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Research on Load Optimization Based on User Demand Response Behavior

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Abstract: Some scholars have studied demand response project based on the power credit mechanism and the preliminary results have been obtained. In this paper, we consider the user's electricity cost and willingness to change to establish a single-objective optimization model with multiple constraints. In the power credit mechanism, the user's response season and credit rating factors are considered. Considering the response season and credit rating, it can effectively guide users to actively participate in demand response project. Finally, numerical simulation was carried out based on the actual data of 22 Canadian residents, and different cases were designed for analysis. The results show that considering the user's response season and credit rating can effectively improve the system load curve and increase the load factor. While ensuring the stable operation of the power system, it can also reduce the electricity cost of users and improve their enthusiasm.

Keywords: Demand response; Response season; Credit rating; Demand credit

1 Introduction

Demand response(DR), as an important form of interaction between supply and demand, is conducive to the coordination and optimization of power generation and demand-side resources. Reasonable demand response subsidy settlement method can effectively improve the user's ability to participate in DR. In recent years, the electricity consumption of urban and rural residents has been growing faster than that of industry. A growing number of scholars are beginning to explore the potential for energy conservation and the ability to improve energy efficiency in the residential sector. China's demand-side resource utilization is changing from administrative management to market response, but it is also faced with such problems as inflexible pricing mechanism, immature market mechanism and incomplete participation of the main body.

The electric power credit mechanism is a relatively compromised incentive mechanism in the absence of incentive sources in the current domestic power market. Sun et al. [1] proposed a new virtual real-time electricity pricing scheme based on the benefits and comfort of the end user, and established a model of the credit mechanism, but the heterogeneity of users was not taken into account in the model. Chen et al. [2] considered the whole process of power credit transaction, and designed a power credit transaction mode involving load agents, so as to achieve the effect of responding to load quota through the credit transaction system, and considered the credit rating of users. There are seasonal differences in users' electricity consumption. Electricity consumption among urban and rural users is even more pronounced. Summer and winter are peak demand periods, and the possibility of grid imbalance is higher than that of spring and autumn. Figure 1 shows the power consumption of the total society and the power consumption of urban and rural residents in China in 2019. It can be seen that the power system ushered in peak power consumption in summer and winter. The credit system has the function of positive incentive and reverse punishment. Certain rewards should be given to those who abide by the credit, and certain punishments should be given to those who violate the trust. Therefore, based on the power credit mechanism and considering the influence of user response season and credit rating, a single-objective optimization model with multiple constraints has been established in this paper, so as to reduce users' electricity cost and their willingness to change to the greatest extent. The less the willingness to change, the more comfortable the user will be. Finally, a

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numerical simulation was carried out based on the actual data of 22 Canadian residents, and different situations were designed for comparative analysis to verify the effectiveness of the model, which can provide theoretical reference for the implementation of DR in China.

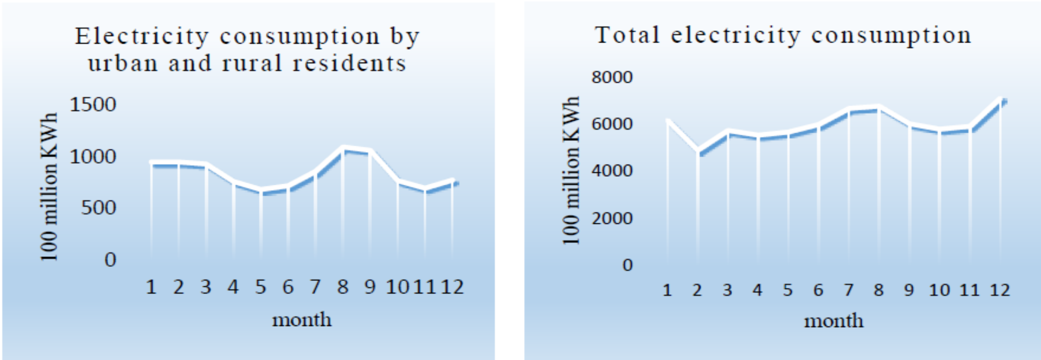

Figure 1: Electricity consumption by urban and rural residents and total electricity consumption in China in 2019.

