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Application of Clustering Algorithm in Fault State Classification of Low Voltage Watt-Hour Meter

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Abstract: - In this paper, a low-voltage digital watt-hour meter monitoring system for smart grid is designed. The system includes information acquisition system, low-voltage digital meter and power service system. The low-voltage digital meter uses RFID chip inside, which can accurately locate the target through high-speed transmission and remote identification. It can effectively overcome the security risks caused by information collision and the problem of slow recognition speed. According to different fault categories, community clustering method is used to classify them. In the actual determination of the fault causes of 32 electric energy meters with this method correctly analyzed the fault causes of 26 electric energy meters. The accuracy rate reached 81.25%.

Keywords: Low-Voltage Watt-Hour Meter; Community Clustering; Fault Inducement Classification; Energy Meter Rotation.

I. INTRODUCTION

People have put forward higher demands for energy saving, environmental protection and other aspects of GDP growth. However, with the rapid growth of China's economy, the problem of energy and resource shortage has become increasingly prominent, which has become an important constraint factor restricting its sustainable development. In terms of energy efficiency, reducing environmental pollution, improving power supply safety and reliability, and reducing transmission network losses, it is a major strategic demand to build "two types", and it is imperative to optimize and transform the system. In the current digital power metering and monitoring system, the use of manual meter reading and IC card pre-payment of two methods, however, in the case of economic and scientific and technological levels continue to improve, these methods have become more and more difficult to adapt to the more intelligent power system for speed, efficiency and quality needs [1]. Manual meter reading not only cannot realize the real-time monitoring of the working condition of the instrument, but also has the problem of large error and low working efficiency in data collection, analysis and statistics. The read and write window of IC card table is a kind of technology that is easy to be hacked and copied, which brings great harm to customers and power system, and can not realize real-time monitoring of power system.

Some researchers have used Bayesian neural networks to identify and forecast fault categories in power systems. According to the Weibull distribution of environmentally friendly electrical appliances, the maximum likelihood method is given to deal with the service life of environmentally friendly LED. Some scholars design online detection methods based on energy meters in the field [2]. However, the existing electric energy measurement analysis methods mainly rely on the existing electric energy measurement mode, and there are shortcomings of poor timeliness and accuracy.

At present, the sales department of the State Grid power supply Company is developing a test version of the electricity meter verification equipment, in order to better realize the effective management of measuring instruments. Power quality assessment includes reliability assessment, measurement anomaly assessment, full event assessment, overload rate assessment and clock battery low voltage assessment. Finally, through the analysis of each score, the comprehensive score of the watt-hour meter is obtained, and the size of the score can reflect the working condition of the watt-hour meter [3]. According to several important reasons for the failure of electric meters, these five types are selected. The method of community clustering was first applied to the field of sociology and computer systems, and later it was also applied to the fault diagnosis of machinery and equipment.

This project intends to organically integrate radio frequency identification (RFID) and digital electric meters, give full play to its advantages of large information transmission range, large data capacity, real-time data

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upgrade, security is difficult to copy, etc., and build a set of low-voltage terminal digital electric meter monitoring system suitable for the rapid development of smart grid [4]. The method of community clustering can better mine the data of electric meter and study the cause of failure of electric meter. The community clustering algorithm is used to "locate" a specific kilowatt-hour meter so as to realize the correct recognition and control of the meter. According to the analysis results of the method, the field personnel can roughly determine the number and number of energy meters that need to be replaced, and the number of energy meters in different places can be effectively allocated for rotation work, providing guidance for power companies to carry out energy meter rotation work.

II. Radio frequency identification technology

Radio Frequency identification (RFID) is a new, no human intervention, fast, no human intervention, fast, wireless sensor-based wireless communication system. This new label is small in size, large in information capacity, long in service life, reusable, and can position the identified object, which makes the application of RFID in smart homes, smart grids and other aspects more extensive [5]. Radio frequency identification technology is mainly divided into low frequency, high frequency, ultra-high frequency and microwave and other frequency bands, the high frequency of the high frequency band means that you can carry out longer transmission, but also faster transmission. This project proposes a new type of sensor based on UHF. Through capacitive coupling, it can accurately locate recognizable objects in a wide range to ensure its safe and stable operation. Rfid technology is based on electronic tags, antennas, readers. The electronic marker is used for data storage of the object under test, comprises a connecting component and a chip, and communicates with a reader through an antenna. Radio frequency identification technology according to its active and passive two categories, that is, active and passive [6]. Active RFID is a radio frequency technology with a built-in battery, which can be detected by a radio frequency reader to achieve effective identification of remote electronic tags, but is limited by its own endurance. Passive radio frequency identification technology, because it does not contain any electrical energy itself, can only obtain electrical energy for transmission and transmission by reading the radio waves emitted by the device, and its transmission range is small, but its working time is longer. The electronic power electronic metering device proposed in this paper can be used in the process of active or passive RFID according to specific needs, thus expanding the application field of power electronic metering device, so that it can be applied to various types of smart grid.

