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Day-ahead Optimal Scheduling Algorithm Considering Uncertainty of Demand Response

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Abstract. In order to solve the influence of uncertainties in the operation process of demand response, the dispatching cost and energy consumption before demand response day are reduced. In this paper, the interruptible load is taken as the research object for the incentive demand response project in China. By calculating the user's baseline load and forecasting the actual load, the load reduction can be obtained. An improved particle swarm optimization (PSO) algorithm based on cloud model is used to establish a mathematical model with the objective of minimizing the scheduling cost of demand response day before. Considering the influence of risk factors in the process of demand response, forward cloud generator is used to transform from uncertain space to specific space, which alleviates the influence of uncertain factors on demand response scheduling. At the same time, the improved particle swarm optimization algorithm of cloud model overcomes the disadvantage that the algorithm is easy to fall into local optimum, and achieves more accurate results. By comparing the average fitness values of all the particles in the current PSO, the PSO is divided into three sub-groups. The normal cloud model is used to dynamically adapt, adjust the inertia weight of the PSO, and then optimize the day-ahead scheduling cost. Comparing with the PSO algorithm, the experimental results show that the proposed method can effectively reduce the scheduling cost before demand response day. Reasonable demand response scheduling strategy can effectively alleviate the contradiction between power supply and demand, save energy and improve the stability of smart grid operation.

Keywords: cloud model, particle swarm optimization, cost optimization, day-ahead scheduling, demand response, interruptible load

1 Introduction

In smart grids, not only the participation of distributed generation but also the interaction of the user side, namely demand response (DR), should be considered to achieve power balance. DR is an important technical means of demand-side management, and it refers to the user's response to price or incentive and changes the original user's electricity consumption mode [1]. DR not only can optimize the operation mode of a power system and improve the stability and efficiency of power grid operations, but it can also enhance the ability of the power grid to absorb extra intermittent distributed energy and improve the interaction level between the power grid and the power users.

In addition, due to the diverse DRs and complexities of combination modes, the various characteristics of a smart grid are affected by numerous uncertainties, including those on new-energy generation, electricity price at different periods, user load forecasting, a user's subjective willingness to use electricity, means of coordination of different time scales, etc. [2-4]. With the development of smart grids and the further improvement and popularization of advanced measurement systems and communication

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technologies, the interaction of the generation side, the distribution side, and the demand side will be frequent, and the uncertainty of DRs will have a relatively deep impact on the grid. If the deterministic model is used to describe DR, then it cannot meet the increasingly difficult coordinated operation of smart grids. By only taking into account the uncertainty of DRs can we make full use of demand-side resources and participate in energy allocation and optimal scheduling of the system.

This paper focuses on the demand response project of incentive mechanism in China, aiming at analyzing and solving the impact of uncertainty of demand response on day-ahead scheduling cost. For the research content of this topic, scholars at home and abroad have also made a response to the research work. At present, the main methods to solve DR uncertainties include the use of stochastic programming model, probability theory, fuzzy theory, etc.

1.1 Stochastic Programming Model

Wu et al. described the uncertainty of wind power load forecasting by chance-constrained programming method, and established a stochastic congestion management model for power market network. By using the probability distribution of random variables, the stochastic optimization model is transformed into an equivalent deterministic model, which achieves high reliability and high utilization of the power supply [5]. This method reduces the scheduling cost of demand response to a certain extent. Aghajani et al. used stochastic programming to model the stochastic behavior of wind and solar power generation. The purpose is to solve the energy efficiency problem of smart grid optimization in the short term such that the operation cost and emissions of renewable energy can be reduced. Then the multi-objective particle swarm optimization (PSO) algorithm based on fuzzy technology is used to solve the model, and the optimal DR results are obtained. The simulation results show that the demand of consumers in DR planning may reduce operation costs and pollution emissions [6]. However, this method has some drawbacks. The traditional method of solving chance-constrained programming is to determine the equivalent classes of chance-constrained programming according to the pre-given confidence level, and then the traditional method is used to solve the equivalent deterministic model. However, this approach cannot be easily applied to complex chance-constrained programming problems.

1.2 Probability Theory and Fuzzy Theory

Considering the uncertainty of renewable energy generation, Shams et al. used Weibull probability distribution function and autocorrelation coefficient to minimize the expected cost of the system in short run time, and solved the load forecasting problem of three uncertain factors: wind speed, cloud amount and temperature. The research results show that DR program can effectively reduce operating costs and improve system security [7]. Zeng et al. used the fuzzy theory to analyze the uncertainties of demand response, and established a model describing the uncertainties caused by human factors under incomplete information. Different types of uncertainties in demand response are standardized and systematized, and the effectiveness of this method is verified on an improved real-time tracking and processing system. However, probability theory and fuzzy theory still have some shortcomings in solving uncertainties. A simple processing of ambiguous information can lead to low prediction accuracy and even impair the quality of the whole system. In improving prediction accuracy, increasing the quantization series is imperative to expand the search scope of rules and reduce the speed of optimal decision-making.

At present, several research fields have entered the stage of complex systems. For the uncertainties in complex systems, strict and accurate mathematical descriptions are virtually impossible. Only by transforming and integrating qualitative and quantitative information can we obtain a complete description of the system. Cloud model theory reportedly can overcome the shortcomings of probability theory and fuzzy mathematics in dealing with uncertainties. Cloud model theory represents an uncertain mapping relationship. Qualitative concepts are quantitatively described by expecting Ex (expected value), En (entropy), and He (hyper entropy); this approach can effectively integrate the two characteristics of randomness and fuzziness and unify non-existent and random fuzzy membership degrees. At present, in the real world, cloud model technology has been successfully applied to data mining, decision analysis, intelligent control, image processing, and several other fields [9-12].

On the basis of the advantages and disadvantages of the abovementioned methods, this paper proposes a dynamic adaptive particle swarm inertia weight optimization method based on cloud model to reduce the day-ahead scheduling cost of DR.

