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Design of Intelligent Information Monitoring System for Distribution Network and Adjustment of Alarm Threshold

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Abstract
In the current distribution network information monitoring system, there are many false alarm information, which forms redundant interference to the fault alarm threshold, and it is difficult to ensure the alarm accuracy of the monitoring system. The distribution network intelligent information monitoring system and the alarm threshold adjustment method based on machine learning are designed, with the physical layer of the system designed to collect the operation status information of each line and equipment of the distribution network according to various sensors, and transfer it to the data layer. The data layer extracts, processes, and classifies the received information, stores it in the database, obtains the abnormal information in the information base, and adjusts the alarm threshold based on the fuzzy clustering method in machine learning, realizing intelligent monitoring of distribution network. The test results show that the detection performance of abnormal information is good, the abnormal information in the data can be obtained accurately, the clustering of the target category of abnormal information can be completed according to the eigenvalue, and has a good threshold adaptive adjustment ability, to maximize the balance between human, machine, and power grid operation state in the process of distribution network monitoring information, ensure real-time and reliable monitoring and alarm results.

Category: Information Retrieval / Web

Keywords: Machine learning; Distribution network; Intelligent monitoring; Information system; Alarm threshold; Fuzzy clustering

I. INTRODUCTION

A distribution network is a power network that realizes the distribution of electric energy. With the evolving smart grid, the network structure is becoming more and more complex. Normally, the structure has a large number of overhead lines, cables, transformers, and other power equipment, and it generates a lot of data information, which requires special system monitoring [1]. Presently, the electricity demand is gradually increasing, the scope of electricity service is constantly expanding, and the number of grid failures is also rising. At the same time, the intelligent distribution network information monitoring system acquires more and more monitoring information [2]. This leads to a large amount of monitoring information, including more false alarm information. And with the continuous expansion of the power grid, the handling capacity of the system is gradually approaching the limit. If the information is not processed accordingly, a large amount of monitoring information is presented to the intelligent system at the same time, which will cause significant fluctuations in the system threshold. This will

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significantly impact the safe operation of the power grid [3].

Zhang et al. [4] and Zhang et al. [5], have previously conducted research on monitoring systems to realize the intelligent monitoring of the distribution network, based on the Internet of Things, ARM, and DSP, respectively. Design the substation intelligent monitoring system to realize the centralized monitoring and alarm processing of the substation. The above systems can all realize the monitoring and information processing of the distribution network. However, there are still some deficiencies in the processing efficiency of monitoring information and the accurate analysis of alarm threshold information. As a science of artificial intelligence, machine learning covers a variety of disciplines and theories. It can have good data processing ability and can realize the specified analysis and processing of data. Based on sample data, it can complete the training and optimization of the machine and realize the processing of the target.

This paper designs a distribution network intelligent information monitoring system based on machine learning to improve the processing efficiency of monitoring information and ensure the timely processing of power grid faults. The alarm threshold can be set to ensure the reliability of the alarm information and the safe operation of the power grid.

II. DESIGN OF INFORMATION MONITORING SYSTEM AND OPTIMAL ADJUSTMENT OF ALARM THRESHOLD

A. System Logic Structure Design

The distribution network intelligent information monitoring system is mainly composed of five layers; the physical layer, data layer, business management layer, information request layer, and terminal display layer, respectively. The overall architecture of the system is shown in Fig. 1.

Physical layer: The physical layer is the basis for system operation, including GPRS, sensors, transformers, GPS, microprocessors, etc., to ensure communication and transmission during system operation. At the same time, it is used to monitor and collect the running status of each line and equipment in the distribution station [6], and transmit it to the data layer.

Data layer: This layer completes the processing of distribution network monitoring information through information extraction, processing, and model training. The information is classified and processed, and stored in the corresponding information bases, which are the picture information base and the video information base, respectively. It also provides technical support for business management [7]. Information that has not been processed by the data layer cannot be transmitted to the business processing layer.

