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Research on Dynamic Maintenance System of Electrical Automation Secondary Equipment in Smart Substation

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Abstract:

At present, the development of power grids is deeply integrated with information technologies such as "Big Cloud IoT Chain". The power grid takes the secondary equipment online monitoring and intelligent diagnosis device as the edge agent, and applies it to analyze and process the secondary equipment operation, alarm, action and other information on the spot. The system realizes secondary equipment operation analysis and abnormal dynamic diagnosis. This paper proposes the overall system architecture and dynamic diagnosis scheme of the secondary equipment dynamic diagnosis technology based on deep learning. Key contents such as plug and play, diagnostic model, automatic generation of IED database, online evaluation and dynamic reconstruction are discussed. The research shows that the method can analyze the defects and find the weak links of the secondary equipment, which provides support for the formulation of defect inspection methods and the formulation of maintenance strategies.

***Keywords**: Intelligent Substation; Electrical Automation; Secondary Equipment; Maintenance System.*

I. INTRODUCTION

The smart grid consists of various power generation, transmission and distribution, energy storage and electrical equipment, and uses modern network communication technology and automatic control technology to build a new power grid. The smart grid takes automation, comprehensive balance, control, and observation as the system design goals, aiming to provide users with clean, efficient and safe electric energy. With the rapid development of scientific and technological information, the technological innovation of smart grid is also advancing by leaps and bounds, which puts forward more stringent requirements for the operation and maintenance of the power grid. With the rapid development of science and technology, the technological innovation of smart grid is also changing with each passing day, which imposes higher requirements on various equipment and operation and maintenance management of the power system. Under the background of major operation and maintenance and major overhaul, in order to avoid falling into the situation of incomplete data acquisition and non-stereoscopic data analysis, smart grid needs to establish a system based on massive data, with data correlation analysis as the entry point, which can analyze the power distribution. It is a power transmission and

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transformation dispatching perception system with comprehensive coverage for system analysis, comprehensive evaluation, and comprehensive coverage of the network. Relying on such demand, the Internet of Things is gradually being applied by the smart grid in the wave of technological development of the times.

The Internet of Things is a network that connects, identifies, locates, tracks and manages various independent physical objects through sensing devices according to related protocols. Whether from the perspective of conceptual definition or from the analysis of technical characteristics, there are certain similarities and interoperability between the smart grid and the Internet of Things. In essence, the smart grid puts forward controllable, detectable and interactive requirements for any accessories that make up the power grid. The Internet of Things is used by the industry to realize the interconnection and mutual influence between things. Therefore, with the continuous development of smart grid technology, the application of the Internet of Things is gradually distributed to the entire power system, especially in the field of power information monitoring, and has obtained a good response. However, with the gradual increase in the data of smart grid operation and maintenance, it has exceeded the ability of IoT data screening and analysis. The cumbersome data processing problem of smart grid has become an obstacle to the further development of limited distribution network, and big data processing has come into being pregnancy.

Big data is an emerging data processing concept following the Internet of Things, and its application after mining should be attributed to the development of Internet cloud data storage and the Internet of Things. Big data uses a series of mature technologies such as mobile network, social evaluation technology, and intelligent sensing to record the movement trajectory data of people or things. These data covering a wide range and variety are big data. In the distribution network, the most used amount of data is the condition maintenance data of the secondary equipment.

The power distribution network plays a very important role in the power system. Intelligent distribution network is a comprehensive information management system integrating computer technology, modern equipment management, control technology and data transmission technology, which is an inevitable trend in the development of distribution network automation. It is an inevitable trend in the development of distribution network automation. Chinese smart distribution network construction is in full swing with the call of Chinese policies. A large number of smart distribution networks appear, which can improve energy utilization efficiency, reduce environmental pollution, and improve the safety and reliability of power supply. With the rapid development of the power grid and the increase of power distribution equipment, the failure rate of power distribution network equipment has also increased. The traditional troubleshooting method, on the one hand, increases the manpower and material resources, on the other hand, the safe and stable operation of the power grid cannot be guaranteed. Therefore, it is necessary to introduce new technologies to solve the problem of distribution network maintenance.

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In the commissioning, maintenance and replacement of the distribution network, how to operate efficiently and energy-saving is a problem that needs to be considered in the normal operation of the distribution network. When the technology is immature, the main way to obtain the status information of the secondary equipment is regular manual inspection, and the maintenance plan is made through experience and preventive tests. Observing and recording the appearance of the equipment with the naked eye, and obtaining equipment status data through instrumentation detection are relatively traditional maintenance methods. The Internet of Things and smart grid make it possible for secondary equipment status maintenance, while the online monitoring system ensures the power system. The normal and stable operation of the Internet of Things plays a role in security monitoring in the smart grid. However, when the distribution network maintenance searches the huge monitoring data, it looks for the precise target and the backward data analysis seriously affects the efficiency of the condition maintenance.

