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Health Assessment Method of Equipment in Distribution Court Based on Big Data Analysis in the Framework of Distribution Network of Things

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ABSTRACT

Focusing on the problem that the quantity of equipment in the distribution court is huge and the operation status is difficult to reliably control, a method of equipment health status assessment in the distribution court based on big data analysis in the distribution network of things architecture is proposed. Firstly, based on the internet of things for power distribution, the evaluation system of equipment status in the distribution court is designed to ensure the efficient analysis of massive data through the cooperation of cloud center and edge computing. Then, at the edge of the system, the grey correlation analysis algorithm and the Granger hypothesis method are used to obtain the correlation and causality of the failure rate of equipment components and the influencing factors so as to understand the accurate failure rate of equipment components. Finally, the weight of factors affecting the equipment failure rate is identified by using the dynamic variable weight analytic hierarchy process, and it is corrected in the cloud center; and the overall health degree of the equipment in the distribution court is obtained through transformation. Based on the selected station area model, the proposed method is experimentally demonstrated. The results show that it can accurately obtain the real-time health status of the court equipment and the evaluation accuracy is close to 98%, which provides theoretical support for the operation and maintenance of the distribution network.

KEYWORDS

Cloud Center, Distribution Courts, Distribution Internet of Things, Dynamic Variable Weight Analytic Hierarchy Process, Edge Computing, Equipment Health Assessment, Grey Correlation Analysis Algorithm

INTRODUCTION

With the continuous improvement of social living standards and the rapid development of social productivity, the demand for and the dependence on electricity are increasing and the requirements for power supply reliability are also increasing (Ai & Zhao, 2021). Due to the demand of intelligent

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power grid construction, the number and types of power grid equipment are increasing, and its shape and structure are becoming more and more complex; this increases the pressure for safe operation and maintenance, especially in the distribution network system that directly connects with customers in which many key technologies of intelligent operation, maintenance, and evaluation are facing serious challenges (Jg et al., 2022; Taghikhani & Afshar, 2021). Therefore, it is of great significance to evaluate the health status of the distribution network and equipment, not only to improve the efficiency of distribution network operation and maintenance, but also to build smart grids (Sun & Li, 2022).

As an important link in the construction of smart grid (SG), the distribution network (DN) connects directly with the end users and undertakes intermittent loads such as electric vehicles and the distributed power supply. Its complex network structure leads to its complex operating conditions, while the variety of equipment and the uneven quality level make the system unable to form a reliable structure (L. Li et al., 2021). With the continuous development of the Internet of Things (IoT), the power IoT (PIoT) has gradually become the key technology for building intelligent control in the station area (Wei et al., 2023). The PIoT uses various network communication technologies and information sensing technologies to identify, classify, and network node switches and to realize the connection, information interaction, and function realization between nodes (Z. Li et al., 2021). On the basis of data acquisition, the remote monitoring of station area is realized through protocol transmission and data analysis. The health status assessment of equipment in the distribution court is also based on the edge computing gateway hardware platform and sensor data, in-depth mining, and the analysis of status characteristics of distribution big data equipment, the assessment of equipment health status, and the early avoidance of power outages caused by equipment failures (C. Li et al., 2021; Liang et al., 2021).

At present, some studies the health status of the equipment (HSoE) in the distribution court have been carried out in China, but most of them are concentrated on the main equipment of the DN and mainly rely on the manual inspection and registration of equipment status data for evaluation. There is a lack of a systematic evaluation model and of evaluation indicators, and its accuracy and timeliness are relatively poor, which is not conducive to the promotion and application of large-scale the distribution network (Cano et al., 2022). As a real-time dynamic system, the HSoE in the distribution court is not only determined by its own operating conditions, but also greatly affected by the changes in the external environment and its own needs. Therefore, its evaluation system needs not only the theory and tools of the system but also the extension of the research object from the equipment to the network as well as the development of a data platform supporting the health theory of the distribution system (Envelope et al., 2022; Song et al., 2022). How to evaluate the overall health status of a large quantity of equipment and systems in the complex dynamic DN poses a key challenge in the development of SG.

RELATED RESEARCH

Due to the late start of domestic sensing technology, the research on distribution equipment condition assessment is limited, and the equipment condition assessment model based on the health index was first proposed by foreign countries and has made considerable development and application; while domestic research is relatively limited, it also has broad research space and potential (Shi et al., 2021). At present, in the research of power system health assessment in China, the research on high-voltage equipment is becoming more and more mature, while the research on low-voltage equipment and the distribution network system is lacking (Hu et al., 2021).