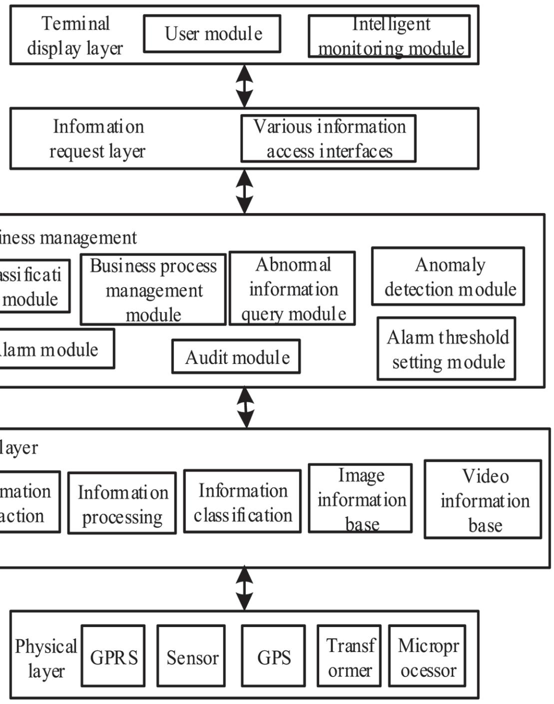

Fig. 1. Overall system architecture.

Business management layer: This layer consists of multiple modules, including a classification module, audit module, process management module, information query module, alarm module, abnormal information detection module, and alarm threshold setting module. This layer can retrieve information from several layers [8], and implement abnormal information monitoring on the information through the support vector machine model of machine learning. According to the set alarm threshold, the judgment is carried out, and the judgment result is transmitted to the terminal display layer through the information request layer.

Information request layer: This layer is the core to ensure normal information transmission of the service management layer and the terminal display layer. In the actual application process of the system, there will be a high concurrency of information [9]. Therefore, to ensure the effective reading of information, the information request layer completes the information reading between layers through various access interfaces.

Terminal display layer: This layer includes a user module and an intelligent monitoring module. The user module is used to complete the management of user information, user request sending, and user identity verification. The information is processed [10] to ensure the safe operation of the power grid.

The physical layer of the system completes the monitoring and collection of the operation information of the distribution network through the microcontroller and various collection devices, and transmits the collected information to the data layer for relevant processing, and completes the classified storage of the information. The business management layer performs anomaly detection and analysis of the collected information to determine whether an anomaly occurred. Then it sends the analysis result to the terminal display layer through the information request layer [11].

B. System Hardware Logic Structure Design

The collection, transmission, and storage of the distribution network information monitoring system will cause a large amount of CPU occupancy rate, which reduces its efficiency. Therefore, when the system is designed, the physical layer adopts ARM and DSP dual-CPU structure design. The main controller of this structure is the ARM, and the data processor is DSP. The ARM is used as the connection between the two CPUs to complete the efficient exchange of information. Moreover, ARM has different interfaces and good control performance [12]. At the same time, it combines with the good computing performance of DSP. On the basis of ensuring efficient operation of the system, the collection of distribution network operation information can be completed. Its structure is shown in Fig. 2.

Through the relay, the high-voltage live detection of the distribution network and the collection of blocking information are completed. Various types of sensors are connected to communication interfaces and smart terminals. The communication controller exercises control over the remote data exchange [13] and it can be connected with

