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Environmental and Economic Dispatch Model for Smart Microgrid Based on Shuffled Frog Leap Algorithm Optimized by Random Nelder Mead

Abstract: *As more and more distributed generation resources are integrated into the grid through smart micro-grid, achieving a more economic and better responsive distributed generation dispatch is of great importance. Economic and environmental characteristics of distributed generation are synthetically combined in a dispatch model with objective function of minimum generation cost and emission cost in this paper, and also a novel algorithm Shuffled Frog Leap Algorithm (SFLA) optimized by random Nelder Mead (RNM) model was proposed to solve the economic and environmental problem. At last, the differences in generation cost and Computation time of RNM-SFLA, Genetic Algorithm (GA), Evolutionary Programming (EP) and Shuffled Frog Leap Algorithm (SFLA) are compared with a numerical example, verifying the feasibility and advancement of environmental and economic dispatch model based on RNM-SFLA.*

Streszczenie. *W artykule przedstawiono model przesyłu energii elektrycznej w systemie elektroenergetycznym, mający na celu minimalizację kosztów wytwarzania i przesyłu energii. Zaproponowano także nowy algorytm SFL (ang. Shuffled Frog Leap), który został zoptymalizowany metodą Nelder'aa-Mead'a. Algorytm ma zastosowanie w rozwiązywaniu zagadnień ekonomicznych i środowiskowych. Przeprowadzona została analiza porównawcza opisanego modelu. (**Ekonomiczny i środowiskowy model zapotrzebowania energetycznego dla inteligentnej mikro-sieci – wykorzystanie algorytmu SFL zoptymalizowanego metodą Nelder'a-Mead'a**).*

Keywords: distributed generation, smart microgrid, environmental and economic dispatch, shuffled frog leap algorithm optimized by random nelder mead
Słowa kluczowe: generacja rozproszona, inteligentne mikro-sieci, zapotrzebowanie ekonomiczne i środowiskowe, algorytm SFL

1 Introduction

As a good supplementary form for large power supply and large-scale energy base, distributed generation system increasingly becomes an important way to meet the needs of load growth, reduce pollution, increase energy utilization efficiency, improve supply reliability and so on[1,2] with its characteristics of small investment and flexible power generation[3]. That distributed generation is integrated into the main grid through intelligent micro-grid and acts as margin capacity with each other, is the best mode for distributed generation integrated into the grid. Smart micro-grid is the integrated application of new electric power technologies, distributed generation, renewable energy and energy storage technologies. It requires the flexibility to start or stimulate the output of distributed generation unit and achieve "plug and play", which presents a huge challenge to distributed energy dispatch[4].Distributed energy will develops rapidly during "12th Five-Year Plan" period. With more and more distributed generation integrated into grid, it has been the great problem to meet the load demand. It is important to get a reasonable and effective arrangements for the distributed generator minimizing the costs of generation and emission costs and improving the response flexibility intelligent smart micro-grid.

There are a large number of scheduling studies for the wind power and other large-scale renewable energy on the power generation side [5-8]. The studies of distributed generation are mainly concentrated in the distributed power planning [9-13], the security and economic impact assessment of grid caused by distributed generation and so on[14-16]. Algorithm [17, 18] can be used to evaluate the probably environmental and economic benefits of wind power integration. Reference [19] and reference [20] build a distributed generation economic dispatch models with maximizing the system economic benefits as their objective functions, and reference [21] constructs an interconnected regional coordination model with the goal of minimizing the pollutant emissions of the entire network. And reference [22] and reference [23] building models based on evolutionary algorithms and genetic algorithms respectively can be used for dispatch problem.

Here we construct a dispatch model with the objective function of minimum generation and emission cost and introduces a new algorithm "Shuffled Frog Leap Algorithm" optimized by "Random Nelder Mead" which ensures fast search speed and high accuracy to obtain the optimal solution. It makes up the shortcomings of traditional genetic algorithm and evolutionary algorithm which can easily fall into local optimum and have a low computational efficiency. At last, the example of a micro-grid system on an island is given out comparing the differences in generation cost and Computation time of GA, EP, the SFLA and RNM-SFLA constructed in this article, which verifies the advanced nature of the model improved in this paper.

