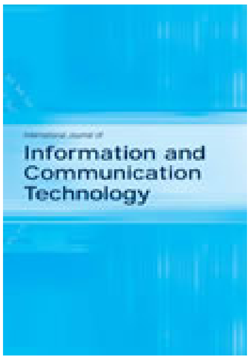

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Real-time monitoring system for power distribution network faults based on deep learning technology

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Abstract: This article aims to propose a reliable real-time monitoring system for distribution network defects, improve intelligent monitoring technology by combining deep learning technology, and analyse the drawbacks of traditional real-time monitoring of distribution network defects in real-time, by improving the algorithm, the basic structure of the algorithm model is constructed. Based on experimental analysis, the data processing of this system is based on deep learning technology. Multiple monitoring modules are used in the system to improve the accuracy and real-time performance of data collection, providing more reliable data support for fault detection. From the simulation experiment, it can be seen that the real-time monitoring system for distribution network defects based on deep learning proposed in this article can play an important role in fault diagnosis and troubleshooting in the distribution network.

Keywords: deep learning; distribution network; defects; real-time monitoring.

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1 Introduction

With the continuous improvement of wide area measurement system (WAMS), distribution management system and data acquisition and monitoring system, it becomes easier to obtain fault recording data of distribution network. Reasonable use of historical fault information and power grid real-time data can not only monitor the power grid operation state, but also further dig these massive data, which can effectively evaluate and diagnose the current power grid operation state or power equipment state. The method based on artificial intelligence will no longer be limited by the problem that massive samples are difficult to obtain. In recent years, experts and scholars have applied machine learning, deep learning and transfer learning to the field of fault line selection, and achieved good results.

The rapid development of the technology era cannot be separated from the strong support of large and complex power systems. Stable power transmission not only provides strong support for the rapid development of industries such as the national economy, energy, and technology, but also safeguards the high-quality social life of humanity. Once a large-scale interconnected integrated power grid fails, it will cause incalculable losses to social production and people's lives. Cascade faults in power network systems refer to the situation where if a node in the network fails, the power flow in the network will be redistributed, and a relatively small local disturbance will trigger a series of grid component failures, which may escalate cascading faults in other networks, causing a significant portion of the network to fail, resulting in costly consequences. Therefore, it is urgent to conduct in-depth research on the structure and operational characteristics of the power grid in order to maintain the safe and reliable operation of the power system.

In a large power network, when a node fails, the load of that node will be transferred to other nodes in the network in some way. In order to control the propagation scale of cascading faults in the power grid, based on overload mechanism and propensity allocation principle, a new fault node load redistribution model is established based on the electrical power information of nodes themselves and neighbouring nodes. On this basis, a power grid cascading fault control strategy based on load distribution is further proposed.

The research on how to carry out reliable fault location methods has been going on for a long time, but the progress of research on fault location problems has not been very smooth. The old method of relying solely on manual visual inspection of power lines consumes a large amount of human resources and also increases resource consumption, greatly reducing the power supply reliability of the distribution network. With the continuous improvement of science and technology in recent years, it has gradually shifted from planned maintenance to current state maintenance. Planned maintenance usually involves routine annual and monthly inspections, which are not targeted enough and have low efficiency. Compared to other methods, condition-based maintenance greatly improves the efficiency of maintenance. This method of analysing the operation status of distribution networks is based on sampling information of monitoring equipment installed in the power grid, which is more conducive to further targeted maintenance. Due to the complexity of distribution network construction and installation, real-time monitoring of it has certain practical significance. The requirement for automatic detection of distribution networks has become more urgent with the development of smart grids. By applying wireless transmission technology to distribution network detection and deploying sensor networks on overhead lines to monitor the operation status of the system, it is easier to locate the location of faults in the distribution network. This is undoubtedly a promising development trend.

In order to improve the monitoring effect of distribution network defects and find the fault points of distribution network in real-time, this paper combines deep learning technology to build a real-time monitoring system for distribution network defects to improve the operation stability of distribution network.

2 Related work

Based on linear or nonlinear data modelling, traditional reconstruction methods can be classified into simplex method and branch method. The traditional reconstruction algorithm model is simple, fast for small networks, and easy to obtain the optimal solution; however, there are significant limitations for large-scale systems. Arun and Sudharson (2023) used the minimum tree generation algorithm to obtain a reconstruction solution with minimal power consumption, harmoniously combining search algorithms and dynamic programming algorithms to form a reconstruction method that can minimise power loss and operating costs. Baumgartl et al. (2020) proposes a multi-objective reconstruction jump algorithm based on hybrid frogs, which can minimise operating costs and improve the security of distribution network reconstruction. However, for the reconstruction problem of large-scale systems, the efficiency of commonly used metaheuristic algorithms is low. Mixed integer programming (MIP) is a commonly used modelling method for mathematical planning of distribution network reconstruction problems. Chen et al. (2022) adopts the introduction of linearisation method to transform the reconstruction model into a MIP problem. One reconstruction method based on dynamic programming is to simplify the reconstruction model by reducing the power of DG and the load under operational constraints. Later, researchers obtained the optimal reconstruction solution by changing the branch, which is the idea of heuristic algorithms. There are generally two methods: branch exchange and optimal flow pattern method. Guo et al. (2020) considers the sensitivity of power flow in distribution networks and calculates the power flow after changing the operating state of the distribution network through branch exchange method. Compared with the previous power flow state, the reconstructed optimal topology structure can be obtained. But it is not as ideal in terms of retrieval speed and finding the global optimal solution. Hu et al. (2022) simplifies the topology of the distribution network into an undirected graph using the optimal flow pattern method, and then converts the undirected graph into a radial topology structure through the principle of spanning trees. Although this method converges quickly, it cannot find the global reconstruction optimal solution. The shortcomings of traditional algorithms and heuristic algorithms are becoming increasingly apparent (Hu and Wang, 2020). Genetic algorithm is a biomimetic algorithm. Its main advantage is that the chromosome encoding in genetic algorithms better represents the switch state in network topology, and is widely used in network reconstruction. Disadvantage: The local convergence speed is fast, and it is prone to a large number of infeasible solutions. To address this issue, Kumar et al. (2020) adopts a method based on cyclic coding, which significantly reduces the occurrence of infeasible solutions, but is no longer effective when the network topology changes. Researchers use the idea of particle swarm optimisation to search for the optimal solution by adjusting the fitness values between random particles and target particles. The principle of this algorithm is simple, the search speed is fast. Lai et al. (2020) addresses the problem of particle swarm optimisation algorithm not being able to obtain a global optimal solution and easily falling into a local optimal solution. A matrix is used as the direction of particle motion to guide its movement, thereby enabling particles to jump out of the local optimal solution. Liu et al. (2020) aims to improve the problem of stagnation and slow search speed in ant colony optimisation algorithms near local optimal solutions. Using a hybrid sequence optimisation ant colony reconstruction algorithm and utilising the source information of the sequence initialisation optimisation algorithm, a satisfactory solution is provided. The improved algorithm can use multiple search rules to improve search efficiency and has less dependence on existing network topologies. Lu et al. (2020) uses taboo search algorithm to expand the search for neighbouring regions by setting multiple taboo tables simultaneously, which can improve the efficiency of network reconstruction, effectively jump out of local optimisation. The main advantages of this method are high flexibility and strong climbing ability. Disadvantage: highly dependent on initial values, repeated searches enter a single state, which affects search speed.

