*Sensors and Materials*, Vol. 35, No. 8 (2023) 3083–3096
MYU Tokyo



S & M 3376

# Identification of Customer–Transformer Relationship Based on Power Metering Sensors and Improved Density-based Spatial Clustering of Applications with Noise Clustering

Guangming Li,[1] Jisheng Huang,[1] Shibo Pan,[2] Xiao Ye,[2*] and Shi Yin[2]

[1]Lincang Power Supply Bureau, Yunnan Power Grid Co., Ltd., Yunnan 677099, China
[2]Faculty of Civil Aviation and Aeronautics, Kunming University of Science and Technology, Yunnan 650500, China

(Received May 16, 2023; accepted August 14, 2023)

***Keywords:*** DBSCAN, SMVT, user–transformer relationship identification, power metering sensors

The line loss management work is closely related to the operation efficiency of a line, the economic benefits of the electric power enterprise, and the safety of power consumption. However, an abnormal relationship between the customer and the transformer will lead to the inaccurate calculation of the line loss in the station area, thus hindering the line loss management work. Therefore, in view of the problems of large workload, high cost, and lack of timeliness of identification results in traditional manual inspection, we first screen abnormal transformers by analyzing the customer–transformer relationship using line loss data collected through power metering sensors. Then, we use the method of trend distance to measure time series similarity, applying the density-based spatial clustering of applications with noise (DBSCAN) clustering algorithm to update and identify any abnormal customer–transformer relationship, and finally verify the design method through experimental simulation analysis.

## 1. Introduction

The growth and rapid development of the scale of the information communication network have given rise to stricter requirements for the fine management of the distribution network side. The accurate identification of the relationship between a customer and the transformer has become the key to realizing such fine management and promoting the construction of a digital power grid. However, because of the complexity of the distribution network lines in the domestic station area, long-term phenomena such as business expansion, new sales, relocation, and load cutting result in frequent line changes. The traditional manual census method inhibits the timely update of the customer–transformer relationship. It is difficult to carry out effective line loss factor investigation, topology connection relationship verification, line loss management, and other work content evaluation, which significantly impacts the power supply reliability of the station area and the profit of power enterprises. Therefore, the study of the method of identifying

*Corresponding author: e-mail: 17623751772@163.com
https://doi.org/10.18494/SAM4518

ISSN 0914-4935 © MYU K.K.
https://myukk.org/

the customer–transformer relationship using data mining has become essential to the liberation of manpower and the improvement of the efficiency of power distribution management.

The customer–transformer relationship refers to the subordinate relationship between the end-user meter and the transformer in the station area.(1) The existing customer–transformer relationship identification methods mainly include the short-time outage method, station area identifier verification, and the automatic identification method. Among them, the automatic identification method can efficiently update the marketing and distribution files and is better than the first two methods regarding identification efficiency and workload. Still, the automatic identification method has higher requirements for data collection work. Since 2018, relevant companies have started working on automatically identifying customer–transformer relationships. The preliminary research mainly focused on work-frequency signal methods,(2) such as the overall average empirical mode decomposition [ensemble empirical mode decomposition (EEMD)] algorithm to improve the superimposed signal decomposition into a single signal wave, using the similarity of the work-frequency signal in the same station area to determine the customer–transformer relationship(3) and the technology of the information channel and phase line identification device of electric power industrial frequency communication to quickly identify the electrical properties of users or power equipment in the grid and to achieve the rapid identification of the customer–transformer relationship.(4) The work-frequency signal method can analyze and collect the analysis signal in real time, but it needs additional equipment, and the actual application is less economical and has low stability. To further improve the stability and anti-interference ability of the customer–transformer relationship identification method, research scholars began to shift the focus of research to the frequency over zero forms. For example, Li *et al.*(5) utilized the energy meter to generate a specific frequency of harmonic current by applying the sliding discrete Fourier transform (DFT) for real-time signal extraction and decoding. Finally, the customer–transformer relationship was determined from the binary information derived from the features. This method can effectively identify the customer–transformer relationship, but it has the disadvantage of a long identification period and that it is easily affected by the station load. For this reason, the data analysis method has become a hot research topic for customer–transformer relationship identification because of its high economy, short identification period, and real-time capability.

