Design of Intelligent Low Voltage Station System Based on Edge Calculation

Guo Shuai1, Song Wei Qiong1, Li Ji1, Bu Zhi Wen1, Li Rui1, Wang Qiang2, Mao Hao Fei2

1 State Grid Beijing Electric Power Research Institute. Beijing 100080, China.
2 Beijing Soarrow Space Technology Co., LTD., Beijing 100076, China
Corresponding author’s e-mail: ZHCYB@htmingdi.com

Abstract: The low-voltage distribution network field wiring is very complicated and there are many changes in the relationship between households and changes, which brings great difficulties to the topology identification and line loss management of the transformer area. This paper proposed an intelligence low-voltage power system based on edge computing in order to improve the automation level of low-voltage distribution area, and to solve problems such as identification inaccuracy of topological relations in the low-voltage distribution area at present and singleness of condition monitoring parameters in station area, etc. The terminal is implanted with two edge calculation models based on artificial intelligence technology, which can realize topology identification and state parameters monitoring. The multistate parameter monitoring and decision analysis provides functions of event monitoring and early warning of abnormal state for the low voltage distribution system. In the topology identification analysis, the Markov random field was applied to establish the mathematical model of non-oriented graph and the joint probability distribution to describe the correlation between the nodes in the distribution network, thus realizing topology-relation identification of nodes in respective layers of the distribution area. On this basis, taking a low-voltage station as an example, a case analysis was undertaken. It was verified via the effectiveness and accuracy of the intelligence low-voltage station, which lays a foundation for research of the intelligent and fine management of the low voltage station system.

1. Introduction

Low-voltage station area is an important foundation of energy internet, and it is the key foothold of serving society and people's livelihood. In recent years, with the rapid development of the power grid, the hardware facilities in the low-voltage substation area have been greatly improved, and the marketization of the power system has put forward more refined management requirements for the power management department. The low-voltage station area at the end of the power grid is an important part of the power grid, and faults and disturbances often occur during operation, thus causing harm to the power system and users [1-4]. In order to analyze the phenomena in the transient process of faults and disturbances, it is necessary to track and monitor the electrical parameters such as current and voltage, so as to comprehensively and dynamically analyze and evaluate the operation status of low-voltage substation.

With the deepening application of distribution automation technology and the rapid development of low-voltage and high-speed power line carrier technology, the number of terminals to be monitored and collected data increase dramatically [5], which brings great challenges to data transmission, data storage
and cloud computing capabilities [6]. At present, a single state parameter is often used to monitor the low-voltage station area, and the calculation complexity of multi-state parameters is high, which brings great difficulties to the monitoring process and cannot meet the requirements of real-time monitoring. Low-voltage distribution network is large in quantity and wide in area, and the topological relationship between transformer-line-household is unclear, which seriously affects its lean management, makes it difficult to observe and visualize, and makes it even more difficult to carry out the energy Internet application with distribution network as the core in low-voltage substation area [7]. Therefore, topology identification has become a key problem to be solved urgently [8].

In this paper, an intelligent monitoring system model of low-voltage station area based on edge computing is proposed. Two edge computing algorithms based on artificial intelligence technology are implanted in the terminal of this model, which can realize topology recognition and status monitoring of the station area. In multi-state parameter monitoring, the frequency slicing wavelet transform method is used to carry out time-frequency analysis on various electrical parameters collected by the monitoring terminal, and a monitoring parameter database is established. On this basis, the association rules of the monitoring parameters are analyzed to realize the comprehensive monitoring of the electrical parameters of the topology system in the low-voltage station area. In the topology recognition algorithm, the mathematical model of undirected graph is established based on Markov random field, and the solving steps and result analysis of topology relationship recognition are proposed according to specific cases, which verifies the accuracy and feasibility of the method.

2. Intelligent Low Voltage Station Area System
The intelligent low-voltage station area system takes the new concentrator as the core, and consists of branch box monitoring terminals at all levels, meter box monitoring terminals, environmental sensors, current transformers, HPLC communication modules, meter boxes, household meters and master stations. The new concentrator communicates with the monitoring terminal of the lower branch box through carrier wave and wireless communication, communicates with various sensors in the local system through wireless communication, and communicates with intelligent circuit breakers and intelligent switches of meter boxes through RS-485. The application standard specification system runs through every part of the connection between system and equipment, from hardware implementation, network communication to data coding, interface protocol and so on. The security system also has an impact on every part of the system, so as to realize the concept of safety and reliability design of the system.