With the continuous development and application of machine learning, many other branch fields have emerged, among which deep learning is a relatively mature one. Hidden neural networks have strong adaptive learning capabilities. At present, deep learning has achieved good results in speech recognition, image retrieval, error diagnosis, and target tracking. With the continuous development of deep learning, it has begun to stand out in the power system and has achieved good results in the research process. In order to effectively evaluate the topology structure within the distributed distribution network, Motevalli et al. (2020) adopts a distribution network topology evaluation method based on convolutional neural network reinforcement extraction to verify the impact of distributed power sources on the topology structure of the distribution network. Niu et al. (2020) utilises short-term energy storage network-based charging load and photovoltaic power generation prediction to accurately predict load and photovoltaic power generation, and improves system safety and stability based on the predicted short-term load. The prediction results indicate that it is more accurate than random forest and neural network algorithms. Qiu et al. (2022) proposes a deep learning-based method for line loss analysis. This method first introduces multiple electrical features and extracts accurate electrical features that affect line loss by analysing historical data. Román et al. (2021) proposes a new reconstruction control strategy using data-driven reinforcement learning algorithms, which can learn control strategies for distribution network reconstruction from historical operation datasets. Therefore a method that can accurately and efficiently obtain the dataset of distribution network reconstruction is a necessary consideration. Due to the intermittency and permeability of distributed generation (DG), the emergence of DG brings a lot of uncertainty to the reconstruction. Traditional fault recovery and reconstruction are often determined offline in the daily plan. However, data-driven methods can use real-time system states to make online decisions, which can significantly reduce the impact of DG uncertainty (Saiz et al., 2021).

The distribution network with distributed power sources has a composite branch topology structurets. The segment localisation problem is to determine the segment where the fault point is located. Section positioning is a necessary guarantee for precise positioning of the fault occurrence point, and also a key foundation for repairing distribution network faults and restoring power supply to the fault location. From the perspective of terminal information extraction methods, due to the numerous nodes in active distribution network sections, fault location requires the use of wide area data detection devices. At present, there is a serious gap in the fault information detection device of the distribution network, and usually only feeder terminal units (FTUs) and other distribution automation devices can be used to obtain fault voltage and current data. Therefore, existing section technologies generally use fault current and voltage data to obtain positioning information (Saqlain et al., 2020).

The problem of locating fault sections in distribution networks essentially belongs to the multi classification problem of targets, and the positioning results are at the level of fault sections. The basic research idea is: each node terminal detects the operating status of the line, transmits various electrical signals to the control centre when a fault occurs, and the control centre calls the positioning algorithm to determine the fault feeder. This method can also be subdivided into two types of algorithms (Shin et al., 2021): direct methods and indirect methods.

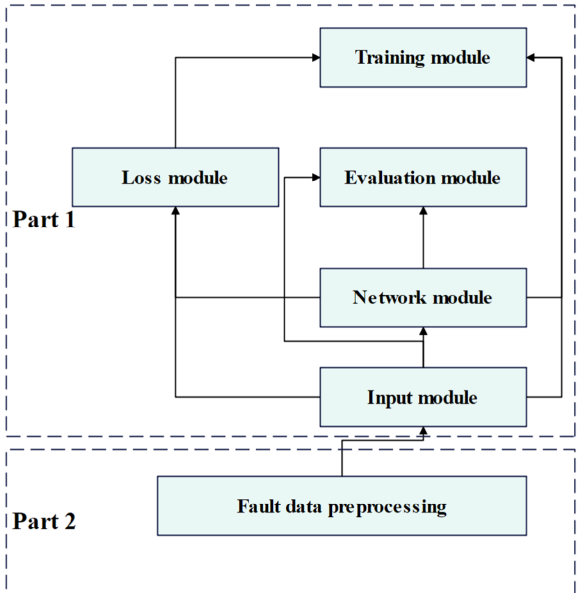
Among the fault section localisation algorithms, matrix algorithm is the most widely used. Wang (2023) divides a complex distribution network into multiple sub networks and proposes an automatic calculation algorithm for sub network vectors that can map fault information. Wang et al. (2022) considers the poor fault tolerance of matrix algorithms and combines them with optimisation algorithms to complement each other's advantages. Firstly, the matrix algorithm is used to roughly determine the fault feeder, reduce the dimensionality of optimisation variables, and then an optimisation simulation is constructed based on the network description matrix to improve the convergence efficiency of the algorithm. Yu et al. (2020) constructs a network relationship matrix based on the topology of the distribution network, and then transmits fault information to the power monitoring system. The fault evaluation function is calculated from the fault diagnosis matrix, and the fault section is located and isolated based on the minimum value of the fault evaluation function.

The most prominent advantage of matrix algorithm is that it is not affected by the direction of power flow, only needs to determine whether there is current data, the positioning principle is simple, and it is easy to implement. However, the matrix method has complex information, low operational efficiency, poor adaptability when distributed power sources are connected to the distribution network, and poor robustness to complex environments. After information distortion, the positioning accuracy decreases significantly (Zhu and Mu, 2020).

3 Distribution network defect recognition algorithm

The data transmission direction in the deep learning model based on TensorFlow is shown in Figure 1, which is mainly divided into two parts: data theory and model building. The first part is the processing of fault data for active distribution networks. Collect overcurrent fault data and node voltage data based on the FTU devices of each node, and combine them with the output of each power source to obtain a fault data vector dataset. At the same time, label and clean the data. The second part is to construct a DNN-based active distribution network fault localisation model within the TensorFlow framework. The model is trained using processed and labelled fault data, and the final fault localisation model is formed after training.