Domestic and foreign research scholars have conducted profound research on data analysis-based customer–transformer relationship identification methods, mainly focusing on the fields of deep learning and clustering algorithms. Wang *et al.*(6) believe that the trend of the change in voltage data can reflect the line–variable relationship of the distribution network. They used the multidimensional scale analysis (MDS) algorithm to downscale the voltage data, and then the improved *K*-means algorithm was used to determine the relationship between the station and the user. This promoted the development of intelligent control of the station, but the problems of rate meter clock drift and station identification signal crosstalk were not considered. Tang *et al.*(7) combined the meter voltage distribution curve with the discrete Frey interval distance based on the FM feature signal to design a customer–transformer relationship identification method. To further improve the accuracy of the customer–transformer relationship recognition method, later research was mainly focused on the improvement of the algorithm performance, the dataset distance measurement method, and data originality. For example, Cui *et al.*[1] improved the DBSCAN algorithm from the original dynamic characteristics of voltage data by using adaptive parameters and test operations. Bai *et al.*[8] preserved the time dependence of voltage signal sequences by using Gram's angle field, the difference characteristics of voltage fluctuations were highlighted by introducing spatial attention in the residual network, and the improved residual network classification feature mapping was used to identify customer–transformer relationships. The temporal characteristics of voltage data were considered, and the customer–transformer relationships were identified by combining the spatial attention of the residual network.[9,10] The dynamic time regularization algorithm, self-organized feature mapping, and *K*-means algorithms have been combined to design an intelligent identification method for the customer–transformer relationship in a distribution station area using the clustering of transformer low-voltage-side data and customer-side voltage timing data, considering the timing characteristics of voltage data.[11,13] The above methods improve the accuracy of customer–transformer relationship recognition from different aspects, but do not consider the impact of the imbalance of actual sample data on the accuracy of the algorithm. After preprocessing and feature extraction, Xu *et al.*[13] inputted the power of distribution lines and the power consumption of each distribution transformer. Subsequently, a model was established using a genetic network to design an intelligent identification method for the distribution network line-to-variable relationship. This method was based on the generative adversarial network (GAN) and aimed at addressing the issue of imbalanced data. The above research resulted in a reasonable and effective method for identifying the customer–transformer relationship using the clustering and deep learning algorithms, but only considered the change of the customer–transformer relationship under the effect of a single factor; unfortunately, a single empirical value is prone to omission and misjudgment.[14] Therefore, we initially utilize the line loss rate to identify abnormal line loss transformers. Subsequently, we employ the improved DBSCAN algorithm to further validate the relationship between the customer and the abnormal transformer. This approach helps prevent misjudgment and miscalculation, ensuring a timely and accurate update of the customer–transformer relationship. To improve the efficiency of the customer–transformer relationship identification method, the mayfly algorithm (MA) is introduced to optimize DBSCAN parameters, abnormal users are identified on the basis of the similarity in the trend of the change of the voltage–time series curve of the same station, and finally, the trend distance measure time series similarity (SMVT) is introduced to measure the distance between the station and each user to achieve an effective identification of the customer–transformer relationship.

## 2. Modelling

### 2.1 Abnormal station area determination

The line loss rate is closely related to the profit income of electric power enterprises. Because the rule of the change in line loss rate in a normal station area should follow a stable trend for a long time, when the relationship between a customer and a transformer is abnormal, the line loss rate may become negative or experience a significant fluctuation within the transformers.[15]

This fluctuation refers to a substantial change in line loss rate within a relatively short period of time, compared with its long-term stable trend. Therefore, the analysis of the line loss rate in a station area enables an intuitive and effective identification of an abnormal station area. Current line loss rate anomalies and their causes are shown in Table 1.

According to the line characteristics of the research object, the abnormal threshold of a 10 kV line loss rate is 10%, so the line loss anomaly identification condition of the existing transformer area is that the line loss rate exceeds 10%. The line loss rate anomaly determination conditions of an urban network and a rural network low-voltage area are line loss rates greater than 8% and 11%, respectively. The line loss rate calculation formula is as follows.

$$\delta = \frac{\sum_{i=1}^{n}\left|\frac{F_{M,i}-f_{M,i}}{F_{M,i}}\times 100\% - \frac{F_{M,i-1}-f_{M,i-1}}{F_{M,i-1}}\times 100\%\right|}{n} \tag{1}$$

Here, $\delta$ represents the line loss rate of the station area, $F_{M,i}$ represents the transformer load of the $M$th station area on the $i$th day, and $f_{M,i-1}$ represents the total power consumption of the $M$th station area users on the $i$th day.

Line loss data for August 1 to August 10, 2022 in six different station areas were calculated using existing data and analyzed using Eq. (1). Because of space limitations, the results for only one station area are shown in Table 2. For the abnormal line loss rate area, the identification of the customer–transformer relationship was reverified.

