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Research on distribution network ground fault feature fusion and anomaly detection method by integrating quantum variational autoencoder

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SUMMARY: *In this research thesis, according to the input properties of the graph neural network model, the structural characteristics and node attribute natures of the distribution network are selected as the input features which are used in the distribution network graph data. Through the comparison of the zero-sequence current wave shapes at the two ends of one section, the earth-fault section can be gotten out.Utilizing the measurement data which come from two sides of the faulted section, a quantum variation autoencoder ranging model which has been studied by us is established. This model makes the broken voltage and current phase wave forms connect with the fault distance. After that, an end-to-end strategy for fault position finding has been devised by us.The distribution network model is constructed and simulation experiments of ground fault detection are carried out. The initial 15 features are downscaled by Pearson's correlation coefficient, and 12 key features are retained after removing redundancy. Based on the experiments which were carried out on 20 test samples, the discrimination error of the method put forward in this paper is obviously better than that of the full connection neural network. When it is put under the simulated load casting and noise interference situations which appear in the process of real working, the average distinguishing error of the method which is written here rises to 0.033. Notwithstanding this point, it yet maintains a relatively elevated degree of stability. The research that this paper has done puts forward a brand new method for the intelligent breakdown judgement of distribution power networks. This method possesses high exactness, strong anti-disturbance abilities, and cheap calculation costs. This possesses very important practical meaning for promoting the safety of power grid movement.*

KEYWORDS: *distribution network ground fault; graph neural network model; quantum variational autoencoder; fault location identification*

1 Introduction

Along with China's economic construction norms moving forward at a quick speed and electric power transmission basic installations are being continuously constructed and enlarged, making the society's electricity consumption increased dramatically, but due to the urban planning and

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construction of the existence of the power grid distribution is unreasonable, resulting in the number of transmission network faults and faults in the form of an increasing number of faults, the distribution network grounding faults is one of the typical faults [1-4]. Distribution network grounding will cause a continuous loss of power in the distribution network, but also cause great damage to the grid loop where the grounding line is located, and there is a great threat to the personal safety of ground personnel [5-7]. For the diagnosis and solution of such hazardous transmission network faults,for the guarantee of the situation's safety, the prompt and effective settlement of power grid breakdowns, and the promotion of electricity supply's efficiency, it is necessary that we use a scientific, reasonable and safe method.[8, 9].

Traditional detection methods, such as artificial check and resistance method, have difficulty in effectively finding the complexity and suddenness of earth faults inside power distribution networks. By comparison, the quantum variation autoencoder unites quantum calculation and variation autoencoder technique, hence it shows outstanding achievement on abnormal thing examination [10, 11]. Quantum computing is a new calculation frame which uses the basic rules of quantum mechanics to carry out calculation work. Its using scopes cover a wide range, especially when it is handling problems that are exceptionally complicated. Therefore, it possesses great potential value [12-14]. And the variational autoencoder (VAE), as an important breakthrough in the field of deep learning, represents the latest progress in generative modeling research [15, 16]. This neural network architecture based on probabilistic graphical models is essentially a probabilistic extension of the traditional selfencoder, which obtains probability modeling of the hidden data space through the incorporation of variational inference methods [17, 18]. The fusion of the two, by using quantum circuits with parameterization as the representation layer and optimizing the angular parameters of the quantum gates during training to achieve the minimized reconstruction error, not only achieves the fusion of distribution network ground fault features, but also achieves accurate anomaly detection [19, 20].

In this paper, the distribution network is processed as non-Euclidean spatial graph data, and the global structural features of the graph and the attribute features of the nodes are jointly used as inputs to the model. The operation process of quantum variational autoencoder is designed to achieve the compression of more data by mapping the gray values of the picture to quantum states after normalization. One method which is used for locating ground faults inside distribution networks is proposed, it depends on measurement data from μPMUs and a quantum variation-type automatic encoder. The structure and node information of distribution lines are provided by rationally configuring μPMUs. The multi-source properties of power distribution lines are put together, and this is afterwards matched with the similarity of zero-sequence current wave shapes to find the wrong sections.Simulation tests are carried out to reconstruct K different frequency band components by decomposing the original signal using VMD, and the collected fault signal is reconstructed to amplify the fault characteristics through decomposition. Carve out the difference between the physical characteristics of high resistance grounding fault and normal working conditions, and construct a fault sample feature library. Under many kinds of situations, the wrong working samples and samples that run normally are carried out the test. After that step, we make a comparison between these results and the results that are processed by a common full connection neural network.The goal of this comparison is to evaluate the fault examination ability and anti-interference performance of the method which is put forward in this paper.

2 Distribution network ground fault localization method based on quantum variational autoencoder

2.1 Distribution map data input feature screening and fusion

In the electric power net, the usage of data gathering and monitoring control (SCADA) system has attained a comparatively high degree of ripeness and is widely utilized, and its structure is shown in Figure 1. The SCADA system in the field of electric power is generally set up next to the feeder switch with a feeder terminal unit (FTU), which one feeder automation remote terminal unit combines the functions like telemetry, remote signal transmission, distant operation, protection and communication. It is able to carry out the monitoring work for the operation state of the distribution network system. The FTU is mainly capable of acquiring two kinds of data quantities: analog quantities and status quantities. Simulation parameters give the real-time situation particulars of the electric system when the monitoring is carried out. These mainly include the amplitude and phase position of voltage and current, and also active power and reactive power. On the opposite side, state variation quantities are given in the form of separated data. State quantities are expressed in the form of discrete data, mainly including circuit breaker status, sectionalized switch status, isolation switch status, alarm signals and so on.

In the research of fault position finding in old-style power distribution networks, the mutual actions between distribution network devices are generally not considered, and the research objects are analyzed in a separate way. Nevertheless, inside the actual distribution network environment, because the distribution network is a special graph-based data that has an obvious topological structure, every wire and important device inside the distribution network can produce different degrees of mutual effect by way of direct or indirect connections.Hence, when we carry out the research work about fault position finding in distribution power networks, this paper therefore takes this influential function into consideration.