2.1. System Architecture Design
Intelligent low-voltage station system is composed of monitoring platform and station equipment. The architecture of the station system can be divided into three layers, which are perception layer, edge layer and data processing layer from bottom to top. Among them, the sensing layer is mainly responsible for obtaining the monitoring parameter information of the system, and can continuously collect various state parameters such as electrical monitoring parameters, environmental parameters and electricity consumption information of household tables of each node of the distribution system in the station area. The edge layer mainly provides data processing, analysis and information transmission services for monitoring data, reduces the operation load of the main station in the station area and improves the data processing efficiency. Edge layer devices are the switch nodes of intelligent monitoring terminals, which together constitute an edge node network, providing lightweight computing power for the edge layer of the system [9]. The data processing layer is the core layer of monitoring equipment, which performs calculation and analysis of monitoring data, communicates with subordinate monitoring terminals in networking, issues networking and communication commands and other signals, analyzes and processes topology analysis data uploaded by branch monitoring terminals, automatically draws the physical topology of the station area, and can also perform abnormal analysis of line loss, remote diagnosis of metering errors, etc., providing users with all-round information and monitoring status of the low-voltage station area system.
2.2. System Equipment Configuration

Sensing layer equipment and configuration. Sensing layer consists of environmental sensors, current transformers, HPLC communication modules, monitoring terminals at all levels, molded case circuit breakers, intelligent switches, etc. Install environmental sensors in the distribution room or JP cabinet; Install monitoring terminals and temperature sensors in the main branch box, subordinate branch boxes and meter boxes of the power distribution room; Install HPLC communication carrier module at the user's table end; Install intelligent auxiliary monitoring equipment such as molded case circuit breaker or intelligent switch in the meter box. It can realize the functions of data acquisition, monitoring and early warning of distribution network in low-voltage station area.

Edge layer device configuration. The intelligent new modular concentrator and switch nodes are regarded as edge layer devices, which together constitute the edge node network, providing lightweight computing power for the edge layer of the system, which can effectively reduce the load of the master station and undertake data processing, decision analysis and other work. The intelligent new modular concentrator receives the information of branch monitoring terminals, various sensors, HPLC communication modules and data acquisition devices, analyzes, processes and calculates the data by using the built-in edge calculation algorithm according to the business application model, and uploads the processing results to the master station.

Configuration of data processing layer. The data processing layer performs the calculation and analysis of monitoring data, issues communication commands and other signals, and communicates with the lower-level concentrators. The station master station receives the data information of the lower-level concentrators and the station master table, transmits the data to the monitoring platform after further processing, and displays according to different module functions, which can realize the functions of topology identification of the whole low-voltage station area, line loss and abnormal fault location, user power failure and electricity stealing incident reporting, distribution room environment monitoring, user power load intelligent sensing, etc.

3. Edge Computing Algorithm

3.1. Feature Extraction Based on Frequency Domain Slice Wavelet Transform

The frequency-domain slice wavelet transform is a classical time-frequency analysis method, which is widely used in signal feature extraction and fault monitoring. It has the advantages of fast Fourier transform and wavelet transform. By introducing the scale factor and frequency slice function, the signal can be accurately described in the time-frequency domain at the same time, and the signal feature extraction in a specific interval can be realized, which is of great significance for the detection of weak electrical signals and environmental signals. The following steps are taken to extract the features of the signals collected by the sensing layer equipment and establish a monitoring parameter feature database.

(1) For the signal \( f(t) \) collected by the sensing layer equipment, the wavelet transform of frequency slice is used to decompose to obtain the time-frequency distribution in the whole frequency band.

\[
W(t, \omega, \sigma) = \frac{1}{2\pi} \int_{-\infty}^{\infty} f(\hat{u}) \lambda(p(x)) e^{i\omega x} dx \quad (1)
\]

Where \( W(t, \omega, \sigma) \) is the time-frequency distribution of the collected signal \( f(t) \) in the whole frequency band, and \( f(\hat{u}) \) is the Fourier transform of the monitoring information; \( \lambda \) is energy coefficient, \( t \) is time, \( \omega \) is frequency; \( \sigma \) is the scale factor; \( \lambda(p(x)) \) is conjugate function of \( p(x) \), \( \lambda(p(x)) \) is Fourier transform of frequency slicing function \( p(t) \).