How to make good use of the secondary equipment status data in the context of big data, ensure the safe and efficient production of the power grid, provide users with high-quality services, and provide good development ideas for technological innovation are problems that need to be solved at present. Firstly, the concept of big data is introduced in detail, and an information aggregation model is established for the application of large data maintenance based on the state model of secondary equipment in the condition maintenance of secondary equipment. Possibility of data secondary equipment condition maintenance. With a large number of substations put into operation, the secondary equipment management and operation and maintenance business have doubled, the number of operation and maintenance personnel is relatively stable, the lack of information technology means, the pressure on the safe operation of secondary equipment has increased, and the requirements and operation and maintenance of the safe operation of the power grid have increased [1]. The contradiction that the pressure continues to increase has become increasingly prominent, and the existing mode of operation and maintenance of secondary equipment is unsustainable. At present, secondary equipment such as relay protection, measurement and control devices, safety devices, merging units, intelligent terminals, and switches in substations need to invest a lot of manual inspections, maintenance tests, abnormal judgments, and disposals. The amount of equipment is large, scattered and complex, and it has not been fully and effectively used. The secondary equipment has the following problems in operation and maintenance:

(1) The operation and maintenance personnel are far away from the equipment, the informatization means are lacking, the data is not fully and effectively used, the equipment status cannot be grasped in a timely, accurate and comprehensive manner, and the abnormal situation is not detected in time. (2) With the increase in the number of substations, the operation inspection period becomes longer, the risk of mis-throwing and missing pressure plates, and the risk of setting incorrect setting exist for a long time, which is a potential "landmine" for the safe operation of substations. (3) Some alarms are automatically reset, and there is a lack of monitoring and diagnostic analysis for defects associated with equipment operating status and secondary circuit status, and the relay protection has the risk of refusal and misoperation. (4) There is a lack of monitoring and diagnostic analysis methods for the operation information of secondary equipment, and the active demining mechanism for key core businesses such

as communication status, secondary circuit, voltage/current, longitudinal channel, and device self-checking is lacking. Once an abnormality occurs, it will directly lead to A secondary equipment abnormality occurs. For this reason, this paper firstly analyzes the defect attributes of secondary equipment in smart substations. According to the characteristics of the attributes, the five attributes of secondary equipment manufacturer, equipment type, discovery method, defect location and defect cause are selected to form the secondary equipment defect data model of smart substation.

II. THE OVERALL STRUCTURE OF DYNAMIC DIAGNOSIS OF SECONDARY EQUIPMENT

Today, with the rapid development of intelligence, the data collection method of the distribution network has been greatly improved compared with the traditional collection method. The first is that the intelligent distribution network has stricter data requirements, which requires a more comprehensive and detailed understanding of the small changes in the system. Therefore, it is necessary to collect as many samples as possible during data collection. In a general automatic dispatching system, there are about 100,000 data points, and the number of distribution networks and data centers can be in the millions or tens of millions. There are a large number of equipment maintenance and a wide variety of sensors. These sensors that record different data must be linked together through a certain commonality or correlation to ensure the unified management and storage of information. This is the composition of Internet of Things. Second, in order to obtain a more complete database and collect information of more types and states, it is necessary to increase the sampling rate of equipment, especially in projects with rapid changes in equipment maintenance. For example, in the partial discharge maintenance of high-voltage equipment, in order to prevent any discharge phenomenon from being missed, the sampling frequency must be set above 200KHz. Therefore, the utilization of big data for condition-based maintenance of distribution network needs to face the challenge of large data sets and rapid changes.

Based on the device-oriented state online perception technology, the overall framework of cloud-edge collaboration is adopted, and the IEC61850 protocol is applied to communicate with the master and slave stations, and a four-level structure of "cloud-pipe-side-end" is constructed [2]. Through edge computing and cloud-edge collaboration mode, it can realize all-round online perception and dynamic diagnosis of secondary equipment, and fully support the application of online monitoring and dynamic diagnosis of secondary equipment. The overall architecture is shown in Figure 1 (the picture is quoted from An intelligent condition-based maintenance platform for rotating machinery).

