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Dynamic environmental economic dispatch using multiobjective differential evolution algorithm with expanded double selection and adaptive random restart

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ABSTRACT

The dynamic environmental economic dispatch (DEED) model is presented in this paper, in which the fuel cost and emission effect over a certain period of time are optimized as conflicting objectives. It is a high dimensional, nonlinear constrained multiobjective optimization problem when generators' valve point effect, ramp rate limits and power load variation are considered. This paper proposes a modified adaptive multiobjective differential evolution (MAMODE) algorithm to solve the problem. In MAMODE, expanded double selection and adaptive random restart operators are proposed to modify the evolutionary processes for avoiding premature and a dynamic heuristic constraint handling (DHCH) approach is introduced to deal with the complicated constraints. The DHCH can lessen infeasible solutions gradually. To illustrate the effectiveness of the method, four cases based on three test power systems are studied. The simulation result indicates that the DEED can be solved quickly. Comparison of numerical results demonstrates the proposed method has higher performance.

1. Introduction

Power system optimal operation needs accurate load forecasting, suitable unit commitment and scientific power load allocation. Generally, power load allocation is operated based on the previously determined unit commitment and predicted load curve; it is usually classified as economic dispatch (ED) [1–5] and dynamic economic dispatch (DED) [6–11] according to the division of schedule period. In the past decades, environmental pollution has received more and more attention. The Clean Air Act Amendments of 1990 [12] have forced the electric power industry to reduce pollution emissions. In addition to installing emission reduction equipment, emission dispatch is an effective alternative choice. Therefore, the economic emission dispatch (EED) model optimizing the fuel cost and emission simultaneously have been intensively studied in the past years [13–19]. However, the EED is a static model which does not consider the generators' ramp rate limits and cannot ensure the global optimization from the whole schedule horizon. In view of the importance of DED and EED as well as their respective shortcomings, the coupling model called dynamic economic emission dispatch (DEED) should be studied. However, there are little literatures for this problem. DEED serves to schedule the generators' outputs over the whole dispatch period with the consideration of multiple objectives, generators' ramp rate limits and power load variation. So it is closer to the practical but it is more difficult to be solved because of the high-dimensional and multiple objectives. If considering the nonlinear factors of power losses, valve point effect and prohibited operating zones further, the problem would be more complicated.

The DEED can be simplified by treating the emission as a constraint and minimizing the fuel cost. However, the emission constraint scope is unclear before. If the trade-off curve between emission and fuel cost is convex, the solution with the minimum fuel cost must locate at the boundary of the emission constraint scope. In this situation, the model equals to the DED and the result is not conducive to scientific decision making. In the recent years, to simplify the problem, weight method [20,21], fuzzy satisfying method [22] and price penalty factor [23] are employed respectively to convert the model into a single objective optimization problem. All of these methods have achieved good results, but only one solution can be obtained after the program run once and the true non-inferior solutions are hard to get. The problem can also be simplified by converting into a series of static EED according to the dispatch period dividing [24]. However, there are many non-dominated solutions for each EED. How to combine these solutions at each interval into complete solutions of the whole dispatch period is a complicated problem. Furthermore, the combined solution may not be global optimization from the perspective of the whole dispatch horizon. In addition to these literatures, the DEED model

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is solved as a true multiobjective problem by using NSGA-II and good results are obtained in [25]. However, due to lack of efficient constraint handling and global search ability, the Pareto front obtained is not distributed widely enough. To date, no other methods can solve the problem efficiently.

Differential evolution (DE) is a powerful algorithm developed by Storn and Price [26] which could achieve good results in both single objective optimization and multiobjective optimization [27–33]. However, it shows premature convergence in solving some complicated problems. In this paper, a modified adaptive multiobjective differential evolution algorithm (MAMODE) is proposed to solve the DEED problem. For avoiding the premature, the evolutionary operators of DE are modified and expanded to strengthen the global search ability. According to the feature of constraints, an effective dynamic heuristic constraint handling (DHCH) approach is presented and embedded into MAMODE to deal with the infeasible solutions. Fast nondominated sorting and external archive strategies are used to select and preserve elite solutions along the evolution, respectively. To verify the effectiveness of the proposed method in solving DEED, four simulation examples are studied based on three power systems. The numerical result shows that the DEED can be well solved quickly.

The rest of this paper is organized as follows: Section 2 presents the problem formulation. Related works and key points of MAMODE are described in Section 3. In Section 4, the proposed method using MAMODE to solve DEED is given. Four cases based on three power systems are studied and the simulation results are discussed in Section 5. The conclusion is summarized in Section 6 followed by an acknowledgement.

2. Problem formulation

2.1. Objectives

2.1.1. Minimization of fuel cost

For each generating unit, the fuel cost of a generating unit considering valve-point effect can be modeled as the sum of a quadratic and a sinusoidal function. The total fuel cost (FC) over the whole dispatch period is expressed as

$$\min \quad \mathrm{FC} = \sum_{t=1}^{T}\sum_{i=1}^{N}[a_i + b_iP_{i,t} + c_i(P_{i,t})^2 + |d_i \sin(e_i(P_{i,\min} - P_{i,t}))|] \tag{1}$$

where T is the number of intervals in the dispatch period; N is the number of generating units; $P_{i,t}$ is the power output of ith generating unit at interval t; $P_{i,\min}$ is the lower output limit for ith generating unit; a_i, b_i, c_i, d_i, and e_i are the coefficients of fuel cost function for the ith generating unit.

2.1.2. Minimization of emission

The main atmospheric pollutants of power system caused by fossil-fueled generators are SO_x, NO_x and CO_2. The emission of each pollutant can be modeled separately. In this paper, the emission of a generating unit is modeled as the sum of a quadratic and an exponential function. The total emission (EM) over the whole dispatch period is expressed as

$$\min \quad \mathrm{EM} = \sum_{t=1}^{T}\sum_{i=1}^{N}[10^{-2}(\alpha_i + \beta_iP_{i,t} + \gamma_i(P_{i,t})^2) + \eta_i \exp(\delta_iP_{i,t})] \tag{2}$$

where α_i, β_i, γ_i, η_i, and δ_i are the coefficients of emission function of the ith generating unit.

