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Research on Distributed Power Distribution Fault Detection Based on Edge Computing

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ABSTRACT With the advent of the era of Internet of Everything, the amount of data generated by edge devices in the distribution network has increased rapidly, bringing higher data transmission bandwidth requirements. At the same time, new applications have placed higher demands on the real-time nature of data processing, and traditional computing models have been unable to cope effectively. This paper proposes distributed power distribution fault detection based on edge computing, which can realize timely sensing and real-time response to distribution network faults, speed up distribution fault processing speed, shorten power outage time, improve power supply reliability and user satisfaction. Secondly, the basic principle of wavelet transform application in signal singularity detection is introduced, and a power signal fault signal analysis method based on wavelet transform is proposed. It not only makes full use of the advantages of wavelet transform in fault signal analysis, but also overcomes the shortcomings of traditional Fourier transform method, and verifies it through examples. Finally, based on the critical requirements of edge computing, such as agile connection, business real-time, data optimization, application intelligence, security and privacy protection, an evaluation system based on edge computing CROSS index fault detection model is proposed.

INDEX TERMS Distribution network, edge computing, wavelet analysis, CROSS indicator.

I. INTRODUCTION

When a distributed distribution line fails, necessary measures must be taken to eliminate the fault as soon as possible and restore the power supply. At present, most intelligent terminals configured through the respective units of the distributed power distribution system communicate with the main system to determine the location of the fault, and a unified matrix method is generally adopted for fault location. In addition, with the rise of advanced computer data processing technologies such as cloud computing, artificial intelligence algorithms are increasingly used for fault location and are receiving increasing attention. Among them, edge computing provides intelligent services at the edge of the network through intelligent processing on the edge of the network, converging network, computing, storage and information technology, and is suitable for technical requirements such as dynamic service management and marginalized security privacy protection with massive data features.

Edge computing uses intelligent processing at the edge of the network to integrate network, computing, storage, and information technology to provide services at the edge of the network. It is suitable for technical requirements such as business dynamic management with massive data characteristics, edge security and privacy protection [1], [2]. Edge computing has become a new computing model. By processing at the edge of the network, it reduces the pressure on the core nodes of the cloud network. At present, the development of this technology has received widespread attention in the industry. Through the continuous research and discovery of a large number of researchers, edge computing will be an ideal solution for large-scale intelligent terminals to realize automatic demand response (ADR) distributed intelligence in the future [3], [4].

In recent years, the application of edge computing to fault detection in distributed distribution networks has become a

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hot issue in academic and industrial research. Li [5] proposed an idea of applying edge computing technology to automatic demand response business. Shi *et al.* [1] proposed the PTN physical architecture model of active distribution network based on edge computing; further constructed a hierarchical adaptive autonomous CPS control model based on edge computing. Shi *et al.* [2] proposed a new method of traveling wave fault location for distribution network based on graph theory pruning algorithm. Yu *et al.* [3] proposed a fault diagnosis method for distribution network based on fault power direction criterion and Petri net. Zhang *et al.* [4] proposed a high-impedance fault detection method using time-frequency analysis. Li *et al.* [5] studied the variation of Clark's current phase angle difference before and after the fault of low-voltage active distribution network, and proposed a fault location method suitable for low-voltage active distribution network. Gong *et al.* [6] proposed a fault detection and localization method based on Stockwell transform (ST) and artificial neural network. Jia *et al.* [7] proposed a fuzzy fault detection and classification scheme based on fuzzy integrated power distribution system. Cheng *et al.* [8] developed a data-driven approach for initial fault detection and location in distribution networks. Most of the current researches have studied the performance of fault detection methods, and all the data sources are aggregated into the cloud for centralized computing, and various intelligent services in the cloud are carried out. However, with the increase in the number of terminals, the cloud computing model cannot effectively meet the real-time demand for massive data transmission, calculation and storage collected by large-scale intelligent terminals.

This paper is based on edge computing for distributed power distribution fault detection. The calculation object is that it can directly optimize the top-level power distribution system, and is not itself a sector control unit of the system control unit. Therefore, the corresponding communication, judgment and other tasks can be completed directly in the section, the communication process between components is shortened, and the data processing efficiency is improved. Provide decision-making basis for low-voltage power distribution fault handling of power grid inspection department, speed up fault processing, shorten power outage time, improve power supply reliability and user satisfaction.

The first chapter of this paper introduces the related content of edge computing and distributed power distribution fault detection;The second chapter describes the architecture of distributed power distribution fault detection system based on edge computing;The third chapter expounds the short-circuit fault detection technology of edge computing in distributed distribution lines;The fourth chapter introduces the theoretical content of wavelet transform and the case examples of wavelet transform;The fifth chapter uses the wavelet transform to monitor and analyze the short circuit and open circuit faults of the distribution network;The sixth chapter builds a fault detection model evaluation system based on the CROSS index of edge computing.

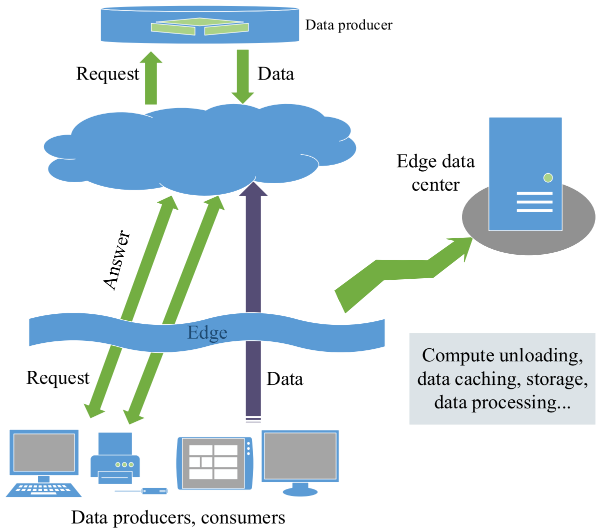

FIGURE 1. Edge computing architecture.

