Research on Demand Response Model of Electric Power Interruptible Load Based on Big Data Analysis

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Abstract. In order to solve the problem of low precision in the analysis of power interruptible load demand using traditional power interruptible load demand response model, a power interruptible load demand response model based on big data analysis is studied in this paper. Firstly, the demand response is implemented by enabling technology, then the dynamic peak-valley price is determined by the demand response. Finally, the power interruptible load demand response model based on big data analysis is realized by using dynamic peak-valley price. The effectiveness of the demand response model based on big data analysis is verified by experiments.

Keywords: Big data analysis · Power interruptible · Load demand response model

1 Introduction

With the increasing scale of new energy access network and the construction of smart grid, the demand for demand-side response and the conditions for flexible dispatching are becoming more and more urgent and mature. As a demand-side resource, demand response has the characteristics of economy and flexibility, and it is an important means to realize flexible interaction of smart grid. At the same time, the demand response, especially interruptible load, can quickly respond to the wind power change and reduce the investment cost of the generation side. It is an ideal backup method for peak shaving in the case of large-scale wind power and other new energy sources connected to the grid. At the present stage, China is still facing the problem of power supply shortage. To ensure the safe and stable operation of the power grid, and to ensure the daily life and economic development of electricity use, is still a subject that will need to be paid attention to [1]. The practice at home and abroad shows that the demand-side management can effectively save energy and alleviate the problem of system capacity and electricity shortage by changing the user's smart electricity mode. Demand response refers to the behavior of electricity users changing their habits according to electricity price signals or other incentives. Demand response is a part of demand-side management. The participation of users in demand response can reduce the operation

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cost of power grid, save electricity and resources, have good economic and environmental benefits, and is one of the best applications of smart grid. The demand response changes the load of the power system and has a great impact on the reliability of the system. The influencing factors of power system reliability are generally system load fluctuation, component reliability column energy, electrical characteristics and network structure. Among them, the system load has the obvious dispersion characteristic, it is difficult to reflect the actual situation with the single load level index, such as peak load, average load evaluation system reliability. However, demand-side management and other means often change the smart load rate and distribution of the system, increase the uncertainty, and have a great impact on the reliability of the system. Habibian et al. [2] studied the flexibility of demanders'participation in the electricity market of power industry users and provided interruptible load reserve. The standard model of optimal strategic consumption is designed, and the reserve supply curve and consumption curve are optimized. The standard model provides an intuitive basis for this interaction. In addition, it provides tailor-made solutions to uncertainties. But the operability of the method is to be improved. Therefore, it is of great significance to study the variation of system reliability with load, to evaluate the impact of the implementation of demand response on the reliability of power system, to coordinate the demand response resources with the traditional generation resources, and to improve the system reliability. Based on big data analysis, the demand response model of power interruptible load is studied.

2 Demand Response Model of Electric Power Interruptible Load Based on Big Data Analysis

2.1 Implementing Demand Response Through Enabling Technology

Among the components of enabling infrastructure, intelligent instruments and advanced metering infrastructure are key components for implementing demand response. The new generation of electronic intelligent instruments have the ability to realize two-way information communication between end users and power supply enterprises. In the implementation of the demand response project, the intelligent instrument can receive the signals from the electric power enterprises, such as the maximum quantity of electricity that can be obtained in a certain period of time, or the signal of the electricity price determined dynamically. The application of intelligent instruments and advanced metrology infrastructure in the world is growing rapidly. AMI is a network system of millions of intelligent instruments [3]. Whether price-based or motivation-based demand response, in order to effectively participate in demand response in the implementation of automatic control, in the field of end-user such as residential, commercial or industrial buildings, The structure of energy management system is also an important part. The general EMS architecture obtains information signals from controllable or uncontrolled end-user loads, including state and power consumption of electrical equipment, etc. Moreover, the EMS can obtain information about the existing power capacity or the conventional power production situation of the renewable energy source. In addition, the signals of all the load service entities, including the instructions in the demand response activities, the price data, and the like, are transmitted to the energy management system through the advanced metering facilities. Considering all the input information, EMS makes the best operation strategy for the end user. The goal is to meet the needs of the load service entity that initiated the demand response and to meet the needs of the end user, without affecting the satisfaction degree of the power service [4]. At present, there are great regional differences in the use of EMS in the world. The United States plays a leading role in the use of EMS, especially in the home EMS market. European power companies also support a number of related pilot projects. It is widely believed that EMS is beneficial to both customers and electricity, and because many large companies, such as Siemens and Intel, have already provided commercial EMS products, EMS will further enter homes in the near future. Business and industry. The key condition for effective implementation of demand response is the ability to handle a large amount of data transmission. A low latency between the load to be controlled by the LSEs, end user EMS, etc., The appropriate bandwidth of information transmission channel is the prerequisite for the implementation of demand response action. The delay here refers to the time lag between the buyer issuing the request information and the Respondent getting the request information and therefore being able to act accordingly. Bandwidth refers to the transmission rate of each enabling device in the information transmission channel. In order to ensure better implementation of the demand response strategy, it is necessary to transmit the requirement response instructions effectively and respond quickly. Therefore, low latency and appropriate bandwidth index are the important guarantee of the demand response performance.