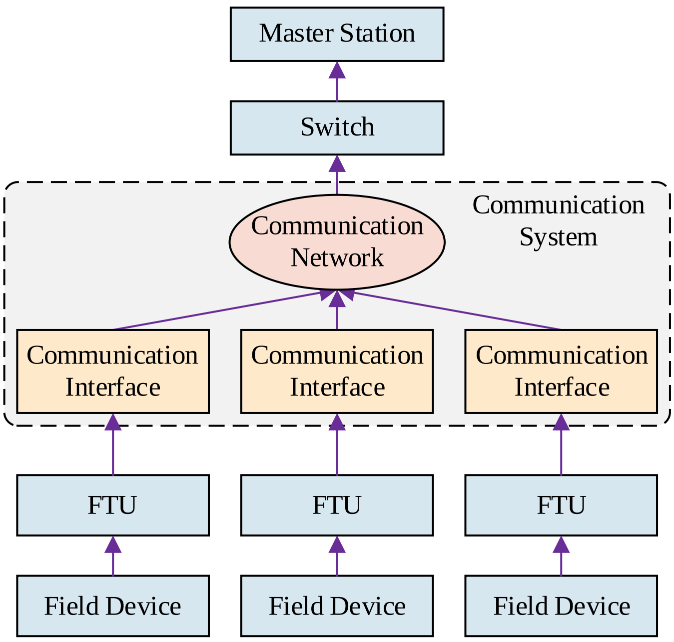


Figure 1: Structure of SCADA

According to the definition of the graph, the distribution system is abstracted as the graph data $G=(V,E)$, and the node V in the graph denotes the busbus, which in general is divided into two types: the bus of the system and the bus of the load, and there are directly connected loads on the load bus. The edge E connecting the vertices denotes the feeder branch, and the edges in the graph are set to be undirected unweighted edges. When we carry out the construction of the graph neural network model, the input components have been split into two segments. On one hand, the data which concerns the topological structure arrangement of the power distribution network is kept, and this is normally expressed by the method of the adjacency matrix, and let the graph G have $|V|=N$ nodes, then the dimension of its adjacency matrix A is $N\times N$, which is defined in the way that is shown in Equation (1). Another one aspect relates to the deposit of the state-connected feature information of every individual node in the electric distribution net.. Since this paper is to abstract the distribution network as an isomorphic graph, for this target, it is necessary that the measurements of the state characteristics of every node inside the graph G are consistent. In order to ensure the sufficient and complete comprehensiveness of node information, the features selected in this research include the amplitude and phase angle of three-phase voltage, the amplitude and phase angle of three-phase current, and also the active power and reactive power that are measured by distribution automation terminals; based on the four kinds of central characteristics of nodes obtained by graph theory computation, which are degree centrality, feature vector centrality, intermediary centrality, and proximity centrality, the node's features are expressed as $\left(V_1,\theta_1^V,V_2,\theta_2^V,V_3,\theta_3^V,I_1,\theta_1^I,I_2,\theta_2^I,I_3,\theta_3^I,P,Q,DC,EC,BC,CC\right)\in R^{18}$. A data sample in the distribution network can be represented as $X\in R^{N\times 18}$.

$$A[i][j]=\begin{cases}1, & \text{If } \langle v_i,v_j\rangle \text{ is an edge in } E(G)\\ 0, & \text{If } \langle v_i,v_j\rangle \text{ is not an edge in } E(G)\end{cases} \tag{1}$$

2.2 Design of quantum variational autoencoder

2.2.1 Basic flow of quantum variational autoencoder

Currently, most of the quantum machine learning algorithms are performed by quantum computers in collaboration with classical computers to accomplish the training task. The main body of the quantum variational autoencoder structure proposed in this paper consists of quantum parametric circuits, while the parameter optimization part is a gradient-based optimization iterative algorithm for deriving the parameters in the objective function. The basic flow of its quantum variational autoencoder is shown in Fig. 2.

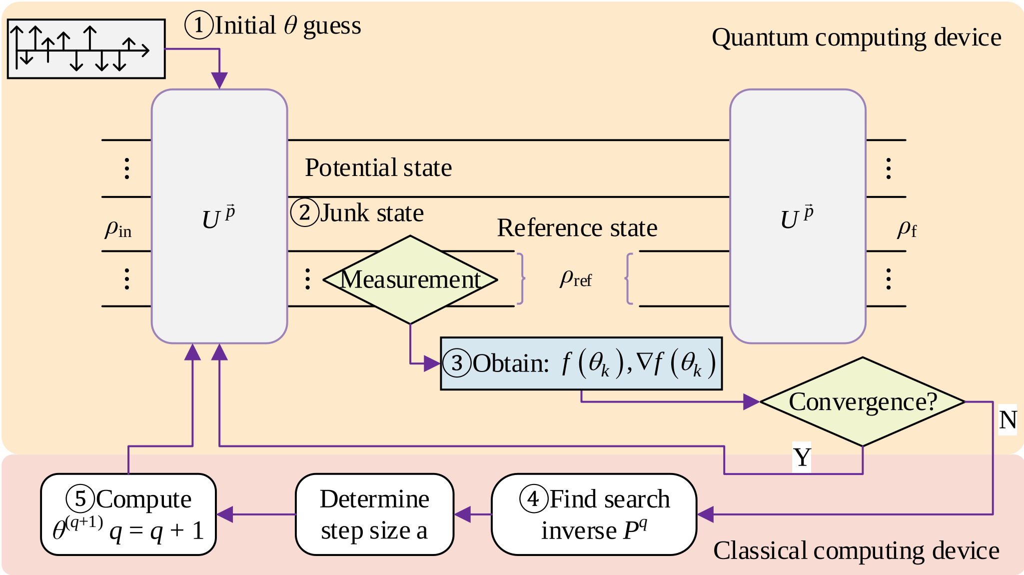


Figure 2: Process of quantum autoencoder

In Fig. 2, the yellow region is performed in a quantum computer, while the pink region is run in a classical computer. Starting with one initial guess for the unknown parameter, the You operator U operation is performed on the input state to generate a better optimized parameter based on the learning results of the experiment, depending on the search direction. The searched unknown parameter is then sent back to the parameterized line to guide the optimization of the optimization strategy with the learning result, and the general procedure is summarized as follows:

Step 1: An initial guess is made for the unknown parameters of the quantum variational autoencoder model;

Step 2: Obtain the You operator $\Phi(U)$ and perform the You operator $\Phi(U)$ operation on the input states to obtain the garbage and potential states;

Step 3: Measure the objective function and gradient, and check whether the objective function converges. Convergence, completed the optimization of You operator U; do not converge, continue to the next step;

Step 4: Determine the direction of gradient search according to the gradient and determine the optimization step;

Step 5: update the parameters, go back to step 2 and continue training.

