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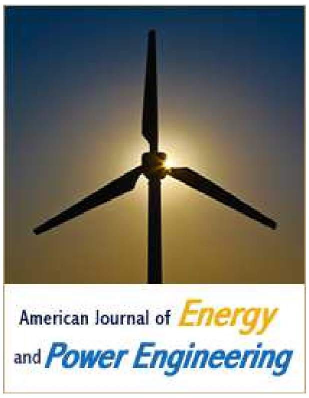

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Representative Load Curve and the Tariff Impact Analyzing

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Abstract
The representative load curves (RLCs) are necessary for utilities in tariffication policy. From the load curves collected in the activity time of a tariff, one representative load curve will be built. The easy way to estimate the impact of a tariff is to analyze some indicators of the RLC. The Fuzzy K-Means (FKM) is utilized in this work to determine RLCs. The compromising of the Cluster validity indexes and determining the suitable weighting exponent *m* are considered to find out the final clusters and their RLCs. The case study for one utility in the South of Vietnam is carried out to show the impacts of the current Time of Use (TOU) tariff.

1. Introduction

For many utilities, the market strategy and setting the price are based on the load curve clustering. The tariff improvement can be formed by using the representative load curve (RLC) of different customer group. From these RLCs the utility can determine the each group contribution in forming the system load curve. Therefore, utility can determine the electrical price for each customer class [1].

For DSM (Demand side management) the RLCs can be served for several targets [2] [11], for example, the problem of direct load control or the determining interruptible load tariff.

One of the popular tariffs is the Time of Use (TOU). Many utilities change this TOU by the time. For example, the TOU in California is changed twice in year. The exertion to find the demand response model is carrying out. This model reflects how the relative change of price leads to change the electricity consumption. But one very simple way to estimate the impact of a TOU can be done by considering the daily load curve. In this case, we must to build one load curve representing all load curves in the activity time of this TOU. In order to compare the effectiveness of two TOU, the two RLCs must be analyzed.

The TOU tariff has been applied in Vietnam for more than ten years and it is used for the industrial plants and commercial customers. It is also changed for several times. The estimation of the TOU impacts on electrical consumption is necessary.

There are some techniques for representative load curve determining.

One technique considered the RLC of a load curve set as the mean load curve. But [3] shows that this is correct if the load curves set has the normal distribution. This work also suggested that the RLC will be determined from the results of load curve clustering.

In the fields of fuzzy clustering analysis, the Fuzzy K-Means algorithm [4] is one of the most popular methods. In fuzzy clustering, each point has a degree of belonging to clusters, as in fuzzy logic, rather than belonging completely to just one cluster.

Therefore, the center of each cluster somehow (the representative of cluster) reflects the form and values of the entire points from the origin set. It is particular suitable for determining the representative load curve of all daily load curves.

This paper focused on the RLCs building and on estimation of a new TOU.

2. Estimation a TOU Impact by Analyzing the RLCs

The indicators of one load curve are the following ratios:

$$K_1 = P_{mean}/P_{min}$$

$$K_2 = P_{min}/P_{max}$$

$$K_3 = \sqrt{\frac{\frac{1}{24}(\sum_{i=1}^{24} P_i^2)}{\frac{1}{24}(\sum_{i=1}^{24} P_i)}} \tag{1}$$

where P_{min} , P_{max} , P_{mean} –minimal, maximal and mean load of a day; P_i-the load at *i*-hour.

If these indicators are moving toward the unity that means their load curve became more flattened. In the ideal case, where the load curve is completely flattened, the above indicators are equal to unity.

So looking at these indicators of RLCs for the time period of tariff activity, one conclusion about its impact on improving the load curve form can be made.

3. Determining RLC

The RLC can be formed based on the following approach [3]

3.1. Test for Normal Distribution of Load Curve (LC)

For testing the normal distribution of LC, the $\chi 2$ or Kormogorov standard in 24 dimensions data will be applied [5]. If the load curve set has the normal distribution, the RLC is the mean load curve; else we will go to the next.