Currently, the domestic research on the evaluation of the distribution network equipment status still needs to be furthered, although many of the research results have been achieved. For example, He et al. (2021) propose a method of equipment health assessment based on the similarity fuzzy dynamic principal component analysis (PCA), which uses error function to fuzzify equipment data and uses the PCA method to analyze the score and residual matrix to complete equipment health assessment by comparing the similarity between fault and normal data; but the environmental impact factors of the equipment are not considered. Cheng et al. (2022) designed a transmission line operation status evaluation method based on the improved combined weighted evaluation model and determined the weight of the evaluation index through subjective and objective integration; thus, they realized the evaluation of the actual line health status. Zhou et al. (2021) designed a risk assessment method for transformers in which the subjective weight coefficient of each state quantity is determined using the Analytic Hierarchy Process (AHP) and the objective weight coefficient of the comprehensive state quantity is determined based on the association rule mining. However, the strong subjectivity of the AHP method calls for the improvement in the reliability of the evaluation results. Gao et al. (2021) proposed a multi-level health evaluation method for transformers and uses the Gaussian cloud model to define the boundary of the evaluation index standard, but its applicability to other equipment has not been demonstrated and its robustness is not high. In a study by Elsisi et al. (2022), in the power transformer status detection based on the Internet of Things, a one-dimensional convolutional neural network for fault diagnosis and network attack is proposed, which can effectively evaluate the status of transformer equipment and avoid major power failure accidents. In a study by Yu et al. (2021), aiming at the low accuracy of the dissolved gas analysis (DGA) method in oil during the transformer fault diagnosis, a comprehensive feature extraction model is proposed, which uses fuzzy information entropy to obtain fault data characteristics and optimizes DGA parameters according to the characteristics to effectively improve the accuracy of equipment status evaluation. However, this method is too targeted, and it is difficult to apply it to the distribution area. Gz et al. (2021) propose a power equipment evaluation model based on the fuzzy logic membership function that improves the evaluation effect of the health status of power plant equipment throughout its life cycle. This method focuses on the whole life cycle of the equipment without considering the health status of each component of the equipment, which is not conducive to the operation and maintenance personnel carrying out equipment maintenance work.

Based on the above analysis, for single equipment, most of the research focuses on estimating the remaining service life without in-depth mining and the connotation of the health index, let alone forming a set of evaluation methods suitable for distribution equipment and network health. Therefore, in view of the lack of systematic equipment health status analysis and assessment in the distribution court, a method of equipment health status assessment in the distribution court based on big data analysis in the distribution network of things architecture is proposed in this paper. The major innovations of the proposed method are described as follows:

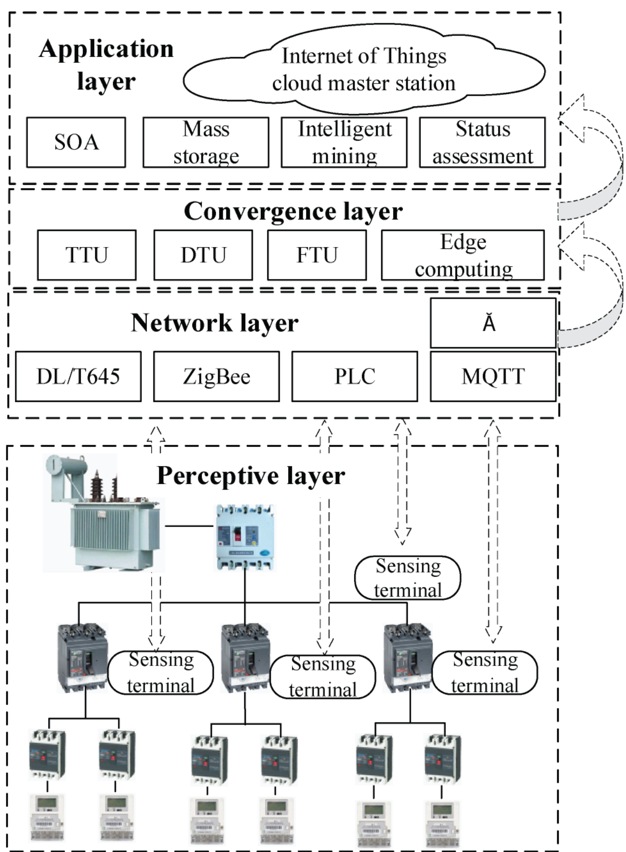
1. To improve the data efficiency in the distribution court, a state evaluation system is designed based on the distribution IoT (DIoT) architecture. Through the cooperation of cloud center and edge computing, the rapid processing of massive data is realized to meet the requirements of the power system.
2. Since most of the evaluation methods focus on the whole equipment and ignore the equipment components, the proposed method uses the grey association mining algorithm to analyze the main influencing factors of the equipment components and to obtain the corresponding failure rate, thus improving the reliability of the equipment fault identification.
3. Focusing on the problem that the complex environment in the distribution court causes inaccurate equipment status assessment, the proposed method uses the dynamic variable weight analytic hierarchy process to determine the weight of the influencing factors and carries out real-time correction according to the environmental factors, thus obtaining the ideal equipment health status assessment results.

Design of Equipment Condition Evaluation System in Court Based on DIoT

The architecture of the DIoT includes four layers – end, pipe, edge, and cloud – which are respectively the perception layer, network layer, convergence layer, and application layer (Wang et al., 2021). For this reason, the architecture of the court status assessment system based on the DIoT is shown in Figure 1.

1. **Sensing layer:** The sensing node converts various data and information in the real world into electrical signals for transmission and executes the program commands transmitted by the system master. The physical entities connected by the sensing layer are connected to the transmission layer through the communication module. In the distribution system, the terminal sensing devices in the court include various types of sensor nodes, voltage and current transformers, distributed energy, smart meters, etc. The perception layer mainly collects data from various devices to provide data foundation for edge computing.
2. **Network layer:** This is the link between the sensing layer and the convergence layer, and it is composed of various wired communication networks, various wireless communication networks, the Internet, and various private networks. Its role is to safely and accurately transmit the information obtained by the sensing layer to the convergence layer and the application layer and then process the information. In the station area equipment status evaluation system, the data are

Figure 1. Architecture of equipment status assessment system based on DIoT



firstly transmitted to the convergence layer through the wired power line carrier (PLC) network and then to the final monitoring platform through the 4G network, which has the characteristics of the network transmission layer of the wired and wireless integration of the distribution network of things.

