Peak-Valley Time Period Partition of TOU Tariff Based on Fuzzy Equivalence Relation Clustering Algorithm

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Abstract—**Time-of-Use (TOU) tariff is one of effective price-based demand response strategy, which can guide consumers to relieve the load peak pressure of power system and tap demand-side response potential. However, without considering the impact of pricing, improper peak-valley time period schemes may lead to a decrease in power supply reliability and an increase in operation costs of the power system. Therefore, this paper presents a peak-valley time period partition scheme of TOU tariff based on fuzzy equivalence relation clustering (FERC) algorithm. First, the solving steps and corresponding mathematical models of FERC algorithm are given, such as the characteristic indicator fuzzy set determined by the membership function and the fuzzy equivalence matrix. Secondly, the peak-valley characteristics of the load are first analyzed, and then a peak-valley period partition clustering based on FERC algorithm is proposed by combining semi-trapezoid membership functions and partition criterion constraints. Finally, the effectiveness of the proposed method is verified under a typical daily load in Hunan province. The results show that the proposed method can not only accurately reflect the peak valley characteristics of the load curve, but also effectively improve the calculation speed and convergence of peak-valley time period partition.**

Index Terms—**Fuzzy equivalence relation, time-of-use, peak-valley period partition, membership function**

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I. INTRODUCTION

TIME-of-use (TOU) tariff is a kind of electricity demand price mechanism widely used by the power utilities around the world [1-3]. TOU tariff has been studied since 1960s, and has been widely used in western developed countries since 1970s. However, the research and application of TOU tariff in China begun in the 1980s. In TOU tariff, the power utility generally divides one day into two time periods (peak and off-peak) or three time periods (peak, flat and valley) with corresponding different electricity prices, and the price for the peak time period is much higher than that of off-peak period or valley period. Therefore, TOU tariff can incentivize electric consumers to reduce electric load demand during peak periods and increase electric load consumption demand during valley periods, effectively reducing user electricity costs and improving peak load reliability of the power system [4, 5].

Due to the price elasticity deviation between time periods, the implementation of TOU price program can change users' electricity consumptions and electricity expenses [6]. In TOU tariff mechanism, there are two distinct aspects: one is the time period partition of peak and valley loads, and the other is the pricing design of peak and valley load periods. In contrast, the TOU pricing design using peak-load pricing theory and demand response strategy has attracted more attention from researchers around the world [7-9]. However, the time partition of peak and valley periods is not only the first priority task in designing peak-valley pricing of TOU tariff, but also the main basis for TOU tariff program, because its reasonable division of time periods directly affects the final implementation effect of peak and valley electricity prices in TOU tariff [10]. Thus it can be seen, how to scientifically divide the peak and valley time periods is a primary issue that needs to be urgently solved in the design and application of TOU tariff.

The research on time division models and solutions for TOU tariff has significant theoretical significance and practical application needs for solving problems such as power balance and large peak-valley differences [11-15]. Literature [16] explores peak-valley time division of TOU tariff from three main aspects: membership function, generation cost, and principal factor analysis, but does not give corresponding comparative analysis of their respective advantages and application scenarios. Similarly, literature [17] summarizes the peak-valley time period partition methods based on membership function, electricity generation cost and user demand response respectively, but does not provide corresponding mathematical models and necessary solutions. In contrast, the membership function method is more suitable for time period clustering because it can use fuzzy mathematics theory to analyze and judge the possibility of load data belonging to peak or valley time periods at each time point, and divide the load curve into different time periods. In summary, time period clustering based on fuzzy membership functions has relatively good advantages in terms of scientificity and operability. Literature [18] proposes a peak-valley time period division method based on semi-trapezoidal membership functions, which gives time division principles such as the length of each period of peak-flat-valley not less than 2 hours and the total length of each period not less than 6 hours. However, this method of averaging the length of peak-flat-valley time periods is too idealistic and difficult to match the variable characteristics of actual electric loads. Literature [19] presents a time period partition method for TOU tariff with high-penetration renewable energy, and uses fuzzy c-means (FCM) clustering algorithm based on membership functions to solve it. Reference [20] provides a TOU time period division method considering fuzzy membership, user response behavior and FCM clustering algorithm, but does not analyze the correlation between different factors, thus unable to obtain reasonable solutions for TOU peak-valley time period partition.