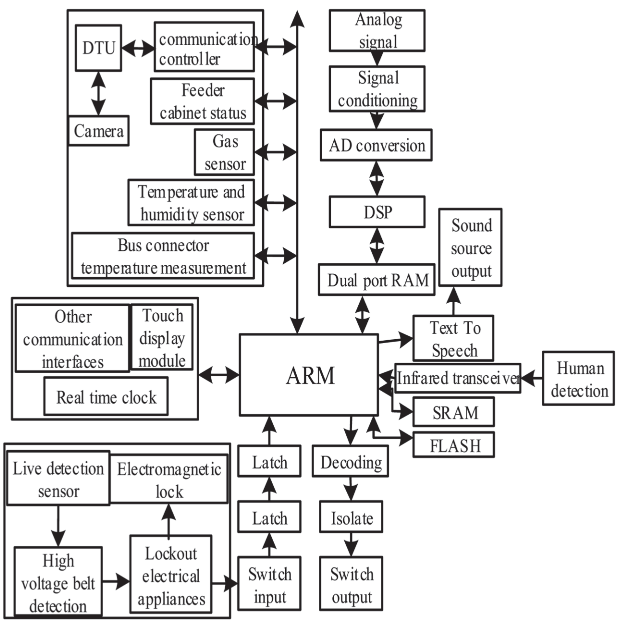

Fig. 2. Intelligent monitoring terminal hardware structure.

DYU. According to the wireless link, the connection and interaction between the monitoring center host and DYU are realized, and the interaction of information monitoring is also realized.

C. Classification of Abnormal Data in Distribution Network based on Machine Learning

As a typical machine learning algorithm, the support vector machine has good generalization ability. To ensure reliable detection of information, it is combined with a linear model and regression model to construct an anomaly information detection model. The model completes the detection of outlier information based on the support vector machine, suppression of the overfitting phenomenon based on the regression model, and realization of the abnormal data classification in the distribution network [14].

Let $\{x_i, i = 1, .., n\}$ represent the sample set and be a positive class. According to the composition concept of the model, calculation of the classification hyperplane is performed. For better results, it is converted into the following formula:

$$\min\left(\frac{1}{2}\|w\|^2 - \rho\right)$$
$$s.t \quad \left(w.\phi\left(x_i\right)\right) \geq \rho \,. \tag{1}$$

$\xi \geq 0$ represents the relaxation factor and is non-negative. To ensure the robustness of the model, the optimal trade-off of complexity is avoided. Introducing ξ into the model for optimization, the formula becomes:

$$\min\left(\frac{1}{2}\|w\|^2 + \frac{1}{vn}\sum_{i=1}^{n}\xi_i - \rho\right)$$
$$s.t \quad \left(w.\phi\left(x_i\right)\right) \geq \rho - \xi_i \quad and \quad \xi \geq 0 \,. \tag{2}$$

In the formula, w and ρ both represent parameters and belong to the superclassification plane. The estimated parameter is denoted as v, which is given in advance, and it represents the upper and lower bounds, that belong to the support vector rate. ϕ stands for nonlinear mapping. $\frac{1}{2}\|w\|^2$ stands for planning item.

The ρ value can be obtained from any sample that satisfies the $0 < \alpha_j < \frac{1}{vn}$ condition, namely:

$$\rho^* = \sum_{i=1}^{n}\alpha_i^*\kappa\left(x_i, x_j\right) \tag{3}$$

At this time, the optimal classification hyperplane is $w^*\phi\left(x\right) - \rho^* = 0$. Based on this, the solution formula of the decision function is:

$$\begin{aligned} f(x) &= \operatorname{sgn}\left(w^* \phi(x) - \rho^*\right) \\ &= \operatorname{sgn}\left(\sum_{i=1}^{n} \alpha_i^* \kappa\left(x_i, x_j\right) - \sum_{i=1}^{n} \alpha_i^* \kappa\left(x_i, x_j\right)\right). \end{aligned} \tag{4}$$

In the formula, $\kappa(x_i, x_j)$ represents the kernel function. α_i^* stands for support vector. If the sample x satisfies the $f(x) \geq \rho$ condition, it means that x is within the area, otherwise, it is out of range. For each $f(x)$, a binary classification function is implemented. If the return value is +1, it means that the information is normal. If the return value is -1, it is abnormal information, and the classification is completed.