3.2. Representative Load Curve Based on the FKM Algorithm

The Fuzzy K-Means algorithm is presented in this paper to determine the RLC. Using fuzzy K-means algorithm leads to several clusters. The center of cluster (representative curve of cluster) is influenced by all curves. This is quiet difference from hard clustering where the center of one cluster is the center only of curves in this cluster. So the representative of each cluster somehow reflects the form and values of the entire curves from the origin set.

The cluster with maximal number of load curve may be chosen as major cluster and its center is chosen as representative curve. The conception of “major” cluster is based on one factor: the difference of curve number (in percentage) between this cluster and the rest clusters is greater than the curve number (in percentage) of the rest clusters.

When the major cluster is not found, the representative load curve can be chosen by:

$$Z_{rep} = \sum_{i=1}^{k} \mu_i Z_i \tag{2}$$

$$\mu_i = (n_i / n) \tag{3}$$

With ni- the number of curves belonged to the cluster i and Z_i-the center of cluster i; k-the cluster number. So the representative (2) has tendency to incline to the cluster having maximal curve number more than the mean curve.

4. Clustering Process

4.1. Fuzzy K-Means Algorithm

Fuzzy K-means (FKM) is based on minimization of the following objective function:

$$F = \sum_{i=1}^{n}\sum_{j=1}^{k} w_{ij}^{m} \left\| X_i - Z_j \right\|^2 \tag{4}$$

where *m* is any real number greater than 1 ($1 < m < \infty$), w_{ij} is the degree of membership of X_i in the cluster j, X_i is the ith of d-dimensional measured data, Z_j is the d-dimension center of the cluster, and ||*|| is any norm expressing the similarity between any measured data and the center. For daily load curve, *d* is equal to 24.

Consider a set of *n* objects $X=\{X_1,X_2,\ldots,X_n\}$ to be clustered into *k* clusters (1<k<n). The steps in this algorithm are as following:

i) Choose *k* and *m*, and initialize the partition matrix $W^{(0)}$.

ii) Calculate the cluster center.

$$Z_i = \frac{\sum_{i=1}^{n} w_{ij}^{m} x_i}{\sum_{i=1}^{n} w_{ij}^{m}} \tag{5}$$

iii) Update the partition matrix $W^{(t)}$ as follows:

$$w_{ij} = \frac{1}{\sum_{t=1}^{k}\left(\frac{\left\|X_i - Z_j\right\|^2}{\left\|X_i - Z_t\right\|^2}\right)^{\frac{2}{m-1}}} \tag{6}$$

iv) If $\| W^{(t+1)} - W^{(t)}\| < \varepsilon$ then STOP; otherwise return to step (ii)

4.2. Cluster Validity

The FKM algorithm requires the user to pre-define the number of clusters (k), and different values of k corresponds to different fuzzy partitions, so the validation of clustering results is needed.

Many cluster validity indexes suitable for this algorithm have been proposed. Bezdek's Partition Coefficient (PC) and Partition Entropy (PE) [6], Rajesh N.Dave's Modified Partition Coefficient (MPC) [7], Xie-Beni (XB) [8], Fuzzy version of PBM-index (PBMF) [9], Yunjie Zhang (W) [10] and so on have been used for measuring validity mathematically.

This paper proposed the following method for validation:

The problem is:

$$\min F = \sum_{l=1}^{q} \left[\frac{f_l(\overset{*}{k}) - f_l(k)}{f_l(\overset{*}{k})}\right]^p \quad (7)$$

where f_1 (k*) is the optimum value of singular objective function l at its optima point k*, f_l (k) is the function value itself, and p is an integer valued exponent that serves to reflect the importance of the objectives; k-the cluster number. Here, the f_1 (k*) is the maximum or minimum value depending on the validity indexes, and q = 6 (PC, PE, MPC, XB, PBMF, W). We choose p = 2.

4.3. Estimation of *m* Value

Determining the suitable weighting exponent *m* for each data set is an important problem for FKM.

Since in this paper the aim is to determine RLC, we proposed one approach to determine the suitable *m* value based on the observation of PC value [6] when changing the weighting exponent *m*. Varying *m* for each problem classification, the suitable *m* is determined. [6] shows that as *m* increases, PC→ 1/*k* and as *m* decreases, PC→ 1. When *m* increases, the element numbers of all clusters have an inclination to become equal.