In general, the time period partition of TOU tariff must accurately reflect peak-valley characteristics of the actual load curve. Thus, it is not a direct way to formulate TOU peak-valley time period partition in terms of power generation cost, demand response and other influencing factors, because these factors are mapped or implied by peak-valley characteristic of the load curve. Furthermore, the necessary correlation between these factors and the peak-valley periods has not been discussed. However, the fuzzy clustering method based on the characteristics of the load curve can effectively utilize peak-valley prices to adjust user electricity demands. Therefore, this paper firstly puts forward theoretical models of fuzzy equivalence relation clustering algorithm, improved membership functions and fuzzy equivalence matrix, and then presents the corresponding method of peak-valley time period partition for TOU tariff.

The main works of this paper is summarized as follows: Section II presents theoretical models of the fuzzy equivalence relation clustering algorithm. Section III presents the daily load peak-valley characteristic analysis and FERC-based peak-valley period partition clustering procedure, consisting of the peak-valley semi-trapezoid membership functions and the partition criterion constraints. Section IV analyzes the performance of the proposed method that is verified in a real power system in Hunan province, China. The conclusions are presented in Section V.

II. Fuzzy Equivalence Relation Clustering Algorithm

A. Fuzzy Clustering Algorithm

Cluster analysis is a new statistical analysis method that studies the classification of samples or indicators based on similarity, and it is also an important algorithm in the fields of data mining, pattern recognition, etc. For different applications, various fuzzy clustering algorithms have been proposed, such as fuzzy similarity clustering, fuzzy equivalence relation clustering (FERC), fuzzy C-means clustering (FCM), and maximum support tree clustering based on fuzzy graph theory [21]. Considering the peak-valley characteristics and their boundary fuzziness, the partition fuzzy clustering method has been widely applied to pattern recognition problems such as peak-valley period partition of TOU tariff. Currently, FERC and FCM are two commonly used partition fuzzy clustering methods.

As we all know, FERC uses membership as the starting point for clustering and fuzzy equivalence matrix as the heuristic rule to achieve classification objectives by horizontal truncation of a given cut set [22-24]. FERC algorithm has obvious advantages such as intuitive principle, simple process, and no need of initial setting. However, it also has problems of slow clustering speed and inaccurate clustering results when dealing with a large number of samples [25].

FCM clustering algorithm adopts the principle of minimizing sum of squared weighted errors within a class, and achieve the optimum classification of sample data by optimizing the objective function [21]. FCM clustering has the advantages of simple calculation, large computable scale, and fast solving speed, but its clustering result is unstable due to the influence of the initial clustering center on its clustering quality and convergence speed.

In summary, FERC is selected in this paper to solve the problem of TOU peak-valley period partition with relatively less numbers of samples, as it only needs to consider the relationship between sample data, does not need to preset any number of clusters like FCM, and also achieves fast clustering speed and more stable clustering results [11, 25].

B. Fuzzy Equivalence Relation Clustering Algorithm

Fuzzy equivalence relation clustering (FERC) algorithm is formulated based on the fuzzy equivalence relation theorem: Suppose R is a fuzzy similar matrix, and then uses the square method to obtain its transitive closure that is the fuzzy equivalent matrix. It can be seen that FERC algorithm constructs the fuzzy equivalence matrix from the fuzzy similarity matrix by solving the transitive closure as to achieve the fuzzy partition [26].

The detailed steps of FERC algorithm are described as below.

