Optimal Combination Control Technology of Demand Side Resources of Distributed Renewable Energy Power Generation

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Abstract

The paper proposes a new unit commitment model that can promote carbon emission reduction in distributed renewable energy power systems. The model first comprehensively considers the optimal combination of low-carbon demand-side resources such as supply-side resources and demand response, electric vehicles, and distributed renewable energy power generation. Secondly, the model unit scheduling rules fully consider the carbon emission target and the economic target and propose a fuzzy dual-objective optimization method that can consider the relative priority of the target. When solving the optimization model, we improved the particle swarm optimization algorithm. We introduced the "cross" and "mutation" operators in the genetic algorithm to improve the particle swarm algorithm's global optimization capability. The paper verifies the effectiveness of the model and algorithm through the analysis of a ten computer system.

Keywords: Unit commitment, demand-side resources, fuzzy dual-objective optimization model, combined control, greenhouse gas emission reduction.

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1 Introduction

The power industry, which is regarded as a significant emitter of greenhouse gas emission reduction, shoulders a huge emission reduction task. Therefore, the unit combination, which is an essential part of the power system's operation, should be changed accordingly. On the one hand, the optimal combination of various resources on both sides of power supply and demand should be pursued [1]. Traditionally, the balance of supply and demand is to call the supply side's resources according to the load demand. The unit combination only arranges the start, stop and output of each unit on the supply side. With the development of intelligent grid-related technologies, demand-side resources such as demand response (DR), electric vehicles, and distributed renewable power sources can play a more significant role in balancing supply and demand. Demand-side resources are mostly low-emissions or even zero-emissions. The marginal cost of increasing unit output on the supply side during peak load periods is high, so demand-side resources also have economic advantages to a certain extent. At present, some experts have begun to consider electric vehicles, user interaction and response separately when studying unit combination problems. Still, few studies integrate various demand-side resources into a unified consideration.

On the other hand, the optimization goal should pursue the minimum total cost and organically integrate the economic goal with the carbon emission goal. Therefore, the unit commitment problem should be a dual-objective optimization problem. Some experts have considered these two goals simultaneously, using some relatively simple methods such as direct weighted summation or transforming one of them into constraint conditions to convert dual-objective optimization into single-objective optimization. Because economic indicators and carbon emissions indicators do not have the same dimension and range of change, how to more effectively integrate the two goals for optimization remains to be further studied [2]. Concerning the solution method of unit commitment, more and more researchers have begun to use intelligent optimization algorithms for calculations, especially the late particle swarm optimization (PSO) algorithm. But this method has the problem that it is easy to fall into the local optimum and converge prematurely. Therefore, some scholars have begun to improve the PSO algorithm to a certain extent.

Under the above background, this paper proposes a new unit commitment model. Simultaneously, several types of demand-side low-carbon resources are considered and combined with traditional units for optimization [3]. We adopt fuzzy dual-objective optimization methods and propose methods that can consider the relative priority of the objectives to integrate economic objectives and carbon emission objectives effectively. In the solving algorithm, new improvements have been made to the PSO algorithm to solve the unit commitment problem better.

2 Unit Commitment Model Considering Low-Carbon Resources on the Demand Side

2.1 Objective Function

2.1.1 Economic goals

The economic objective considers the power generation cost of conventional power plants and various demand-side resources' deployment costs. In this paper, the respective collections of DR, electric vehicle discharge to the grid (V2G), and distributed power generation (DG) are regarded as a particular generator set. Considering the participation characteristics of user-side resources, the marginal cost should increase with the increase of the call volume, so the cost function is nonlinear, which is represented by a quadratic function in this article.

(1) Cost of conventional power plants
The fuel cost of generator set i in period t is:

$$C_{Fi}(P_{i,t}) = a_i + b_i P_{i,t} + c_i P_{i,t}^2 \tag{1}$$

$P_{i,t}$ is the output of unit i in period t; a_i is the cost coefficient of unit i. The start-up cost of generator set i in period t is:

$$C_{Si,t} = \begin{cases} h_{Si} & M_{Di} \leq X_{i,t}^{off} \leq M_{Di} + T_i \\ c_{Si} & X_{i,t}^{off} > M_{Di} + T_i \end{cases} \tag{2}$$

M_{Di} is the minimum continuous shutdown time of unit i; $X_{i,t}^{off}$ is the time that unit i has been continuously shut down during period t; T_i is the cold start time of unit i.