III. Intelligent monitoring of low voltage terminal voltage transformer

A. System Principles

The system includes information acquisition system, low-voltage digital energy meter and electricity service system [7]. The information acquisition system first collects and transmits the customer's electricity consumption information, and then processes, stores and transmits the collected electricity consumption data through the low-voltage digital electricity meter, and processes the collected information through the power supply business system, so as to control the low-voltage electronic metering meter. Through the rapid transmission and processing of information and data between various components, the operation status of the power system can be monitored and managed in real time, and the accurate positioning and rapid disposal of faults can be realized, so as to improve the reliability of the power system, ensure the stable operation of the power system, and protect the rights and interests of customers and enterprises. Figure 1 shows the system connection diagram (the picture is quoted in 5G Edge Intelligence-based Refined Power Distribution Monitoring Technology and Application).

B. Design of low-voltage digital watt-hour meter

The invention relates to a special power chip, a microprocessor, a clock chip, a liquid crystal display, a memory, a keyboard, an RFID chip, an intelligent switch, a power module, a power management module and a battery. The special power chip transmits the data of power consumption to the single chip computer, which stores and analyzes the data and displays the user's power data on the liquid crystal display screen. If at this time, when the microprocessor detects a failure in the power grid, the RFID chip will immediately store the data, and then send the data to the power supply department in the background, so that the rapid overhaul of these devices can be achieved [8]. At the same time, it is also connected to a micro computer, which can cut off the customer's line in time. Figure 2 is a block diagram of the low-voltage digital Energy Meter structure (the picture is quoted in the Research on Three-Phase Electronic Multifunctional Energy Meter).

