J. Electrical Systems 20-2 (2024): 1339-1349

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Application of SSA-KNN Algorithm in Fault Analysis of Power Metering Automation System

Abstract: - In view of the great pressure of operation and maintenance of power energy data collection terminal after putting into operation, an intelligent fault diagnosis system for power equipment terminal based on computer was developed. This paper proposes an Agent based on autonomy, promotility, cooperation and interactivity. It also provides a flexible interactive communication interface and load balancing optimization method. It can meet a variety of data transmission specifications and a large number of data service transmission requirements. The SA-KNN algorithm is used to analyze the power quality. Methods The operation data of maintenance electricity were collected. Learning and cluster analysis are carried out by using relevant data, and the calculation model of automatic check device failure is established. At the same time, the outlier points in the collected data are used to accurately locate the fault points of the power grid. This method can realize the comprehensive fault diagnosis of the power grid by using the interaction between the power grid and each component.

Keywords: Agent Technology; Fault Diagnosis; Measurement Automation System; Field Terminal.

I. INTRODUCTION

In recent years, the power company has actively promoted the construction of metering automation system, and now has built more than 4 million different types of power energy data collection field terminals, which have realized load forecasting and control, electricity monitoring and abnormal analysis, anti-theft, "quarter" line loss statistics, and customer demand side management services for local power supply bureaus. With an advanced and efficient technical method [1]. However, due to the increasing scale of power metering automation system, the maintenance and overhaul of on-site equipment is increasingly difficult. If people can combine the actual situation of China's power industry, design and develop the terminal equipment fault diagnosis system. The system can complete the real-time detection and analysis of the equipment's real-time faults [2]. Through on-site installation, maintenance and fault analysis of the power company, it can greatly reduce the maintenance work of the power company and reduce the maintenance cost of the system. Because various types of measurement automation field terminals have the characteristics of large number, wide distribution and large amount of information data, in the design and development process, it is necessary to support complex and diverse communication protocol interfaces, and to have the technical characteristics of load balancing, multi-threading concurrency, strong real-time and high stability.

At present, the shortcomings of the intelligent verification system used for electric energy detection in China are as follows: 1) most of the detection schemes are collected by using a variety of sensor technologies, video technologies, messages, etc., while the conventional data mining method is used, the data collected is incomplete on the whole. 2) Due to the short operating cycle of the system, the method for error warning requires less data. Therefore, the effective processing of big data is very difficult. 3) In the process of electric energy measurement, there is coordination and interaction between various devices. The current device fault diagnosis is mainly based on a single hardware, and the relationship between electric energy measurement and electric energy measurement system is not comprehensively analyzed, resulting in unsatisfactory overall diagnosis results of the system.

Multi-agent system technology is a hot topic in current research. This project intends to build a multi-agent fault diagnosis software model, give full play to the agent's autonomy, premobility, collaboration, interaction and other characteristics, and build a set of flexible human-computer interaction communication interface and load-balanced agent model to meet the communication requirements of various data communication specifications and a large number of services [3]. The flexibility, adaptability and robustness of the diagnostic system are enhanced.

II. CONSTRUCTION OF POWER GRID METERING AUTOMATION SYSTEM

The company has implemented a set of measurement automation system across the province, and now the system has a considerable scale of 21 localities and municipal power supply bureaus in the province have put into

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use all kinds of metering automation on-site terminals have exceeded 400,000 units. The measurement automation system consists of three main components: main station, field terminal and communication channel: Load management system, plant metering telemetry system, distribution metering monitoring system, and low voltage centralized meter reading system (Figure 1 cited in Cognitive radio based smart grid communications).

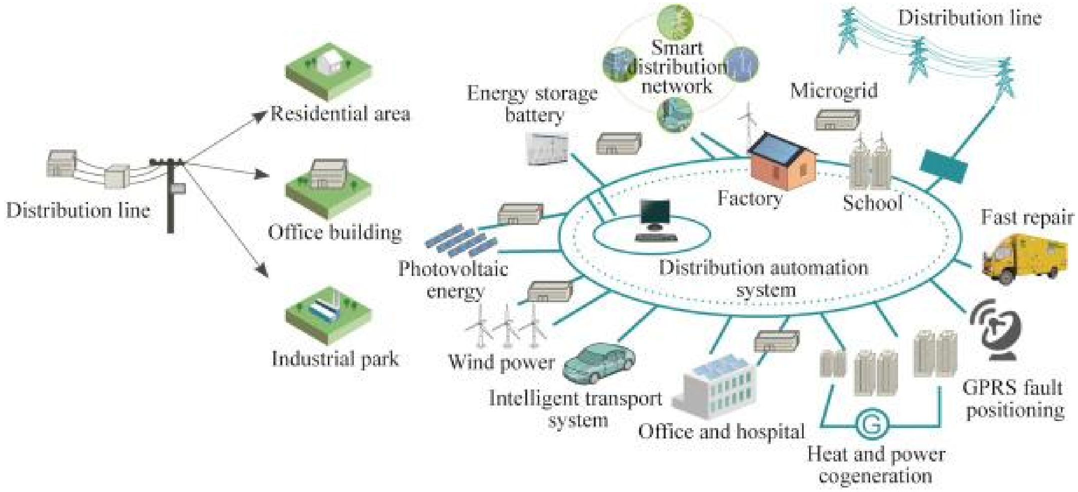

Fig.1 Architecture diagram of measurement automation system

The automated metering infrastructure (AMI) system facilitates telemetry, load supervision, and demand regulation on the generation side, alongside offering comprehensive services such as pre-emption, line loss computations, and power quality evaluations to consumers. Additionally, it provides energy conservation assessments for customers, enhancing power delivery quality, mitigating distribution losses, and augmenting economic returns[4]. However, due to the continuous expansion of the construction scale of the power grid, the terminal equipment maintenance work of the local and municipal power supply bureaus is facing great pressure.