2.2. Constraints

(1) Generator capacity constraints

$$P_{i,\min} \leqslant P_{i,t} \leqslant P_{i,\max}, \quad (i = 1,2,\ldots,N; t = 1,2,\ldots,T) \tag{3}$$

where $P_{i,min}$, $P_{i,max}$ are the lower and up generation output limit of the ith generating unit.

(2) Real power balance constraints

$$\sum_{i=1}^{N}P_{i,t} - P_{L,t} - P_{D,t} = 0, \quad (t = 1,\ldots,T) \tag{4}$$

where $P_{D,t}$ and $P_{L,t}$ are the load demand and power loss at interval t, respectively. The exact value of $P_{L,t}$ can be determined by a power flow solution, but the most popular approach for finding an approximate value is by the way of Kron's loss formula:

$$P_{L,t} = \sum_{i=1}^{N}\sum_{j=1}^{N}P_{i,t}B_{ij}P_{j,t} + \sum_{i=1}^{N}P_{i,t}B_{i0} + B_{00}, \quad (t = 1,\ldots,T) \tag{5}$$

where B_{ij} is the ijth element of the loss coefficient square matrix, B_{i0} and B_{00} are ith element of the loss coefficient vector and the loss coefficient constant, respectively.

(3) Generators' ramp rate limits

$$\begin{cases} P_{i,t} - P_{i,t-1} \leqslant UR_i \cdot \Delta t \\ P_{i,t-1} - P_{i,t} \geqslant DR_i \cdot \Delta t \end{cases}, \quad (i = 1,2,\ldots,N;\ t = 1,2,\ldots,T) \tag{6}$$

where UR_i and DR_i are the ramp up and down rate limits of ith generating unit, respectively, Δt is the length of each time interval.

2.3. Mathematical model

Aggregating the objectives and constraints listed above, the DEED problem can be formulated as a nonlinear constrained multiobjective optimization problem (MOP). Without loss of generality, the MOP can be described mathematically as follows [34]:

$$\begin{aligned} \min \quad & \boldsymbol{y} = (f_1(\boldsymbol{x}), f_2(\boldsymbol{x}), \ldots, f_k(\boldsymbol{x})) \\ \text{s.t.} \quad & g_i(\boldsymbol{x}) = 0, \quad i = 1,2,\ldots,p \\ & h_j(\boldsymbol{x}) \leqslant 0, \quad j = 1,2,\ldots,q \end{aligned} \tag{7}$$

where $\boldsymbol{x}$ is a decision vector which represents a solution of the problem; $\boldsymbol{y}$ is the objective function vector with k objectives; $f_i(\boldsymbol{x})$ is the ith objective function; p and q are the numbers of equality and inequality constraints, respectively.

The purpose of MOP is exploring the relationship among the involved conflicting objectives and providing decision support. A MOP gives rise to a set of Pareto optimal solutions instead of one optimal solution. The concept of Pareto optimal is based on the definition of "dominate". For a minimization MOP, a solution $\boldsymbol{x}_1$ dominates $\boldsymbol{x}_2$ (written as $\boldsymbol{x}_1 \prec \boldsymbol{x}_2$) if and only if the following two conditions satisfied: (1) $\forall i \in \{1, 2, \ldots, k\}$: $f_i(\boldsymbol{x}_1) \leqslant f_i(\boldsymbol{x}_2)$ and (2) $\exists j \in \{1, 2, \ldots, k\}$: $f_i(\boldsymbol{x}_1) < f_i(\boldsymbol{x}_2)$. In general, the solution which is not dominated by any other solution is called nondominated or Pareto optimal solution. The set of all nondominated solutions is called Pareto optimal set, the corresponding set in objective space is called Pareto optimal front (POF).

3. Related works and key points of MAMODE

3.1. Classic differential evolution

DE starts from a random initialized population $\boldsymbol{P}$ which comprises of N_p floating-point encoded individuals. Each individual $\boldsymbol{x}_i = (x_{i1}, x_{i2}, \ldots, x_{in})$ is a vector containing t decision variables. DE gets an optimal solution by repeating Mutation–Crossover–Selection operators over $G_{\max}$ generations.

3.1.1. Mutation

The Mutation operator creates mutant vector $\boldsymbol{v}_i = (v_{i1}, v_{i2}, \ldots, v_{in})$ by disturbing a randomly selected vector $\boldsymbol{x}_a$ with the difference of two other randomly selected vectors $\boldsymbol{x}_b$ and $\boldsymbol{x}_c$.

$$\boldsymbol{v}_i = \boldsymbol{x}_a + F(\boldsymbol{x}_b - \boldsymbol{x}_c) \tag{8}$$

where $\boldsymbol{x}_a$, $\boldsymbol{x}_b$ and $\boldsymbol{x}_c$ ($a \neq b \neq c \neq i$) are randomly chosen vectors from the population $\boldsymbol{P}$ and selected anew for each parent vector. The scaling constant F is an algorithm control parameter used to control the perturbation size of the mutation.

3.1.2. Crossover

The Crossover operator generates trial vector $\boldsymbol{u}_i = (u_{i1}, u_{i2}, \ldots, u_{in})$ by selecting the corresponding components between $\boldsymbol{v}_i$ and the target vector $\boldsymbol{x}_i$ according to a selected probability C_R.

$$u_{ij} = \begin{cases} v_{ij}, & \text{if } r_j \leqslant C_R \text{ or } j = q \\ x_{ij}, & \text{otherwise} \end{cases} \tag{9}$$

where r_j is a uniformly distributed random number within [0,1] and renewed for each j. The parameter C_R controls the diversity of the population and aids the algorithm to escape from local optima. q is a randomly chosen index from $\{1, 2, \ldots, N_p\}$. The Crossover operator guarantees that the trial vector $\boldsymbol{u}_i$ gets at least one parameter from the mutant vector $\boldsymbol{v}_i$.

3.1.3. Selection

The Selection operator determines the population between the trial vector $\boldsymbol{u}_i$ and target vector $\boldsymbol{x}_i$, the individuals with a better fitness is selected.

$$\boldsymbol{x}_i = \begin{cases} \boldsymbol{u}_i, & \text{if } f(\boldsymbol{u}_i) < f(\boldsymbol{x}_i) \\ \boldsymbol{x}_i, & \text{otherwise} \end{cases} \tag{10}$$

3.2. Expanded double selection

For avoiding the premature of DE in solving high-dimensional and multiobjective problems, the evolutionary operators should be modified to improve the global search ability. In the original DE, the search process passes by Mutation, Crossover and Selection operators. After analysis carefully, it is easy to find the Mutation operator plays the global search role by disturbing a solution with the difference of two others; on the contrary, the Crossover operator plays more of a local search role because of it cuts down the variety of Mutation operator. On the other hand, the mutant vector $\boldsymbol{v}_i$ is thrown away after Crossover and its information is not used enough in class DE.