(2) On the basis of time-frequency distribution, analyze the time-frequency distribution map of time-frequency distribution \( W(t, \omega, \sigma) \) in the whole frequency band, and segment out regions containing typical time-frequency characteristics, wherein the segmented typical time-frequency characteristic regions include frequency band region \( T_1 \) and frequency band region \( T_2 \), and if there are time-continuous frequency-stable time-frequency components in any frequency range, set the frequency band as
frequency band region $T_1$ containing typical time-frequency characteristics; If there are time-frequency components with time discontinuity, frequency fluctuation and irregularity in any frequency range, it will be regarded as the time-frequency region with noise interference, and will be recorded as the frequency band region $T_2$. Let $\sigma = \omega / \kappa$, $\kappa$ be the time-frequency resolution coefficient and $\eta = m \cdot \omega$, $m \in [0, 1]$, $\eta$ be the frequency ratio of $\omega$, then there are:

$$W(t, \omega, \kappa) = \frac{1}{2\pi} \int_{-\infty}^{+\infty} f(u) p(u) \chi^{\omega} du$$

Among them, $y = \kappa \frac{\omega - \omega}{\omega}$.

(3) Carry out time-frequency threshold filtering on the band areas $T_1$ and $T_2$ divided in step (2), where the filtering threshold is $q_n = \sigma \sqrt{2 \log L}$, $\sigma$ is the intermediate value of $W(t, \omega, \sigma) / 0.6745$, and $L$ is the length of monitoring information $f(t)$, then.

$$w(t, \omega, \sigma) = \begin{cases} W(t, \omega, \kappa), & W(t, \omega, \kappa) \geq q_n \\ 0, & W(t, \omega, \kappa) \leq q_n \end{cases}$$

(4) Carry out frequency slice wavelet transform on frequency band $T_1$ and frequency band $T_2$ marked in step (2), after frequency slice wavelet transform, check whether there are new time-frequency components in the obtained time-frequency distribution map with frequency band $T_1$ and frequency band $T_2$ as the range, if there are new time-frequency components, record the new time-frequency components, compare them with the frequency value of monitoring information $f(t)$, and judge whether they are the natural frequency of monitoring $f(t)$, If it is different from the natural frequency of monitoring information $f(t)$, it is judged that the monitoring information $f(t)$ has fault characteristics, otherwise, continue to execute step (5); And.

(5) The filtered frequency band region $T_1$ and frequency band region $T_2$ are respectively subjected to inverse transformation, and effective signal components are reconstructed and separated, specifically as follows.

$$f^*(t) = \frac{1}{2\pi} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} w(\tau, \omega, \kappa) d\tau d\omega$$

Comparing the similarity between the reconstructed signal $f^*(t)$ and the monitoring information $f(t)$, if the similarity between the reconstructed signal $f^*(t)$ and the monitoring information $f(t)$ is greater than a set comparison threshold, the reconstructed signal is considered valid.

(6) The reconstructed signal $f^*(t)$ is filtered, and the waveform of $f^*(t)$ is compared with that of monitoring information $f(t)$. If there is no frequency component in the frequency band area $T_2$ in the frequency slice wavelet transform time-frequency distribution diagram of the reconstructed signal $f^*(t)$, it is judged that the monitoring information $f(t)$ has fault features, and the original and fault features of monitoring information $f(t)$ can be obtained through the feature components extracted from the time-frequency band area $T_1$.

(7) Finally, the signal monitoring parameter database D is established by using the combination of fault data in time t. Among them, time t is usually the working cycle when the low-voltage distribution system fails.

3.2. Apriori Association Rule Algorithm

3.2.1. Fundamental Principle

The idea of association rule algorithm is to search the candidate itemsets that meet the requirements layer by layer to generate frequent itemsets that contain the most items\cite{10}. Then search for association rules according to the set support and confidence.
In association rule algorithm, two indexes, support and confidence, are used to evaluate association rules. In association rule algorithm, two indexes, support and confidence, are used to evaluate association rules. Among them, the meaning of support refers to the probability of a certain type of transaction; confidence refers to the credibility of association rules, which indicates the number of times a certain itemset appears in a transaction containing another itemset. The implication expression \( X \rightarrow Y \) is used to express the association rules that if item \( X \) appears, then item \( Y \) also appears, \( X \subset 1 \), \( Y \subset 1 \) and \( X \cap Y \neq \phi \). The expressions of support and confidence are shown in formula (5) and formula (6).

\[
\text{support}(X \rightarrow Y) = P(X \cap Y) = \frac{\text{count}(X \cap Y)}{N} \quad (5)
\]

\[
\text{confidence}(X \rightarrow Y) = \frac{P(X \cap Y)}{P(X)} = \frac{\text{count}(X \cap Y)}{\text{count}(X)} \quad (6)
\]

Where, count represents the number of occurrences in the database, and \( N \) represents the number of fault combinations in the database. Support is used to measure the frequency of co-occurrence of related items \( (X, Y) \) in the database, as shown in formula (5), and confidence means the probability that item \( Y \) must appear when item \( X \) occurs, as shown in formula (6).

3.2.2. Implementation Method
The implementation of Apriori association rules algorithm consists of two parts: generating frequent itemsets and generating association rules.