In the body of the quantum self-encoder is a quantum parameterized circuit and the input data are quantum states. Before we carry out the work of encoding data into the quantum encoder, the classical data needs to be subjected to pre-processing. This step of pre-processing is very important because it maps the classical data to the quantum data. The encoder of quantum is a circuit. It is constituted by a sequence of quantum doors, and these doors possess specific parameters. This kind of configuration lets the quantum encoder have very high suitability for optimization tasks. After the quantum data has been finished encoding through this quantum parameterized circuit, it is divided into two kinds of states: the useless garbage states and the hopeful possible states. After that, the garbage states are thrown away, and the potential states are undergone decoding and restoration. By discarding the garbage state, the dimensionality reduction effect is achieved. The dimensionality reduction process of quantum self-encoder is a lossy process.

2.2.2 Classical data encoding

In quantum machine learning area, the encoding of classical data is one key important step. In this section, the most direct encoding method is used to transform classical data into quantum states. Given a 2D grayscale image $F=(F_{i,j})_{M,L}$, where $F_{i,j}$ denotes that the pixel values are located at (i,j), where $i=1,2,\cdots,M$ and $j=1,2,\cdots,L$. The matrix F of the 2D grayscale image is transformed to form a vector $\vec{f}$ of $M\times L$ elements, where the first M elements of $\vec{f}$ are the first columns of F, followed by the second columns of F, and so on.

$$\vec{f}=vec(F)=\left(F_{1,1},F_{2,1},\cdots,F_{M,1},F_{1,2},\cdots,F_{i,j},\cdots,F_{M,L}\right)^{T} \tag{2}$$

Thus, the image data $\vec{f}$ can be mapped into one by one pure quantum states:

$$|f\rangle=\sum_{k=0}^{2^{n}-1}C_k|k\rangle \tag{3}$$

where $n=\lceil\log_2(ML)\rceil$, the computational base $|k\rangle$ denotes the position (i,j) of each pixel value, and the value of this coefficient, C_k, denotes the encoded pixel value:

$$C_k=F_{i,j}\Big/\left(\sum F_{i,j}^{2}\right)^{1/2} \tag{4}$$

where $k<M\times L$. When $C_k=0$, then $k\geq M\times L$.Generally speaking, before pixel values are written into a quantum state, they must be scaled through a suitable factor, therefore the quantum state can become normalized. When image data is stored by us in quantum random access memory, this mapping just occurs $O(n)$ steps. Furthermore, it is shown that if C_k and $\sum_k|C_k|^2$ can be computed efficiently by a classical algorithm, then constructing the n quantum bit states takes $O(poly(n))$ steps. After the image data have been gotten converted into quantum states, therefore, they can be processed through the use of many kinds of quantum algorithms. The main advantage of this point is that it lets quantum bits express a huge number of traditional data, therefore the quantity is increasing by exponential way.

2.2.3 Line design for quantum variational self-coding

On classical computers, the self-encoder uses a neural network structure. In contrast, on quantum computers, parameterized lines are used to implement the quantum encoder model.The parameterized quantum wires need to be separated into quantum circuits which are good suitable for optimization. Furthermore, the number of parameters and the amount of quantum logic gates inside the quantum lines show polynomial scaling with regard to the count of input quantum bits. Because of this reason, therefore, the model of the quantum variation self-encoder which is put forward in this paper utilizes programmable quantum circuits. Programmable quantum circuits are constituted by prearranged combinations of quantum logical gates.Programmable quantum circuits enhance the flexibility of the model by reusing fixed combinations of quantum logic gates. A quantum variational autoencoder uses a two-qubit universal logic gate as a fixed combination of logic gates. A two-qubit universal gate is composed of a rotary gate R_z and a rotary gate R_y as well as a CNOT gate, which consists of 9 R_z, 6 R_y, and 3 CONT gates, for a total of 18 quantum logic gates, whereas the parameters of the 3 CONT gates are known, and a single combination requires the optimization of 15 unknown parameters. The Figure 3 gives depiction of the universal gate line for two qubits. In this place, every possible combination among quantum bits is got into consideration.

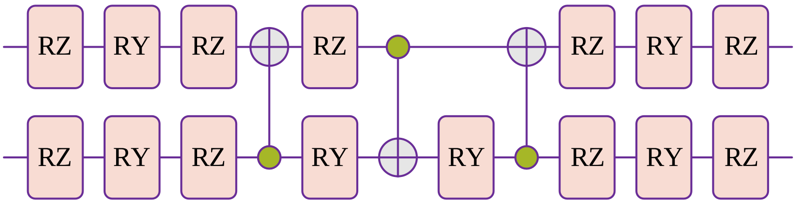


Figure 3: Two-qubit universal circuit

2.3 Positioning method and parameter selection

Figure 4 has drawn the flow of the distribution network fault position-finding method which depends on waveform similarity and a quantum change-shaped automatic encoder.At the first, the quantum variation autoencoder is undergone the training. Concretely speaking, the known fault sample data are utilized by us to carry out the training work for this quantum variation autoencoder. When a fault has occurrence, the fault region is determined on the basis of all existing data in μPMU. Finally, the data of the fault zone is taken out and processed to obtain the localization results using the quantum variational autoencoder.