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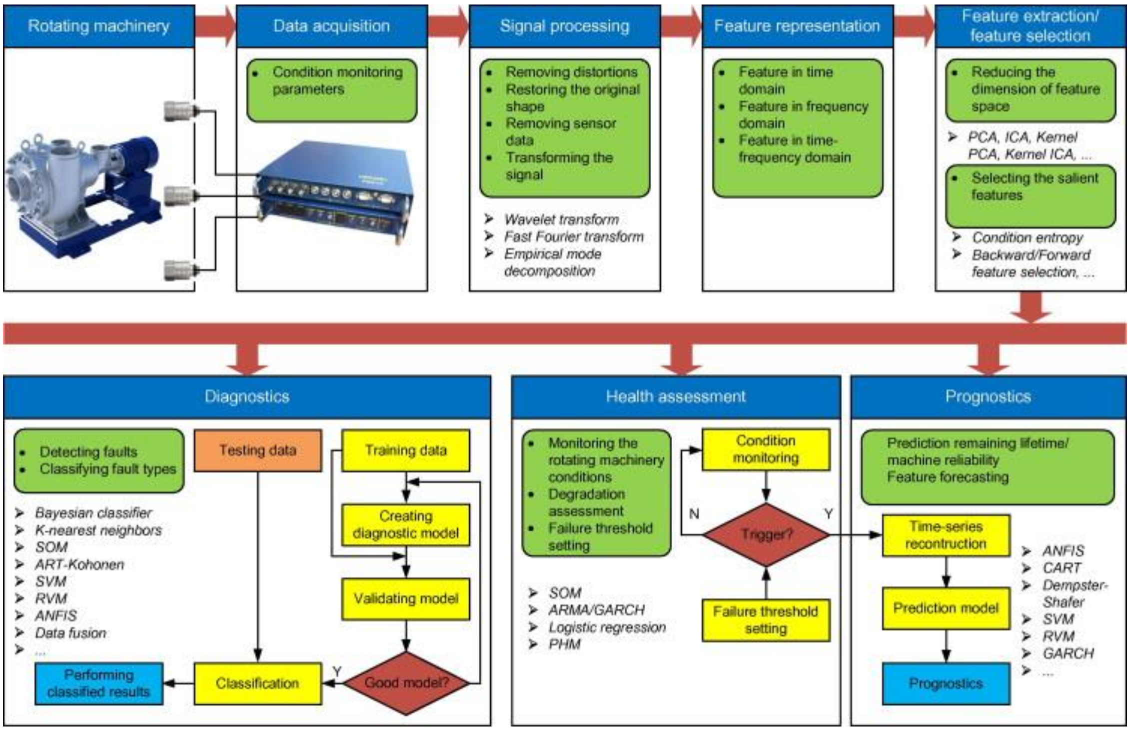

Fig.1 Overall architecture

Deploy edge agents (secondary equipment online monitoring and intelligent diagnostic devices) on the substation side to collect online operation data and status data of secondary equipment such as relay protection, measurement and control devices, safety devices, merging units, intelligent terminals, switches, etc., and make full use of The on-line monitoring and intelligent diagnosis device of the secondary equipment has the local and nearby data collection and edge computing capabilities at the substation, and dynamically diagnoses the communication status of the secondary equipment, the secondary circuit, the voltage/current, the pilot channel, the device self-check and other abnormal conditions [3]. Actively discover hidden faults and abnormal defects of secondary equipment, directly generate diagnosis results at edge nodes, and send them to the dispatcher through the communication module of the main substation. The dispatcher analyzes the dynamic diagnosis results of each edge computing in the control cloud for application display and fusion analysis , comprehensively improve the management and control capabilities and online diagnosis and analysis capabilities of secondary equipment in substations, rely on online data for intelligent research and judgment, and conduct dynamic diagnosis and analysis of the operating status of secondary equipment.

The intelligence of the distribution network needs to realize the all-round collection of system data, and to ensure the fast and efficient transmission and processing of the data when the data is not real, so that it can become a unified and uninterrupted data transmission that can ensure the integration of power, information flow and business flow. processing channels. Therefore, the first consideration in electric power big data is how to establish a unified structure model for data from different equipment sources and different structures, and comprehensively analyze it. On the other hand, in the operation and maintenance management of the system, it is still necessary to resolutely overcome the problem of "a lot

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of data, and it is difficult to filter the target information", quickly and accurately dig out the valuable and potentially usable information in the data, and extract it. It is really applied to the condition maintenance of the distribution network. At present, it is difficult to achieve the above two goals according to the traditional information processing method, so it is necessary to introduce data mining technology and information aggregation technology. Big data technology for condition-based maintenance of distribution network is a very hot research topic at present. The condition-based maintenance of the distribution network includes the condition-based maintenance of the power generation system, power transmission and transformation system, GIS system, and transformer system. Operation and maintenance help is limited, and its role has not been fully utilized.

In recent years, thanks to the development of the Internet of Things technology, the condition-based maintenance of the distribution network has been fully developed and widely used, and the condition-based maintenance data has grown exponentially. Distribution network data includes maintenance data, operating status data, equipment factory information data, etc. The data itself is large in volume, rich in types, and requires fast processing speed. Therefore, the use of big data technology to deal with distribution network maintenance is the right time. Time.

Under the background of big data maintenance of distribution network, big data statistics and analysis are mainly to analyze and summarize the massive state data under the state of the distribution network, and obtain a large amount of practical application data with incomplete information from the distribution network. , to obtain the potential hidden information process that plays a key role in the condition maintenance of the distribution network. Through the calculation of various algorithms, the state of the distribution network has been predicted, and it has the role of guiding opinions for maintenance.

In the stage of continuous optimization of the power transmission and transformation business of the power grid, making full use of big data technology to study the state of the distribution network can establish real-time monitoring of the state of the distribution network and regulate its future operating state. It can improve the management level of the entire distribution network. Compared with the planned maintenance and unscheduled maintenance in the past, it can save a lot of manpower and material resources, save the maintenance cost of the distribution network, and save unnecessary maintenance and inspection. The use of big data can solve the problem of finding the weak links of the power grid in different geographical environments, from the time dimension and the space dimension, and carry out normative transformation.