In this paper, the Expanded Double Selection (EDS) is proposed to strengthen the global search ability by expanding the evolutionary operators of DE and make full use of the information of the mutant vector $\boldsymbol{v}_i$ and the trial vector $\boldsymbol{u}_i$. EDS expands the Mutation–Crossover–Selection of DE to Mutation–Selection (I)–Crossover–Selection (II). The Selection (I) takes place between $\boldsymbol{x}_i$ and $\boldsymbol{v}_i$ after Mutation, the Selection (II) takes place between $\boldsymbol{x}_i$ and $\boldsymbol{u}_i$ after Crossover. In addition, the solutions are replaced only when the new one having better fitness for single objective optimization in classic DE. But in multiobjective problem, for improving the global search ability further, the solutions will be replaced as long as the new one is not dominated by it. The EDS can be defined as follows. The first Selection (I) is

$$\boldsymbol{x}_i = \begin{cases} \boldsymbol{x}_i, & \text{if } \boldsymbol{x}_i \prec \boldsymbol{v}_i \\ \boldsymbol{v}_i, & \text{otherwise} \end{cases} \tag{11}$$

The second Selection (II) is

$$\boldsymbol{x}_i = \begin{cases} \boldsymbol{x}_i, & \text{if } \boldsymbol{x}_i \prec \boldsymbol{u}_i \\ \boldsymbol{u}_i, & \text{otherwise} \end{cases} \tag{12}$$

That is to say, not only after Crossover operator but also following Mutation operator is the evolving individual $\boldsymbol{x}_i$ replaced by the new generated solution if it does not dominate the new one.

3.3. Dynamic heuristic constraint handling

As well as high-dimensional and multiple objectives, strong constraint is another important factor making the DEED problem hard to be solved. The strong constraint makes the feasible region of the problem to be very narrow. If searching randomly in the whole space, the algorithm would be very inefficient. The key to solving the DEED problem is how to handle the strong constraints efficiently. For equality constraints, it can be handled easily by setting the over-limited values to the corresponding boundary. But for the equality constraints, it is more difficult to deal with because of the strong coupling among decision variables. In this paper, the DHCH method is employed to handle the equality constraints. For each infeasible solution $\boldsymbol{x}$, the DHCH is done interval by interval.

The DHCH is an iterative correction process. For avoiding spending too much time on the DHCH, a maximum iteration number L and a constraint violation threshold ε are set in advance to control the DHCH. In this paper, we set $L = 10$, $\varepsilon = 10^{-6}$. The processes of DHCH are listed as follows.

Step 1: Set the iteration number of adjusting operation $l = 0$.
Step 2: Calculate the violation $V(\boldsymbol{x}, t)$ of the real power balance constraint at interval t:

$$V(\boldsymbol{x}, t) = P_{D,t} + P_{L,t} - \sum_{i=1}^{N} P_{i,t} \tag{13}$$

If $V(\boldsymbol{x}, t) > \varepsilon$ and $l < L$, then go to Step 3; otherwise go to Step 4.
Step 3: Modify the real power output of all generating units at interval t:

$$P_{i,t} = P_{i,t} + V(\boldsymbol{x}, t)/N, \quad (i = 1, 2, \ldots, N) \tag{14}$$

If the new $P_{i,t}$ violates the inequality constraints, it is handled according inequality constraints handling method. Let $l = l + 1$, and go to Step 2.
Step 4: The termination of the constraint handling procedure at the interval t is done.

3.4. Constraint Pareto dominance

Although the DHCH can eliminate the number or the violation degree of infeasible solutions, there are still some solutions violating the constraints in the early periods because of the limit of maximum iteration and violation threshold. The total violation $V(\boldsymbol{x})$ of the solution $\boldsymbol{x}$ is calculated as:

$$V(\boldsymbol{x}) = \sum_{t=1}^{T} |V(\boldsymbol{x}, t)| \tag{15}$$

In MAMODE, the selection strategy considering the constraint violation is employed to choose the better solutions, it can be described as follows. Solution $\boldsymbol{x}_1$, Constraint Pareto Dominate $\boldsymbol{x}_2$ (denoted as $\boldsymbol{x}_1 \preccurlyeq \boldsymbol{x}_2$) as long as one of the following conditions satisfied: (a) $V(\boldsymbol{x}_1) \leqslant V_{\mathrm{TH}}$ and $V(\boldsymbol{x}_2) > V_{\mathrm{TH}}$; (b) $V(\boldsymbol{x}_1) \leqslant V_{\mathrm{TH}}$, $V(\boldsymbol{x}_2) \leqslant V_{\mathrm{TH}}$ and $\boldsymbol{x}_1 \prec \boldsymbol{x}_2$; and (c) $V(\boldsymbol{x}_1) > V_{\mathrm{TH}}$, $V(\boldsymbol{x}_1) > V_{\mathrm{TH}}$ and $V(\boldsymbol{x}_1) < V(\boldsymbol{x}_2)$. Here V_{TH} is the total violation threshold of a solution which decides whether an infeasible solution can be selected. Setting the threshold

V_{TH} can ensure the population containing some infeasible solutions, to some extent that can enhance the local search ability of the algorithm. In this paper, the violation threshold $V_{TH} = 0.1$ for all the cases.