D. Adjustment of Alarm Threshold Based on Fuzzy Clustering

1) Threshold Adjustment

In the abnormal information of the distribution network, there is a certain amount of false alarm information. Too much false alarm information will lead to a large amount of information processing and low efficiency. Therefore, to quickly identify the real abnormality, the alarm threshold is set, which is done by fuzzy clustering.

Fuzzy clustering can simplify information and complete the classification and analysis of similar information. It divides the abnormal information detected in Section II-3 to form several categories and recombine variables with similar information characteristics. It is guaranteed that the information similarity in any category is high, and the similarity between each category is low [15]. Fuzzy clustering does not require a given number of classifications because it can establish a fuzzy matrix to classify the attributes of the information. The detailed steps are as follows.

a) Standardization of information:

$\{x_1, x_2, ..., x_n\}$ represents the information to be classified, which is composed of abnormal information x, and its evaluation index is represented by $x_i = \{x_{i1}, x_{i2}, ..., x_{im}\}$, and $i = 1, 2, ..., n$. Its quantity is represented by m, and x_i describes the operation level, and the processing purpose is the same dimension. For difference information is processed by standardization. It is completed by translation range transformation using the processing formula below:

$$x'_{ij} = \left(x_{ij} - \overline{x_j}\right) / s_j, \, j = 1, 2, ..., m \tag{5}$$

In the formula,

$$s_j = \left[\frac{1}{n}\sum_{i=1}^{n}\left(x_{ij} - \overline{x_j}\right)\right]^{1/2}, \, j = 1, 2, ..., m; \; \overline{x_j} = \frac{1}{n}\sum_{i=1}^{n} x_{ij}.$$

b) Build a fuzzy matrix:

r_{ij} represents the similarity coefficient, and the corresponding distance index can be used according to the difference in the nature of the information. Its value ranges from 0 to 1, and the closer it is to 1, the higher the similarity between variables. Otherwise, the similarity is lower. This paper uses Euclidean distance to describe the similarity between the two indicators, and its calculated using the formula below:

$$r_{ij} = 1 - c \cdot d\left(x_i, x_j\right) \tag{6}$$

In the formula, any parameter is denoted by c, which can be used to realize $0 \leq r_{ij} \leq 1$. $d\left(x_i, x_j\right) = \sqrt{\sum_{k=1}^{m}\left(x_{ik}, x_{jk}\right)^2}$ stands for distance.

c) Constitute a dynamic cluster map:

The dynamic clustering graph is done by the transitive closure method, and the similarity matrix is denoted by R. The transfer packet of R is denoted by $t(R)$, and its construction is done according to the flat method. And $t(R) = R'$, according to the dynamic eigenvalue λ, complete the classification of research objects.

d) Alarm threshold setting:

The alarm threshold of an alarm object is expressed as the average value of the alarm objects in any class. N represents the number of alarm objects. After fuzzy clustering is performed, the number of categories that can be divided is represented by n, and the formula for the alarm threshold is:

$$\mu_{nm} = \frac{1}{p}\sum_{i=1}^{p} x_{im} \tag{7}$$

where p represents the number of alarms, belonging to the n-th type of alarm object. The x_{im} value is the m-th indicator, which belongs to the i-th alarm object.

According to the set alarm threshold, the abnormal information classification can be completed. If the alarm threshold is higher than the alarm threshold, an alarm will occur, and if the alarm threshold is lower, no alarm will occur. In this way, efficient processing of distribution network information monitoring can be achieved.

2) Alarm Threshold Optimization

During the processing of the alarm information, it is necessary to complete the alarm information processing through the operation of the personnel. Therefore, there is a certain degree of difference in the ability and efficiency of personnel, which will lead to differences in the real-time and reliability of alarm information processing, resulting in missed or false alarms. In addition, the operating state of the distribution network itself has a certain change, and after the threshold is set, it is a fixed value. When the grid changes, the fixed threshold cannot accurately describe whether the change is significant.