This method can not only be used to classify an independent method, but also to find a suitable distribution pattern from the sample, or a preprocessing step of other algorithms. An automatic measurement system of intelligent distribution network based on fuzzy set theory is proposed [5]. In this case, the method of clustering can be used to automatically determine and form multiple clusters without manual preset errors. Then, the fault types expressed in each class are classified by experts to achieve automatic diagnosis of various faults in electrical energy measurement. The construction steps of the system are as follows:

1) By using intelligent devices and sensor clusters, daily working data and fault feedback data, log data and external data of some enterprises of automatic power measurement are collected, and specific data is selected for analysis.

2) Through the initialization of each feature sampling point, the corresponding feature vector and feature sampling are obtained, and the SA-KNN method is used to process them, so as to obtain the pre-set training samples.

3) The sample set with obvious errors is selected and imported into the modeling of the clustering algorithm, and the corresponding sample set is obtained and typical errors are selected as samples, thus forming the sample set.

4) Uncertain data with uncertain failure causes and failure forms are selected and input into the modeling of clustering algorithm to form a diagnostic sample set. By comparing the Euclidean distance with each feature vector, the closest group or N group is selected as the input.

5) Assign weights to each type of error according to the diagnostic sample library ratio. They are all sorted according to the weight of fault types from the largest to the smallest, and the fault diagnosis results of each diagnosis sample are preferentially output. The pattern for Fault Diagnosis is shown in Figure 2 (image cited in Power Grid Fault Diagnosis Method Using Intuitionistic Fuzzy Petri Nets Based on Time Series) Matching).

III. Design of intelligent terminal fault diagnosis system

A. *Overall system design*

By intercepting the communication frame between the field terminal and the measurement automation master station, the working state of the terminal and the potential cause of failure can be judged [6]. If some terminal failure is caused by improper parameter setting, then set and correct according to the correct parameters given.

From the function point of view, the system is composed of three parts: data acquisition, data analysis and intelligent fault. Figure 3 shows the system architecture.