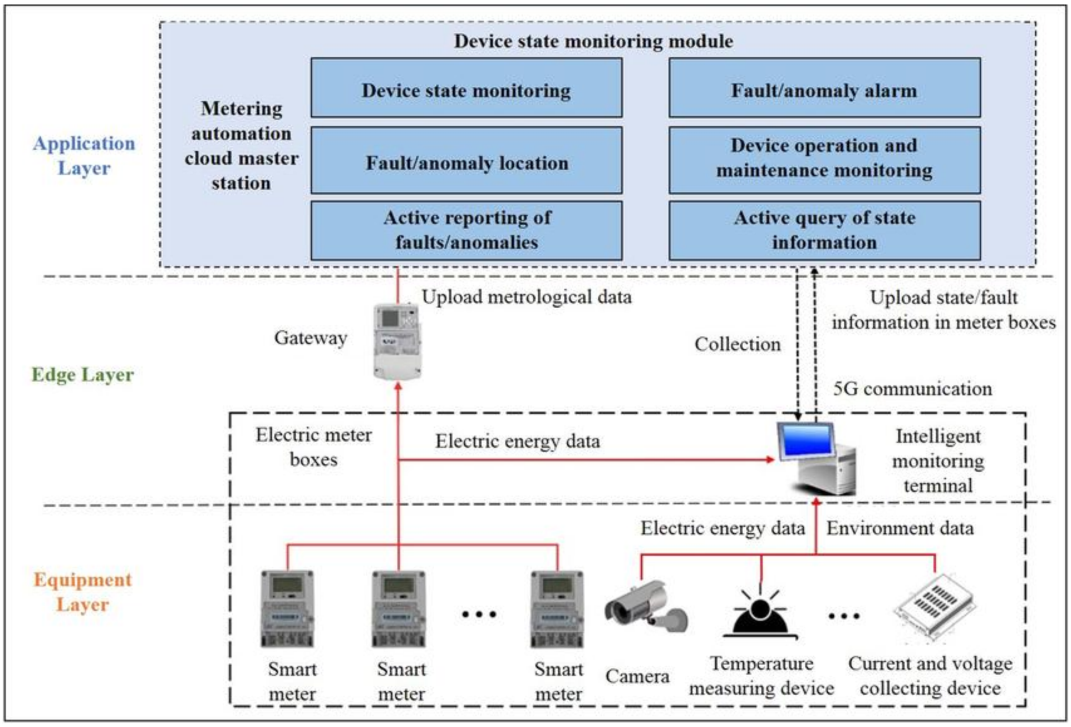

Fig.1 Connection diagram of low-voltage watt-hour meter fault monitoring system

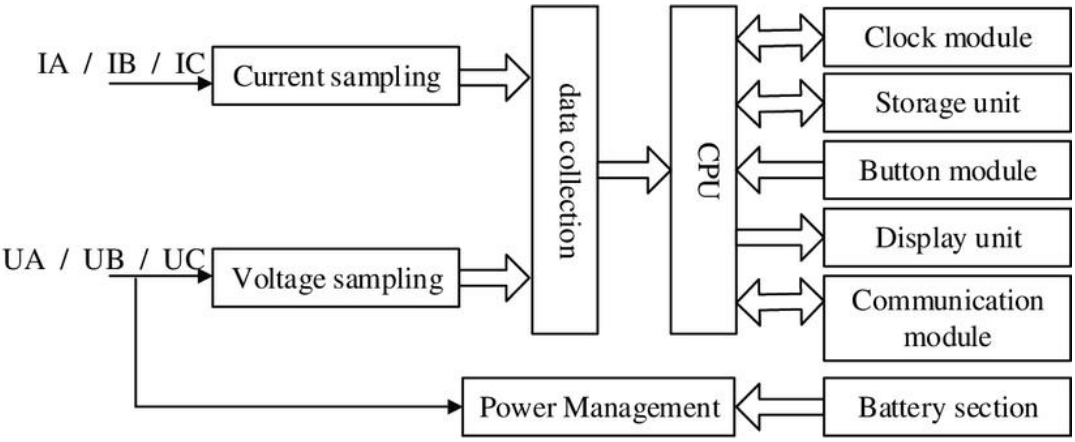

Fig.2 Low voltage end digital energy meter structure block diagram

C. Characteristics of low voltage terminal watt-hour meter verification device

Low voltage terminal digital watt-hour meter test system has the following characteristics: 1) RFID technology and smart grid organic integration, convenient real-time monitoring and control of the state of the power grid, thereby enhancing the response to the fault signal, can find the accurate electrical fault location in a short time, and the first time to send maintenance personnel to repair, thus enhancing the reliability of the power grid, to ensure the safety and stability of the power grid. 2) For low-voltage terminals, active or passive RFID modules can be used to expand their application to a variety of smart grids. 3) The integration of radio frequency identification (RFID) and smart grid can effectively overcome the problems of information conflict, poor security, and long identification time, ensure the normal operation of the system, and adapt to the production and life needs of the country.

D. Software Design

In the smart grid, the software part of the low-voltage digital power meter monitoring system has the following functions: through the power meter monitoring system to store and analyze the data collected by the information acquisition system, if there is a fault, the fault information and fault direction is transmitted to the power supply department. The main process is shown in Figure 3 (the image is referenced in Energies 2023, 16(23), 7850).