II. EDGE COMPUTING AND DISTRIBUTED POWER DISTRIBUTION FAULT DETECTION

A. CHALLENGES OF TRADITIONAL DISTRIBUTION AUTOMATION

At present, the construction of power distribution automation system of power grid company is mainly for 10k V urban distribution network. When the distribution network fails, the distribution automation master station will quickly determine the fault area according to the collected information, automatically isolate the fault area, and transfer the non-faulty area customers to other lines as soon as possible to resume power supply. The main sensing layer devices are from FTU, DTU and TTU, and the communication network is a fiber-optic private network or a wireless channel such as GPRS/4G.

When power distribution system equipment needs to achieve fault location and isolation, the high-cost fault-aware technology, high-reliability communication technology, and technical architecture for centralized database of traditional distribution automation systems are facing great challenges.

For data collection and processing of massive power distribution facilities, the Internet of Things and cloud computing models are undoubtedly more competitive [9].

B. ENERGY INTERNET OF THINGS AND CLOUD COMPUTING ARCHITECTURE MODEL

Edge computing not only handles local data and services local decisions, but also integrates and interoperates across vendors and applications in heterogeneous environments. The downstream data of the edge represents the cloud computing service, and the upstream data table represents the interconnection service, wherein the network edge can be any functional entity from the data source to the cloud center [10].

Entities carry edge computing platforms that integrate network, computing, storage, and application core functions

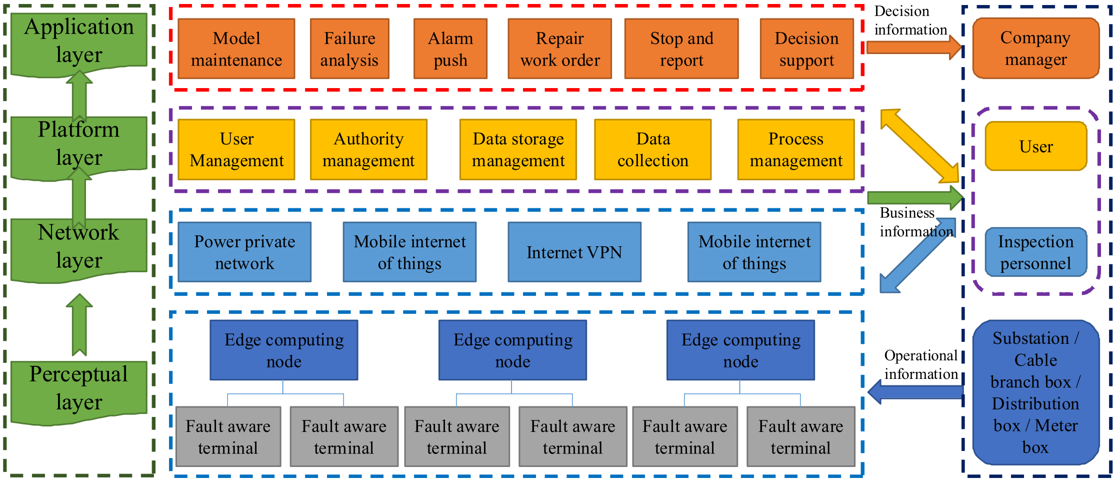

FIGURE 2. Overall structure of the power distribution fault handling system.

to provide end users with real-time, dynamic, and intelligent computing services. The "edge computing" architecture model is shown in Figure 1. It can be seen that for distribution network fault handling, edge computing is a very suitable solution.

C. DISTRIBUTION FAULT HANDLING EDGE COMPUTING ARCHITECTURE ISSUES TO BE SOLVED

Specific to the practical needs of power distribution fault handling, the following three core components need to be solved when adopting the edge computing architecture:

1)Low-cost, large-scale deployment of fault-aware devices.

2)Edge node devices with edge computing capabilities.

3)A cloud platform and application that supports massive power distribution data collection and storage and can be coordinated with edge computing nodes.

III. EDGE COMPUTING AND DISTRIBUTED POWER DISTRIBUTION FAULT DETECTION ARCHITECTURE

A. GENERAL STRUCTURE OF DISTRIBUTION FAULT DETECTON SYSTEM BASED ON THE EDGE COMPUTING

The overall structure of the distributed power distribution fault handling system based on edge computing is shown in Figure 2. The system consists of the sensing layer, the network layer, the platform layer and the application layer, and has typical ubiquitous power Internet of Things structure features [11]–[13].

1) PERCEPTUAL LAYER

The device includes fault-aware terminals and edge computing nodes deployed in distributed power distribution systems such as substation/cable branch boxes/power cabinets/user meter boxes. The fault-aware terminal and the edge computing node are both embedded hardware devices, and the fault-aware terminal has an adaptable communication interface, and accesses the edge computing node through multiple communication methods.

2) NETWORK LAYER

including power private network (fiber), Internet of Things private network, Internet (operator broadband) and mobile Internet (4G). The edge computing node accesses the platform layer through the network layer through the network adapter.