2 Environmental and Economic Dispatch Model for Smart Micro-grid

Environmental and economic dispatch for Smart micro-grid can make minimize the cost of power generation and greenhouse gas emission through the rational dispatch of distributed generators in micro grid, and balance the supply and demand of power generation.

2.1 Power output model.

In the smart micro grid built in this paper, we assume the renewable energy generation units including include wind generation units and photovoltaic power generation units, with the power output model formulated as follows:

$$P_W = \begin{cases} 0, & 0 \le s < s_{c1} \\ P_{W,r} \times \dfrac{s - s_{c1}}{s_r - s_{c1}}, & s_{c1} \le s < s_r \\ P_{W,r}, & s_r \le s \le s_{c2} \\ 0 & s_{c2} < s_i \end{cases} \tag{1}$$

$$P_S = \begin{cases} P_{S,r} \times \dfrac{R_j^{\,2}}{R' \cdot R}, 0 \le R_j < R \\ P_{S,r} \times \dfrac{R_j}{R'} \quad , R \le R_j \le R' \\ P_{S,r} \quad , R_j > R' \end{cases} \tag{2}$$

where P_W is the power output function of the wind turbine generation unit; s is the actual wind speed, s_{c1} is the wind turbine cut-in speed (i.e. the minimum wind speed at hub height when wind turbine starts), s_r is the wind turbine rated wind speed, s_{c2} is the wind turbine cut-out speed, (i.e. the maximum wind speed at hub height while the wind turbine maintains rated power output), $P_{W,r}$ is the rated output power of the wind turbine, R_j is the solar radiation predicted with the solar radiation intensity level j, P_S is the output power of the solar power with the solar radiation intensity level j; R' is the solar radiation intensity under the standard, $P_{S,r}$ is the rated output capacity the solar power equivalent to.

The total power output of the renewable energy generation units can be expressed as:

$$P_i = P_{W,i} + P_{S,i}, i = 1, 2, ..., 24 \tag{3}$$

2.2 Objective function.

$$MinTC(q_i) = \sum_{i=1}^{n} C_{dg,i}(q_i) + \sum_{i=1}^{n} C_{de,i}(q_i) \tag{4}$$

where TC(•) is the total operation cost function; n the number of generator unit in microgrid; $C_{dg,i}$(•) is the generation cost of *ith* distributed generation unit; $C_{de,i}$(•) is the emission cost of *ith* distributed generation unit; q_i is the power generation of *ith* distributed generation unit.

The generation cost of distributed generation units includes fuel costs, operation costs and maintenance costs, just as shown in formula (5):

$$C_{dg,i}(q_i) = C_{df,i}(q_i) + C_{do,i}(q_i) \tag{5}$$

where $C_{df,i}$(•) is the fuel cost of *ith* distributed generation unit; $C_{do,i}$(•) is the maintenance cost of *ith* distributed generation unit.

Fuel cost is shown as:

$$C_{df,i}(q_i) = \xi_{df,i} \times q_i \tag{6}$$

where $\xi_{df,I}$ is the coefficient of fuel consumption of *ith* distributed generation unit, which means the fuel costs of generating 1kWh electricity by distributed generation unit.

Maintenance cost is shown as :

$$C_{do,i}(q_i) = \xi_{do,i} \times q_i \tag{7}$$

where $\xi_{do,I}$ is the coefficient of Maintenance of *ith* distributed generation unit (yuan/kWh), which means the maintenance costs of generating 1kWh electricity by distributed generation unit.

Emission cost is shown as:

$$C_{de,i}(q_i) = \xi_{de,i} \times H_{de} \times q_i \tag{8}$$

where $\xi_{de,I}$ is the coefficient of carbon emission reduction of *ith* distributed generation unit (kg/kWh), which mean the greenhouse gas emissions of generating 1kWh electricity by distributed generation unit; H_{de} is the emission cost of greenhouse gas.

2.3 Constraint condition.

When achieving environmental and economic dispatch in the micro-grid, it needs to meet the power balance constraint, just as shown in (9):

$$Q = \sum_{i=1}^{n} q_i \tag{9}$$

where Q is the total demand load.

In order to achieve safe and stable operation of the micro-grid when integrated into the grid, real power output of each distributed generator is restricted by lower and upper limits, just as shown in (10):

$$q_{i\min} \le q_i \le q_{i\max} \tag{10}$$

where q_{imax} and q_{imin} are the upper limit and lower limit of power output of *ith* distributed generation unit respectively.