Table 1
Line loss phenomena and causes.

| Index | Phenomenon | Cause |
|---|---|---|
| 1 | Adjacent-area line loss rate 'waxing and waning' | User–transformer relationship anomaly<br>System–client relationship is not updated in time |
| 2 | Overall instability of line loss rate, high frequency of abnormal fluctuations | Meter reading error |
| 3 | Line loss rate short-term instability | User–transformer relationship anomaly<br>Meter reading error |
| 4 | Long-term high line loss rate | Three-phase load imbalance of transformer |

Table 2
Example of line loss rate data.

| Area number | Date | Line loss rate (%) |
|---|---|---|
| 017*****030 | 2022-08-01 | 3.23 |
| 017*****030 | 2022-08-02 | 2.13 |
| 017*****030 | 2022-08-03 | 3.41 |
| 017*****030 | 2022-08-04 | 4.56 |
| 017*****030 | 2022-08-05 | 4.23 |
| 017*****030 | 2022-08-06 | 4.51 |
| 017*****030 | 2022-08-07 | 6.42 |
| 017*****030 | 2022-08-08 | 10.76 |
| 017*****030 | 2022-08-09 | 3.17 |
| 017*****030 | 2022-08-10 | 3.28 |

## 2.2 Data processing model

The line loss data of six districts in 2022 are analyzed using existing data, and the results are shown in Table 2. For the abnormal line loss rate area, the identification of the customer–transformer relationship is reverified.

With the continuous advancement of digital power grid construction, the use of smart meters is gradually becoming popular in daily life, laying a technical foundation for the online identification of customer–transformer relationships and further promoting the fine management of power enterprises. The connection mode of the electric energy meter, collector, concentrator, and main station adopted at the present stage is shown in Fig. 1.

With the data acquisition scheme shown above, the voltage, current, and power data over a certain time period can be collected, but there are still irregular missing links in data acquisition and transmission mitigation. Because cubic spline interpolation has the advantages of simple calculation and good convergence and is effective in optimizing the smoothness of curves, it is widely used in the design of ships, automobiles, and spacecraft. Here, the cubic spline interpolation algorithm is used to process the missing values.

If function $S(x) \in C^2[a,b]$ is a cubic polynomial at each interval $[x_j, x_{j+1}]$, where $a = x_0 < x_1 < ... < x_n = b$ is a given node, then $S(x)$ is called a cubic spline function on node $x_0, x_1, ..., x_n$. If the function value $y_j = f(x_j)(j = 0, ..., n)$ is given on node $x_j$ and satisfies $S(x_j) = y_j$, then $S(x)$ is a cubic spline interpolation function. To calculate the cubic spline interpolation, in addition to the conditions mentioned above, it is necessary to satisfy the boundary conditions and determine a unique spline interpolation. Among them, the existing boundary conditions are mainly the following three kinds:

(1) The first-order derivative values at both ends are known.

$$S'(x_0) = f'(x_0), S'(x_n) = f'(x_n) \tag{2}$$

(2) The second derivative at both ends is known.

$$S''(x_0) = f''(x_0), S''(x_n) = f''(x_n) \tag{3}$$

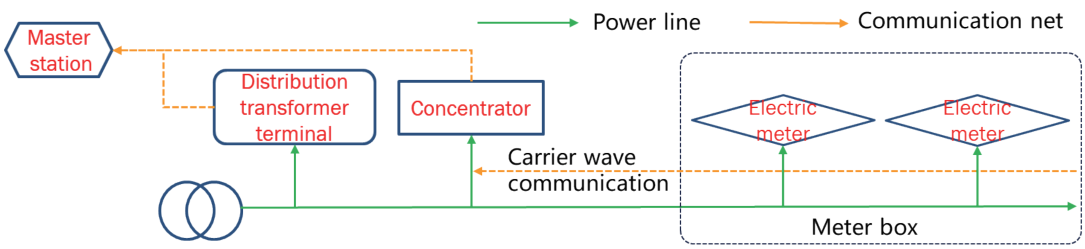


Fig. 1. (Color online) Data acquisition scheme.

When $S^{"}(x_0) = S^{"}(x_n) = 0$, the boundary condition becomes a self-admission boundary condition.

(3) When $f(x)$ is a periodic function with period $x_n - x_0$ and $S(x)$ is also a periodic function, the boundary condition is

$$\begin{cases} S(x_0 + 0) = S(x_n - 0), \\ S^{'}(x_0 + 0) = S^{'}(x_n - 0), \\ S^{"}(x_0 + 0) = S^{"}(x_n - 0). \end{cases} \tag{4}$$

Let $S(x)$ be the second derivative on node $a = x_0 < x_1 < ... < x_n = b$, $S^{"}(x_j) = M_j \, (j = 0,1,...,n)$, and $h_j = x_{j+1} - x_j$. Since $S(x)$ is a cubic polynomial at the interval $[x_j, x_{j+1}]$, $S(x)$ is a linear function on it. Combining this condition with $S(x_j) = y_j$ and $S(x_{j+1}) = y_{j+1}$, the following equation is obtained:

$$S^{"}(x) = M_j \frac{x_{j+1} - x}{h_j} + M_{j+1} \frac{x - x_j}{h_j}. \tag{5}$$