The introduction of big data can improve the big data application capabilities of distribution network enterprises, lay a good foundation for data mining and data utilization in the future, and make data management more centralized, services more comprehensive, utilization more efficient, and quality better. reliable.

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III. MULTI-DIMENSIONAL RELATED INFORMATION AGGREGATION OF SECONDARY EQUIPMENT BASED ON BIG DATA

This paper uses the information aggregation structure to analyze the big data of secondary equipment maintenance, and by screening the state data obtained in the distribution network, the distribution network decoration index is used as the dependent variable, and the factors that affect the hidden trouble of the distribution network equipment are used as the independent variable. Through the univariate linear regression, the relationship between each equipment failure influencing factor and the maintenance index dependent variable is established; through the multiple linear regression, the secondary equipment maintenance index is established as the dependent variable, and all factors affecting the equipment failure are used as the independent variable [4]. Linear relationship, analyze the influence of each factor change on the fault of distribution network equipment; analyze the correlation between the fault index influencing factors of the distribution network to find the complex correlation coefficient, and find the relationship between independent variables and independent variables. Through the above information aggregation, and using the correlation equation, the change of the independent variable corresponding to the dependent variable is analyzed to cause the change of the dependent variable, so as to obtain the basis for the secondary equipment maintenance. Through big data information aggregation, use univariate linear regression and multiple linear regression to determine the relationship between dependent variables and independent variables, and use complex correlation and partial correlation to determine the weighting coefficient, make full use of the advantages of big data processing, and gather information aggregation models, which can quickly and accurately Locate the maintenance object, find the cause of the failure, optimize the maintenance sequence and maintenance structure, thus saving the maintenance cost. Therefore, according to the basic structure of information aggregation for secondary equipment maintenance, according to the characteristics of each information process and object, and synthesizing the main points of secondary equipment maintenance, the corresponding information aggregation model architecture is proposed (Figure 2 is quoted in On-site Smart Operation and Maintenance System for Substation Equipment Based on Mobile Network).

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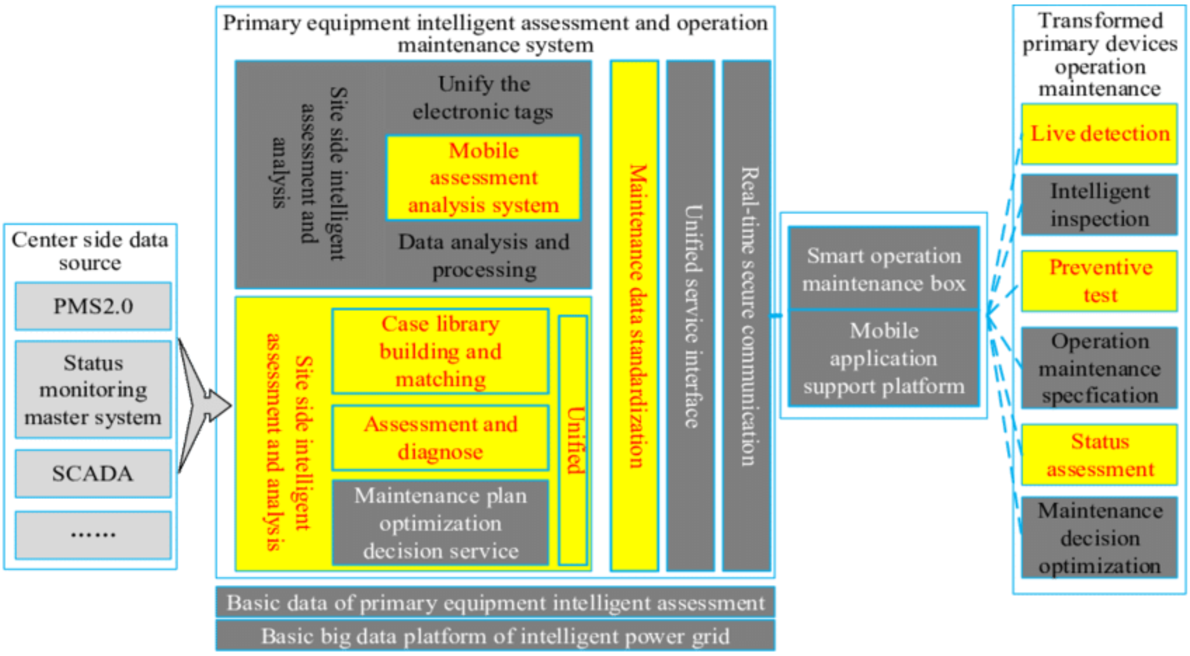

Fig.2 Architecture diagram of secondary equipment maintenance system

According to the characteristics of the detection object, the information aggregation method will give different aggregation systems. It is divided into multi-level, multi-source information aggregation model and ladder-type aggregation [5]. As shown in the figure below, each field in the multi-level and multi-source information aggregation model system covers the data layer, the feature layer and the decision layer (Figure 3 refers to Sustainable and secure trajectories for the military Internet of Drones (IoD) through an efficient Medium Access Control (MAC) protocol).

