Proceeding of the 2015 IEEE
International Conference on Information and Automation
Lijiang, China, August 2015

Application of Clustering Technique to Electricity Customer Classification for Load Forecasting

Yanlong Wang
Department of Control Science and Engineering
Zhejiang University
Hangzhou, Zhejiang 310027, China
15551195159@163.com

Li Li
Beijing Institute of Astronautical Systems Engineering
Beijing, 100076, China
eprimrose11@163.com

Qinmin Yang
State Key Laboratory of Industrial Control Technology
Zhejiang University
Hangzhou, Zhejiang 310027, China
qmyang@zju.edu.cn

***Abstract*-With the development of smart grid and opening-up progress of the electricity market, Customer Relationship Management (CRM) plays a more and more important role in the power electric industry. Conducting medium and long term consumption pattern analysis of major customers can help the electricity providers grasp the changing trends of the future consumption, and thus better formulate the dedicated tariff offers and provide professional services according to various consumer demands. However, it's computationally costly and impossible to conduct such analysis for every single customer. To overcome this complexity, this paper aims to provide an effective solution to group customers into certain number of categories with similar electrical behavior by utilizing clustering techniques. By combining distance and correlation, a novel clustering validity indicator is proposed to evaluate the effectiveness of clustering procedure, which is subsequently helpful for choosing algorithms and the optimum number of clusters. Eventually, a case study has been conducted with electricity market data including various electricity customers from different industrial fields. Two frequently-used clustering algorithms have been employed to illustrate the feasibility of the proposed approach.**

Index Terms-CRM, consumption pattern, data similarity, clustering technique, priority indicator.

I. Introduction

Enhanced knowledge on the shape of the medium and long term electricity consumption can be directly useful to the analysis of the demand characteristics of key customers. Thus, the power electric industry can effectively deal with management of power system including overhaul plan and loads for energy system planning and operation [1]. What's more, under the premise of fully understanding the consumption tendency of key customers, the power electric industry can provide more professional service, which is of great importance under the background of electric power market liberalization.

For most power grid companies, who have thousands of key customers, it's computationally impossible to build a model for every single key customer for consumption pattern analysis and load forecasting. Alternatively, conducting load pattern analysis by clustering load curves is proved to be an effective method for obtaining the typical load profiles (TLPs) of electricity consumption. Generally, TLPs are obtained by compromising between consumption patterns belonging to the same cluster [2]. In recent decades, lots of clustering techniques have been present for short-term load pattern analysis, which is further used for load control [3], abnormal electricity consumption detection [4], designing electricity tariff offers [5], developing market strategies [6] and demand side response policy [7]. However, medium and long term demand forecasting using clustering techniques is rarely discussed in literature. Therefore, this paper focuses on clustering technique for medium and long term consumption pattern analysis in order to support electricity providers.

Recently, many methods have been proposed in literature to group customers appropriately with similar characteristic [8], including k-means [9], modified follow-the-leader [10], fuzzy c-means (FCM) [11],[12], statistic-fuzzy technique [13], the self-organizing map (SOM) [14], support vector machines (SVM) [15], and extreme learning machine [4]. For a given key electricity customers data set, several clustering methods can be employed for clustering analysis. Under the given number of groups, each clustering method may identify groups whose member objects are different. In order to assess the performance of each algorithm, research in this area has been conducted to design clustering validity indicators, such as the mean index adequacy (MIA), the clustering dispersion indicator (CDI), the similarity matrix indicator (SMI), the Davies-Bolden indicator (DBI), the scatter index (SI) and the mean square error [16]. It should be noted that all these indicators are distance-based by using a metric to assess the effectiveness of clustering. This metric merges together the compactness of the consumption patterns belonging to the same class and inversely the inter-distance among different clusters, which can actually interpret the compactness of the pattern in the same class and the alienation between the classes.

The clustering validity indicators mentioned above can be used for clustering effectiveness assessment in various areas, such as user characteristics of identification with similar buying patterns in retail business, customer fraud detection in financial field and consumption patterns analysis in energy field. However, sometimes clustering performance should be assessed according to the actual needs in different areas. For example, sometimes the data set is used to analyze the change of power consumption demand and predict the future electricity need. Under this circumstance, the correlation between consumption patterns used to build forecasting model should be as an important index. In this case, one model is used to matching all the consumption patterns in the same group. So, high correlation between samples within the same group is expected. Considering this situation, this paper builds a new clustering validity indicator in order to improve correlation coefficient between samples in the same group and lower it among different groups.