Generate frequent itemsets. In association rule algorithm, frequent itemsets refer to the set of items whose support degree is greater than or equal to min_sup, which is expressed by \( L_k \), where \( K \) represents the number of items in frequent itemsets. Apriori algorithm is a classical algorithm for finding frequent itemsets. Considering the prior knowledge that any subset of frequent itemsets must be frequent, \( L_k \) itemsets are explored by iterative use of \( L_{k-1} \) itemsets, with specific operations including frequent itemsets splicing and candidate set pruning. The following steps of Apriori algorithm are given.

(1) Calculate the support degree of all 1-itemsets, and find all frequent 1-itemsets \( L_1 \) by screening;
(2) Splicing data items of frequent 1-item set \( L_1 \) into candidate set \( C_2 \);
(3) Starting from the candidate item set \( C_2 \), \( L_2 \) is generated by filtering the support degree \( S \), and \( L_2 \) is spliced into the candidate item set \( C_3 \) according to Apriori principle; \( C_3 \) generates \( L_3 \) through support filtering, and so on, mining layer by layer generates frequent set \( L_{k-1} \).
(4) Delete the items that do not meet the requirements in the final set \( L_k \), filter them step by step, and then generate the frequent set \( L_k \) after the connection step.

Generate association rules. For frequent itemsets \( L_k \), all non-empty proper subset is generated, and \( N \) association rules are obtained according to the generated non-empty proper subset. The specific steps are as follows.

(1) For n-order frequent itemsets, \( 2^n \) association rules are generated according to the random combination method.
(2) According to the frequency and correlation of fault signals, the threshold values of support and confidence are set.
(3) The confidence of each rule generated in (1) is calculated separately. When the confidence is greater than the given confidence threshold \( C \), the association rule is a strong association rule. Strong association rules should meet the requirements of minimum support and minimum confidence.

3.3. Model Design Based on Markov Random Field
According to the knowledge of graph theory, the topological structure of a topological network can be described by the node-branch association matrix. Traditional topology identification methods need to obtain data such as voltage amplitude, phase angle, active power, reactive power and even current \([11]\). This algorithm can reconstruct the topology only by the voltage amplitude, and embed the topology identification algorithm in the monitoring terminal of the station area system, which can realize the topology identification and analysis of the four-level distribution network of concentrator, branch box, meter box and user intelligent watt-hour meter while monitoring the state.
The whole topological network is modeled based on undirected graph model. The topology identification network of low-voltage substation is regarded as a Markov random field. As a typical Markov network, the joint probability distribution among multiple variables can be decomposed into the product of multiple factors based on clique, and each factor is only related to one clique. The network structure of distribution system is defined as a quadruple \( M = (X, E, \Phi, \Psi) \), where \( (x, e) \) is an undirected random variable image. \( X \) is the vertex set of graph, which represents nodes in distribution system, and \( E \) is the edge set of graph, which represents power lines connecting nodes in distribution system. Then, potential functions \( \Phi \) and \( \Psi \) describing the relationship between distribution system nodes and connections are established to quantitatively characterize the variable characteristics of distribution system nodes and connections. The potential functions describing the relationship between distribution system nodes and connections are defined as follows.

\[
\Phi(X_u) = \exp\{E(X_u)\} \quad (7)
\]

\[
\Psi(X_{uv}) = \exp\{E(X_u, X_v)\} \quad (8)
\]

In this formula, \( X_u \) and \( X_v \) are random variables representing nodes \( u \) and \( v \), \( X_{uv} \) represents random variables corresponding to edges connecting nodes \( u \) and \( v \), and \( E \) is called energy function.

The joint probability distribution model of topological network is established based on Markov random field, and the objective function is the joint probability distribution of node correlation of topological network, as shown in formula (9).

\[
P(Y) = \frac{1}{Z} \prod_u \Phi(X_u) \prod_{u \neq v} \Psi(X_{uv}) \quad (9)
\]

\[
Z = \sum_X \prod_u \Phi(X_u) \prod_{u \neq v} \Psi(X_{uv}) \quad (10)
\]

Its parameterized form is:

\[
P(Y) = \frac{1}{Z} \exp\left\{ \sum_u V^u d^u(X_u) + \sum_{u \neq v} W^u b^u(X_u, X_v) \right\} \quad (11)
\]

\[
Z = \sum_X \exp\left\{ \sum_u V^u d^u(X_u) + \sum_{u \neq v} W^u b^u(X_u, X_v) \right\} \quad (12)
\]

In equations (7) and (8), \( X_{uv} \) represents a random variable connecting node \( u \) and node \( v \). \( (u, v) \) is the line between nodes \( u \) and \( v \) in the distribution system. \( V_u \) is the weight of node \( u \) in the low-voltage substation system; \( W_{uv} \) is the weight of the line connecting nodes \( u \) and \( v \); \( d_u \) is a state feature, which defines the feature function on nodes, \( b_{uv} \) is a transition feature, which defines the feature function on edges, \( \Phi \) and \( \Psi \) are potential functions based on probability graph model, \( \Phi \) represents the potential of nodes, \( \Psi \) represents the potential of edges connecting nodes, and \( Z \) is a partition function, which is a normalized function and defined as the sum of all possible assignments.