Figure 1 Deep learning model based on TensorFlow framework (see online version for colours)



With the expansion of distribution network scale, the topology of distribution network is more complex and there are many physical nodes. In view of the current development of distribution network automation technology, the lack of monitoring data, and the extensive access of DG leads to the expansion of information dimension, based on complex network theory, an important model of distribution network topology nodes considering importance and reliability is established, so as to allocate acquisition and measurement points economically and reasonably.

Generally, complex distribution network can be regarded as undirected and unauthorised network. Therefore, firstly, the whole power grid is abstracted into a network composed of nodes and edges. Power plants, tie lines and loads in the power grid are abstracted as nodes and represented by S_n (n represents node numbers), while lines in the power grid are abstracted as edges and represented by L_n (n represents line numbers). Some nodes in distribution network topology are usually connected with multiple branches, which are of great importance in electrical structure. The nodes are equipped with terminal devices, which can monitor the fault characteristics of multiple branches. The connectivity of a node is defined as the number of remaining nodes directly connected to the node. Borrowing this definition, the distribution network topology is regarded as an undirected and unauthorised network, and the degree of each node is calculated, as shown in equation (1) (Wéber et al., 2022).

$$D_n = \sum_{j=1}^{j=m, j\neq 1} a_{ij} \tag{1}$$

Among them, D_n represents the degree of node n, a_{ij} represents the connection state between node i and node j. Directly connected is 1, and the rest are 0.

According to the system topology, power nodes and load nodes are determined. Power nodes include main power nodes and distributed power nodes. The importance of power access point to the system is obvious, and its measurement data supports reliable power supply in distribution network. It is defined that the closer the electrical distance from the power supply node is, the greater the importance of the node. The importance of the node is expressed as equation (2).

$$D_{sn} = \sum_{i=1}^{m} \frac{P_{Gi}}{L_{ni}} \tag{2}$$

Among them, D_{sn} represents the importance of nodes in distribution network system. m represents the number of distributed generators. L_{ni} represents the shortest electrical distance between the node and the i-number power supply, and P_{Gi} is the power generation capacity of the i-number power supply.

Based on the above definition, considering the importance and reliability of each node as a reference, the importance model of distribution network nodes is established. The importance of each node of distribution network topology is as follows (Kumar et al., 2022):

$$F_n = \alpha D_n + \beta D_{sn} \tag{3}$$

Among them, F_n represents the importance of the node, and α and β are the adjustment coefficient is used to ensure the normalisation between the importance of the node and the connectivity of the node.

According to the existing distribution network topology parameters, the node importance model of distribution network is established, and the importance of each node is calculated, and the data importance of each node in distribution network is sorted to express the sequence of measuring point configuration.

$$a = \left[i_{1,}\ i_2, \ldots, i_n, u_1, u_2, \ldots, u_n, P_{DG1}, P_{DG2}, \ldots, P_{DGm} \right] \tag{4}$$

Among them, it is assumed that the topology is configured with n measuring points.

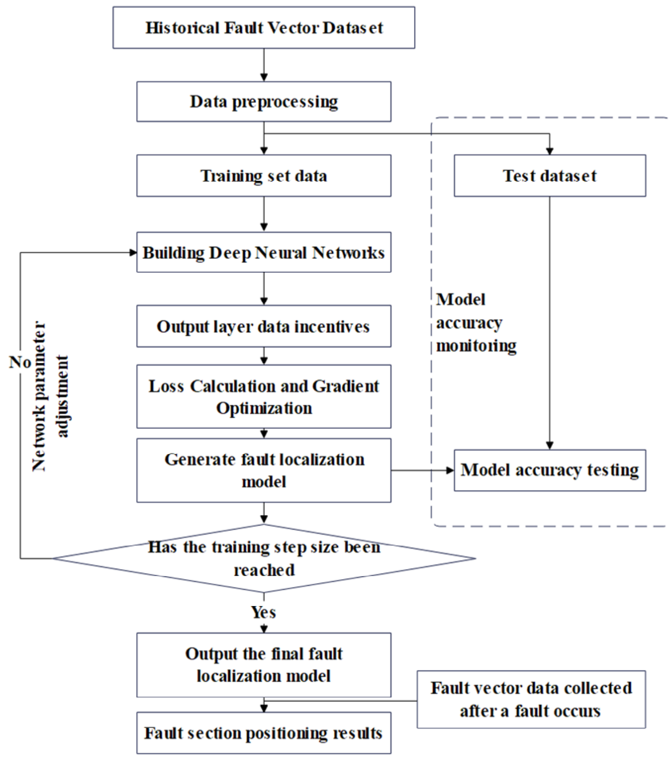
The min-max method is used for normalisation, and its main calculation methods are as follows (Fogliatto et al., 2022):

$$y_n^* = \frac{y_n - \min(n)}{\max(n) - \min(n)} \tag{5}$$

Among them, $y = [y_1, y_2, y_3, \ldots, y_i]$, i is the dimension of training set, y is the dataset.

In this section, a fault location model of active distribution network based on deep neural network is constructed. The basic logic structure of the network model is shown in Figure 2. In this model, the nonlinear mapping relationship between fault branches and fault data is mined by deep learning, and the fault section is located.

Figure 2 Fault location method diagram of active distribution network



In the input module, the activation function is needed to excite the data of the network output layer, which is mainly reflected in the data excitation part of Figure 2.

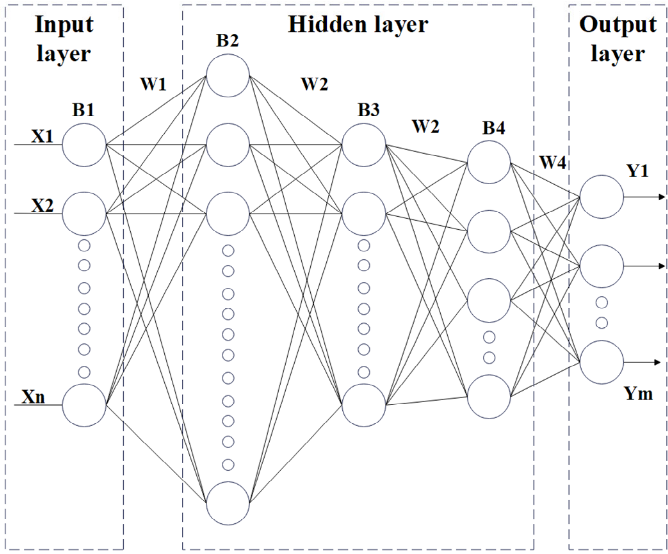
$$\sigma_j(z) = \frac{e^{z_j}}{\sum_{i=1}^{k} e^{z_j}} \tag{6}$$

Among them, j is the number of classifications and $z = [z_1, z_2, z_3, \ldots, z_i]$ is the output layer prediction vector. $\sigma_j(z)$ represents the probability of belonging to a j-class (Sun and Qiu, 2021).