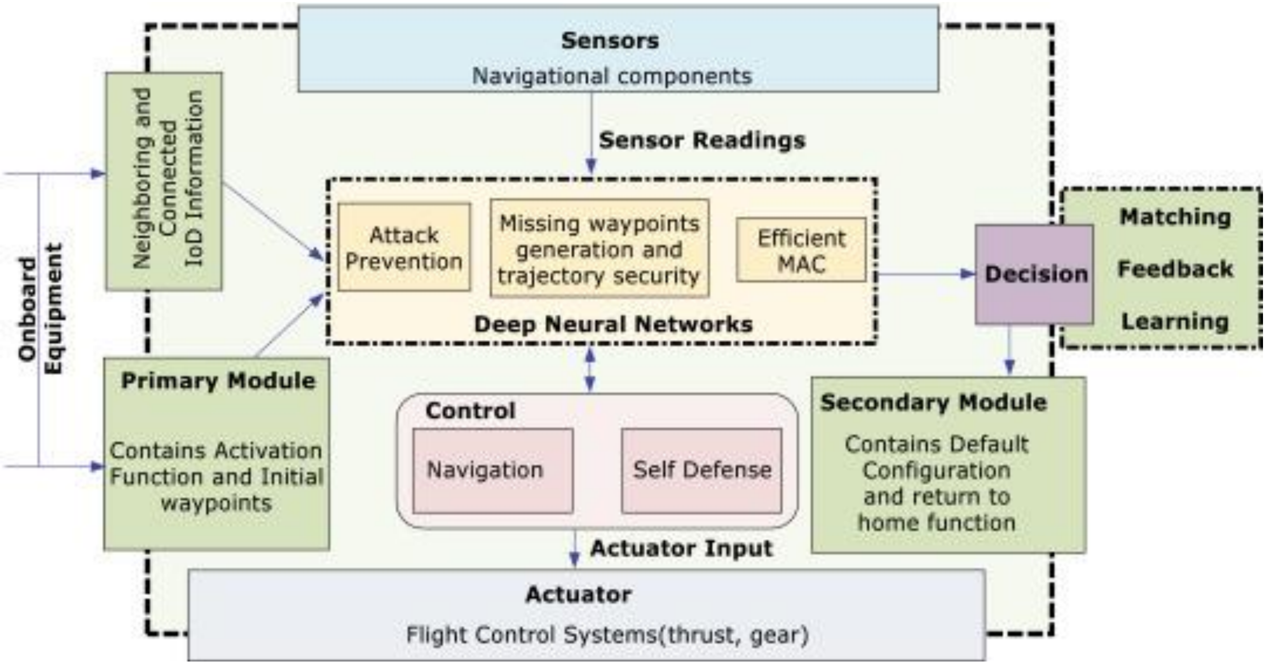

Fig.3 Information matching model by region

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The data collected in the secondary equipment inspection is nothing more than electrical quantity, state quantity, and process quantity, so the data should be classified before data-level aggregation, so as to improve the efficiency of data aggregation. Aggregating money at the data level requires two-dimensional association of the same type of data [6]. That is, between electrical quantities, between process quantities, and between state quantities, cross-category secondary associations are carried out through physical models or artificial experience, that is, between electrical quantities and process quantities, between process quantities and state quantities, and state quantities. associated with electrical quantities. This level of association can lead to clearer goals and more precise data analysis results. The data-level aggregation method is shown in Figure 4 below (the picture is quoted from Review of the false data injection attack against the cyber-physical power system):