4. Practical Application of Algorithms Based on Edge Computing in Station Area

In the intelligent low-voltage station area system, the original classic concentrator is replaced by a new modular concentrator, which provides hardware support for the function of edge computing. In addition, the monitor terminals of meter boxes and branch boxes at all levels are integrated with IC modules with edge computing function, which have functions of lightweight computing and data storage. The monitor terminal transfers some data processing steps of the concentrator and the master station system to the edge layer, where the functions of equipment management, data processing, data cache and the like are realized, thus lowering the network bandwidth costs and reducing the probability of data loss caused by network outages. Thereby it improves the operation and maintenance level of the power system.

4.1. Analysis of Max Relevance Topology Identification Based on Undirected Graph

According to the mathematical model based on undirected graph established by Markov Random Field algorithm, the voltage time series data collected in the test station area are analyzed as an example. The station area is a four-level topology network of concentrator-branch box-meter box-household meter. The minimum number of nodes 5 is taken for test analysis, realizing the topological relationship
identification of the station area. The specific solution steps are as follows.

1) The concentrator sends the file information of each meter in the station area to the meter box monitor terminal through the power line carrier.
2) The concentrator sends a timing instruction to nodes of each group to achieve the time consistency between the monitor terminals such as household meter and the meter box and the concentrator.
3) The concentrator sends topology identification instructions through power line carriers.
4) That data of the voltage time series of the user’s smart meter and the concentrator is acquired and taken as samples.
5) The acquired time data is preprocessed to obtain random variables corresponding to nodes.
6) The mathematical model and objective function are established by using random variables corresponding to nodes.
7) Weight parameters of objective function of undirected graph mathematical model are solved.
8) The correlation matrix K is synthesized according to the weight parameter W. The gradient descent method is used to solve the log likelihood equation, and the weight parameter W is obtained. According to the formula, the weight parameters are synthesized, and finally the node correlation matrix representing the connection tightness of each physical node in the distribution network is obtained.

\[ K_{uv} = \sum_{i=1}^{N} \sum_{j=1}^{N} W_{ij} e^{W_{ij}} \]  \hspace{1cm} (13)

1) The correlation matrix K is iterated, and the nodes with the highest correlation are screened out and connected together to form a node cluster.
2) Iterative computation is carried out on each row of correlation matrix K to obtain the maximum value and position of each row and the updated adjacency matrix.
3) According to the adjacency matrix, the topological relationship diagram of the low-voltage station area system is obtained.
4) Verification is conducted with the existing physical topology information to complete the data correction and iteration.

A correlation matrix K is obtained based on the solution of steps 6)-8):

\[
K = \begin{bmatrix}
0 & 0.51 & 0.83 & 0.47 & 0.15 \\
0 & 0 & 0.95 & 0.34 & 0.21 \\
0 & 0 & 0 & 0.45 & 0.96 \\
0 & 0 & 0 & 0.85 & 0.32 \\
0 & 0 & 0 & 0 & 0 \\
\end{bmatrix}
\]  \hspace{1cm} (14)

Traversing each row in K, we find out the position of the maximum element in each row, and set the element in the same position of A to 1. In this paper, the largest element in the first row of K is 0.83, and the position is K13, so A13 of matrix A is set to 1. After traversing K, we get the result A:

\[
A = \begin{bmatrix}
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 \\
\end{bmatrix}
\]  \hspace{1cm} (15)

Since the element a13=a23=a35=a45=1 in the matrix A, the topological identification relationship of the station area can be derived, and the schematic diagram is shown in Figure 1.
4.2. Condition Monitoring of Station Area Systems Based on Multi-parameters

Low-voltage station area system monitoring refers to on-line evaluation and tracking of power grid operation status, capturing and analyzing faults and disturbances during operation, and effectively predicting its future development trend through real-time acquisition of electrical parameter information such as current, voltage, ambient temperature, high-frequency discharge signals, and operating power during power grid operation [8]. Fundamentally, data analysis is critical for online monitoring in low-voltage station areas and needs to conduct deep computing and overall consideration on multi-state parameters. The use of parameter information at a single moment only may be prone to miscalculation, which is not good for the accurate and effective monitoring of the power grid. Considering the problem that the existing methods have difficulty in processing multi-state parameters in real time, a multi-state parameter monitoring method based on association rule analysis is proposed. The method consists of offline training and online monitoring. The overall process of the method is shown in Figure 2.