The network module is mainly to build a deep neural network model. The network structure parameters are determined according to the input data dimension and label data dimension used in Figure 2. In order to locate the fault segment accurately, this paper uses a DNN structure composed of three-layer FCN. The DNN model structure is shown in Figure 3.

Among them, in the input layer, $x = [x_1, x_2, \ldots, x_n]$ is fault data vector, $y = [y_1, y_2, \ldots, y_m]$, and m represents the number of fault branch labels in the data. W_1, W_2, W_3 and W_4 are the second-order weight matrix, which represents the connection weights of adjacent network layers. B_1, B_2, B_3 and B_4 are the offset matrix, which represents the offset value of each neuron of the layer network.

Figure 3 Deep neural network structure



In the loss module, the function which is mainly reflected in the loss calculation part, and its size reflects the deviation distance. The cross entropy loss function is shown in.

$$f_{loss} = -\sum_{i=1}^{n} y_{label} \log\left(y_{pre}\right) \tag{7}$$

In the training module, according to the data structure, the best optimisation function is adopted to reduce the output loss of the loss module. It is mainly reflected in the gradient optimisation part of Figure 2, which can back-propagate data, feedback and adjust network parameters in the training process, and realise the training and learning of the model. Considering that data labels use one-hot encoding rule and the label matrix is sparse, the optimisation function generally adopts Adam, SGD or momentum functions, can effectively carry out adjustment feedback learning. The function training step size to the standard value is set as 0.01.

In the evaluation module, it is necessary to monitor the accuracy of model positioning, which is mainly reflected in the accuracy of calculation model in Figure 2. At the end of each training step, an active distribution network fault location model with different parameters will be formed. At this time, it is necessary to input test set data to test the model and verify the correctness of the model.

The label data is defined as the fault branch sign number, and the evaluation algorithm are as formulas (8) and (9) (Li et al., 2021):

$$H[x, y] = \begin{cases} 0, & x \neq y \\ 1, & x = y \end{cases} \tag{8}$$

$$P_{acc} = \frac{\sum_{i=1}^{n} H\left[LOC_{\max}\left(y_{label}\right), LOC_{\max}\left(y_{pre}\right)\right]}{n} \tag{9}$$

The difference of fault characteristic quantity in the same position is mainly manifested as the difference of amplitude, phase and waveform. Therefore, multi-class noisy signal data is constructed to characterise the difference of amplitude characteristic quantity of fault characteristic signal, and the adaptability of the algorithm is verified.

The amplitude vector of N groups of sequences is $X = [X_1, X_2, \ldots, X_N]$, and N represents categories, that is, N labels. If each class sequence contains M signal data, the expression of the h^{th} signal data ($h \in M$) in class k is as follows:

$$X_{i+1} = X_i + |X_2 - X_1| \tag{10}$$

$$x_{ij} = \frac{X_i}{\|X\|}\sin(\omega t) + \delta_{ij}(t) \tag{11}$$

Among them, x_{ij} is the j^{th} signal data of the i^{th} class, X_i is the signal amplitude of the i^{th} class, and $\delta_{ij}(t)$ is a standard white Gaussian noise sequence with a mean value of 0 and a variance of 1 superimposed on the j^{th} signal data of the i^{th} class. X represents the modulus of the amplitude vector to normalise the signal data. The amplitude of each group of signal data in N-class sequence is different, which is used to characterise the difference of the amplitude of fault feature quantity. Each kind of signal is superimposed with varying noise quantity, which is used to characterise the fluctuation of power output and load in distribution network system.

4 Construction and test of real-time monitoring model of distribution network

4.1 Model building

There are still the following problems in the research of traditional algorithms in solving fault location in distribution networks. Firstly, in traditional single power distribution networks, the positive direction of switch coding design can be determined based on the power direction of the power supply system. However, when it comes to the application of multi power supply systems, the positive direction in the system often cannot be determined solely based on the power direction of the power supply system, because there are more than one power supply in the system, and the influence of different power sources needs to be considered simultaneously, In this way, the original switching function cannot be applied to the model building of the system, and the application of the model will be greatly limited. Secondly, when traditional algorithms are used for fault location research on multi power supply systems, most studies are conducted under a single assumption, ignoring the mutual influence between multi power supply systems. Based on this, different single power supply systems are assumed, and multiple algorithms are used for location solution in each single power supply system. In this way, although it is possible to locate the fault location in the feeder section through multiple algorithm runs, it essentially only decomposes the distribution network lines independently. Although it reduces the probability of missed and false judgments to a certain extent, it also greatly increases the workload, improves the time cost of algorithm optimisation, and reduces the overall efficiency of algorithm fault location.

In order to meet the requirements of system design objectives, this paper designs the system from the perspective of system security, technology progressiveness, expandability, openness, system practicability and system maintainability.

1 Considering the safety of the system, the fault identification system of the distribution network mainly obtains online basic data of the distribution network from the database, including regional topology data, graphic data, historical operation data, etc. When the system is actually put into use, it may obtain operation and other related data from the actual power system. Therefore, the system must ensure high safety, which minimises the impact on the operation of the distribution network and other related systems, and avoid external harm to the system itself. The security guarantee of the system can be achieved from multiple perspectives, including network architecture design, software and hardware security prevention and control settings, application architecture planning, system construction, and database security guarantee.

2 Progressiveness technology In order to realise online calculation, analysis and display, the distribution network fault identification system must be supported by advanced distribution network fault identification algorithms and guaranteed by advanced cutting-edge technology. Moreover, establishing a fault identification system for distribution networks is a long-term and dynamic process in practice, and the system must be continuously improved, updated, and adjusted with the changes in actual conditions and the accumulation of historical data. Therefore, the system design needs to have a certain degree of foresight, so this article chooses deep learning technology that has superior performance in multiple fields.

3 Due to the complexity and long-term nature of fault identification in distribution networks, scalability should be fully considered in system design. For example, storage capacity, performance, and other requirements should be fully considered, as well as the issue of interaction with other systems, providing users with a platform for interoperability and reference.

4 The trend towards openness in today's internet technology is towards adopting open systems, using service forms such as clients/servers or browsers/servers. The system built in this article should be able to connect with different manufacturers, support multiple network service protocols, achieve compatibility with application products from multiple suppliers, and comply with international standards. Only in this way can we ensure the openness and compatibility of network configuration and application methods.