Based on big data's analysis, three fields of data communication should be considered in the establishment of power interruptible load demand response model: intelligent instrument field, internet field and home local area network field. Home Local area Network (HLAN) is a generic concept that can refer to residential, industrial or commercial user-end buildings. The field of intelligent instruments is a network composed of many intelligent instruments. The Internet is a platform for computing and information management in the IT industry and is used by the public through service providers. The home local area network is the gateway connecting the internet and intelligent instrument field, which is used to realize the interaction between the end user EMS and controllable load, electrical adjustment. The EMS obtains the signal through the intelligent instrument domain, and carries out the action through the home local area network [5]. The Internet is an interface where multiple systems with Internet protocols can exchange information with each other, so as to achieve a desired task, such as providing direct load control to a certain load at the end user. The communication requirements of the intelligent power grid are different due to the different application programs of the intelligent power grid, some applications of the intelligent power grid are sensitive to the time delay, the signals or other information must be transmitted in a specific time, and the other applications can adopt the low-rate communication scheme. There are many communication mechanisms suitable for delay and bandwidth standards in different data communication domains. Generally speaking, communication technology can be divided into wireless and wired technology. Wireless communication technology has lower investment cost because it avoids the cost of wiring. In addition, the wireless signal can reach the actual physical connection where difficulties, thus enhancing the location of the endpoint flexibility. However, wireless transmission has a greater signal loss in the propagation process, thus limiting the effective communication range [6]. Also, to avoid unauthorized access, wireless technology requires powerful security measures. ZigBee, Z-wave, WIFI, Wi-max, cognitive radio and recent cellular technologies can be used as major wireless communication technologies and can be used in many areas of communication in the operation of demand response smart grid. Wired communication technology can use existing lines or external wiring for signal transmission. Existing wired technologies include power line communication, optical fiber, Ethernet and so on. In order to ensure the successful implementation of demand response, the scalability, reproducibility, practicability, reliability and security of the proposed solution should be further analyzed, regardless of whether it is wireline or wireless.

2.2 Dynamic Peak-Valley Pricing Based on Demand Response

With the development and perfection of the electricity market, the main body of interest gradually presents diversification. The demand response can strengthen the interaction among the participants in the electricity market, which is an essential part of the future electricity market [7]. The demand response can be divided into DR based on electricity price and DR. based on incentive according to the different response modes of the participants in the demand response project. The classification is shown in Fig. 1.

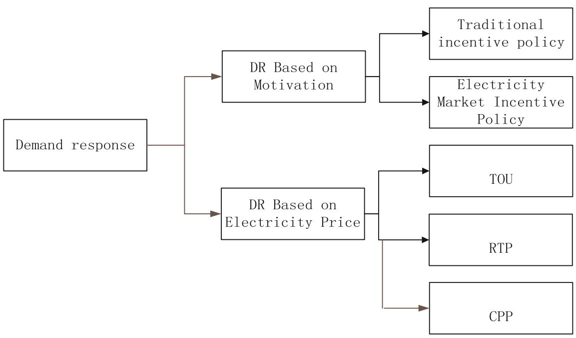
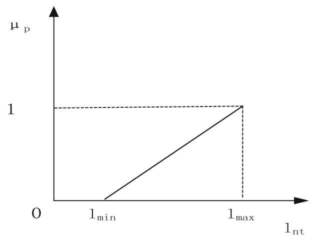