2 Theoretical model of power credit mechanism

Users should get different incentives to participate in DR in different seasons. For example, in summer and winter, users should be given extra credit when they successfully participate in DR. At present, the implementation of DR project is mainly carried out on the premise of signing a contract, and the performance of the contract is also an indicator of evaluating user credit. Power operators can divide users' credit ratings into four categories based on their credit history: A-good, B-fair, C-warning, and D-untrustworthy. The specific user rating measurement standard is determined by the system operator. Therefore, based on factors such as user type, user credit rating, and response season, the theoretical model of power credit mechanism established in this paper is shown as follow:

$$credit_c(t) = \omega_c(\eta, q, L(x)) \cdot (d_{oc}(t) - d_c(t)) \cdot (\sum\nolimits_{c=1}^{N} d_c(t) - \bar{D}), \tag{1}$$

$$\omega_c(\eta, q, L(x)) = \eta_c \cdot q_c \cdot L_c(x), \tag{2}$$

where $credit_c(t)$ is the credit earned by user c at time t, $\omega_c(\eta, q, L(x))$ is the credit coefficient which is related to the credit factor η_c, the seasonal factor q_c, and the credit rating factor $L_c(x)$. $d_{oc}(t)$ is the original load of user c at time t, $d_c(t)$ is the optimized load of user c at time t, $\bar{D}$ is the daily average load of all users, $\bar{D} = \sum_c \sum_{t=1}^{24} d_o c(t)/T$.

$$L_c(x) = \sum_{i=1}^{n} (l_{ic} \cdot x_{ic}). \tag{3}$$

where i the i-th indicator for evaluating the cedit rating, x_{ic} is the credit rating of user c under the i-th rating indicator, l_{ic} is the weight of the i-th indicator for user c. Table 2 shows the correlation index values in the model.

For example, if users with credit rating A successfully participate in DR in spring or autumn, the credit coefficient is 1.1 times the base value, and if he(she) successfully participate in DR in summer or winter, the credit coefficient is 1.21 times the base value. If users with credit rating D successfully participate in DR in spring or autumn, the credit coefficient is 0.7 times the base value,and if he(she) successfully participate in DR in summer or winter, the credit coefficient is 0.77 times the base value. These parameters can be obtained in advance based on the user's historical information.

Table 1: Correlation index value

Index	Value	Note
η	1	down or up
	0	other
q	base	Spring or Autumn
	1.1*base	Summer or Winter
L(x)	1.1*base	A
	base	B
	0.9*base	C
	0.7*base	D

3 System model

3.1 Object function

The goal of the model is to minimize electricity cost and willingness to change for all users.

$$min \quad F = \sum_{t=1}^{24} [\alpha \cdot C^{'}(t) + (1-\alpha) \cdot O^{'}(t)], \tag{4}$$

$$\begin{cases} C^{'}(t) = \frac{C(t) - \min_{1 \le \tau \le 24} C(\tau)}{\max_{1 \le \tau \le 24} C(\tau) - \min_{1 \le \tau \le 24} C(\tau)}, \\ \\ O^{'}(t) = \frac{O(t) - \min_{1 \le \tau \le 24} O(\tau)}{\max_{1 \le \tau \le 24} O(\tau) - \min_{1 \le \tau \le 24} O(\tau)}, \end{cases} \tag{5}$$

where $C(t)$ and $O(t)$ represent the electricity cost and willingness to change for all users at time t, respectively. The willingness to change reflects the user's satisfaction, that is, the more satisfied the user is with the current behavior, the lower the willingness to change will be. $C^{'}(t)$ and $O^{'}(t)$ are the normalized results of $C(t)$ and $O(t)$, respectively. α is the weight factor, and the range is [0,1]. The larger the α, the more attention user pay for electricity cost.