Firstly, for China's DR projects that are based on the incentive mechanism, the baseline load of users is calculated, and a correction factor is introduced through the load ratio method to yield a calculated value that is close to the actual production situation, predict the actual load of users, and obtain the load-reduction amount of users for the corresponding period.

Secondly, the forward cloud generator is used to transform the scenarios from uncertain space to deterministic space, thus reducing the influence of uncertain factors in the process of DR scheduling.

Thirdly, a mathematical model with the objective of minimizing the day-ahead scheduling cost is established, and an improved PSO algorithm based on the cloud model is used to predict the day-ahead scheduling cost.

Finally, the simulation experiments are carried out on the data of residential and industrial power consumption of a certain area. The simulation results verify the validity and correctness of the method. Compared with the traditional PSO method, the improved cloud model can fully consider DR uncertainty, further reduce the day-ahead scheduling cost of DR projects, reduce power losses caused by peak-valley differences during peak periods, alleviate environmental pressure, and achieve economic benefits.

2 Baseline Load

In incentive DR projects, the calculation of customer baseline load (CBL) is the key for decision makers in estimating load reduction and user compensation settlement. User baseline load provides a basis for quantitatively evaluating the reduction of user load in various power DR projects. User baseline load is also an important prerequisite for user compensation settlement and implementation effect evaluation. In addition, user baseline load provides an evaluation basis for incentive-based DR projects [13].

Foreign scholars have conducted considerable research on the theory and method of power system load forecasting [14-15]. The calculation method of single-user baseline load and demand reduction in incentive DR projects is similar to the short-term load forecasting method. However, the calculation method forecasts the total load of many users, whereas user baseline load forecasts the load of each user. The calculation methods of baseline load in existing research can be roughly divided into two categories: averaging and regression methods [16-17].

The average method refers to the average value of the historical load value of the corresponding hour for a period of time before the occurrence of the demand response event as the baseline load value. This method only integrates, analyses and calculates the historical load data, without considering the factors affecting demand response scheduling on that day. Although this method has its shortcomings, it is widely used in appropriate fields due to its simplicity. Because the most common and easily understood interruptible load project in the incentive demand response is studied in this paper, the model should not be too complex, so this method is used to calculate the baseline load value.

2.1 Data Selection

Before calculating the baseline load with the average method, the historical load data should be selected first. The selection principle is to select the historical load data from the corresponding demand response period of N days before the forecast day, in which the historical load data need to exclude weekends and holidays. In this project, the total load of residential and industrial electricity from July 11, 2017 to July 26, 2017, provided by a district power supply bureau in Beijing, is considered the data sample. For each period of the sample data, the power load is defined as an array.

$$P = \{P_{dk}\} \quad d = 1,2,...16; k = 1,2,...24, \tag{1}$$

where d is the number of days of the sample data with a total of 16 days, and k is the time of sample data in a day with a total of 24 h.

2.2 Baseline Load Calculation

Using average method to calculate user's baseline load needs to integrate load data of similar days before demand response events, and analyze and calculate user's historical load data. After eliminating similar days such as rest days and special event days, the date of typical historical load data remains.

(1) The historical load data are selected as the data samples, which are 24 hours a day in two weeks before the forecast date, namely, the total load of residential and industrial power consumption from July 11, 2017 to July 26, 2017, and the forecast date is July 27, 2017.

(2) This paper assumes that there are no special rest days and normal operation of the factory. Considering that the load data generated by users and factories fluctuate greatly during the weekend period, there are no special event days such as holidays in the sample data period. Therefore, the power load data of Saturdays and Sundays in the array composed of user historical load data are eliminated, and the historical load data of 12 days and 24 corresponding periods are obtained, that is, a data matrix of 12 rows and 24 columns is obtained.

$$P' = \left\{ P'_{dk} \right\} \quad d = 1, 2, \ldots 12; k = 1, 2, \ldots 24 \tag{2}$$

(3) Finally, the average value of each column in the matrix is calculated to get the baseline load value per hour on the predicted day.

$$L_{B,j,k} = \frac{1}{12} \sum_{d=1}^{D} P_{dk} \quad d = 1, 2, \ldots 12; k = 1, 2, \ldots 24 \tag{3}$$

where d is the sample data days, D is the total sample days, a total of 12 days, K is the sample data hours in a day, a total of 24 hours, $L_{B,j,k}$ is the baseline load value of user j participating in the demand response project during period k.

2.3 Baseline Load Correction

Given the weather, production, and other effects on DR event days, the baseline load can be high or low [18]. To align the baseline load with the load situation of the day, the calculated baseline load can be multiplied by a correction factor to obtain the revised load. The adjustment factor can be defined as the ratio of actual load to the forecasted load 2 h before the start of DR events. That is,

$$\theta_j = \frac{L_{A,j,h-2} + L_{A,j,h-1}}{L_{B,j,h-2} + L_{B,j,h-1}}. \tag{4}$$

In the formula, θ_j is the baseline load correction factor of user j on day of forecast, and the DR events on that day begin at hour h. $L_{A,j,h-1}$ and $L_{A,j,h-2}$ correspond to the actual load values of user j h-1 and h-2 hours, respectively. $L_{B,j,h-1}$ and $L_{B,j,h-2}$ correspond to the baseline load values of user j h-1 and h-2 hours, respectively.

$$L'_{B,d,t} = \theta_d L_{B,d,t} \quad t \geq j, \tag{5}$$

where $L'_{B,j,k}$ are the baseline loads corrected by the correction factor in k hour of user j, and $L_{B,j,k}$ are unmodified baseline loads.

On the basis of the data samples of residential and industrial power loads from July 11, 2017 to July 26, 2017 provided by a district power supply bureau in Beijing and the calculated baseline load values, the correction factor is calculated as 0.7987 according to Formula (4), and then the baseline load correction values are calculated according to Formula (5) (Fig. 1).