It is an attention on this *m* that makes PC greater than 1/k. For one value of *m*, if it can find out the value of *k* corresponding to simultaneously minimum of (PE, XB and W) and maximum of (PC, MPC and PBMF), then this *k* will be selected. If the results of these validity indexes are different, the *k* which minimizes the (7) will be chosen. Varying *m*, we will choose the most stable value of *k*. It is regarded as the number of clusters for the given consumers. We denote the values of *m* corresponded to this *k* as $\{m_1\}$.

As mentioned above, if for several *m* among $\{m_1\}$ the major cluster are found, we will select the minimal value of them for the purpose of obtaining more curve number in this cluster. It assures the representativeness of the major cluster.

For the case, where the major cluster is not found, according to [6] when m →1 we have:

$$Z_i = \frac{\sum_{x_j \in i} X_j}{n_i} = Z_{mean\_i} \quad (8)$$

and (2) becomes the mean curve for the origin set. So the maximal *m* will be selected among $\{m_1\}$ to avoid this.

5. Case Study

The TOU tariff in Vietnam has 3 zones per day: the peak price for peak moments; the valley price for low load moments and normal price in the normal hours. The peak moments consist of the following hours: 9h30' to 11h30'; 17h to 20h. The valley load moments are: 21h to 4 h. The remained hours are belonged to the normal moments. There are three times for tariff changing in two years (2011 and 2012). The first one is at 3/1/2011; the second at 12/20/2011; the third-at 6/30/2012. Every time, the next TOU has the prices for three zones are higher than the previous TOU.

The daily load curves of one utility in the South of Vietnam and its substations 110/22 kV in the year of 2010, 2011, 2012 were used.

The RLCs of this utility and substation were built.

5.1. For Whole Utility

The test for normal distribution is carried out and the results show that none of the given load curve sets was belonged to normal distribution.

The FKM was carried out and the suitable value of m is 1.5. The four RLCs for the whole utility (corresponding to 3 times of TOU changing) are displayed on the Fig.1, Fig.2, Fig.3 and Fig.4.

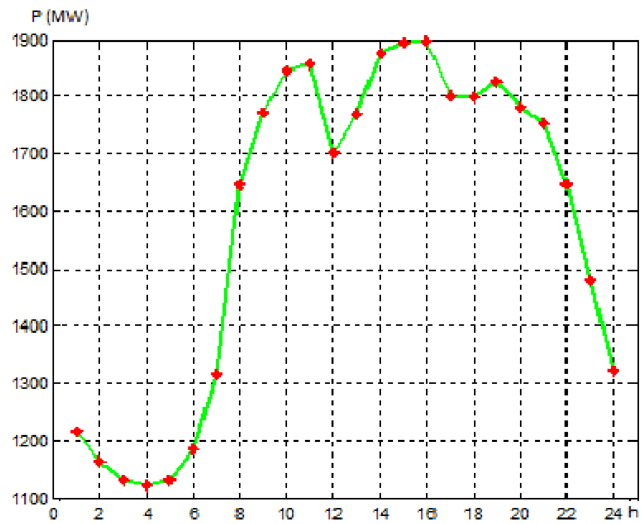

Fig. 1. *The RLC of the utility from 1/1/2011 to 2/29/2011.*

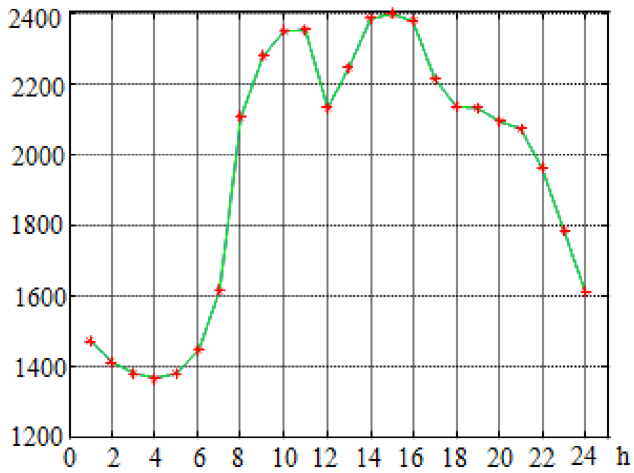

Fig. 2. The RLC of the utility from 3/1/2011 to 12/19/2011.