3.5. External archive updating

Elitist strategy which was first introduced by Zitzler [35] is a mechanism to preserve the best solutions of the current generation using an external archive set (denoted as $\boldsymbol{Q}$) along the search process. Elitist strategy can be realized either by placing one or more of the nondominated solutions directly into the archive set or by replacing only those solutions that are dominated by the nondominated solutions. In this paper, the method we used to update the external archive $\boldsymbol{Q}$ can be described as follows. (1) Mix the population $\boldsymbol{P}$ and $\boldsymbol{Q}$ to a population $\boldsymbol{R} = \boldsymbol{P} \cup \boldsymbol{Q}$. (2) Clear the archive $\boldsymbol{Q}$ and classify the population $\boldsymbol{R}$ using the fast nondominated sorting [36]. (3) Place the best nondominated set $\boldsymbol{F}_1$ of the mixed population $\boldsymbol{R}$ to the external archive set $\boldsymbol{Q}$ directly. But to limit computation source, the size of $\boldsymbol{Q}$ is usually a constant (N_q). If the size of $\boldsymbol{F}_1$ is less than N_q, the second-best nondominated set $\boldsymbol{F}_2$ will be placed in $\boldsymbol{Q}$ also until the archive set $\boldsymbol{Q}$ is filled. On the other hand, if the size of $\boldsymbol{Q}$ after updating is more than N_q, a truncation operator is needed to maintain the size of $\boldsymbol{Q}$ by eliminating the redundant individuals. In this paper, the crowding distance based on the normalized objective value [37] is used to pick out individuals.

The pseudo-codes of this operation are as follows

```
classify the population R
for i = 1 to the maximum rank of R
   place the set F_i to Q directly
   if |Q| < N_q
      i = i + 1;
      else if |Q| > N_q
         run truncation for Q;
         break;
   end if
end for
```

3.6. Adaptive random restart

Due to employing the external archive, the nondominated solutions are preserved to keep the elitist information of the evolutionary population. In MAMODE, an adaptive random restart (ARR) operator is proposed to use the elitist information for enhancing the algorithm. In ARR, the half worse solutions of the population $\boldsymbol{P}$ with higher rank or smaller crowding distance is replaced by new random generated solutions as:

$$x_{ij} = \begin{cases} l_j + \zeta_{ij} \times (u_j - l_j) & \text{if } n_{\mathrm{NDS}} \geqslant N_q/2 \\ x_{i,\min} + \zeta_{ij} \times (x_{i,\max} - x_{i,\min}) & \text{otherwise} \end{cases} \tag{16}$$

where ζ_{ij} is an uniformly distributed random number generated in $[0,1]$ and is renewed for each solution $\boldsymbol{x}_i$. n_{NDS} is the number of nondominated solutions of the current generation. l_j and u_j are the lower and upper value of the jth dimension of all nondominated solutions and can be expressed as

$$\begin{cases} l_j = \min\{x_{ij} | i = 1, 2, \ldots, N_q;\ \boldsymbol{x}_i \in \boldsymbol{Q}\} \\ u_j = \max\{x_{ij} | i = 1, 2, \ldots, N_q;\ \boldsymbol{x}_i \in \boldsymbol{Q}\} \end{cases} \tag{17}$$

As the search progresses, the distance between l_j and u_j will be narrower and narrower, so the ARR operator is adjusted adaptively from global search to local improvement.

4. Proposed method using MAMODE to solve DEED

4.1. Solution coding and initialization

In MAMODE, the population $\boldsymbol{P}$ consists of N_p individuals. Each individual is composed of NT decision variables of real power output at each interval, the population $\boldsymbol{P}$ and individual $\boldsymbol{X}_i$ can be represented as (18) and (19).

$$\boldsymbol{P} = \{\boldsymbol{X}_1, \boldsymbol{X}_2, \ldots, \boldsymbol{X}_{N_p}\} \tag{18}$$

$$\boldsymbol{X}_i = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1T} \\ P_{21} & P_{21} & \cdots & P_{2T} \\ \vdots & \vdots & \vdots & \vdots \\ P_{N1} & P_{N2} & \cdots & P_{NT} \end{bmatrix} \tag{19}$$

In initialization process, each individual $\boldsymbol{X}_i \in \boldsymbol{P}_0$ is randomly generated within the power output limits:

$$P_{i,t} = P_{i,\min} + \xi_{i,t} \times (P_{i,\max} - P_{i,\min}) \tag{20}$$

where $\xi_{i,t}$ is a uniformly distributed random number generated in $[0,1]$ and renewed for each i at each time interval t.

4.2. Fuzzy-based decision making

Generally, there are more than one Pareto solutions obtained in the final generation. However, only one solution is needed for practical applications. Such a solution which is commonly called the best compromise solution must satisfy all the different objectives to some extent. According to the imprecise nature of the judgments of decision makers, fuzzy set theory has been implemented to derive a candidate Pareto solution [38,39]. The proposed method used the fuzzy-based mechanism to extract the best compromise solution based on the final external archive. The processes of fuzzy-based decision making are as follows.

(a) Find the minimum and maximum values (denoted as $f_{k,min}$ and $f_{k,max}$ respectively) of the kth objective function among the solutions of the external archive.
(b) Calculate the membership function μ_{ik} of the kth objective of ith solution.

$$\mu_{ik} = \begin{cases} 1 & f_{i,k} \leqslant f_{k,\min} \\ \frac{f_{k,\max} - f_{i,k}}{f_{k,\max} - f_{i,\min}}, & f_{k,\min} < f_{i,k} < f_{k,\max} \\ 0 & f_{i,k} \geqslant f_{k,\max} \end{cases} \tag{21}$$

(c) Calculate the normalized membership function μ_i for each solution of the external archive:

$$\mu_i = \frac{\sum_{k=1}^{K} \mu_{i,k}}{\sum_{i=1}^{I} \sum_{k=1}^{K} \mu_{i,k}} \tag{22}$$

where K is the number of objective functions, I is the number of solutions in external archive.

(d) Select the solution with the maximum value of μ_i as the best compromise solution.

4.3. Procedures for solving DEED

Step 1: $g = 0$, initialize the population $\boldsymbol{P}_0$ and set the external archive $\boldsymbol{Q}_0 = \Phi$.
Step 2: for each individual $\boldsymbol{x}_i \in \boldsymbol{P}_g$, run DHCH for $\boldsymbol{x}_i$ and then evaluate it.
Step 3: run expanded evolution operators for each solution $\boldsymbol{x}_i \in \boldsymbol{P}_g$.
3.1: run Mutation operator to generate a mutation solution $\boldsymbol{v}_i$.