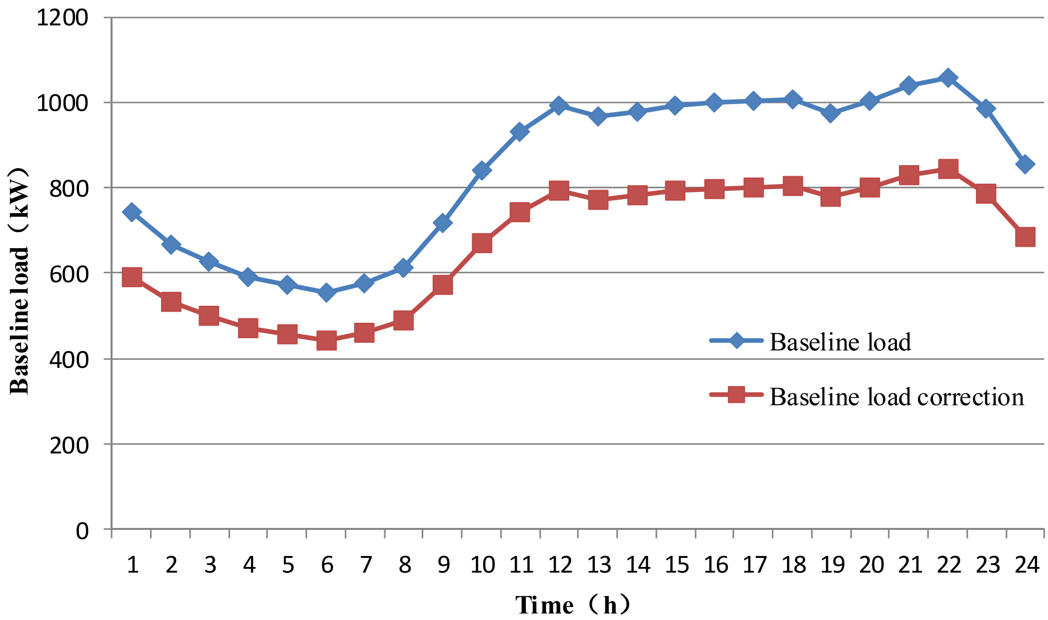

Fig. 1. Hourly baseline load value on July 27, 2017

Fig. 1 shows the baseline load values of 24 time periods on the forecast day (July 27, 2017) obtained by the average method. The load data reflects the load used when the user is not involved in the demand response project on that day. Due to the unexpected situation on the day of the implementation of the demand response project, such as weather conditions, work arrangements and other aspects, the unadjusted baseline load of users is generally high. In this paper, the correction factor is used to modify the data value, so that the baseline load value of the user is closer to the actual power consumption situation on the day of the forecast, so as to prepare for the subsequent calculation of load reduction of demand response projects.

3 Forecasting of DR Load

The accuracy of power system load forecasting is one of the remarkable signs to measure the modernization of power system operation and management [19]. In order to achieve the goal of optimizing the total cost of day-to-day dispatch of power system, this paper needs to calculate the amount of load reduction of users, and the prediction of actual load of users is the key step for decision makers to estimate the amount of load reduction. In the process of demand response, the load forecasting of power system is affected by many factors, which have extremely complex non-linearity and uncontrollability. Therefore, solving the influence of these complex non-linearity factors has become one of the difficulties of load forecasting. Faced with such problems, artificial neural network has shown excellent processing ability, among which BP (Back Propagation, BP) neural network is the most widely used type in the world.

BP neural network is a multi-layer feedforward network trained by error back propagation algorithm. It has a supervised learning structure of multi-layer forward perceptron. It can transfer error calculation along the reverse way with network calculation, so as to solve the weight of neuron connection. Because BP neural network has the advantages of simple calculation method, strong non-linear mapping and good network generalization performance in the stage of load forecasting of power system, this paper uses BP neural network method to predict the actual load of users participating in demand response in the stage of load forecasting of demand response.

3.1 Parameter Selection

Historical load data. An average load of 24 h per day (corresponding to daily electricity consumption) in the two weeks before the forecast date is selected for the historical load data.

Number of input layer nodes. The number of nodes in the input layer is usually selected according to the dimension of the input vector. The historical load data of the input layer in this paper are two weeks before the forecast date, namely 14 days. Therefore, the number of nodes in the input layer of the neural network is 14.

Number of hidden layer nodes. In this study, the number of hidden layer nodes is selected according to the following formula to train a three-layer BP neural network with a single hidden layer.

$$n_h = \sqrt{n+m} + a, \tag{6}$$

where n is the number of input nodes, n=14, m is the number of output nodes, m=1, and a is a constant between 1 and 10. Given that the number of nodes in each layer of BP neural network has a great impact on the performance of the network, the number of nodes in the hidden layer must be properly selected. After many times of data training and from the training results, the results are reasonable when a=8 and the number of hidden layer nodes is 12. Therefore, this study uses the number of hidden layer nodes n_h = 12.

3.2 DR Load Forecasting Results

In this training, the number of training iterations is 100, the learning rate is 0.1, and the number of hidden layer nodes is 12.

In this prediction, the experimental results are compared to verify the effectiveness of the algorithm. Therefore, the relative error formula is used.

$$\sigma_{j,k} = \frac{L_{A,j,k} - L'_{A,j,k}}{L'_{A,j,k}} \times 100\% \tag{7}$$

In the formula, $L_{A,j,k}$ is the actual load value of the user j at the k forecasting time point. In this paper, the forecasting date is selected from 1 to 24 time points, therefore $k \in [1, 24]$. $L'_{A,j,k}$ is the actual value of the corresponding point.

The DR load is predicted by BP neural network, and the relative error is solved according to Formula (7). The experimental results are shown in Fig. 2.

