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سیرشماره، استراتژی‌های تکنولوژی - توزیع شبکه - برنامه‌ریزی شبکه‌های توزیع - روش‌ها و ابزارها
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تahas گریزه:
کلمات کلیدی:
اطلاع از بار پسته‌های توزیع با استقرار توسعه، بهبود مصرف و کنترل شبکه، همواره از اهمیت ویژه‌ای برخوردار بوده است. شبکه‌های توزیع
به دلیل پیوستگی خاص، با جایگاه کلیدی تجهیزات اندازه‌گیری مواضع هستند. تخمین بار پسته‌های توزیع به عنوان راهکاری برای تحلیل با این مشکل پیشنهادگری است. در این مقاله یک روش جدید برای تخمین بار پسته‌های توزیع بر اساس نسبت‌های الکتریکی استفاده می‌شود، سیستم با قرار دادن نسبت‌ها بر روی ترانسفورماتورهای توزیع برای یک درصد مشخص، پروفاویل به دست می‌آید. در حالی که برای ارائه آنها با استفاده از یک روش خیاط استخراج شده است. در نهایت این پروفاویل بر
کلیه ترانسفورماتورها را با استفاده از این دو پارامتر بار نموده تخمین زده می‌شود. در این مطالعه تعداد تجهیزات اندازه‌گیری در دسترس
حداکثر فرض شده است. مطالعه مذکور بر روی یک شبکه 33 باسی ای استاندارد انجام گرفته است.

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Abstract - The accurate information about distribution substations' load plays an important role in network expansion, operation and control. Distribution networks are usually confronted with lack of measurement devices due to their special configurations. Load estimation is suggested as one of the ways dealing with this problem. This paper proposes a new method of load estimation related to 20kv distribution substations. In the first step, fuzzy c-means clustering (FCM) is employed in order to determine the most appropriate places of meters to install. Then, hourly loads in a specific period is obtained using measurement devices installed on distribution substations. In the next step, the load profiles of representative substations are used to construct pattern load profiles (PLPs). Finally, load profiles of all substations are estimated from extracted PLPs. The paper assumes the minimum number of measurement devices. In addition, the analyses are performed for a 33-bus standard system in order to approve method's transparent application.

Keywords– Load profile, clustering, fuzzy c-means, meter placement, distribution system

1- Introduction

For technical or operational issues measurements have not been placed on every node in a distribution system. Although with sufficient number of measurement, data can be noisy, corrupted or missed. Hence, unavailable data have to be estimated to provide a real time or detail view of system. Unknown parameters can be estimated finding a relation between measured and unknown parameters. At most of the time, estimation error cannot be eliminated but it can be minimizing by measuring significant and sufficient data.

In literature estimation of customer’s load profile has been practiced [1]. Various clustering technique is very common in customer profile estimation. Hierarchical clustering, k-means clustering and fuzzy c-mean are most popular [2]. Although, Time series and neural network method are used but mostly for forecasting load behavior [3]. Using fuzzy numbers and fuzzy clustering is one of the most famous method that have acceptable errors but this error is dependent on the customer behavior and method has to be set for any particular data [4]. The clustering method is widely studied and categorize in literature [5].

In this paper a clustering method has been presented based on the fuzzy c-mean algorithm to estimate the load profile for each distribution substations. According to local distribution company’s policy in Iran, two different customer type (residential and commercial) has been considered. Unlike similar research in this field, each substation considered to feed mixture of residential or commercial customer.

This paper has been organized as follows: FCM Algorithm and network data have been presented in section 2. Main contribution has been presented in section 3. Simulation and the results is presented in section 4. Finally, this paper concluded in section 5.

2- Clustering Using FCM Method

2-1- Fuzzy C-Means Algorithm

The purpose of clustering is to identify groupings of a data set to show system's behavior briefly. In this procedure, data will be grouped to a specific number of clusters in a way that the members of each cluster have the maximum similarity to that cluster and minimum similarity to other clusters [6].

