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Feature Analysis of Generalized Load Patterns Considering Active Load Response to Real-Time Pricing

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ABSTRACT In the future Smart Grid, it is necessary to study the generalized load (GL) patterns feature considering the impact of active load response to real-time pricing (RTP). There are two challenges in the study. Firstly, how to quantitatively calculate the impact of RTP on GL is the main difficulty of the research. Secondly, the conventional indexes cannot accurately reflect the evolution trend of GL pattern feature. To overcome the first challenge, this paper proposed a novel calculation method based on elasticity coefficient. Elasticity coefficient can effectively formulate the relationship between RTP fluctuation and load response. The GL data after demand response (DR) is generated based on the elasticity coefficient. For the second challenge, based on the generated GL data, the hierarchical clustering method is used to extract the typical GL patterns. Then, new indexes are added to measure the evolution trend of GL pattern feature, including the proportion of maximum load decrease (PMALD), the proportion of minimum load increase (PMILI), the proportion of peak-valley difference of load decrease (PPVDLD), the proportion of large peak-valley difference of load (PLPVDL), and the proportion of large hourly climbing load (PLHCL), etc. The feature of GL patterns is investigated by a case study using the data of ISO New England. This study will provide significant auxiliary information for load control, load forecasting, and electricity price setting of smart grid.

INDEX TERMS Active load, clustering analysis, demand response, elasticity coefficient, load pattern, real-time pricing.

I. INTRODUCTION

Load pattern feature plays a key role in load forecasting and control [1]–[3], energy allocation [4], the detection of abnormal electricity consumption [5], and designing electricity tariff offers [6], etc. So far, the study of load pattern feature has been attached much importance in academic.

Traditional load pattern feature analysis generally studies the impact of holidays, climate, and electricity structure on normal load patterns based on historical load data. The research can be divided into two categories. The first category is to describe the load pattern feature by indexes after the

load data are processed by statistical methods [7]–[9]. The other category is to analyze the correlation between load and influencing factors and study the change of load pattern caused by influencing factors [10]–[12].

Due to the clean, low-carbon, and green development direction of global energy, some new loads, such as distributed renewable energy, electric vehicles, and energy storage, are connected to the power grid on a large scale. As a result, the traditional load becomes generalized load (GL) with rich connotations. Among them, energy storage, electric vehicles, and flexible loads etc. can actively adjust electricity consumption and time according to price fluctuation. They are called active load. It can be predicted that with the development of smart grid, the proportion of active load

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will become larger and larger. Therefore, it is necessary to consider the influence of demand response (DR) behavior of active load response to real-time pricing (RTP) on GL pattern.

Current research on DR focuses on the economy of DR [13], [14], the operation mode of DR [15], [16], the formulation of response project [17], [18], and the evaluation of user response capability [19], [20], etc. There are few studies on the impact of DR on load pattern feature. Reference [21] analyses and simulates real-time pricing (RTP), and points out that the implementation of RTP can achieve smoother and lower load curve. However, the reference only qualitatively describes the impact of DR without quantitative description. Reference [22] discusses the impact of DR on load pattern feature based on time-of-use electricity price (TOU). Nevertheless, it only compares the peak-valley difference and load rate before and after DR, and does not excavate more load pattern feature. Besides, it does not consider the impact of RTP on load pattern.

Different from traditional load pattern feature analysis, GL data considering DR cannot be obtained directly by Supervisor Control and Data Acquisition. Therefore, how to quantitatively calculate the impact of electricity price on GL is the key. The elasticity coefficient based on Econometrics is often used to analyze DR behavior. When analyzing the DR based on TOU, the usual method is to obtain the elasticity coefficient between the peak-flat-valley period through user reporting [23] and social survey [24], so as to calculate the load data after DR. However, for RTP, the electricity price is fluctuating, and it will change in every hour or less. It is impossible to set the elasticity coefficient using the commonly used method. In [21], the load sequence is simplified into three sections: peak, non-peak, and valley. Then, the impact of RTP on load is calculated by setting the elasticity coefficient between three sections, and the load data after DR is obtained. This method weakens the user's sensitivity to electricity price and cannot accurately measure the impact of RTP on load. Therefore, on the basis of the above research, this paper proposes a novel calculation method based on elasticity coefficient. The elasticity coefficient is generated by Gauss function. Based on elasticity coefficient, GL data after DR can be obtained. Then, the load pattern feature after DR is analyzed.

Another critical problem in the study of load pattern feature considering DR is how to measure the change of load pattern feature before and after DR. Conventional indexes such as maximum load, minimum load, peak and valley difference, load rate, load deviation, and climbing load can only represent the static characteristics of load pattern, and cannot accurately describe the evolution trend of load pattern feature in DR. Therefore, in this paper, based on the simulation data, the typical patterns of load after DR are extracted by hierarchical clustering method. Then, the typical load pattern features after DR are described by new indexes such as the proportion of maximum load decrease (PMALD), the proportion of minimum load increase (PMIL), the proportion of peak-valley difference of load decrease (PPVDLD), the proportion of

large peak-valley difference of load (PLPVDL), and the proportion of large hourly climbing load (PLHCL).

The example shows that the proposed method can calculate the impact of RTP on GL in various situations, and the proposed indexes can well reflect the evolution trend of load pattern in DR.

The major contributions of this paper are as follows:

- a) A model of active load transfer driven by electricity price difference in DR is established. The transferred active load is calculated quantitatively by a novel method based on elasticity coefficient, then the GL data considering DR is generated.
- b) The typical GL patterns considering DR are extracted by hierarchical clustering method, and new indexes are proposed to quantitatively describe the typical GL pattern feature.
- c) The influence of DR behavior of active load response to RTP on GL pattern is analyzed qualitatively and quantitatively.

The remainder of this paper is organized as follows. The calculation method based on elasticity coefficient is presented in Section II. In Section III, the typical load patterns are extracted by hierarchical clustering method, and the updated indexes are proposed to analyze load pattern feature. The simulation and results analysis are performed in Section IV. Finally, Section V concludes this paper.