978-1-4673-9104-7/15/$31.00 ©2015 IEEE

This paper is organized as follows: Section II introduces the clustering procedure along with a flow chart. In section III two kinds of frequently-used clustering technologies are introduced. Section IV proposes a new clustering validity indicator for the choice of most suitable algorithm and optimum number of clusters. Section V presents a case study and demonstrates the effectiveness of indicator by correlation analysis among samples. Section VI gives some discussion and talks about the subsequent work of consumption forecasting using clustering technique mentioned.

II. CLUSTERING PROCEDURE

When building one forecasting model to a large of consumption patterns, we generally implement model based on typical consumption patterns. Typical consumption patterns including most information of all the consumption patterns are obtained by carrying out clustering to primitive key customers data set. Subsequently, on the basis of the forecasting model, the electric providers can deal with effective management of Power system overhaul plan and loads for energy system planning and operation. In this section, we discuss the clustering process in detail, the flow chart is show in Fig. 1.

Step 1) Customers selection: Medium and long term consumption patterns analysis is typically performed on the electricity consumption data of key customers. Here, key customer means industries with high demand for electricity and voltage. Firstly, the demand characteristic of the key customers is more representative. What's more, the changes in demand of the key customers can reflect the changes of complete electricity market more realistic. So, this paper selects key customers scattering in various industrial areas of a province in southern China.

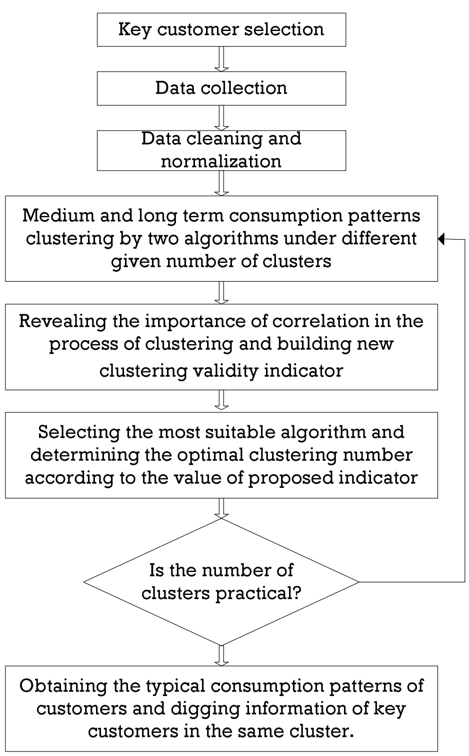

Fig. 1Flow chart of clustering procedure

Step 2) Data collection: From the viewpoint of time, various periods of datum are stored in power database. Considering the efficiency and timeliness of the data, the quarterly chronological consumption curves for each key customer are determined as objects of research. As for the time span, consumption data from Jan.2008 to Dec.2014 are researched.

Step 3) Data cleaning and normalization: In this part, invalid data is detected and eliminated in order to ensure that the consumption patterns used for key customers clustering correspond to normal consumption conditions. Missing values and unreasonable consumption patterns caused by network failure or statistical error can be detected easily. Alternatively, unreasonable consumption patterns can be "cleaned" by replacing original data with appropriate corrections. Finally, in order to eliminate the gaps of order in terms of consumption magnitude, normalization is performed. Normalization is particularly useful for distance-based clustering algorithms. In this paper, the data is scaled to a determinate range [0.0, 1.0] by dividing the maximum value of a certain customer to all the value this customer. Thus, all the key customer consumption patterns have uniform maximum value 1.0 but at different time periods.

Step 4) Clustering phase: After the data normalization, all the key customers have the consumption patterns with uniform range. In this part, all the consumption pattern groups are identified with two frequently-used clustering algorithms. Here, the two objective clustering algorithms are k-means(KM) and fuzzy c-means(FCM). The specific meaning of the two algorithms will be illustrated in the next section. Similarity of consumption patterns are standard of clustering.

After clustering , key customers with similar consumption patterns are divided into the same cluster. Traditionally, the effectiveness of clustering is evaluated by averaging the distances between samples and cluster centers. Since the clusters are frequently used to forecasting the consumption trend of key customers, the correlation between samples in the same cluster should be considered carefully. So after clustering, we research the correlation from different aspects in order to reveal the correlation attributes existing in the process of clustering.