(2) DR cost

$$C_{DP}(P_{DRt}) = a_{DR} + b_{DR} P_{DRt} + c_{DR} P_{DRt}^2 \tag{3}$$

In the formula: P_{DRt} is the "output" of the demand response resource in period t (the power load is reduced); a_{DR}, b_{DR}, c_{DR} is the cost coefficient of DR.

(3) V2G cost

$$C_{V2G}(P_{V2Gt}) = a_{V2G} + b_{V2G}P_{V2Gt} + c_{V2G}P_{V2GT}^2 \tag{4}$$

In the formula: P_{V2Gt} is the power returned to the grid by the electric vehicle operating in mode $V2G$ during the period t; $a_{V2G}, b_{V2G}, c_{V2G}$ is the $V2G$ cost coefficient.

(4) DG cost

In this paper, DGa is used to denote DG for user's use, and DGb is used to denote DGwhich is connected to the grid. The cost of DGB is:

$$C_{DG}(P_{DGbt}) = a_{DGb} + b_{DGb}P_{DGbt} + c_{DGb}P_{DGbt}^2 \tag{5}$$

In the formula: P_{DGbt} is the power of DG connected to the grid during t period; $a_{DGb}, b_{DGb}, c_{DGb}$ is the cost coefficient of DG connected to the grid. In summary, the total cost of system operation is:

$$\begin{aligned} C = &\sum_{t=1}^{H}\sum_{i=1}^{N}[C_{Fi}(P_{i,t})I_{i,t} + I_{i,t}(1 - I_{i,t-1})C_{Si,t}] \\ &+ \sum_{t=1}^{H}[C_{DR}(P_{DPt}) + C_{V2G}(P_{V2Gt}) + C_{DG}(P_{DGbt}) \end{aligned} \tag{6}$$

In the formula: H is the total number of periods of the research cycle, usually 24; N is the number of generators that can be called by the system; $I_{i,t}$ is the switch status of unit i in t period, taking 1 to indicate on, and 0 to indicate off. The economic goal of the unit commitment problem is: $\min C$.

2.1.2 Carbon emission target

In recent years, as energy conservation and emission reduction have become more and more severe, there has been a unit combination optimization problem with the minimum total emissions as the objective function [4]. The carbon emissions of generator set i in period t are:

$$E_i(P_{i,t}) = a_i + \beta_i P_{i,t} + \gamma_i P_{i,t}^2 \tag{7}$$

a_i, β_i, γ_i is the emission coefficient of unit i. We believe that demand-side resources are all zero emissions, so the total emissions of the system are:

$$E = \sum_{k=1}^{H}\sum_{i=1}^{N}[E_i(P_{i,t})I_{i,t}] \tag{8}$$

Then the carbon emission target for the unit commitment problem is $\min E$.

2.2 Constraints

Traditionally, unit commitment problems include power balance constraints, spinning reserve constraints, unit maximum and minimum output constraints, and minimum start-up and stop time constraints [5]. Combining with the various demand-side resources considered in this article, we have performed some of the above constraints. The modifications are as follows:

(1) Power balance constraints

$$\sum_{i=1}^{N}(P_{i,t}I_{i,t}) = O_t - P_{DRt} + P_{G2Vt} - P_{V2Gt} - P_{DGat} - P_{DGbt} + L_t \tag{9}$$

In the formula: $\sum_{i=1}^{N}(P_{i,t}I_{i,t})$ is the total output of each conventional unit; O_t is the original load level of the system in period t; P_{G2Vt} is the power delivered by the grid to the electric vehicle in the mode $V2G$ in period t (the reserve load of $V2G$); P_{DGat} is the user's use in period t L_t is the net loss of the system in period t. This article assumes that the net loss has been considered in the system load O_t.