II. QUANTITATIVE CALCULATION OF THE IMPACT OF RTP ON GL BASED ON ELASTICITY COEFFICIENT

The demand side response based on price includes three pricing forms: TOU pricing, RTP, and critical peak pricing. For regulating the balance of power supply and demand, RTP is often considered to be the most effective pricing form. In theory, RTP fluctuates in real time. But in practice, consumers can generally get RTP one day or several hours in advance, so as to adjust power consumption. The change of GL pattern caused by DR is caused by the behavior of active load response to electricity price. Therefore, we first analyze the behavior of active load response to electricity price, and then calculate it quantitatively according to elasticity coefficient.

A. BEHAVIOR ANALYSIS OF ACTIVE LOAD RESPONSE TO ELECTRICITY PRICE

Active load mainly responds to electricity price by means of transfer [25]. As pointed out by [26], [27], in the purpose of reducing costs, electricity price is the main factor to guide the transfer of active load.

According to the length of time for users to obtain electricity price information in advance, the transferable interval of active load is defined as S_{t_i} . For example, if users get electricity price information N hours in advance, the S_{t_i} of active load in period t_i is $\{t_i - N, t_i + N\}$ hours. Consumers can compare the electricity price between period t_i and the period within S_{t_i} , and transfer load from the higher-price period to the lower-price period, so as to improve economic benefits.

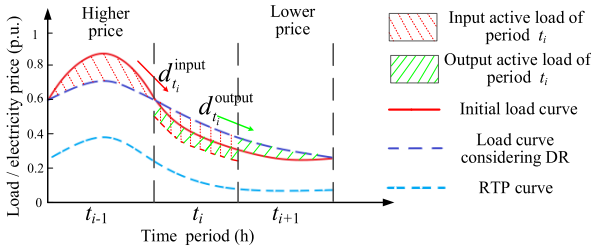


FIGURE 1. The transfer of active load.

The diagram of active load transfer caused by electricity price difference is shown in Fig.1.

In Fig.1, the arrow represents the direction of the active load transfer. Driven by electricity price difference, the active load in higher price periods t_{i-1} will transfer to period t_i , while the active load in period t_i will transfer to lower price period t_{i+1} . As we can see, $d_{t_i}^{\text{input}}$ is the active load transferred from higher price periods to period t_i , and $d_{t_i}^{\text{output}}$ is the active load transferred from period t_i to lower price periods. Thus, the load change of period t_i after DR, namely the change of active load is as follows:

$$\Delta d_{t_i} = d_{t_i}^{\text{input}} - d_{t_i}^{\text{output}}. \quad (1)$$

Then, the load in period t_i after DR can be expressed as:

$$L'_{t_i} = L_{t_i} + \Delta d_{t_i} = L_{t_i} + d_{t_i}^{\text{input}} - d_{t_i}^{\text{output}}, \quad (2)$$

where L_{t_i} and L'_{t_i} are the loads in period t_i before and after DR, respectively.

The $d_{t_i}^{\text{input}}$ includes the active load transferred from each higher price period to period t_i , so it can be expressed as:

$$d_{t_i}^{\text{input}} = \sum_{t_j \in S_{t_i}^{\text{input}}} d_{t_j \rightarrow t_i}, \quad (3)$$

where $S_{t_i}^{\text{input}}$ is the available input transfer period set for period t_i . The $S_{t_i}^{\text{input}}$ consists of all periods in which the electricity price is higher in S_{t_i} than that in period t_i . $d_{t_j \rightarrow t_i}$ is the active load transferred from period t_j to period t_i during DR. Similarly, the $d_{t_i}^{\text{output}}$ can be expressed as:

$$d_{t_i}^{\text{output}} = \sum_{t_k \in S_{t_i}^{\text{output}}} d_{t_i \rightarrow t_k}, \quad (4)$$

where $S_{t_i}^{\text{output}}$ is the available output transfer period set for period t_i . The $S_{t_i}^{\text{output}}$ consists of all periods in which the electricity price is lower in S_{t_i} than that in period t_i . $d_{t_i \rightarrow t_k}$ is the active load transferred from period t_i to period t_k during DR. So, (2) can be written as:

$$L'_{t_i} = L_{t_i} + \sum_{t_j \in S_{t_i}^{\text{input}}} d_{t_j \rightarrow t_i} - \sum_{t_k \in S_{t_i}^{\text{output}}} d_{t_i \rightarrow t_k}. \quad (5)$$

In (5), the L_{t_i} is known. Therefore, in order to get the L'_{t_i} , the key is to calculate the $d_{t_j \rightarrow t_i}$ and $d_{t_i \rightarrow t_k}$, which are the active loads transferred between two periods.

Next, the calculation method based on elasticity coefficient is introduced.

B. ELASTICITY COEFFICIENT THEORY

Elasticity coefficient is defined as the ratio of relative change of demand to the corresponding relative change of price [28]. Therefore, the elastic coefficient is directly connected to the load data before and after the response. Based on elasticity coefficient, the variation of load demand with electricity price can be calculated. The elasticity coefficient of periods t_j to t_i can be formulated as:

$$\varepsilon_{t_j \rightarrow t_i} = \frac{\Delta L_{t_j \rightarrow t_i} / L_{t_j}}{(\rho_{t_j} - \rho_{t_i}) / \rho_{t_j}}, \quad (6)$$

where $\Delta L_{t_j \rightarrow t_i}$ is the load transferred from period t_j to period t_i , ρ_{t_j} and ρ_{t_i} are the price of period t_j and t_i , respectively. Then, the load transferred from period t_j to period t_i is:

$$\Delta L_{t_j \rightarrow t_i} = \varepsilon_{t_j \rightarrow t_i} L_{t_j} (\rho_{t_j} - \rho_{t_i}) / \rho_{t_j}. \quad (7)$$

In (7), L_{t_j} , ρ_{t_j} , and ρ_{t_i} are known. Thus, as long as the elasticity coefficient $\varepsilon_{t_j \rightarrow t_i}$ is obtained, the transferred load $\Delta L_{t_j \rightarrow t_i}$, which is the transferred active load $d_{t_j \rightarrow t_i}$ in Section II-A, can be calculated.