5 The practicality of the system must be aimed at meeting the actual needs of users in order to carry out system planning and design work. It is necessary to combine usability principles with advanced management experience and interface display methods, so that the system can not only reflect the risk level and fault location results of the distribution network, but also make the actual operation and use process of users more concise and clear. In addition, in the system design process, consideration should also be given to minimising the use of prior training and investment in process maintenance costs.

6 Considering the maintainability of the system, the establishment process of the distribution network is a dynamic process, during which the modelling and data

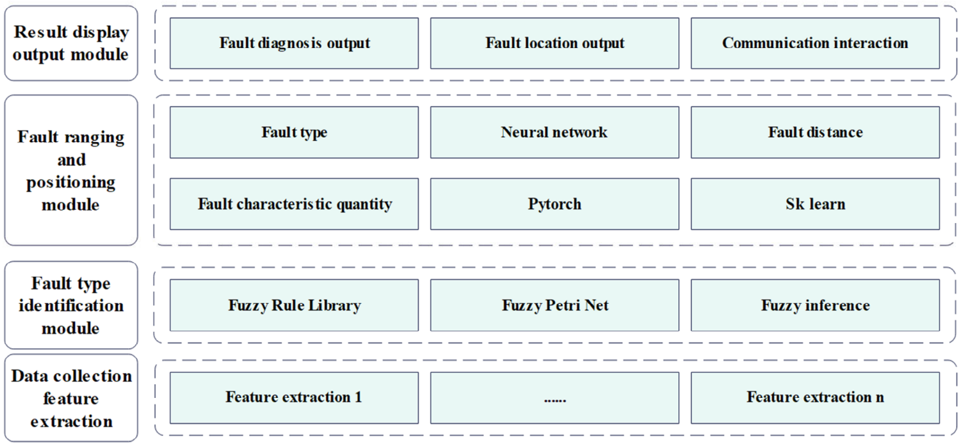
measurement of the distribution network will undergo varying degrees of changes. Therefore, it is necessary to ensure that the hardware and software of the system have good maintainability. In terms of system management, the main parameters in the system should be set, and resources and services in the system should be managed and monitored. In addition, it is necessary to achieve real-time operation, recording, alarm, and operation and maintenance of the provided services.

If the power nodes at both ends or one end of the power line are located within the information blind zone, the observability of the power line will be lost. If a fibre optic line fault occurs in the power grid, the communication unit connected to it will interrupt contact with the command centre, causing some nodes or areas of the power system to lose monitoring and control functions. This chapter is called the information blind zone. The power nodes within the information blind zone will lose observability, and the loss of observability of power nodes will also lead to the loss of controllability of the node; when the power nodes at both ends of the power line have observability, the line also has observability loss, and the command centre cannot perceive its operating status. This will make it difficult to locate the fault when the power line fails, and it is not possible to reconstruct the power line with unknown operating status. In addition, repair personnel can only use inspection methods or repair according to the order of load importance, the process of network reconstruction and repair of faulty components that affect system fault recovery; At the same time, power nodes within the information blind zone will lose controllability, leading to the loss of control of the DG and interconnection switches connected to the power node, and thus unable to participate in the network reconstruction and island division of system fault recovery, delaying the recovery of non fault area loads.

With the continuous development of communication technology and intelligent distribution network technology, the interaction and coupling between communication systems and intelligent distribution networks are gradually deepening. Communication systems provide technical support for the observability and controllability of distribution systems. However, the occurrence of extreme events not only causes damage to the power system, but also damages the communication system, making it difficult to transmit the parameter information and control information required for active distribution network fault recovery, this further affects the fault recovery of the active distribution network. Correctly evaluating and improving the resilience of the power grid under communication fault system conditions is beneficial for reducing the losses caused by disasters to the power grid. This chapter considers the impact of communication system failures on the recovery of active distribution network failures and evaluates the resilience. Adopt different fault recovery measures for normal communication and communication failure states, and compare the recovery capabilities in both situations. Setup different fault scenarios, calculate the elasticity values under normal communication and communication fault states, and compare them. Analyse the impact of different power system fault scenarios on the resilience of distribution networks under communication fault states, and propose measures to improve resilience.

This prototype system adopts modular design, and each module transmits data and interacts through the network, thus realising efficient and reliable fault diagnosis and location functions. The data processing of this system is based on deep learning technology, and several monitoring modules are used in the system to improve the accuracy and real-time of data acquisition, which provides more reliable data support for fault detection. The overall structure is shown in Figure 4.

Figure 4 Overall structure diagram of the system (see online version for colours)



According to the above system modules, the hardware of this prototype system adopts modular design idea, which consists of three parts: data acquisition unit, signal processing unit and signal management unit, as shown in Figure 5. In system development, a 'prototype' is usually a simplified, functional version used to evaluate user requirements, design system architecture, and test system performance. Therefore, it is also emphasised that the preliminary version and original samples of the design system should be used to verify the feasibility and effectiveness of the above algorithms and models. The important modules are as follows:

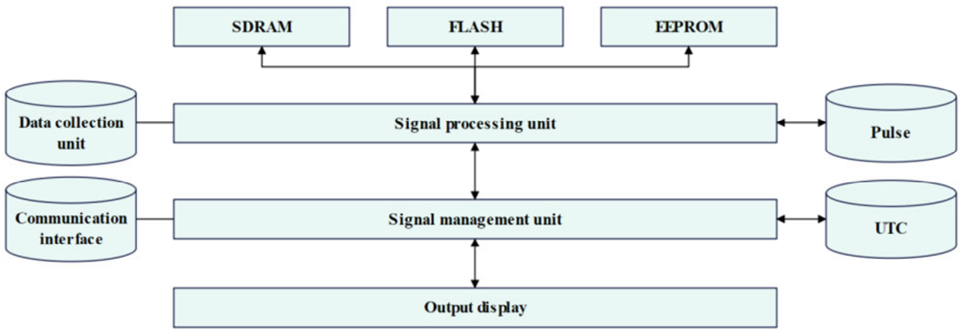
1 Data acquisition and feature extraction module: This module collects distribution network waveform data through PMU, and uses methods such as EEMD, wavelet transform, and PCA to extract fault feature quantities for fault type recognition and distance measurement positioning.

2 Fault type recognition module: This module adopts the fuzzy Petri net algorithm, which can effectively handle uncertainty problems and diagnose fault types based on feature quantities and fuzzy rule libraries.

3 Fault distance measurement module: This module includes components such as fault type, fault feature quantity, neural network, fault distance measurement, Python, and Sk learn. When a fault occurs, input the fault type and feature quantity into the neural network model, and use tools such as Pytorch and Sk learn for model training and testing to achieve fault localisation.