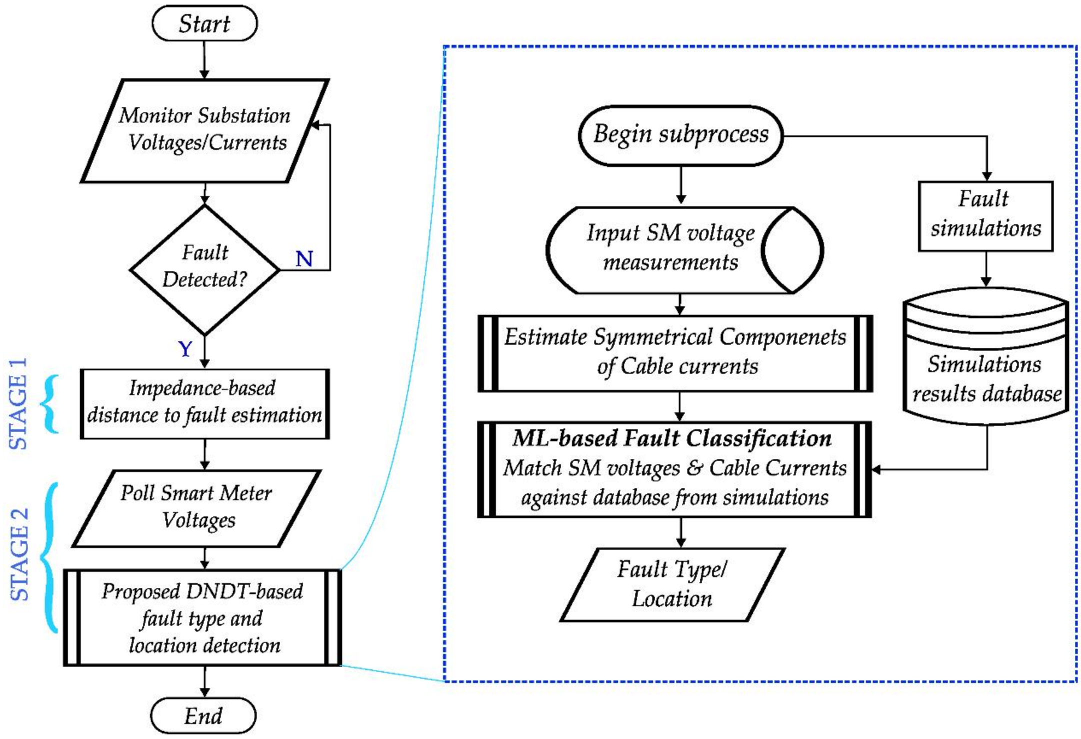

Fig.3 Main process

Part of the block diagram of the meter monitoring system is given in Figure 4 (the picture is quoted in Three-Phase Power Metering ICs). The meter monitoring device transmits data to the microcomputer, in the case of no problems, in the case of no problems, it is stored and displayed on the LCD screen, if there is a problem, it reads the fault information and the fault location information through the RFID system, and transmits the problem information and the fault location information to the power supply business system for processing. A trip request signal is also issued, and the smart switch will trip at the fault location.

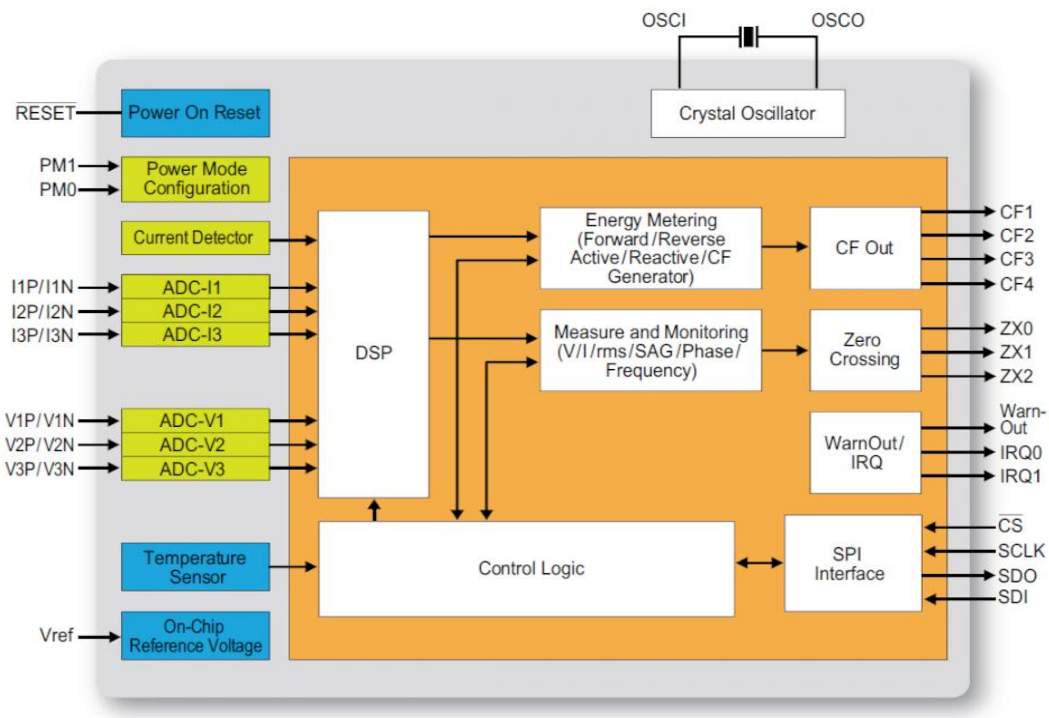

Fig.4 Flow chart of watt-hour meter monitoring system

IV. THE INTRODUCTION OF GROUP CLUSTERING ALGORITHM

The intelligent recognition method of low voltage watt-hour meter based on this method has the following advantages: there is no need to set the number of categories in advance; Suitable for objects with multiple characteristic factors. These two characteristics determine that the method is different from the general clustering method, especially suitable for power system fault type identification and fault cause analysis in power system [9]. The classification criteria of the association is to use various scientific and technological means in the network to divide the nodes close to each other into several independent organizations. The contact nodes are divided into several communities, so that the contact nodes in the network are as close as possible to the nodes in the network. The division of community in complex network can be divided into global community division and local community division. This paper presents a complete community division method based on social organization. Only one set of social organizations can be unearthed at a time, and only one set of nodes in the network can be studied.

Community clustering is an algorithm that groups close nodes into the same community. In the power metering system, the power metering system is regarded as a complex power grid. In this method, various failure factors arising from the normal operation of an electric meter are regarded as a node in the power grid. The dependent elements are regarded as a set of edges composed of nodes [10]. Then, the group clustering method is used to group each country. Each state variable in the state evaluation is regarded as a node in a network in which connected nodes are connected by connected connections and there are no connections between unconnected nodes. This is just as there are many reasons for the failure of power meters, some factors are correlated with each other and some factors are unrelated, and community clustering is used to bring together factors with similar effects[11].