Figure 1. The schematic diagram of topology identification results in the station area

Figure 2. The flowchart of multi-state parameter monitoring algorithm based on edge computing

4.2.1. Offline Training

The off-line training part mainly analyzes the characteristics of monitoring information, captures the combination of multi-parameter faults when various faults occur, constructs the detection parameter
database and generates association rules. The stages of offline training are briefly described as follows.

1) Firstly, the perception layer equipment collects the power supply data and the data information of various monitoring parameters in the station area system. The collected monitoring information includes: the current, voltage, ambient temperature, and power factor of each node of the station area system, and the current, voltage, ambient temperature, power, power factor, etc. of the household electricity meter.

2) Then, for the monitoring information captured in a sampling period t, the frequency slice wavelet transform (FSWT) method is used to extract features to capture the fault data in the monitoring information, and the symbol D is used to describe the fault data set.

3) The association rule mining algorithm Apriori is further used to generate frequent itemsets, set support and confidence thresholds according to the frequency of fault parameters, and select several strong association rules R1, R2... Rn with higher confidence for storage, providing a basis for online monitoring in determining multiple faults.

4.2.2. Online Monitoring
The on-line monitoring part carries out on-line status monitoring by real-time analysis of the captured new multiple parameter information. If any state parameter in the monitoring information is determined to be a fault state, fault analysis is carried out according to the decision rule R obtained by offline training, and if the corresponding state parameter in the frequent itemset Lk generated by the database D meets the above-mentioned decision rule R, fault information will be immediately reported. The methods for stages of online monitoring are described as follows.

1) Acquisition of monitoring information
When the perception layer equipment is used for information collection and state monitoring of the low-voltage station area, new monitoring information can be obtained in real time. The specific category of monitoring information acquired is consistent with the dimension of information required in the monitoring parameter database D established by offline training.

2) Fault parameter capture
The frequency slice wavelet transform method is used in real time to analyze the characteristics of the monitoring information acquired in the previous stage, and determine whether any state parameter in the monitoring information is a fault state. If there is a parameter a fault state, then go to the next stage.

3) Fault analysis and reporting
After acquiring the parameters that are known to be in a fault state, the fault analysis is carried out according to the decision rule Rn (n=1, 2, 3... n) obtained by offline training. When the fault state parameters meet the decision rule Rn (n=1, 2, 3... n) obtained by offline training, the fault state combination involved in the rule Rn (n=1, 2, 3... n) is reported as complete fault information. When the association rule is the decision rule R and there is a certain fault F1, the monitor terminals can simultaneously determine the existence of other faults F2... Fn. Therefore, when the fault information F1 is reported, other faults F2... Fn will be reported at the same time, and the event monitoring and the timely early warning of abnormal states in the low-voltage station area are reliably realized.

4.2.3. Case Analysis in the Station Area
In order to verify the feasibility of the method described in this paper, a low-voltage station area is taken as an example for analysis. A database is established with the signals monitored within the past 192 hours as a reference. In this example, all users belong to the same station area. The perception layer equipment summarizes various state parameters such as voltage, current, and ambient temperature of node equipment at different levels collected during the system operation and establishes a monitoring parameter database D. These data include the time when the fault occurred, the warning signal when the fault occurred, the actual position of the fault report, etc. The database model after extraction and processing of the data from different sources and of various types is shown in Table 1.
Table 1 The monitoring parameter database D of a station area

| Report time             | Warning signal                                                  | Faulty equipment                                                                 |
|-------------------------|----------------------------------------------------------------|---------------------------------------------------------------------------------|
| 12:37, November 4.      | Power abnormality of user 1A. 1.1                               | Household meter 1A. 1.1 in branch 1 of the station area                           |
| 00:15, November 2.      | Carrier communication dysfunction of monitor terminal 1-1-1     | Monitor terminal 1-1-1                                                           |
| 17:25, October 30.      | Abnormal power and current values at the incoming end of meter box 1 and meter box 2 | Meter box 1, meter box 2                                                         |
| 17:25, October 30.      | Carrier communication dysfunction of monitor terminal 1 and monitor terminal 1-1 | Monitor terminal 1, Monitor terminal 1-1                                           |
| 17:24, October 30.      | Abnormal current and power at the lead-in terminal of cable branch box 1 | Cable branch box 1                                                                |
| 17:23, October 30.      | Abnormal current and power at outlet terminal of MCCB          | Moulded case circuit breaker (MCCB)                                              |