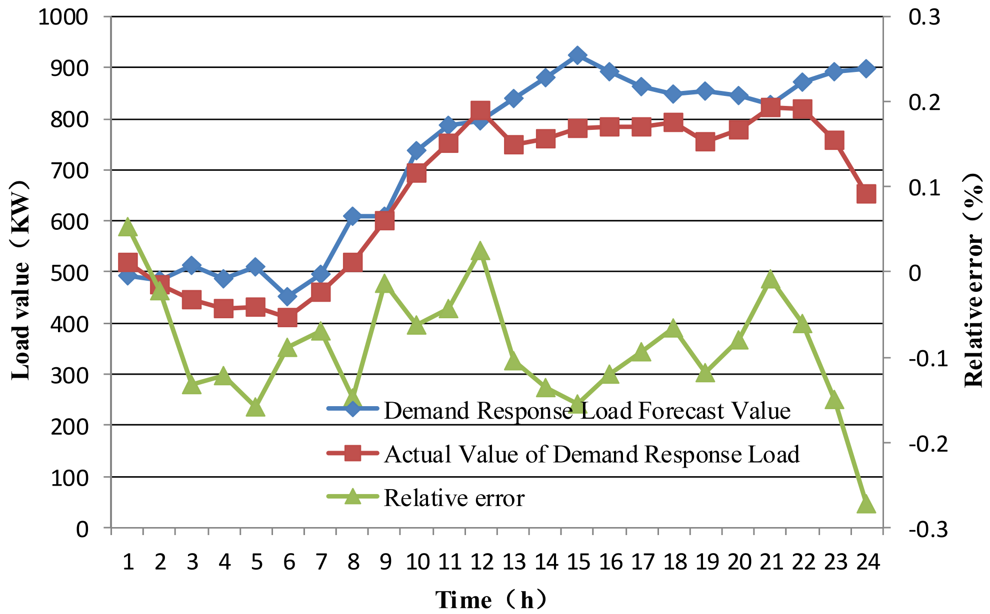

Fig. 2. Actual load value per hour in DR event date

From Fig. 2, it can be seen intuitively that the user load value predicted by BP neural network on the day of demand response events is basically similar to the actual value, and the relative error results are controlled between 0.1% and -0.3%, which verifies the effectiveness of the algorithm. The accurate prediction of this data lays a foundation for calculating the load reduction of users in the next step.

3.3 Load Reduction

Load reduction can be obtained from the difference between the predicted baseline load and the actual load data, and the calculation formula is as follows:

$$L_{R,j,k} = L_{B,j,k} - L_{A,j,k} \tag{8}$$

where $L_{R,j,k}$ is the load reduction amount of user j in k period participating in interruptible load demand response, $L_{B,j,k}$ is the baseline load value of user j in k period participating in interruptible load demand response, $L_{A,j,k}$ is the actual load value of user j in k period participating in interruptible load demand response.

Calculating load reduction is a key step in the settlement of compensation costs for demand response projects. Before the implementation of demand response projects, power enterprises need to sign demand response contracts with users who participate in demand response. The contracts need to include compensation unit price, penalty unit price and load reduction capacity of users who participate in demand response. After the load reduction signal of demand response is issued, users participating in demand response should take the initiative to reduce the corresponding load capacity and fulfill the contract agreement. The implementing agencies should regularly settle the expenses of the users who participate in demand response, and implement reasonable compensation and punishment, so as to encourage consumers to actively and reliably participate in interruptible load projects. Through the contract content of interruptible load, we can know the compensation unit price, penalty unit price and capacity reduction requirements. The actual load reduction amount of users is compared with the contractual load reduction capacity, and the compensation and penalty costs are calculated according to the comparison results. When the amount of load reduction of users participating in demand response does not reach the agreed amount of load, economic compensation is given according to the actual amount of load reduction of users, and corresponding penalties are given according to the amount of load that does not reach the agreed amount of contract. When the user's response exceeds the amount of reduction agreed in the contract, compensation shall be made according to the amount of load reduction agreed in the contract.

This paper calculates, modifies and predicts the baseline load value and the actual load value of user participation in demand response through three subsections of 2.2, 2.3 and 3.2, and then calculates the user's load reduction on the same day according to formula (8), as shown in Fig. 3.

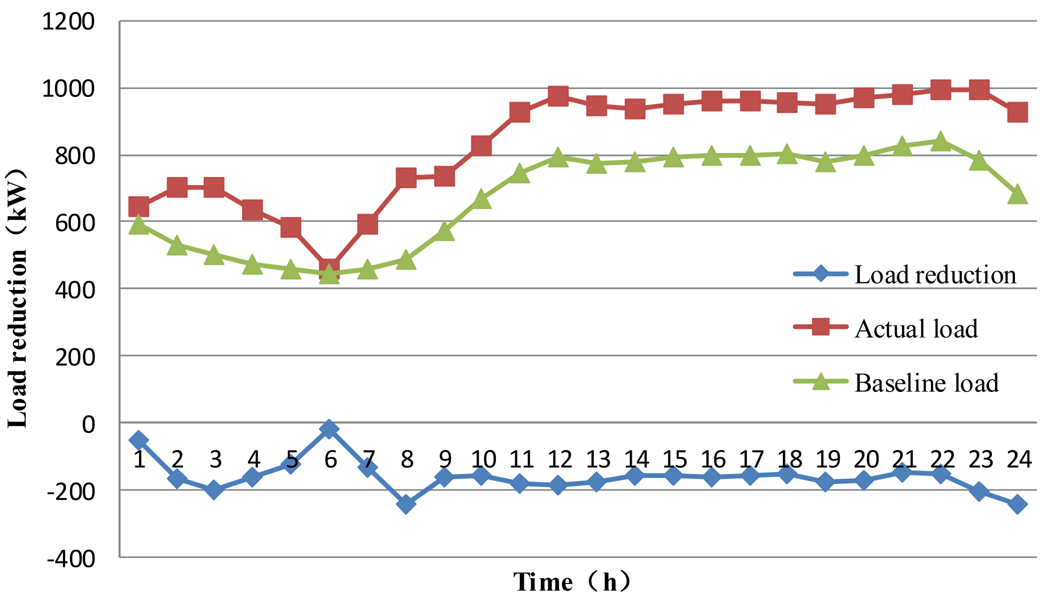

Fig. 3. Load reduction for each period

Fig. 3 shows the load reduction on the day when the user participates in the demand response project. The difference between the baseline load and the actual load predicted at 6 o'clock on the day of demand response event is the smallest, and the user load reduction is the smallest. After 13 o'clock, the user load reduction reaches a stable level, which indicates that the demand response project proceeds smoothly in this period. By forecasting the amount of load reduction and actual load reduction, the compensation and penalty costs of demand response projects can be calculated, which can stimulate the enthusiasm of users to participate in demand response projects.