A. Order and order assignment

The connectivity score of a vertex denotes the number of edges linked to it. Within an oriented network, the edge count of vertices may be categorized into two types: in-degree and out-degree. To put it succinctly, a vertex with a higher edge count holds a more significant position to some extent. The significance of a vertex is quantified as the mean of the vertex's importance as calculated by a probability distribution function.

B. Average path Length

The distance s_{ij} between two nodes i and j in the network [12]. The maximum distance between any two nodes is denoted by S:

$$S = \max_{i,j} s_{ij} \tag{1}$$

The average path length of the network L is in the network, namely:

$$L = \frac{1}{\frac{1}{2}M(M+1)} \sum_{i \geq j} s_{ij} \tag{2}$$

Where M is the number of network nodes. For mathematical purposes, the distance from the node to itself is included in formula (2). If the distance from the node to itself is not taken into account, the right end of the formula (2) is multiplied by a factor $(M+1)/(M-1)$.

C. Clustering coefficient

In everyone's social network, the two people that everyone knows may also know each other, which is called the clustering property of the network. In general, when a node in a network is assumed to have an edge connecting it to other nodes, this node is called the node's neighbor node, and there are at most $t_i(t_i-1)/2$ edges between this node [13]. The ratio between the number of edges W that actually exists between t_i nodes and the total number of possible edges $t_i(t_i-1)/2$ is defined as the clustering coefficient λ_i of the node H, namely.

$$\lambda_i = 2W_i / (t_i(t_i - 1)) \tag{3}$$

The clustering coefficient of the whole network. Obviously, the clustering coefficient is greater than 0 and less than 1. When all nodes are independent nodes $\lambda=0$, there is no connecting edge in the whole network [14]. When any two nodes in the entire network are connected, $\lambda=1$. Many large complex networks have distinctive clustering effect, which shows that the general complex networks are not completely random distribution, they are also divided into different categories based on certain rules.

D. Similarity

In the study of complex networks, it is often necessary to find out the significant differences between different individuals, so as to better understand the correlation between different individuals and even the whole. In the process of community division, the relationship between samples must be analyzed [15]. In complex networks, similarity refers to the comparison of similarities between two nodes. Comparing the two features of two nodes, if the distance between two nodes is short, it means that the similarity between two nodes is greater. The farther away, the less it looks. There are two objects X, Y that both contain M dimensional features, $X = (x_1, x_2, x_3, \text{L L}, x_n)$, $Y = (y_1, y_2, y_3, \text{L L}, y_n)$, and calculate the similarity of X and Y. Euclidean distance is needed to analyze and solve the community clustering algorithm. Euclidean distance is calculated as follows:

$$s_{ij} = \sqrt{(u_{i1} - u_{j2})^2 + (u_{i2} - u_{j2})^2 + \cdots + (u_{ip} - u_{jp})^2} \tag{4}$$

The greater the distance to Europe, the lower the similarity between the two. It can be divided into linear similarity, inverse proportional similarity, exponential similarity and elliptic similarity [16]. In general, we define that itself to be 0. After studying social clustering methods, we choose the most suitable method for exponential similarity through the analysis of relevant data.

$$\varphi_{ij} = \exp(-\eta * s_{ij}) \tag{5}$$

η 10 is the most reasonable. The goal of this similarity function is to enable the existence of complex networks with good social organization [17]. The degree of similarity of associations is similar, and the degree of similarity of associations is very different. The similarity between the node itself and itself is defined as 0, and the similarity between the two nodes is equal, so the similarity matrix ϕ is a symmetric matrix. The similarity matrix is:

$$\phi = \begin{bmatrix} \varphi_{11} & \varphi_{12} & \cdots & \varphi_{1n} \\ \varphi_{21} & \varphi_{22} & \cdots & \varphi_{2n} \\ & & \cdots & \\ \varphi_{n1} & \varphi_{n2} & \cdots & \varphi_{nm} \end{bmatrix} \tag{6}$$

The appropriate discriminant factor ϕ is selected for the similarity. When the similarity is greater than ϕ, it is set to 1, indicating that there is ϕ connection between nodes; when the similarity is less than ϕ, it is set to 0, indicating that there is no connection between nodes [18]. Then the similarity matrix of formula ϕ above becomes a matrix with only 0 and 1, which is the similarity adjacency matrix.