Therefore, the objective function which belongs to the alarm threshold is optimized, and is realized together with the adaptive adjustment of the weights. φ represents the people factor, and its association with μ_{nm} is:

$$\mu_{t\varphi}\begin{cases} move\ \ to\ \ the\ \ right\left(increa\sin g\right) & \varphi\in\left[0,0.5\right) \\ don't\ \ change & \varphi=0.5 \\ ove\ \ to\ \ the\ \ left\left(decrea\sin g\right) & \varphi\in\left[0.5,1\right) \end{cases} \tag{8}$$

In the case of $P\in[0,\ 0.5)$, then:

$$\varphi'=\frac{\varphi-\varphi_{\min}}{\varphi_{\max}-\varphi_{\min}} \tag{9}$$

$$w_2/w_1=w_2/w_1\times\varphi' \tag{10}$$

where $\varphi_{max}=0.5$, $\varphi_{min}=0$, then $w_2<w_1$, which means that in this case, the false alarm rate increases, the threshold increases, and the false alarm rate decreases.

After introducing the weights w_1 and w_2, the optimization objective function of the alarm threshold is obtained, and its calculation formula is:

$$MinJ{=}w_1\times\gamma\left(\frac{\varphi_{FAR}}{\varphi_{RFAR}}\right)+w_2\times\gamma\left(\frac{\varphi_{FAR}}{\varphi_{RFAR}}\right) \tag{11}$$

Where the false alarm rate and the false alarm rate are represented by φ_{RFAR} and φ_{FAR}, respectively, and are the system requirement standards. $\gamma(x)$ represents the change function, which belongs to the scale. $\mu_{t\varphi}$ represents a given threshold range, and the best optimization result can be obtained in this range.

III. TEST ANALYSIS

To test the application performance of the system in this paper, the monitoring data of the voltage of a 10 kV power supply bus in a city distribution network for 10 consecutive days is selected as the research object. The bus is used for power distribution in industrial areas, residential areas, and towns. The collected data is classified and processed through the data classification management module. The aim is to realize the classified storage of power data, power consumption data, and power quality data, as well as reliable and efficient comprehensive management of data resources. The server parameter settings mainly include the server IP address, port number, and the mechanism of starting the server in the server/client architecture, so that the device monitoring data can actively connect to the server. The data contains the operation data of five bus bars, and the number is 1000 groups. The voltage signal fluctuation variable value of the data is obtained, and the result is shown in Fig. 3.

Fig. 3 shows both normal and abnormal data; data that exceed the standard limit are abnormal.

To test the detection performance of the system in this paper for abnormal data, the abnormal data points that exceed the standard limit in Fig. 3 are detected. The detection results of the system are compared with the actual

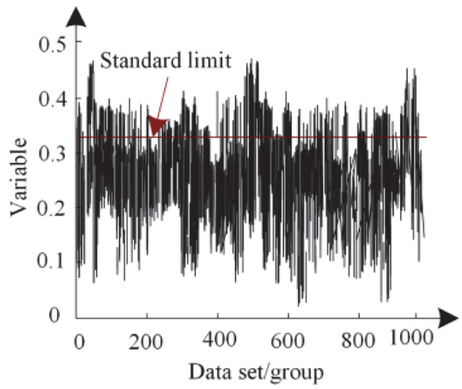

Fig. 3. Changes in experimental data variables.