Step 1. Determine sample characteristic indicators and establish initial data matrix. For the purpose of clustering, it is necessary to scientifically select representative characteristics or attributes with practical significance as sample characteristic indicators.

Definition: Set the universe $U=\{x_1,x_2,\cdots x_i,\cdots,x_n\}$ as the sample element set, and each element x_i is represented by m indicators as indicator characteristics: $x_i = \{x_{1i},x_{2i},\cdots x_{ci},\cdots,x_{mi}\}$, so the set A_c is defined as a fuzzy set determined by the membership $\mu_c(x_i)\in[0,1]$, which is used to indicate the degree to which x_i belongs to A_c [21].

Therefore, the initial data matrix X for the membership values of all sample elements is obtained by Eq. (2).

$$A_c = \{(x_i, \mu_c(x_i)) \mid \mu_c(x_i) \in [0,1], x_i \in U\} \quad (1)$$

$$X = (\mu_c(x_i))_{m\times n} \quad (2)$$

Where, i denotes the number of sample elements x and $i = 1, 2, \cdots, n$, c denotes the number of the fuzzy set A_c and $c = 1, 2, \cdots, m$.

Step 2. Standardize sample characteristic indicator matrix. In the study of most practical problems, different data usually have different dimensions, so it is necessary to standardize the sample characteristic indicator matrix as to eliminate dimensional differences and obtain the same caliber. Usually, this can be obtained by translation standard deviation transformation [21, 23].

$$\mu_c'(x_i) = (\mu_c(x_i) - \bar{\mu}_c)/S_c \quad (3)$$

$$\bar{\mu}_c = \frac{1}{n}\sum_{i=1}^{n}\mu_c(x_i) \quad (4)$$

$$S_c = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\mu_c(x_i) - \bar{\mu}_c)^2} \quad (5)$$

Where, $\mu_c'(x_i)$ denotes new data after standardization of initial data $\mu_c(x_i)$, $\bar{\mu}_c$ denotes mean value of membership values $\mu_c(x_i)$, S_c denotes the standard deviation.

Step 3. Establish a fuzzy similarity matrix. According to the standardized data set, the fuzzy similarity relation matrix $R_{i,j}$ can be obtained by the followings [21, 22].

$$r_{i,j} = \alpha\sum_{c=1}^{m}(\mu_c'(x_i) - \mu_c'(x_j)) \quad (6)$$

$$R_{i,j} = \begin{bmatrix} r_{1,1} & \cdots & r_{1,m} \\ \vdots & \ddots & \vdots \\ r_{n,1} & \cdots & r_{n,m} \end{bmatrix} \quad (7)$$

Where, $r_{i,j}$ denotes the similarity between the i_{th} data and the j_{th} data with values ranging from [0,1], α denotes a coefficient, $\mu_c'(x_i)$ and $\mu_c'(x_j)$ denotes the standardized data of $\mu_c(x_i)$ and $\mu_c(x_j)$, respectively.

Step 4. Build transitive closure to construct fuzzy equivalent matrix. The transitive closure is the minimum transitive matrix containing fuzzy similarity relation $R_{i,j}$. Generally, the square method is used to build the transitive closure $\hat{R}_{i,j}$.

$$\hat{R}_{i,j} = (\gamma_{i,j})_{n\times n} \quad (8)$$

Step 5. Select a proper threshold λ to carry out dynamic clustering according to the λ -cut relationship. $\hat{R}_{i,j}(\lambda)$ is a λ intercept matrix of the fuzzy equivalent matrix $\hat{R}_{i,j}$ to obtain fuzzy equivalent classification at the level λ .

$$\hat{R}_{i,j}(\lambda) = (\gamma_{i,j}(\lambda))_{n\times n} \quad (9)$$

$$\gamma_{i,j}(\lambda) = \begin{cases} 1, & \gamma_{i,j} \ge \lambda \\ 0, & \gamma_{i,j} < \lambda \end{cases} \quad (10)$$

In fuzzy equivalence relationship clustering analysis, the selection of threshold λ is very important. Different thresholds will change the corresponding classification results. If threshold λ is smaller, the clustering is rough and the number of clusters is less. On the contrary, if threshold λ is larger, the clustering is complete and the number of clusters is more. Therefore, threshold λ could be preset based on specific regulations or experiences to achieve satisfactory classification results.