4 Mathematical Model of DR Scheduling Cost

4.1 Objective Function

The basic background of this study is the interruptible load project in China's DR project as the main body. Considering the uncertainty of user response, a single-objective mathematical model is established to minimize the total cost of interruptible loads. The objective function is as follows:

$$D_{\min} = \sum_{k=1}^{K}\sum_{j=1}^{J} x_{j,k} \cdot C_{total} , \tag{9}$$

where $x_{j,k}$ is an interruptible load state variable, $x_{j,k} = 1$ represents the load of user j interrupting the agreed capacity of the contract during period k, and $x_{j,k} = 0$ represents the normal power consumption of the user.

Among them, the total dispatching cost Ctotal includes two parts, one is the deterministic compensation cost and the other is the uncertainty compensation cost. Thus, the objective function can be transformed into the following:

$$D_{\min} = \sum_{k=1}^{K}\sum_{j=1}^{J} x_{j,k} \cdot \left(C_{cons,j,k} + C_{\alpha,j,k} \right). \tag{10}$$

Due to the uncertainty of user response, users may be under-responding or over-responding; that is, the actual load reduction of users may be less or more than that agreed in the contract. For determining the user response and then calculating the compensation basis, α is defined as the difference between the actual load reduction of the user and the agreed load reduction in the contract.

In Formula (10), the deterministic compensation cost is calculated as follows:

$$C_{cons,j,k} = L_{agree} \cdot p_{comp} . \tag{11}$$

In the same formula, the calculation method of uncertainty compensation cost is as follows:

$$C_{\alpha,j,k} = \begin{cases} 0 & \alpha \geq 0 \\ \alpha \cdot \left(p_{comp} + p_{punish} \right) & -L_{agree,j,k} < \alpha < 0 \\ \alpha \cdot p_{punish} - L_{agree} \cdot p_{comp} & \alpha < -L_{agree,j,k} \end{cases} . \tag{12}$$

In Formulas (11) and (12), L_{agree} reduces the amount of conformity agreed in the contract, p_{comp} is the amount of unit compensation, and p_{punish} is the amount of unit penalty.

For the calculation of uncertainty cost in the DR project in this research, the influence of risk factors on the uncertainty cost is considered. The uncertainty of user response leads to the risk cost in the scheduling decision of interruptible loads in DR projects.

The following is the calculation of risk cost:

$$C_{risk,j,k} = \int_{-\infty}^{+\infty} p_{outage}\left(\alpha_j\right) \cdot \left|\alpha_j\right| \cdot g\left(\alpha_j\right) d\alpha_j , \tag{13}$$

$$p_{outage}\left(\alpha_j\right) = \begin{cases} p_{sale} & \alpha_j < 0 \\ 0 & \alpha_j = 0 \\ p_{outage} & \alpha_j > 0 \end{cases} . \tag{14}$$

In the given formulas, we assume that the user response of power companies based on historical statistical data is a probability distribution, and $g(\alpha_j)$ is a probability density function of α_j. When power companies bear the risk of reducing electricity sales, price loss occurs. p_{sale} is the current selling price at this time, and p_{outage} is the unit outage loss.

In summary, the objective function of the total cost of interruptible load scheduling in DR is transformed into the following:

$$D_{\min} = \sum_{k=1}^{K}\sum_{j=1}^{J} x_{j,k} \cdot \left[C_{cons,j,k} + \left(C_{\alpha,j,k} + C_{risk,j,k} \right) \right] \quad \textbf{(15)}$$

The total cost of demand response scheduling includes both deterministic compensation cost and risk cost caused by uncertainty of user response.

4.2 Constraint Conditions

The objective function must satisfy the following constraints.

Reduction of interval constraints.

$$|m-n| \geq K_{\min,j} \quad j = 1,2,3...,J, \quad \textbf{(16)}$$

where time periods m and n are between time periods a and b of the DR event. $x_{j,m-1} = 0$ and $x_{j,m} = 1$ at m-1 and m, respectively. $x_{j,n-1} = 1$ and $x_{j,n} = 0$ at n-1 and n, respectively. $K_{min,j}$ is the minimum time between two load reduction events agreed by user j in the contract.

Reduction of duration constraints.

$$\sum_{k=a}^{K_{dur,j}+a-1} x_{j,a} = K_{dur,j} \quad j = 1,2,3...,J, \quad \textbf{(17)}$$

where period m is between the periods a and b of the required response event. $x_{j,m-1} = 0$ and $x_{j,m} = 1$ at m-1 and m, respectively. $K_{dur,j}$ is the duration of load reduction agreed by user j in the contract.

Reduction of the total number of constraints.

$$\sum_{k=1}^{K} x_{j,k} \leq J_{K,j} \quad j = 1,2,3...,J \quad \textbf{(18)}$$

J_K is the maximum number of cuts for user j in period k as agreed in the contract.

5 Improved PSO Algorithm Based on Cloud Model

As a heuristic intelligent algorithm widely used in real life, PSO has played an active role in many fields, such as scientific research and engineering applications, in only over 10 years. Although PSO has many excellent characteristics, it inevitably has certain drawbacks; it easily falls into local optima and converges during latter stages. Therefore, this study employs PSO as the main body algorithm, constructs a PSO algorithm improved by cloud model, and uses this method to solve certain problems of demand-side scheduling.

5.1 Basic PSO Algorithm

Inspired by the foraging process of birds, PSO algorithm regards a bird as a particle in the search space. Each particle has speed to determine their flight direction and distance. Such particles also have a fitness value determined by their corresponding optimization function [20-21]. Then, the particles follow the current best particles and search in the solution space.

During the searching process, a particle can dynamically adjust its search direction and position by learning two extremes. One is the individual extreme value of P_{best}, which is the best value that the particle can find at present. The other is the global extreme value of G_{best}, which is the best value that all the particles can currently find. Particles obtain two extremes by sharing information, and then self-update, adjust their position X_i and velocity V_i until the end of the iteration, and output the optimal solution of the problem [22].