3.2: run DHCH for $\boldsymbol{v_i}$ and evaluate it.
3.3: run Selection (I) operator to update $\boldsymbol{x_i}$.
3.4: run Crossover operator to generate a trial solution $\boldsymbol{u_i}$.
3.5: run DHCH for $\boldsymbol{u_i}$ and evaluate it.
3.6: run Selection (II) operator to update $\boldsymbol{x_i}$.
Step 4: mix $\boldsymbol{P_g}$ and $\boldsymbol{Q_g}$ to a temp population $\boldsymbol{R_g}$ and clear $\boldsymbol{Q_g}$.
Step 5: classify $\boldsymbol{R_g}$ using fast nondominated sorting mechanism and then update $\boldsymbol{Q_g}$.
Step 6: increase the generation by $g = g + 1$, if $g < G_{\max}$, run ARR opera go back to Step 2, otherwise go to Step 7.
Step 7: stop the procedures and output archive Q or the best compromise solution selected by the fuzzy-based mechanism as the final result.

5. Simulation examples

To verify the feasibility and effectiveness of the proposed algorithm, four cases with three test systems are studied in this section. The testing systems are described in Section 5.1 and the simulation results are expressed and analyzed in Section 5.2. In this paper, all the programs have been implemented in Java (SE1.7) on a PC (Intel(R) Core(TM) 2 Duo CPU, T6670, 2.20 GHZ, Win 7 (32bit) operation system).

5.1. Description of the test systems

(1) The System 1 is the IEEE 30-bus power system with six generating units [24]. Both the non-smooth fuel cost and emission level functions of generating units and the nonlinear power loss of the network are considered. The unit data of the system and power loss formula coefficients can be found in [40], the power load demand can be found in [24].
(2) The System 2 is a 10 generating unit power system [23,25]. Both non-smooth fuel cost and emission level functions of generating units and power loss of network are considered. The unit data of the system which was modified from [41] and transmission loss formula coefficients can be found in [25].
(3) The System 3 is the IEEE 118-bus power system with 14 generating units [24]. For comparison, two scenarios are considered based on this system. In two scenarios, both non-smooth fuel cost and emission level functions of generating units are considered. But in one scenario, the power loss is not considered as done in [24]. In another scenario, the power loss is taken into account for further demonstrating the global search ability of the proposed method in solving DEED with highly nonlinear equality constraints. The unit data of this system can be found in [40]. The transmission loss formula coefficients can be found in [42].

Based on the above three test systems, four cases studied are listed in Table 1. In all cases, the dispatch period is 24 h with 1 h intervals; the demand load curve over the dispatch period has been divided into 24 intervals.

Table 1
List of four studied cases.

Case no.	System no.	Considering power loss	Number of decision variables	Number of equality constraints
Case 1	System 1	Yes	$6 \times 24 = 144$	24
Case 2	System 2	Yes	$10 \times 24 = 240$	24
Case 3	System 3	No	$14 \times 24 = 336$	24
Case 4	System 3	Yes	$14 \times 24 = 336$	24

5.2. Simulation results and analysis

5.2.1. Case 1

In this case, the IEEE 30-bus system [24] is solved by the proposed method. The non-smooth fuel cost function and power loss are considered in DEED model. The parameters of the presented method used in this case are listed as follows: $N_p = 300$, $N_q = 70$, $G_{\max} = 2000$; $F = 0.8$, and $P_c = 0.3$, respectively. Based on the above parameter setting, the system is tested and the Pareto front obtained by the MAMODE is shown in Fig. 1. The minimum values obtained of each objective and the time consumed by MAMODE and other three methods [24] are listed as Table 2. For comparison, the results of the best compromise solution obtained by MAMODE and GSOMP [24] are listed in Table 3, where the objective values obtained by GSOMP are calculated from the details of the final solution [24]. The detail information about the best compromise solution obtained by the MAMODE is given in Table 4.

From Fig. 1 we can see directly that the Pareto optimal solutions are widely and uniformly distributed in the objective space. Furthermore, it is clear to see that the best compromise solution obtained by MAMODE has better results than that obtained by GSOMP [24]. In Table 2, the minimum objective values obtained by MAMODE are not good enough as that obtained by the other three methods, but all of them are close to each other, the difference is very small. But it should be noted that the numerical results in [24] are “the sum of their minimal values obtained at each hour, over the 24 h”. Whether the solution having the extremely objective values while satisfying all the constraints exist or not cannot be confirmed in [24]. In Table 3, the best compromise solution obtained by MAMODE is compared with the final solution in [24]. It is clear to find that the best compromise solution obtained by the proposed method is better than the final solution in [24] in terms of objective values and the time consumed. It should be mentioned that the computing time makes the proposed approach to be promising for solving the DEED in practice. From the results listed in Table 4, the power balance constraints can be checked based on the detailed information of the compromise solution. We can see that the sum of the output of generating units equals to the power load plus power loss at each interval.

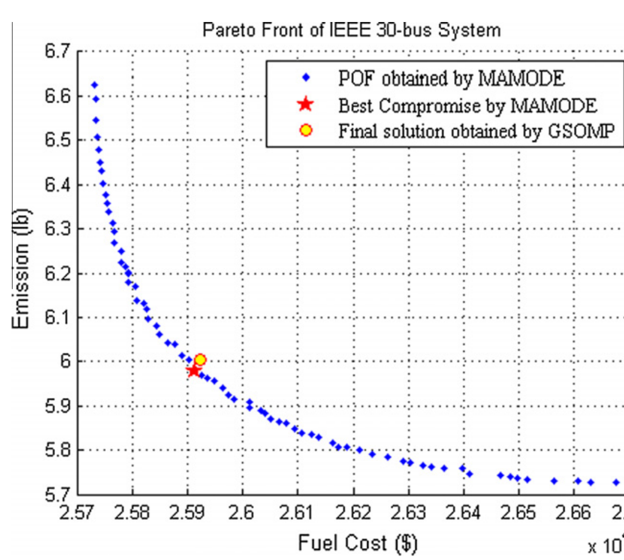

Fig. 1. POF of case 1 obtained by MAMODE.

Table 2
Comparison of the minimum objective value of case 1.

	MAMODE	GSOMP [24]	MOPSO [24]	NSGA-II [24]
FC_{min} ($)	25732.0	25493.0	25633.2	25507.4
EM_{min} (lb)	5.7283	5.6847	5.6863	5.6881
Time (s)	428	1262.0	1095.8	4341.3

Table 3
Comparison of the final (compromise) solution of the case 1.