3 Frog Leap Algorithm Optimized by Random Nelder Mead

3.1 Shuffled Frog Leaping Algorithm.

SFLA, originally developed by Eusuff and Lansey in 2003, can be used to solve many complex optimization problems that are nonlinear, nondifferentiable, and multi-modal. It is characterized by simple concept, fast convergence, fewer parameters, the good global search ability and easy implementation, so SFLA has been successfully applied to several engineering optimization problems such as tide optimization and production design problem [25].

The SFLA is a meta-heuristic optimization method which is based on observing, imitating, and modeling the behavior of a group of frogs when searching for the location which has the maximum amount of available food[26]. In SFLA, there is a population of possible solutions defined by a set of virtual frogs partitioned into different groups which are described as memeplexes, each performing a local search. Within each memeplex, the individual frogs hold ideas, which can be infected by the ideas of other frogs. After a defined number of memetic evolution steps, ideas are passed between memeplexes in a shuffling process. The local search and the shuffling process continue until the defined convergence criteria are satisfied.

In the first step of this algorithm, an initial population of P frogs is randomly generated within the feasible search space. The position of the *i*th frog is represented as $U_i = (u_{i1}, u_{i2}, ..., u_{in})$. Then, the frogs are sorted in descending order according to their fitness. Afterwards, the entire population is partitioned into m subsets referred to as memeplexes, each containing F frogs (i.e. $P = m \cdot F$). The strategy of the partitioning is as follows: the first frog goes to the first memeplex, the second frog goes to the second memeplex, the m^{th} frog goes to the m^{th} memeplex, the $(m+1)^{th}$ frog goes back to the first memeplex, and so forth.

In each memeplex, the positions of frogs with the best and worst fitnesses are identified as U_b and U_w, respectively. Also the position of a frog with the global best fitness is identified as X_g. Then, within each memeplex, the algorithm is applied to improve only the frog with the worst fitness (not all frogs) in each cycle. Therefore, the position of the frog with the worst fitness leaps toward the position of the best frog, as follows[27]:

$$\lambda_i = R \times (U_b - U_w) \tag{11}$$

$$U'_w = U_w + \lambda_i, (\lambda_{i\min} < \lambda_i < \lambda_{i\max}) \tag{12}$$

where R is the random number in [0,1]; $\lambda_{i\max}$ and $\lambda_{i\min}$ are the maximum and minimum step sizes allowed for a frog's position, respectively. If this process produces a better solution, it will replace the worst frog. Otherwise, the calculations in (11) and (12) are repeated but U_w is replaced by U'_w . If there is no improvement in this case, a new solution U_w will be randomly generated within the feasible space to replace it. The calculations will continue for a specific number of iterations.

After a predefined number of memetic evolutionary steps within each memeplex, the solutions of evolved memeplexes are replaced into new population. The shuffling process promotes a global information exchange among the frogs. Then, the population is sorted in order of decreasing performance value and updates the population best frog's position, repartition the frog group into memeplexes, and progress the evolution within each memeplex until the conversion criteria are satisfied. Usually, the convergence criteria can be defined as follows: (1) the global optimal solution does not significantly improve after K times exchanging the global information; (2) The maximum predefined number of shuffling iteration has been obtained.

3.2 Random Nelder-Mead simpex methods.

NM simplex method is an improved algorithm proposed by Nelder and Mead in 1965. The NM simplex search method is designed for unconstrained classical optimization problems. It aims at generating search directions and then adopting five basic operations to look for a better vertex. Search directions in NM are obtained by calculating the objective function values rather than the gradient information. Actually, the directions are the centroids from the worst vertices to all other vertices. Besides, the five basic operations include reflection, expansion, inside contraction, outside contraction and shrink[28]. In Figure 1, V is a search direction in NM, and X_r, X_e, X_{ic} and X_{oc} denote shrinkage point, expansion point, inside/outside contraction point respectively, where X is a 2-dimension vector, (μ,ζ).