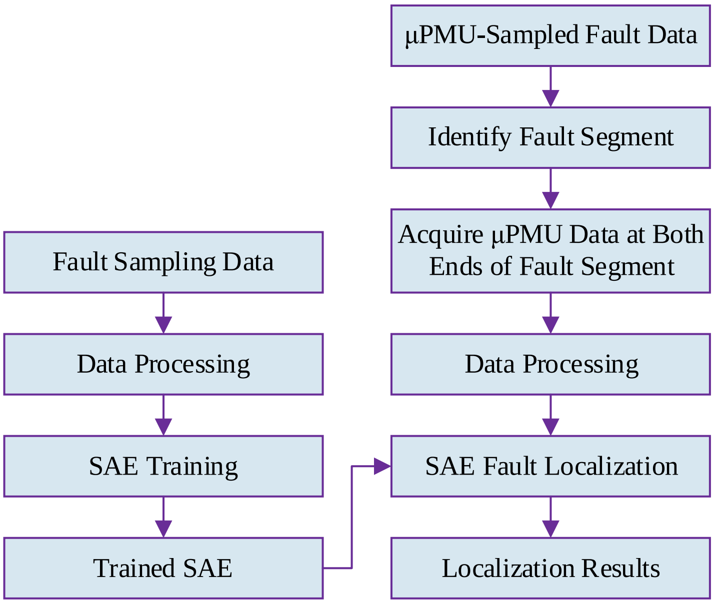


Figure 4: Process of fault location method in distribution network

The quantum variational autoencoder-based fault localization method for distribution networks consists of two main parts: fault segment determination based on waveform similarity and fault ranging based on quantum variational autoencoder. In a distribution network topology with μPMU at both ends, the fault area is cut into T shapes or “one” shapes. Single-ended μPMU measurements are mapped to distance. By utilizing the mapping relationship of double-ended μPMU measurements, the effect of grounding resistance can be reduced. The two terminals are trained with quantum variational autoencoders to obtain the fault distances L1 and L2, respectively, and the midpoint of the overlapping area of the distances at both ends is the fault point, taking into account the localization error.

2.3.1 Fault Area Classification and Determination

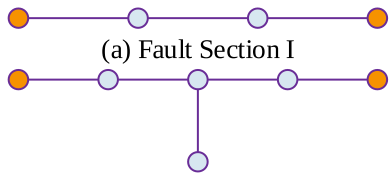
When a problem appears in the power distribution net, the first step which people must take is to confirm the region in which the breakdown has occurred.Therefore, it is crucial to delineate the fault zone band and allocate μPMU this point. Due to the high economy of configuration in the distribution network and the limited communication bandwidth of the grid, it is unrealistic for all nodes to be configured with μPMU ; secondly, all nodes are configured with μPMU to realize real-time on-line synchronous transmission of signals, which is a large amount of signals and difficult to be processed by the computer. Due to the above two reasons, it is necessary to choose a suitable configuration scheme, and the corresponding fault area can only be found when fewer μPMU are configured.

First, fault zoning is performed throughout the distribution network. In order to prevent too many μPMU configurations, large fault ranges, and redundancy of fault data, the fault zoning should cover the smallest μPMU in addition to ensuring accurate fault localization. The allocation and partitioning of μPMU shall be based on the following principles:

The division of fault zones mainly includes the following two types:

(1)According to what is shown in Figure 5(a), Fault Zone I is given. It consists of multiple nodes with branches between nodes. Only the first and last nodes are installed μPMU , which satisfy the above constraints.

(2) Fault zone II, as shown in Fig. 5(b). It consists of multiple nodes forming a T shaped wiring. On the trunk line, the first and last nodes are installed μPMU and the intermediate nodes and branches are not installed μPMU , satisfying the above constraints.



(a) Fault Section I

(b) Fault Section II

Figure 5: Division of the fault section

Because the zero-sequence current wave shapes on two sides of the broken part are not same, hence the zero-sequence current wave shapes at two ends of the part before the broken part are similar. After we complete the calculation of the correlation coefficient, the correlation among the zero-sequence currents that exist at every measurement point is ascertained.For two strictly aligned sequences x and y of length n, the correlation can be expressed by the Pearson correlation coefficient $C(x,y)$, which calculation is carried out as what is shown in equation (5):

$$C(x,y)=\frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2\sum_{i=1}^{n}(y_i-\bar{y})^2}} \tag{5}$$

where x_i and y_i refer to the i th element in the sequences x and y, respectively, and $\overline{x}$ and $\overline{y}$ are the average values of the sequences x and y. The correlation coefficient $C(x, y)$ indicates the similarity between two waveforms. The value of this coefficient is between -1.0 and 1.0. If it is close to 0, it means no correlation; if it is close to 1 or -1, it means strong correlation.

Through carrying out the analysis of the correlation between zero-sequence current wave shapes at measurement points which are on the two sides of the wrong section, the wrong section can be found out.First, compare the waveform similarity of the two measurement points at both ends of the line in the first exit section, if $C(x, y) > \theta$ indicates the instantaneous zero-sequence current wave shapes on two sides of the area possess similarity. After that, we then carry out the evaluation of the similarity of the wave forms at the measurement points on the two ends of the following area; if $C(x, y) < \theta$ determines that it is a faulty zone. If $C(x, y) > \theta$ continue the comparison of zero-sequence current on two ends of next zone, until a proper first fault zone is found out.

2.3.2 Data processing

For making the sample bias become smaller and cancel the influence of the starting condition, the data which are collected from two ends of the fault segment are undergone pre-processing. According to the sampling frequency of engineering applications and μPMU, this paper designs the sampling frequency as 5kHz and the data window length as 0.05s. After determining the MN segment as the fault segment, the voltage and current data of M and N are taken. The data collected at M end are $\dot{V}_1$ and $\dot{I}_1$; the data collected at N end are $\dot{V}_2$ and $\dot{I}_2$. For different fault types, the V and I

The data which relate to faults include the amplitude and phase angle of both voltage and current. These amplitude values and phase-angle values have respectively different measuring scales and value ranges. In the present research paper, the amplitude as well as the phase angle are converted by us into real components and imaginary components. This conversion is implemented by us for the attainment of the standardization of the amplitude, while at the same time it still retains the completeness of the data. The voltage is V, the current is I, the phase angle is θ, and the transformation is shown in equation (6):

$$\begin{cases} V^r = V\cos\theta & I^r = I\cos\theta \\ V^i = V\sin\theta & I^i = I\sin\theta \end{cases} \tag{6}$$