The expression of $S(x)$ can be further obtained by integrating Eq. (5) twice, as shown in Eq. (6).

$$\begin{aligned} S(x) = M_j \frac{\left(x_{j+1} - x\right)^3}{6h_j} + M_{j+1} \frac{\left(x - x_j\right)}{6h_j} + \left( y_j - \frac{M_j h_j^2}{6} \right) \frac{x_{j+1} - x}{h_j} \\ + \left( y_{i+1} - \frac{M_{j+1} h_j^2}{6} \right) \frac{x - x_j}{h_j}, \ j = 0,1, \, ..., \, n-1 \end{aligned} \tag{6}$$

Introduce $S^{'}(x_0 + 0) = S^{'}(x_n - 0)$ into the availability:

$$\mu_j M_{j-1} + 2M_j + \lambda_j M_{j+1} = d_j, \ j = 1,2, \, ..., \, n-1, \tag{7}$$

$${}_{j} = \frac{h_{j-1}}{h_{j-1} + h_j}, \ \lambda_j = \frac{h_j}{h_{j-1} + h_j}, \tag{8}$$

$$d_j = 6 \frac{f[x_j, x_{j+1}] - f[x_{j-1}, x_j]}{h_{j-1} + h_j} = 6 f[x_{j-1}, x_j, x_{j+1}], \ j = 1,2, \, ..., \, n-1. \tag{9}$$

Since the trend of the change in user voltage time series data follows a trigonometric function with time, it is periodic. To obtain $M_0, M_1, ..., M_n$, boundary condition 3 is used to further optimize Eq. (6).

$$\lambda_n = \frac{h_0}{h_{n-1} + h_0}, \ \mu_n = 1 - \lambda_n \tag{10}$$

$$d_n = 6\frac{f[x_0, x_1] - f[x_{n-1}, x_n]}{h_{n-1} + h_0} \tag{11}$$

Convert Eq. (7) into a matrix form:

$$\begin{pmatrix} 2 & \lambda_1 & & & \mu_1 \\ \mu_2 & 2 & \lambda_2 & & \\ & \ddots & \ddots & \ddots & \\ & & \mu_{n\text{-}1} & 2 & \lambda_{n\text{-}1} \\ \lambda_n & & & \mu_n & 2 \end{pmatrix} \begin{pmatrix} M_1 \\ M_2 \\ \vdots \\ M_{n-1} \\ M_n \end{pmatrix} = \begin{pmatrix} d_1 \\ d_2 \\ \vdots \\ d_{n-1} \\ d_n \end{pmatrix}. \tag{12}$$

### 2.3 Trend similarity of time series data

The classical time series similarity measures are the Euclidean distance (ED) and dynamic time bending distance (DTW). ED has the advantage of being simple and easy to implement but does not take into account the temporal characteristics of the time series data. Although DTW overcomes this drawback, the calculation is complex, and the application range needs to be greater. Since the similarity measure of the time series trend can quickly compress time series data and objectively evaluate the movement of data change, it can be an effective measure of data. Therefore, on the basis of a similar trend of user voltage time series data in the same station area, SMVT is used to measure the distance between each user and the station area. Firstly, the dimension reduction of the time series is realized by piecewise aggregation approximation, and the time series data are symbolized. The time series is measured from the perspective of the change trend to classify the research user data intuitively and effectively. According to the literature,[16] the trend–distance (TD) formula is

$$TD(X_1, X_2) = Dist(M, N), \tag{13}$$

where *M* and *N* represent the dimensions of the input time series. The calculation method is

$$\begin{cases} Dist(0,0)=0, \\ Dist(i,0)=Dist(i-1,0)+\mu_d, \\ Dist(0,j)=Dist(i-1,j)+\mu_i, \\ Dist(i,j)=\min\{Dist(i-1,j)+\mu_d, \\ \qquad\qquad Dist(i,j-1)+\mu_i, \\ \qquad\qquad Dist(i-1,j-1)+\mu_r(i,j)\}, \\ \sigma_{\max}=\max\{abs(\max(X_1))-\min(X_2), \\ \qquad abs(\min(X_1-\max(X_2)))\}, \\ \mu_t(i,j)=abs(x_{1i}-x_{2i})/\sigma_{max}, \end{cases} \tag{14}$$

where $\mu_d$, $\mu_i$, and $\mu_r$ represent the costs of insert, delete, and replace operations, respectively; $\mu_d$ and $\mu_i$ are 1, and $\mu_r \in (0,1]$.