Figure 3. Schematic diagram of topology identification for low-voltage distribution areas

In the analysis of fault correlation relationship, the feature information and diagnosis results when faults occur are generally taken as feature quantities, and frequent items are mined for different types of faults. In this example, because some faults are of accidental type and are less frequently seen in the monitoring database, it is inappropriate to set the support too high in the process of analyzing fault association rules. The support in this example is set to 10%. Before analyzing the fault, the Apriori algorithm is used to screen out the fault sets and generates some frequent itemsets. On this basis, it generates strong association rules, so as to find out the association relationship between the fault warning signal and the faulty equipment. Still taking the above-mentioned certain station area as an example, the database D is screened out to generate frequent itemsets, and the confidence threshold is set to 20% to screen out the rules that meet the requirements. See Table 2 for more details.

Table 2 Association Rules Derived from Monitoring Parameter Database D of a Certain Station Area

| Serial No. | Association rule                                      | Confidence |
|------------|-------------------------------------------------------|------------|
| 1          | Power abnormality of household meter 1A.1.1→fault of household meter 1A.1.1 | 17.8%      |
In the condition monitoring of low-voltage station areas, the data in Table 2 can provide reference for troubleshooting in the station area. The operation and maintenance personnel in the station area can monitor the operation status of the whole station area system in real time on the system monitoring platform, analyze the corresponding relationship between the fault superficial characteristics and the faulty equipment according to the warning signal sent by the system and the corresponding ID number of faulty equipment, conduct field inspection and maintenance, and complete fault location and troubleshooting.

In order to verify the effectiveness of the above-mentioned method, the historical data of a certain station area is used for association analysis verification. The warning signal “power abnormality of 1A.1.1” of the household meter in Table 2 is taken as a condition, and the latter event of the association rule is taken as a result for simulation verification, as shown in Figure 4.

As seen from the analysis of Figure 6, on the premise that the warning signal “abnormal power and current fault of household meter 1A.1.1” is taken as the association rule, the corresponding faulty equipment could be line fault at the lead-in terminal of meter box 1, fault of household meter 1A.1.1, fault of monitoring terminal 1-1-1, or fault of cable branch box 1. In the confidence and lift simulation curves, the support and confidence of line fault in meter box 1 are the highest, that is, when there is abnormal power and current fault in household meter 1A.1.1, the equipment most likely to fail is meter box 1. Maintenance personnel should focus on checking the lines of outlet terminals and lead-in terminals of meter box 1 and the internal MCCB, etc. to ensure that the line connection is normal and there is no virtual connection or line damage. If there is no fault in meter box 1, then the household meter should be checked. If there is fault in the household meter, it should be replaced in time. If there is no fault, other fault location equipment will be checked one by one.

4.3. Event Report and Real-time Analysis of Systems in Intelligent Station Area
The intelligent low-voltage station area system taking the new modular concentrator as the core consists of branch box monitor terminals at all levels, meter box monitor terminals, various sensors, HPLC...
communication modules, meter boxes, household meters, master stations, etc. The platform of low-voltage station area monitoring system supports the functions of automatic drawing of physical topology in the station area, line loss abnormality analysis, remote diagnosis of metering error, real-time electricity stealing analysis and automatic file identification, etc. It can realize comprehensive monitoring of operation status of the station area.

4.3.1. Condition monitoring of temporal-spatial characteristics of charges in the station area

The meter box monitor terminals can collect multi-parameter data of household meters in real time, and transmit the collected signals to the concentrator through carrier communication. The concentrator analyzes and processes the data according to its embedded edge computing algorithm. Based on the topology of low-voltage station area, the high-precision AC sampling and metering function of monitor terminals at all levels and the function of edge computing, and according to the principle of current conservation, real-time electricity stealing analysis can be realized. And the power is calculated according to the spatial-temporal relationship of load.

According to Kirchhoff’s current law, the sum of inflow node currents equals to the sum of outflow node currents, and the node voltage remains unchanged. For a station area, the current will flow from the nodes of the station area to the lower-level branch nodes that flow gradually along the physical line to the user charge side. The node current and power of the station area’s concentrator are set to \( I_0 \) and \( P_0 \), and the outflow current and power of lower-level nodes at all levels are respectively \( I_{A1}, P_{A1} \), \( I_{A2}, P_{A2} \), ..., \( I_{AN}, P_{AN} \). The formula is as follows.

\[
I_0 = I_{A1} + I_{A2} + \ldots + I_{An} + \Delta I_a
\]

\[
P_0 = P_{A1} + P_{A2} + \ldots + P_{An} + \Delta P_a
\]

In formula (12) and formula (13) \( \Delta I_a, \Delta P_a \) are respectively the total loss of current and power between the concentrator’s outlet terminal node A0 and the lower-level branch line nodes at all levels. For the line loss at the same level, since the line is very short, it can be ignored. Because the spatial-temporal characteristic relationship of charge reflects the basic relationship attributes between node equipment in the station area, it can be applied to the identification and verification of physical topological relationship in the station area. In addition, it can also realize the monitoring of power lines, and complete line loss measurement and electricity stealing analysis.