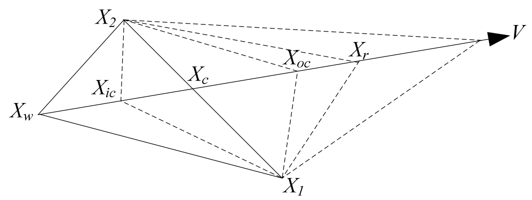

Fig.1. The searching direction and vertices of reflection, expansion, outside and inside contraction of NM

Assuming that a simplex S is the convex hull of N+1 vertices and f(x) corresponds to fitness function values of these vertices. The local behavior of objective function is taken into consideration in NM. Indeed, NM method can be modified to solve constrained optimization problem. Each iteration of the modified NM includes three parts [29]:

(1) Ordering: X_b, X_w and X_{sw} are defined as the best, worst and second-worst vertices in the current simplex S.

(2) Centroid: The centroid of simplex is calculated in the absence of the best vector as follows:

$$X_c = \frac{1}{N}\sum_{\substack{j=0 \\ j\neq b}}^{N} X_j \tag{13}$$

where X_c is the centroid of all vertices except the worst one.

(3) Transformation: The new simplex S is generated from the current one. The worst vertex X_w is improved by reflection, expansion and contraction. If these attempts failed, shrink the simplex towards the best vertex and get N new vertices.

RNM adopted in this paper is the improvement of the primary NM. Random search parameters are employed and perturb around reflection, expansion and contraction parameters. According to the basic procedures of NM, the steps of RNM algorithm are shown as follows.

Step 1: Reflection: The reflection vertex is generated by reflecting the worst point, as is shown:

$$X_r(i,j,l) = X_c(i,j,l) + H_r(X_c(i,j,l) - X_w(i,j,l)) \tag{14}$$

where $H_r=[r+C_r\times R,\ldots,r+C_r\times R]_{l\times d}$ is point multiplication; $0 < C_r < 1$ is the controlling factor and is typically supposed to be 0.5; R is the random number in [0,1]. If $f(X_b)\leq f(X_r)\leq f(X_{sw})$, replace X_w with X_r and end the iteration process. If $f(X_b) < f(X_r)$, proceed with expansion, otherwise proceed with contraction.

Step 2: Expansion: The simplex expands in the same direction, as shown in Equation 15:

$$X_e(i,j,l) = X_r(i,j,l) + H_e(X_r(i,j,l) - X_w(i,j,l)) \tag{15}$$

where $H_e=[e+C_r\times R,\ldots,e+C_r\times R]_{l\times d}$ is expansion factor matrix; $0 < C_r\leq 1$ is the controlling factor and is typically supposed to be 0.5; R is the random number in [0,1].

Step 3: Contraction: There are mainly two kinds of contractions, outside contraction and inside contraction.

(1)Outside contraction: If $f(X_{sw})\leq f(X_r) < f(X_w)$, the contraction vector is stated as Equation 16:

$$X_{oc}(i,j,l) = X_c(i,j,l) + H_{oc}(X_c(i,j,l) - X_r(i,j,l)) \tag{16}$$

where $H_{ic}=[\gamma_{ic}+C_r\times R,\ldots,\gamma_{ic}+C_r\times R]_{l\times d}$ is outside contraction factor matrix; $0 < C_r\leq 1$ is the controlling factor and is typically supposed to be 0.5; R is the random number in [0,1].

If $f(X_c) < f(X_r)$, replace X_w with X_c and end the iteration process; Otherwise, perform a shrink transformation.

(2)Inside contraction: If $f(X_w)\leq f(X_r)$, the contraction vector is stated as Equation 17:

$$X_{ic}(i,j,l) = X_c(i,j,l) + H_{ic}(X_w(i,j,l) - X_c(i,j,l)) \tag{17}$$

where $H_{oc}=[\gamma_{oc}+C_r\times R,\ldots,\gamma_{oc}+C_r\times R]_{l\times d}$ is inside contraction factor matrix; $0 < C_r\leq 1$ is the controlling factor and is typically supposed to be 0.5; R is the random number in [0,1].

If $f(X_c)\leq f(X_w)$, replace X_w with X_c and end the iteration process; Otherwise perform a shrink transformation.

Step 4: Shrink: Shrink all the vertices except X_b as is shown in Equation 18:

$$X_j = X_b + \delta(X_j - X_b), 0 < \delta < 1 \tag{18}$$

where δ is the shrinkage parameter suggested to be 0.5.