3. **Convergence layer:** This completes the fusion and processing of system data. The physical device that realizes the functions of the convergence layer is the edge computing gateway, which mainly includes the core devices such as the new distribution transformer intelligent terminal. The edge computing terminal is the integration of information and physical nodes, and it has modules for data collection, communication transmission, and data calculation. These modules are used to collect and control sensing node data on the bottom and to realize key data interaction with the cloud master of the Internet of Things on the top. To meet the demand for real-time rapid response, and to weaken the high dependence on the cloud master station and reduce the computing pressure of the cloud master station, the edge computing terminal uses the "edge computing" technology to localize the online monitoring and intelligent analysis of the status of the equipment in the court and at the same time support the computing sharing and data interaction with the cloud master station. In the court equipment condition evaluation system, the distribution transformer terminal unit (TTU) is used as the edge computing gateway to analyze and judge the data transmitted by the sensing layer so as to realize the local establishment of the topology on the edge computing side as well as to mine and analyze the fault rate of each part of the equipment more efficiently.
4. **Application layer:** This is the information processing through the cloud computing platform. In the system, the cloud side uses the power distribution Internet of Things cloud master station to provide data interfaces for the lower layer through database and other technologies and combines the industry needs to complete the integration and intelligent application of data information. In the court equipment status evaluation system, the cloud master station of the IoT, as the application layer of the system, receives the topological structure data after the decision of the convergence layer through the MQTT (Message Queuing Telemetry Transport) bus interface; and it realizes the court equipment health status evaluation based on the established topology system, providing a basis for the operation and maintenance of the distribution system.

FAILURE RATE ANALYSIS OF EQUIPMENT COMPONENTS BASED ON GRAY CORRELATION MINING AT THE EDGE

Grey Correlation Analysis Algorithm

Grey correlation analysis (GCA) is used to analyze the correlation between various factors in the system including known information and unknown information using the grey system theory, which can well measure the correlation between various factors (S. Li et al., 2022). Grey correlation analysis quantifies the magnitude of the correlation between various factors, and this is called the correlation degree. When the two factors have the same changing trend, it is considered that their correlationis are high. When the changing trend of the two factors is significantly different, with little or no synchronous change, the correlation between them is considered to be low (J. Li, 2021). The correlation degree reflects the degree of the relationship between the sample sequence and the proximity of the discrete sequence space.

The GCA is used to compare several number series with the set reference number series, to form the data of correlation degree through the similarity of geometric shape between them, and to judge the tightness of their relationship (Q. Li et al., 2021). The specific steps of GCA are as follows:

Step 1: Determine the Reference and Comparison Sequence

Reference sequence refers to the system behavior characteristics and the final state characteristics of the system or the sequence formed by the data of the factors being compared under different circumstances. In the power distribution system, it can be considered as the final running state sequence of the system equipment. The reference sequence $\hat{X}$ is expressed as:

$$\hat{X} = \left\{ \hat{X}\left(k\right) \middle| k = 1,2,\cdots,n \right\} \tag{1}$$

The comparison sequence refers to the sequence composed of the factors that affect the system behavior characteristics and the final state of the system. In the distribution system, the comparison sequence can be considered as the collection of all the factors that affect the final operation status of the system equipment. The comparison sequence X_i is expressed as:

$$X_i = \left\{ X_i\left(k\right) \middle| k = 1,2,\cdots,n \right\}, i = 1,2,\cdots,m \tag{2}$$

Step 2: Raw Data Transformation

One should transform the original data to ensure the quality of data and the accuracy of system analysis, that is, to minimize the impact of various factor dimensions and render the various influencing factors comparable. For the original data sequence $x' = \left(x'\left(1\right), x'\left(2\right), \cdots, x'\left(n\right)\right)$, the mapping is:

$$\begin{aligned} &f : x \to y \\ &f\left(x'\left(k\right)\right) = x\left(k\right), k = 1,2,\cdots,n \end{aligned} \tag{3}$$

The interval transformation is used to realize the data transformation from sequence x' to sequence x. The mathematical expression of interval transformation is:

$$f\left(x\left(k\right)\right) = \frac{x'\left(k\right) - \min_k x'\left(k\right)}{\max_k x'\left(k\right) - \min_k x'\left(k\right)} \tag{4}$$

Step 3: Calculate the Correlation Coefficient

After completing the data transformation of $\hat{X}$ and the X_i, calculate the correlation coefficient ζ_i of each $\hat{X}$ and X_i. The ζ_i between the i-th X_i $x_i\left(k\right), k = 1,2,\cdots,n$ and the $\hat{X}$ $\hat{x}\left(k\right), k = 1,2,\cdots,n$ in X_i is calculated as:

$$\zeta_i\left(k\right) = \frac{\Delta_{\min} + \gamma\Delta_{\max}}{\Delta_i\left(k\right) + \gamma\Delta_{\max}} \tag{5}$$

where $\Delta_i\left(k\right) = \left|\hat{x}\left(k\right) - x_i\left(k\right)\right|$; $\Delta_{\min} = \min_i \min_k \Delta_i\left(k\right)$ represents the minimum difference between the two poles, and $\Delta_{\max} = \max_i \max_k \Delta_i\left(k\right)$ represents the maximum difference between the two poles, γ is the resolution coefficient whose usual value range is (0,1). When γ ≤w.5463, the algorithm has the best resolution, so set γ to 0.5.