3) PLATFORM LAYER

It is a cloud service platform deployed under the commercial public cloud/private cloud system, with complete Iaa S/Paa S platform support capability. The platform layer deploys basic service software such as user management, rights management, log management, and data storage.

4) APPLICATION LAYER

It is the development and deployment of fault-related applications on the platform layer, such as model maintenance, fault analysis, alarm push, repair work orders, stop and power notification, statistics and auxiliary decision analysis, APP applications and other software.

B. DISTRIBUTION FAULT AWARENESS TERMINAL

The most widely used measuring equipment in the existing power distribution system is a multi-function meter or a power meter. These devices do not have the function of fault monitoring, and are large in size, poor in expandability, and inconvenient to install.

As shown in Figure 3, the device can accurately collect data such as loop current, voltage, residual current, temperature, etc., and has fault monitoring, analysis and judgment, and fault recording capability. When a fault is detected, a fault alarm signal can be generated. The device can communicate with the edge computing nodes via various communication modes such as Zig Bee/Lo Ra/RS 485. The device has an

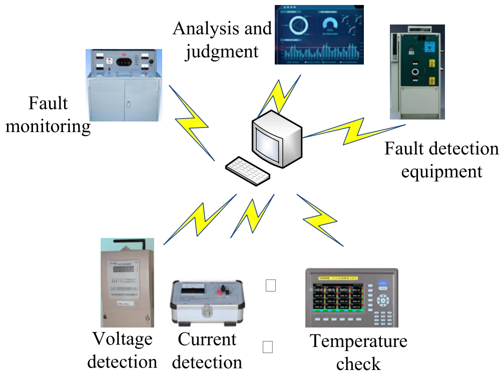

FIGURE 3. Distribution fault-aware terminal.

energy storage module that provides short-term power supply when the external power source is lost, so that the device can upload information to the edge computing node before completely losing power [14].

C. TROUBLESHOOTING EDGE COMPUTING NODE

In the hardware structure, the edge computing node is a small embedded industrial computer running real-time Linux operating system, communicating with fault-aware devices and cloud platforms.

According to the size of the distribution area, hardware platforms of different specifications can be selected, and the software system is completely consistent. The edge computing node stores the local power distribution network model, deploys the fault handling application, and configures event processing rules. The edge computing node performs local data processing, fault monitoring analysis, and transmits the processed result information to the cloud platform at the first time when the real-time data is received. In this mode, fault analysis and alarm tasks can be completed in milliseconds. The edge computing node has a distribution network model object information model that is completely consistent with the cloud platform, and forms a data mutual backup mechanism with the cloud platform.

D. EDGE COMPUTING ALGORITHM EXECUTION FRAMEWORK

There are many implementation frameworks designed for the characteristics of machine learning algorithms, such as TensorFlow [15] released by Google in 2016 and Caffe [16] which relies on the development of the open source community. But these frameworks run more in cloud data centers and are not directly applicable to edge devices. As shown in Table 1, cloud data centers and edge devices have large differences in the requirements for algorithm execution frameworks. In the cloud data center, the algorithm execution framework performs more of the model training tasks. Their inputs are large-scale batch data sets, focusing on the iteration speed, convergence rate, and scalability of the framework during training. Edge devices perform more predictive tasks, inputting real-time small-scale data. Due to the relative limitations of edge device computing resources and storage resources, they pay more attention to the speed, memory usage and energy efficiency of algorithm execution framework prediction [17].

TABLE 1. Comparison of algorithm execution frameworks for cloud data centers and edge devices.

Factor	Cloud Servers	Edge Devices
Input	Large-cale,patch	Small-scale,real-time
Task	Train,inference	Inference
	Training Speed	Inference Latency
Concerns	Convergence Rate	Memory Resource Usage
	Scalability	Energy Efficiency

IV. SHORT-CIRCUIT FAULT DETECTION TECHNOLOGY FOR DISTRIBUTED DISTRIBUTION LINES BASED ON EDGE COMPUTING

When the line of the power distribution system generates a short circuit fault, the main fault types are two-phase and three-phase short-circuit faults, as well as ground short-circuit faults (including two-phase and single-phase ground short-circuit types). If it is necessary to detect the short circuit fault of the system line, it is necessary to distinguish by these types. The characteristics of the short circuit fault of the distribution line are as follows:

A. THREE-PHASE SHORT CIRCUIT FAULT CHARACTERISTICS

If it is detected that the line current value of the whole system is greater than the rated current of the system, and the characteristics of the three-phase current voltage symmetry do not change, the type of fault that occurs is a three-phase short-circuit fault. At this time, if the line of the power distribution system detects a short circuit fault, it can be judged by using these evaluation criteria, that is, the value of the current in the line is significantly higher than the rated current of the line. At the same time, the three-phase symmetry characteristic of the current and voltage is maintained, and then it can be concluded that a three-phase short-circuit fault has occurred in the line at this time.

B. TWO-PHASE SHORT-CIRCUIT FAULT CHARACTERISTICS

The main performance of the two-phase short-circuit fault in the distribution system is the short-circuit of the two-phase line. In the case of a two-phase circuit in which a short circuit occurs, the direction of current flowing therethrough is opposite, and the phase angle between the two is 180°. Therefore, by this current characteristic between the two-phase circuits, it can be judged whether or not a two-phase short-circuit fault has occurred. In the circuit of the section, the current angle difference measured in any two-phase circuit is 180°, and it can be concluded that the two-phase circuit short-circuit fault occurs.