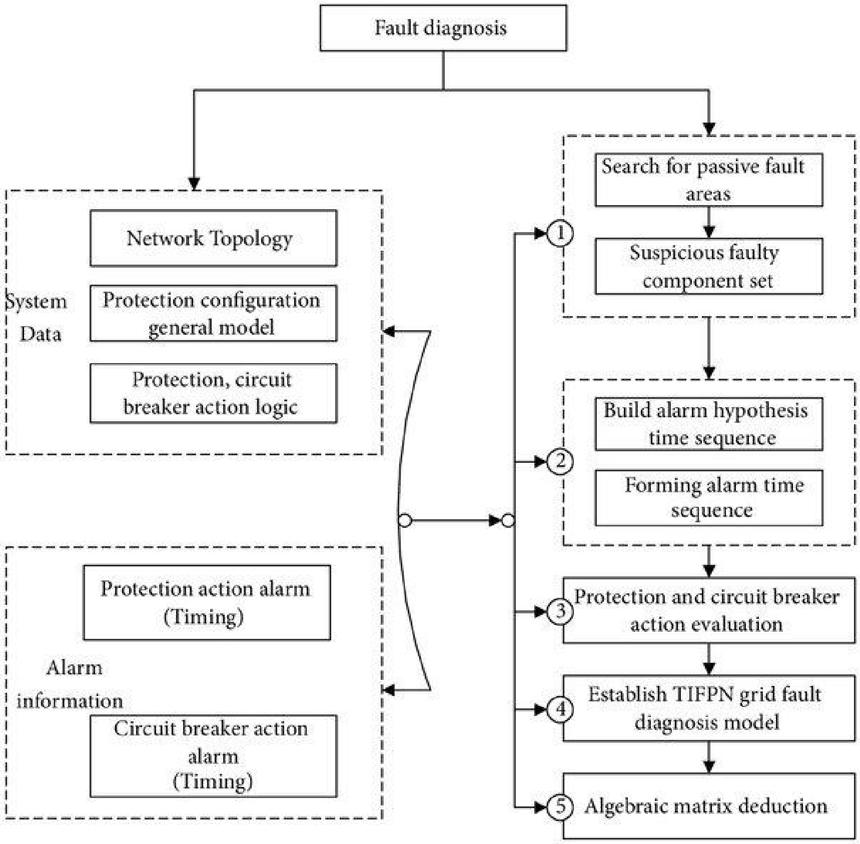

Fig.2 Schematic diagram of fault diagnosis model

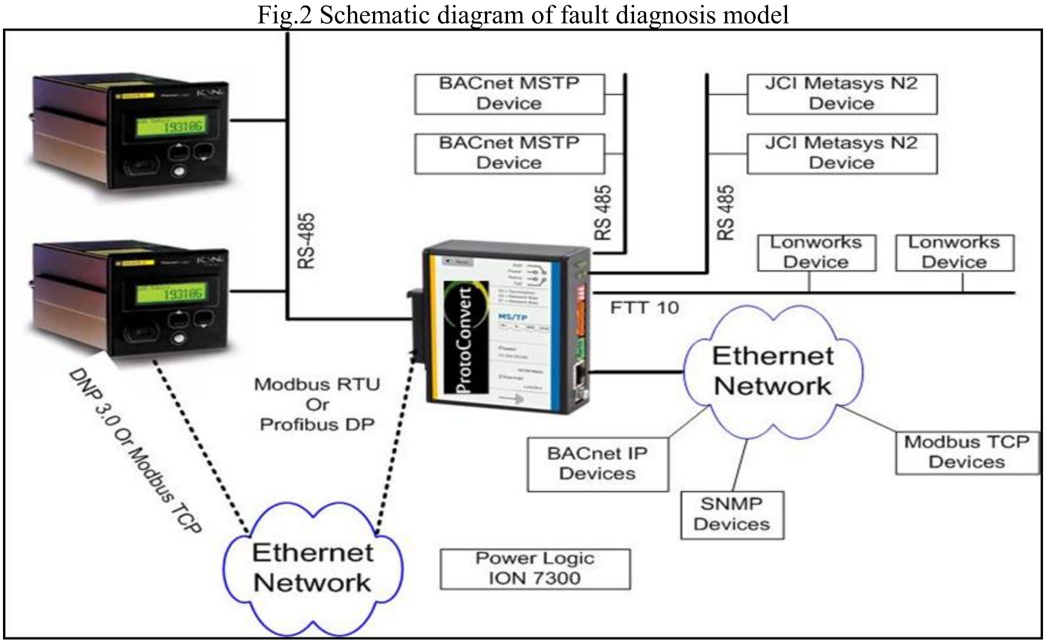

Fig.3 Architecture design of power metering automation system

a) The data acquisition component is the cornerstone of the system, which not only maintains contact with the communication channel between the terminal and the master station system, but also analyzes, stores and forwards the communication protocols of various types of terminal equipment; The system consists of communication channel module, data parsing module, data acquisition management module, message recording module and data call module. b) Terminal data analysis module can carry out statistical analysis of terminal working status data, including communication status statistics, task statistics, alarm status analysis, indicator data management, etc. Its function is to monitor the communication, task, alarm and other performance data of each terminal, so as to diagnose the fault of the terminal intelligently. c) Intelligent diagnosis module, through the construction of a fault diagnosis expert system including diagnosis item definition, diagnosis knowledge base, logical reasoning mechanism, etc. Then this paper analyzes and monitors the terminal in real time, and evaluates its working condition.

B. System module design

a. agent Type

This paper presents an agent-based method to design the module of the system. a) The monitoring agent function is responsible for starting and stopping the entire fault diagnosis system program, monitoring the running status of other agents, resource allocation, load balancing scheduling and other functions. b) One of the service core components of the system whose role is to perform various data acquisition tasks and control instructions to implement a rulebase with many different communication specifications for a wide variety of different terminals. c) Data processing agent is an important part of the system service, it will process some original data according to the requirements of the program, and then write to the database. d) User interface intermediary is an intelligent interface, which is an intelligent interface delivered to the outside by the error diagnosis system. Its main functions are: maintenance rule base, diagnosis rule base, diagnosis items, etc. e) Communication agents enable interfaces for various types of communication channels.

b. Proxy functions

The communication information channel between each agent can use Socket communication method, so that each agent can be distributed on multiple machines, thus improving the scalability and robustness of the system. The component functions of the agent implementation pattern include:

a) External interface segment. The agent's interactions with the outside world are composed of environmental models and other agents. A cooperative working mode based on multiple agents is proposed. b) Information receiving component. The message receiving is the message receiving through a separate thread; After receiving the message, it is placed in the cache of the received message, and raises a message handler, according to the basis of the agent's interaction protocol, extracts the content of the message, and informs it to the controller. c) Message transfer Department. The controller starts a state machine based on the state of the agent, the messages received, the data set, and the knowledge base. The State machine is a quadruple In which in is the input information, State is the state, Proc is one, and one is the output information; The state machine controls the transition state of the agent itself, and the transmitted information is processed through the transmission message to form the knowledge inquiry operation language. The message is placed in the transmission message buffer and transmitted to the message transmitter. d) Other functions. The controller is mainly used to control the coordination and synchronization between the working lines. According to the function of each agent in the agent business logic model, the corresponding database and knowledge base are carried out [7]. The knowledge base of the agent interaction protocol defines specific specifications for the interaction behavior between agents.