Step 4: Calculate the Correlation Degree (CD)

The correlation coefficient is the CD between each value in the X_i and the corresponding value of the reference sequence. The calculation result is bigger than one; thus, the scattered data cannot express the correlation degree between X_i (influencing factor) and $\hat{X}$ (final result) as a whole. Therefore, it is necessary to take the average value of the correlation coefficient at each time and integrate it into a value – that is, the CD – to express the degree of correlation between $\hat{X}$ and X_i. The correlation degree ϑ_i is calculated as:

$$\vartheta_i = \frac{1}{n}\sum_{k=1}^{n}\zeta_i\left(k\right), k = 1,2,\cdots,n \tag{6}$$

Step 5: Sort by Relevance Degree

The ranking of the influencing factors can be obtained by sorting the degree of correlation according to the size. At the same time, the correlation between any two influencing factors can be obtained according to the size of different factors (Zhao et al., 2022).

Mining and Analysis of Failure Rate for Each Part of Equipment in Distribution Court

At the edge of the distribution network of things, the grey correlation analysis and the causal analysis are used to form the correlation matrix of the obtained data results to analyze the status impact factors for each part of the equipment in the distribution court (Gupta & Gupta, 2022; Zhao & Zhou, 2022). The Granger hypothesis method is used for a causal analysis. Let A_T and B_T be the values at *T* time, δ_1 and δ_2 represent the random white noise, and α_i, β_i, $\tilde{\alpha}_i$, $\tilde{\beta}_i$ represent the proportional coefficient. If $B_T = \sum_{i=1}^{T-1}\alpha_i A_i + \sum_{j=1}^{T-1}\beta_j B_j + \delta_1$ is established, *A* is the reason for the change of *B*; if $A_T = \sum_{i=1}^{T-1}\tilde{\alpha}_i A_i + \sum_{j=1}^{T-1}\tilde{\beta}_j B_j + \delta_2$ is established, *B* is the cause of change in *A*. The scale factor is between 0-1.

When mining and analyzing the fault rate of each part of the equipment in the distribution court, if the fault node is X_d, the relevant result set is recorded as $\left\{\pi^1\left(X_d\right),\pi^2\left(X_d\right),\cdots,\pi^m\left(X_d\right)\right\}$, where $\pi^i\left(X_d\right)$ represents the causal relationship with the i-th node. The specific calculation probability of the failure rate for each part of the equipment in the court is as follows:

1. The GCA algorithm is used to analyze the correlation of the original data Φ to retain the data with high correlation and to form the set *E*.
2. Carry out the causal analysis on *E* and obtain data with strong causal correlation to form set *F*.
3. Select voltage, current, oscillation, and service life as multidimensional sequence data $\hat{X}_1,\hat{X}_2,\cdots,\hat{X}_m$.
4. Set the correlation analysis threshold, and keep the sequence exceeding the threshold as $\widehat{E}_1,\widehat{E}_2,\cdots,\widehat{E}_m$.
5. Set the causal analysis threshold, and keep the sequence exceeding the threshold as $\widehat{F}_1,\widehat{F}_2,\cdots,\widehat{F}_m$.

6. The failure rate for each part of the equipment in the court is calculated as follows: $P\left(X_d \middle| \pi\left(X_d\right)\right) = P\left(X_d \middle| X_1, X_2, \cdots, X_{d-1}\right)$.

OVERALL EQUIPMENT HEALTH ASSESSMENT METHOD BASED ON DYNAMIC VARIABLE WEIGHT AHP IN CLOUD CENTER

Dynamic Variable Weight AHP

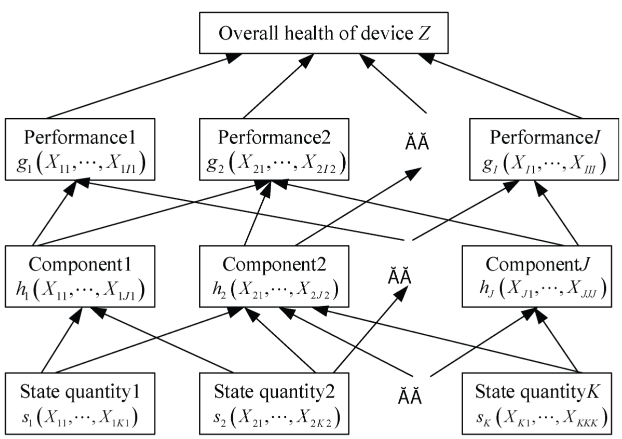
Because the traditional AHP is too subjective, the proposed method uses a dynamic way to determine the weight of each factor, and the weight can change with the change in the value of the factor; this can better reflect the dynamic and the nonlinear between the factors.

According to the characteristics of distribution network equipment, the factors affecting the overall power network equipment can be divided into four levels, as shown in Figure 2. The sequence is: target set *Z*, evaluate the overall HSoE; performance set $g_1, g_2, \cdots, g_I$ to evaluate the performance of the equipment; component set $h_1, h_2, \cdots, h_J$ to evaluate the operation status of each component of the equipment; and state set $s_1, s_2, \cdots, s_K$ to evaluate the specific operation of each state.