Many clustering methods have been introduced till now [7]. One of the most useful clustering methods is Fuzzy c-means. FCM is a clustering technique which groups data into c clusters with every data point in the dataset belonging to every cluster to a certain degree. Today, FCM algorithm has many usages in issues such as feature analysis, pattern recognition, image processing and classifier design [8, 9]. Although FCM method has some disadvantages like sensitivity to noise, heavy computational burden and falling in local minima somehow, there are some brilliant benefits such as being...
supervision and imminent convergence which assure researchers to utilize it.

The FCM procedure is actually a minimization problem which is based on the following objective function [10]:

\[
J_m = \sum_{i=1}^{n} \sum_{j=1}^{N} u_{ij}^m \cdot d(x_i, c_j)
\]

(1)

Where
- \(x\) – is the features vector
- \(c\) – is the center of \(i\)-th cluster
- \(d(x_i,c_j)\) – is the distance between feature vector \(x_i\) and the center of cluster
- \(u_{ij}\) – is the degree of membership of vector \(x_i\) to cluster \(i\)
- \(N\) – number of clusters
- \(n\) – number of data vectors
- \(m\) – level of fuzzy overlap between clusters

FCM algorithm has the following steps:

Step 1) Initializing the value of \(m\), \(n\) and \(c\). Usually, number of the clusters depending on the work is determined, otherwise it is necessary to identify the best value of it. Besides, the reasonable value of \(m\) obtained \(m=2\) in [11].

Step 2) Calculating the center of clusters.

\[
c_i = \frac{\sum_{j=1}^{n} (u_{ij})^m \cdot x_i}{\sum_{j=1}^{n} (u_{ij})^m}
\]

(2)

Step 3) Calculating the membership matrix from clusters’ center.

\[
u_i^j = \left( \frac{d(x_i, c_j)^{\frac{1}{m}}}{\sum_{k=1}^{N} d(x_i, c_k)^{\frac{1}{m}}} \right)
\]

(3)

Step 4) If \(|U^{(k+1)} - U^{(k)}| \leq \varepsilon\) the algorithm will be stopped; otherwise return to step 2.

2-2- Distribution Substations Clustering

The case study examined in this research (shown in fig. 1) is a 33-bus radial distribution system. It is assumed there is a MV/LV (20kv/0.4kv) distribution transformer at each node of the network which is connected to specific amount of customers. There are just two class of consumers: residential and commercial.

In order to cluster a set of data, some features are required. To obtain a desirable result of clustering, a proper choice of features is necessary. Here, the only available information of transformers is the number of users of each consumption class, so these features could be chosen to use in FCM as input data. It has been realized from the results of many trials, utilizing the number of each class of consumers does not lead to a reasonable output but, percent of consumers of each class is more suitable and seems to separate data properly. Accordingly, values that should be adopted from transformers data obtain through the following formula:

\[
F_{i,j} = \frac{n_j}{\sum_{j=1}^{n} n_j}
\]

(4)

Where
- \(F_{i,j}\) – is the feature \(i\) of transformer \(j\)
- \(cc\) – number of consumption classes
- \(n_i\) – number of users of class \(i\)

The proposed methodology in this paper suggests the number of clusters equal to number of consumption classes, and that is for the sake of estimation method which is mentioned in the following sections. Thus, the number of clusters evolved for this study is 2. It means that, if there were four classes of consumers (e.g. residential, commercial, industrial and agricultural) the number of clusters should be adopted 4. Then, FCM algorithm have been run in 100 iterations, values of minimum improvement in objective function between two consecutive iterations and the level of fuzzy overlap between clusters are \(10^{-5}\) and 2, respectively. The results of FCM convergence and transformers grouping objective function are shown in Fig. 2 and Table 1, respectively.
Table 1 Clustering Result

<table>
<thead>
<tr>
<th>Cluster No.</th>
<th>Substation No.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2,4,6,8,10,17,18,19,22,25,28,31</td>
</tr>
<tr>
<td>2</td>
<td>1,3,5,7,9,11,12,13,14,15,16,20,21,23,24,26,27,29,30,32,33</td>
</tr>
</tbody>
</table>

Since, percent of variety of each class of users were adopted as clustering features and the number of consumption class of users is 2, clustering procedure changes to one-dimension problem. For instance, for a specific transformer, if the percent of residential users was \( a \) then the percent of commercial users would be \( (1-a) \). Generally, in this method the dimension of problem reduces one time. For instance, for a specific transformer, if the percent of residential users was \( a \) then the percent of commercial users would be \( (1-a) \). Accordingly, to realize the result of grouping of transformers with a better sensation, transformers are shown by their number of residential and commercial users which is shown in Table 2.