C. Development of intelligent fault detection system

Among them, the intelligent diagnosis function is the core, which is based on man-machine dialogue interface, diagnostic knowledge base, diagnostic inference machine, interpreter and integrated database. This structure is shown in Figure 4 (image cited in Eng.Proc.2021, 10(1), 46).

a) Human-machine interactive interface means that through the interface, the diagnostic device interacts with the user, so as to determine the final fault diagnosis project, customize the diagnosis plan, display the diagnosis results, and display the results, and display the results.

b) Diagnosis knowledge base provides the basis for terminal fault diagnosis, which is composed of working environment, terminal fault characteristic value, fault diagnosis algorithm, inference rules, etc. A new method based on fault diagnosis is proposed.

c) The diagnostic inference machine is used to store the rules used and the control strategies used. The obtained data were analyzed by various methods and the diagnostic conclusions were drawn.

d) The interpreter explains the operation of the expert system to the user, which explains whether the inferred result is correct, why the system outputs other alternatives, and gives corresponding solutions.

e) The integrated database, also known as the global database, is used to store terminal parameters, raw diagnostic data, inference procedures, contents of the knowledge base, diagnostic conclusions and diagnostic recommendations [8]. Figure 5 shows the final troubleshooting process (image cited in Fault Diagnosis and Abnormality Detection of Lithium-ion Battery Packs Based on Statistical) Distribution). The diagnostic inference machine obtains the diagnostic knowledge associated with the diagnostic items from the diagnostic knowledge base, and the index data and some related terminal parameters from the synthetic database to get the diagnostic conclusion.