C. THE CALCULATION OF TRANSFERRED ACTIVE LOAD BASED ON ELASTICITY COEFFICIENT

As mentioned in Section I, the elasticity coefficient of RTP cannot be obtained by conventional methods. It is necessary to set the elasticity coefficient according to the response law of active load.

1) SETTING THE ELASTICITY COEFFICIENT

Changes in electricity consumption will affect consumers' daily lives. Consumers often want to shift power consumption to nearby periods. Therefore, for the active load of the same category, the smaller the transfer time distance, the stronger the willingness to transfer, and the higher the transfer rate, the greater the elasticity coefficient. The distribution of elasticity coefficients is similar to the normal distribution when the mathematical expectation μ is 0. Normal distribution is a statistical model of quantitative phenomena in natural science and behavioral science. Various psychological tests and natural phenomena have been found to obey normal distribution approximately, although the underlying causes of these phenomena are often unknown. In theory, it can be proved that if many small effects are considered as a variable, then the variable obeys normal distribution. Therefore, we can think that the distribution of elasticity coefficients obeys normal distribution approximately. As a density function of normal distribution, Gauss function is used to calculate the elasticity coefficient. The function is as follows:

$$\varepsilon_{t_j \rightarrow t_i} = \frac{1}{\sqrt{2\pi}\sigma} \exp \left[-\frac{(j-i)^2}{2\sigma^2} \right], \quad (8)$$

where σ is the parameter that regulates the decreasing intensity of elasticity coefficient according to the increasing of transfer time distance. Greater influence of transfer time distance on load is, smaller corresponding σ will be. The setting of parameter σ for different categories of active load will be discussed in Section IV-B1.

2) CALCULATION OF TRANSFERRED ACTIVE LOAD

After the elasticity coefficient $\varepsilon_{t_j \rightarrow t_i}$ is determined, the transferred active load can be calculated by (7). As mentioned in Section II-A, the active load will transfer from higher price period to lower price period. At the same time, the active load will transfer only when there is a price difference between the two periods. Hence, the active load transferred from period t_j to period t_i can be modified to (9):

$$d_{t_j \rightarrow t_i} = \begin{cases} \frac{\varepsilon_{t_j \rightarrow t_i} L_{t_j} \Delta \rho_{ji}}{\rho_{t_j}}, & j \neq i, \Delta \rho_{ji} = \rho_{t_j} - \rho_{t_i} > 0 \\ 0, & j \neq i, \Delta \rho_{ji} = \rho_{t_j} - \rho_{t_i} \leq 0 \\ 0, & j = i, \Delta \rho_{ji} = \rho_{t_j} - \rho_{t_i} = 0. \end{cases} \quad (9)$$

Equation (9) shows that active load transfer only occurs between different periods with price difference, and the direction of transfer is from higher price period to lower price period. In other cases, the active load transfer will not occur, so the transferred active load is 0.

3) ANALYSIS OF DEFICIENCIES IN THE CALCULATION

In (9), the amount limitation of transferred active load in each period is not taken into account. Thus, the actual transferred active load are not equal to the available active load in the period. The unbalance of transferred active load is shown in Fig.2:

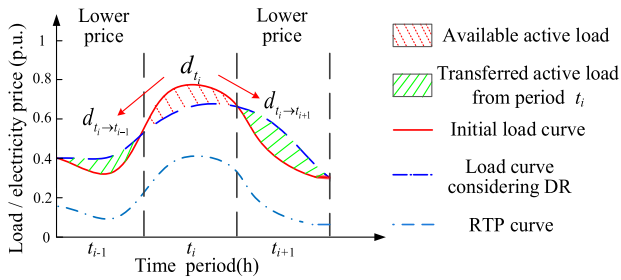


FIGURE 2. The unbalance of transferred active load.

where d_{t_i} is the total active load in period t_i before DR, $d_{t_i \rightarrow t_{i-1}}$ and $d_{t_i \rightarrow t_{i+1}}$ are active loads transferred from period t_i to period t_{i-1} and t_{i+1} , respectively. However, the sum of $d_{t_i \rightarrow t_{i-1}}$ and $d_{t_i \rightarrow t_{i+1}}$ may not necessarily equal to d_{t_i} , which results in a load imbalance before and after DR. To deal with the problem, the calculation result should be corrected. In this paper, a normalized correction method is used.

D. THE CORRECTION OF TRANSFERRED ACTIVE LOAD

The normalized correction method, that is, for period t_i , it is to allocate the active load of period t_i according to the proportion

of the calculated active load transferred to each period to the sum of the calculated transferred active load. It can be formulated as:

$$m_{t_i \rightarrow t_k} = \frac{d_{t_i \rightarrow t_k}}{\sum_{t_j \in S_i^{\text{output}}} d_{t_i \rightarrow t_j}}, \quad (10)$$

$$d'_{t_i \rightarrow t_k} = m_{t_i \rightarrow t_k} d_{t_i}, \quad (11)$$

where $d_{t_i \rightarrow t_k}$ is the active load transferred from period t_i to period t_k before correction, $\sum_{t_j \in S_i^{\text{output}}} d_{t_i \rightarrow t_j}$ is the sum of

active load transferred from period t_i to other periods before correction, $d'_{t_i \rightarrow t_k}$ is the active load transferred from period t_i to period t_k after correction, and $m_{t_i \rightarrow t_k}$ represents the ratio of $d_{t_i \rightarrow t_k}$ to $\sum_{t_j \in S_i^{\text{output}}} d_{t_i \rightarrow t_j}$. When the ratio of $d'_{t_i \rightarrow t_k}$ to d_{t_i} is equal

to $m_{t_i \rightarrow t_k}$, the corrected transferred active load $d'_{t_i \rightarrow t_k}$ can be obtained. The sum of transferred active load from period t_i is equal to the available active load by using (10) and (11). Then, we can get the corrected results.