	MAMODE	GSOMP [24]
FC ($)	25912.89419	25924.45557
EM (lb)	5.979548	6.004152
Time (s)	428	1262.9

5.2.2. Case 2

In this case, the 10 generating unit test system with the consideration of power loss is tested. The problem has 24 nonlinear equality constraints. The parameters of the presented method used in this case are set as follows: $N_p = 200$, $N_q = 60$, $G_{\max} = 1000$, $F = 0.7$, and $P_c = 0.2$. Based on the above parameter setting, the POF obtained by MAMODE and related results from [25] are shown in Fig. 2. The POF obtained by NSGA-II [25] is given in Fig. 3. For the convenience of comparison, the results obtained by MAMODE, IBFA [23], NSGA-II [25], linear combined ($w = 0.5$) optimization by RCGA [25], dynamic economic dispatch by RCGA [25], and dynamic emission dispatch by RCGA [25] are summarized in Table 5.

From Fig. 2, it is clear to see that the Pareto solutions obtained by the proposed method are well distributed in the objective space. By comparing Fig. 2 with Fig. 3, it is easy to find that the Pareto solutions obtained by MAMODE distribute more widely than that obtained in [25]. In addition, we can see from Fig. 2 that the best compromise solution obtained by MAMODE is better than the best compromise solution obtained by NSGA-II [25], the best fuel cost solution, the best emission solution and the best solution of linear combined optimization ($w = 0.5$) obtained by RCGA [25].

From Table 5, we compare the minimum fuel cost firstly obtained by different methods. The minimum fuel cost obtained by

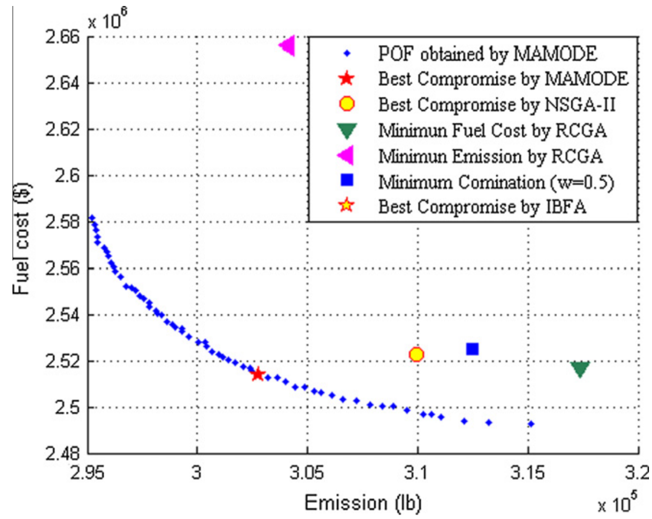

Fig. 2. POF of case 2 obtained by MAMODE.

MAMODE (2.492451×10^6 $) is more than the value obtained by IBFA [23] (2.481773×10^6 $), but less than the value obtained by RCGA (2.5168×10^6 $). Secondly, we compare the minimum emission obtained by different methods. The minimum emission obtained by MAMODE (2.95244×10^5 lb) is much less than the value obtained by IBFA (2.95883×10^5 lb) and RCGA (3.0412×10^5 lb). Thirdly, we compare the compromise solution obtained by different methods. From the perspective of fuel cost, the result obtained by MAMODE (2.514113×10^6 $) is less than that of IBFA (2.517116×10^6 $), NSGA-II ($2.5226 \times 10^6$ $), and that of linear combination objective by RCGA (2.5251×10^6 $). On the other hand, from the perspective of emission effect, the result obtained by the MAMODE (3.02742×10^5 lb) is more than that of IBFA (2.99036×10^5 lb), but less than that of NSGA-II (3.0994×10^5 lb) and that of linear combination optimization by RCGA (3.1246×10^5 lb). In summary, from the perspective of both effects, the compromise solution obtained by MAMODE is better than that of NSGA-II and that of linear combination optimization

Table 4
The best compromise solution of case 1 obtained by MAMODE (/MW).

t	P_1	P_2	P_3	P_4	P_5	P_6	Total	P_L	P_D
1	0.50360	0.50000	0.53564	0.71952	0.53125	0.50936	3.29937	0.04937	3.25
2	0.51078	0.51645	0.83277	0.91291	0.66584	0.51794	3.95668	0.05668	3.90
3	0.50157	0.50184	0.58741	0.79953	0.65325	0.50880	3.55240	0.05240	3.50
4	0.50000	0.50060	0.50627	0.53431	0.50423	0.50000	3.04540	0.04540	3.00
5	0.50246	0.50530	0.56232	0.79353	0.52825	0.50887	3.40072	0.05072	3.35
6	0.50971	0.50278	0.73482	0.98747	0.82037	0.50507	4.06022	0.06021	4.00
7	0.52234	0.61407	0.95315	1.12284	0.91105	0.70233	4.82579	0.07579	4.75
8	0.56194	0.63102	1.02812	1.24146	0.91239	0.76163	5.13655	0.08655	5.05
9	0.53034	0.67932	1.13455	1.26576	1.12759	0.80435	5.54191	0.09191	5.45
10	0.55067	0.65774	1.04143	1.19163	1.08015	0.76684	5.28845	0.08845	5.20
11	0.54533	0.64585	1.20538	1.24681	1.11388	0.83536	5.59261	0.09261	5.50
12	0.59317	0.71320	1.14356	1.42606	1.13137	0.85077	5.85812	0.10812	5.75
13	0.52469	0.65465	1.09103	1.22374	1.07445	0.76781	5.33636	0.08636	5.25
14	0.50560	0.60084	1.03323	1.22734	1.04617	0.82081	5.23400	0.08400	5.15
15	0.51007	0.67906	0.95899	1.13631	0.85954	0.68159	4.82556	0.07556	4.75
16	0.53469	0.68599	1.12259	1.23908	1.05799	0.74771	5.38804	0.08804	5.30
17	0.52331	0.64701	1.05372	1.25145	0.99131	0.76821	5.23500	0.08500	5.15
18	0.59079	0.78520	1.12479	1.31603	1.13454	0.90822	5.85957	0.10957	5.75
19	0.53307	0.74636	1.09486	1.23886	1.01038	0.71467	5.33819	0.08819	5.25
20	0.52511	0.62362	1.11703	1.23514	1.12796	0.70590	5.33475	0.08475	5.25
21	0.51071	0.56845	0.96567	1.07560	0.94015	0.55740	4.61798	0.06798	4.55
22	0.50792	0.52514	0.91424	1.07138	0.75179	0.54202	4.31250	0.06250	4.25
23	0.50682	0.55119	0.85538	1.01619	0.71330	0.67182	4.31470	0.06470	4.25
24	0.50082	0.52474	0.79579	0.88548	0.81260	0.53846	4.05790	0.05790	4.00