3.1.1 Cost function

The electricity cost $C_c(t)$ of user c at time t is equal to the product of the optimized real time price and the optimized load, and $C(t)$ is the total electricity cost of all users.

$$C(t) = \sum_{c=1}^{N} C_c(t) = \sum_{c=1}^{N} (p_c(t) \cdot x_c(t)), \tag{6}$$

where $p_c(t)$ and $d_c(t)$ represent the optimized real-time electricity price and optimized load of user c at time t, respectively.

$$\Delta p_c(t) = \begin{cases} \frac{\theta_1(t)}{d_c(t)} \cdot \frac{credit_c(t)}{\sum_{c=1}^{N} credit_c(t)} \cdot \frac{\sum_{c=1}^{N} d_c(t) - \bar{D}}{\sum_{t \in T_1} (\sum_{c=1}^{N} d_o c(t) - \bar{D})} & t \in T_1, \\ \\ \frac{\theta_2(t)}{d_c(t)} \cdot \frac{credit_c(t)}{\sum_{c=1}^{N} credit_c(t)} \cdot \frac{\bar{D} - \sum_{c=1}^{N} d_c(t)}{\sum_{t \in T_2} (\bar{D} - \sum_{c=1}^{N} d_o c(t))} & t \in T_2, \end{cases} \tag{7}$$

where $\Delta p_c(t)$ is the price discount obtained by user c at time t, and the peak time of the system is $T_1 = t \mid \sum_{c=1}^{N} d_{oc}(t) > \bar{D}$, the valley time is $T_2 = t \mid \sum_{c=1}^{N} d_{oc}(t) \le \bar{D}$. θ_1 and θ_2 are the subsidies provided by system operator at time t for peak and valley time, respectively. The real time electricity price $p_c(t)$ of user c at time t is:

$$p_c(t) = p_{tou}(t) - \Delta p_c(t), \tag{8}$$

where $p_{tou}(t)$ is the original time-of-use pricing.

3.1.2 Willingness to change function

In the DR project, each user needs to consider how to obtain the maximum economic benefit with the minimum willingness to change, which means to find a balance between the willingness to change and the electricity cost. The user's willingness to change is shown as follow [1]:

$$O(t) = \sum\nolimits_{c=1}^{N} O_c(t) = \sum\nolimits_{c=1}^{N} [\beta_c(t) \cdot (d_c(t) - d_{oc}(t))^2], \tag{9}$$

where $O_c(t)$ is the willingness to change of user c time t, and $\beta_c(t)$ is the willingness factor of user c at time t. $O(t)$ is the total willingness to change for all users at time t.

3.2 Constraint function

The upper bound of electricity price is to protect the benefit of users, and the lower bound is to protect the benefit of system operator.

$$P_c^{min}(t) \leq p_c(t) \leq P_c^{max}(t), \tag{10}$$

The load of user c at any time is between the $d_c^{min}(t)$ and $d_c^{max}(t)$.

$$d_c^{min}(t) \leq d_c(t) \leq d_c^{max}(t), \tag{11}$$

Considering that users participate in DR project, the user's daily electricity cost is lower than the original electricity cost.

$$\sum\nolimits_{t=1}^{24} (p_c(t) \cdot d_c(t)) = \sum\nolimits_{t=1}^{24} (p_{tou}(t) \cdot d_{oc}(t)). \tag{12}$$

4 Numerical simulation and results

We used actual data from 22 residents of vancouver, Canada to verify the validity of the model. The data set was donated by resident users of Canadian power company BCHydro[4]. In Canada, the electricity price between 9: 00-11: 00 and 15: 00-23: 00 is 1.0011 yuan/kWh, and it's 0.3242 yuan/kWh at other times. The study selected a typical daily load curve, which was in august and summer in Canada [5]. Based on the limitation of data, this paper classifies the user's credit rating according to the coverage rate of the data submitted by the user, and Table 2 is the classification criteria. Data coverage is the percentage of data not lost in the data set submitted by users during the statistical period. If no data is lost, the coverage is 1. The model in this paper is a nonlinear single-objective optimization model with multiple constraints,

Table 2: Classification criteria for credit ratings.