III. PEAK-VALLEY PERIOD PARTITION CLUSTERING

A. Peak-Valley Characteristics Analysis

The aggravation of load fluctuations on a time scale is not conducive to the economic operation of the power system, and the peak-valley characteristics are typical evaluation indicators commonly used to analyze the characteristics of power load curves. Along with dynamic adjustment of various industrial structures, large-scale renewable energy grid-connected generation, and dynamic interactive response of demand-side users, the complex peak-valley characteristics and their economy are becoming highlighted issues in the operation of the power system.

The practices at home and abroad show that TOU tariff is an effective peak-shaving demand response strategy and is widely used around the world, because it can better reflect power supply-demand changes and operating cost characteristics of the power system. In TOU tariff, power utility usually divides a whole day into peak and valley periods, and sets higher price for the peak period and lower price for the valley period. Therefore, TOU tariff can guide consumers to shift flexible loads from the peak period to the valley period to reduce economic costs.

The basic principle of TOU peak-valley period partition is to use the peak-valley feature categories of a typical daily power load as a fuzzy set, and then use an appropriate fuzzy clustering algorithm to solve the peak-valley period division. Therefore, fuzzy semi-trapezoidal membership functions are used to determine the probability that load data at each time point is in peak and valley periods. Load data during peak-hours and its adjacent periods is more likely to appear during peak periods, and less likely to be during valley periods. Similarly, load data during valley hours and its adjacent periods is more likely to appear during valley periods, and less likely to be during peak periods [17, 27-29].

In order to facilitate the division of peak-valley time periods, a sample set of daily power load data can be obtained from Eq. (10) and Eq. (11).

$$T = \{t_1, t_2, \cdots, t_n\} \quad (11)$$

$$P = \{P_1, P_2, \cdots, P_n\} \quad (12)$$

Where, T is the set of each time point data t_i , P is the set of each load data P_t at time t.

Combined the peak-valley characteristics of the load curve shown in Fig.1, a larger semi-trapezoid membership function is used to determine the probability of load samples being in the peak period, and a smaller semi-trapezoid membership function is used to determine the probability of load samples being in the valley period.

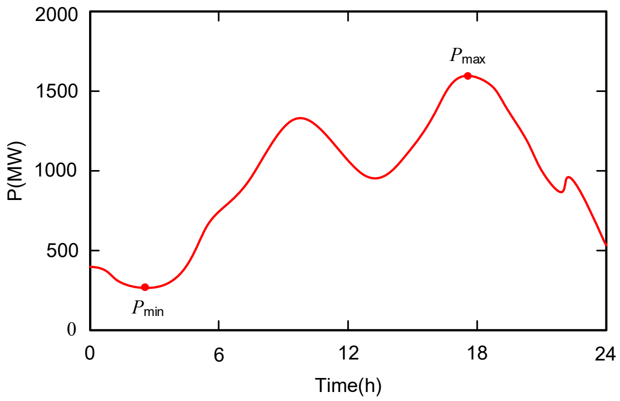

Fig. 1. Diagram of a typical daily load profile.

$$\mu_p(P_t)=\begin{cases}0, & P<P_{\min}\\ \dfrac{P_{\max}-P_t}{P_{\max}-P_{\min}}, & P_{\min}\le P\le P_{\max}\\ 1, & P>P_{\max}\end{cases} \tag{13}$$

$$\mu_v(P_t)=\begin{cases}0, & P>P_{\max}\\ \dfrac{P_t-P_{\min}}{P_{\max}-P_{\min}}, & P_{\min}\le P\le P_{\max}\\ 1, & P<P_{\min}\end{cases} \tag{14}$$

$$P_{\max}=\max P_t \tag{15}$$

$$P_{\min}=\min P_t \tag{16}$$

Where, $\mu_p(P_t)$ and $\mu_v(P_t)$ are the fuzzy membership functions of load P_t during peak and valley periods, respectively; $P_{\max}$ and $P_{\min}$ are the maximum peak load and the minimum valley load, respectively.