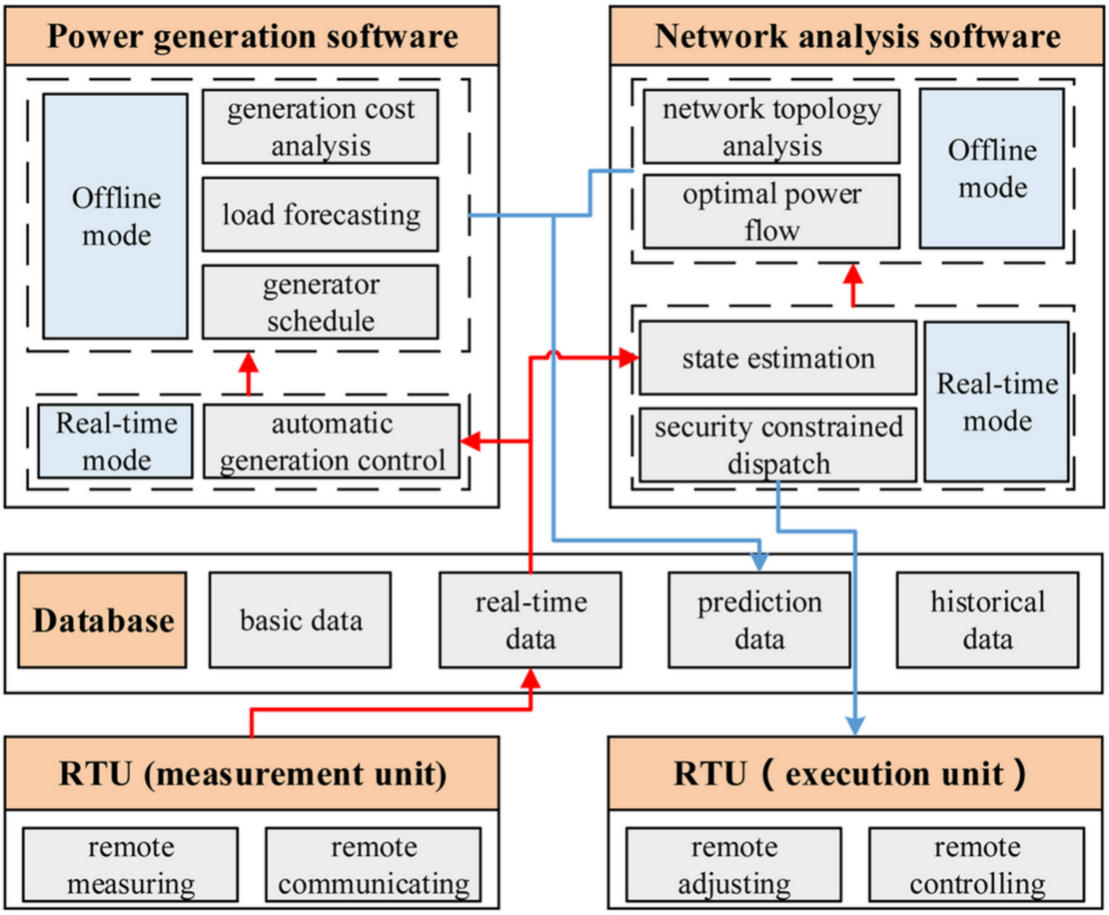

Fig.4 Formation of two-dimensional relationship of maintenance information

Data-level aggregation is based on data that has been cleaned. This part of the data has certain reliability and maturity. In the process of data-level aggregation, the requirements of information aggregation must be taken as the goal. Clarify the meaning of aggregation. The continuous in-depth research on the inspection and maintenance of secondary equipment has made the aggregation of distribution network big data more pertinent and comprehensive. It currently has the following features:

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First, data-level aggregation is built on experimental experience and physical structure models. In the aggregation at this level, whether it is artificial experience or physical data, it is justified, and the data source is objective [7]. At the same time, whether it is the same or cross-class data association, there is a basis, which is also a data-level Basic requirements for aggregation.

Secondly, it caters to the requirements of information aggregation. In data-level aggregation, it is generally based on the requirements of information aggregation, and a series of transformation and reorganization of data are also required, including the following points:

3.1 Aggregate data backup and storage

In order to find the original data in the information aggregation later, or after the data is accidentally damaged, the backup data can be called to reduce incomplete information caused by data loss. In other words, data storage and backup are the basis for subsequent information aggregation.

3.2 Data rearrangement, filtering, sorting and feature value extraction

In order to extract the eigenvalues of different levels and different objects, data-level aggregation extracts different eigenvalues for data from different data sources, and reclassifies them according to data characteristics and uses according to different data sources. Sorting, filtering the attributes, characteristics, usage and other rules of the data, and finally obtaining the feature quantity required for high-level information aggregation.

3.3 Associate and fuse the aggregated data at the data level

In order to further discover the hidden value in the data and find the internal laws and connections, it is necessary to use mathematical modeling to deeply mine the correlation between multiple data volumes to show the most comprehensive state of the data. In addition to data association, data fusion is also a method of discovering the internal connection of data and exploring deeper utilization values. After data classification, aggregation, and fusion, more valuable parts of the data can be obtained.

Univariate linear correlation analysis is to analyze the correlation between variables and determine the relationship between variables. The method is based on theoretical foundations and experience, and is generally represented in the form of graphs and lines [8]. The easiest way to analyze univariate linearity is the product-difference method, which uses the covariance of two variables and the standard deviation of the two variables to calculate the odds ratio. The following is the expression:

$$\mathrm{r}=\frac{\sigma_{xy}^{2}}{\sigma_{x}\sigma_{y}}=\frac{\sum(x-\bar{x})(y-\bar{y})}{\sqrt{\left(\sum(x-\bar{x})^{2}\right)\sum(y-\bar{y})^{2}}}=\frac{\overline{xy}-\bar{x}g\bar{y}}{\sqrt{\left(\overline{x^{2}}-\bar{x}^{2}\right)\left(\overline{y^{2}}-\bar{y}^{2}\right)}}=\frac{n\sum xy-\sum x\sum y}{\sqrt{n\sum x^{2}-\left(\sum x\right)^{2}}\sqrt{n\sum y^{2}-\left(\sum y\right)^{2}}} \tag{1}$$

