Evaluation of Thermostatically Controlled Residential Load Demand Response Potential Based on Smart Meter Data

CHEN Yue [1], HOU Hui [1*], LI Xianqiang[1], WU Xixiu[1], WEI Meifang[2], TANG Aihong[1]

(1. School of Automation, Wuhan University of Technology, Wuhan 430070, China;

2. State Grid Hunan Electric Power Co., Ltd., Changsha 410005, China)

ABSTRACT

Residential thermostatically controlled loads are considered as an important demand response resource. Evaluating their response potential before demand response will help to improve the response effect. Based on the above situation, driven by smart meter data of residents, the electricity consumption mode of residential users is explored. A response potential evaluation model is proposed. Firstly, the residential load is clustered. And the basic curves of thermostatically controlled loads are given. Secondly, in demand response, a demand-side management scheme is proposed through quantitative optimization of user satisfaction. At the same time, the demand response potential is evaluated. Finally, the load data of households are selected for simulation to verify the validity of the evaluation model.

Keywords: smart meter; demand response; thermostatically controlled load; user satisfaction; potential evaluation;

1. INTRODUCTION

Smart meters play a vital role in demand-side management (DSM). Analysis and application of smart meter data can make DSM more effectively while ensuring the safety of the power system [1]. According to relevant statistics, current demand response schemes have not yet been implemented popularized among residential users [2]. And the potential of residential load response has not been fully exploited. At the same time, Users' thermostatically controlled load (TCL) accounts for up to 60% of the residential load. Flexible and widely distributed TCL is a high-quality demand response resource [3~4].

Analyzing the demand response potential of TCL through smart meter data will help utilities to imply demand response timely and efficiently. [5~6] used k-means clustering to analyze smart meter data to accurately estimate load patterns. [7] employed multi-level clustering for data analysis. [8] applied the Gaussian mixture model to obtain users' probabilistic behavior from historical data of smart meters. [9~10] discussed the response of residents under the factor of electricity price. [11] applied a linear regression algorithm to obtain the users' thermal sensitivity of consumption. [12~13] applied data to model residential buildings aimed to determine demand response schemes. But this study cannot be applied in a wider range. [14~15] all mentioned the commercial TCL control technology based on set-point control. The results show this method could achieve an energy-saving effect.

Through the analysis of the above literature, we can find in terms of response potential analysis, the focus is on the predictive analysis of the load curve after response schemes, and lacks determination and comparative analysis of the user's baseline load before the demand response. Based on previous research, this paper proposes a residential TCL demand response potential evaluation model driven by data. The steps are as follows:

1) The basic load curves and TCL mode of resident users are presented through linear regression and k-means clustering.

2) Through the fuzzy comprehensive evaluation method, user satisfaction is

quantitative optimized.

3) The TCL demand response potential is evaluated through the comparative analysis of the basic curve of TCL.

The rest of this paper is organized as follows: Section 2 describes the residential TCL basic load curves and evaluation TCL response potential. Section 3 proves the validity of the model by simulation. And the conclusions are made in Section 4.

2. ESTABLISHMENT OF MODEL

2.1 Establishment of basic curve

2.1.1 Regression analysis of loads

The correlation coefficient between temperature and energy consumption is strong. To characterize this correlation, this section uses the linear regression method. User energy consumption and real-time TCL are described as follows [16]:

$$W = \alpha.(1-S(t)) + S(t)*(\beta + \gamma*(T(t)-C_p)) \tag{1}$$

$$W_{tcl} = \beta + \gamma*(T(t)-C_p)\text{-}\alpha \tag{2}$$

where W is the user's hourly energy consumption; W_{TCL} is TCL consumption; T(t) is a temperature function; α is the hourly baseload; Cp is the temperature turning point; β , γ is the intercept and slope of the regression model respectively; S(t) is the TCL status.

The process is as follows: 1) Determine the change point Cp by traversing the temperature point who makes the regression effect the best. 2) Perform regression analysis through data to describe the temperature response status of a single residential user. 3) Calculate TCL from the temperature response model. Determine whether the customers use TCL and period for turning on. The regression analysis results are shown in Fig. 1.