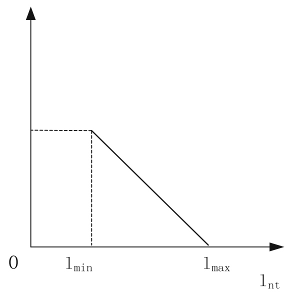
Fig. 1. Classification of requirements response

The DR based on incentive refers to the incentive contract signed in advance between the demand response implementing agency and the user. If the signing user makes the due response according to the agreement requirement, he will get a certain reward from the implementing agency. If the user fails to respond according to the contract, he will be punished accordingly. Users should fully understand the content of the agreement and choose voluntarily whether to participate in the demand response project according to their own conditions and electricity usage [8]. Incentive demand response protocols usually include the amplitude of load, the duration of load reduction and the frequency of response according to the DR signal. The incentive fee is independent of the retail price of the electric power, including both the electricity price discount and the cutting load compensation. In the establishment of the power-interruptible load demand response model based on big data analysis, the main interruptible load measures are to adopt the time-division price. The peak and valley price is especially common in time-sharing price, that is, according to the load level of power system, the whole day can be divided into three periods: peak, level and valley, and different price standards are carried out in each period. The price of electricity in normal period is close to the normal price, the price in peak period is higher than that in normal section, and the price in period of valley is lower than that in normal section [9]. Through the difference of electricity price in three periods to produce certain economic benefits, when the economic benefits are attractive to the users, the participants can be guided to adjust their own electricity consumption mode, so that the power consumption can be transferred from the peak period to the valley, and the load curve can be improved. To achieve the role of peak filling. However, the traditional peak-valley price does not fully consider the characteristics of user load, and the lack of dynamic adjustment mechanism makes it impossible to mobilize the enthusiasm of users. If the traditional fixed peak and valley price difference is too small to cause the user response, the effect of peak cutting and valley filling is very weak, and the main significance of implementing the demand response project is lost. If the price difference between peak and valley electricity is too large, it may lead to excessive response, even peak and valley inversion. The demand response model of power interruptible load based on big data's analysis needs to fully mine and extract the user characteristics, and therefore, based on the traditional peak-valley electricity price, the adjustment mechanism is introduced, and the dynamic peak-valley electricity price is formulated to avoid the above situation.

Big data analysis of the comprehensive users in the whole region shows that the daily load curve fluctuates steadily, and the division of peak, level and valley periods is more stable, and it will not change frequently in all kinds of periods. The membership degree of peak and valley at each time point is obtained by using fuzzy membership function, and based on this, the initial division of peak and valley period is carried out at each time point. Because there are fuzzy attributes in the partition results, it is necessary to classify the time points at different time intervals accurately according to the response ability and technical constraints of the actual users [10]. The common membership function includes Gao Si type, bell shape, trapezoid and triangle, and so on, which should be reasonably selected according to the characteristics of the processing target and the requirement of the processing result. The highest point corresponding to the daily load curve of electric power users must belong to the peak period, that is, the peak membership degree of this time point is 100 kum, while the valley membership degree is 0. The fluctuation of the integrated power user load curve is continuous and stable, so the higher the load value near the highest point or other points of the curve is, the higher the probability that the corresponding time point belongs to the peak period. In contrast, the lowest point of the load curve corresponds to a valley membership degree of 100, while the peak membership degree is 0. Other time points of the load curve only need to determine the corresponding load power value and the peak point and the lowest point load power comparability can get the specific peak and valley membership degree. The peak membership degree and valley membership degree of each time point of the load curve are obtained by using the linear part of the partial large-scale semi-trapezoidal membership function and the partial small semi-trapezoidal membership function. The membership function of semi-trapezoid is shown in Fig. 2.