### 2.4 Improved DBSCAN algorithm based on MA

The DBSCAN algorithm is a density-based clustering algorithm. It can find the neighborhood of each point in accordance with the given object radius and density to determine the density reachable and core points, so as to complete the classification of research data. Compared with the traditional clustering algorithm, there is no need to specify the clustering center, but the radius and density must be set artificially, which will have a certain impact on the recognition results. The MA is a biomimetic intelligent algorithm that simulates the reproduction and flight of a mayfly. Compared with classical heuristic algorithms such as the genetic algorithm and particle swarm optimization, it has an excellent global search ability and can quickly obtain the optimal solution.[17] Therefore, the MA is used to optimize the parameters of the DBSCAN clustering algorithm. The specific flow chart is shown in Fig. 2.

## 3. Flow of User–transformer Relationship Identification Algorithm

Step 1: Obtain the power data of each station area, use Eq. (1) to calculate the line loss rate of each station area, screen out the abnormal line loss station area, and re-identify the customer–transformer change relationship for the abnormal transformer.

Step 2: On the basis of the existing transformer relationship, collect the voltage data of the transformer area and corresponding users. Process the collected data using Eqs. (10)–(12).

Step 3: Input the processed data into the improved DBSCAN algorithm based on the MA, and calculate the similarity distance of time series data between a certain station and each user using Eq. (14).

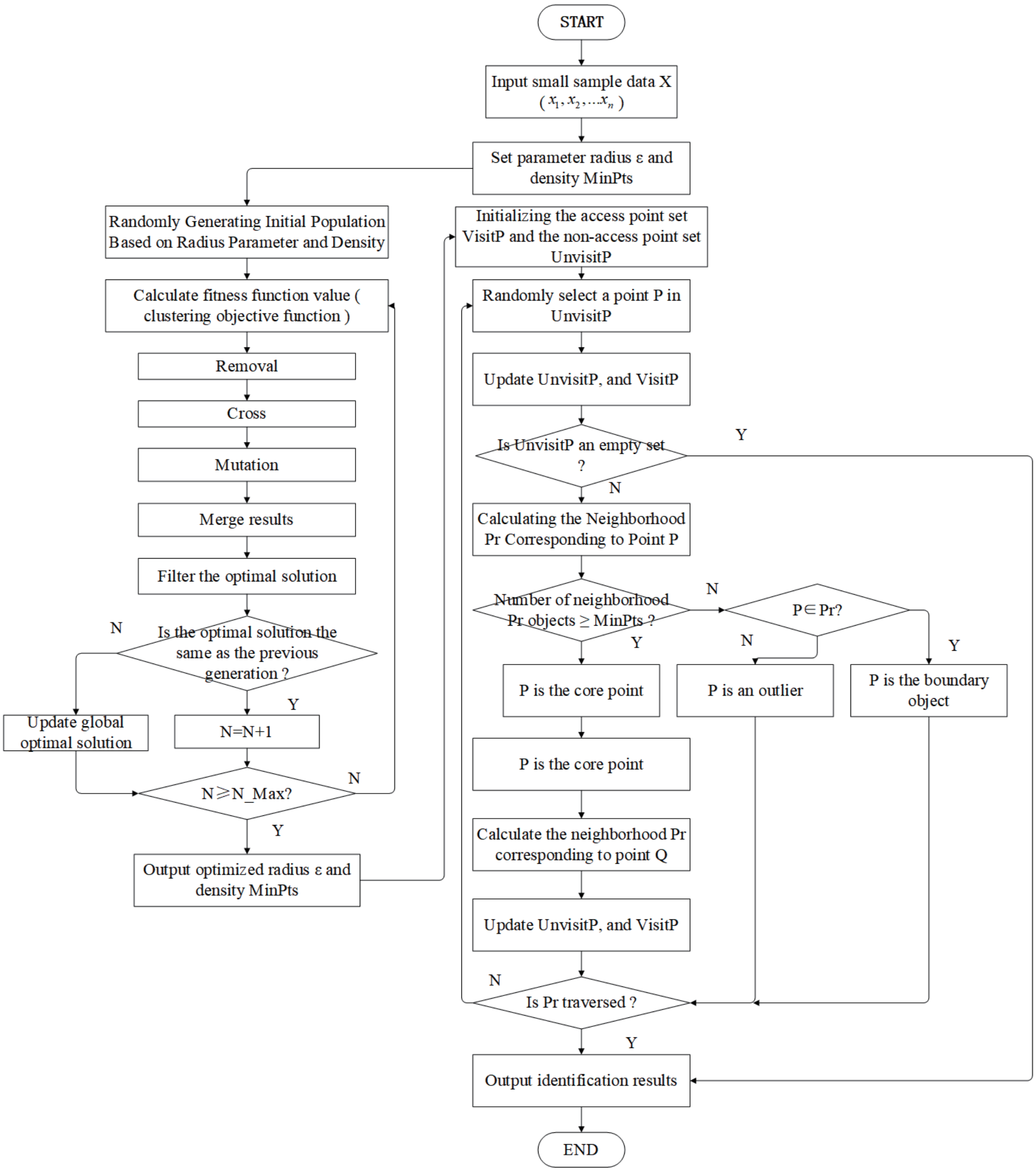


Fig. 2. Improved DBSCAN algorithm flow chart based on MA.