The dynamic variable weight vector generally includes three types of incentive, penalty, and mixed variable weight (Andriamaharosoa et al., 2022). In the proposed method, the penalty variable weight is selected according to the characteristic that the lower the failure rate is, the better the HSoE in the distribution station area is. It cannot only punish some indicator status values, but it can also achieve the balanced treatment of the weight of the whole evaluation index system, fully showing the complexity and dynamic of the equipment health evaluation index system in the distribution court. The variable weight function in the dynamic variable weight AHP method is:

$$f\left(x\right) = \begin{cases} \dfrac{c_2 - c_1}{\tau - \nu} \nu \ln \dfrac{\nu}{x} + c_2, \left(0, \nu\right] \\ -\dfrac{c_2 - c_1}{\tau - \nu} x + \dfrac{c_2 \tau - c_1 \nu}{\tau - \nu}, \left(\nu, \tau\right] \\ \dfrac{c_2 - c_1}{2\left(\tau - \nu\right)\left(\chi - \tau\right)} \left(x - \chi\right)^2 + c, \left(\tau, \chi\right] \\ c, \left(\chi, 1\right] \end{cases} \tag{8}$$

Figure 2. Dynamic variable weight hierarchy of equipment in distribution station area



where c_1, c_2, c are the weight adjustment parameters, and $0 < c < c_1 < c_2 < 1$; $\left(0, \nu\right]$ is an extremely strong punishment interval (the equipment is in an extremely dangerous state), $\left(\nu, \tau\right]$ is a strong penalty interval (the equipment is in a dangerous state), $\left(\tau, \chi\right]$ is the initial penalty interval (the equipment is in the hidden danger state), and $\left(\chi, 1\right]$ is the qualified interval (the equipment is in the normal qualified state). According to the constructed equipment health state variable weight function, the penalty intensity is greater than the excitation intensity, and ν, τ, and χ are set to 0.3, 0.5, and 0.9, respectively.

Health Assessment of Equipment in Distribution Court

In the proposed method, the equipment in the distribution court is mainly divided into six categories: overhead lines, cables, distribution transformers, switches, low-voltage branch boxes, and energy meters. $P_{0(u)}\left(1 \leq u \leq 6\right)$ represents the failure rate of class u equipment, and $P_{0(u)}$ represents the failure rate of each part $P\left(X_d \middle| \pi\left(X_d\right)\right)$.

At the same time, there are many factors affecting the overall health of the equipment, which can be summarized as overload, heavy rain, lightning, high temperature, and other factors. The corresponding weight is set as $\omega_1, \omega_2, \omega_3, \omega_4, \omega_5$. The weight matrix W of the overall failure factors for various equipment can be obtained through the dynamic variable weight AHP method, which is shown as follows:

$$W = \begin{bmatrix} \omega_{(1)1} & \omega_{(1)2} & \omega_{(1)3} & \omega_{(1)4} & \omega_{(1)5} \\ \omega_{(2)1} & \omega_{(2)2} & \omega_{(2)3} & \omega_{(2)4} & \omega_{(2)5} \\ \omega_{(3)1} & \omega_{(3)2} & \omega_{(3)3} & \omega_{(3)4} & \omega_{(3)5} \\ \omega_{(4)1} & \omega_{(4)2} & \omega_{(4)3} & \omega_{(4)4} & \omega_{(4)5} \\ \omega_{(5)1} & \omega_{(5)2} & \omega_{(5)3} & \omega_{(5)4} & \omega_{(5)5} \\ \omega_{(6)1} & \omega_{(6)2} & \omega_{(6)3} & \omega_{(6)4} & \omega_{(6)5} \end{bmatrix} \tag{9}$$

where $\omega_{(u)v}$ is the weight of class u equipment failure caused by factor v, and $1 \leq v \leq 5$.

Since each failure factor has different effects on the equipment status, the failure rate is modified according to the scenario factor, and its correction coefficient matrix ψ is as follows:

$$\psi = \begin{bmatrix} \varphi_{(1)1} & \varphi_{(1)2} & \varphi_{(1)3} & \varphi_{(1)4} & \varphi_{(1)5} \\ \varphi_{(2)1} & \varphi_{(2)2} & \varphi_{(2)3} & \varphi_{(2)4} & \varphi_{(2)5} \\ \varphi_{(3)1} & \varphi_{(3)2} & \varphi_{(3)3} & \varphi_{(3)4} & \varphi_{(3)5} \\ \varphi_{(4)1} & \varphi_{(4)2} & \varphi_{(4)3} & \varphi_{(4)4} & \varphi_{(4)5} \\ \varphi_{(5)1} & \varphi_{(5)2} & \varphi_{(5)3} & \varphi_{(5)4} & \varphi_{(5)5} \\ \varphi_{(6)1} & \varphi_{(6)2} & \varphi_{(6)3} & \varphi_{(6)4} & \varphi_{(6)5} \end{bmatrix} \tag{10}$$

where $\varphi_{(u)v}$ is the correction factor of class v fault factor to class u equipment.

According to the W and ψ, the correction matrix of failure rate Ψ with multiple factors can be obtained:

$$\Psi = W \cdot \psi = \left(\varsigma_1, \varsigma_2, \varsigma_3, \varsigma_4, \varsigma_5, \varsigma_6\right) \tag{11}$$

where $\varsigma_u \left(1 \le u \le 6\right)$ is the overall correction factor of the failure rate of class u distribution equipment.