Step 5) Clustering analysis: Key customers are divided into different groups based on the similarity of the consumption characteristic. In this part, we build a clustering validity indicator combining the conclusion of correlation analysis. The clustering validity indicator is used to evaluate the effectiveness of clustering. Since it considers the correlation effectively, it's especially efficient in the cases with high demand to the correlation of objects in the same class. What's more, with the help of the target indicator, the most suitable algorithm and the optimum number of the clusters are easily chosen. The determination of the number of clusters is a key issue in clustering, which will be of great importance to the accuracy of the subsequent analysis. On the one hand, the number of final customer groups can't be too high, for too much groups will aggravate the modeling workload. On the other hands, if the number of final customer groups is too low, there will be too much customers in one group.

Step 6) Typical consumption patterns: However, it's difficult to find useful information directly. After clustering phase and clustering analysis, consumption patterns in the same cluster have high correlation coefficient and inversely among different clusters. Before subsequent analysis, we used to obtain typical load patterns(TLPs) by averaging all the patterns in the same cluster. Generally, TLPs contain most information of the group. Therefore, analyzing towards TLPs instead of all patterns of the group is time-saving and efficient.

III. CLUSTERING PHASE

On the basis of the consumption patterns defined, clustering techniques are generally applied to perform consumption grouping. In this section, two frequently-used clustering algorithms used for clustering consumption patterns of key electricity customers are illustrated. The purpose of clustering is to improve the similarity of key customers in the same cluster as much as possible and lower it among different clusters.

A. Distance-based Framework

In the beginning of this section, some basic information which is of great importance to the comprehension of the algorithms is introduced. Mathematically, a key customer consumption pattern can be understood as a vector with one-quarter interval points as its components here. For example, $X^{(m)}$ represents one of the key electricity customers of the mentioned province above, then $X^{(m)}$ can be comprehended as a vector matrix:

$$X^{(m)} = \{x^{(m)}{}_1, x^{(m)}{}_2 \ldots x^{(m)}{}_h\}$$

Here, $x^{(m)}{}_h$ denotes the value of the electricity consumption of a certain quarter from Jan.2008 to Dec.2014 of the customer $X^{(m)}$. Here, $h = 28$ corresponds to the number of data points of one consumption pattern. Thus, the whole set of consumption patterns can be characterized by the following vector matrix:

$$X = \{X^{(m)}, m = 1, \ldots, M\}$$

M is the total number of the customers. The two known algorithms are performed on the whole set X. After clustering analysis, the customer data set is divided into k groups, that means:

$$X = \{X_1, X_2, \ldots X_k\}$$

this paper uses X_{kq} to represent the $q-th$ customers of the group k.

In the distance-based framework used, various types of distance are defined as follows:

- Customer-to-customer distance, e.g., for two customers $X^{(m)}$ and $X^{(n)}$, both have h components

$$d(X^{(m)}, X^{(n)}) = \sqrt{\frac{1}{H}\sum_{h=1}^{H}(x^{(m)}{}_h - x^{(n)}{}_h)^2} \tag{1}$$

- Customer-to-group distance, computed by using the distances between the customer $X^{(m)}$ and each of the M customers of group X_k.

$$d(X^{(m)}, X_k) = \sqrt{\frac{1}{M}\sum_{X^{(n)}\in X_k} d^2(X^{(m)}, X^{(n)})} \tag{2}$$

- Average group-to-group distance, given by the mean distance between all pairs of customers X_{mq} of the group $X_m, m \le k$ (with Q customers) and X_{nj} of the group $X_n, n \le k$ (with J customers).

$$d(X_m, X_n) = \frac{1}{QJ}\sum_{q=1}^{Q}\sum_{j=1}^{J} d(X_{mq}, X_{nj}) \tag{3}$$

- Internal distance, computed by using the customer-to-group distance for the M customers of the group X_k.

$$\hat{d}(X_k) = \sqrt{\frac{1}{M}\sum_{m=1}^{M} d^2(X_{km}, X_k)} \tag{4}$$

B. K-Means

K-means(KM) clustering is an efficient method for processing large data sets because of its high efficiency. K-means clustering accept the final number of clusters as input parameter and divide the target customer data set into k groups with the objective of enhancing the intra-cluster similarity and lowing the inter-cluster similarity.