(2) Spinning reserve constraint

$$\begin{aligned}\sum_{i=1}^{N}(P_{i,t\max}I_{i,t}) + P_{DRt,\max} + P_{V2Gt,\max} + P_{DGat} + P_{DGbt,\max} \\ \geq O_t + P_{G2Vt} + L_t + R_t\end{aligned} \tag{10}$$

$P_{i,t\max}$ is the maximum adjustable output of unit i during t period; $P_{DRt,\max}$ is the maximum adjustable power DR during t period; $P_{V2Gt,\max}$ is the maximum adjustable power $V2G$ during t period; $P_{DGbt,\max}$ is the maximum adjustable power DGconnected to the grid during t; R_t is the system spinning reserve capacity.

(3) Output constraints of conventional units

$$P_{i,\min} \leq P_{i,t} \leq P_{i,\max} \tag{11}$$

$P_{i,\min}, P_{i,\max}$ is the minimum and maximum output of unit i, respectively.

(4) The minimum on-off time constraints of conventional units

$$\begin{cases}(1 - I_{i,t+1})M_{Ui} & I_{i,t} = 1 \\ I_{i,t+1}M_{Di} \le X_{i,t}^{off} & I_{i,t} = 0\end{cases} \tag{12}$$

In the formula: M_{Ui} is the minimum continuous operation time of unit i; $X_{i,t}^{on}$ is the time that unit i has been continuously operating during period t. Given that this article considers several low-carbon demands-side resources, some new constraints need to be added. DR is divided into two parts: production electricity and residential electricity to consider its reduction potential. According to users' electricity consumption characteristics, the two types of loads have different upper limits that can be reduced in each period [6]. Besides, taking into account the public image and work requirements of the grid company, it is believed that there are requirements for the upper limit of the proportion of the hourly load reduction and the upper limit of the total daily load reduction.

(5) The upper limit constraint can be reduced for production and residential electricity load in each period

$$P_{DRt} \le P_{DRat,\max} + P_{DRbt,\max} \tag{13}$$

(6) The upper limit constraint of load ratio can be reduced

$$P_{DRt} \le aO_t \tag{14}$$

In the formula: α is the upper limit of the load ratio to be reduced per hour to the original load.

(7) Upper limit of daily total load reduction

$$\sum_{t=1}^{H} P_{DRt} \le P_{DRd\,\max} \tag{15}$$

For $V2G$, set the car battery capacity constraint and the car controllable state constraint. Besides, to protect the battery life and facilitate car owners' use, the upper and lower limits of the battery state of charge (SOC) are taken into account. And believe that SOC will not be lower than the initial level after a scheduling day [7]. Finally, because of the reverse power flow caused by $V2G$, the paper sets an upper limit for each period $V2G$ from power grid security.

(8) Electric vehicle $V2G$ capacity constraints

$$\sum_{t=1}^{H} P_{V2Gt,i} \leq B_i \tag{16}$$

B_i is the battery capacity of the ith electric car.

(9) Constraints on the controllable state of electric vehicles

$$P_{V2Gt,i} = 0t \notin [t_{i1}, t_{i2}] \tag{17}$$

In the formula: t_{i1} and t_{i2} are respectively according to the agreement between the owner of the ith electric car and the dispatcher, the car can be dispatched for the period of $V2G$.

(10) SOC upper and lower limit constraints

$$S_{\min} \leq S_{t,i} \leq S_{\max} \tag{18}$$

$$S_{t,i} = \frac{C_{0,i} + \sum_{u=1}^{t} P_{G2Vu,i} - \sum_{u=1}^{t} P_{V2Gu,i}}{C_i} \tag{19}$$

In the formula: $S_{t,i}$ is the SOC of the i electric vehicle in time t; $C_{0,i}$ is the initial power in the i electric vehicle battery, and C_i is the battery capacity of the i electric vehicle.