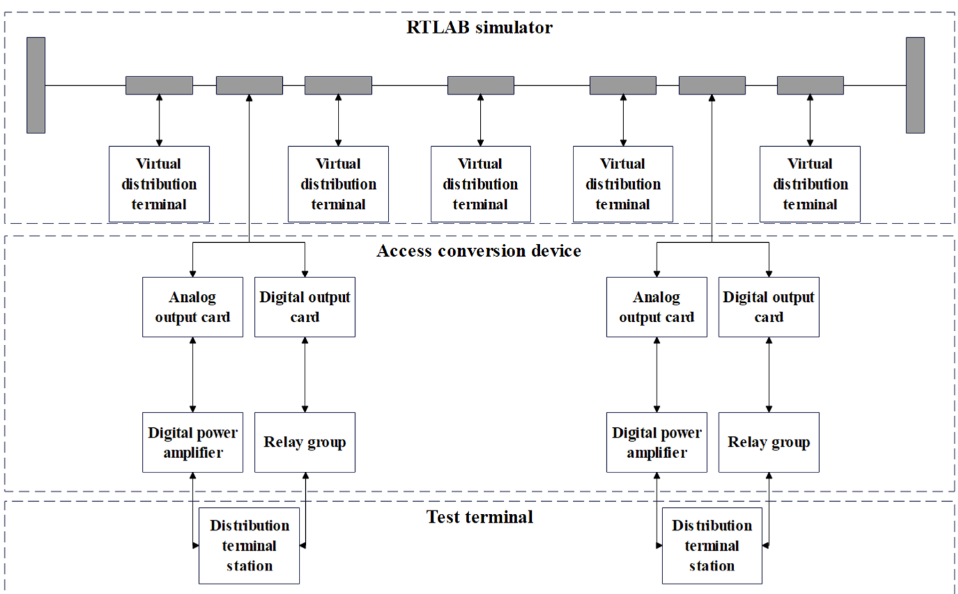
4 Result display output module: This module is responsible for visualising the fault diagnosis output, fault location output, and other results, and provides communication and interaction functions to guide practical operations.

Figure 5 Hardware structure diagram of the system (see online version for colours)



The overall architecture of the local feeder automatic test system is shown in Figure 6. The test system is mainly composed of RTLAB real-time simulator, interface device and actual feeder terminal. The primary system of distribution network and virtual feeder terminals run in RTLAB real-time simulator, and the actual feeder terminals are connected to RTLAB real-time simulator instead of one or more virtual feeder terminals through interface devices, thus forming a complete feeder automatic test system combining virtual and real.

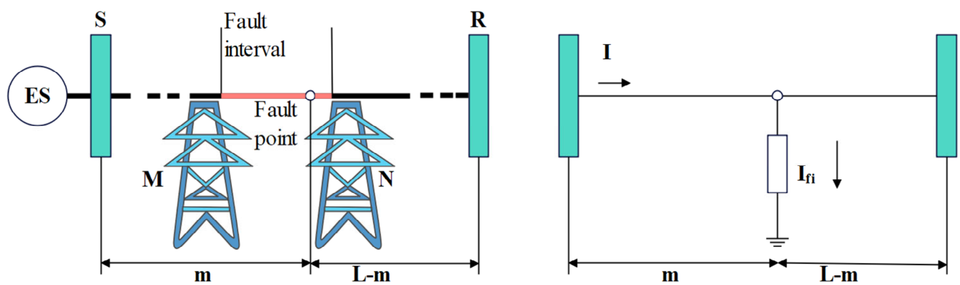
Figure 6 Overall block diagram of feeder automatic test system



4.2 Test

The electrical properties of distribution network are usually characterised by parameters such as impedance and admittance. Because the structural parameters are evenly distributed along the distribution network, there will be impedance and admittance even when the length of distribution network is very small, which makes the line modelling complicated. Therefore, in this paper, lumped parameters are directly selected instead of distributed parameters when establishing distribution network model. Distribution network system generally uses a single power supply to supply power to the electrical load. Under the ideal model, the grounding system through arc suppression coil is adopted. The block diagram of single-ended power distribution network established in this paper is shown in Figure 7.

Figure 7 Structure diagram of distribution network system (see online version for colours)



Based on Figure 7, the single-phase grounding fault (SPGF) of the line is simulated, and the SPGF occurs in phase A.

The method proposed in this article constructs I-LSTM and U-LSTM, with an output dimension of 90, using dropout with a ratio of 0.5, and Adam optimisation function learning rate as the default value. The DNN model based on TensorFlow consists of three hidden layers, each with 100 neurons. The activation function uses the ReLu function, and the Adam optimisation function has a default learning rate. A convolutional neural network model based on TensorFlow, with CSCS layers, pooling and convolution kernels 3 × 3, activation function as ReLu function, and Adam optimisation function learning rate as the default value. During training, while ensuring that all network models are in convergence, the training step size is fixed.

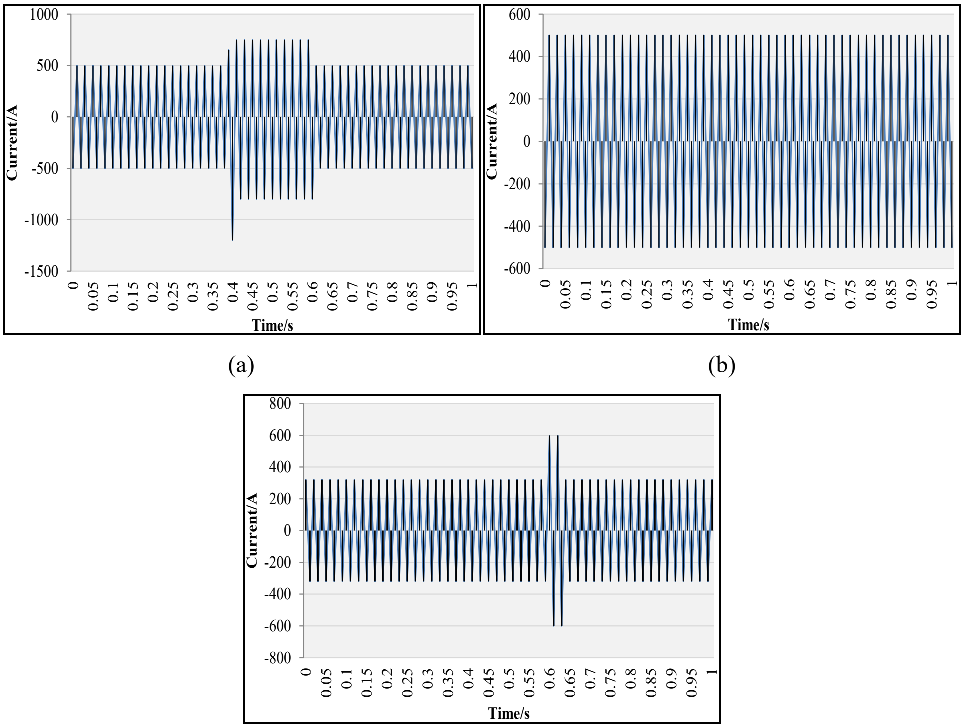
4.3 Results

Compare the method proposed in this article with the method proposed in question (Motevalli et al., 2020), and conduct a study by setting fault point simulation. A total of 20 sets of comparative experiments were conducted, and the results are shown in Table 1.