(a) Partial large-scale semi-trapezoidal membership function



(b) Semi-trapezoidal membership function

Fig. 2. Membership function of semi-trapezoid with partial size and small size

In the semi-trapezoidal membership function of partial large and small scale, the other time points of load sequence correspond to peak and valley membership degree can be obtained from formulas (1) and (2), respectively.

$$\mu_p(\mathrm{l}_{\mathrm{n}t}) = \frac{\mathrm{l}_{\mathrm{n}t} - \mathrm{l}_{\min}}{\mathrm{l}_{\max} - \mathrm{l}_{\min}} \tag{1}$$

$$\mu_v(\mathrm{l}_{\mathrm{n}t}) = \frac{\mathrm{l}_{\max} - \mathrm{l}_{\mathrm{n}t}}{\mathrm{l}_{\max} - \mathrm{l}_{\min}} \tag{2}$$

Among that, lnt represents the time point nt corresponding load power; lmin and lmax represents the minimum and maximum values in the daily load time series, respectively; $\mu_p(\mathrm{l}_{\mathrm{n}t})$ and $\mu_v(\mathrm{l}_{\mathrm{n}t})$ represents peak membership degree and Valley membership degree of time Point nt respectively. The preliminary results of the time series of the load time series by using the fuzzy membership function can be used as an important basis for the time period division of the peak. taking into account the restriction of the user's life, the stability of production and the current limit of the electricity price technology and the facility level at present, and determining the peak, the level and the valley time duration should not be shorter than two hours so as to avoid the frequent switching of the electricity price, and the total time of each time period of each day should not be less than 4 h, in order to stabilize that production condition of the user's life and enhance the influence of the peak-to-valley electricity price [11]. The total length of the daily peak, the level and the valley time is 8 h, and the peak and valley membership of each time can be in time according to the peak of each time. Divide the constraints and adjust the peak and valley periods for determining the daily load sequence.

The determination of peak-valley price includes two aspects: dividing the peak and valley time and determining the price standard of each time period. After dividing each time period of peak and level valley, it is necessary to adjust the original peak and valley electricity price according to the load capacity in different load value difference area [12]. Because the power users are all users in a certain area, the basic shape of the clustering load curve is similar. At the same time, the load value in the numerical difference region is obviously higher than that in the non-numerical difference area. Therefore, the greater the load value in the numerical difference area, the greater the difference between peak and valley electricity prices is needed to reduce the power supply pressure during the peak period of power consumption. To improve the demand response peak filling effect. Through large numbers According to the analysis, the peak price, the average price and the valley price of p_{po}, p_{fo} and p_{vo}, are called standard peak and valley price respectively, then the peak and valley price of the predicted day can be determined by formula (3).

$$\begin{bmatrix} p_{pnd} = p_{fo} + (p_{po} - p_{fo})s_{nd} \\ p_{fnd} = p_{fo} \\ p_{vnd} = p_{fo} - (p_{fo} - p_{vo})s_{nd} \end{bmatrix} \tag{3}$$

Among this, $p_{pnd}, p_{fnd}, p_{vnd}$ respectively representing the predicted daily peak and valley electricity prices; s_{nd} represents the standard value of the day load of the nd.

2.3 Realization of Demand Response Model of Electric Power Interruptible Load

The identification of user response parameters is introduced into the demand response model of interruptible load through dynamic peak-valley pricing. In order to make dynamic peak-valley electricity price, we should fully excavate and analyze the characteristics of user load, and introduce dynamic adjustment mechanism into peak-valley electricity price, so that we can better arouse the enthusiasm of user demand response. Based on big data analysis, it is necessary to accurately identify the user response parameters and determine the response degree of the user when dealing with the different price difference of power supply to establish the demand response model of electric power interruptible load. If the price difference between peak and valley electricity is relatively small, the economic benefit is not enough to guide users to change their power consumption habits, the demand response is weak, and the load transfer rate is low, even because of the influence of non-electricity price factors or the strong randomness of users, such as negative load clipping rate, this part is called "dead zone"; If the price difference between peak and valley is too large to break through the limit of user's electricity elasticity, the potential of user's demand response will not produce any other response after being fully excavated, that is, the electricity consumption has reached. To the range threshold, this part is called "saturation zone"; Only within a reasonable range between "dead zone" and "saturation zone" is the price difference between peak and valley electricity. Through a large amount of data in the power market, the load transfer rate and the price difference of the user's response can approximate the quasi-synthetic linear function, and the load transfer rate is positive. This part is called the "linear region". Based on big data's analysis, a demand response model of power interruptible load is established. For different types of users, there are great differences in response parameters. The model is suitable not only for comprehensive users, but also for each class of specific users with significant characteristics. And because of non-price factors, Under the influence of uncertain conditions such as prime, all load transfer rates of interruptible load are constrained by reasonable range of variation and have fuzzy properties.