(11) Constraints on the SOC relationship between the beginning and end of the scheduling day

$$S_{24,i} \geq S_{1,i} \tag{20}$$

(12) V2G power grid security constraints

$$P_{V2Gt} = \sum_{i=1}^{n} P_{V2Gt,i} \leq P_{V2G\max} \tag{21}$$

n is the number of electric vehicles dispatched according to the V2G mode. According to the time distribution characteristics of related resources, DG has different callable upper limits in each period [8]. At the same time, considering the social responsibility of grid dispatching to promote the integration of distributed renewable energy power generation, the lower limit of the total daily use of DG resources is set. Besides, considering the volatility and intermittent news of distributed renewable energy power generation and its impact on the power grid's operation, we also need to ensure that its penetration rate does not exceed the upper limit.

(13) The upper limit of DG resources that can be called in each period

$$P_{DGbt} \leq P_{DGbt,\max} \tag{22}$$

(14) Constraint on the lower limit of total daily invocation of DG resources

$$\sum_{t=1}^{H} P_{DGbt} \geq P_{DGbd\min} \tag{23}$$

(15) DG permeability upper limit constraint

$$\eta_t = \frac{P_{DGbt}}{\sum_{i=1}^{N}(P_{i,t}I_{i,t}) + P_{V2Gt} + P_{DGbt}} \leq \eta_{\max} \tag{24}$$

η_t is the penetration rate of distributed renewable energy power generation in period t.

3 Fuzzy Dual Objective Optimization Method

3.1 Fuzzy Dual-objective Optimization Regardless of the Priority of the Objective

In this paper, the fuzzy solution method is used to deal with the dual-objective optimization problem. The main steps are as follows.

(1) The paper takes the lowest cost as the objective function to optimize the calculation and obtains the lowest cost as F_{1m}, and obtains the emission at this time as F_{2m}. (2) The paper uses the most negligible emission as the objective function to optimize the calculation to obtain the lowest emission level as F_{2m}, and the cost at this time as F_{1m}. (3) We fuzzify the optimal attribute of the objective function value and establish a mapping from the single objective function value to the degree of membership [9]. It is assumed here that the membership function is determined according to the linear rule, then the membership of the economic objective function value:

$$\mu(f_1) = \begin{cases} 1 & f_1 \leq F_{1m} \\ \dfrac{F_{1M} - f_1}{F_{1M} - F_{1m}} & F_{1m} < f_1 < F_{1M} \\ 0 & f_1 \geq F_{1M} \end{cases} \tag{25}$$

The membership degree of the carbon emission objective function value:

$$\mu(f_2) = \begin{cases} 1 & f_2 \leq F_{2m} \\ \dfrac{F_{2M} - f_2}{F_{2M} - F_{2m}} & F_{2m} < f_2 < F_{2M} \\ 0 & f_2 \geq F_{2M} \end{cases} \tag{26}$$

(4) Integrate the membership degrees of the two objective functions:

$$F = \min\{\mu(f_1), \mu(f_2)\} \tag{27}$$

The optimization goal is $\max F$ or $\min(-F)$, this article takes the latter.

3.2 Fuzzy Dual-objective Optimization Taking Into Account the Priority of Objectives

If there is a relative priority relationship between two targets, we can distinguish the targets' priority by selecting different membership functions. The membership function only needs to satisfy $\mu(F_{1m}) = 1$ and $\mu(F_{1M}) = 0$. The membership function selection rule can be: $\mu(f_1) = (\frac{F_{1M}-f_1}{F_{1M}-F_{1m}})^q$, where $q = 1, 2, \frac{1}{2}, 3, \frac{1}{3}, \ldots$. The faster the membership function decreases near the optimal solution, the stronger the objective function's emphasis. For example, when target 1 is more important than target 2, if the membership function of target 1 is still selected according to formula (28), then the membership function of target 2 can be taken as:

$$\mu(f_2) = \begin{cases} 1 & f_2 \leq F_{2m} \\ \left(\dfrac{F_{2M} - f_2}{F_{2M} - F_{2m}}\right)^{\frac{1}{2}} & F_{2m} < f_2 < F_{2M} \\ 0 & f_2 \geq F_{2M} \end{cases} \tag{28}$$