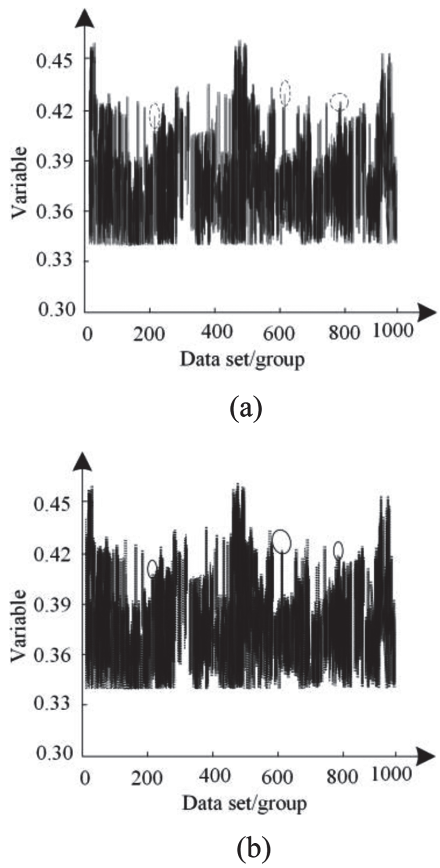

Fig. 4. Results of abnormal data detection using the approach presented in this paper: (a) actual abnormal data and (b) abnormal data detection results.

anomaly distribution results to measure the detection performance of the system. The results are shown in Fig. 4.

According to the test results in Fig. 4, using the system presented in this paper to detect abnormal data, only a few abnormal data detection results were not detected. The overall obtained detection results are almost completely consistent with the actual abnormal data results. The results show that the system has good detection performance for abnormal information, and can accurately obtain abnormal information in the data, which provides a basis for abnormal data analysis.

When the system performs fuzzy clustering on abnormal information, after the dynamic clustering graph is generated, the abnormal information is classified according to the dynamic characteristic value λ. This value is the dynamic eigenvalue λ set in the process of setting the alarm threshold based on fuzzy clustering studied in Section II-4, when a dynamic clustering graph is formed. The dynamic cluster map completes the classification of the research objects according to the eigenvalues. Using the system in this paper, fuzzy clustering is performed on the abnormal data obtained in Fig. 4, and a dynamic clustering diagram is obtained, as shown in Fig. 5. Among them, the number of targets for classification is three categories.

According to the test results in Fig. 5, it can be seen that to realize the clustering of three categories, the value λ of the dynamic characteristic value needs to be 0.696, which means that the clustering of the three types of abnormal alarm information is completed. The top of the figure describes different λ values, and the number of horizontal lines that each value passes vertically downward is the final number of classifications. And the corresponding classification numbers are presented at the bottom of the cluster diagram. The results show that the system can cluster information objects into different categories according to the value of λ.

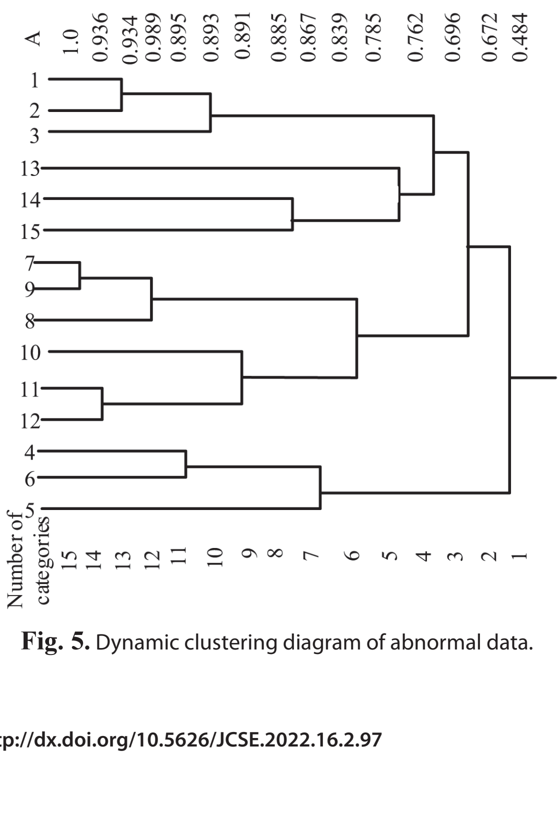

Fig. 5. Dynamic clustering diagram of abnormal data.

Based on the clustering results, three types of bus alarm thresholds are set. According to the threshold setting standard of the method in this paper, it is necessary to obtain the three-phase 95% probability average of each busbar of the three types as the early warning threshold of each type of busbar. If the threshold is exceeded, an alarm is sent. The threshold setting results are shown in Fig. 6.