When evaluating the overall HSoE in the distribution court through the distribution network of things, researchers first use the gray correlation analysis algorithm and the factor analysis to get the failure rate $P\left(X_d \middle| \pi\left(X_d\right)\right)$ of each component of the equipment on the edge side, and then upload it to the cloud center. The cloud center obtains the weight matrix of the overall equipment failure factors based on the dynamic variable weight AHP method and calculates the correction coefficient of the equipment with the Ψ so as to obtain the real-time failure rate P_{now} consistent with the actual status of the equipment (Sathiyamoorthi et al., 2021):

$$P_{now} = \varsigma_u \times P_0 \tag{12}$$

Finally, the real-time health degree Z_{now} of equipment is calculated according to the relationship between HSoE and P_{now}:

$$Z_{now} = \frac{1}{C} \times \ln\left(\frac{P_{now}}{Q}\right) \tag{13}$$

where Q is the scale factor and C s the curvature coefficient.

EXPERIMENTS AND ANALYSIS

Experimental Environment

In the experiment, eight distribution courts under the jurisdiction of a certain power supply company were selected for equipment health assessment, including eight distribution transformers, 820 power meters, 54 switches of various types, 30 branch boxes, 10 overhead lines, and 29 cables. The topology is shown in Figure 3. In addition, this experiment was completed on the 64-bit Windows 10 operating system.

Analysis Results of Equipment Component Failure Rate

Take the transformer oil of distribution transformer as an example to carry out the experimental demonstration of the failure rate of equipment components where the threshold values of correlation analysis and causal analysis are set to 0.7 and 0.05, respectively, and three levels of high, medium, and low are set according to the factors with high correlations. The analysis results are shown in Figure 4a and 4b.

From Figure 4a and 4b, it can be seen that the factors with a correlation degree higher than the threshold value include current, temperature, and others – in particular, the correlation degree of gas concentration is more than 0.7. Based on this, the factors with causality values higher than the threshold include high current, high temperature, low insulation level, high gas concentration, and

Figure 3. Model test outcomes for the proposed design

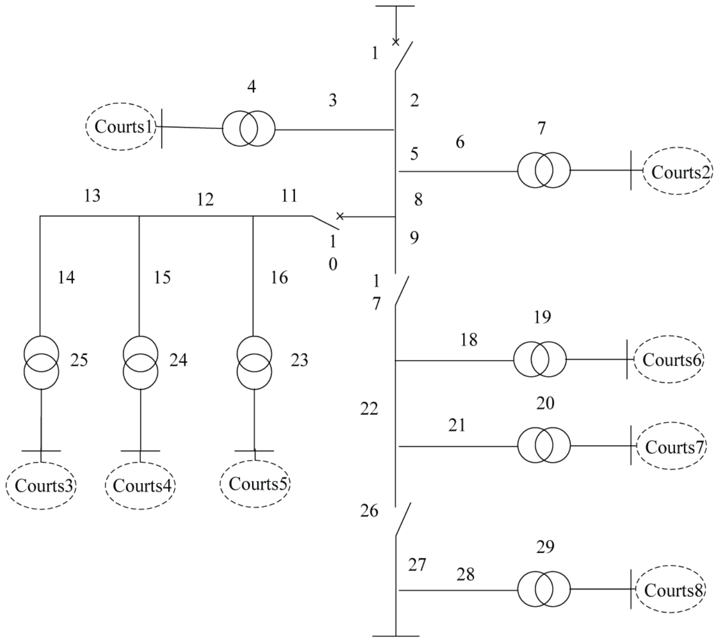
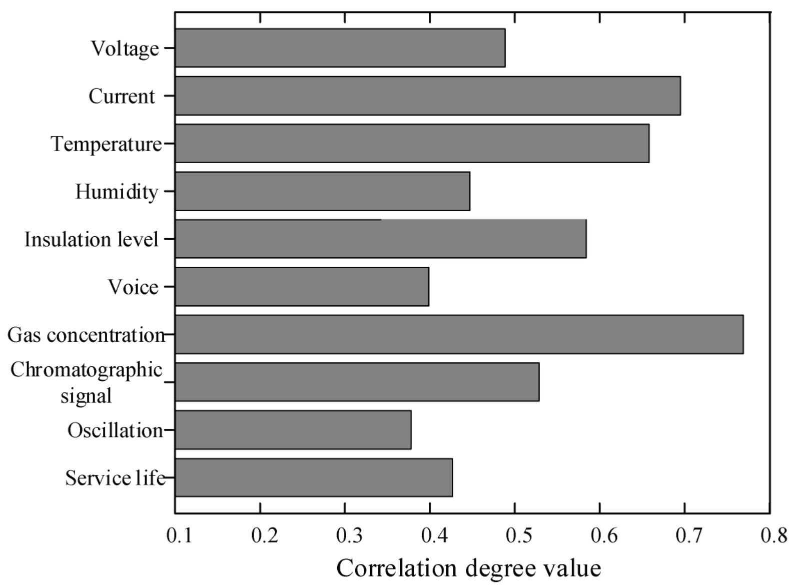