C. SINGLE-PHASE GROUNDING SHORT-CIRCUIT FAULT CHARACTERISTICS

When it is judged that the grounding short circuit fault occurs in the entire distribution system, it can be firstly judged as a single-phase grounding short-circuit fault because this type of ground fault has the highest frequency. The single-phase grounding short-circuit fault is mainly divided into two types: the neutral point is not grounded, and the neutral point is grounded by the arc-suppression coil according to the difference of the neutral grounding mode. If a neutral point ungrounded fault occurs in the single-phase line of the distribution line, the zero-sequence current flowing in the ungrounded line system is equal to the vector sum of the capacitor currents in all normal lines except the fault line. At the same time, the direction of the capacitive reactive power on the faulty line is opposite to the direction of the reactive power on the normal line. When judging the type of line fault, by comparing the magnitude of the zero sequence current of the faulty line with the sum of the capacitor currents on the normal line, and detecting whether the direction of the reactive power of the fault line current is consistent with the direction of the current reactive power of the normal working line, To determine whether the type of fault occurring in the line is a single-phase short-circuit fault [18].

V. FAULT DETECTION OF DISTRIBUTION NETWORK BASED ON WAVELET TRANSFORM

The power distribution fault-aware terminal is an embedded intelligent terminal. The input of the equipment is the three-phase current and three-phase voltage signals of the monitoring circuit. The frequency tracking and synchronous sampling technology are adopted. After the analog quantity is pre-low-pass filtered, it is converted into a digital signal by sampling. The fault analysis and calculation adopts wavelet transform algorithm, which has strong anti-interference ability. The device can actively report the amount of remote signals to the edge computing nodes, including loop power / power failure, trips, current limit violations, etc., and can also receive edge node queries to upload fault record data.

A. EDGE COMPUTATION NODE DISTRIBUTED COORDINATION FAULT PROCESSING

As shown in Figure 4, the voltage power distribution system is divided into different zones according to the area. Each edge is responsible for local data acquisition and fault analysis calculation by an edge computing node.

The edge computing node and the cloud service platform establish a synchronization mechanism to obtain distribution network model information within the partition and store the model information locally. The edge location calculation node deploys a fault location analysis application. In actual operation, the edge computing node obtains the data information sent by the fault-aware device in real time, completes the topology real-time analysis, fault monitoring, fault location analysis, and sends the fault processing result to the cloud service platform.

For cross-region fault location analysis, such as tripping, the cloud nodes deployed on the fault processing cloud platform will report and report the information after summarizing the partitions.

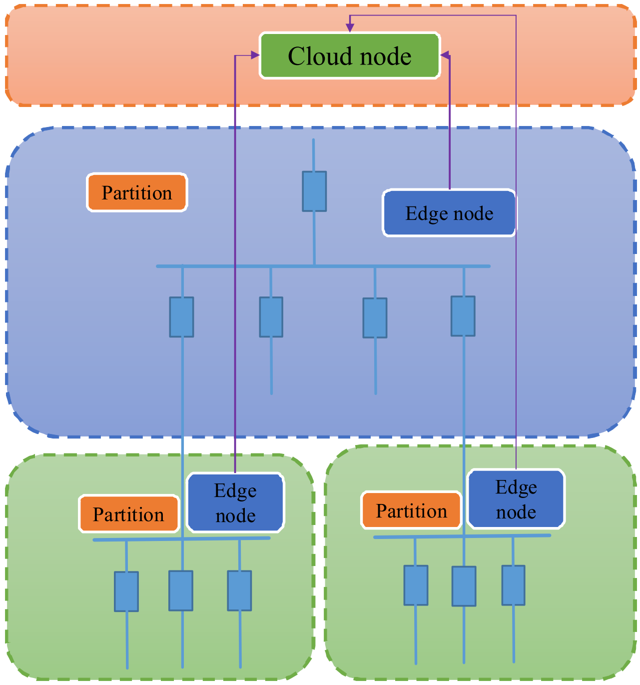

FIGURE 4. Distributed coordination fault processing of edge computing nodes.

B. DEFINITION OF SIGNAL SINGULARITY

In mathematics, an infinite number of lines that can be smoothed to a function has no singularity. If the function has a discontinuity or a derivative of a certain order is discontinuous, the function is said to have singularity here, which is a singular point. Singularity reflects the degree of irregularity of the signal, and the singularity of the signal is described and measured by the Lipschitz index [19]–[23].

Definition 1: Let n be a non-negative integer, $n \leq \alpha \leq n + 1$, if there are 2 constants A and $h_0(> 0)$, and the nth degree polynomial $P_n(t)$, so that for any $h < h_0$, there are:

$$|f(t_0 + h) - P_n(h)| \leq A\,|h|^{\alpha} \tag{1}$$

Then $f(t)$ is Lipschitz α at point t_0.

It can be seen that the Lipschitz exponent characterizes the singularity of the function $f(t)$ at point t_0. The larger the Lipschitz index α, the smoother the function $f(t)$. If the function $f(t)$ is continuous and differentiable at point t_0, then the Lipschitz index is $\alpha = 1$. If the point t_0 is not continuous but bounded, then the Lipschitz index $\alpha = 0$. When the Lipschitz index $\alpha < 1$, the function $f(t)$ is singular at point t_0.

C. WAVELET TRANSFORM AND SIGNAL SINGULARITY

The wavelet transform convolves the signal with a translational stretching wavelet basis function with localization properties in both time and frequency domains, and decomposes the signal into components located in different frequency bands-time periods [24]–[26].