According to the test results in Fig. 6, it can be seen that the system completes the setting of alarm thresholds for three types of information based on the dynamic clustering diagram. The setting result shows that the bus bar of the second information is abnormal, and the alarm thresholds of the other two types of information are lower, indicating that the text system can effectively complete the alarm threshold setting. It can also be seen that the system can complete the corresponding alarm threshold setting according to the actual application object, and obtain accurate alarm information more reliably.

To test the adaptive ability of the alarm threshold before and after the optimization of the alarm threshold of the text system, we randomly extract the changes of the alarm threshold of bus 4 for different time ranges. This way, the performance of the system under different time and power operation conditions is measured, and the results are shown in Fig. 7.

According to the test results in Fig. 7, it can be seen that in different grid operating hours, the alarm threshold before optimization can complete the abnormal classification according to the characteristic value, and the set threshold can be completed according to the abnormal category. After the threshold is optimized, the adaptive adjustment of the threshold can be completed based on the abnormal category setting, combined with the actual operating status of the bus and the human factors of monitoring and processing personnel. Therefore, it can adaptively adjust the alarm threshold in different periods,

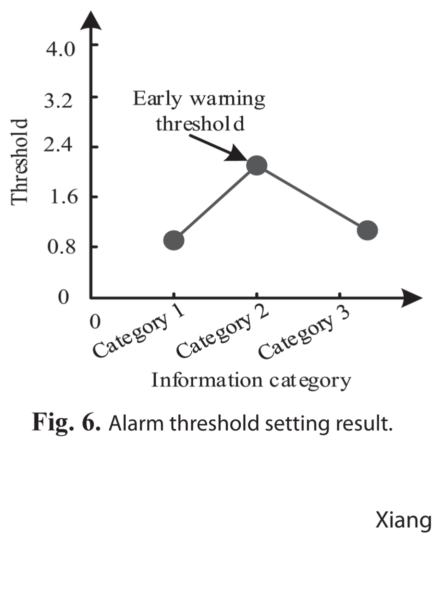

Fig. 6. Alarm threshold setting result.

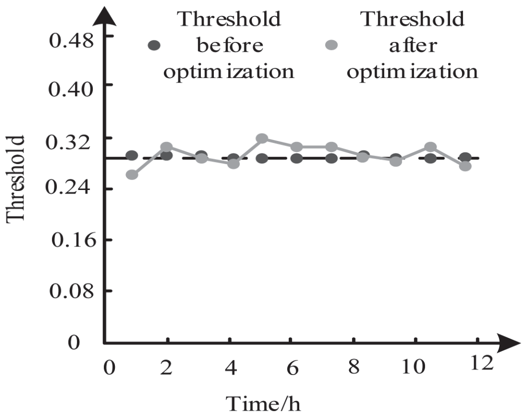

Fig. 7. System adaptive ability test results.

and the threshold shows adjustment fluctuations. The results show that this system has a good self-adaptive adjustment ability, and achieves a balance between human, machine, and power grid operating status in the process of distribution network information monitoring to the greatest extent. The method in this paper ensures real-time and reliable monitoring and alarming results.

IV. CONCLUSION

Herein we presented an intelligent information monitoring system and alarm threshold analysis for distribution network information monitoring based on machine learning, which is used to achieve effective analysis and accurate alarming of distribution network monitoring information. The system improves the fault handling efficiency of distribution network monitoring staff, and effectively solves the problem. The system can effectively process the collected information, complete the detection of abnormal information in historical data, and further complete the construction of a dynamic clustering diagram of abnormal information. By optimizing the set threshold value, the system can ensure a real-time and reliable processing of the alarm threshold value.

The system has a good self-adaptive adjustment performance which allows setting of the alarm threshold. However, due to space limitations, the comprehensiveness of system testing is relatively insufficient. The next step will be to test the overall applicability of the system in information monitoring and the application effect under various conditions to expand the application performance of the system.

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