The KM proceeds as follows. Firstly, it identifies the final number of clusters which is assigned by users. Then, it selects k objects as cluster mean or centers randomly. For each of the remaining objects, the distances to the k objects selected randomly are calculated respectively. Based on the minimum distance, the remaining objects are assigned to a certain cluster center which is most similar to the target object. After that, the new mean for each cluster is computed. The process iterates until the criterion function converges and the clusters come to stability. Typically, the square-error criterion is defined as:

$$E = \sum_{j=1}^{k}\sum_{p\in C_j}\left|p - s_j\right|^2 \tag{5}$$

where

E sum of the square error for all objects in the data set;

p a certain object of cluster C_j

s_j center of the cluster C_j (p and s_j have same dimensionality)

By using the criterion function outlined above, the KM tries to make the resulting objects in the same cluster as compact as possible and objects among different clusters as separate as possible.

C. Fuzzy c-means (FCM)

Fuzzy c-means (FCM) is an effective unsupervised method for the analysis of mass data. Based on the function optimization method, FCM calculates the optimal cost function by using calculus technology. FCM provides a method to divide data points that populate some multidimensional space into a specific member of different clusters. That means each data point is geared to different clusters to some degree which is expressed by a membership grade. J_q means the value of objective function. The optimal value of the J_q is calculated by minimizing the following objective function.

$$J_q = \sum_{i=1}^{k}\sum_{j=1}^{N} \mu^q{}_{ij} \left\| x_j - s_i \right\|^2 \qquad (6)$$

Where ,

x_i a certain customer in data set;

s_j the center of the jth cluster;

μ_{ji} the degree of membership x_i in the jth cluster;

N number of customers in data set;

k number of clusters;

q fuzzy-coefficient, in general, $q = 2$;

here, we consider a data set with N customers to be clustered into k clusters. The steps using the proposal algorithm are as follows:

Step 1) Assign the values of k, q threshold ε and initialize the membership grade matrix $\mu_{ij}(0)$.

Step 2) Obtain the k cluster centers .

$$s_i(L) = (\sum_{j=1}^{N}(\mu_{ij}{}^q(L)x_j)) / (\sum_{j=1}^{N}(\mu_{ij}{}^q(L))) \qquad (7)$$

for $1 \le i \le k, 1 \le i \le N.$

Step 3) Update the membership grade matrix for the $(L+1)th$ step

$$\mu_{ij}(L+1) = 1 / \sum_{p=1}^{k}(\left\| x_j - s_i(L) \right\|^2 / \left\| x_j - s_p(L) \right\|^2)^{1/(q-1)} \qquad (8)$$

For all i, p note that:

$$\sum_{i=1}^{k}\mu_{ip}(L) = 1, \mu_{ip}(L) \in [0,1]. \qquad (9)$$

Step 4) Stop if $\left\| J_q(L+1) - J_q(L) \right\| < \varepsilon;$ otherwise, $L = L+1,$ and go to step 2).

From the procedure of the FCM, we can conclude that: Each vector is assigned to k clusters illuminated by k membership grades. Firstly, the initial value of the membership grades are chosen randomly. Then the k cluster centers can be obtained according to the membership grades. Afterwards, the membership grades are updated on the basic of the latest values of the cluster centers. The iterations continue until the residual error meets requirement.

IV. Clustering Validity Assessment

Generally, one important purpose of clustering is to improve the similarity between the objects in the same cluster as soon as possible. However, how to define the similarity between objects from the angle of the mathematics still is a controversy. Commonly, distance-based index is used to evaluate the similarity between objects, which regards the shorter distance as the higher similarity. Nevertheless, there still exists one circumstance, for two objects, they may have roughly the same changing tendency though their distance may be large. Under this circumstance, correlation between two objects should be considered as the index of similarity. Therefore, this paper introduces a new index which evaluate the similarity on the basis of both distance and correlation.