E. CALCULATION OF TRANSFERRED ACTIVE LOAD IN MULTI-PERIODS

The calculation process of transferred active load for a single period is described above. For multi-periods, as mentioned in Section II-A, each period will get the active load from higher price periods, and its own active load will also transfer to lower price periods. Therefore, the calculation of transferred active load in multi-periods should actually be (12) and (13):

$$\begin{aligned} \begin{bmatrix} d_{t_1}^{\text{input}} \\ d_{t_2}^{\text{input}} \\ \vdots \\ d_{t_T}^{\text{input}} \end{bmatrix} &= \begin{bmatrix} \sum_{t_j \in S_{t_1}^{\text{input}}} d_{t_j \rightarrow t_1} \\ \sum_{t_j \in S_{t_2}^{\text{input}}} d_{t_j \rightarrow t_2} \\ \vdots \\ \sum_{t_j \in S_{t_T}^{\text{input}}} d_{t_j \rightarrow t_T} \end{bmatrix} \\ &= \begin{bmatrix} m_{t_1 \rightarrow t_1} & m_{t_2 \rightarrow t_1} & \dots & m_{t_T \rightarrow t_1} \\ m_{t_1 \rightarrow t_2} & m_{t_2 \rightarrow t_2} & \dots & m_{t_T \rightarrow t_2} \\ \vdots & \dots & \dots & \vdots \\ m_{t_1 \rightarrow t_T} & m_{t_2 \rightarrow t_T} & \dots & m_{t_T \rightarrow t_T} \end{bmatrix} \begin{bmatrix} d_{t_1} \\ d_{t_2} \\ \vdots \\ d_{t_T} \end{bmatrix}, \\ &\sum_{j=1}^T m_{t_i \rightarrow t_j} = 1; m_{t_i \rightarrow t_j} \geq 0 \quad (12) \\ &\begin{bmatrix} d_{t_1}^{\text{output}} \\ d_{t_2}^{\text{output}} \\ \vdots \\ d_{t_T}^{\text{output}} \end{bmatrix} = \begin{bmatrix} \sum_{t_j \in S_{t_1}^{\text{output}}} d_{t_1 \rightarrow t_j} \\ \sum_{t_j \in S_{t_2}^{\text{output}}} d_{t_2 \rightarrow t_j} \\ \vdots \\ \sum_{t_j \in S_{t_T}^{\text{output}}} d_{t_T \rightarrow t_j} \end{bmatrix} \end{aligned}$$

$$= \begin{bmatrix} d_{t_1} (m_{t_1 \rightarrow t_1} + m_{t_1 \rightarrow t_2} + \cdots m_{t_1 \rightarrow t_T}) \\ d_{t_2} (m_{t_2 \rightarrow t_1} + m_{t_2 \rightarrow t_2} + \cdots m_{t_2 \rightarrow t_T}) \\ \vdots \\ d_{t_T} (m_{t_T \rightarrow t_1} + m_{t_T \rightarrow t_2} + \cdots m_{t_T \rightarrow t_T}) \end{bmatrix},$$

$$\sum_{j=1}^T m_{t_i \rightarrow t_j} = 1; m_{t_i \rightarrow t_j} \geq 0 \quad (13)$$

where T is the number of periods. When the price of period t_i is smaller than that of period t_j , the active load in period t_i cannot transfer to period t_j , then the $m_{t_i \rightarrow t_j}$ is 0.

According to (2), after the transferred active load is obtained, the load after DR is calculated by (14):

$$L' = L + d^{\text{input}} - d^{\text{output}}, \quad (14)$$

where L and L' are the load matrices before and after DR, respectively.

III. FEATURES ANALYSIS OF GL PATTERNS

Based on the simulated data, features of GL pattern considering DR in smart grid can be analyzed.

The simulation produced a large number of load data, which are mixed together, making it inconvenient to extract load pattern features. It is necessary to process the simulation data for further analysis. Clustering is a common and effective processing method, which can divide load data into several typical categories, thus forming typical load patterns. Then, by analyzing the peak-valley distribution, load fluctuation and other indexes of typical load patterns, the feature information of GL can be obtained.

The commonly used load pattern clustering methods include hierarchical clustering [29], K-means clustering [30] and fuzzy C-means clustering [31]. K-means clustering is a widely used clustering method, which classifies samples by finding the shortest distance between the samples and the clustering center. However, it needs to determine the number of clusters in advance, which limits the flexibility of clustering. Moreover, the initial value of K-means clustering is randomly selected, which leads to the instability of clustering results. Fuzzy C-means clustering is mainly aimed at the fuzzy data set. Its computation is complex, and the performance of the algorithm depends on the initial clustering center. Hierarchical clustering can cluster the samples by merging the nearest samples to form tree-like clustering results, and then cut them at the specific level of the clustering tree to get the corresponding clustering results. This method is simple and convenient, and usually has better performance in extracting the outliers as much as possible [32].

Therefore, after comparing the results of load pattern clustering of the above methods, this paper chooses the hierarchical clustering method with the best clustering effect.

The general process of extracting typical load patterns by clustering is shown in Fig.3.

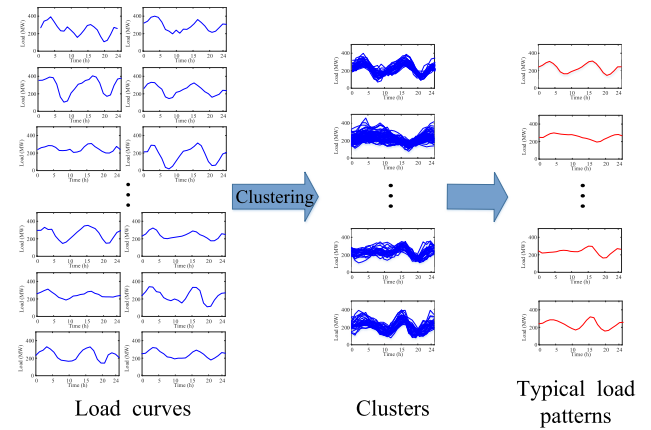


FIGURE 3. Extracting typical load patterns by clustering.