4 Improved PSO Algorithm Introducing Crossover and Mutation Operators

PSO is a new evolutionary algorithm developed in recent years and is widely used in unit commitment research by domestic and foreign scholars. One of the main disadvantages of PSO is that it tends to converge prematurely and fall into a local optimum. To solve this shortcoming of PSO and enhance the algorithm's global optimization ability when solving multi-dimensional optimization problems. This paper introduces the "crossover" operator and "mutation" operator in the genetic algorithm based on the traditional PSO algorithm [10]. In each iteration of the PSO algorithm, when all particles' position is updated, the crossover and mutation of the particles are carried out with a certain probability to enhance the motivation of each particle to jump out of the optimal local solution and continue to search for the best solution.

5 Case Analysis

The paper takes the 10-machine system commonly used in the study of unit commitments as an example to verify the effectiveness of the model and algorithm proposed in this paper. The system has ten conventional units and demand-side resources. Assume that the spinning reserve Rt = 0.1 Ot. We set the upper limit of the reduction of production electricity load between 08: 00 and 18: 00 to 50 MW per hour, and the upper limit of 10 MW for the rest of the period; the upper limit of reduction of residential electricity consumption between 08: 00 and 18: 00 is 20 MW per hour. The upper limit for the rest of the period is 70 MW. The upper limit of the total response during DR is 5% of the load, and the upper limit of the total daily response is 1400 MW·h. Assume that electric vehicles in the V2G mode are charged in the late night and early morning hours when the original load demand is the lowest and can be dispatched to the grid during the evening peak hours. The upper and lower limits of the SOC of each car are 90% and 40%, respectively, and the initial state is the lower limit level. Assuming that each vehicle's battery capacity is 18kW·h, the number of electric vehicles in V2G mode is 5000, and the upper limit of the grid receiving and transmitting power is 120 MW each hour. Because photovoltaic power generation will become the main component of DG for some time in the future, this article assumes that the power generation of DG during the day (07: 00-17: 00) is relatively high, at 150 MW, and as low as 15 MW in other periods. Two-thirds of them are for self-use, and one-third can be connected to the grid. The lower limit of the total daily call of the grid-connected DG is 250 MW·h. The upper limit of DG permeability is 6%.

In this paper's calculation examples, the optimization solutions under five objective functions are carried out: single economic target, carbon emission single target, non-priority fuzzy dual target, economic priority fuzzy dual target, carbon emission priority fuzzy dual target. Table 1 compares the total cost and total emissions under the five scenarios. It can be seen that the fuzzy

Table 1 Total costs and total emissions under the five scenarios

Scene Number	Aims	Total Cost/USD	Total Emissions/t
1	Economic Single Target	542710	259324
2	Single carbon emission target	717716	95746
3	Fuzzy dual goals (no priority)	607096	158928
4	Fuzzy dual goals (economic goals first)	594878	183779
5	Fuzzy dual goals (Priority to carbon emission goals)	635230	148573

Table 2 Demand-side resource utilization under five scenarios

Scene Number	Aims	Demand-side Resources "Output"/(MW·h)	Proportion/%
1	Economic Single Target	611	2.32
2	Single carbon emission target	2381	9.05
3	Fuzzy dual goals (no priority)	1662	6.31
4	Fuzzy dual goals (economic goals first)	1490	5.66
5	Fuzzy dual goals (Priority to carbon emission goals)	1764	6.7

dual-objective optimization method can effectively balance economic goals and carbon emission goals for collaborative optimization. By comparing the results of the latter three scenarios, it can be seen that the model proposed in this paper can reflect the relative priority between targets.

When optimizing according to the single economic goal, the output of traditional units is relatively large, especially the units with a better economy but higher emission levels represented by Unit1 and Unit2. When optimizing following carbon emission targets, low-carbon demand-side resources can be mobilized to the greatest extent. In the three fuzzy dual-target scenarios, the output of traditional units and the demand-side resource "output" are between the single economic and single carbon emission targets. Table 2 lists the demand-side resource utilization in each scenario and its proportion in the supply and demand sides' total resource output.