For the purpose of counteracting the influence of the starting condition, the value which is at the starting time is taken away from the sampled value which is at each time point, just as what is displayed in equation (7), where $V_o^r, I_o^r, I_o^r, I_o^i$ are the quantities at the initial moment.

$$\begin{cases} V^r = V^r - V_o^r & I^r = I^r - I_o^r \\ V^i = V^i - V_o^i & I^i = I^i - I_o^i \end{cases} \tag{7}$$

Normalize V_t^r, I_t^r,the results of fault positioning depend on the change speed of the wave shape instead of its amplitude magnitude. Maxmin normalization is used here. Each input signal must pass through the process of normalization, therefore the range of its numerical values is compressed to lie inside the interval from 0 to 1.. The normalization formula is shown in

Equation (8), where $\max(x_i)$ and $\min(x_i)$ are the extreme numerical values (both the maximum and the minimum) which come after the normalization process, x_i is the original value and z is the normalized value:

$$z = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)} \tag{8}$$

The data which have been processed are put together to build a high-dimensional matrix that contains fault samples.Taking A phase ground fault as an example, Eq. (9) and Eq. (10) show the characteristic sequence of voltage and current, and Eq.the high-dimension fault sample sequence is gotten with voltage and current, and it is marked as (11).

$$\hat{V}_A = \left[V_A^r(1), V_A^r(2) \cdots V_A^r(T), V_A^i(1), V_A^i(2) \cdots V_A^i(T)\right] \tag{9}$$

$$\hat{I}_A = \left[I_A^r(1), I_A^r(2) \cdots I_A^r(T), I_A^i(1), I_A^i(2) \cdots I_A^i(T)\right] \tag{10}$$

$$g = \left[\hat{V}_A, \hat{I}_A\right] \tag{11}$$

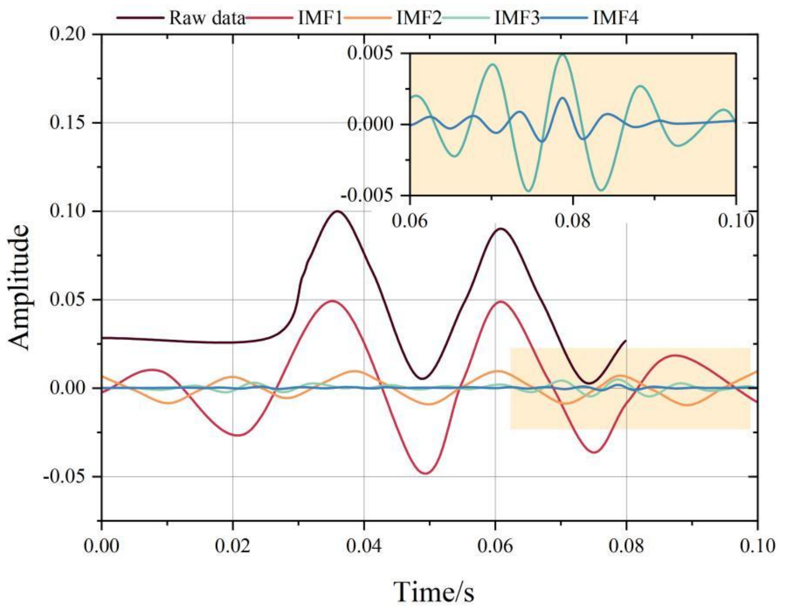
3 Simulation Analysis of Distribution Network Ground Fault Feature Fusion and Anomaly Detection

In this present research paper, fault examinations are carried out upon the distribution network model for collecting data and verifying the effect of the put-forward method. Furthermore, the model of distribution network is constructed by utilization of PSCAD software. The network which distributes electric power operates in a frequency that is 60Hz. The main transformer possesses a Y-Y wiring structure, whose high-voltage (HV) side is directly connected to ground, and whose low-voltage (LV) side is connected to ground through a high-resistance joint. The monitoring instrument catches electricity information at the busbar exit and feeder connection points.

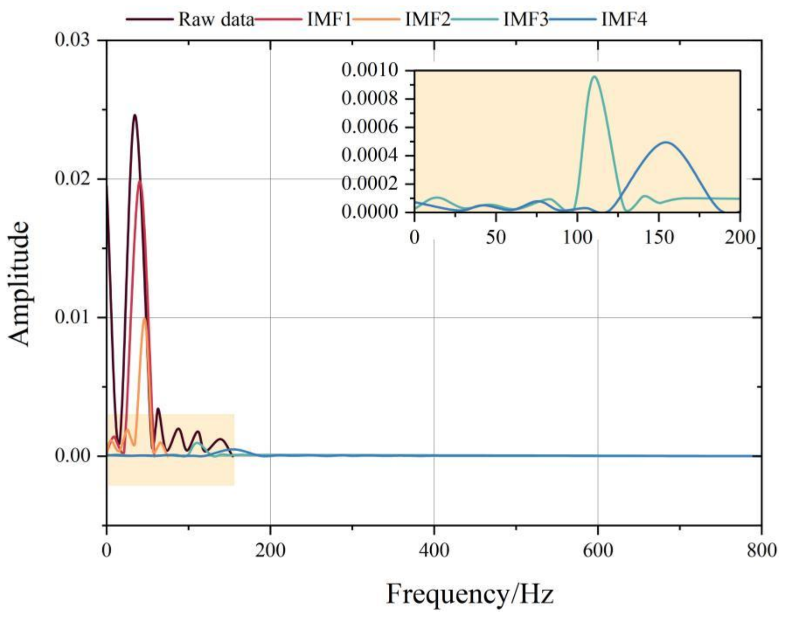
3.1 VMD parameter selection

For the purpose of information loss prevention, the high-frequency composition of the signal which appears at the time when a fault takes place is extracted. After that, the VMD decomposition work is conducted through the method of steadily increasing the K value. To every adjacent mode which is got from the decomposition, the mean value of the central frequency is calculated. When this average value of the central frequency goes beyond the system's industrial frequency, that is, the low-frequency signal generated by decomposition is much lower than the industrial frequency when K=5, so the decomposition scale with a K value of 4 is selected. Considering the size of the feature matrix after signal processing, combining 50 groups of zero-sequence current signals and 50 groups of fault phase voltage signals decomposition scale K value selects the variable mode component as 4, so as to ensure the effectiveness of the decomposition signal, but also to maximize the retention of fault characteristic information.