E. Community module degree

Modularity is used to measure the effectiveness of group segmentation. The ratio of edges at the intrinsic nodes of the connecting social organization, plus the ratio with any two nodes of the same organization [19]. It is found that the similarity of internal nodes is high, while the similarity of external nodes is low. The higher the level of modularity of organizational structure, the greater the hierarchical effect of association. The expression of the module degree is as follows:

$$R=\frac{1}{2n}\sum_{i,j}\left[\phi_{i,j}-\frac{t_i t_j}{2m}\right]\gamma(z_i,z_j) \tag{7}$$

Where, $m=\frac{1}{2}\sum_{i,j}\phi_{i,j}$ represents all the weights in the network, $\phi_{i,j}$ represents the weights between node i and node j, $t_i=\sum_j\phi_{i,j}t_i$ represents the weights of the edges connected to vertex i, z_j represents the community to which the vertices are assigned, and $\gamma(z_i,z_j)$ determines whether node i and node j belong to the same community. For a network with λ communities, the formula for community modularity can be simplified as:

$$R=\sum_{a=1}^{\lambda}e_{aa}-\sum_{a=1}^{\lambda}(\sum_{b=1}^{\lambda}e_{ab})^2 \tag{8}$$

$\sum_{a=1}^{\lambda}e_{aa}$ indicates the node connections within the community, and $R=\sum_{a=1}^{\lambda}(\sum_{b=1}^{\lambda}e_{ab})^2$ indicates the node connections between the community.

V. Establishment of community clustering and classification model

In the analysis process of this method, the influence factors of the region, appearance damage and other additional information of the watt-hour meter are not considered, and only the data factors of the watt-hour meter are considered. All metering meters are from common variable to single phase complex rate remote metering 2.0 meters. All seven batches of electric energy meters in each county and city of Zhejiang Province are scored by group clustering method [20]. The data used are the scores of various impact factors of each kind of electric energy meter. The classification results provide guidance and reference for the rotation work of the power company, and facilitate the power workers to determine the fault factors. The troubleshooting procedure is as follows:

(1) Input batch watt-hour meter reliability score, metering anomaly score, total event score, overload rate score, clock battery undervoltage score, calculate European-style distance, exponential similarity, calculate clustering coefficient, set discrimination factor ξ, construct similarity adjacency matrix ϕ, and establish fault sample model $F(X,\phi)$;

(2) Initialize the network and divide the data into Z subsets to ensure that the number of communities is greater than the fault type;

(3) Calculate community module degree R, calculate the change of community merger index $\Delta\xi$ corresponding to each community after the initial community merger, and find out the maximum value in $\Delta\xi$. If the calculation result always contains $\Delta\xi>0$, continue until the calculation result $\Delta\xi<0$;

(4) Output data classification corresponding to $\Delta\xi$ to achieve fault state analysis.

VI. Case analysis

Because a meter with a total score of less than 70 is likely to be a faulty meter, the meter with a total score of less than 70 will be determined according to the total score of each batch when the meter is classified by the corporate cluster. The scores of each failure factor are normalized and then clustered, and the power meter clusters with similar values are combined together [21]. Through the comparison of various data, the discrimination of various failures is realized. One or more failure factors of a certain type of energy meter have data and are very high, so this kind of failure is the main reason for the failure of energy meter. Batch ϕ Because the overall score of the batch is very low, a total of 78 energy meters with less than 10 scores are selected through the screening method for community clustering. Take batch ϕ as an example. Because the total event score of this batch is zero, the total event score of this batch is not considered. The scores of watt-hour meters in batch ϕ for unreliability, abnormal metering, overload rate, and undervoltage of clock battery are shown in Table 1. Due to the large number of watt-hour meters in batch ϕ, only some watt-hour meter scores are listed here.

Table 1 Energy meter score of batch ϕ part

batch ϕ Energy meter serial number	Unreliability score	Measurement anomaly score	Overload rate scoring	Clock battery undervoltage score
1	90.81	0	0	99.89
2	90.91	0	0	0
3	90.91	0	0.10	46.67
4	90.81	0	0	91.41
5	91.41	0	3.53	99.99
6	90.61	0	0.09	99.70
7	90.91	0	15.99	99.89
8	92.73	0	0	0
9	90.81	0	0	99.58
10	88.69	94.95	0	0

The score of each failure cause of 78 kilowatt-hour meters in batch ϕ is shown in Figure 5, which is used to represent four kinds of failure inducing factors, such as unreliability of the meter, abnormal metering, overload rate and insufficient clock battery, represented by the vertical axis. The energy meter failure cause score after the standardization of this batch of scores is shown in Figure 6, and its horizontal axis is consistent with that of Figure 5, while the standardized electrical energy score value is taken as the vertical axis.