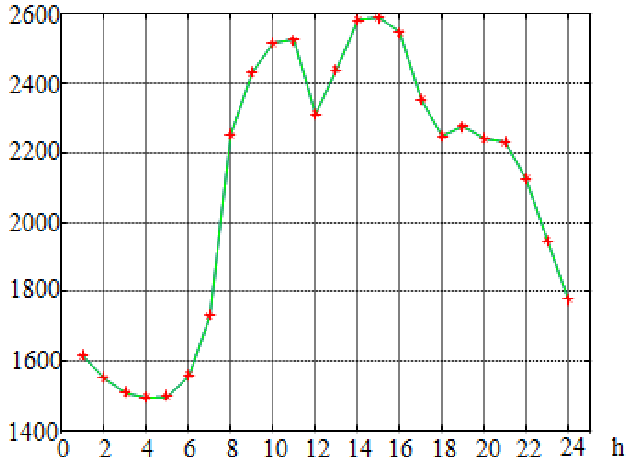

Fig. 3. The RLC of the utility from 12/20/2011 to 6/30//2012.

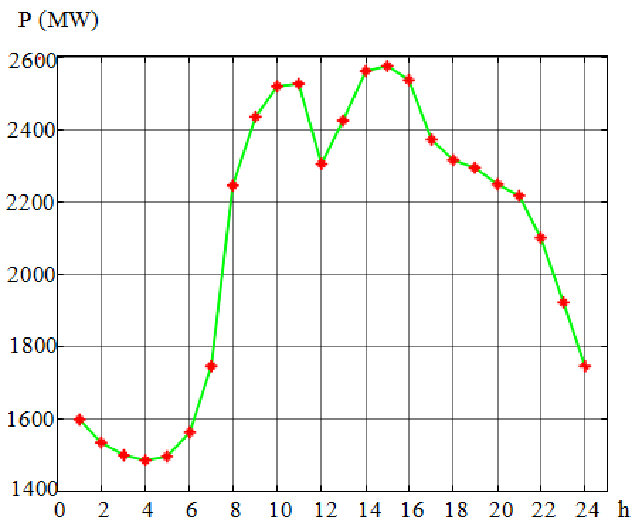

Fig. 4. The RLC of the utility from 7/1/2012 to 12/20/2012.

Observing the above RLCs leads to the following remarks: The main indicators for RLC are presented in Tabl.1

Table 1. *The main indicators for RLC.*

Period	K_1	K_2	K_3
1/1/2011-2/29/2011	1.0163	0.59158	1.4096
3/1/2011 -12/19/2011	1.0181	0.57045	1.423
12/20/2012 – 6/30/2012	1.017	0.578	1.4023
1/7/2012-20/12/2012	1.0174	0.577	1.4096

In the normal moment, there is a peak from 14-16 h. This is the afternoon peak load and very large and this also is the maximal load in day.

The ratios between the morning and the afternoon peak are: 0.97; 0.97; 0.97; 0.98 and are not improved.

The ratios between the P_{min}/P_{max} are in the range of 0.57-0.59, even for the last TOU changing, it is decreased.

The ratio P_{min}/P_{peak} is not better as presented in Tabl.2. Here P_{peak} is the morning peak load. This peak plays an important role because is belonged to the peak hours that are default by the EVN (Vietnam Electricity). And one of the aims in DSM policy of EVN is to reduce the ratio P_{min}/ P_{peak}.

