Artificial Neural Networks-Based Fault Diagnosis Model for Distribution Network

Zexi Chen[1], Pu Wang[1], Bin Li[1], Ergang Zhao[2,*],
Zhigang Hao[1] and Dongqiang Jia[1]

[1]*State Grid Beijing Electric Power Company, Beijing 100031, China*
[2]*Wuxi Research Institute of Applied Technologies, Tsinghua University, Binhu District 214072, Jiangsu Province, China*
E-mail: zhaoeg10@163.com
[*]*Corresponding Author*

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Abstract

With many branch lines in radiant distribution networks, diagnosing faults in a distribution network is very difficult. It is of great significance to identify different types of faults quickly and accurately for the stable operation of the power grid. This research presents a fault identification model for a distribution network based on artificial neural networks. The principal component analysis first extracts features from transitory data in a distribution network. The resulting low-dimensional data is subsequently used to update the artificial neural network model. The artificial neural network may also identify the type of fault. The proposed model's fault detection accuracy is improved over the traditional approach by examining distribution network fault data during the simulation test.

Keywords: Fault diagnosis, distribution network, neural network, principal component analysis, accuracy.

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1 Introduction

Maintaining a steady electrical supply in a power system with prone-to-failure equipment is difficult. Electronic equipment can be harmed and disrupted by short circuits. Consequently, it is essential to accurately and promptly identify the issue. Protection software enhances system recovery by locating defective components [1]. The estimation of the failure region made possible by the protection device's input limits the disruption's ability to reach the health network. Dependability indicators typically characterize power outages. These metrics gauge system performance and show the general health of a network's performance and quality of service while it is under load. The average system outage frequency index and the average system outage duration index are utilities' most often utilized indicators. The average number of outages clients encounter is the average frequency of system unavailability [2]. This is measured in one year of downtime/customer. The average system downtime index refers to the annual average system downtime per customer [3]. Customer downtime minutes are another name for this index. An efficient fault identification approach is required to increase reliability for distribution network failures to maintain good service quality and restore the power supply promptly [4]. It makes it more difficult to locate and identify distribution network failures. The distribution network will also be divided by frequent changes to lateral (branch), distributed load, and feeder arrangement. Early failure detection and diagnosis can hasten business recovery and minimize downtime. For the electricity system to operate steadily, it is crucial to promptly and precisely identify different sorts of defects.

Switching characteristics are evident when a transmission line fails, and fault features can be brought on by using high voltage in the cross-section [5]. The following attributes describe the current error detection and distribution system. (1) The development of the distribution network is wide and complex. Anomaly electrical data is acquired from fault indicators on adjacent lines and the fault indicator nearest to the fault spot when a problem arises on a line. The information on ocean crime is unconnected to past research. (2) Different sorts of defects exist in the distribution network. Additionally, the variance in fault kinds is negligible, which makes fault treatment less effective [4]. (3) The distribution system's voltage level, grounding mode, and line parameters vary depending on the region, as do the fault characteristics of the recorded fault data. The distribution network is also distinct due to load split-on, lateral/split-on, radial operation, erroneous feeder layout, phase imbalance, and fault resistance fluctuation. Therefore, researchers' interest has been drawn to distribution network problem diagnosis.

Existing distribution network fault identification methods can be divided into two categories. The first type is the traditional fault recognition methods, such as the Petri network [6, 7], expert system [8, 9], and other recognition methods based on knowledge analysis [10]. Expert systems use various reasoning techniques to analyze information about the object being diagnosed that has been gathered by computer using various criteria. In addition, it can call different programs as necessary and prompt the user for data as needed during an activity. The user can then immediately confirm the ultimate or most likely failure. Expert systems are incredibly successful because they combine a lot of skills with problem-solving techniques that closely resemble the rules of the human mind. Knowledge bases, inference engines, databases, knowledge acquisition modules, interpreters, and human-machine interfaces make up the majority of expert systems [11]. It can utilize human professionals' knowledge and problem-solving techniques to solve problems since it possesses the expertise and experience of specialists in that sector. Expert systems are quick and real-time because the issues they address typically lack an algorithmic answer and are frequently inferred from and drawn conclusions based on insufficient data.

The second is the classification network fault recognition model based on model recognition and machine learning. Some classical fault signal processing methods extract features and then use machine learning for fault detection [12]. For instance, a support vector machine and wavelet transform are combined to provide a new magnetic assured current and defect detection system. The wavelet transform theory is used to determine the fault data's characteristics. Data are separated and recognized using a multi-stage support vector machine. The self-learning capability of the neural network's data features is employed in this study to extract the features that are illegal based on the conventional private network. For instance, a deep learning method is created using multi-stage non-negative autoencoders, and the Softmax classifier can produce high-speed early detection [13]. Stacked autoencoders are employed for multi-level concept learning in the transient stability evaluation of power systems. Support vector machines classify the data after gathering the main features [14]. Finally, real-time online identification of the transient stability of the power system is realized.