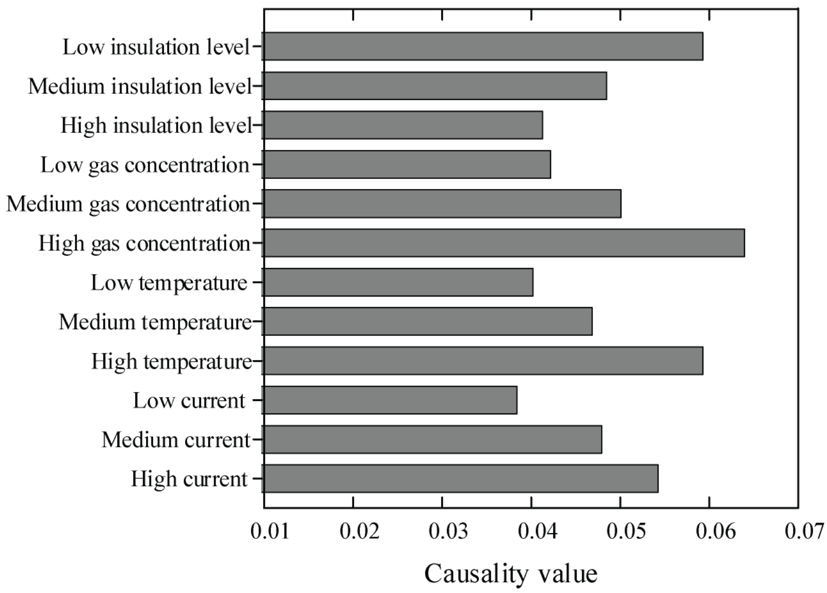
Figure 4a. Analysis results of influencing factors for equipment component failure rate correlation analysis results



medium gas concentration. Especially, the high gas solubility has a great impact on the failure rate of equipment components, exceeding 0.06.

Through the correlation analysis and the causal analysis, the failure influencing factors of distribution transformer oil are integrated into the failure rate calculation model and the probability

Figure 4b. Analysis results of influencing factors for equipment component failure rate results of causal analysis



of abnormal equipment status caused by high current, high temperature, low insulation level, gas concentration exceeding 1.3 times the threshold, and gas concentration exceeding one time the threshold is 64.21%, 70.97%, 68.05%, 73.64%, and 66.73%, respectively.

Overall Health Status Assessment Results of Equipment

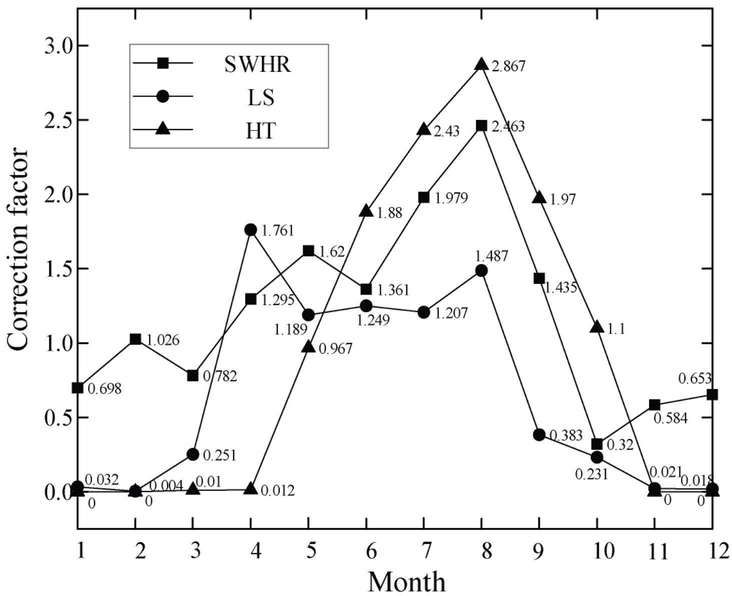
The weights of various fault factors (heavy load and overload HOL, heavy wind and heavy rain SWHR, lightning stroke LS, high temperature HT and others) of the whole equipment are calculated by using the dynamic variable weight AHP method, and the results are shown in Table 1.

As seen in Table 1, cables, meter boxes, and other equipment are basically covered by physical entities and are less affected by strong winds, heavy rain, and lightning strikes; while overhead lines and branch boxes are greatly affected by the environment. For overhead lines, the weight of strong winds and heavy rain accounts for 0.251. In order to better investigate the impact of environmental factors, the meteorological factors within one year are selected for weight correction. The correction coefficients of SWHR, LS, and HT are shown in Figure 5.

Table 1. Weight value of fault factors of whole equipment

Device Type	HOL	SWHR	LS	HT	Other
Overhead line	0.186	0.251	0.122	0.189	0.252
Cable	0.202	0.095	0.099	0.070	0.534
Transformer	0.234	0.095	0.049	0.127	0.495
Switch	0.185	0.136	0.167	0.125	0.387
Branch box	0.153	0.274	0.195	0.218	0.160
Electric meter	0.179	0.052	0.016	0.241	0.512

Figure 5. Meteorological correction coefficient value



From Figure 5, the meteorological factors in July and August are complex. Taking August as an example, the correction coefficients of SWHR, LS, and HT reached 2.463, 1.478, and 2.867, respectively. However, the lightning weather and high temperature correction coefficients in winter and spring are both 0, and the influence factors show little change.

The real-time failure rate and the health index of each equipment are calculated by comprehensively considering the weight and correction coefficient of each failure factor of the equipment, as shown in Table 2, where Q and C are 0.058 and 0.016.

As seen in Table 2, the real-time failure rate and the health index of all kinds of equipment in the distribution court can be obtained by integrating the operational status of equipment and the meteorological environment, among which the real-time health degree of the electric energy meter is the smallest (70.34%). Because of its large number and simple device, it is prone to failure. However, the failure rate of the transformer is low, at only 1.71%, and it is in a healthy operation state. By grasping the HSoE operation in the distribution court, the maintainer can formulate the operation and maintenance plan more scientifically. At the same time, the maintainer can quickly locate the equipment failure parts according to the failure rate of each part of the equipment so as to improve

Table 2. Real-time failure rate and health index of equipment in distribution area

Device	Fault Rate/%	Health Degree
Overhead line	2.18	76.19
Cable	1.24	85.25
Transformer	1.71	82.87
Switch	1.96	80.03
Branch box	2.07	79.56
Electric meter	3.54	70.34

the efficiency of maintenance, thus comprehensively improving the power supply reliability of the distribution network.