5.2 Cloud Model Improvement Strategy

In order to solve the uncertainties in the process of demand response scheduling, forward cloud generators are used to transform cloud droplets one by one by giving three digital characteristics. Finally, the transformation operation from uncertain space to specific and deterministic space can be completed, and an optimization chain describing the concept of uncertainty with specific quantitative data can be formed. On the basis of PSO and cloud model technology, the uncertainties can be solved, and the optimization effect of PSO can also be optimized.

The ω of PSO algorithm has a great influence on the algorithm. Its ω can keep the memory part of particles and has the inertia of motion. ω then performs the motion search in the search space. By analyzing the evolutionary formula of PSO, the velocity of the first particle in t is far from the individual and global extreme values when ω is large. Such velocity may also deviate from the optimal value, thus searching in a large range is easy and beneficial to the initial search. Although small ω is good for the later key search, its value does not linearly decrease. Thus, complex search defects may occur.

Fully synthesizing the settings of inertia weight values and choosing reasonable values can make the algorithm achieve an excellent optimization accuracy and fast search speed. Therefore, considering the advantages of cloud model technology in solving uncertainties and the shortcomings of particle swarm optimization, we can make full use of the forward cloud generator in cloud model to solve this problem. Therefore, this study combines cloud model theory with the self-renewal mechanism of PSO to form an improved cloud model adaptive particle swarm method (CAPSO). The specific ways of improvement are as follows:

First, take the average fitness of all particles in particle swarm degree f_{avg}, setting $f_{avg} = \frac{1}{N}\sum_{i=1}^{N} f_i$ as the average fitness value of the population. Second, the population is divided into three subgroups according to the mean value, with f_i being the fitness value of particle X_i. Before that, the fitness value, which is better than f_{avg}, is calculated and averaged to obtain value f'_{avg}. The fitness value next to f_{avg} averages value f''_{avg}, and then divides the population into three subgroups according to the following rules.

(1) f_i is superior to f'_{avg}.

This particle has a fitness value of less than f'_{avg}. This kind of particle is also close to the global optimum value. f_i only needs to speed up its global convergence speed, thus ω is 0.4.

(2) f_i is superior to f''_{avg} but inferior to f'_{avg}.

Such particles either as good or bad particles must be treated with emphasis. The new algorithm for dynamically and nonlinearly adjusting the ω of particle X_i according to the normal cloud generator is as follows:

$$E_x = f'_{avg}, \tag{19}$$

$$E_n = \left(f'_{avg} - f_{\min}\right) / c_1, \tag{20}$$

$$H_e = E_n / c_2, \tag{21}$$

$$E'_n = normrnd\left(E_n, H_e\right), \tag{22}$$

$$\omega = 0.9 - 0.5 * e^{\frac{-(f_i - E_x)^2}{2(E_n')^2}} \tag{23}$$

Among them, c_1 and c_2 are the control parameters. Given that $0 < \frac{-(f_i - E_x)^2}{2(E_n')^2} < 1$, $\omega \in [0.4, 0.9]$. In addition, ω decreases as the fitness value of particles decreases. Moreover, a small ω can be obtained by dynamically realizing the small ω value of particles.

(3) f_i is inferior to f''_{avg}.

The poor particles in the population satisfy this condition. These particles are far from the global best position. Thus, ω is 0.9.

6 Cost Calculation and Analysis of DR Scheduling

6.1 Scheduling Optimization Results of DR Deterministic Model

Aiming at the deterministic model of demand response proposed in this paper, an example is given to simulate the total load data of residential and industrial power consumption in a certain area of Beijing from 6 a.m. to 18 p.m. on July 27, 2017. According to the calculated load reduction data, we set the particle swarm size as 50, the learning factor in formulas (20) and (21) as $c_1 = c_2 = 0.5$, the inertia weight of the basic PSO algorithm ω=0.5, the inertia weight of the improved cloud model algorithm in formula (23) as $\omega_{\min} = 0.4$, $\omega_{\max} = 0.9$, and the maximum number of iterations is 50. The load reduction agreed in the interruptible load demand response contract is 50 kW. According to the parameter settings in current demand response research, the unit compensation amount is 1 yuan, the unit penalty amount is 2 yuan, and the unit electricity price is 1 yuan. Considering only the deterministic model, the improved and improved PSO algorithm is used to optimize the scheduling cost of demand response for 12 periods from 6:00 to 18:00 on July 27, 2017. The results are shown in Table 1.

Table 1. Day-ahead scheduling optimization results of demand response deterministic model

Algorithm	Cost expectation (10,000 yuan)	Percentage decrease in cost
PSO	75.4	16.6%
CAPSO	62.9	

From the results of Table 1, it can be seen that the cloud model improved particle swarm optimization algorithm is superior to the basic particle swarm optimization algorithm in the optimization of scheduling costs, and the cost reduction rate reaches 16.6%. The simulation results verify the effectiveness of the improved PSO algorithm, which can achieve the goal of safe and economic operation of power system to a certain extent, and reduce the total cost of demand response day-ahead scheduling.

6.2 Scheduling Optimization Results of DR Uncertainty Model

Aiming at the uncertain model of demand response proposed in this paper, the basic PSO and cloud model are used to improve the PSO algorithm, and the simulation results of the example data with the same parameters as the contract content are given. Considering the influence of uncertainties, the risk cost should also be considered when calculating the total cost of demand response scheduling. Users may have insufficient response. At this time, power companies need to spend a lot of money to purchase additional reserve capacity and maintain the stable operation of the power grid. Referring to the parameter settings in the current demand response uncertainty study, the unit outage loss is assumed to be 10 yuan. Aiming at the uncertainty model, the improved PSO algorithm is used to optimize the scheduling cost of demand response for 12 periods on July 27, 2017. The results are shown in Table 2.