In Fig.3, clustering divides a large number of load curves into several clusters with different characteristics, and then the typical load patterns can be extracted from the clusters.

A. EXTRACTING TYPICAL LOAD PATTERNS BY HIERARCHICAL CLUSTERING METHOD

Hierarchical clustering works in a gradually amalgamated way [33]. The basic steps of hierarchical clustering for load pattern clustering are as follows:

- Set every load pattern as an individual category and calculate the similarity between each any two categories.
- Merge the two categories with maximum similarity. As a result, the number of categories is one less than before.
- Calculating the similarity between each any two categories based on new category clusters.
- Repeat b) and c) until the generated category clusters meet the needs.

The key to realize hierarchical clustering is to calculate the similarity of two categories. Many common methods can serve the calculation, such as the longest distance, shortest distance, average distance, Euclidean distance, and Manhattan distance, etc. The calculation of similarity has a great impact on the clustering effect. After many tests, the longest distances are chosen in this paper, which is shown as below:

For example, two categories are set as $\mathcal{Q}_1 = \{d_{1,1}, \dots, d_{1,e}\}$ and $\mathcal{Q}_2 = \{d_{2,1}, \dots, d_{2,f}\}$, corresponding to load patterns e and f respectively. The similarity of two categories is calculated by the below equation:

$$\begin{cases} C_{ij} = \text{COV}(d_{1,i}, d_{2,j}) \\ C_{\mathcal{Q}_1 - \mathcal{Q}_2} = \min_{1 \leq i \leq e, 1 \leq j \leq f} C_{ij}, \end{cases} \quad (15)$$

where $\text{COV}(\cdot, \cdot)$ is the correlation coefficient between two vectors with the same dimension, C_{ij} represents the correlation coefficient of $d_{1,i}$ and $d_{2,j}$, and $C_{\mathcal{Q}_1 - \mathcal{Q}_2}$ is the longest distance between $\mathcal{Q}_1$ and $\mathcal{Q}_2$, which is the minimum similarity in this paper.

After clustering the load patterns to get the preset number of clusters, the mean value method is used to extract typical

patterns for each cluster. Then, indexes are used to describe the features of typical load patterns quantitatively.

B. THE INDEXES TO DESCRIBE GL PATTERN FEATURE

As mentioned in Section I, maximum load, minimum load, peak and valley difference, load rate, load deviation, and climbing load are the commonly indexes used for load pattern analysis. Based on the above indexes, this paper proposes some new indexes to reflect the evolution trend of load patterns in DR.

Some of these indexes can be expressed as follows.

a) PMALD: proportion of maximum load decrease

$$\text{PMALD} = \frac{\text{MMAL}' - \text{MMAL}''}{\text{MMAL}} \times 100\%, \quad (16)$$

where MMAL' and MMAL'' are the mean daily maximum load before and after DR, respectively.

The PMALD reflects the peak-cutting degree of load in DR.

b) PMILI: proportion of minimum load increase

$$\text{PMILI} = \frac{\text{MMIL}'' - \text{MMIL}'}{\text{MMIL}'} \times 100\%, \quad (17)$$

where MMIL' and MMIL'' are the mean daily minimum load before and after DR, respectively.

The PMILI reflects the valley-filling degree of load in DR.

c) PPVDLD: proportion of peak-valley difference of load decrease

$$\text{PPVDLD} = \frac{u}{g} \times 100\%, \quad (18)$$

where g is the total number of days, and u is the number of days when the daily peak-valley difference of load after DR is less than that before DR.

The PPVDLD quantitatively describes the proportion of time in which peak-valley difference of load is reduced and load pattern is improved in DR.

d) PLPVDL: proportion of large peak-valley difference of load

$$\text{PLPVDL} = \frac{v}{g} \times 100\%, \quad (19)$$

where g is the total number of days, and v is the number of days when the daily peak-valley difference of load is larger than a threshold of large peak-valley difference of load. The threshold is about 30% of the maximum daily load. In this paper, the threshold is 6000 MW.

The large peak-valley difference of load means huge peak shaving pressure in power system. The smaller the PLPVDL, the better the economy and security of the system, and the better the load evolution trend.

e) PLHCL: proportion of large hourly climbing load

$$\text{PLHCL} = \frac{w}{n} \times 100\%, \quad (20)$$

where n is the total number of hours, and w is the number of hours when the hourly climbing load is larger than a threshold

of large hourly climbing load. The threshold is about 4% of the maximum daily load. In this paper, the threshold is 700 MW.

The large hourly climbing load means that the local variation of the load form is large, which requires the power system to have a large climbing capacity and enough spinning reserve. The smaller the PLHCL, the better the economy and security of the system, and the better the load evolution trend.

IV. CASE STUDY

A. CASE DESCRIPTION

The case data are published by ISO New England, which contains hourly day-ahead pricing (DAP), RTP, weather data and system load demand in ISO New England Control Area (ISO NE CA) [34]. In this paper, the data of ISO NE CA from January 1, 2017 to December 31, 2017 are chosen for simulation.

The RTP is released three hours in advance, and the DAP is released at 15:00 p.m. one day ahead of schedule.

There is a hypothesis that active load accounts for a certain proportion of system load. The active load consists of three categories, which respectively has a short, medium, and long transfer time interval. The capacity of each category of active load accounts for 1/3 of the total active load. To simulate electricity market, the active load with short transfer time interval (short-interval) responds to RTP, and active load with medium and long transfer time interval (medium-interval & long-interval) responds to DAP [26], [27].

The influence degree of DR on load pattern is closely related to the category and proportion of active load participating in response. Different categories of active loads have different response characteristics, so they have different elasticity coefficients in response. The larger the proportion of the active load participating in the DR to the total load of the system, the greater the influence of the DR on the load pattern.

Therefore, we first analyze the key factors in the DR, such as the category and proportion of active loads, so as to set these factors reasonably. Then, the simulation settings and result are explained. Finally, the GL pattern features are qualitatively and quantitatively analyzed by clustering and index respectively.