In the case analysis of the station area in section 4.2.3, there were abnormal current and abnormal active power faults of user 1A.1.1 during the historical condition monitoring of the station area. According to the simulation analysis of association rules, it was preliminarily determined as line fault at the terminals of meter box 1. At this time, the load spatial-temporal relationship of equation (16) and equation (17) could not apply to the household meter and the meter box. After receiving the abnormal information from the edge layer, the data processing layer of the station area monitoring system reports the fault event to the main station system after data analysis and processing, and enables the automatic fault identification function of the system to analyze the real-time electricity stealing and line loss calculation, as shown in Figure 5 and Figure 6 respectively. After preliminary judgment, there may be faults such as artificial electricity stealing or abnormal line loss.

![Electricity stealing calculation](image)

Figure 5. Statistical chart of automatic calculation about stealing electricity.
4.3.2. Display of System Functions

The installation and deployment of system monitoring equipment are realized by setting up monitor terminals, various sensors and HPLC communication modules at each outlet terminal of the branch box and the meter box. The function modules of automatic drawing of physical topology in the station area, line loss abnormality analysis, remote diagnosis of metering error, real-time electricity stealing analysis and automatic file identification, etc. are further added into the master station to realize comprehensive condition monitoring of the station area system. The various functions of the master station are displayed below.

According to Markov Random Field topology identification algorithm, the collected voltage data are processed and the undirected graph mathematical model is established. After solving the weight parameters W, K and adjacency matrix A of the objective function, branch and household meter identification can be completed. The built-in software algorithm of the concentrator is used to automatically draw the topological relationship diagram of the low-voltage station area to provide visual display of the low-voltage distribution network structure at the global scope. The online topology identification rendering is shown in Figure 7.
In the example of topology identification of the station area, the station area is composed of a four-layer network of concentrator, branch box, meter box and household meter. There are 78 household meters tested, and 75 household meters are correctly identified, with an identification accuracy rate of 96.15%, which takes 4 hours and 39 minutes. The technical indicators meet the design requirements.

The monitor terminals can monitor the working status of branch switch, meter box switch and air switch in front of or behind the meter in real time, and have the function of actively reporting power outage events. Based on the precise topology of low-voltage station area, it can realize accurate reporting of power outage and resumption faults at all levels within 60 seconds. The software platform of the master station can study and determine the logical relationship of power outage information, determine the fault type and affected area, send emergency repair work orders to personnel at different levels, convert passive emergency repair into active emergency repair, and improve customer satisfaction rate. In addition to the above-mentioned functions, the low-voltage distribution network monitoring system platform also has the function of automatic file identification, and supports accessing external data information to assist the management of low-voltage distribution network and the realization of fault location function.

5. Conclusion
Based on the problems existing in the distribution network monitoring and fine management of low voltage area, this paper designed a complete set of low voltage intelligent area system. This paper proposed an intelligent low-voltage station system design method based on edge computing. Two edge computing algorithms based on artificial intelligence were embedded into the terminal, which can realize topology identification and multi-state parameter monitoring. In condition monitoring, the fault correlation relationship is analyzed by setting the confidence and correlation threshold of association rules, and the correlation relationship between fault warning signals and faulty equipment is found out to realize fault locating. In the analysis of topology identification, the maximum correlation filtering algorithm is used to establish a station area topology identification model based on undirected graph. By solving the weight parameters W, K and adjacency matrix A of the objective function, the branch and household meter identification can be completed. The practical analysis of a station area shows that the online test results meet the expected requirements, which verifies the feasibility of the station area model design. By designing and deploying each monitoring equipment of the system, the functions of automatic identification of electricity meter files, automatic drawing of station area topology diagram, analysis of line loss and electricity stealing, real-time reporting of events and the like can be realized, thus effectively improving the intelligent level of low-voltage station area.
In the practical application design of the station area system, the function can be expanded according to the specific needs to realize the functions of environmental temperature and humidity monitoring, power failure event reporting, and remote real-time monitoring of the station area system through mobile phone APP. The system is the specific manifestation and application of the power Internet of Things in the low voltage side. It is not only the innovation of technology, but also the improvement of management thinking and the innovation of management concept, which makes the operation of low voltage power grid safer, more lean management and better service.

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