Cover	Credit Rank
Above 0.99	A
0.95∼0.99	B
0.9∼0.95	C
under 0.9	D

which is optimized by using Quantum Genetic Algorithm. In order to improve the efficiency of the algorithm, the penalty function is introduced. In this paper, four cases are designed for comparative analysis. Case 1: α = 0.2; Case 2: α = 0.7; Case 3: α = 0.9; Case 4: response season and credit ratings are not taken into account.

The optimized load under four cases is shown in Figure 2. The red horizontal line is the daily average load $\bar{D}$, the peak time is above the horizontal line, and the valley time is below the horizontal line. As can be seen from Figure 2, as long as the user successfully participates in DR, the user's load curve will be improved and the effect of valley filling will be more obvious. If the user's credit rating and the seasonal factors are not taken into account, sometimes it can lead to worse behavior. For example, at 8 a.m. and 14 p.m., this is the peak time for the power system, but users increase the load (demand). Compared with the first three cases, it can be found that the user curve peak clipping and valley value filling effect of case 2 (α= 0.7) is better than that of case 1 and 3.

Figure 3 shows the user's electricity cost under four cases. As can be seen from Figure 3, at the peak of the system, the user's electricity cost was greatly reduced in all four cases. During peak times, the user's load is reduced, which

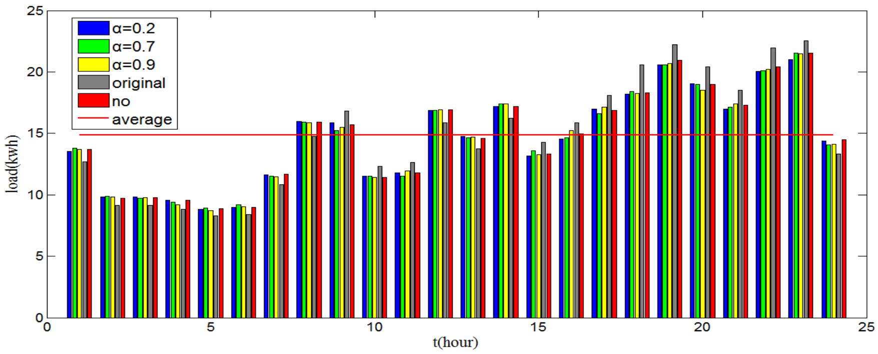

Figure 2: User load curve under four cases.

promotes the reduction of the user's electricity cost. At 14 o'clock, the users' load increases, which in turn leads to an increase in cost, but the rest of the time brings more cost savings. Table 4 shows the indicators of the four cases and original conditions. From Table 4, it can be seen that the largest cost savings is in Case 3. In Case 3, the user saved 25.21 yuan. The user in Case 4 with the least cost savings of 23.66 yuan. The load factor reflects the smoothness of the system load curve. The larger the load factor is, the more conducive to the stable operation of the power system. As you can see from Table 4, all four cases have improved the system load factor, but the largest increase was in Case 2. In this case, the load factor is 69.65%, and the system peak-valley difference is the smallest, which is 12.17 kW. In four cases, the user's willingness to change is shown in Figure 4. When the user's power consumption habits change, the user will show different willingness to change. The less willingness to change, the more satisfied users will be with the current power consumption pattern, that is, the higher the comfort level. The model in this paper is a single-objective optimization model, which can minimize the user's electricity cost and willingness to change. Based on the previous analysis, we know that the best result is Case 2, which is $\alpha = 0.7$. The electricity cost saved for the user is 25.12 yuan, the system load factor is 69.65 %, and the user's willingness to change is 3.78. By comparing Case 4 with the first three cases, it can be found