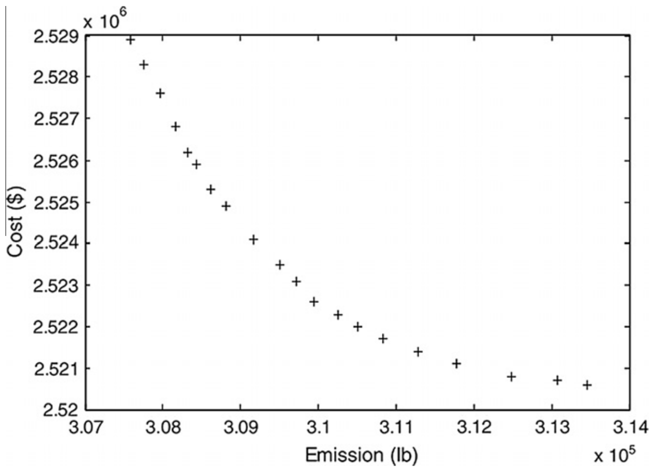

Fig. 3. POF of case 2 obtained by the method in [25].

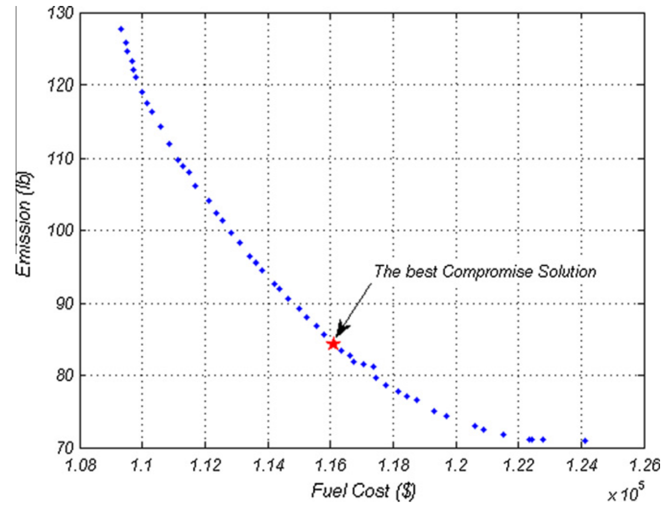

Fig. 4. POF of case 3 obtained by MAMODE.

Table 5
Comparison of the simulation results of case 2.

Method	Time consumed	Objective option	FC/10^6 ($)	EM/10^5 (lb)
MAMODE	8 min 25 s	Best FC	2.492451	3.15119
		Best EM	2.581621	2.95244
		Best compromise	2.514113	3.02742
IBFA[23]	5.2017 s	Best FC	2.481773	3.27501
		Best EM	2.614341	2.95883
		Best compromise	2.517116	2.99036
NSGA-II [25]	20 min 11.475 s	Best compromise	2.5226	3.0994
RCGA [25]	About 18 min	Min FC	2.5168	3.1740
	About 18 min	Min EM	2.6563	3.0412
	18 min 25.363 s	Min combination	2.5251	3.1246

by RCGA, it is nondominated by that of IBFA each other. However, it is noted that both IBFA and RCGA are single-objective optimization which can get only one best solution after the program run once.

The details of the compromise solution obtained by MAMODE are listed in Table 6 from which the power balance constraints can be validated. At each time interval, the sum of the output of generating units matches the power load plus the power loss mutually, the solution does not violate the equality constraints at each interval. The time consumed of the proposed method is 8 min and 25 s which demonstrates that the proposed algorithm the stronger search ability and is very promising in practice. From the above result comparisons we can conclude that, compared with other comparative methods, the proposed method can provide better results, the effectiveness of the proposed for solving DEED problem is verified again.

Table 6
The best compromise solution of case 2 obtained by MAMODE (/MW).

t	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	P_L
1	152.98	135.35	142.72	115.51	83.13	145.64	128.27	116.54	24.10	11.28	19.52
2	150.72	138.38	89.21	123.90	130.74	160.00	130.00	119.97	49.38	40.04	22.34
3	150.00	136.16	149.27	150.62	172.88	155.39	125.63	119.98	71.55	54.98	28.46
4	153.93	194.58	210.09	130.34	221.42	151.47	129.85	119.81	79.68	51.01	36.17
5	156.18	216.46	195.22	178.24	229.00	160.00	130.00	120.00	80.00	55.00	40.09
6	205.81	246.16	214.04	223.27	243.00	160.00	130.00	120.00	80.00	55.00	49.29
7	198.04	202.03	294.04	273.27	243.00	160.00	130.00	120.00	80.00	55.00	53.38
8	221.73	271.38	258.38	296.00	242.94	159.94	129.94	119.95	79.94	54.95	59.15
9	294.78	296.29	317.57	298.40	242.97	159.97	129.97	119.97	79.97	54.97	70.86
10	330.15	343.55	339.95	299.93	242.99	160.00	130.00	120.00	80.00	55.00	79.56
11	381.40	388.24	340.00	296.33	243.00	160.00	129.99	120.00	80.00	55.00	87.96
12	403.94	411.43	339.98	299.99	242.99	159.77	129.99	119.41	80.00	54.99	92.50
13	368.06	360.54	339.99	300.00	242.98	159.99	129.98	119.98	79.98	54.99	84.47
14	288.37	324.95	297.64	299.06	242.74	159.98	129.74	119.44	78.26	54.95	71.13
15	211.62	265.16	274.72	295.70	242.96	159.96	129.99	119.95	79.96	54.95	58.97
16	151.18	219.44	195.23	246.48	242.64	159.64	129.64	119.64	79.64	54.64	44.16
17	170.60	144.04	184.03	237.41	242.90	157.63	129.48	118.98	79.57	55.00	39.64
18	228.51	219.13	204.59	237.05	243.00	160.00	130.00	120.00	80.00	55.00	49.27
19	225.22	254.01	281.03	286.73	243.00	160.00	130.00	120.00	80.00	55.00	58.99
20	296.46	325.35	337.08	300.00	243.00	160.00	130.00	120.00	80.00	55.00	74.89
21	291.94	288.71	329.06	299.52	243.00	159.29	129.69	119.54	79.50	54.50	70.75
22	213.68	209.86	249.31	252.32	212.57	160.00	130.00	119.62	80.00	49.64	48.99
23	150.52	137.44	172.95	203.68	167.86	160.00	126.24	111.63	79.98	53.55	31.85
24	150.12	135.72	117.94	154.05	205.08	148.92	124.05	96.92	51.71	24.73	25.23