From the membership functions of the peak and valley periods mentioned above, it can be seen that judging which period of peak or valley period the load sample at a certain point in time belongs to only depends on the maximum load value and the minimum load value, as well as the ratio relationship between the value of load sample at that time point and the different between the maximum and minimum loads, and is not related to the load value at each time point.

B. Peak-valley Period Partition Clustering

The peak-valley period partition of TOU tariff is a typical fuzzy clustering problem, so it can be achieved through the previously proposed peak and valley membership functions and FERC algorithm. The flowchart of peak-valley period partition based on FERC algorithm is shown in Fig.2, and the detailed descriptions are listed as below.

Step 1. Collect load data and determine a fuzzy set of peak-valley periods according to Eq. (1), and then establish a fuzzy membership value matrix based on the fuzzy membership functions of peak-valley load characteristics given in Eq. (13) and Eq. (14).

Step 2. Standardize initial data of peak-valley membership values to eliminate the impact of different dimensions according to Eq.(3) to Eq.(5).

Step 3. Establish a similarity matrix by Eq.(7), and use the square method by means of Eq.(8) to obtain the transitive closure, that is, the fuzzy equivalence matrix.

Step 4. Select an appropriate threshold λ according to Eq.

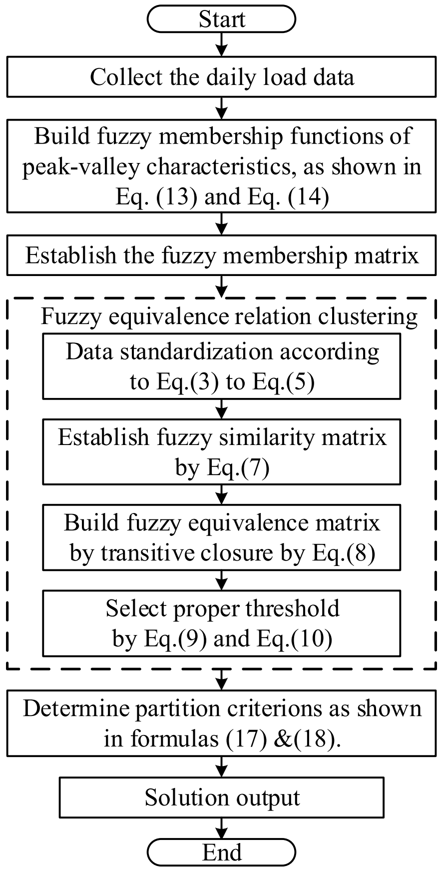

Fig. 2. Peak-valley period partition clustering flowchart based on FERC

(9) and Eq. (10) to intercept all elements of the obtained fuzzy equivalence matrix.

Step 5. Determine the necessary partition criterions, as shown in Formula (17) and Formula (18), to obtain a feasible satisfied division result, because the peak-valley period partition of TOU tariff is not just a simple data clustering analysis, but also needs to consider some specific engineering physics principles such as the minimum start-stop time constraints and the peak-valley balance requirements.

$$T_{g,\tau}\ge\varepsilon \tag{17}$$

$$\left|T_p-T_v\right|\le\omega \tag{18}$$

Where, $T_{g,\tau}$ is the duration length of a certain continuous period τ in a kind of time period g like the peak, flat or valley periods, T_p and T_v are the total duration length of peak and valley periods respectively, ε and ω are the minimum duration length of any continuous peak and valley periods and the difference between the maximum peak and valley periods, respectively.