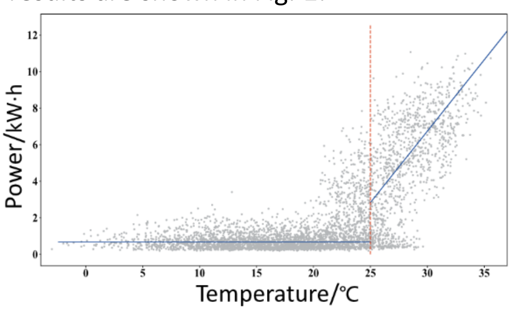

Fig. 1 User energy consumption

2.1.2 Clustering of TCL

Based on the regression model, the user with the slope $\gamma > 0$ is judged to be a TCL user. We cluster these users to get their similar load patterns. TCL characteristic data volume is large, the structure is relatively simple. It's suitable for k-means clustering [17]. The k-means clustering is a commonly used clustering algorithm. Because of its simple principle and small calculation, k-means clustering converges faster than other clustering algorithms. Its objective function is to minimize the sum of squares of errors (*SSE*).

$$SSE = \sum_{i=1}^{k}\sum_{x\in c_i}\left\| x-u_i \right\|^2 \tag{3}$$

where k is the number of clusters. c_i is the sample set of clusters; u_i is the cluster center.

2.2 User satisfaction quantification

In demand response, users will make rational decisions. The evaluation of user behavior is a key part of the response

2.2.1 Evaluation of user satisfaction

Residential satisfaction mainly includes two indicators: environmental comfort and electricity expenditure. Users' intuitive feelings with temperature and prices are usually fuzzy concepts. We use the fuzzy comprehensive evaluation to analyze the user satisfaction [18].

The basic of the fuzzy comprehensive evaluation is to quantify the intermediate state of the fuzzy membership. Then make a comprehensive evaluation of various indicators of multiple factors.

The steps of fuzzy comprehensive evaluation are as follows:

1) Determine the evaluation factor set U, comment set V, and weight set A, shown in Tab. 1.

Tab. 1 Fuzzy comprehensive evaluation index

fuzzy evaluation	factor set U	weight set A	comment set V		
Satisfaction	T_{in}	a_1	comfo-rttable		hot
	cost	a_2	ch-eap	pro-per	expe-nsive

2) Determine the comprehensive evaluation matrix.

The single-factor evaluation vector r_i is obtained from the fuzzy membership function to form the fuzzy membership matrix R. The fuzzy membership function is trapezoidal distribution [19].

$$r_{i,j} = \begin{cases} 0 & x < a \\ \dfrac{x-a}{b-a} & a < x < b \\ 1 & b < x < c \\ \dfrac{x-c}{d-c} & c < x < d \\ 0 & x > d \end{cases} \quad (4)$$

where a, b, c, d is upper and lower bounds of the function.

3) Process the evaluation vector [20].

The rank of each level is defined as a continuous integer of 1, 2, ..., j, …, m. Then the rank is weighted and summed to obtain the relative position of the evaluation object, that is, user satisfaction. For the evaluation factor set U, the user satisfaction is the following Equation (5).

$$y_U = \frac{\sum_{j=1}^{m} b_j^k \bullet}{\sum_{j=1}^{m} b_j^k} \quad (5)$$

2.2.2 Maximum satisfaction of users

In the context of response schemes, at a certain time t, the electricity price is P_{ToU}, the outdoor temperature is Tout. For users, by adjusting the TCL state S, the indoor temperature can be changed. Then the cost and temperature constitute a fuzzy evaluation set: $U_i = \{P_{ToU}, c_i\}$. Evaluate Ui by formula (5) to get the user satisfaction y_U.

So, the objective function of this model can be measured as follows:

$$f(T_{in}) = max\{y_{U_i}\} \quad (6)$$

where T_{in} is the indoor temperature corresponding to the maximum user satisfaction.

The constraint conditions can be described as follows:

1) Temperature setting has a range:

$$T_{\min} \le T_{in} \le T_{max} \le T_{out} \quad (7)$$

2) Variables are non-negative:

$$p \ge 0, c \ge 0 \quad (8)$$

3) Factor evaluation weight balance:

$$\sum_{i=1}^{m} a_i = 1 \quad (9)$$

For the user, there are only limited TCL set temperatures to choose, which satisfies Equation (7). The optimization problem in this model will traverse all the available temperatures to optimize the comprehensive satisfaction.