If the basic wavelet function $\Psi(t) \in L^2(R)$, satisfied:

$$C_\Psi = \int_R \frac{|\Psi(\omega)|^2}{\omega} d\omega < +\infty \tag{2}$$

Then the wavelet transform of the function (signal) $f(t) \in L^2(R)$ at the scale s and the position t is defined as:

$$Wf(s,t) = f(t) \cdot \Psi_s(t) = \int_R f(\tau)\Psi_s(t-\tau)d\tau \tag{3}$$

The telescopic wavelet is defined as the $s > 0$ scaling factor in $\Psi_s(t) = \frac{1}{s}\Psi(\frac{t}{s})$.

The Fourier transform of a wavelet transform on a variable is:

$$Wf(s,\omega) = f(\omega) \cdot \Psi_s(\omega) \tag{4}$$

In the formula $\Psi_s = \Psi(s, \omega)$.

It can be seen from the characteristics of the wavelet transform that the value of the wavelet transform $Wf(s, t_0)$ strongly depends on the value of the signal $f(t)$ near the field at the point t_0, and the smaller the scale s, the smaller the domain interval. So at the right scale, $Wf(s, t_0)$ will provide local information about the desired signal near t_0. The following theorem gives the relationship between the attenuation of the signal wavelet transform along the scale and the local Lipschitz exponent of the signal, and the characteristics of the signal singularity are obtained.

For convenience, assume that the wavelet function $\Psi(t)$ is a continuous differentiable function, and is a real number and has a tight support set, when $|t| \to +\infty$, $|\Psi(t)| \leq o(\frac{1}{1+t^2})$.

Theorem 1: Let $f(t) \in L^2(R)$, $\Psi(t)$ be the basic wavelet, then the necessary and sufficient condition for $f(t)$ to be Lipschitz exponent α in an open interval is:

$$|Wf(s, t_0)| \leq As^\alpha \tag{5}$$

Theorem 1 gives the speed at which $|Wf(s, t_0)|$ decays when $s \to 0$. The Lipschitz α given above is a partial engraving of the singularity of the signal in the interval, not just the overall engraving on the real domain.

Theorem 2: Let n be a positive number, $\Psi(t)$ be a wavelet function with a compact support set, with n order vanishing moment and n order continuously differentiable. Well, if there is a scale $s_0 > 0$ makes it to all $s < s_0$ and $t \in [a, b]$. And $|Wf(s,t)|$ has no local maxima, then for $\varepsilon > 0$ and $\alpha < n$, $f(t)$ has Lipschitz α consistent in interval $[a - \varepsilon, a + \varepsilon]$.

The theorem states that if the wavelet transform has no local maximum, the signal is not singular in this interval. It can be further inferred that the closure of the point t of $f(t)$ non-Lipschitz n is included in the closure of the extreme value of the wavelet transform modulus of $f(t)$, indicating that all singular points of $f(t)$ can be located along the wavelet transform extremum chain. In practical applications, the signal singular points are obtained by examining the modulus extreme points of the wavelet transform. From the characteristic analysis of the singular signal under wavelet transform, it can be concluded that the extreme point of the signal wavelet transform mode is the singular point of the signal, while the description of the signal singularity Lipschitz exponent is calculated by the attenuation along the scale of the wavelet transform. This has important application value for signal analysis and feature extraction.

D. ALGORITHM VERIFICATION

This paper uses Matlab to tune the signal containing odd points. From the original signal, other sinusoidal signals are added in the second half of the sinusoidal signal, and the signal is decomposed into the third layer by the "db3" wavelet. It can be found from the figure that when the above-mentioned signals are detected by selecting the orthogonal wavelet db3 having a tight support set, a good effect is obtained, and the result is shown in Figure 5.

VI. EXAMPLE ANALYSIS

Wavelet analysis is widely used in fault diagnosis: singular signal detection, signal-to-noise separation and frequency band analysis. From the research of singular signal detection, the singularity index is used to measure the singularity of the distribution network signal, so as to realize the fault detection of the distribution network.

The magnitude of the signal singularity index reflects the extent of the fault. The occurrence of a fault often causes a sudden change in the peak of the time domain waveform. Therefore, through the singularity index extraction and statistics, it can be used as the characteristic factor of the signal time domain to realize the automatic detection of distribution network faults. Figure 6 shows the sensor's normal signal for the distribution network.

A. SHORT-WAVELENGTH FAULT MONITORING OF DISTRIBUTION NETWORK WITH WAVELET TRANSFORM

The short-circuit fault voltage obtained by the above simulation is taken as the original signal. By comparison, it is found that the orthogonal wavelet db3 with tight support is used to detect the above signal, and good results are obtained. In the MATLAB programming environment, the db3 wavelet is used to decompose the low-frequency signal and the high-frequency signal of the original signal in three layers, and a total of six layers of detailed signals are obtained.

As can be seen from Figure 7, the exact position of the abrupt point is clearly shown in the detail portion of the signal decomposition from the first layer (d1 = 350) to the third layer (d3 = 350). It is thus possible to introduce a sudden change in the original signal at this point in time, which is in complete agreement with the set parameter settings.