The case study contains four parts:

- Analysis of key factors in DR, shown in Section IV-B;
- Simulation settings and result, shown in Section IV-C;
- Clustering analysis of load pattern considering DR, shown in Section IV-D;
- Index analysis in typical scenes, shown in Section IV-E.

B. ANALYSIS OF KEY FACTORS IN DR

Load pattern considering DR is highly affected by the responsive behaviors and proportion of active load. Thus, the impact of these two key factors on load pattern is specially analyzed below. Key parameters of typical scenes are determined at the same time.

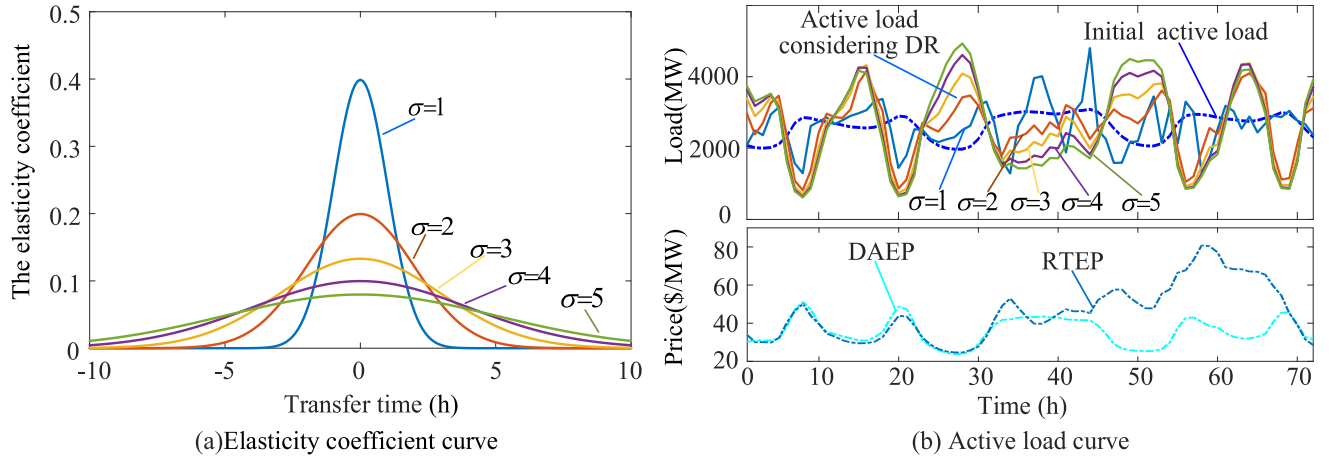


FIGURE 4. Elasticity coefficient curves and the responsive behavior of corresponding active load.

1) THE IMPACT OF DIFFERENT CATEGORIES OF ACTIVE LOAD

Response behavior of active load is closely related to the category of active load. The larger the transfer interval of active load is, the more average the elastic coefficient distribution is, and the larger the corresponding parameters σ are. Transfer features of different categories of active load are described by the elasticity coefficient curves with proper parameter σ . Considering the transfer features of different categories of active load, the range of parameter σ is $1 \leq \sigma \leq 5$ in this paper. Elasticity coefficient curves with $\sigma = 1, 2, 3, 4, 5$ and the response behavior of corresponding active load are shown in Fig.4.

In Fig.4 (a), each curve represents the response feature of a category of active load. The larger elasticity coefficient means the greater amount of active load transferred to corresponding transfer time under the same price difference condition. When $\sigma = 1$, elasticity coefficients of $\{-3, 3\}$ hours are much larger than that of other transfer time in the curve. It implies that the transferrable interval of corresponding active load is approximately in the range of $\{-3, 3\}$ hours, which conforms to the case of short-interval active load responding to RTP [27]. Thus, the active load of short-interval is characterized by $\sigma = 1$. In the same way, active loads of medium and long-interval are characterized by $\sigma = 3$ and $\sigma = 5$.

2) THE IMPACT OF DIFFERENT PROPORTIONS OF ACTIVE LOAD

After the determination of parameter σ for active load, the influence of active load with different proportions can be furtherly analyzed. Set the proportions of active load as 5%, 10%, 15%, and 20%, and load curves considering DR of seven days are shown in Fig.5.

Obviously, after active load responds to electricity price change, the original peak of load is reduced, and the valley is filled, so that the time of peak zone has changed greatly. It indicates that active load is guided from the peak zone to the valley zone, which brings great benefits to the formulation

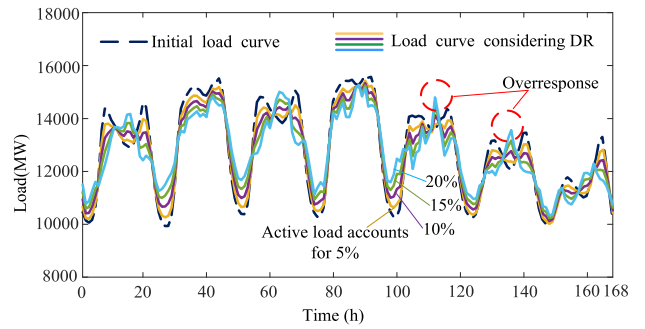


FIGURE 5. Load curves with different proportions of active load.

of safe and economical operation, scheduling, and planning. However, the short-time fluctuation of load is obviously stronger than before so that a higher ability of fast adjustment is required to distribution network.

Comparing the results of active load with different proportions, the greater proportion of active load, it can be seen that the more obvious pattern features of load considering DR. When the proportion of active load is 20%, there will be a phenomenon of overresponse, that is, massive active load is concentrated in some low-price regions which causes the appearance of new peak, as shown in the red circles. It brings a disadvantage to the operation of smart grid and can be eliminated by regulating the price. To better reflect the pattern features of load considering DR, the proportion of active load in the typical scene is set to 15%.