Table 2. Day-ahead scheduling optimization results of demand response uncertainty model

Algorithm	Cost expectation (10,000 Yuan)	Percentage decrease in cost
PSO	45.1	17.8%
CAPSO	37.1	

By comparing the results in Table 2, the efficiency of cloud model improved particle swarm optimization is significantly improved, and the cost reduction rate of uncertain model is 17.8%. Compared with Table 1, on the premise of the same parameters and contract content, the reduced rate of scheduling cost of the improved algorithm is basically the same, and the reduced range is basically the same. The experimental results verify the effectiveness of the algorithm. The improved algorithm of cloud model makes the minimum cost expected value of power system better after optimization calculation. Therefore, the cloud model adaptive particle swarm optimization algorithm of inertia weight can make the power system achieve more economic, safe and efficient objectives to a certain extent, and achieve better interconnection and operation control between the supply side and the demand side.

6.3 Effect of Uncertainty on DR Scheduling Cost

In order to compare the impact of uncertainties on scheduling cost more intuitively, in two scenarios of certainty and uncertainty, PSO and cloud model are used to improve PSO to optimize scheduling cost, and the results are presented as a three-dimensional histogram, as shown in Fig. 4.

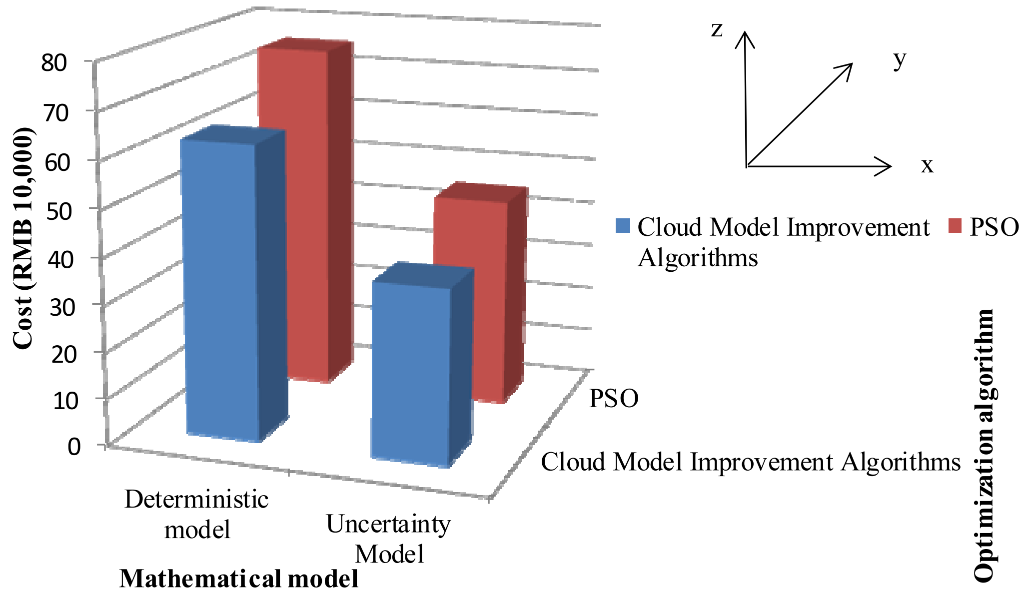

Fig. 4. DR scheduling cost of different mathematical models

In Fig. 4, the x-axis is the two mathematical models considering uncertainty, the y-axis is the two particle swarm optimization algorithms before and after improvement, and the z-axis is the optimal scheduling cost. Under the same mathematical model, the cost of the improved cloud model algorithm is lower than that of the basic particle swarm optimization algorithm; under the same optimization algorithm, the day-ahead scheduling cost of the deterministic model is higher than that of the uncertain model. This is because only the deterministic compensation cost is considered, which makes the fixed compensation cost in the results of demand response optimization lower, and the uncertain factors are not taken into account in the cost optimization, thus affecting the total cost of demand response scheduling, resulting in the overall high scheduling cost. In contrast, considering the uncertainties in the operation of demand response, the cost of uncertainty is lower, and the total cost of interruptible load demand response dispatch is lower. In conclusion, considering uncertainties can make the day-ahead dispatching decision of power system more reasonable and economical.

6.4 User Positivity in DR

Because the optimization efficiency of the improved particle swarm optimization algorithm is quite different, the scheduling cost is different, which affects the enthusiasm of users to participate in demand response projects. In order to judge the reduction of agreed load reductions in contracts by users at different time periods in demand response project forecast day. Assuming that the content of the demand response contract signed by the user and the power company is the same, that is, the contract stipulates a load reduction of 50 kW, a unit compensation amount of 1 yuan, a unit penalty amount of 2 yuan, and a unit price of 1 yuan. When the user response is insufficient, the power company needs to pay a high price for additional reserve capacity and maintain the stable operation of the power grid. At this time, the unit outage loss is 10 yuan. Finally, the time period of users' participation in demand response events is divided into 12 periods. PSO and cloud model are used to improve the PSO algorithm, and the participation of users in demand response at each period of the forecast day is calculated, as shown in Fig. 5.