From formula (17), it can be seen that the length of any continuous period in the peak-flat-valley periods cannot be too short, and must exceed the minimum starting-stopping time lengths of the generator unit and electric load. Formula (18) also indicates that the total time difference between peak and valley periods should not be too large, otherwise it will be difficult to achieve the expected effect of peak-shaving and valley-filling. In addition, in order to quickly obtain the appropriate threshold, it is much better to first select a larger value (such as 0.8) for the clustering analysis, and then make corresponding adjustments until satisfactory results of peak-valley time period partition are achieved.

IV. Results and Analyses

With a power utility in Hunan province as an example, the daily loads in summer reason are selected for peak-valley period partition clustering of TOU tariff. In order to accurately describe the peak-valley characteristics of the load curves and verify the effectiveness of the proposed method in this paper, we select two typical daily load data on July-15 and August-15, 2021, and collect them at 30-minutes intervals to divide an entire day into 48 time points.

According to the actual operation characteristics and basic peak-valley regulations of the power system, the criteria for peak-valley time period partition are pre-set as below: (i) The minimum duration of any continuous peak or valley period is set to 1 hour, i.e, ε=1 hour. (ii) The maximum difference of peak and valley periods is 4 hours, i.e., ω=4 hours.

Fig. 3 and Fig. 4 show the peak-valley time period partition clustering on July-15 and August-15, respectively. These two results are both obtained by using the previously proposed peak-valley period partition clustering method based on FERC algorithm.

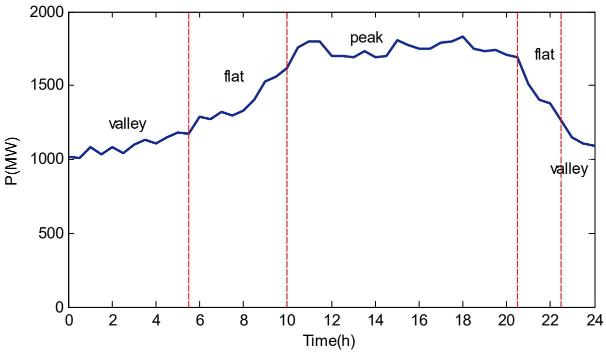

Fig. 3. Peak-valley period partition clustering result in Jul.15.

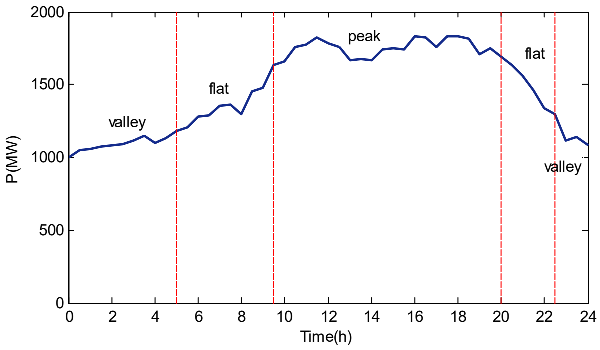

Fig. 4. Peak-valley period partition clustering result in Aug. 15.

Combining Fig. 3 and Fig. 4, it is obvious to know that a day is divided into three typical different periods, such as peak, flat and valley periods. The time period pattern shape is "valley-flat-peak-flat-valley". This result is consistent with the actual scheme of peak-valley period division of TOU pricing in Hunan power utility. In addition, the total length of all peak time periods is much longer (10.5 hours) and all lay in the daytime, compared to the flat and valley time periods.

To investigate in-depth comparison and analysis of these two results, the detailed analyses are shown in Table I for Jul. 15 and in Table II for Aug. 15, respectively. It can be seen that the total time lengths of peak, flat and valley periods are different, but the duration of each corresponding time period on different days is the same: 10.5 hours for peak periods, 6.5 hours for flat period, and 7 hours for valley period.