Correlation analysis is often used to measure the consistency of two vectors, with correlation coefficient as quantitative representation. The correlation coefficient of two vectors is obtained according to the following formula. The range of correlation coefficient is [-1,1], among which, [-1,0] means two vectors have negative correlation and the bigger the absolute value, the stronger the correlation. Rule is also effective to the range of [0,1].

$$r_{xy} = \frac{\sum_{i=1}^{N}[(x_i - \overline{x})(y_i - \overline{y})]}{\sqrt{[\sum_{i=1}^{N}(x_i - \overline{x})^2]}\sqrt{[\sum_{i=1}^{N}(y_i - \overline{y})^2]}} \qquad (10)$$

To one degree or another, bigger value of correlation coefficient means higher similarity of two vectors. Comprehensive consideration of distance and correlation, this paper introduces a new index to evaluate the quality of clustering. The index is calculated by the following formula:

$$Q(x) = \mu d(x) + (1-\mu) r(x), 0 \le \mu \le 1 \qquad (11)$$

$$d(x) = \frac{\overline{d}_i(x)}{\overline{d}_o(x)}, r(x) = \frac{\overline{r}_o(x)}{\overline{r}_i(x)} \qquad (12)$$

where

$\overline{d}_i(x)$ the average of distances from all the objects of the data set to corresponding clustering centers;

$\overline{d}_o(x)$ the average distance between cluster centers;

$\overline{r}_i(x)$ the average correlation between consumption curves and corresponding clustering centers;

$\overline{r}_o(x)$ the average correlation between clustering centers;

The proposed index is easy to comprehend. $d(x)$ represents the distance characteristic in the process of clustering. By weighing the distance between the clusters and distance in the same cluster, $d(x)$ can express the distance characteristic effectively. Correspondingly, $r(x)$ can represent the correlation characteristic efficiently by overall consideration of the correlation characteristic between the clusters and in the same cluster. Thus $Q(x)$ can evaluate the quality of the clustering form the view of both distance and correlation. What's more, adjusting the value of μ can change the proportion of distance and correlation according to the actual circumstance.

V. Case Study Of Customer Data In Southern China

In this part, a set of key customers in terms of electricity consumption in southern China has been researched. Firstly, the data sources and industries involved are described. Secondly, we show the graphs of consumption obtained by handling the original data of consumption with aforementioned methods. Finally, the clustering phase is performed and the clustering results are evaluated by the proposal index.

We collected quarterly electricity consumption from more than 140 key customers of a certain province in southern China. These key customers cover agriculture, manufacture, business and so on. Then, the consumption data is cleared and handled by the methods introduced in the second part. After that, we get 137 consumption curves showed in Fig. 2. Clearly, there are several different changing trends in the figure. Therefore, the performance of distinguishing the different changing trends of electricity consumption is an important standard in evaluating the quality of clustering.

A. *The Most Suitable Algorithm and the Optimum Number of clusters*

Here, clustering to consumption curves is performed by using the proposal two algorithms: k-means and fuzzy c-means (FCM). In order to confirm the most suitable algorithm and the optimum number of clusters, we have performed the two clustering algorithms by varying the number of clusters from 3 to 10 according to the actual needs. Then, the clustering validity assessment is performed by using the index introduced in the fourth part. Firstly, the index ($\mu = 0.5$) is calculated after each clustering procedure. Then, the most suitable algorithm and the optimal number of clusters are chosen based on the results with the minimum index value. Table 1 shows the index values of the two algorithms under the given number of clusters from 3 to 10. Fig. 3is drawn so as to compare the index values under different given number intuitively.

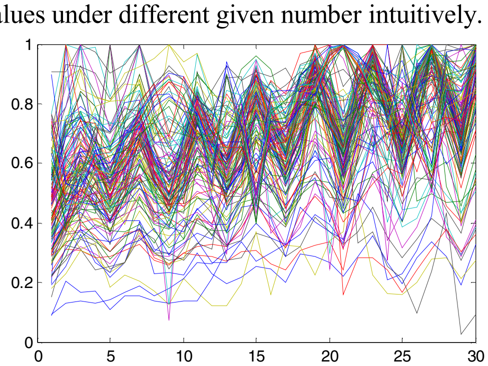

Fig. 2 Electricity consumption curves of key industries

TABLE I

INDEX VALUE OF TWO ALGORITHMS UNDER DIFFERENT GIVEN NUMBER OF CLUSTERS FROM 3 TO 10

Algorithms	The index value of the clustering results under different given number							
	3	4	5	6	7	8	9	10
k-means	0.51	0.45	0.38	0.32	0.40	0.38	0.43	0.45
FCM	0.48	0.47	0.42	0.38	0.37	0.35	0.45	0.48