Step 4: On the basis of the optimized ε and MinPts parameters, calculate the core and density reachable points, and continuously update the classification results. The specific process is shown in Fig. 2.

Step 5: Refer to the classification results to compare and analyze the relationship between each user and the transformer area. Verify the accuracy of the design method using the customer–transformer relationship during the normal period of the line loss rate of the transformer area so as to determine the recognition accuracy of the customer–transformer relationship of the abnormal transformer area.

## 4. Experimental Analysis

The 10-day voltage data from August 1 to August 10, 2022 of 269 end users in six transformer areas in a certain area are selected to verify the proposed method. The relative positional relationship between each transformer area and the user is shown in Fig. 3.

On the basis of the actual collected data, the Davies-Bouldin Index of the clustering algorithm is taken as the target value, and the clustering radius ε and density MinPts of the DASCAN algorithm are determined to be 2 and 7, respectively, by using the MA. Taking the trend similarity of voltage time series data between users as the distance, the DASCAN algorithm is used to identify abnormal users. The identification results are shown in Fig. 4, and the final analysis results are shown in Table 3 and Table 4.

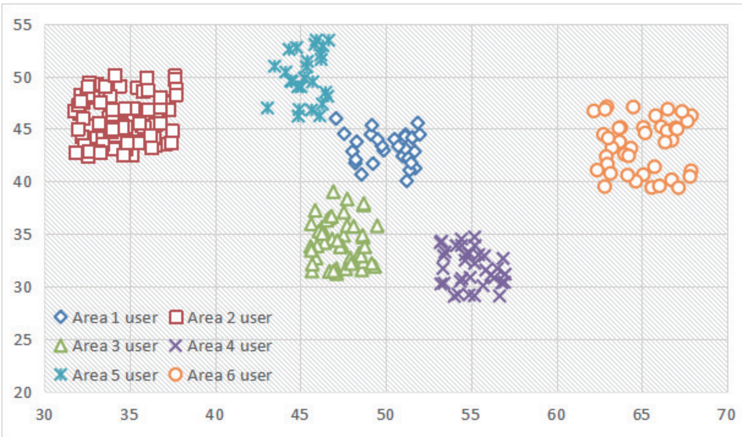


Fig. 3. (Color online) Original marketing relationship of each user.

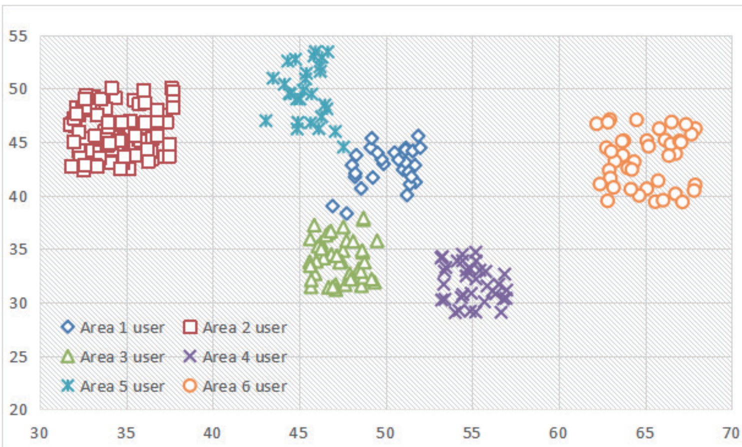


Fig. 4. (Color online) User–transformer relationship identification results.

Table 3
Identification method accuracy.

| Method | Accuracy (%) |
|---|---|
| *K*-means | 81.2 |
| OPTICS | 84.9 |
| DBSCAN | 86.25 |
| Design method | 96.3 |

Table 4
Example of line loss rate data.

| Index | Number of users/customers |
|---|---|
| 1 | 29 |
| 2 | 93 |
| 3 | 43 |
| 4 | 35 |
| 5 | 28 |
| 6 | 41 |
| Total | 269 |