The use of neural networks in fault detection is a recent study area that has advanced quickly over the past ten years compared to the error detection method. The expert approach involves reasoning to resolve the issue; however, it is time-consuming and contains numerous regulations [15]. Although Petri nets can parallel data processing, simultaneous processing becomes a routine task, thus increasing the complexity [3]. The causal network illustrates the connection between the failure and the protective device's operation. Nodes, relays, and circuit breakers are also included for all faults. Concatenation, memory integration, self-association, sub-learning, and non-linear feature mapping are all skills that a neural network can perform [16]. It can process complex data, analyze it, and offer precise classification. As a result, it can be used to recognize and quantify state changes brought on by equipment flaws, offering new techniques for fault detection and state monitoring. The neural network has numerous advantages in fault detection, including the connection's structure, its high level of self-adaptability, its strong ability to learn on its own, its ability to tolerate guilt, and the integration of knowledge representation, storage, and cognition.

Despite the numerous developed and proposed methods, a comprehensive, trustworthy, and secure diagnostic approach is still required. In order to segregate problems in distribution networks and identify them, this research suggests an approach based on artificial neural networks. In order to tackle the distribution network multiple estimating problems, the suggested fault section identification phase is started before the fault finding phase, with multiple crossing points corresponding to the computed fault points. The following is a summary of the contributions made by this paper: Create a novel fault identification technique that can be used with distribution network systems, and (ii) the suggested technique can quickly and precisely gather the details of a defect's characteristics. By using this technique, the challenging and ineffective process of manually extracting features from voluminous transient fault data can be avoided.

The remainder of this essay is structured as follows. Section 2 illustrates the distribution network's difficulty in identifying faults. The defect recognition model and process of artificial neural networks are then suggested in Section 3. The results of the defect identification are then presented in Section 4. Finally, Section 5 presents the conclusions.

2 Problem Description

The service provider must ensure the system is repaired after a breakdown to deliver efficient customer service. Accurate fault location identification facilitates rapid recovery. Predicting fault segments in situations with numerous failures, unforeseen circuit breaker tripping, and relay failures is challenging. This prolongs recovery and lengthens the time it takes to find the problem segment [17]. These issues have caused electricity shortages in more populous places. The investigation of this issue becomes extremely laborious when several sirens are going off at once.

This information is often insufficient to determine which segment has failed. Most importantly, operators can be freed from analyzing complex cases [18]. It is possible to gain insight into the state of the power system by collecting comprehensive data on circuit breaker failures, primary and standby relay failures, and equipment malfunctions. It is necessary to presume that all safety measures have achieved their maximum capacity and will only activate in the case of a malfunction. A device's switch status can be secured using binary notation. The relay or circuit breaker will not work if the system works properly. Rapid identification of fail-safe devices is necessary.

3 Neural Network Model Framework

3.1 Data Processing

A significant amount of fault transient history data can be gathered by placing fault lights on the tracks [19]. The primary system of the distribution network receives the fault indicator's transient voltage and current waveforms during a failure. Each recording file contains seven channels of three-phase voltage, three-phase current, and zero sequence current [20]. By selecting waveform data of each channel, the model training data set of this study is constructed. The data set contains many ground fault data, fault data and invalid data. According to the effective fault data set, the fault types are divided into three types. 1. One-way grounding fault: including A one-way phase grounding (AO), B phase one-way grounding (BO), C phase one-way grounding (CO). (2), short circuit fault: AB phase line short circuit (AB) 3, two-phase contact: A phase, B phase two contact ground (ABO), A phase, C phase two contact ground (ACO). Other types of failure datasets are insufficient for network training [21]. Therefore, the training samples used in the experiment are the defect data of AO, BO, CO, AB, ABO and ACO.

