6625
P8	132.1147	169.5561	208.4068	249.4712	270.2169	335.2919	369.4619
P9	124.6620	149.6263	183.7925	224.6640	252.5837	287.4033	324.4974
P10	118.8382	150.5627	190.0441	220.5946	274.8657	302.1718	341.9780
P11	113.7038	155.3168	186.0224	221.1228	252.3396	277.9991	332.6638
Time(s)	9.8	11.2	12.4	14.3	14.6	12.8	11.9

In order to further validate the performance of the proposed algorithm, γ-iteration, GA and gravitational search algorithm (GSA) [53] are also chosen to make comparisons [12]. The power demand is 2500. The coefficients are same to Table 7. The comparisons results are listed in Table 10. It can be observed that the result of EMODE is better than γ-iteration, GA and GSA.

Table 10. Comparison of the results for test system ($P_D = 2500$ MW).

Algorithm	Costs	Emissions
γ-iteration	12,424.94	908.7
GA	12,423.77	908.5
Proposed GSA	12,422.66	908.54
EMODE	12,403	902.2

(3) Test systems considering the power lost

This test system is different from the above two test systems. The power lost is considered. It has six generators, too. The coefficients are the same as Table 3. The B matrix of the loss formula is as follows:

$$B = \begin{bmatrix} 0.000140 & 0.000017 & 0.000015 & 0.000019 & 0.000026 & 0.000022 \\ 0.000017 & 0.000060 & 0.000013 & 0.000016 & 0.000015 & 0.000020 \\ 0.000015 & 0.000013 & 0.000065 & 0.000017 & 0.000024 & 0.000019 \\ 0.000019 & 0.000016 & 0.000017 & 0.000071 & 0.000030 & 0.000025 \\ 0.000026 & 0.000015 & 0.000024 & 0.000030 & 0.000069 & 0.000032 \\ 0.000022 & 0.000020 & 0.000019 & 0.000025 & 0.000032 & 0.000085 \end{bmatrix}$$

The proposed method is compared with four MOEAs, including the NSGAII, PDE, SPEA 2 and MODE. The results of the four MOEAs are directly taken from [54]. To make a fair comparison, the functional evaluation numbers are same. The best compromise solutions and results from the five MOEAs are presented in Table 11. It can be observed that the EMODE has achieved 64,827$ costs, which is the smallest among the five methods. The emissions are 582.9 kg, which is a littler worse than the results from NSGAII and PDE. However, the result is better the results from the SPEA 2 and MODE and it can dominate their results. Thus, the proposed method is better than the SPEA 2 and MODE in the third test system.

Table 11. Comparison of fuel costs and emissions for the six-generator system considering the power lost.

	NSGAII	PDE	SPEA 2	MODE	EMODE
P1	113.1259	107.3965	104.1573	108.6284	104.3959
P2	116.4488	122.1418	122.9807	115.9456	119.5126
P3	217.4191	206.7536	214.9553	206.7969	224.9859
P4	207.9492	203.7047	203.1387	210.000	195.8249
P5	304.6641	308.1045	316.0302	301.8884	296.9230
P6	291.5969	303.3797	289.9396	308.4127	309.6791
Costs ($)	64,962	64,920	64,884	64,843	**64,827**
Emissions (kg)	**581.1**	**581.1**	582.9	583.3	582.9

5. Conclusions

The EED problem is a typical constraint MOP. The two objectives are fuel costs and emissions. They conflict with each other. A novel EMODE is proposed to solve the EED problem. The proposed algorithm converts the equality constraints of the EED problem into the inequality constraints. Then, the two mutation strategies DE/rand/1 and DE/current-to-rand/1 are implemented in the EMODE. The proposed algorithm can accelerate optimization while retaining the diversity of the population.

The performance of the proposed algorithm is evaluated using six benchmark test functions and the numerical results have indicated that the proposed algorithm is effective. Then, the proposed algorithm has been tested on a series of six generators and eleven generators EED problems. Compared with the latest single optimization, the proposed algorithm is better than the recursive, PSO, DE and improved recursive. Compared with MOEAs, EMODE is better than MODE and SPEA 2. The NSGAII, PDE and EMODE have achieved similar performance. The results have demonstrated that the proposed algorithm can provide high quality solutions. It can be observed that the proposed algorithm is a promising algorithm to solve the EED problem. It can provide an approach to realize the transition from China-Made to China-Innovation.

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