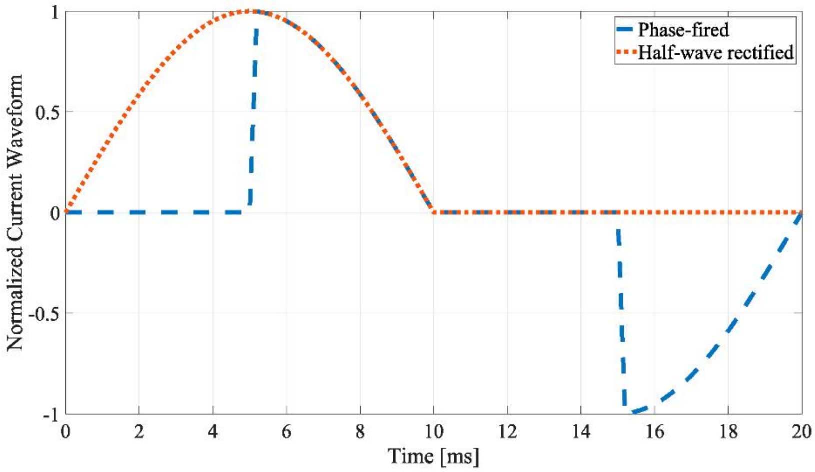

Fig.5 Breakdown factor score diagram of watt-hour meter

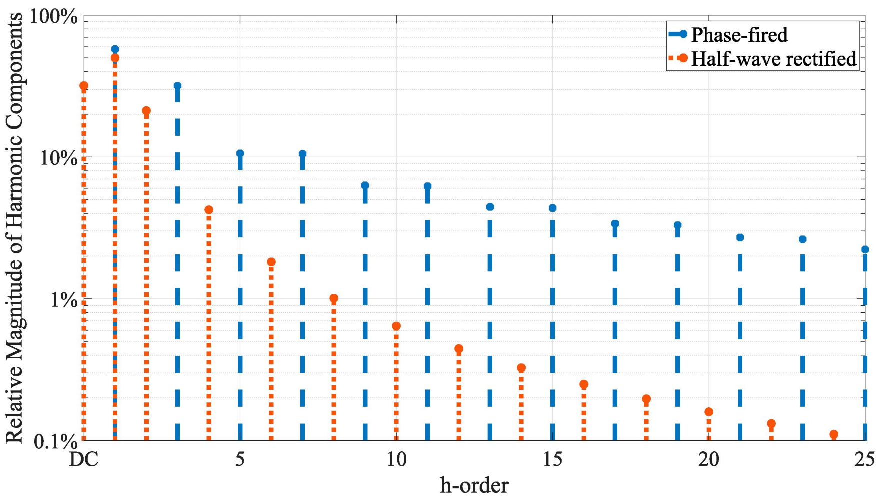

Fig.6 Diagram of the normalization of watt-hour meter fault factor scores

The clustering analysis of this batch shows that the clustering results of this batch can be divided into 5 categories. Among them, the first level is 41 units, 28 power meters, the third level is 4 units, the fourth level is 3 units, and the fifth category has 2 energy meters. Because the number of result tables for categories 4 and 5 is too small to be representative, we will not discuss them here. The results of normalized cluster scores for categories 1, 2, and 3 are illustrated in Figures 7, 8, and 9:

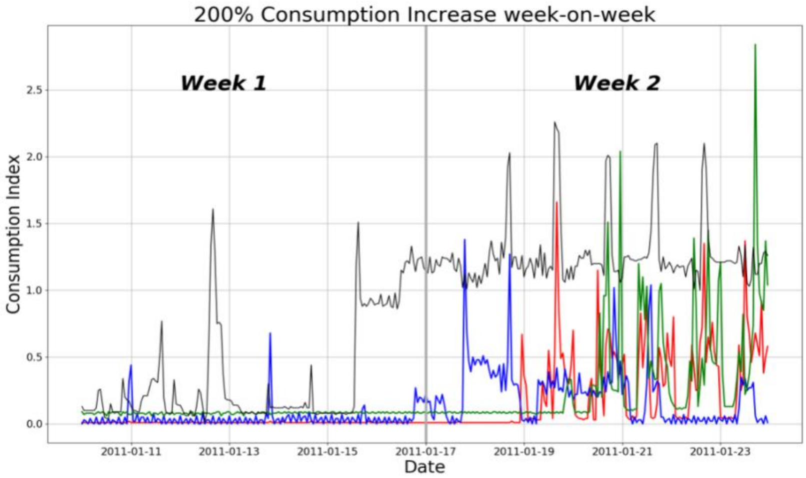

Fig.7 Diagram of clustering the first type of results

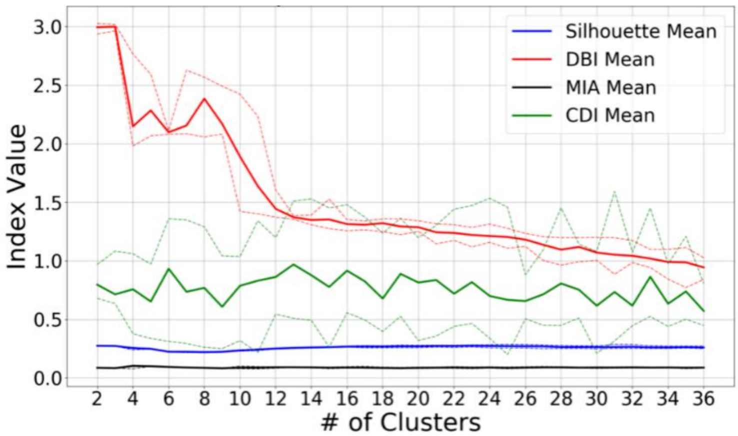

Fig.8 Diagram of the calculation results of the second type of clustering

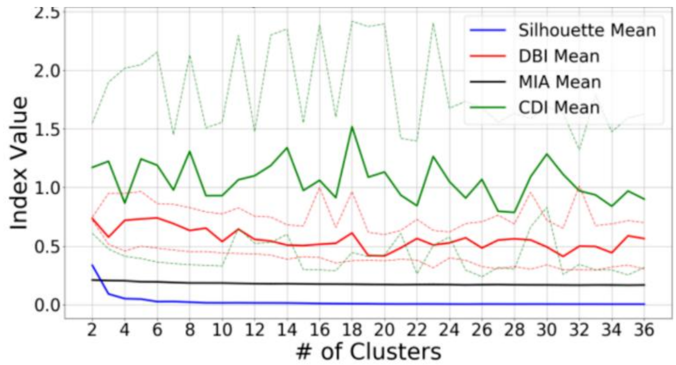

Fig.9 Diagram of the result of the third type of clustering calculation

The data of associations after merger and acquisition are highly similar, which indicates that it is reasonable to use association clustering method to classify associations [22]. According to the fault list obtained by clustering, the classification is made, one type of watt-hour meter because the number 1 and 4 are relatively large, so the possible failure of this type of watt-hour meter is relatively high in unreliability, and there are some abnormal clock failures; The second type of meter, because the number 1 is larger, the unreliability of the second type of meter is higher, and the third type of meter has the overload rate of the meter; The third type of meter, because level 1 is very high, therefore, the failure of type 3 is due to the very high unreliability of this class. The failure table of the enterprise cluster by batch is shown in Table 2.

Table 2 Number of community cluster classification categories for each batch of energy meter

lot	Community clustering Number of categories
A	Category 5
B	Category 5
C	Four kinds
D	Nine categories
E	The second kind
F	Seven categories

Because most of the watt-hour meters below 70 points in this batch are 66-70 points, in order to reduce the clustering error, 154 watt-hour meters below 66 points are selected by filtering method as community clusters; Group C, Group D, Group E, Group F, and Group G all select watt-hour meter groups below 70 percentage points, with cluster targets of watt-hour meter 153,101,202,284, and 28 groups. The reasons for batch clustering failure are listed in Table 3:

Table 3 Causes of failure in cluster analysis of each batch community

lot	Community cluster analysis causes
A	The first category: unreliability, clock battery undervoltage
	The second category: unreliability, energy meter overload rate
	The third category: unreliability
B	The first category: measurement anomalies
	The second category: overload rate of electricity meter
	Category 3: Total event
C	The first category: measurement anomalies
	The second category: overload rate of electricity meter
D	The first category: abnormal metering, overload rate of electricity meter
	The second category: abnormal measurement
	The third category: abnormal metering, clock battery undervoltage
	The fourth category: energy meter overload rate, clock battery undervoltage
	Category 5: Full event, clock battery undervoltage
E	The first category: measurement anomalies
	The second category: abnormal metering, energy meter overload rate
F	The first category: unreliability, clock battery undervoltage
	The second category: abnormal measurement
	Category 3: Total event
	The fourth category: overload rate of electricity meter

In view of the lack of comprehensive inspection of the energy meters collected by most electric power enterprises, this paper only calculates the classification accuracy and reliability of the energy meters with fault causes. There are a total of 32 instruments with the result of fault cause inspection in each batch, of which 26 instruments can judge the correct fault cause through modeling, and the accuracy reaches 81.25%. This correct rate shows that using the company clustering algorithm to judge the failure cause of the electricity meter is credible, and can be gradually applied to the actual instrument inspection in the future. This paper classifies the causes of electric meter faults by means of community clustering method, and can summarize and identify the faults of electric meter. The preliminary determination of the cause of the failure is convenient for the actual judgment of the power workers in the process of dismantling and testing, and provides guidance for the power supply company's energy meter replacement to a certain extent.

VII. CONCLUSION

This project intends to integrate radio frequency identification (RFID) with smart grid, which can effectively overcome the problems of information conflict, poor security, long identification time and improve the response ability to failure information on the premise of ensuring information transmission. The failure of electric meter is preliminarily judged. The association cluster model can make a preliminary determination of the cause of the failure of the suspicious energy meter, so that it can be predicted in the future, and help the power supply personnel to better grasp the number of energy meter failures and the cause of the failure, so that the power supply enterprise work load has been greatly reduced, saving a lot of manpower and resources.

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