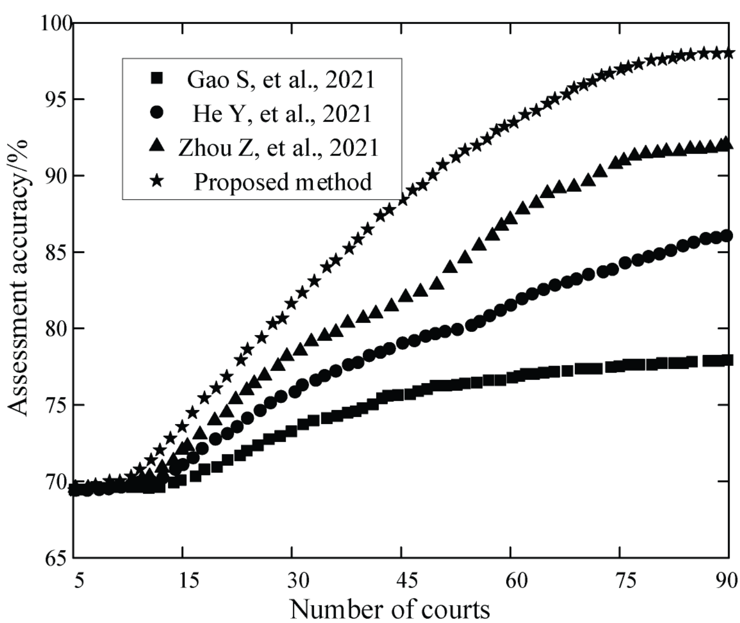
Comparison of Evaluation Results

Since the number of courts has a great impact on the evaluation effect, the proposed method is compared with studies by He et al. (2021), Zhou et al. (2021), and Gao et al. (2021) under different numbers of courts; and the evaluation accuracy is shown in Figure 6.

From Figure 6, it can be seen that the number of distribution courts is increasing and the accuracy of the equipment health assessment of the four methods has been improved. However, the proposed method is based on the distribution network of things architecture and strengthens the processing ability of data through the combination of cloud and edge, meaning that the larger the number of courts is, the more obvious the advantages of accurate assessment and analysis will be. Additionally, the accuracy of the proposed method is close to 98%. It combines the grey association mining algorithm and the dynamic variable weight AHP method to analyze the failure rate of equipment from parts to the whole and obtains the health degree according to the equipment characteristics, further ensuring the accuracy of the evaluation.

In addition, He et al. (2021) proposed an equipment health status assessment method based on similarity fuzzy PCA, which achieved the equipment health assessment through similarity comparison but lacked a consideration of equipment environmental impact factors. When the number of distribution courts is 90, the evaluation accuracy is only 78%. Zhou et al. (2021) proposed a transformer state risk assessment method, and its assessment accuracy rate exceeded 90%. However, the subjectivity of the AHP method is too strong, and the assessment results still need to be improved compared with the proposed method. The multi-level health assessment method is proposed by Gao et al. (2021), but this method is relatively simple and is only studied on transformers. Its universality is poor, and its assessment accuracy is less than 86%.

Figure 6. Comparison results of accuracy of equipment health status assessment by different methods



CONCLUSION

With the increasing popularity of smart grid, problems including the accurate assessment of equipment health in the distribution court, the reasonable arrangement of equipment maintenance plan, the prevention of large-scale power failure, the effective prevention of accidental accidents, and the extension of equipment life cycle are needing to be solved. To this end, a method for assessing the health status of equipment in the distribution court based on big data analysis in the distribution network of things is proposed to accurately obtain the operation status of equipment. Based on the design of the distribution network of things, the equipment status assessment system in the distribution court uses the gray correlation analysis algorithm and the Granger hypothesis method to obtain the correlation and the causality of the failure rate of each component in the equipment and the influencing factors at the edge side; this is meant to obtain the accurate failure rate of the equipment components. In addition, the dynamic variable weight AHP method is used in the distribution cloud center to obtain the weight of the factors affecting the equipment failure rate and to correct it; this is meant to obtain the overall health of the equipment in the distribution court. In addition, the proposed method is experimentally demonstrated based on the selected equipment data in the distribution court, and the results show that:

1. Through the fusion of grey association mining algorithm and the dynamic variable weight AHP method, the failure rate analysis of equipment from parts to the whole is realized and the accurate real-time health status of equipment in the substation court is obtained. The real-time health degree of the electric energy meter is the minimum, 70.34%.
2. The collaborative mode of cloud center and edge computing in the distribution IoT improves the efficient analysis capability of massive data, and its evaluation accuracy is close to 98%, which is superior to other comparison methods.

Due to the lack of monitoring devices and technical means for power distribution equipment. The accuracy of the proposed method in collecting the actual failure rate data of the equipment still needs to be discussed. In the next study, more data should be collected to render the evaluation method more accurate. At the same time, the authors will try to build a condition evaluation platform, which will be presented to the operation and maintenance personnel in a more intuitive way so as to facilitate the maintenance work.

AUTHOR CONTRIBUTIONS

Long Su, Kai Wang, Qiaochu Liang, and Lifeng Zhang are responsible for the manuscript.

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CONFLICTS OF INTEREST

The authors declare that publication of this paper does not involve any conflicts of interest.

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