3 Experimental Results and Analysis

In the course of the experiment, the power-interruptible load demand in a certain area is the experimental object, and the power-interruptible load demand in the area can be analyzed by the power-interruptible load demand response model based on the big data analysis. In order to ensure the effectiveness of the experiment, the traditional power-interruptible load demand response model is compared with the power-interruptible load demand response model based on big data analysis, and the experimental results are observed. This paper first describes the peak-valley membership degree of the predicted daily load curve by using the semi-trapezoidal membership function. However, according to the peak-valley membership degree value, there is ambiguity in the partition of the peak, flat and valley periods, so it is necessary to combine the specific period partition constraints. Determine the predicted day, peak and valley time. The actual load of a power network in a certain area is selected, and the peak and valley membership degree of each time point is calculated. According to the membership degree of peak and valley at each time point, the time period of the peak and valley is preliminarily divided, and it is found that all three time points of 1 h–9 h–(23 h) are single hour for normal period. 24 h is a single hour period. Frequent switching in different time periods can easily affect the life of users and make production stable. At the same time, it brings great challenges to the technology and facility level of time-sharing electricity price. Combined with time division constraints, the prediction of peak and valley time division is finally determined. Then, according to the load standard value of the day value difference area, the electricity price of all kinds of time periods and standard peak valley electricity price of the predicted day peak level valley are obtained. And the peak and valley electricity prices on the forecast day. By using the obtained results, the experimental parameters of the power interruptible load demand response model based on big data analysis are set up. Maximum positive load rate of Random response of users without Peak-Valley Price difference $\lambda_{0max} = 0.5\%$, Maximum negative load rate $\lambda_{0min} = -0.5\%$; Demand response load transfer response critical price difference a = 0.1YUAN; Demand response load transfer saturation critical price difference b = 0.8YUAN; Maximum power transfer rate in saturated area $\lambda_{1max} = 5\%$. Under the scheme of forecasting daily peak and valley electricity price, the demand response model of interruptible load based on big data and the traditional demand response model of power interruptible load are used to analyze the demand of interruptible load in this area. The analytical accuracy of the two is shown in Fig. 3.

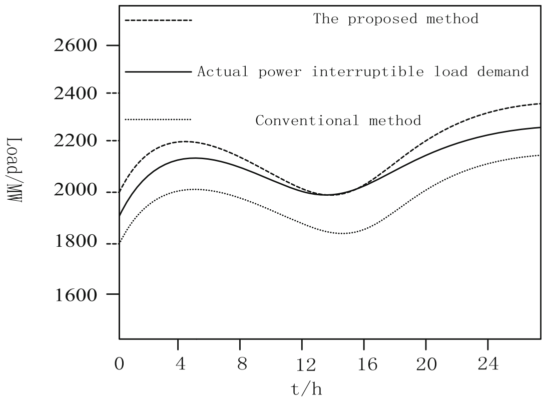


Fig. 3. Comparison of analytical accuracy

Figure 3 shows that, Using the power interruptible load demand response model based on big data analysis to analyze the power interruptible load demand in this area on the same day, compared with the traditional power interruptible load demand response model for the same day electric power demand response model in this area. The results of the analysis of interruptible load demand are closer to the actual power interruptible load demand on the same day in the region. That is, the accuracy of the analysis is higher.

4 Conduction

Using the interruptible load demand response model based on big data analysis, the analysis accuracy of the interruptible load demand can be improved, which has certain practicability and scalability. It plays an important role in improving the load curve and increasing the load rate, and can alleviate the power supply tension. Situation and improve the security of system operation.

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