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The above formula is generally calculated based on the original data, so the obtained data results are relatively accurate, and it is a common linear analysis equation. Its influence coefficient generally takes the value in [-1, 1], positive and negative respectively indicate positive correlation or negative correlation. The linear equation regression model is:

$$y_c = a + bx \tag{2}$$

In the above formula, yc, x, a, b represent the estimated theoretical value of the dependent variable, the actual value of the independent variable, and the constant coefficient, respectively. Meanwhile, a and b represent the geometric meaning of the intercept and slope of the linear equation system, respectively. From an economic point of view, when x=0, y=a, b is an increase of x by one unit, the increase or decrease of y. B is the regression coefficient. Among them, the expressions of a and b are:

$$b = \frac{n\sum xy - \sum x \sum y}{n\sum x^2 - (\sum x)^2} \tag{3}$$

$$a = \overline{y} - b\overline{x} \tag{4}$$

Standard error is the average error between the actual value and the theoretical value. The expression is:

$$S_{yx} = \sqrt{\frac{\sum (y - y_c)^2}{n-2}} \tag{5}$$

After the square root of $\sum (y - y_c)^2$, it needs to be divided by n-2, not n. Since the estimated regression line of two degrees of freedom has been lost in the formula, 2 is subtracted from the number n, but when the value of n is large (generally When n>1000), replace n-2 in the formula directly, then the formula will be transformed into:

$$S_{yx} = \sqrt{\frac{\sum (y - y_c)^2}{n}} \tag{6}$$

$$S_{yx} = \sqrt{\frac{\sum y^2 - a\sum y - b\sum xy}{n}} \tag{7}$$

When the number of independent variables in the system is large, it is necessary to establish a correlation between a dependent variable and multiple independent variables, which is called

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multivariate correlation analysis [9]. The regression analysis is called multiple regression analysis. According to whether it is linear, it can be divided into multiple linear regression equations and nonlinear regression equations. The multiple linear regression model expression is as follows:

$$y_i = b_0 + b_1 x_{i1} + b_2 x_{i2} + b_3 x_{i3} + \ldots + b_m x_{im} + u_i \tag{8}$$

In Equation 8, b_0 is the intercept, b_0, b_1, …, b_m are the slopes of the relationship between the dependent variable and their respective variables, and u_i is the residual residual value, subject to $u_i \sim (0, \sigma^2)$. The multiple regression equation is as follows:

$$y_i = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + \ldots + b_m x_m \tag{9}$$

The equations for parameters b_0, b_1, …are:

$$\begin{aligned}
\sum y &= nb_0 + b_1 \sum x_1 + b_2 \sum x_2 + b_3 \sum x_3 + \ldots + b_m \sum x_m \\
\sum x_1 y &= b_0 \sum x_1 + b_1 \sum x_1^2 + b_2 \sum x_1 x_2 + \ldots + b_m \sum x_1 x_m \\
\sum x_2 y &= b_0 \sum x_2 + b_1 \sum x_2 x_1 + b_2 \sum x_2^2 + \ldots + b_m \sum x_2 x_m \\
\sum x_m y &= b_0 \sum x_m + b_1 \sum x_m x_1 + b_2 \sum x_m x_2 + \ldots + b_m \sum x_m^2
\end{aligned} \tag{10}$$

IV. EXPERIMENTAL DETECTION

The first step is the learning process. Use a large number of training samples for adaptive learning, and adjust the weights according to the limited learning rules, so that the network can achieve the desired output [10]. The second step is the classification process. Using the weight vector in learning, the input variables are used for system identification| (Figure 5 and Table 1, the picture is quoted from https://www.nginx.com/blog/kubernetes-networking-101/).

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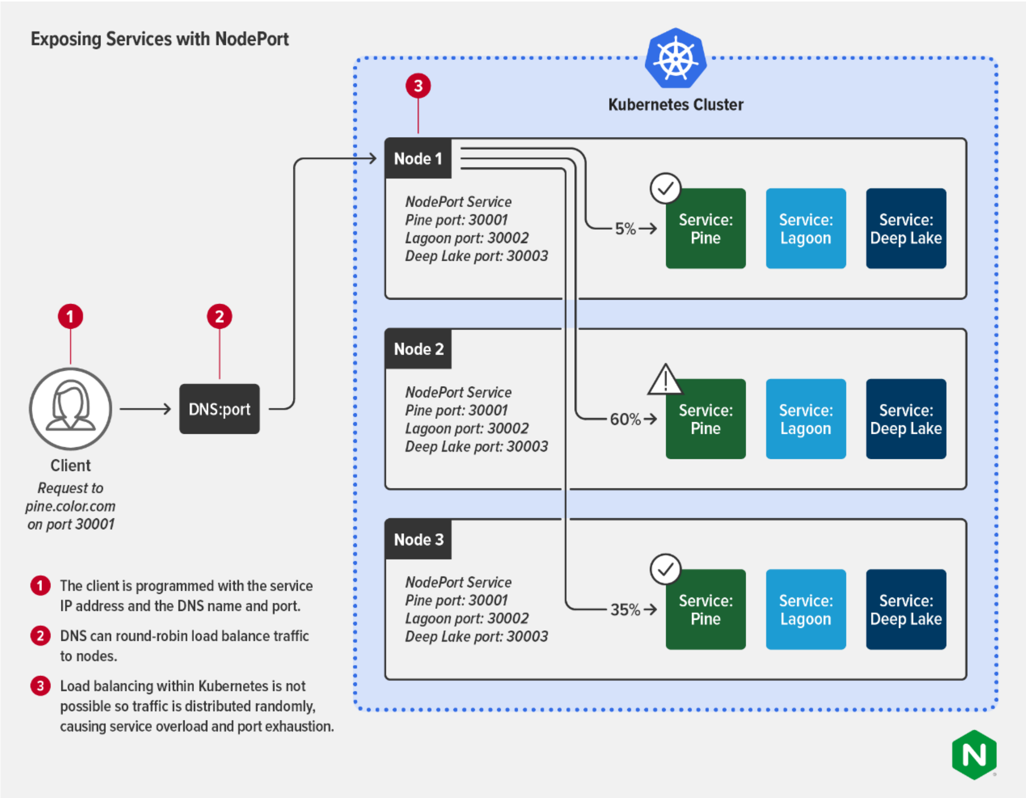