Table 2. *The P_{min}/ P_{peak} of the whole utility.*

Period	P_{min}/P_{peak}
1/1/2011-2/29/2011	0.605
3/1/2011-12/19/2011	0.59
1/1/2012 – 6/30/2012	0.596
7/1/2012-12/20/2012	0.592

5.2. For customers

5.2.1. The Commercial and Service Customer

The FKM was applied and the appropriate m is equal to 1.8. The RLCs of one customer for the above periods are displayed in Fig. 5. In this figure, Q_{td1}, Q_{td2}, Q_{td3}, Q_{td4} are the RLCs of four tariff periods. Analyzing these indicators of the RLCs of all the commercial and service customers shows that each TOU changing did not lead to the change of load curve form. The ratios P_{min}/P_{max} is: 0.52, 0.57, 0.58, 0.56, and these ratios are also the ratios P_{min}/P_{peak} .

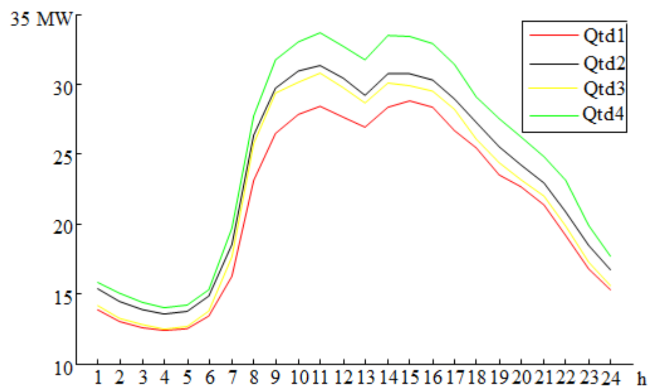

Fig. 5. The RLCs of one commercial and service customer for 4 periods.

5.2.2. The Industrial Customer

The RLCs of four periods are displayed in Fig. 6 as the result of FKM process with m=1.4. The ratios P_{min}/P_{max} are : 0.65, 0.63, 0.62, 0.62, and these ratios are also the ratio P_{min}/P_{peak}. For this type of customer, the morning load peak is highest. The four changes of TOU did not lead to improve the forms of load curves.

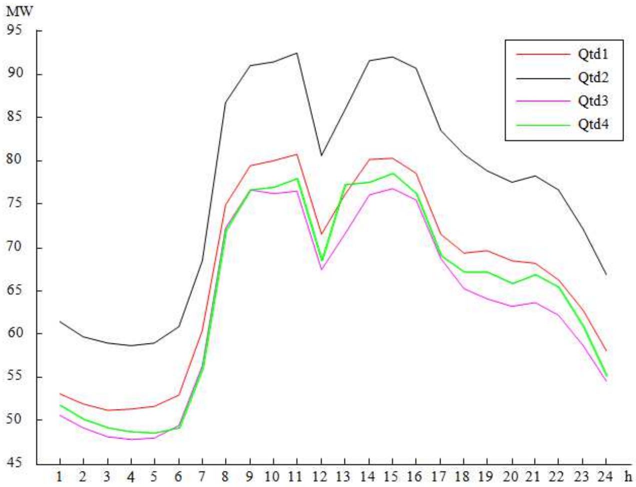

Fig. 6. *The RLCs of one industrial customer for 4 periods.*

So for this utility, the demand response is not positive. Although there was an increasing the price at the peak moments and at the normal moment, every time, but many customers in this utility had concentrated electricity consumption in the afternoon hours. It was explained that the difference between the prices at the peak and the valley moments is not large enough to encourage customers to shift their consumption into the night hours. That leads to the new afternoon peak, and for some customers, this peak is higher than the peaks default by the TOU. It also mentioned that the structure of TOU must be changed if the utility wants to eliminate the afternoon peak: the afternoon hours must be regarded as the peak moment.

6. Conclusion

By analyzing the RLC in the activity time of a TOU, the impact of the tariff on the electricity consumption can be extracted. This helps utility to improve its tariffication policy. The RLCs are not the mean curve and can be built by the FKM. The combining some validity indexes, the proper determining of weighting exponent *m* are important factors to find out the final clusters. The case study of one utility in the South of Vietnam shows that the series of new TOU tariffs is not rational from the point of improving the forms of daily load curves. It also shows that the relationship between the prices of three zones must be changed.

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