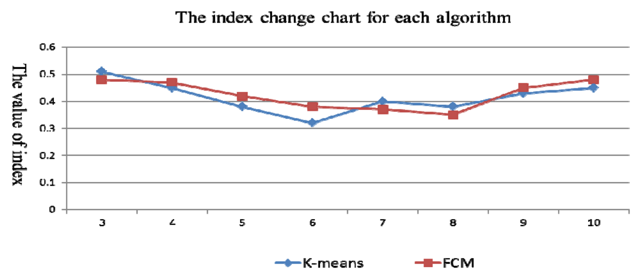

Fig. 3 Clustering validity assessment index change chart

Fig. 3 shows the proposed index get the minimum value at the point $k = 6$ under k-means algorithm. According to the proposed index, k-means is selected as the most suitable algorithm and $k = 6$ is selected as the optimum number of clusters under this circumstance. The corresponding results of the clustering will be showed in the next part.

B. *Clustering results*

Fig. 4 shows the results of clustering under k-means algorithm with $k = 6$. Clustering results indicate the target algorithm and number of clusters perform well, which can classify the key customers with satisfactory results. After clustering, we get six different load profiles of key customers, which have respective characteristic of electricity consumption demand. Key customers in the same cluster have higher similarity from the view of both distance and correlation.

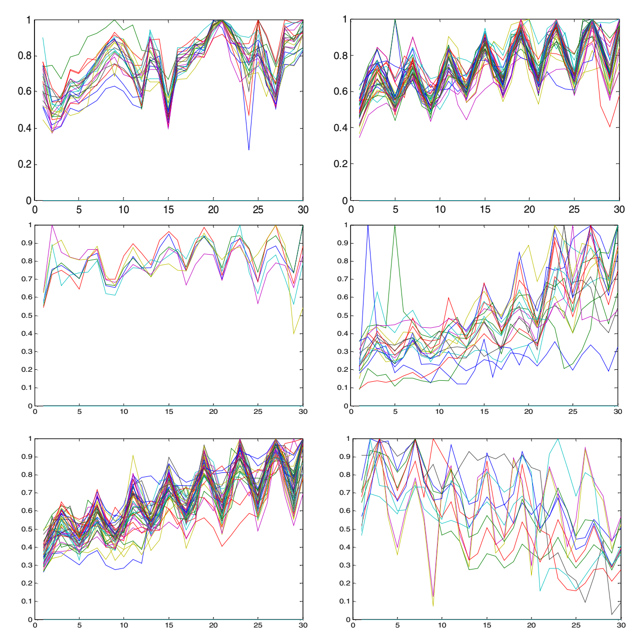

Fig. 4 Clustering results (K-means, k=6)

In order to research the properties of correlation, this paper calculate the correlation coefficient of key customers within the same cluster. Fig. 5 shows the results of correlation analysis, which expresses the correlation coefficient among each two key customers in the same cluster. Therefore, each detail drawing is symmetrical. Fig. 5 is corresponding to the Fig. 4. From these two figures, we could find key customers in the same cluster have bigger value of correlation coefficient, which prove the effectiveness of the proposed index.

VI. CONCLUSION

Clustering to key customers is an effective way of customer analysis to power enterprises, especially under the background of big data in power system database. The selection of most suitable algorithms and the optimum number of clusters is still a controversy in the clustering problem. Therefore, this paper presents a clustering validity assessment index which is helpful for determining of the most suitable algorithm and the optimum number of the clusters. Primarily, this paper introduces two kinds of commonly used clustering algorithms. Then clustering are performed with two propose algorithms under given number of clusters. According to the assessment index, the most suitable algorithm and the optimum number of clusters are determined. Through the analysis of clustering results, the correctness is verified. Correlation analysis can be used to the improvement of clustering algorithm in follow –up studies.