2.3 Process of demand response potential evaluation

In the demand response, our model is used to simulate user decisions and determine their response. Through a comprehensive comparison of TCL basic curves, the demand response potential can be obtained. The main process is as follows:

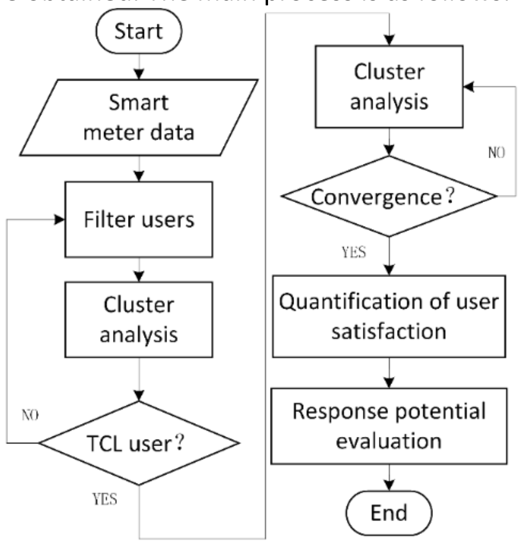

Fig. 2 The flow chart of TCL demand response potential evaluation

3. SIMULATION

To verify the correctness of the model, this paper takes an area in East China as an example. Assume there are 1500 residential users in this area. In our simulation, the demand response scheme adopted is the time-of-use price [21].

This paper takes the data of the smart meter in one year for simulation analysis. Performs regression analysis on these data. The distribution of regression parameters is shown in Fig. 3. Fig. 3(a) shows thermal characteristic turning point Cp, which is mainly distributed around 15~20℃. We can obtain than most users turn on their TCL around this temperature point. Fig. 3(b) is the regression slope. It shows the changes in load caused by a unit temperature fluctuation, which can characterize the user's temperature response sensitivity. The slopes are all positive and mainly distributed around 0.25. This value represents the temperature response level of most residential TCL.

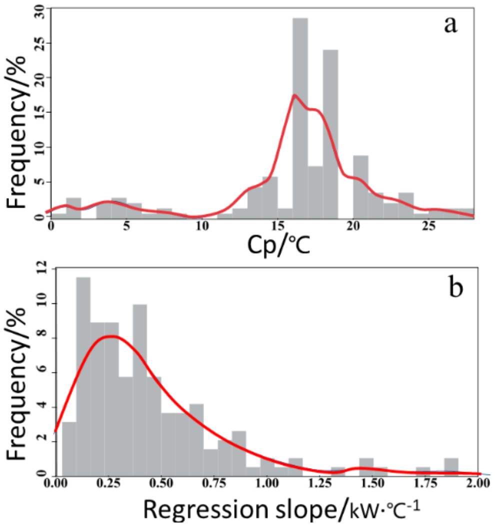

Fig. 3 Distribution of regression parameters

For the regression results, the daily curves of TCL are shown in Fig. 4. Regression results show that TCL reaches peak load at 10: 00, then continued until 20: 00. And then shows a downward trend. The trough is from 0: 00 to 5: 00 at midnight. In a world, TCL daily load curve is an obvious "peak and valley" phenomenon. And TCL is a high-quality demand response resource.

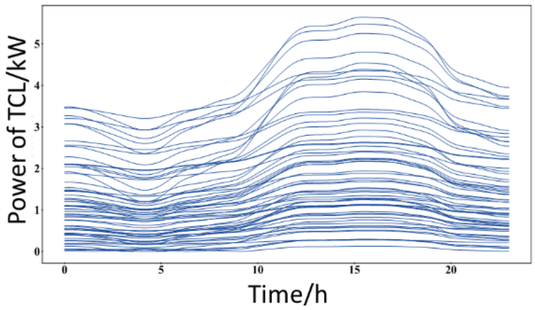

Fig. 4 Residential TCL curves

According to the TCL regression characteristic parameters, k-means clustering can be used to analyze these curves, and the results are shown in Fig. 5. Fig. 5(a) shows the clustering results of TCL users, and Fig. 5(b) shows the frequency of each cluster. In Fig. 5(a), users are mainly concentrated in the first type, accounting for 73%. We set it as the TCL basic curve and applied for analysis later.

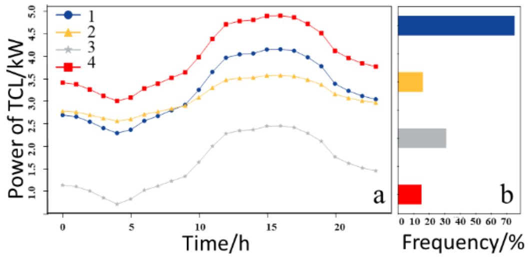

Fig. 5 TCL power curve clustering results

The demand response behavior of the first type users can be analyzed according to our model. To simplify the calculation, the weight is set as $a_1 = a_2 = 0.5$. The initial value of the indoor temperature is the same as the outdoors. A single TCL user is simulated and the result is shown in Fig. 6.