Fig. 5 Diagram of the cluster identification process of circuit breaker operating status information

TABLE 1 Sample Diagnostic Data

serial number	I_2	I_1	I_3	t_1	t_2	t_3	t_4	t_5	Corresponding fault
1	1.11	1.61	1.12	13.4	27.8	32.4	36.7	40.2	Normal
2	1.1	1.62	1.14	13.48	27.76	32.47	36.43	40.24	The idle travel of the closing iron core is too large
3	1.18	1.61	1.17	13.23	27.88	32.28	36.48	40.11	Iron core jam
4	1.1	1.48	1.11	13.46	27.82	32.38	36.61	40.18	low operating voltage
5	1.18	1.61	1.11	13.26	27.87	32.38	36.83	40.08	Poor contact of auxiliary switch action
6	1.11	1.63	1.12	13.14	28.72	31.81	34.83	38.81	The operating mechanism is jammed
7	1.18	1.6	1.11	13.1	28.7	31.8	34.8	38.8	Iron core jam
8	1.18	1.6	1.12	13.14	28.68	31.81	34.88	38.78	low operating voltage
9	1.17	1.48	1.08	13.07	28.72	31.76	34.8	38.74	The idle travel of the closing iron core is too large

After mapping the selected 28 groups of data to the 2, 3, 4, 5, and 6-dimensional spaces, the calculated error data obtained are shown in Table 25 below.

TABLE 2 Sample data dimension and corresponding error table

dimension	2	3	4	5	6
Error	8.2761e-006	5.6758e-007	4.0778e-008	8.2828e-008	1.8872e-008

According to the above chart, it can be found that the error gradually decreases as the number of dimensions increases, especially in the three-dimensional increase of two-dimensional, the decreasing trend of the error is larger [11], but from three-dimensional to four-dimensional and even to

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six-dimensional, although the error also shows a decreasing trend, but the magnitude of the reduction has moderated, and observe the scatter plot below. If the data selected in the table is mapped into three-dimensional space, the results obtained are more obvious. Therefore, the data about the circuit breaker in the table is mapped into the three-dimensional space, and the result is shown in Table 3 [12].

TABLE 3 Results of circuit breaker fault diagnosis sample data mapped to 3 dimensions

serial number	Y_1	Y_2	Y_3	Corresponding fault
1	-1.4808	-3.8135	1.518	Normal
2	-1.5418	-4.1185	1.5555	The idle travel of the
3	-1.5183	-3.8555	1.8583	Iron core jam
4	-1.455	-4.0433	1.5388	low operating voltage
5	-1.1818	-3.8514	1.5358	Poor contact of auxiliary
6	-0.55058	-3.1433	4.5501	The operating mechanism
7	-0.81581	-3.1538	4.5851	Iron core jam
8	-0.58555	-3.3158	4.5835	low operating voltage
9	-0.85518	-3.15	4.5511	The idle travel of the

Table 4 shows the 5 groups of diagnostic data and the corresponding fault types randomly selected in Table 3. All the above 5 groups of data are mapped to the 3-dimensional space of 28 groups of data, and then the corresponding faults are found in the data, and the results are shown in the table 5. The diagnosis result obtained by this method is consistent with the actual fault type.

TABLE 4 Diagnostic data CCA processing results

serial number	CCA processing results		
	Y_1	Y_2	Y_3
1	-1.612	-4.1279	2.9936
2	-0.97969	-3.2299	4.9062
3	6.2969	6.2336	-0.29971
4	-3.4463	-4.202	3.4062
5	-1.6977	-0.72216	-1.2471

TABLE 5 BMU and corresponding faults

serial number	BMU	Diagnostic result	Actual failure
1	93	Normal	Normal
2	98	The idle travel of the closing	The idle travel of the closing iron
3	86	Iron core jam	Iron core jam
4	42		low operating voltage
5	1		The operating mechanism is

V. CONCLUSION

This paper proposes a defect database model for secondary equipment in smart substations, and obtains association rules through data mining through an improved regression analysis algorithm, which can effectively improve the speed of the algorithm, reduce memory requirements, and obtain more

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effective association rules. The association rules of defect data can be used to analyze familial defects, find the weak links of defects in secondary equipment, and provide suggestions for maintenance personnel when troubleshooting defect locations and defect causes.

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