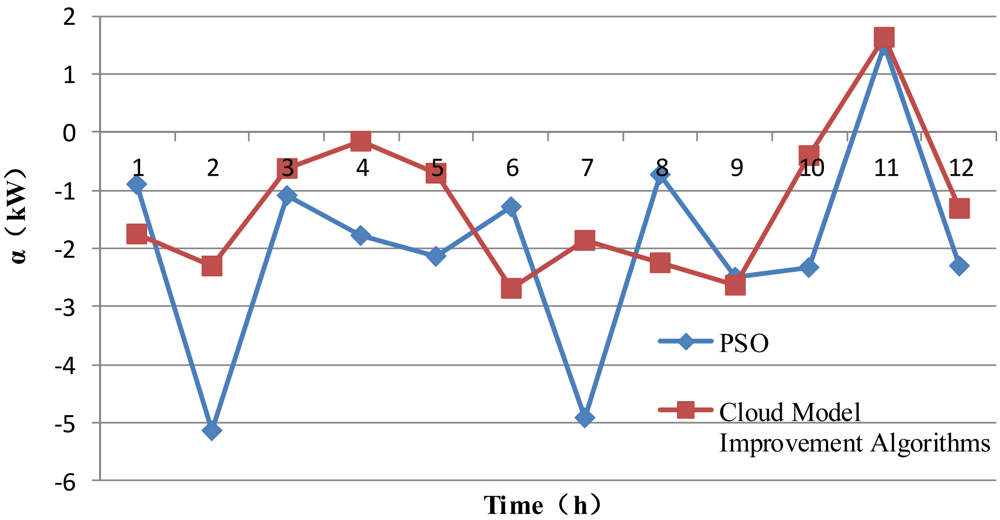

Fig. 5. Prediction of daily user DR in different periods

As defined in section 4.1, α in the figure above is the difference between the actual load reduction of the user on the forecast day and the agreed load reduction in the demand response contract. On the premise that the content of the demand response contract signed by users is the same, the user response of different particle swarm optimization algorithms before and after improvement can be visually seen by judging the positive or negative situation of alpha or equal to zero.

When $\alpha > 0$, users overreact and show high enthusiasm. When $\alpha < 0$, users are not highly responsive and display low enthusiasm. When $\alpha = 0$, the actual load reduction of users matches that in the contract agreement.

From the results of Fig. 5, we can see that compared with PSO, the response of users in the second, third, fourth, fifth, seventh, tenth, eleventh and twelfth periods of the predicted day is better than that of the unmodified particle swarm optimization algorithm, and the overall user's under-response is less, and the user shows a higher response enthusiasm.

6.5 Influence of Risk Coefficient

In the current market environment, different power enterprises have various emphases on risk. Therefore, risk factors can be set for optimization objectives. The purpose of setting risk coefficient is to control the cost of decision making and scheduling by adjusting the magnitude of the risk coefficient to select the degree of risk uncertainty. After the risk factor is added, the objective function of the total cost of the DR scheduling is as follows:

$$D_{\min} = \sum_{k=1}^{K}\sum_{j=1}^{J} x_{j,k} \cdot \left(\beta \cdot C_{cons,j,k} + (1\text{-}\beta) \cdot \left(C_{\alpha,j,k} + C_{risk,j,k}\right)\right). \quad \textbf{(24)}$$

In the formula, β is the risk factor. $\beta < 0.5$ signifies a risk-averse user (that is, low-risk user). $\beta > 0.5$ denotes a risk-taking user (that is, high-risk user) $\beta = 0.5$ represents a moderately risky user, and the expected scheduling cost is minimized.

The change of risk coefficient will inevitably lead to different trends of demand response scheduling cost in Fig. 6. The figure shows three different modes of demand response scheduling cost when the risk coefficient rises from 0 to 1.

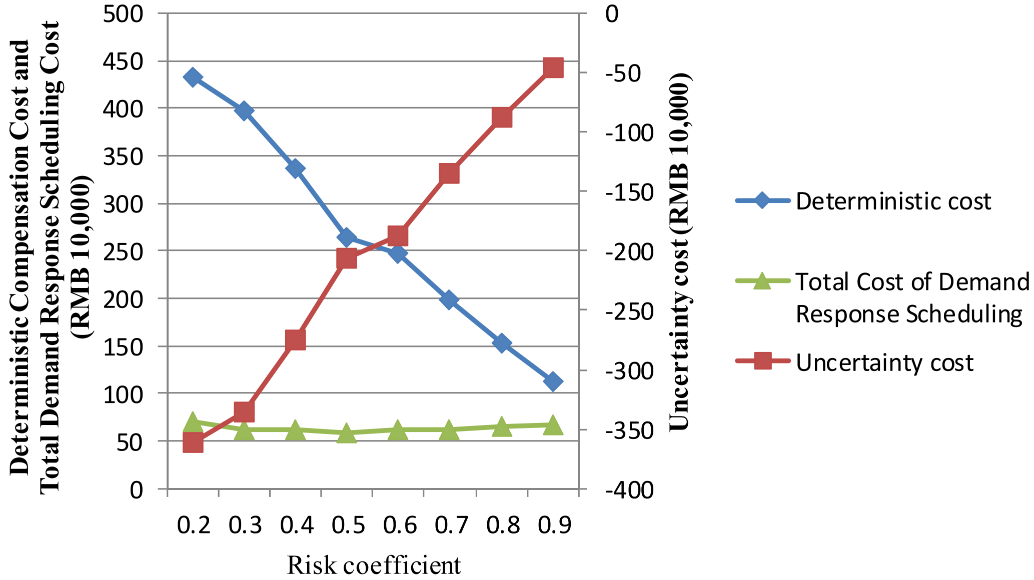

Fig. 6. Change of dispatching cost with the change of risk coefficient

As shown in Fig. 6, in the process of increasing the risk coefficient from 0 to 1, the deterministic compensation cost of demand response in the optimization results decreases, and the uncertain compensation cost increases, which makes it more suitable to prefer the high-risk type of power enterprises. When the risk coefficient is 0.5, the total cost of demand response scheduling reaches the minimum. Further analysis of the different costs of different risk coefficients can effectively reduce the cost losses of enterprises in the power market in the process of optimal decision-making, and find a more suitable power load dispatching scheme.

7 Conclusions

(1) An improved PSO algorithm is used to realize the transformation from uncertain space to specific space by using forward cloud generator, which solves the risk problem caused by uncertainties in demand response scheduling and makes the algorithm converge to the optimal value faster. The method of cloud model adaptive particle swarm ω can effectively reduce the power loss caused by peak–valley difference during the peak period of power consumption. The day-ahead dispatching cost borne by enterprises can also be reduced. In addition, economic and environmental benefits coexist.

(2) The numerical calculation proves that the cloud model adaptive particle swarm ω algorithm can solve problems well, revealing its effectiveness and feasibility in generating social benefits.

(3) Future research can consider various types of DR comprehensively in the model and perform detailed uncertainty analysis. For other incentive demand-related projects in China, performing scheduling optimization research on DR uncertainty is also necessary.

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