It should be noted that when C_r=0, RNM is the same as NM. With respect to RNM, the search parameters in the $(i+1)^{th}$ iteration are different from those in the i^{th} iteration. Hence, this algorithm cannot be blocked in the *ith* iteration and a new vertex is obtained. That is to say, overall search is successfully cancelled in RNM.

3.3 Shuffled Frog Leap Algorithm Optimized by Random Nelder Mead.

When SFLA is calculated by (11) and (12) or replacing U_b with U_g finding the better frog, it possibly occurs the situation that there is no optimum frog existing. A frog will be randomly generated in the search space and continue optimizing, but the new frogs may worse than the previous worst frog. RNM can improve the local search capabilities of SFLA, so as to avoid the occurrence of the above situation, and the specific method is as follows.

The vector dimension of RNM is one more than the variable number, thus requiring the frog number of each memeplex to be equal to N+1. This paper set the memeplex contains N +1 frog. When SFLA cannot find the better frog with (8) and (9) or replacing U_b with U_g, RNM should be used to instead the method of randomly generating frogs in the search space. The input vector of RNM is the $(N+1)^{th}$ frogs of the memeplex, and its output will replace the worst frog in the memeplex. Figure 2 is the flowchart of RNM-SFLA.

When using RNM-SFLA to solve the micro-network environmental and economic dispatch model, what SFLA frog stands for in the actual issue should be cleared. As shown in section 2.2, the objective function is to minimize total operation costs of the distributed generation unit, and the function variable is the power generation of every distributed generation unit. Therefore, the frogs in the SFLA denote the vector expression of the power generation of the generation unit in the practical problems, which means the i^{th} frog is expressed as $U_i = (q_{i1}, q_{i2}, ..., q_{in})$, and n is the total number of generation unit. Fitness of each frog corresponds to the value of objective function in this problem, so the worst frog is the power generation of each unit vector which has the largest objective function value, and the best frog is the power generation of each unit vector which has the lowest objective function value.

4 Examples and Results

In order to verify the validity and advantage of RNM-SFLA, here we introduce an example based on the data of certain islands with isolated grid on September 2, 2010. In this region, there are one wind farm and four micro-gas-fired units in the power system, and load data for the every period of September 2, 2010 is shown in table 1, and wind power generation curve is shown in Figure 3.