C. SIMULATION SETTINGS AND RESULT

From the analysis above in Section IV, the settings of the simulation are as follows:

a) The proportion of active load to system load is 15%. The active load consists of three categories, which respectively has a short, medium, and long transfer time interval. The capacity of each category of active load accounts for 1/3 of the total active load. Their elasticity coefficients are simulated by normal distribution with $\sigma = 1, \sigma = 3$, and $\sigma = 5$, respectively.

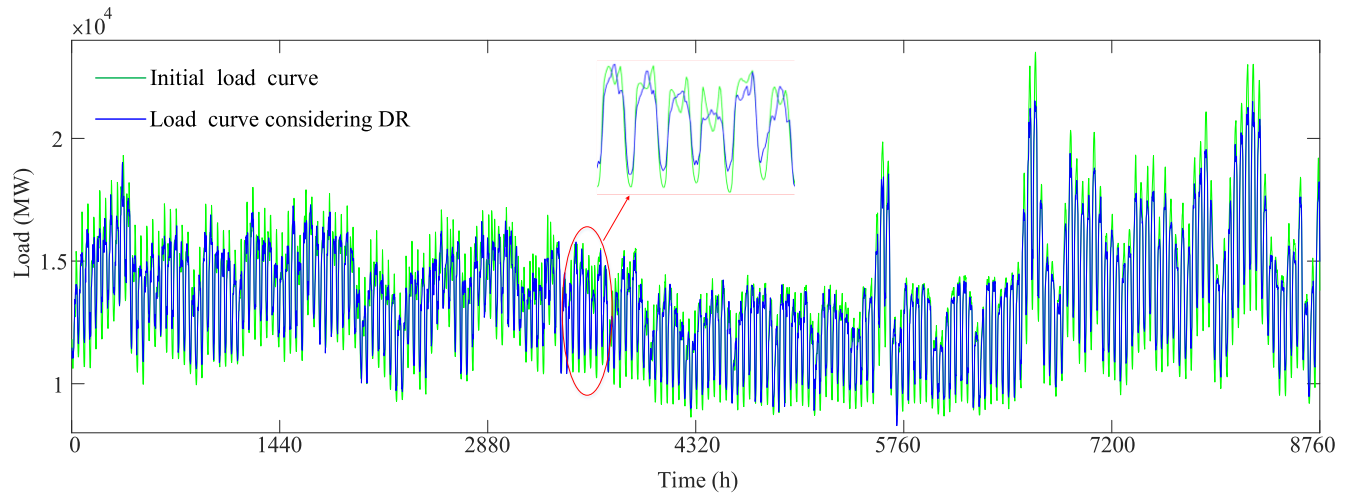


FIGURE 6. Load curves before and after response.

b) To simulate electricity market, the active load with short transfer time interval responds to RTP, which means that the load can be transferred within three hours before and after the original time period. Active load with medium and long transfer time interval responds to DAP, which means that the load adjustment plan can be made one day in advance and the load can be transferred throughout the day on the original date.

After these settings, the load data considering DR can be obtained through (8)-(14).

Load curves before and after response are shown in Fig.6.

As shown in Fig.6, the load curve after response changes significantly. The peak load decreases, the valley load increases, and the peak-valley difference is improved. Next, the GL pattern features are qualitatively and quantitatively analyzed by clustering and indexes respectively.

D. ANALYSIS OF LOAD PATTERN FEATURES

1) CLUSTERING ANALYSIS OF ACTIVE LOAD PATTERN CONSIDERING DR

The change of active load is the source of load change. Patterns of active load considering DR contain both similarities and differences. Clustering analysis is a significant manner to summarize and mine the pattern features for active load. On the basis of clustering effect, active load considering DR is classified into five categories according to the shape, shown in Table 1.

Clustering result shows that the applied clustering method holds a better effect in the classification of active load considering DR. After active load responds to RTP, its pattern becomes more diversified and complicated. Many typical patterns with different features appear in clustering result. Summarily, the peak of active load considering DR has the occurrence time in {3, 4}, {15, 16}, and {22, 23} hours. The valley is likely to be in {7, 9}, {11, 12}, and {17, 21} hours. Concretely, various categories of active load pattern considering DR have different effects on the load pattern. Thus,

GL pattern considering DR will be clustered and analyzed below.

2) CLUSTERING ANALYSIS OF GL PATTERN CONSIDERING DR

According to clustering results, five typical patterns of GL considering DR are obtained, shown in Table 2.

Compared with traditional load, the pattern of GL considering DR changes dramatically. Overall, the obvious two-peak shape of general traditional load pattern is disappeared in GL pattern considering DR. The shape of GL pattern considering DR becomes flatter than before. So, the distance of the load in day and late night is smaller as well in GL pattern considering DR. It is highly beneficial to improve the absorptive capacity of wind power and the operation economy for smart grid. However, considering DR becomes diversified from a relatively single pattern, meaning the uncertainty is increased. It will bring some negative effects on the formulation of the operation plan.

To concretely quantify the feature and evolutionary trend of GL pattern in DR, feature indexes will be used to analyze the typical scene next.

E. QUANTITATIVE ANALYSIS ON GL FEATURE BY INDEXES

As mentioned above, maximum load, minimum load, peak and valley difference, load rate, load deviation, and climbing load are the focus. The GL considering DR and without DR of one year are statistically analyzed by numerical indexes in Table 3.

The results in Table 3 show that indexes such as maximum load, minimum load, peak and valley difference, load rate, load deviation, and climbing load of GL considering DR are optimized.

As shown in Table 3, mean daily maximum load falls from 15964 MW to 15240 MW, with a decline rate of 4.54%. Mean daily minimum load increases from 10493 MW to 11121 MW, with an increase rate of 5.98%. This shows that DR reduces the maximum daily load by 4.54%, increases the

TABLE 1. Typical patterns and features of active load considering DR.