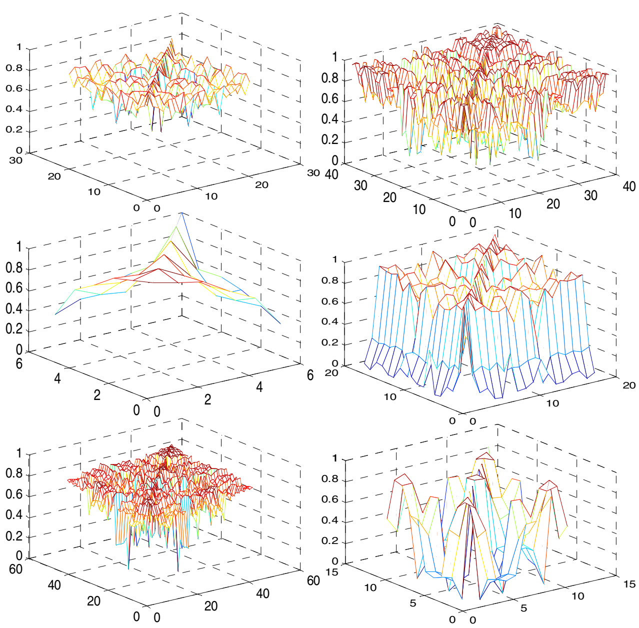

Fig. 5 values of correlation in the same clusters

REFERENCES

[1] Celik AN. Effect of different load profiles on the loss-of-load probability of stand-alone photovoltaic systems. Renewable Energy 2007;32(12):2096e115.

[2] G. Q. Zhang, J. Lu, X. P. Feng, and W. C. Yang, "A new index and classification approach for load pattern analysis of large electricity customers," IEEE Trans. Power Syst., vol. 27, no. 1, pp. 153–160, Feb. 2012.

[3] ElNozahy, M.S.; Salama, M.M.A.; Seethapathy, R. "A probabilistic load modelling approach using clustering algorithms", Power and Energy Society General Meeting (PES), 2013 IEEE, On page(s): 1 - 5

[4] A. H. Nizar, Z. Y. Dong, and Y.Wang, "Power utility nontechnical loss analysis with extreme learning machine method," IEEE Trans. Power Syst., vol. 23, no. 3, pp. 946–955, Aug. 2008.

[5] Teixeira, B.; Silva, F.; Pinto, T.; Praca, I.; Santos, G.; Vale, Z. "Data mining approach to support the generation of Realistic Scenarios for multi-agent simulation of electricity markets", Intelligent Agents (IA), 2014 IEEE Symposium on, On page(s): 8 - 15

[6] Garamvolgyi, M.; Varga, L. "Electricity pricing in liberalized market using consumer characterization", Energy Market, 2009. EEM 2009. 6th International Conference on the European, On page(s): 1 - 6

[7] S. Valero, M. Ortiz, C. Senabre, C. Alvarez, F. J. G. Franco, and A.Gabaldon, "Methods for customer and demand response policies selection in new electricity markets," IET Gen., Transm., Distrib., vol. 1, no. 1, pp. 104–110, 2007.

[8] Chicco G. Overview and performance assessment of the clustering methods for electrical load pattern grouping. Energy 2012;42:68e80.

[9] V. Figueiredo, F. Rodrigues, Z. Vale, and J. B. Gouveia, "An electric energy consumer characterization framework based on data mining techniques," IEEE Trans. Power Syst., vol. 20, no. 2, pp. 596–602, May 2005.

[10] G. Chicco, R. Napoli, and F. Piglione, "Application of clustering algorithms and self organising maps to classify electricity customers," in Proc. IEEE Bologna Power Tech Conf., Jun. 23–26, 2003.

[11] Anuar, N.; Zakaria, Z. "Determination of fuzziness parameter in load profiling via Fuzzy C-Means", Control and System Graduate Research Colloquium (ICSGRC), 2011 IEEE, On page(s): 139 - 142

[12] Anuar, N.; Zakaria, Z. "Determination of fuzziness parameter in load profiling via Fuzzy C-Means", Control and System Graduate Research Colloquium (ICSGRC), 2011 IEEE, On page(s): 139 - 142

[13] W. Y. Li, J. Q. Zhou, X. F. Xiong, and J. P. Lu, "A statistic-fuzzy technique for clustering load curves," IEEE Trans. Power Syst., vol. 22, no. 2, pp. 890–891, May 2007.

[14] Grigoras, G.; Cartina, G.; Bobric, E.C. "An improved fuzzy method for energy losses evaluation in distribution networks", MELECON 2010 - 2010 15th IEEE Mediterranean Electrotechnical Conference, On page(s): 131 - 135

[15] Chicco, G.; Ionel, O.-M.; Porumb, R. "Electrical Load Pattern Grouping Based on Centroid Model With Ant Colony Clustering", Power Systems, IEEE Transactions on, On page(s): 1706 - 1715 Volume: 28, Issue: 2, May 2013

[16] Rogers, D.F.; Polak, G.G. "Optimal Clustering of Time Periods for Electricity Demand-Side Management", Power Systems, IEEE Transactions on, On page(s): 3842 - 3851 Volume: 28, Issue: 4, Nov. 2013