From Table 1, it can be seen that the real-time detection accuracy of the model in this paper for distribution network faults and defects is distributed between [88, 94], while the real-time detection accuracy of the model in Motevalli et al. (2020) for distribution network faults and defects is distributed between [82, 89]. This verifies that the method proposed in this paper has certain advantages over traditional methods in real-time detection of distribution network faults and defects

The obtained voltage waveform and current waveform (CW) are shown in Figure 8.

Figure 8 Waveform of SPGF current, (a) phase A CW (b) phase B CW (c) phase C CW (see online version for colours)



(a) (b)

(c)

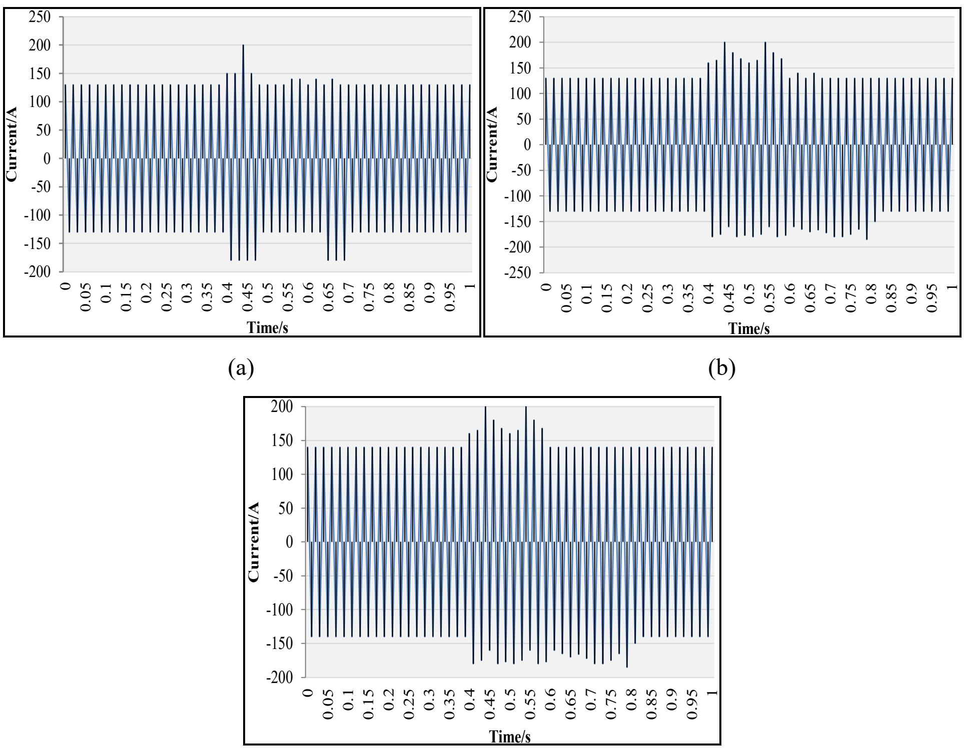
Table 1 Comparison test results statistics

No.	*The method of this article*	*The method of Motevalli et al. (2020)*
1	88.852	85.651
2	90.295	88.935
3	93.374	83.868
4	92.912	84.009
5	88.246	84.140
6	91.653	87.507
7	88.133	88.047
8	88.425	85.948
9	88.269	84.327
10	92.759	87.311
11	91.063	87.846
12	91.822	82.873
13	93.409	87.996
14	89.039	84.757
15	93.952	85.223

Table 1 Comparison test results statistics (continued)

No.	*The method of this article*	*The method of Motevalli et al. (2020)*
16	93.594	83.544
17	88.987	85.541
18	92.944	82.535
19	91.447	88.913
20	91.273	83.632

Figure 9 Interphase short circuit fault CW, (a) phase A CW (b) phase B CW (c) phase C CW (see online version for colours)

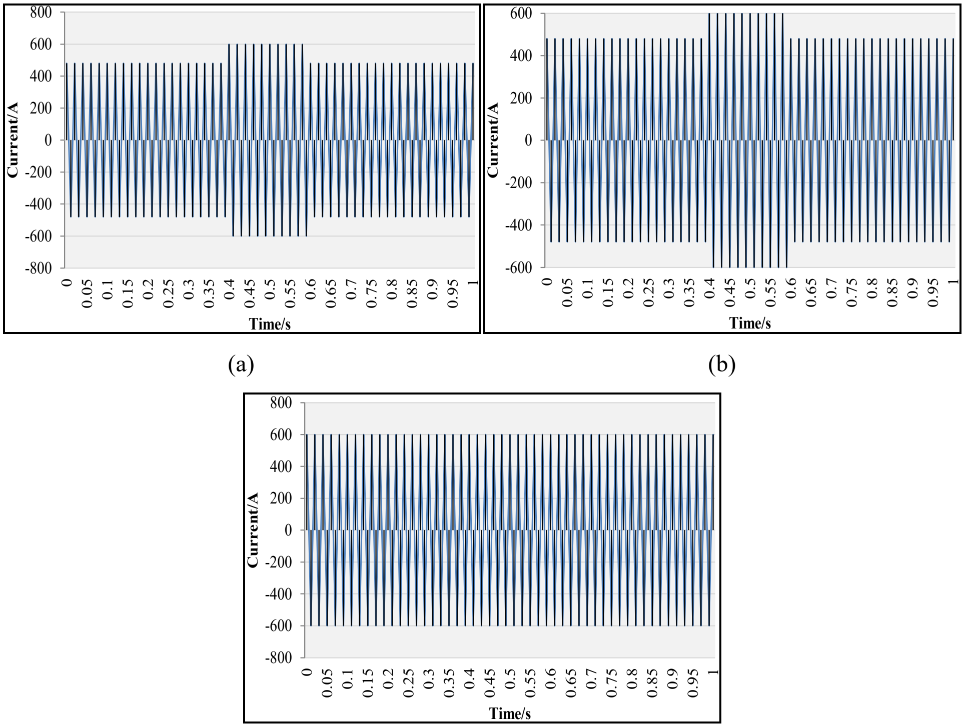


Based on the distribution network simulation model of Figure 7, the SPGF of the line is simulated, and the phase-to-phase short circuit fault occurs in A and C, and the obtained voltage waveform and CW are shown in Figure 9.