Principle Component Analysis, a popular method for dimensional reduction, reveals important traits in the initial data. The m-th line of the data set represented by DM, which represents the attributes of the m-th client, should be deducted from the average value of these qualities. The formula below can be used to calculate the covariance matrix:

$$\mathrm{Cov} = \sum_m (d_m - \mu)(d_m - \mu)^T \tag{1}$$

$$\mathrm{A_n} := \sum_m d_m d_m^T \tag{2}$$

$$\mathrm{B_n} := \sum_m d_m \tag{3}$$

$$\mathrm{Cov} = \sum_{\mathrm{n}} \mathrm{A_n} - \frac{\sum_{\mathrm{n}} B_{\mathrm{n}} \left(\sum_{\mathrm{n}} B_{\mathrm{n}}\right)^T}{\sum_{\mathrm{n}} c_{\mathrm{n}}} \tag{4}$$

The eigenvectors and eigenvalues of the covariance matrix Cov are then determined using singular value decomposition. The projection matrix is formed from the subsets of eigenvectors with higher eigenvalues, and the following formulas are used to determine the dimensionality reduction feature vector for the m-th consumer and the feature matrix for the consumer served by the retailer:

$$\mathrm{d}_m^1 = \mathrm{d_m T} \tag{5}$$

$$\mathrm{D}_m^1 = \mathrm{D_m T} \tag{6}$$

Additional Additive homomorphic encryption can be used to achieve feature extraction that protects private information. An efficient method for partial additive homomorphic cryptography is the Paillier algorithm. It supports multiplying an encrypted integer by an unencrypted integer and adding two encrypted numbers together. In the actual world, the data that needs to be encrypted may not always be an integer. Fortunately, floating point numbers can be used with the Paillier cryptosystem.

3.2 Neural Network

Six types of faults may occur in the distribution network: AO faults, BO faults, CO faults, AB faults, ABO faults, and ACO faults. Based on the above, a single neural network model is trained to identify the fault part according to the fault type detected in the system. Using an artificial neural network model for each fault type increases the learnability of the artificial neural network model, decreases the size of hidden layer neurons, and improves the accuracy of the artificial neural network model [22]. Therefore, the

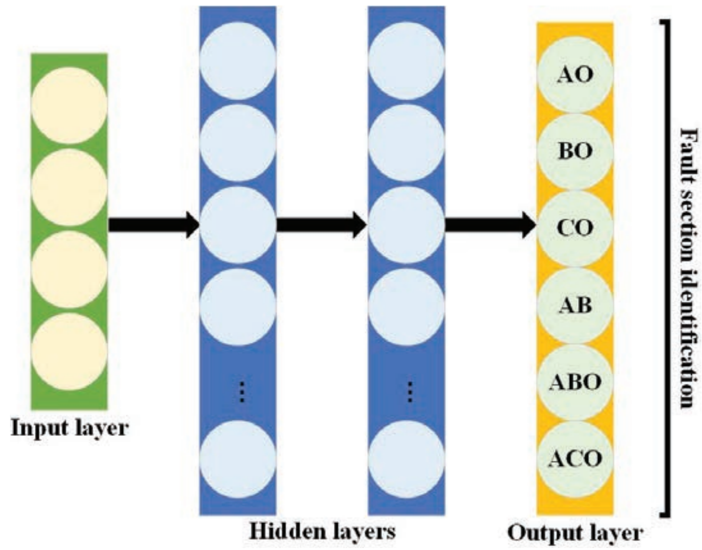

Figure 1 Architecture of the artificial neural network model for the fault section identification.

proposed fault partial recognition algorithm consists of a reverse propagation neural network model. During the training of the neural network, each neural network acquires knowledge about the problem from the training data set and stores the knowledge obtained through synaptic weights between neurons.

The number of layer neurons, hidden layer neurons, learning rate, and activation function was changed during the discovery experiment. In the hidden layer and output layer of the defect diagnosis artificial neural network model, the relu activation function is applied. Other enabling features were also tested but did not work very well. The topology of an artificial neural network model intended for fault diagnostics is depicted in Figure 1.

The neural network size (number of neurons in hidden layers), correlation coefficients, error histograms, and testing using untrained data sets are performance metrics used to choose the best artificial neural network model. The accuracy of an untrained data set is determined by the artificial neural network's accuracy error percentage.

3.3 Proposed Algorithm

Figure 2 depicts the framework for transient defect recognition using a neural network. The fault signal's waveform is examined using principal component