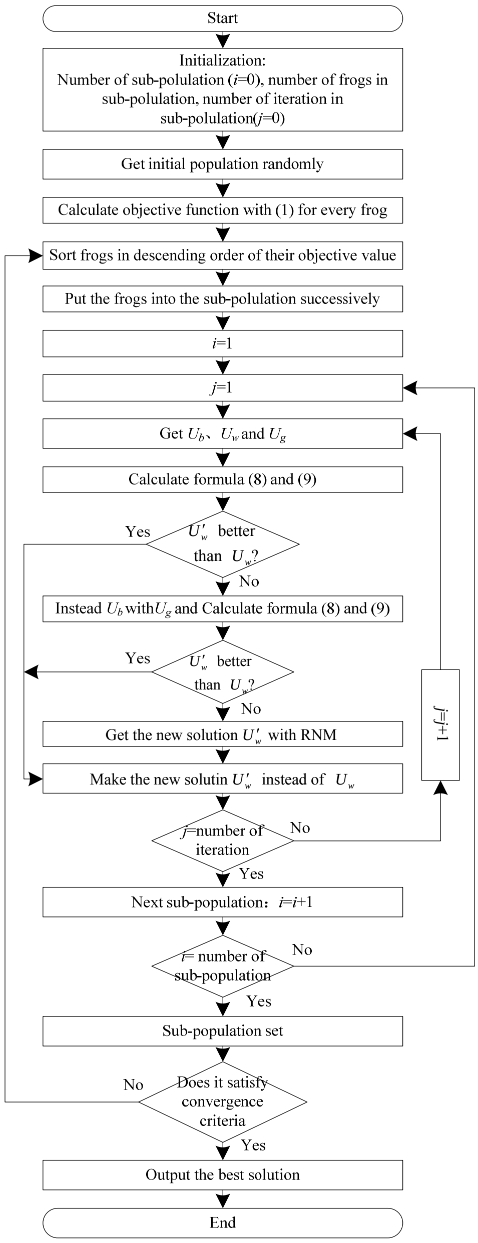

Fig. 2. The flowchart of RNM-SFLA

In the wind farm, there are 20 parallel operation wind turbines with the same model, and the total rated generation capacity is 120MW. Dispatch is based on the prediction of wind turbine output and probable power to transmit. The minimum generation unit output is 30MW, and maximum generation unit output is 120MW. Figure 4 shows the convergence of power generation operation costs of the day. In this wind farm, the evolution of generation is 200, the memeplex is 20, and the calculation number is 10. Operation costs of the micro-grid system converges to the minimum cost of 149,357 yuan. To assess the rationality of the model constructed in this paper, we compare and analyze the results by GA, EP, SFLA, and RNM-SFLA. The total cost of power generation and the corresponding computation time on September 2, 2010 are shown in Table 2.

Table 1. Total load historical data of each time period for generators on September 2, 2010

Time (h)	Load(MW)	Time (h)	Load (MW)
1	267	13	786
2	271	14	724
3	239	15	790
4	225	16	804
5	248	17	710
6	257	18	681
7	351	19	670
8	676	20	608
9	813	21	514
10	843	22	490
11	856	23	465
12	892	24	389

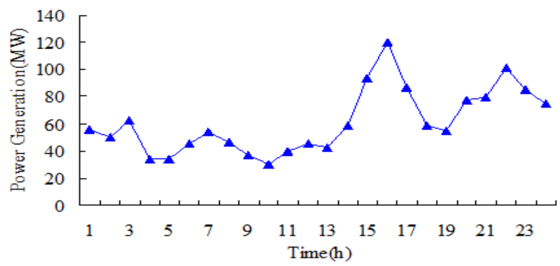

Fig.3. Output power of each time period for the wind farm on September 2, 2010

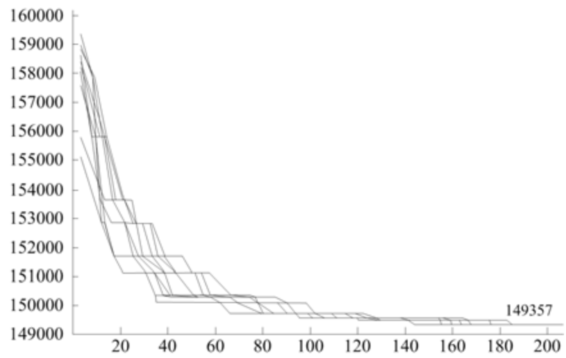

Fig. 4. The convergence scenario for total generation cost based on RNM-SFLA

By comparing these methods of the average convergence cost of power generation, it can be found that the RNM-SFLA algorithm can save more scheduling cost than SFLA, EP and GA, with respectively 1387 yuan, 2227 yuan and 2902 yuan. At the same time, comparing with several other algorithms, the average Computation time of RNM-SFLA built in this article has the shorter computation time which is respectively 60.6% of GA, 33.1% of EP, and 28.2% of SFLA.

Table.2. Comparison of results and computation time by using the referring five methods

Algorithm	Convergence cost of generation (yuan)			Computation time (s)		
	Min.	Max.	Ave.	Min.	Max.	Ave.
GA	152768	153289	153029	4.76	6.37	5.57
EP	152097	152610	152354	3.85	5.63	4.74
SFLA	150793	152235	151514	2.23	2.94	2.59
RNM-SFLA	149357	150896	150127	1.21	1.92	1.57

Generally speaking, the economy and computation time of the RNM SFLA and SFLA are superior to the GA and EP, and RNM-SFLA works best. Different from GA, EP and SFLA which avoid the local optimum trap based on probability, RNM-SFLA improves the local search ability of SFLA, so the search direction is more accurate and it is more easily to find the potential replacement point in the vicinity of search direction. Therefore we can find the global optimal solution with a faster search speed and a higher convergence rate.

5 Conclusions

This paper introduces the RNM to overcome the weakness of SFLA which easily traps in a local optimum by generating a random set of variables, and the global optimal solution can be found with a fast search speed and high accuracy. Example studies have shown that, comparing with traditional GA and EP, the model built in this paper can save more than 2200 yuan of the generation cost and also save 3/5 of the calculation time. It can achieve requirements of distributed generation dispatch for economy and response speed in the future. Especially for large-scale distributed generation dispatch in the future, this model will produce greater economic and social benefits, so the proposed method has a high practical value.

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