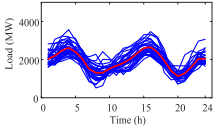
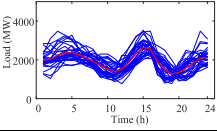
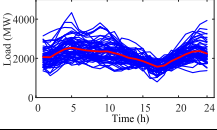
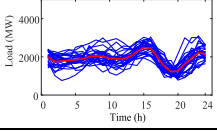
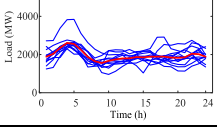
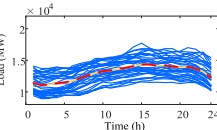
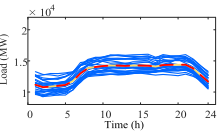
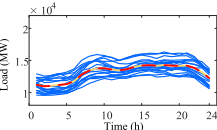
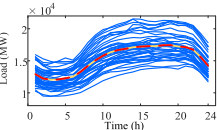
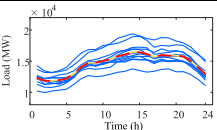
Typical patterns	The ratio account for the total	Pattern features
	32.1%	The shape of active load considering DR contains two relatively sharp peaks and valleys. The maximums of peaks are respectively in {3, 4} and {16, 17} hours, and the minimums of valleys are respectively in {7, 9} and {20, 21} hours.
	19.8%	It is similar to the previous overall. But the first peak is flatter and the minimum of the first valley shifts to {11, 12} hours.
	30.6%	The overall shape is relatively flat, and there are two little peaks with the maximum in {3, 4} and {22, 23} hours and a valley with the minimum in {14, 16} hours.
	11.8%	The first half is smooth, and the latter half contains a peak and a valley. The maximum of the peak and the minimum of the valley is respectively in {15, 16} and {19, 20} hours.
	5.7%	There is a peak zone in {1, 9} hours with the maximum in {3, 4} hours. The rest is relatively flat.

TABLE 2. Typical patterns and features of generalized load considering DR.

Typical patterns	The ratio account for the total	Pattern features
	24.9%	The load of the whole day has little difference, and gradually rises from night to day.
	41.0%	The load consists of two smooth stages in day time and night time respectively, and the numerical difference between the two stages is relatively small. Additionally, the load in the climbing period changes rapidly.
	9.0%	This type of load is generally similar to the previous one, but there is a small peak at {7, 9} hours.
	19.4%	There is a valley at night and a flat in the daytime. The gap between day load and night load is relatively large.
	5.7%	The load curve is unimodal, and the peak zone is relatively gentle, with a maximum at {13, 15} hours.

minimum daily load by 5.98% on average. Thus, DR plays a role in reducing peak load and filling valley load to a certain extent, so as to optimize resource allocation and meet the anticipated demand of power market.

In addition, mean daily load rate increases from 0.86 to 0.89, with an increase rate of 3.5%. Mean daily load deviation reduces from 1625 MW to 1257 MW, with a decline rate of 22.64%. Mean daily peak-valley difference of load reduces

TABLE 3. The indexes of load feature without DR and considering DR.

Indexes	Load without DR	Load considering DR	Indexes	load without DR	Load considering DR
mean load (MW)	13573	13573	mean daily peak-valley difference of load (MW)	5471	4010
mean daily maximum load (MW)	15964	15240	maximum daily peak-valley difference of load (MW)	11317	7731
PMALD (%)	-	4.54%	minimum daily peak-valley difference of load (MW)	3080	1847
mean daily minimum load(MW)	10493	11121	PPVDLD (%)	-	99.53%
PMILI (%)	-	5.98%	PLPVDL (%)	25.94%	9.91%
mean daily load rate	0.86	0.89	mean hourly climbing load (MW)	491	383
mean minimum daily load rate	0.66	0.73	maximum hourly climbing load (MW)	2348	2160
mean daily load deviation (MW)	1625	1257	PLHCL (%)	28.54%	17.33%

from 5471 MW to 4010 MW, with a decline rate of 26.70%. This shows that DR increases the daily load rate by 3.5%, reduces the daily load deviation by 22.64%, and reduces the daily load peak-valley difference by 26.7% on average. Therefore, DR reduces load fluctuation, makes the load curve smoother and improves load quality.

Moreover, PPVDLD is 99.53%, and PLPVDL declined from 25.94% to 9.91%. This shows that DR not only reduces the peak and valley difference almost every day, but also dramatically reduces the days of large peak and valley difference. Therefore, the load pattern has been comprehensively improved on the time scale, and the economy and security of the system have also been comprehensively improved.

In terms of load change speed, mean hourly climbing load declines from 491 MW to 383 MW, with a decline rate of 22.00%. Maximum hourly climbing load reduces from 2348 MW to 2160 MW, with a decline rate of 8%. Additionally, PLHCL declines from 28.54% to 17.33%. This shows that DR not only reduces the local variation of load in general, but also greatly reduces the time of large climbing load. Therefore, the load pattern is locally flatter, the reserve capacity of the system can be greatly reduced, and the economy and security are improved.

V. CONCLUSION

In this paper, a calculation method based on elasticity coefficient is proposed for the impact of RTP on GL. By setting different parameters σ of elasticity coefficient and load composition, the response behavior of active load to RTP can be simulated in various situations. Based on the simulation data, the typical load patterns are extracted by hierarchical clustering method and described by novel indexes.

The simulation results show that the DR plays a certain role in peak shaving and valley filling. The difference between day load and night load is smaller, and the GL curve considering DR is flatter overall and locally. The indexes of GL have been improved, and the same to load quality. It can be concluded that the load pattern has a better development direction during

DR, meets the expected requirements, and can effectively improve the economy and security of smart grid operation.

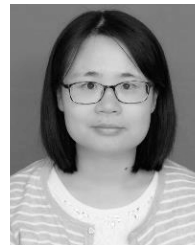
At the same time, we can also see that the GL pattern after DR is more diverse, load peaks and valleys are distributed over a wider period of time, which shows that the GL pattern after DR has greater uncertainty, bringing challenges to smart grid scheduling operation.

The influence of DR behavior of active load response to RTP on GL pattern in smart grid is discussed in this paper. This paper ignores the influence of load change on RTP caused by DR, which needs to be considered in the future.

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