B. MONITORING OF BREAKING FAULTS IN DISTRIBUTION NETWORK WITH WAVELET TRANSFORM

In this paper, the breaking fault voltage of the distribution network is the original signal. When the voltage signal of the distribution network is detected by selecting the orthogonal wavelet db3 with tight support, it is found that the signal

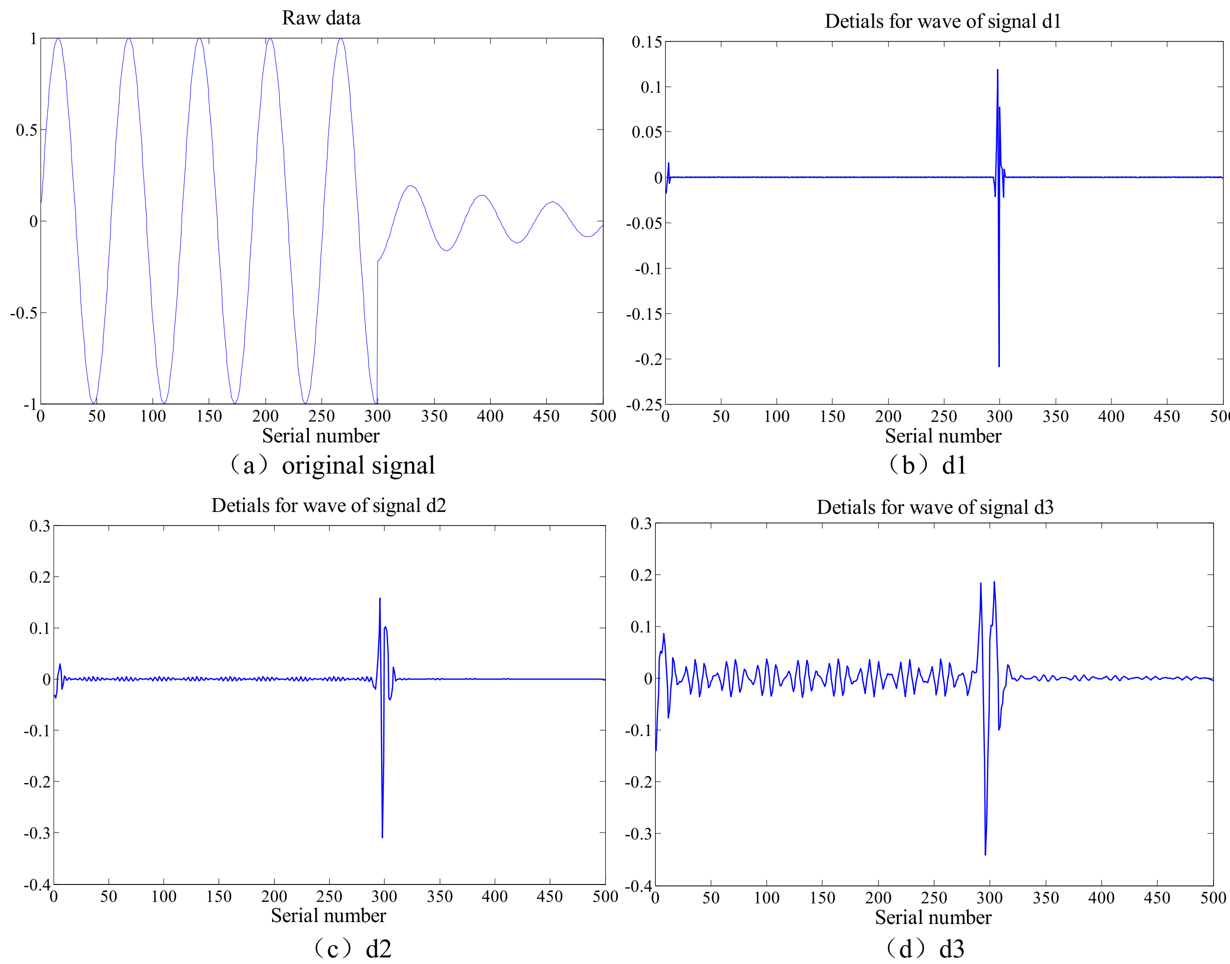

FIGURE 5. Signal singularity detection for wavelet analysis.

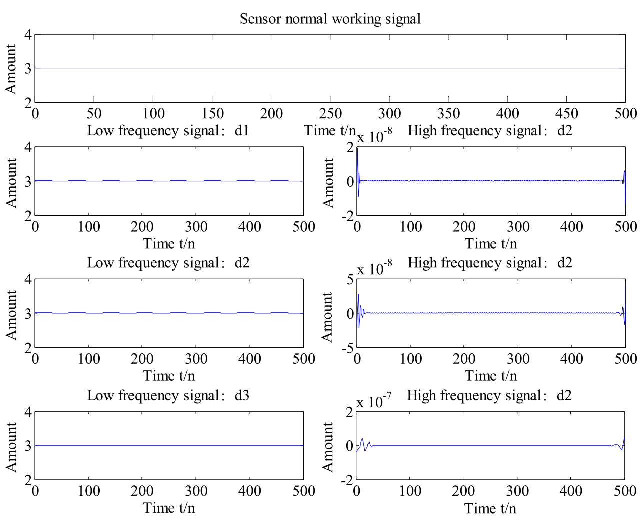

FIGURE 6. Normal signal detected by the distribution network.