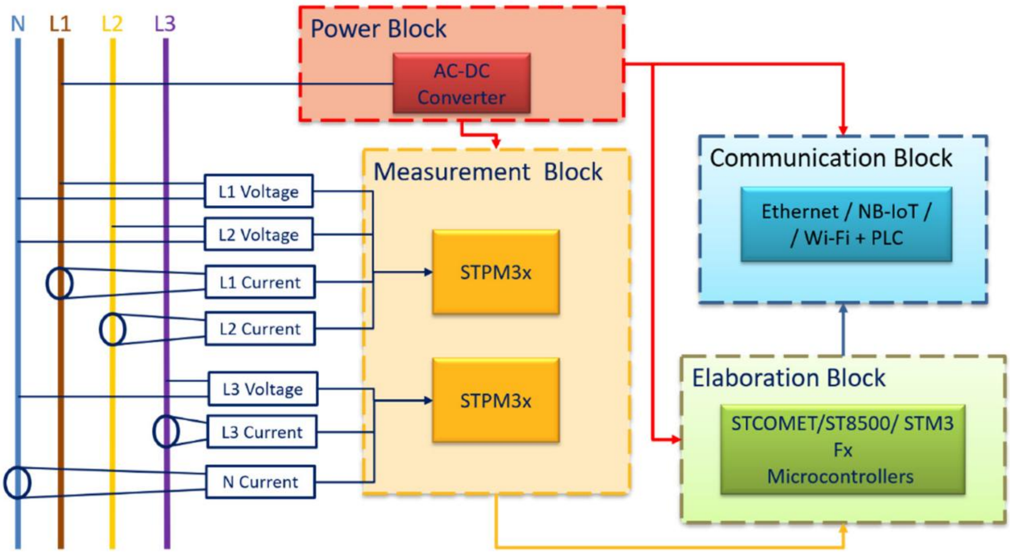

Fig.4 Intelligent diagnosis module

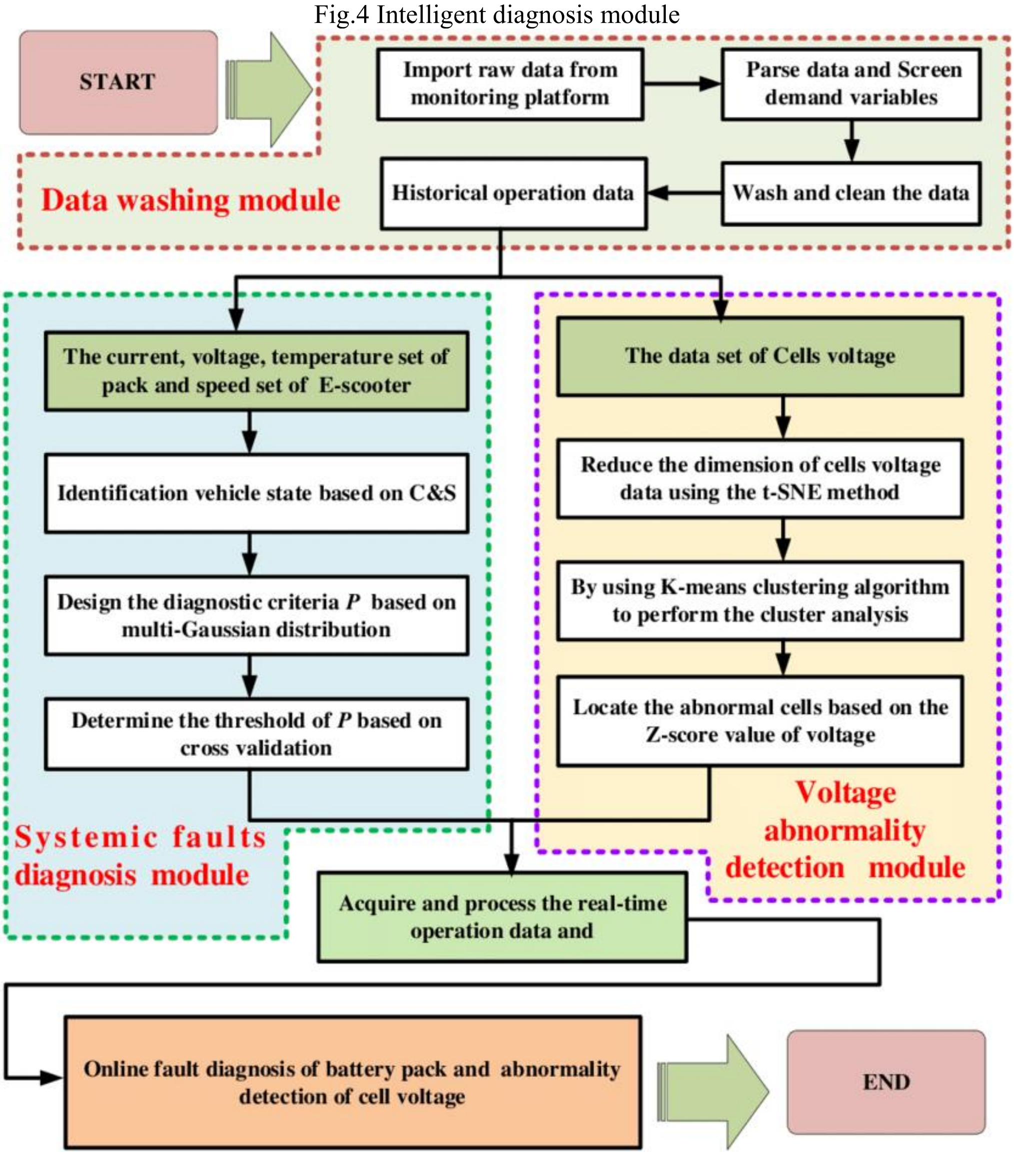

Fig.5 Terminal fault diagnosis process

When analyzing the fault of electric energy measuring equipment, the output fault information inevitably contains the mutation quantity and mutation quantity, and also contains some unsteady state noise. In order to accurately analyze this type of signal, it is necessary to process it accordingly, remove the noise in it, and retain useful information [9]. In terms of denoising, the conventional Fourier transform can not achieve the ideal denoising effect, because all steps of Fourier decomposition are carried out in the time domain, so it can not reflect the sudden change of the signal in real time, and when the signal changes at a certain time, it will cause serious damage to the whole image. However, wavelet analysis can simultaneously perform multi-line processing of the signal from both time and frequency aspects, improve the time-frequency resolution, improve the resolution in the frequency range, improve the frequency range, and achieve self-focusing of the focus [10]. Therefore, wavelet analysis can effectively remove noise and mutation points, so as to achieve the effect of noise reduction. In the process of using wavelet analysis method for signal, a lot of valuable information will be reflected from the numerical value of the coefficient, so when analyzing and processing the signal, an appropriate threshold can be set to store the effective coefficient. This makes it easier to extract valuable information based on the value of the coefficient. The method can effectively separate the interference signal from the effective signal and realize the suppression of the target signal. Two different threshold algorithms are usually used: hard threshold algorithm and soft threshold algorithm [11]. Any phenomenon that causes the accuracy of the electrical energy measurement results to decrease is called the failure of the electrical energy measurement system.

Voltage transformer plays the role of converting a high voltage into a second high voltage, and then transmitting it to the energy meter, so as to support the relevant measurement work. The voltage transformer is a step-down transformer, which can change the size of the current and facilitate the transmission of electric energy [12]. However, the number of side rings is greater than the total number of secondary side rings, so the original side rings are more likely to fail. The most important factor causing this situation is the winding coil between turns short circuit or broken line. For this simple fault, after detecting and judging the voltage transformer, the voltage value in the ordinary state recorded in the previous test can be compared with the voltage value of the transformer collected at present to determine whether there is a fault. As shown in figure 6 for the voltage transformer (image references on https://studyelectrical.com/2014/03/capacitor-voltage-transformer.html).