Table 2. Candidate Transformers

<table>
<thead>
<tr>
<th>Cluster No.</th>
<th>Candidate Substation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>15</td>
</tr>
</tbody>
</table>

3- Pattern Load Profile Extraction

3-1- Meter Placement

As aforesaid, one of the assumptions undertaken in this study is lack of metering devices. In this network there are two classes of consumers therefore the minimum number of required measurements in order to attain a probable load estimation must be 2. Metering devices have the ability to record active power in 1 hour intervals. For the aim of obtaining an acceptable load pattern (LP) and then load estimation, a suitable meter placement matters. Means that it is obligatory to install measurement devices at substations which are more representing the characteristics of their cluster.

In this stage, a linear procedure for pattern load profile extraction is proposed. This method uses two measured profiles to obtain PLPs of residential and commercial consumers. For this aim, residential and commercial LP for each hour obtain through solving the following linear equations:

\[
\alpha_c' P_a + \beta_c' P_r = P_{cr} \\
\alpha_c' P_a + \beta_c' P_r = P_{c_r}
\]

3-2- Pattern Extraction

Measurement devices have been installed and recorded hourly active power for 30 days. A joint representation of average typical daily loads of candidate transformers in order to depict the consumption pattern is shown in Fig. 5. The point is comprehended from Fig. 5 is high similarity of load profiles to a residential user consumption pattern. This is obvious because this case study is an urban feeder which the majority of its consumers are residential users.
Where $\alpha_i$ and $\beta_i$ are number of residential and commercial users of candidate transformer of cluster $i$, respectively

$p_{\alpha}^t$ - is measured load of candidate transformer $i$ at hour $t$

$p^0_{\alpha}$ and $p^0_{\beta}$ are the LP of residential and commercial users at hour $t$, respectively

The extracted PLPs are shown in Fig. 6.

![Residential Pattern](image)

![Commercial Pattern](image)

4. Load Estimation

In this section, the pattern loads of residential and commercial users are employed to estimate the hourly load of distribution substations. The actual values of substations' loads are available and will be used to calculate the accuracy of estimation.

The estimated loads of distribution substations are obtained via following equation:

$$\alpha_i \cdot p^0_{\alpha} + \beta_i \cdot p^0_{\beta} = p^t_i$$  (6)

Where $\alpha_i$ and $\beta_i$ are number of residential and commercial users of transformer $i$, respectively

$p^0_{\alpha}$ - is estimated load of transformer $i$ at hour $t$

$p^0_{\beta}$ and $p^0_{\beta}$ are the LP of residential and commercial

In order to show the results of load estimation and precision of method, the percent of maximum and mean error of estimated hourly loads are presented in Fig. 7.

![Fig. 7. Estimation Error for each substation](image)

It was expected that value of estimated loads for bus 15 and 25 which have measurement devices contains no error. According to the results, the mean and the maximum value of hourly errors is near %1 and %5, respectively. In addition, the results of some random meter placement are presented in Table 3.

<table>
<thead>
<tr>
<th>Selected Buses</th>
<th>Max Errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>9, 19</td>
<td>%20.8</td>
</tr>
<tr>
<td>16, 4</td>
<td>%22</td>
</tr>
<tr>
<td>24, 33</td>
<td>%25</td>
</tr>
<tr>
<td>30, 22</td>
<td>%29</td>
</tr>
<tr>
<td>26, 17</td>
<td>%31.5</td>
</tr>
</tbody>
</table>

5. Conclusion

In this paper, a novel approach for the load estimation of distribution substations based on pattern load profiles was proposed. This approach divided into three step. In step 1, fuzzy c-means clustering method was employed to determine the meter placement truly. In step 2, a heuristic method was used to extract the pattern load profiles from the recorded values. In step 3, load profiles of all substations were calculated from patterns. Finally, results of load estimation properly affirmed that the accuracy of estimation with purposeful meter placement is higher than random meter placement.

References