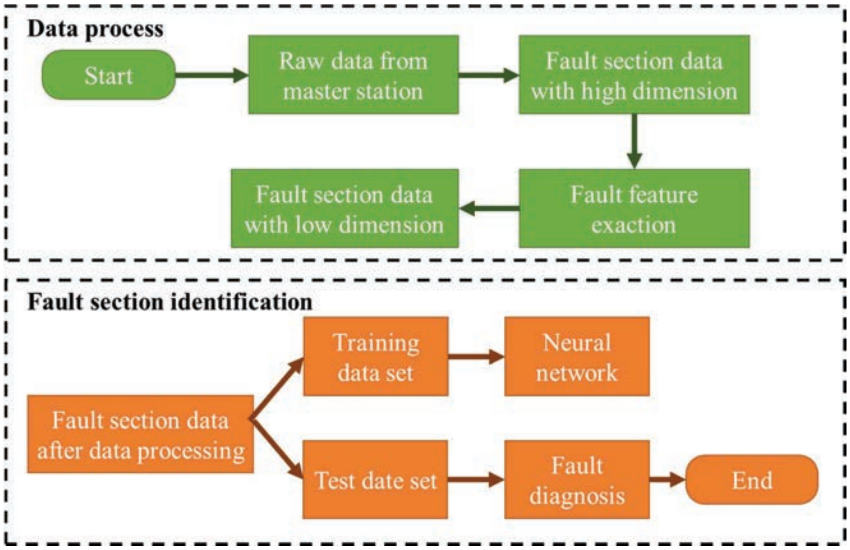

Figure 2 Fault identification flowchart based on artificial neural network.

analysis. The data is used as the neural network model's input following dimensional reduction. Utilizing the reference's fault classification algorithm suggested by the author, a specific neural network model is chosen. Three stages make up the majority of the full model architecture. (1) On the spur of the moment, the fault data preprocessing backend from the main system power distribution automation fault data set. (2) Principal components analysis automatically extracts the features of the transient fault data sets. (3) detect transient fault data after a gender dimension reduction using neural networks.

The transient record file is first obtained from the master station system in the fault data processing section. The waveform file's voltage channel data is then gathered, and the data fragment at the fault's moment is blocked. The data with significant dimensional errors are then normalized. It reduces the size of extracted defect data and presents them as multidimensional features using principal component analysis (PCA). All samples are split into training and test sets for the defect identification phase. The training of neural networks was done with training sample data. The training course's recognition accuracy is calculated. Next, 0.9 is chosen as the training accuracy threshold. A transient error data test set is utilized for error identification if the network accuracy satisfies the specifications. If not, change the network's parameters and try again with the training. Through a classifier layer, the network categorizes fault features and generates results for defect recognition.

4 Results and Discussion

4.1 Parameter Setting

The 256 three-phase voltage samples taken before and after the problem spot make up the selected sample data. There are 1800 failure data in total. As a result, the training sample's data dimension prior to principal component analysis is 768. Each training sample entering a neural network has a data dimension of 20 once the principal component analysis is applied.

Matrices of input, output, synaptic weight, and deviation vector realise neural networks. Using batch mode to supervise the learning – which updates network weights and deviations based on mistakes between network outputs and targets – the training data set is provided to the neural network in order. The batch mode iteration continues until the resulting training errors are reduced. To avoid mining the number of hidden layer neurons, the number of hidden layer neurons in the artificial neural network model is searched. Additionally, tests have been used to determine the frequency. The range of the training epoch number is 500 to 3500.

4.2 Result

The neural network can be trained to learn the characteristics of the failure data. The best training and test set ratios for neural network model training

Table 1 Artificial neural network parameters

	Parameter Name	Value
Structural parameters	Input neurons	**20**
	Hidden layer neurons	50
	Hidden layer neurons	50
	Output neurons	6
Training parameters	Learning rate	0.001
	Batch size	32
	Training times	80
	Training algorithm	Scaled conjugate gradient
	Active function	Relu
	Weight update method	Batch-mode

Table 2 The accuracy of the neural network for the optimal proportion of the training and test datasets

The Proportion of the Training Dataset and Test Dataset	Value
50%:50%	0.715
60%:40%	0.815
70%:30%	0.932
80%:20%	0.915
90%:10%	0.849

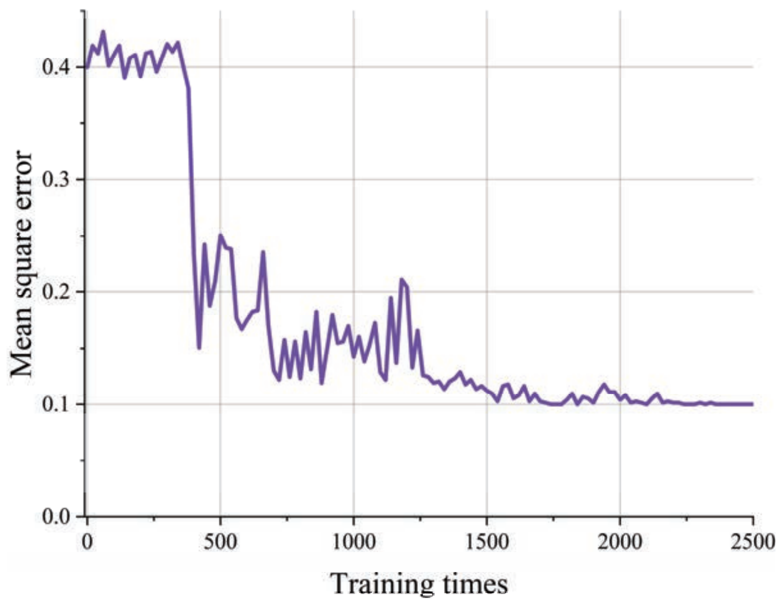

Figure 3 Training process.