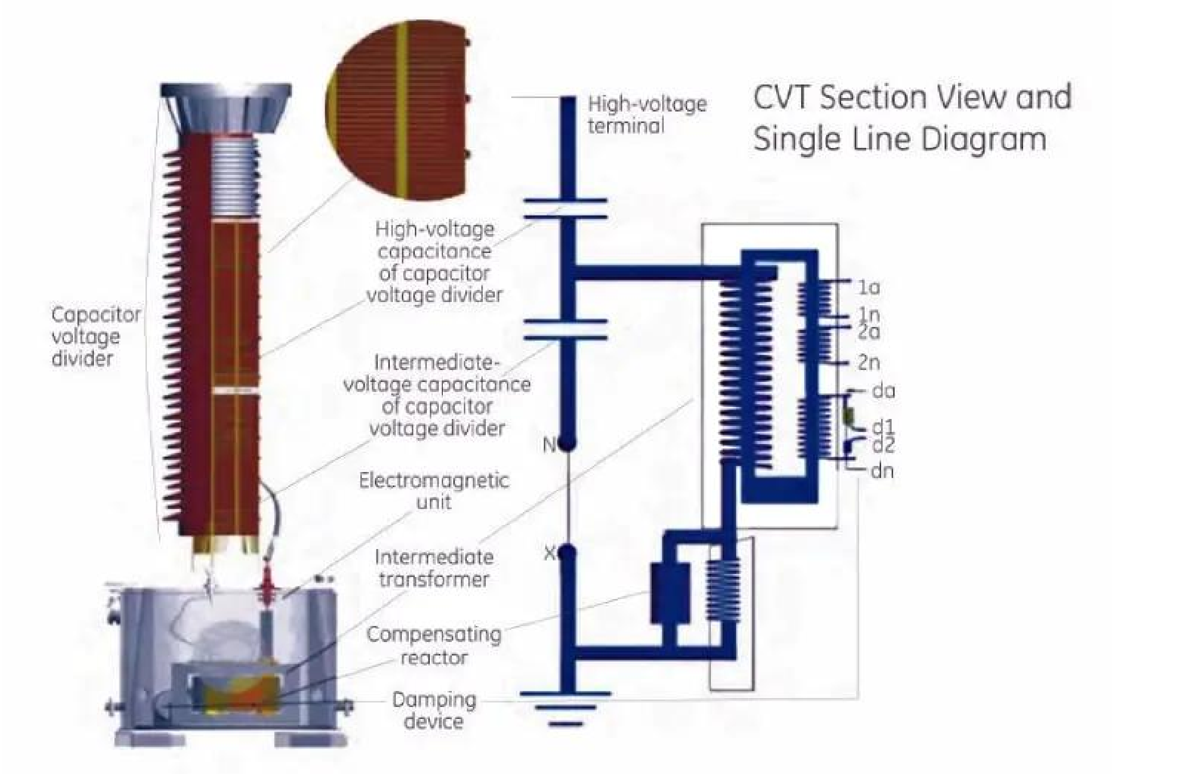

Fig.6 Voltage transformer

The current transmitted in the power generation and consumption system that exceeds the ordinary norm should be reduced to the level of the ordinary norm [13]. The common problem of current transformers is short-circuit fault, also known as short circuit, and the short-circuit on the secondary side of the two current transformers. Since the winding connected to the power supply, that is, the primary winding, its voltage is high, it is difficult to carry out direct sampling, and the blocking effect on the current is not large, and the impedance changes after the short-circuit fault of the primary winding, which also brings difficulties to the test. Voltammetry is generally used for impedance testing to determine the type of fault. As shown in figure 7 for current transformer (image references on https://www.electronics-tutorials.ws/transformer/current-transformer.html).

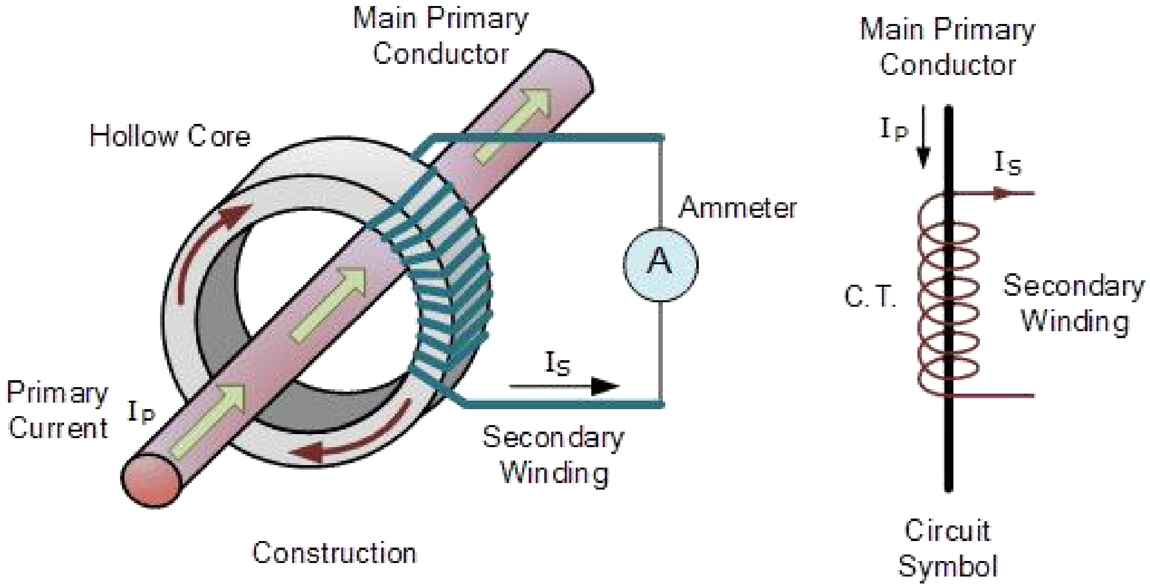

Fig.7 Current transformer

D. Balancing System Load

In fault diagnosis, it is necessary to make full use of the interaction of many people and massive data information to ensure the stability and real-time of the system. The monitoring agent module is responsible for scheduling and scheduling the work of the whole system, and can monitor the operation of the agent in time. After the load imbalance is detected, it is changed from a busy agent to an idle agent to achieve load balancing [14]. When the monitoring Agent finds a busy Agent, it sends a query message to the agent. The Agent provides information to monitor the Agent's reply. When an Agent wants to send a task monitoring Agent, it will send a task assignment information to the associated free Agent; After the idle agent receives the information of a work assignment, the busy agent starts the work. After the work transfer is complete, the busy agent sends a confirmation message to the free agent.