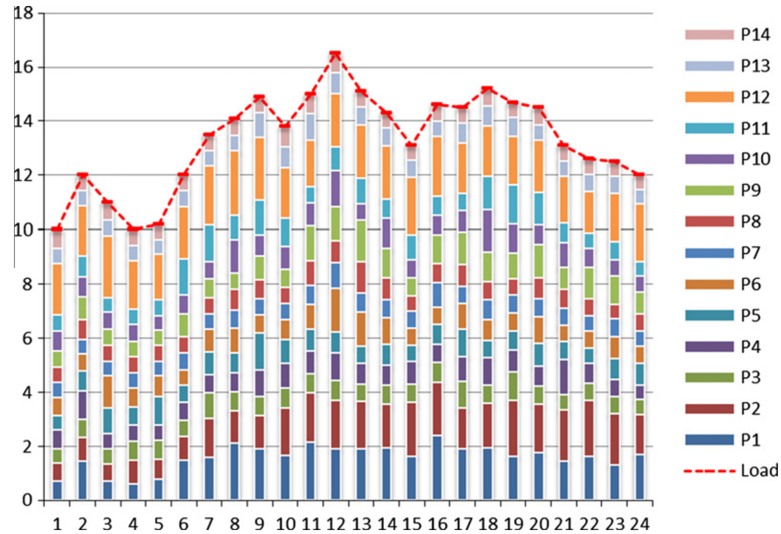

Fig. 5. Constraints checking of the best compromise solution.

Table 7
Comparison of the final results of case 3.

	MAMODE	GSOMP [24]	MOPSO [24]	NSGA-II [24]
FC ($)	114709.2	142547.2	143218.3	145790.5
EM (lb)	70.21	331.23	359.07	348.58
Time (s)	235	5321.0	4733.0	14123.2

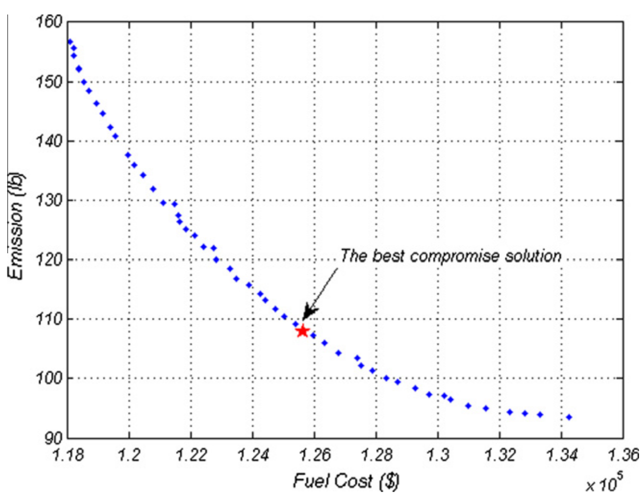

Fig. 6. POF of case 4 obtained by MAMODE.

Table 8
The results of case 4 obtained by the MAMODE.

	Minimum	Maximum	Best compromise
FC ($)	118094.70	134258.849082	125648.735817
EM (lb)	93.597782	156.481978	107.850296

5.2.3. Case 3

In this case, the IEEE 118-bus system with 14 generating units [40] without considering the power loss is studied to verify the effectiveness of the proposed algorithm in solving high dimensional DEED problem. The parameters of MAMODE used in this case are set as: $N_p = 100$, $N_q = 50$, $G_{\max} = 1000$, $F = 0.5$, and $P_c = 0.2$.

Based on the above parameter setting, The Pareto front of this case obtained by the proposed method is shown in Fig. 4. The power balance constraints checking for the best compromise solution is displayed in Fig. 5. The detailed results of the best compromise solution are given in Table 7. For the convenience of comparison, the final results of the same problem reported in [24] are summarized in Table 7 too. It is clear to see that the Pareto solutions are distributed uniformly in the objective space from Fig. 4. Fig. 5 shows that the power balance constraints at each interval are satisfied. From Table 7, it is easy to find that the result of the proposed method is better than that of the other three methods. Due to the limited size, the details of the best compromise solution are not listed here.

5.2.4. Case 4

In this case, the IEEE 118-bus system with 14 generating units considering the power loss of the network is studied to verify the effectiveness in solving high dimensional DEED problem with nonlinear objectives and constraints. The parameters used in this case are set as $N_p = 100$, $N_q = 50$, $G_{\max} = 1000$, $F = 0.55$, and $P_c = 0.2$.

Based on the above parameter setting, The Pareto front obtained by the proposed method is shown in Fig. 6. From this figure, we can see directly that the Pareto solutions are widely and well distributed. Due to the limited size of the paper, the details of the compromise solution are not given here, too. The minimum, maximum of each objective value and the best compromise solution obtained by the proposed MAMODE method are listed in Table 8.

6. Conclusion

The DEED model is presented in this paper. In this model, the total fuel cost and emission are optimized as conflicting objectives over a certain dispatch period. The nonlinear factors of the generators' ramp rate limits, valve point effect, power load variation and power losses are taken into consideration. A modified adaptive multiobjective differential evolutionary algorithm is proposed to solve the problem. In the proposed method, the evolutionary operators are modified and expanded to strengthen the global search ability for avoiding premature convergence. Fast nondominated sorting and elite strategy are employed to select and preserve better solutions. An effective dynamic heuristic constraint handling approach is used to deal with the complicated constraints. By testing on four cases of three power systems, the simulation results show that DEED is well solved by the proposed method and a set of well and widely distributed Pareto optimal solutions can be obtained quickly. Comparison of results with these methods proposed in related literature indicates that the proposed approach has higher performances and better potential applications.

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