are supported by different classifications of fault data attributes. We changed the experiment's data set's percentages to 90%, 80%, 70%, 60%, and 50%. The accuracy of various training data percentages is displayed in Table 2. The model's fault identification effect is at its finest when the training set to test set ratio is 70%:30%. A neural network model experiment was carried out according to the ideal learning ratio.

The loss function and accuracy curve for the neural network model's learning process is shown in Figure 3. The mean square error and the network

Table 3 Simulation result of F1 score

	Decision Tree	Support Vector Machine	Proposed
AO	0.815	0.845	0.912
BO	0.821	0.865	0.951
CO	0.715	0.849	0.948
AB	0.615	0.712	0.939
ABO	0.610	0.715	0.915
ACO	0.666	0.610	0.910

structure parameters tend to settle as the learning period hits 2500, and the test set's ultimate loss function value converges to 0.106. So, the requirement for the suspension of training is 2500. The overall accuracy of recognition was 93.2%. On failure data, neural network models have a good fault recognition impact.

The F1 scores for various models under various faults are shown in Table 3. The identification model's accuracy and recall ratio are harmonically averaged to produce the F1 score. According to Table 3, all models accurately predict single-phase grounding failures. However, the F1 points for short-circuit and multiphase grounding faults were decreased. The F1 score of the neural network is higher than that of the decision tree and support vector machine for short circuit fault and multiphase grounding fault. This outcome validates the reliability and accuracy of the suggested neural network-based error link recognition model.

5 Conclusion

A misidentification model for distribution networks based on artificial neural networks is proposed. First, the main component analysis method extracts functions from the distribution network's transient data. The resulting low-dimensional data is then imported into the artificial neural network model. Finally, the artificial neural network is used to identify the type of error. This method improves the network's functional extraction capacity and efficiency. Interference and errors in human factors are reduced. Based on the measured transient error data, the identification experiment is performed based on the neural network model. The neural network model is compared to the decision tree and support vector machine. The results show that the neural network model has a high recall ratio and accuracy and has advantages in transient error recognition.

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Biographies

Zexi Chen received the bachelor's degree in electrical engineering and automation from Huazhong University of Science and Technology in 2013, the master's degree in Electrical Engineering from University of Southern California in 2015, and the philosophy of doctorate degree in renewable energy from North China Electric Power University in 2022, respectively. He is currently working as a senior engineer in State Grid Beijing Electric Power Company. His research areas include smart grid, integrated energy technologies, power system risk assessment, renewable energy and energy storage. He is a standing director of IEEE Power&Energy Society Satellite Technical Council – China.

Pu Wang, received the bachelor's degree in electrical engineering and automation from Xi'an University of Technology in 2005, and the master's degree in electrical engineering from Beijing Jiaotong University. He is currently working as a senior engineer in State Grid Beijing Electric Power Company. His research interests include smart grid, integrated energy technologies and digital grid.

Bin Li received the B.E. and M.E. degrees in electrical engineering and automation from Tianjin University, Tianjing, China, in 2002, and 2005. He is currently working as a senior engineer in State Grid Beijing Electric Power Company. His research interests include power system transient stability assessment, power flow analysis, and distribution network planning.

Erang Zhao received the bachelor's degree in electrical engineering from Hebei of University Technology in 2014 and the master's degree in electrical engineering from Tsinghua University in 2021, respectively. He is currently working as a researcher at Wuxi Research Institute of Applied Technologies, Tsinghua University. His research areas include power system operation and planning, microgrid operation.

Zhigang Hao, received a bachelor's degree from Tianjin University from 1996 to 2000, specializing in power system automation, and a master's degree from Tianjin University from 2000 to 2003, specializing in power market. He is currently working as a senior engineer in State Grid Beijing Electric Power Company. His research area includes power supply reliability, smart grid and power security.

Dongqiang Jia, received the bachelor's degree in Electrical Engineering from China Agricultural University in 2009, the Ph.D. degree from the University of Chinese Academy of Sciences in 2015. He is currently working as a senior engineer in State Grid Beijing Electric Power Company. His research interests include power quality and integrated energy technologies.