IV. SA-KNN ALGORITHM DESCRIPTION AND OPTIMIZATION METHOD

Suppose you are given training set $U \in R^{n\times s}$ and test set $V \in R^{m\times s}$, where s is the sample dimension and n, m is the number of samples [15]. This paper hopes to find a projection transformation matrix $R \in R^{n\times m}$ and determine the value of K required for classification through R. Obviously, it is more reasonable for the loss function model to choose the least squares loss model, that is:

$$\min_R \| V - R^T U \|_G^2 \tag{1}$$

Considering that formula (1) is A convex function, its solution can be expressed as: $R^* = (U^T U)^{-1} U^T V$, but $(U^T U)$ has irreversible problems, usually consider using ridge regression to introduce a r_2 norm to solve:

$$\min_R \| V - R^T U \|_G^2 + \xi \| R \|_2^2 \tag{2}$$

At this time, the solution of formula (2) is: $R^* = (U^T U + \xi I)^{-1} U^T V$, while R is a real matrix without sparse terms. When applied to KNN classification, K usually samples n, which is obviously unreasonable [16]. Because, just as the noise sample problem usually exists in the data mentioned in the introduction of this paper, $K = n$ is to select all the sample data and not remove the noise sample. Therefore, in this paper, the r_2 norm based on ridge regression is changed to $r_{2,1}$ norm with sparsity, so that the principle of sparse learning can be used to make the noise samples become zero and remove the non-correlation noise samples. At the same time, the local preserving projection (LPP) algorithm is introduced to keep the manifold structure of the sample data unchanged in the process of spatial projection transformation. The conditional properties of the test sample U

were used to reconstruct the test sample V and find the correlation function between V and U, that is, the correlation matrix R was obtained, which represents the correlation between the test sample and the training sample. The value of the corresponding position of the R matrix reflects the degree of correlation, so the correlation between the samples was utilized. So the model the paper used is as follows:

$$\min_{R} \| V - R^T U \|_G^2 + \xi_1 \| R \|_{2,1} + \xi_2 * tr(R^T U R U^T R) \tag{3}$$

Where, U is the training sample, V is the test sample, R is the Laplace matrix described in formula (2), and ξ_1 and ξ_2 are two adjustment parameters.

Our goal is to find the relationship between U and V by projecting U onto the space of V, that is, to find an optimization matrix R that makes V and $R^T U$ as close as possible [17]. In order to improve the effect of classification, according to the principle of manifold, it is obvious that the local structure of U needs to be maintained in the new space. According to formula (1), this regularization term is $tr(R^T U R U^T R), \xi_2$ to regulate this regularization term. Specifically, ξ_2 is used to control the order of magnitude of the LPP part and the order of magnitude of the least-square loss model part, so that the manifold structure of the sample U in the new space can be kept unchanged.

In the model, ξ_1 controls the sparsity of rows of the W matrix, that is, the number of behavior zeros in R increases when its value is larger, and the number of behavior zeros decreases when its value is smaller. A suitable R matrix is generated by a suitable ξ_1, so that the rows of R corresponding to the noise samples are sparse, even if the noise samples are zero. For example, suppose the paper gets a 5×4 matrix through the model:

$$R = \begin{bmatrix} 0.2 & 0.1 & 0.3 & 0.8 \\ 0 & 0 & 0 & 0 \\ 0.1 & 0.5 & 0.7 & 0.6 \\ 0.6 & 0.4 & 0.8 & 0.9 \\ 0 & 0 & 0 & 0 \end{bmatrix} \tag{4}$$

One line represents a training sample, one column represents a test sample, one value represents a test sample, and one value represents the relationship between the two data, which is relatively large, so it is necessary to use this data for reconstruction. For example, for a training sample, rows 1,3, and 4 of the test samples were not 0, indicating that they were related to the training sample, so 1,3, and 4 test samples should be selected during reconstruction [18]. On the other hand, due to the sparsity of the data, the data has zero in behavior, that is, the samples with noise are not associated with other test samples. During reconstruction, these samples are ignored by multiplying the rows with zero R, and the remaining samples are reconstructed. According to the rules described above, the value of K can be determined to be 3, that is, the number of rows that are not zero, thus completing the function of automatic selection of K values according to the characteristics of the sample. The existing K value selection method uses users to select a fixed value without considering the characteristics of the data. The ten-fold cross-validation method also fails to consider the correlation between samples and the local structure of samples. The K of the algorithm in this paper is obtained by learning, and the correlation between samples and local structure are considered in the learning process, and the influence of noise is removed.

V. FAULT DIAGNOSIS MODEL TEST VERIFICATION

A. Experimental Content

The design is carried out by using C++ and PHP languages based on the adaptive communication environment and Mysql database, and the intelligent fault diagnosis based on Mysql is realized by using Lua technology with good scalability [19]. After nearly a year of research and development, it has been tested in the local and municipal power supply bureaus, and its working environment is as follows.

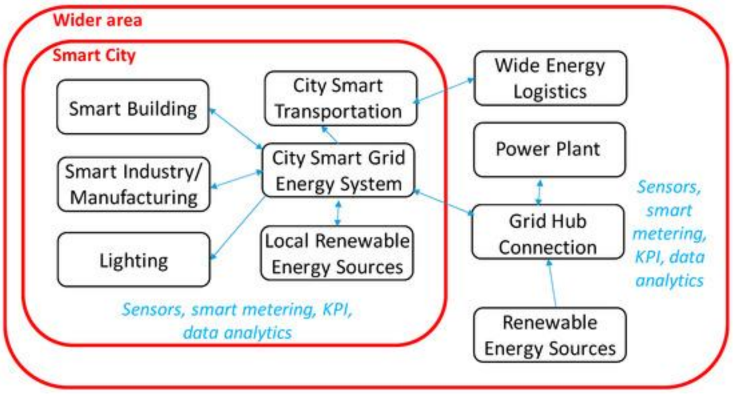

Fig.8 Diagnose the system operating environment

Through the analysis and diagnosis of the communication state, response time, the accuracy of the data packet, the integrity of the uploaded data and the correctness of the service processing logic, the corresponding evaluation score and improvement suggestions are put forward [20]. This provides an effective method for engineers in the power department to diagnose and analyze terminal faults in the field, thus reducing the workload of maintenance personnel.