When K=4, the decomposition results are shown in Fig. 6 (a~b), the decomposition of the obtained IMF components have obvious spectral peaks, and there is no spectral aliasing, IMF3 and IMF4 have obvious high-frequency information at the fault moment, and the rest of the components have fluctuating variations at the fault moment.



(a)VMD decomposition



(b)Frequency spectrum

Figure 6: IMF components and their spectral comparison at K=4

3.2 Single-phase ground fault feature extraction

Because single-phase ground fault is the fault type with the highest occurrence rate in power systems, therefore, the characteristics of the collected fault signal are extracted on the basis of the E-VMD principle.

(1) VMD decomposition is performed on the collected fault signal to obtain its corresponding mode components.Figure 7 gives the results which are obtained by the VMD (Variational Mode Decomposition) of the A-phase voltage and zero-sequence current on the

low-voltage side of the main transformer at the moment when a single-phase ground fault occurs. In the situation when a one-phase earth fault takes place, every element of the voltage signal of the faulted phase and the zero-sequence current signal has obvious fluctuations at the beginning and finishing of the fault, therefore the corresponding amplitudes of every mode component have differences. The constitution elements of mode constitution elements 1 and 2 are obviously non-smooth and include obvious high-frequency fault characteristic details.

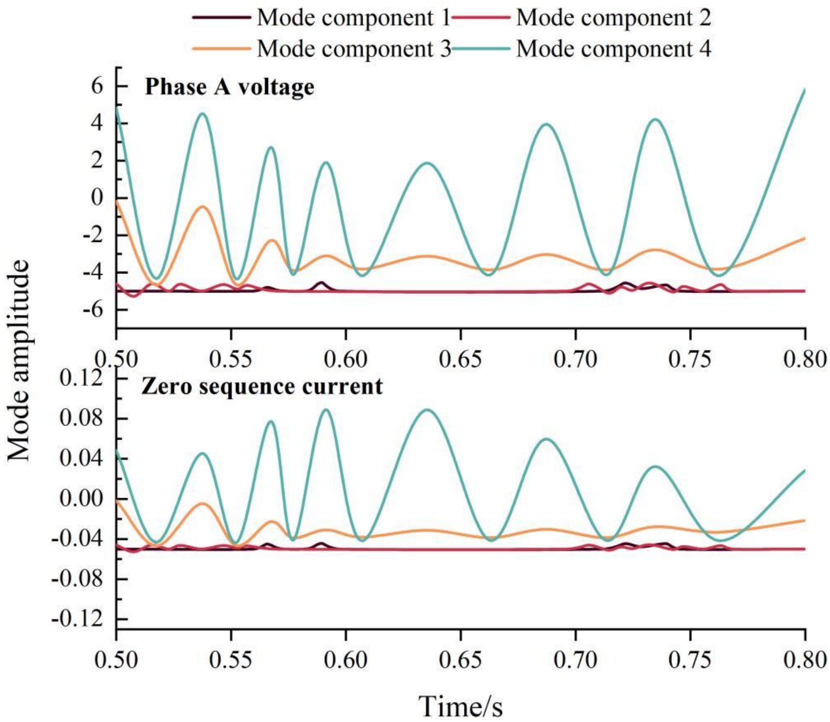


Figure 7: VMD decomposition results

(2) The decomposed mode components are divided into 6 segments with the simulation cycle length of 0.50~0.80s,after that, the feature particulars of each segment are separately extracted to obtain a horizontal magnitude with a length of 6. Following that step, through placing these things one after another along the horizontal direction, a horizontal data array that has the size of 1×50 can be got by us.(3) Perform the feature extraction operation for each mode component in turn, and obtain the feature quantity of size 6×50 in the order of mode components from top to bottom, and perform normalization processing so that the smaller feature values are not covered.

(4)To each obtained fault signal, the aforementioned operation must be performed one more time to extract the characteristic information of every individual signal. After that, you should put these details in order according to the principle of space position arrangement. Therefore, the feature matrix of the three-dimensional curved surface, which is shown in Figure 8, can be got.Through the three-dimensional surface map, the feature distribution of fault signals in different modes can be observed, and the feature changes of different mode components in different time periods can be demonstrated more intuitively.