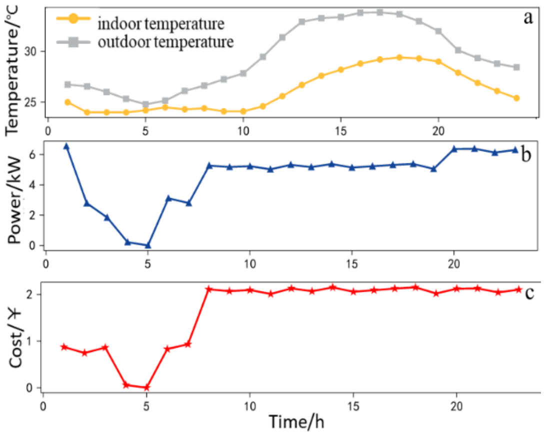

Fig. 6 Decision results of individual users

Fig. 6(a) is the outdoor temperature and indoor temperature. The indoor temperature follows the outdoors in certain periods, such as 10:00-20:00. Fig. 6(b) shows the real-time TCL power curve of the user, and there is no obvious peak after the user participates in the regulation. The demand valley is in 1:00~5:00. It's due to the low midnight temperature, and users reduce the consumption of TCL. Especially at 5:00, TCL is completely closed during this period. The load and cost are all zero. Fig. 6(c) is the user's bill, which is determined by price and consumption.

To simulate the group TCL, we adopt the above temperature and price. The group is the typical curves clustered in the first category [22]. The related parameters value of 1500 TCL groups are shown in Tab. 2

Tab. 2 TCL group parameter value

Parameter	Distribution pattern	Distributed parameter
Power	Uniform distribution	2~5
Energy consumption rate	Uniform distribution	3~3.6
Thermal capacity	Constant	5.56
Thermal resistance	Normal distribution	$\mu=1, \quad \sigma=0.05$
Weight	Normal distribution	$\mu=0.5, \quad \sigma=1$

The calculation result is shown in Fig. 7. The circular mark curve is the group loads after demand response, and the triangle mark curve is the basic load before demand response.

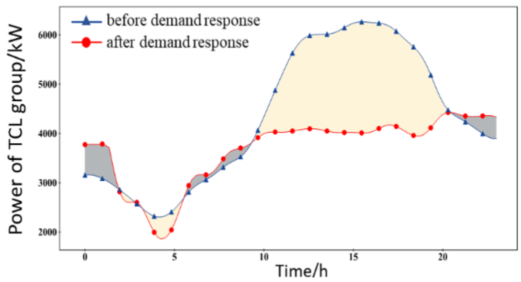

Fig. 7 TCL graph before and after response

In Fig. 7, from noon to evening, the trend of the group loads participating in demand response is more stable than the basic, rather than an obvious peak. In this period, the price is high. Considering the cost, users appropriately increase temperature and follow the outdoors. Consequently, the bill decreases and the load is relatively stable. During the midnight time, Considering combined with temperature and price, the residential indoor temperature set-point follows the outdoor temperature at this period. And the loads are reduced.

The TCL operation parameters before and after the demand response are shown in Tab. 3. Compared with basic curves, the load is reduced by 13.9%. The TCL demand response potential in this scenario is the capacity difference:1.82MW. The Residential bill is reduced by 12.1%. At the same time, the load fluctuations are greatly smoothed, with an average reduction of 32.69%, and the fluctuation variance is significantly reduced, which greatly improves the load stability and is conducive to the safety of the grid system.

Tab. 3 TCL operation parameters

response mode	TCL load /MW·h	cost/ ¥	fluctuation /MW	fluctuation variance
before response	101.12	9.60	39.11	1.89
after response	87.37	8.32	26.54	0.42

It can be seen that in the TCL demand response, all indicators after the response are better than those before the response.

4 CONCLUSIONS

This paper summarizes the data analysis methods of smart meters and the current application status in the field of demand response, and analyzes the potential response of residential users' TCL. The main results are as follows:

(1) Based on the user's historical data of smart meters, through linear regression and k-means clustering to propose a user TCL energy consumption basic load curve.

(2) In the demand response scenario, the fuzzy comprehensive evaluation method is used to quantify the comprehensive satisfaction with the user's environment temperature and bills. And the residential behave is simulated by maximizing user satisfaction.

It should be pointed out that this paper only considers the cooling effect of TCL for residential users in summer. At the same time, the thermoelectric model parameters of TCL are simple first-order models. Therefore, establishing more accurate models might be regarded as the next research topic.

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