The working diary of some automatic energy measuring devices collected by the testing center of State Grid Power Supply Company is used to ensure the accuracy of the established method [21]. The method is learned by selecting 1000 samples collected in real time under normal operation and defect condition, and randomly selecting 250,500,750 samples and a total of 4 training sample sets from these samples. This paper also compares the accuracy of the proposed algorithm model, artificial neural network algorithm, decision tree classification algorithm and Bayes classification algorithm among 200 existing failure/normal test data. The results obtained are shown in Table 1.

Table 1 Fault detection model test

number of training samples /	Fault diagnosis accuracy /%			
	K-Means	Artificial neural network	Decision tree classification	Bayesian classification
260	72	66	70	66
521	91	83	80	80
781	95	88	85	86
1042	99	95	89	92

The worst under four different algorithm modes, while the performance of ANN and Bayes method is not different under the same training times. Compared with the other three methods, the selected SA-KNN method has better fault accuracy and stability under four different training levels. Bayes algorithm is a new algorithm for data processing based on existing information [22]. However, for complex scenarios, the effectiveness of this method is obviously not enough. When the method is used to analyze the continuous domain, it often ignores the relationship between the attributes. In an uneven situation, the performance of information extraction tends to favor multiple numerical characteristics, leading to errors. However, the number of parameters required by ANN is too large, and its performance is not ideal in the case of small samples and unbalance. In addition, this method also has the defects of labeling data and not being able to cluster it (Figure 9 is cited).

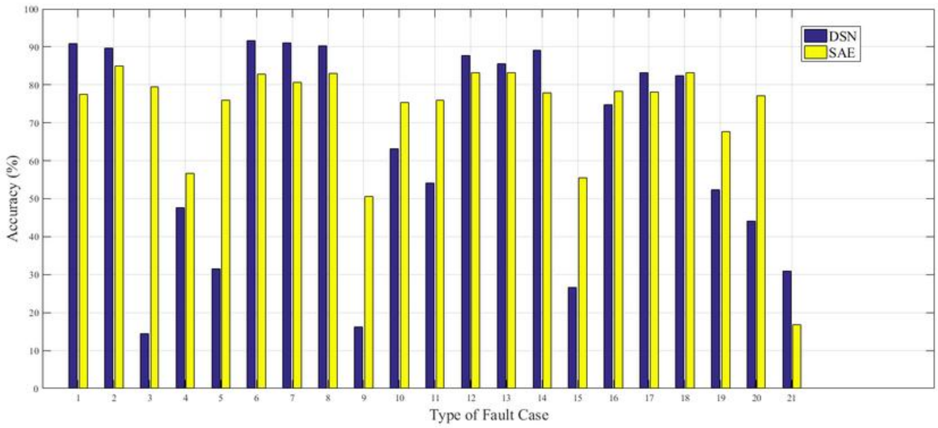

Fig.9 Comparison of fault detection accuracy rates

B. Analysis of experimental results

In more realistic working environments, the types of failure situations are diverse and difficult to collect. Therefore, compared with other methods that require higher prior information or have exact labels, undirected learning has better performance in the case of small samples. The K-Means model can accurately distinguish between normal and failed samples under the condition of a small amount of artificial labeling, and has a stronger understanding of samples. This also proves that its promotion ability is stronger. In the presence of independent samples, better discriminant results can be obtained.

In addition, SA-KNN has lower labeling requirements for people than other methods, and can sometimes perform unguided learning. Under the premise of reducing human interference, the method can ensure the accuracy of the model and reduce the cost of acquisition and marking. Since the failure rate in the electrical energy measurement industry is very small, most detection methods can not meet the requirements. Because SA-KNN has the characteristics of unsupervised and automatic clustering, its performance on such data is very good, and it can basically meet the error alarm requirements proposed by the manufacturer. Although the basic method of SA-KNN still has some shortcomings, with further processing, better results will be obtained. Therefore, the SA-KNN method has a good adaptability to the actual situation in actual production.

This project intends to adopt K-Means classification method and integrate SA-KNN algorithm with collected continuous operation data to establish a new fault identification method of electric energy measurement system. Through experiments, the SA-KNN algorithm is compared with artificial neural network, decision classification tree and Bayesian classification algorithm, and the accuracy of fault diagnosis is obtained under various training levels. Experiments show that SA-KNN has high accuracy and stability. The research results of this project will provide an important theoretical basis for the automation of electric energy measurement, provide a new idea for the automatic measurement of electric energy, and provide a new idea for the automation of electric energy measurement. Although cluster analysis has shown good performance in intelligent diagnosis, its clustering and machine learning related technologies are still in the groping process, and more research is needed.

VI. CONCLUSION

In this paper, an intelligent fault diagnosis mode of terminal equipment in power market is established, and a preliminary test is carried out in the power department, and good results are obtained. An agent-based software development approach is proposed, which improves the scalability and stability of the system through higher abstraction, better communication interface and better load balancing strategy.

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