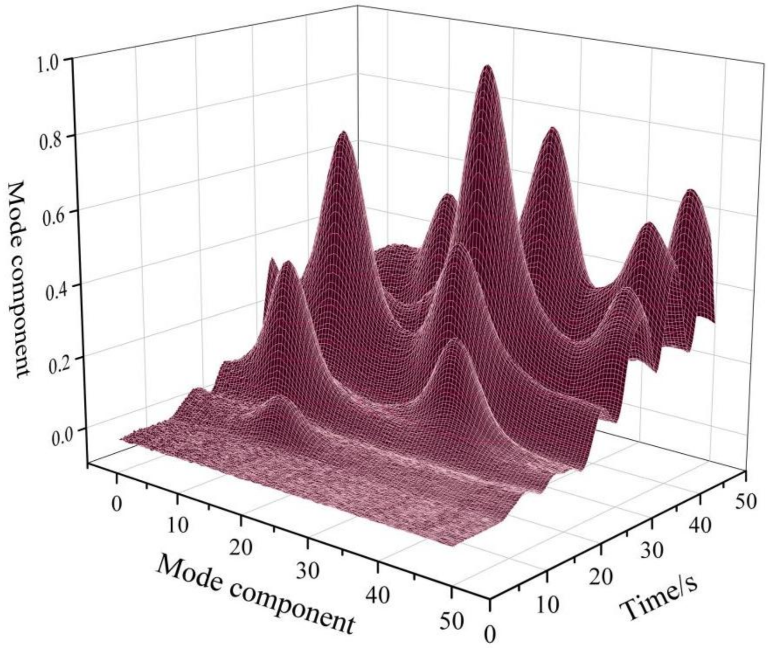


Figure 8: 3D surface of single-phase grounding fault characteristics

3.3 Fault Feature Fusion

3.3.1 Zero sequence current signal difference analysis

Considering the zero-sequence currents under both high-impedance fault (HIF) and normal disturbance conditions are non-stationary, hence their frequency changes with the time, the signal characteristics cannot be fully characterized only from the time or frequency domain, so time-frequency analysis is required.VMD is a time-frequency analysis method that can effectively deal with non-linear and non-smooth signals. By dividing the zero-sequence current sequence into intrinsic modal functions of different frequencies through VMD, the smoothness and variability of fault signal characteristics can be improved. For researching the difference on time and frequency of zero-sequence currents when high-impedance fault (HIF) happens and when the system works under normal operating conditions, this paper uses Variational Mode Decomposition (VMD) to carry out this work. By this method, the zero-sequence current sequence is decomposed into four Intrinsic Mode Function (IMF) components that have different frequencies, which is shown in Figure 9. It is very obvious that the zero-sequence current signals which correspond to different working situations are decomposed by people into four different frequency components, and the components of the zero-sequence current of the HIF after VMD are more regular than the CS and LS over time, with smaller changes in the amplitude of the components, whereas the components obtained by the CS and LS are mainly concentrated in the first cycle of the change of the operating conditions, and the amplitude of the amplitude oscillation is obvious. Because the zero-sequence current initial waveforms of High-Impedance Fault (HIF) and Incipient Current (IC) are similar, the components that Variational Mode Decomposition (VMD) obtains still have obvious differences. Nevertheless, through looking at Figure 9, it can be seen that, regarding time distribution, IC has more order than HIF.

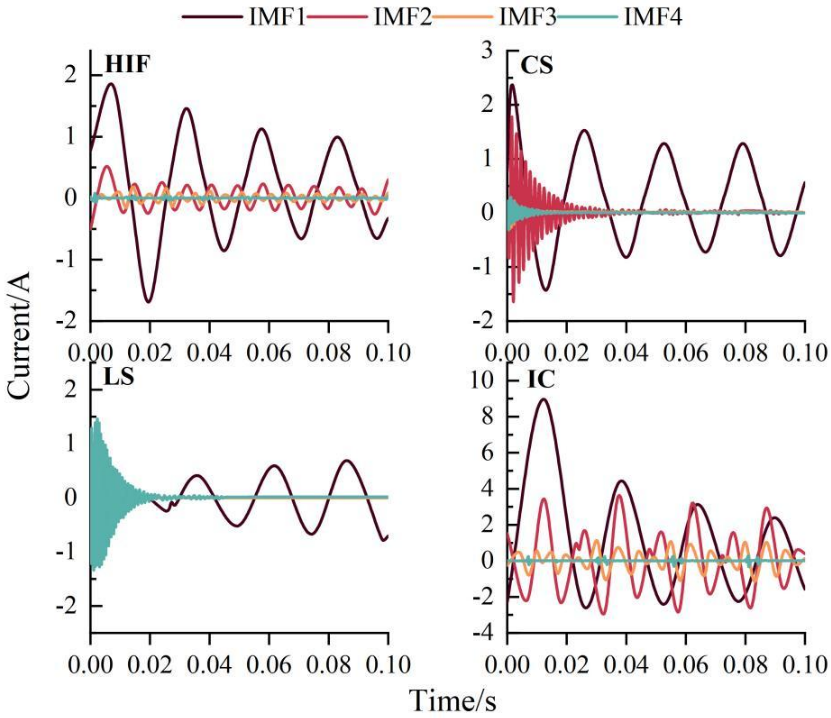


Figure 9: Zero-sequence current decomposition for different operating conditions

3.3.2 Sample library construction of fault features

A total of 15 features are selected for global structural features and node attribute features, however, with the increase of feature dimensionality, there may be duplications between features in describing the signal variability, resulting in the phenomenon of feature redundancy, which increases the computational burden of subsequent fault detection. The reduction of feature dimension possesses the capacity to decrease the complexity of data, which therefore cuts down the calculation cost and hence improves the performance of the model to a certain extent. In this research paper, we use the Pearson correlation coefficient to achieve the reduction of feature dimensionality. This procedure includes removing unnecessary features, reducing feature repetition, and lightening the calculation load in the following repeated calculations of the high-resistance ground fault check model. The usage of the Pearson correlation coefficient not only realizes the reduction of feature dimensionality but also removes the features that have strong correlation relationships. Furthermore, it thus keeps the original characteristics which are sensitive and important. In a certain degree, this has proven that the chosen features have appropriate suitability.

The Pearson correlation coefficient is calculated between the 15 features selected in this paper, and the feature with the largest correlation coefficient is obtained, and the correlation coefficient matrix is shown in Fig. 10. By calculating the correlation coefficient between the 15 features, a 15×15 coefficient matrix is obtained, and the strongest feature corresponding to the correlation of each feature is filtered. The strength of correlation is decided by how close the correlation coefficient gets to some certain values. Concretely speaking, when the correlation coefficient gets close to 1, this shows a stronger degree of correlation. By opposite way, when the value becomes nearer to 0, the correlation gets more weak. After calculation, 6 global structure features, i.e., A1~A5 and A7, and 6 node attribute features, i.e., B1~B3 and B6~B8, totaling 12 features, are obtained after screening.