It can be seen from Table 2 that the contribution of the total "output" of demand-side resources in the balance of power supply and demand in the five scenarios is between 2% and 10%, which is a relatively reasonable range, and it has effectively played its role in promoting the carbon of the power system. The advantages of reducing emissions are more practical and feasible. The total amount of demand-side resources in Scenario 3, Scenario 4, and Scenario 5 is 2.72, 2.44, and 2.89 times that of Scenario 1, respectively. It can be seen that the fuzzy dual-objective model proposed in this paper can effectively mobilize demand-side resources according to the priority of the object.

Combining Tables 1 and 2, we can see the relationship between demand-side resource utilization and carbon emission reduction. In the five scenarios, the more outstanding the contribution of demand-side resources to the balance of power supply and demand, the smaller the total emissions. The two show an apparent positive correlation trend. From an economic point of view, even in the economic single-target scenario, some demand-side resources are used, indicating that demand-side resources have the advantage of emissions and have economic advantages in some cases. This is reflected in the peak load period. It's more noticeable. It can be seen that the unit commitment model proposed in this paper can effectively integrate the resources of the power supply side and the demand side and make the operation of the power system more economical. The invocation of demand-side resources reduces the fluctuations in the output of thermal power units. For example, in Scenario

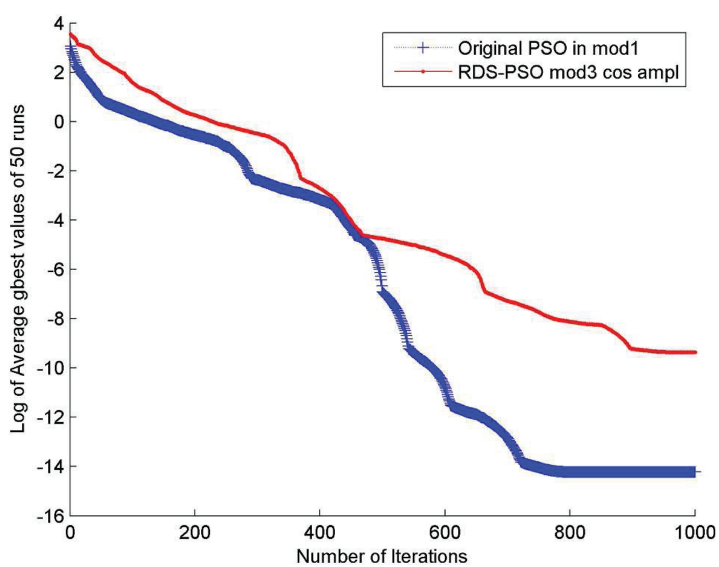

Figure 1 Traditional PSO and improved PSO iterative optimization performance comparison.

1, after considering demand-side resources, the peak-to-valley rate of thermal power output fluctuation dropped from 50.0% to 39.6%. The reason is that demand-side resources will be used more during peak load periods, and the maximum total output of thermal power will be reduced. It can be seen that demand-side resources can alleviate thermal power units' peak shaving pressure and improve their operating efficiency. In terms of algorithm, we compared the effect of using traditional PSO with the improved PSO solution proposed in this paper. Figure 1 shows the changes in the fitness value of the two typical iterative optimizations. It can be seen that the improved algorithm proposed in this paper enhances the global optimization capability, especially in the middle and late stages of the iterative process. As the probability of the "crossover" and "mutation" operators increases, the particles have greater motivation to jump out of the optimal local solution.

6 Conclusion

This paper proposes a new unit combination model that considers demand-side low-carbon resources. In the day-ahead market, various demand-side resources such as DR, V2G, DG, and supply-side resources are comprehensively dispatched, aligning with the development characteristics and energy saving of intelligent grids. Platoon requirements. Simultaneously, the model adopts a fuzzy dual-objective optimization method to combine economic goals and carbon emission goals organically and take into account the relative priorities of the objective functions. In the solution method, the crossover and mutation operators are introduced based on traditional PSO, enhancing the ability of multi-dimensional global optimization. The calculation examples show that the model proposed in this paper can significantly reduce the carbon emissions of the power system operation.

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