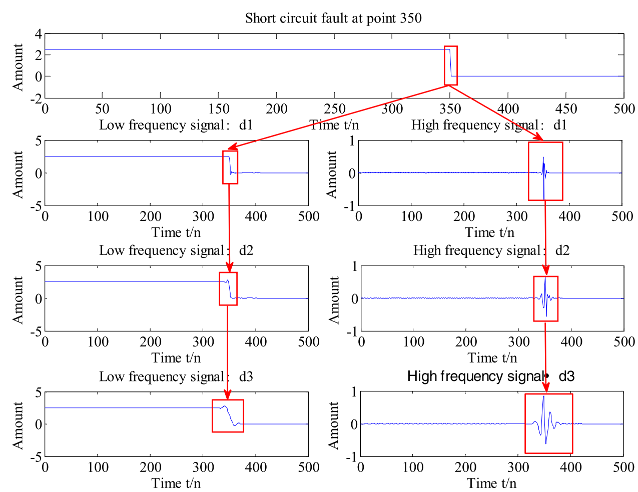

FIGURE 7. Monitoring of short-circuit faults in distribution network with wavelet transform.

suddenly rises at 350. Using the db3 wavelet, the low-frequency signal and the high-frequency signal of the original signal are respectively decomposed into three layers, and a total of six layers of detailed signals are obtained.

As can be seen from Figure 8, the exact position of the abrupt point is clearly shown in the details of the signal decomposition from the first layer (d1 = 350) to the third layer (d3 = 350). As a result, the original signal can be

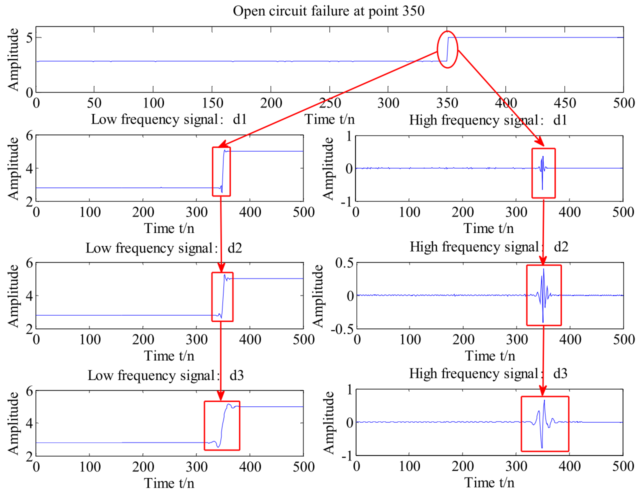

FIGURE 8. Monitoring of disconnection faults in distribution network with wavelet transform.

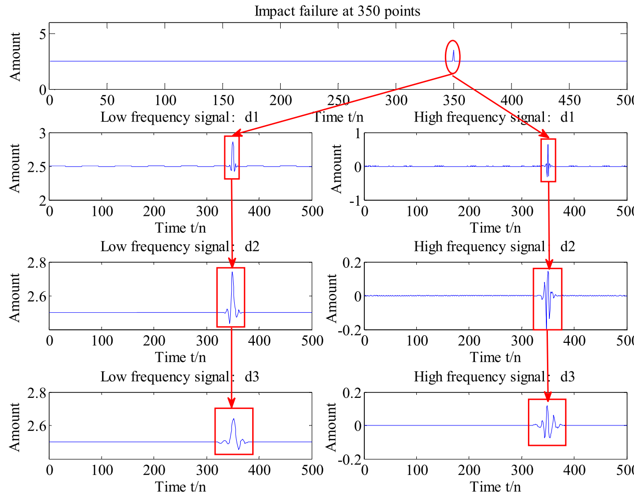

FIGURE 9. Monitoring of shock faults in distribution network with wavelet transform.

mutated at this point in time, indicating that the distribution network has an open circuit fault at 350.

C. MONITORING OF SHOCK FAULTS IN DISTRIBUTION NETWORK WITH WAVELET TRANSFORM

Statistics show that the lightning damage rate of distribution transformers in medium thunderstorm days is 1%. When the lightning wave is invaded by the low-voltage line, the low-voltage winding of the distribution transformer has an inrush current flowing, and it will also generate an induced electromotive force on the high-voltage winding according to the turns ratio. The neutral potential of the high voltage side is greatly increased, and the gradient voltage between the layers and the crucible is correspondingly increased. As shown in Figure 9, when the distribution network has an impact fault, the wavelet analysis can accurately detect that the impact fault occurs at point 350.

Through the experiments of using wavelet transform to monitor the distribution network for short circuit, open circuit and impact faults, it is found that the wavelet transform can accurately detect the faults of the distribution network.

VII. APPLICATION OF CROSS INDEX BASED ON EDGE COMPUTING IN FAULT DETECTION AND CONTROL OF DISTRIBUTION NETWORK

A. ANALYSIS OF DETECTION AND CONTROL MODEL OF DISTRIBUTION NETWORK BASED ON EDGE COMPUTING

For a distribution network that contains controllable resources such as distributed energy, energy storage, and flexible loads, traditional centralized management methods cannot meet the requirements of self-configuration, self-optimization, and self-healing control of the distribution network. Therefore, it is considered to adopt a multi-level centralized and distributed hierarchical control structure such as global, intermediate, and local to achieve a ''bottom-up, distributed autonomy, coordinated management, and global optimization'' management mode for the distribution

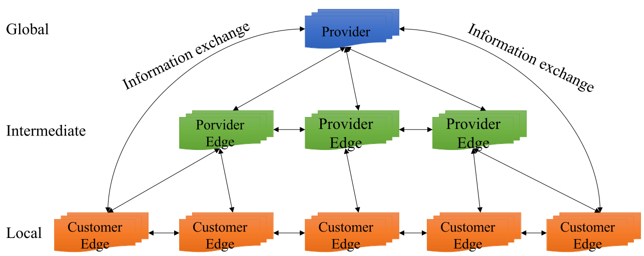

FIGURE 10. Fault detection management model for distribution network.

network. The control structure model of its distribution network is shown in Figure 10. Among them, CE equipment is terminal edge equipment; PE equipment is edge aggregation / access equipment with aggregation function; P equipment is core equipment.