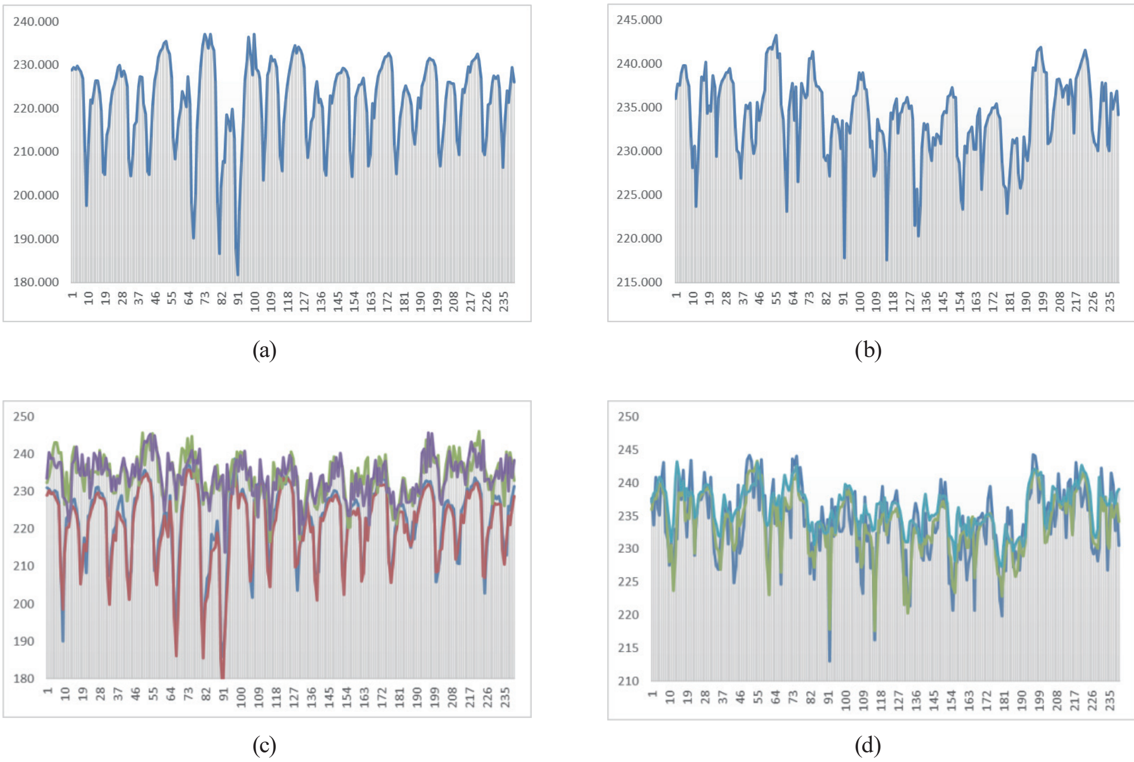


Fig. 5. (Color online) Voltage time series curve of the station area and some users. (a) Voltage curve of area 1, (b) voltage curve of area 2, (c) station 1 user voltage sequence curve, and (d) voltage time series curve of station 2 user.

From the clustering results in Fig. 4, a schematic diagram of the transformer substation relationship can be obtained. The results for the example of the 28 users of transformer No. 5 are shown in Fig. 5. The results for the other categories are essentially the same.

The voltage time series curves obtained using the clustering results are shown in Fig. 5 for two stations and some corresponding other users. Among them, the station area is equivalent to the cluster center, and the curves in Figs. 5(a) and 5(b) are the cluster center curves of station areas 1 and 2, respectively. The curve clusters in Figs. 5(c) and 5(d) are the time series voltage curves of some other users in categories 1 and 2. It can be seen from Fig. 5 that the change trend, peak, and trough of the user voltage time series curve in the same station area are highly similar, while the cluster center and user curves in different categories show obvious differences. By the shape-based clustering method for time series data, the user voltage curves with similar fluctuation trends can be clustered into one class, which represents the commonality of all user voltage curves in that class, and good results in the study of the relationship identification of the distribution transformer area have been achieved.

## 5. Conclusions

Using the DBSCAN algorithm, we studied the clustering of time series data in a power distribution station area. In view of the lack of data collected using equipment, the cubic spline interpolation algorithm was used to process the original data, followed by the calculation of the line loss rate of each station area using the power data of the station area and the user. Then, the abnormal station area was screened out. On the basis of the principle that the voltage time series curves of the same station area have the same trend, the improved DBSCAN clustering algorithm was used to recheck the relationship of the abnormal station area using the trend similarity of the time series data as the distance. The application of the method proposed in this paper can save manpower and material costs and further promote the development of digital power grids. Because of the effects of data acquisition time, power outage correlation, user address, and other factors, we examined only the voltage time series curve and line loss data; this reduced the calculation amount and improved the recognition efficiency to a certain extent. However, the scope of application of the algorithm and the stability of the calculation results must still be further studied.

## Acknowledgments

This work was supported by the Science and Technology Project of China Southern Power Grid Co., Ltd., under grant YNKJXM20222483.