Based on the distribution network simulation model of Figure 7, the SPGF of the line is simulated, and the voltage waveform and CW obtained by setting the phase-to-phase short circuit fault of A and B are shown in Figure 10.

In this section, for all cases, the first 8,800 data points of the dataset are used for training, and the following 4,400 data points are used for testing. The accuracy of the training and testing sets of the system is shown in Figure 11.

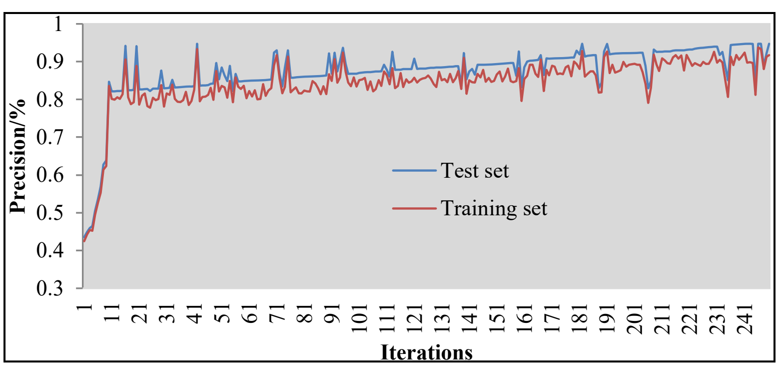
Figure 10 Two-phase grounding fault CW, (a) phase A CW (b) phase B CW (c) phase C CW (see online version for colours)



(a) (b)

(c)

Figure 11 Average accuracy of classification results (see online version for colours)



From Figure 11, it can be seen that the accuracy of the model can converge to a relatively high level. At node 136 in Figure 11, the accuracy of the training and testing sets is 0.9598 and 0.9482, respectively, which belong to a relatively high level.

After implementing the summary design of the system, this article provides a detailed design and implementation of the system's functional modules. This includes system user login and user information viewing functions to ensure system security and facilitate user management. Secondly, the design and implementation of geographic location information display function, meteorological data query and maintenance function, as well as distribution network system fault related data query and maintenance function, enable users to easily call the system interface through buttons to view and maintain fault related information. The test results obtained in this article are shown in Table 2.

Table 2 System feasibility test evaluation

	User interface	*User management*	*Display function*	*Maintenance functions*	*Visualisation*
1	85.458	81.514	77.675	78.505	77.675
2	85.496	78.353	75.508	82.781	73.522
3	87.797	78.165	72.277	78.028	74.362
4	89.881	77.874	76.448	82.577	74.267
5	89.960	76.390	75.306	79.682	74.236

4.4 Analysis and discussion

The development of computer technology enables data-driven fault localisation methods to further explore the potential and application value of data. This article combines the application trend of deep learning in the distribution network level of power systems under the background of big data technology to study the fault location technology of active distribution networks. The main research content is carried out from two aspects, namely the fault localisation technology combined with deep learning algorithms applied in different scenarios and the fault phase selection technology based on transfer learning.

As can be seen from Figure 10, when two-phase grounding faults occur in phases A and B of distribution network, the current of phases A and B lines is obviously larger than that of phase C lines, but the increase of current is smaller than that of phases A and C short circuit. For the voltage, the voltage of phases A and B is less than that of phase C, and the amplitude of voltage decrease is the smallest among the three faults.

As can be seen from Figure 8, when a SPGF occurs in phase A of distribution network, the current of phase A line is obviously larger than that of other two-phase lines, the current direction of Phase A line changes, and the voltage of phase A line is smaller than that of other two-phase lines.

As can be seen from Figure 9, when phase-to-phase short circuit fault occurs in phases A and C of distribution network, the current of phases A and C lines is obviously greater than that of phase B lines. In terms of voltage, the voltage of phases A and C lines is less than that of phase B.

From Table 2, it can be seen that in the feasibility analysis of the system, the user interface, user management, display functions, maintenance functions, Visualisation, and other aspects have performed well. Therefore, it can be concluded that the feasibility of the system in this article is good and meets the actual needs of users for the system.

From the above simulation experiments, it can be seen that the real-time monitoring system of distribution network defects proposed in this paper can monitor and diagnose various faults in distribution network in real-time, identify the fault characteristics of distribution network, effectively improve the timely identification and elimination of faults, and promote the stable operation of distribution network.

5 Conclusions

Distribution network is an important part of distribution system and the lifeblood of power grid transportation. Therefore, timely and accurate fault location is the key to improve the operation of the whole power grid. With the development of computer technology, the data-driven fault location method can further tap the potential and application value of data. Combined with the application trend of deep learning in distribution network of power system under the background of big data technology, this paper studies the fault location technology of active distribution network. The main research contents are carried out from two aspects, namely, fault location technology combined with deep learning algorithm applied in different scenarios and fault phase selection technology based on transfer learning. After that, a fault location method for active distribution network based on deep neural network is proposed, and a reasonable configuration strategy of measuring points is proposed, which takes the importance of nodes as the standard to reduce the redundancy of measuring points and improve the economy of system configuration. Through multi-step training until the model converges, the model can effectively reduce the investment of equipment and the economic cost of operation and maintenance by rationally configuring measuring points, and can accurately and quickly locate single fault. Finally, it can be seen from the simulation experiment that the real-time monitoring system of distribution network defects based on deep learning proposed in this paper can play an important role in fault diagnosis and elimination in distribution network.

The model in this article is only applicable when the topology structure remains unchanged, but when the switch state constantly changes during the actual operation of the power grid. If the method proposed above is used to calculate distribution network losses, the calculation results will be inaccurate. Therefore, the next step is to consider how to accurately analyse the calculation of network losses in substation distribution networks when the switch state changes. The power grid has the characteristics of three-phase branch parameter asymmetry and three-phase load imbalance. Therefore, the reconstruction of three-phase unbalanced power grids, including distributed power sources, will be the next research topic. The load model has a significant impact on the flow calculation results, as well as on the optimisation of DG configuration and distribution network renovation. During the reconstruction process, it is believed that the load remains constant, but in reality, load fluctuations always exist. Therefore, further research is needed to construct a truly accurate load model.

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