B. EVALUATION SYSTEM OF FAULT DETECTION AND CONTROL MODEL BASED ON EDGE COMPUTING CROSS INDICATOR

The edge computing consortium (ECC) proposes the CROSS value from the perspective of industrial value chain integration, which includes five attributes: connection, business real-time, data optimization, smart,security. Applying edge computing technology to distribution network fault detection model can meet the key requirements of distribution network digitization in connection, real-time, data optimization, smart,security [27]. This paper uses C_{CROSS}, which refers to the value and opportunity of the edge computing CROSS indicator in the application of CE equipment in distribution network. The CE device's CROSS indicator contains five attributes, $C_{CROSS} = \{C_o, R_t, D_o, S_m, S_e\}$.

Among them, $C_o = \{C_{o1}, C_{o2}, \ldots, C_{ol}\}$ is the decision variable of agile connection of CE equipment, such as network quality, reliability, performance, flexible expansion capability and management simplicity; $R_t = \{R_{t1}, R_{t2}, \ldots, R_{tm}\}$ is a real-time decision variable of the CE

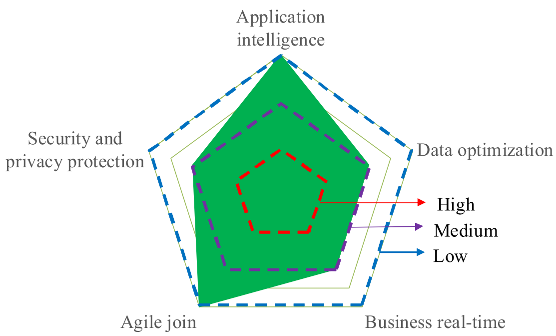

FIGURE 11. C_{CROSS} **indicator quantitative model.**

device service, such as communication mode and device configuration. $D_o = \{D_{o1}, D_{o2}, \ldots, D_{on}\}$ is a decision variable for CE device data optimization, such as heterogeneous data, data volume, data aggregation and interoperation, data optimization algorithms, etc. $S_m = \{S_{m1}, S_{m2}, \ldots, S_{mk}\}$ applies intelligent decision variables to CE devices, such as data analysis and business automatic processing capabilities, self-optimization capabilities, etc. $S_e = \{S_{e1}, S_{e2}, \ldots, S_{et}\}$ is a decision-making variable for security and privacy protection, such as device security, network security, data security, application security, perceived security, communication security, and information storage security.

The above analysis shows that agile connections, business real-time, data optimization, application intelligence, security and privacy protection are the key factors determining the C_{CROSS} index. Each key factor is divided into three levels: high, medium and low, which are set to 1, 2, 3. Combined with five key factors, the quantitative model of the aaa index is shown in Figure 11.

The model uses each attribute value as a quantization factor for the C_{CROSS} indicator. The sum of the areas surrounded by the attribute links is represented by S_s, and the sum of the areas surrounded by the maximum value of each attribute value is represented by S_t. The controllable capability of the active distribution network CE equipment is expressed as C_{CROSS} quality of service (Qo S), defined as:

$$Q_C = \frac{S_s}{S_t} \tag{6}$$

At the same time, Q_C will be divided into three levels of high, medium and low, namely $Q_C = \{H, M, L\}$; among them, the specific formula is as follows:

$$\begin{cases} 0 \leq C_{CROSS} \leq \frac{1}{3}; & (\mathrm{Q_C : L}) \\ \frac{1}{3} \leq C_{CROSS} \leq \frac{2}{3}; & (\mathrm{Q_C{:}M}) \\ \frac{2}{3} \leq C_{CROSS} \leq 1; & (\mathrm{Q_C{:}H}) \end{cases} \tag{7}$$

Among them, Q_C high-level equipment with self-prevention and self-recovery capabilities, such as information exchange with adjacent CE devices, determine their own action logic, can achieve fault location, isolation and fast recovery of power supply in non-faulty areas a CE device with Q_C level requires the presence of a control center (PE device). a CE device with a low Q_C level has poor self-healing control and requires global control of the P device.

VIII. CONCLUSION

Edge computing integrates networks, computing, storage, etc. on the edge of the network to provide intelligent services, which is very suitable for power automatic demand response service applications with a large number of distributed intelligent terminals. This paper studies the distributed power distribution fault processing based on edge computing, and gives the system solution from the sensing layer, network layer, platform layer and application layer. The system can significantly improve the fault diagnosis and fault location of low-voltage power distribution, speed up fault handling, and improve power supply reliability and user satisfaction. Furthermore, through the above analysis, it can be found that the db3 wavelet can quickly and accurately detect the singular points of the distribution network fault signal. Moreover, it can determine the position of the singular point and the size of the singularity, can effectively analyze the non-stationary signal, and effectively detect the fault of the distribution network. Finally, the service quality of the edge computing CROSS index in distribution network fault detection is analyzed. As technology continues to mature, the biggest difficulty for edge computing is how to deploy computing and storage capabilities dynamically and on a large scale, and how to efficiently collaborate and seamlessly connect cloud and edge devices is an area to be expanded.

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