TABLE I
Peak-Valley Period Clustering Results in Jul. 15

Type	Time periods	Duration(hrs)	Total time length(hrs)
Peak	10:00-20:30	10.5	10.5
Flat	05:30-10:00	4.5	6.5
	20:30-22:30	2	
Valley	00:00-05:30	5.5	7
	22:30-24:00	1.5	

TABLE II
Peak-Valley Period Clustering Results in Aug. 15

Type	Time periods	Duration(hrs)	Total time length(hrs)
Peak	9:30-20:00	10.5	10.5
Flat	05:00-9:30	4.5	7
	20:00-22:30	2.5	
Valley	00:00-05:00	5	6.5
	22:30-24:00	1.5	

However, there are still a bit difference at certain time points in the boundary areas between different time periods through the comparison between Table I and Table II. From Table I, it can be clearly seen that the boundary time points of peak-flat-valley periods in July month are mainly concentrated at the following five time points: 05:30, 10:00, 20:30, 22:30, 24:00. From Table II, the boundary time points of peak-flat-valley periods in August month are mainly at these five time points: 05:00, 9:30, 20:00, 22:30, 24:00.

To clearly investigate the specific differences between two results of peak-valley time period partition clustering on different days, Table III shows a detailed comparative analysis of boundary time points, different time points, and error ratio of peak period. As we all know that the fuzzy membership function method cannot accurately determine the time period attributes at different time period boundaries between peak and flat periods, as well as between flat and valley periods.

TABLE III
Comparison Analysis of Boundary Time Points

Type	15-Jul.	15-Aug.	Remarks
Boundary time points	05:30	05:00	0.5hour shifting between July and August
	10:00	09:30	
	20:30	20:00	
	22:30	22:30	
	24:00	24:00	
Different time point	05:30	05:00	0.5hour shifting between July and August
	10:00	09:30	
	20:30	20:00	
Error ratio	4.76%		For peak period

Therefore, we can draw a conclusion that the random and temporary variations in time-series load are the direct reasons for the differences in the clustering results of peak-valley time period partition between July and August. Regarding clustering accuracy, the error ratio of peak time period clustering is 4.76%, which is allowed because it could not cause a serious impact on the actual economic operation of the power system. The differences between July and August in the duration of the entire flat and valley periods, as well as the start and end time points of each continuous time periods, are all 0.5 hours, which is also allowed. In addition, the duration of the minimum continuous time period is 1.5 hours during the valley periods, which is much friendly for electric power users to adjust their consumption behaviors, as it well meets the minimum start-stop time regulations of most electric equipment.

In conclusion, these results demonstrate convincingly that the proposed peak-valley time period partition method based on fuzzy equivalence relation clustering algorithm is effective and feasible, because it can give full play to TOU pricing in peak shaving, valley filling and cost reduction.

V. COLLUSION

Aiming at the problem of peak-valley time period partition for TOU tariff in the power demand management, this paper first compares and analyzes the performance advantages of various fuzzy clustering algorithms, and then proposes a peak-valley periods partition method based on FERC algorithm. The basic principles and corresponding mathematical models of FERC algorithm are first presented, such as the fuzzy set of characteristic indicators determined by membership functions, the standardized sample characteristic indicator matrix, the fuzzy equivalence matrix and its intercept matrix, etc. Secondly, fuzzy semi-trapezoid membership functions are given to determine the probability of load samples being in the peak and valley periods, and the specific solution is proposed for the peak-valley time period partition of TOU tariff based on FERC algorithm and necessary time partition criterions. Finally, the effectiveness of the proposed method is verified well in the actual power system in Hunan province, China. In conclusion, this paper presents a simple and effective approach to solve the problem of peak-valley time period partition of TOU tariff, which not only accurately reflects the peak-valley characteristics of daily load, but also achieve the effect of peak-shaving, valley-filling, and cost reduction in combination with different power prices.

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