## References


1 X. Cui, S. Liu, W. Jin, Z. Lin, Y. Xuan, and H. Wang: J. Power Syst. Technol. **45** (2021) 3034. https://doi.org/10.13335/j.1000-3673.pst.2020.1508
2 Z. Hong and Q. Lin: Electron. Test **18** (2019) 28. https://doi.org/10.16520/j.cnki.1000-8519.2019.18.011
3 M. Yu, R. Yu, Z. Lin, and Z. Song: J. East China Jiaotong University **37** (2020) 88. https://doi.org/10.16749/j.cnki.jecjtu.2020.01.012
4 Z. Pan, W. Zhu, and J. Pei: J. Power Demand Side Manage. **1** (2005) 32. https://doi.org/10.3969/j.issn.1009-1831.2005.01.013
5 X. Li, W. Wang, Y. Ge, L. Yao, and C. Lu: J. Electri. Meas. Instrum. **58** (2021) 115. https://doi.org/10.19753/j.issn1001-1390.2021.09.017
6 J. Wang, Z. Wan, Z. He, J. Wang, Z. Xie, and X. Wang: J. Power Syst. Autom. **42** (2020) 56.
7 D. Tang, P. Ni, Z. Jie, Y. Liu, Y. Li, and Z. Qiang: J. Autom. Electr. Power Syst. **45** (2021) 223. https://doi.org/10.7500/AEPS20200704003
8 Y. Bai, J. Xion, Y. Yang, and R. Xiao: J. Chongqing University of Technology (Natural Science) **35** (2021) 189. https://doi.org/10.3969/j.issn.1674-8425(z).2021.12.024
9 W. Song, S. Guo, J. Li, H. Liu, Q. Guo, and W. Hu: Proc. CSU-EPSA **34** (2022) 48. https://doi.org/10.19635/j.cnki.csu-epsa.000812

10 S. Liu, C. Huang, S. Hou, S. Huang, and Q. Li: J. Autom. Electr. Power Syst. **45** (2021) 71. https://doi.org/10.7500/AEPS20201123001
11 J. Yang, Y. Zhou, and J. Liu: J. Power Syst. Autom. **34** (2022) 1. https://doi.org/10.19635/j.cnki.csu-epsa.000860
12 Y. Wang, X. Zhang, H. Liu, B. Li, J. Yu, K. Liu, and L. Qin: Sustainability **14** (2022) 14. https://doi.org/10.3390/su14148611
13 M. Xu, J. Zhao, X. Wang, L. Li, Y. Xuan, and X. Xu: J. Power Syst. Prot. Control **50** (2022) 92. https://doi.org/10.19783/j.cnki.pspc.210618
14 Y. Cai, J. Tang, H. Que, J. Li, and W. Guo: J. Guangong Electr. Power **34** (2021) 50. https://doi.org/10.3969/j.issn.1007-290X.2021.008.007
15 B. Chen, K. Xiang, L. Yang, Q. Su, D. Huang, and T. Huang: 2018 China Int. Conf. Electricity Distribution (CICED) (2018) 2531.
16 H. Zhang, Z. Li, Y. Sun, and W. Zhang: J. Comput. Eng. Design **35** (2014) 1279. https://doi.org/10.3969/j.issn.1000-7024.2014.04.031
17 K. Zervoudakis and S. Tsafarakis: J. Comput. Ind. Eng. **145** (2020) 23. https://doi.org/10.1016/j.cie.2020.106559


## About the Authors


**Guangming Li** is currently the deputy director of the Busan Power Supply Station within the Lincang Power Supply Bureau of the Yunnan Power Grid Co., Ltd. He attained his junior college degree from Zhengzhou Electric Power College in 2003. Now, he is the assistant engineer and technician, and primarily focuses on various areas including marketing, measurement, distribution, and customer service. (13988305894@163.com)



**Jisheng Huang** born in November 1985, currently holds the position of Technology Innovation Management Specialist at Lincang Power Supply Bureau, Yunnan Power Grid Co., Ltd. He graduated with a bachelor's degree in Electrical Engineering and Automation from Kunming University of Science and Technology in 2008. He is currently primarily engaged in research and innovation management in the field of power transmission and distribution operation and maintenance technology. (59100051@qq.com)



**Shibo Pan** is currently a master's student at the Civil Aviation College of Kunming University of Science and Technology. (1027949014@qq.com)

**Xiao Ye** received her B.S. degree in transportation from Chongqing Jiaotong University, Chongqing, China, in 2021. She is currently working toward an M.S. degree in transportation in the Faculty of Civil Aviation and Aeronautics, Kunming University of Science and Technology, Kunming, China. Her research interests include artificial intelligence.

**Shi Yin** is currently a lecturer in the Faculty of Civil Aviation and Aeronautics, Kunming University of Science and Technology, Kunming , China. He obtained his doctoral degree from Beijing University of Aeronautics and Astronautics in 2020. Now his work involves the technical solutions related to tobacco, logistics and power industry based on swarm intelligence, multidisciplinary design optimization and flight test of near space aircraft, cooperative control of UAV cluster and bionic meta-heuristic algorithm. (buaays@163.com)