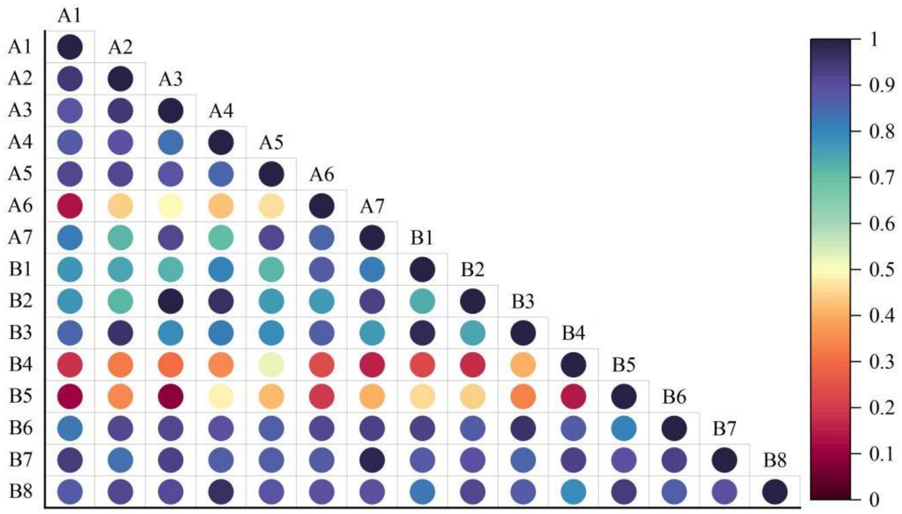


Figure 10: Correlation coefficient matrix

3.4 Ground fault detection

3.4.1 Training tests

We have chosen the fully-connected neural network model (FC) to be the method for comparison. Figure 11 gives a comparison of the recognition mistakes between the method which is put forward in this paper and the contrast method through 20 samples. It is very obvious that, the recognition results of the method that is in this paper, which based on a quantum variation autoencoder, are more close to the real label values. This method can with higher precision detect high-resistance earth faults in the distribution network earth connection system. Furthermore, all the values of recognition error are within 0.03.

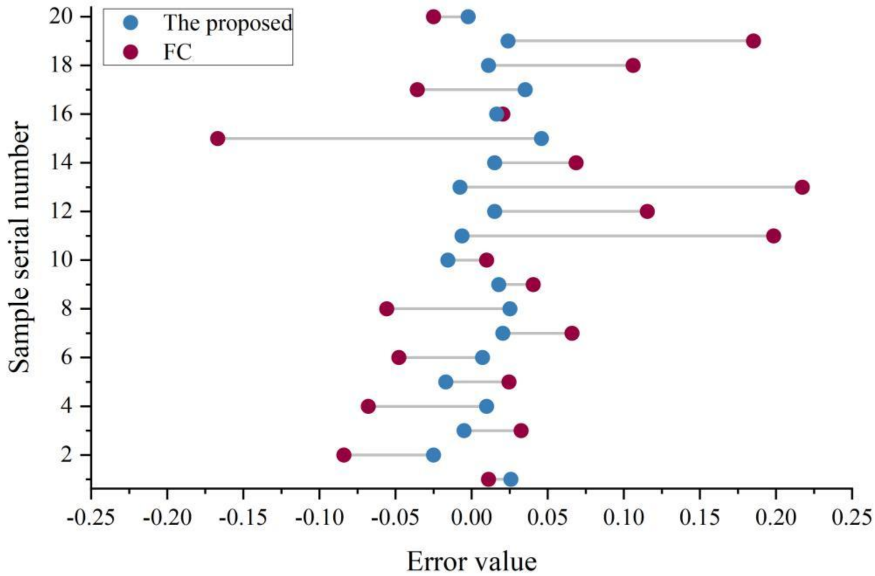


Figure 11: Comparison of identification errors

3.4.2 Anti-interference capability

Considering that the changes in electrical quantities when load casting and noise disturbances occur in the distribution network are similar to the occurrence of high-resistance ground faults, such disturbances are imposed when collecting test samples. The comparison of the discrimination errors between this paper's method and the comparison method in 20 samples is shown in Fig. 12. Although the error between the sample identification results and the labeled values becomes larger, the method of this paper can still control the error in a small range, and the error value does not exceed 0.09, that is, the method of this paper has a certain degree of immunity to interference.

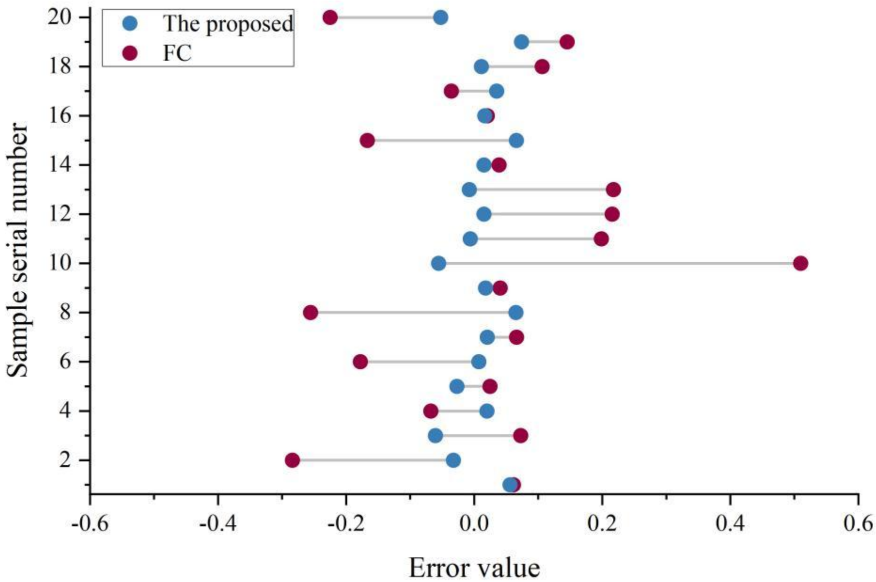


Figure 12: Comparison of identification errors in anti-interference experiments

4 Conclusion

Inside this research paper, the graph neural network model and quantum computing technique are brought into the fault diagnosis of the distribution network, specially solving the problem of ground fault positioning inside distribution networks, and a fusion of ground fault features and anomaly detection method for distribution networks with fusion of quantum variational autoencoders is proposed. The research discoveries of this written article are showed in the below way:

Experimentally, 50 groups of zero sequence current signals and 50 groups of fault phase voltage signals are collected, and the optimal decomposition scale is determined to be K=4 after several experiments, at which time the peaks of each IMF spectrum are distinct, and IMF3 and IMF4 present significant high-frequency information at the fault moment. After we have eliminated the unnecessary features, six big structural features, that is A1, A2, A3, A4, A5, and A7, together with six node attribute features, which specifically are B1, B2, B3, B6, B7, and B8, are obtained.

In 20 test samples, the average recognition error of this paper's method is 0.017, and in the case of adding load casting and noise interference, the error rises but is still controlled within 0.09, which indicates that, regarding both the correctness of high-resistance ground fault identification and anti-disturbance abilities, the method we put forward has better performance than the traditional method.

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