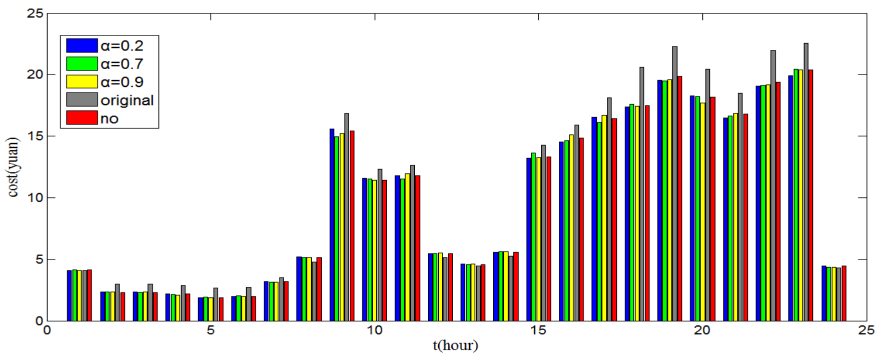

Figure 3: User cost curve under four cases.

that due consideration of user response season and user credit rating can effectively reduce users' electricity cost, improve the stability of system operation, and improve the users' enthusiasm to participate in DR.

5 Conclusion

In this paper, a single objective optimization model with multiple constraints is established based on a comprehensive consideration of user's electricity cost and willingness to change. In the power credit mechanism, the seasonal factor and

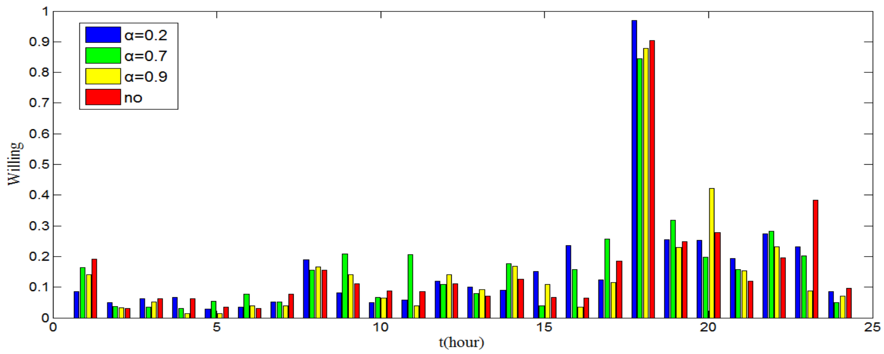

Figure 4: Willingness under four cases.

Table 3: Indicators of different categories in four cases

Case	Cost(yuan)			Load factor(%)		Peak to Valley(kw)	
	Original	Optimal	Save	Original	Optimal	Original	Optimal
α=0.2	262.20	237.79	24.41	66.03	68.19	14.28	12.77
α=0.7	262.20	237.08	25.12	66.03	69.65	14.28	12.17
α=0.9	262.20	236.99	25.21	66.03	68.01	14.28	12.59
no	262.20	238.54	23.66	66.03	68.21	14.28	12.70

credit rating factor of user participation in DR were considered. Actual data from 22 Canadian residents were used in numerical simulations and case studies. The analysis of system indicators and economic indicators of simulation results shows that compared with the model without considering seasonal factor and user credit factor, the system load curve of the model is improved, the system peak to valley difference is reduced, and the load factor is significantly improved. The overall willingness to change is relatively small, and the cost of electricity is reduced. The validity of the model has been verified. In the context of further deepening the reform of the power system, this paper conducted an in-depth study of the power credit mechanism, and established an optimization model of the user's economic interests and willingness to change. Ensure the economy and comfort of user participation in demand response, and improve the decision-making ability of operators in the implementation of the program. The validity of the simulation results shows that the model can provide reference for the future development of the power market.

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