

Research on Deep Learning Based Fault Diagnosis and Prediction Methods for Power Systems

Guangyu LIU^{a,1}, Xinying Qum^a and Dongzhe QU^a

^a*Yingkou Power Supply Company State Grid Liaoning Electric Power Co., Ltd.,
Yingkou 115000, China*

Abstract. The deep learning-based power system fault diagnosis and prediction method combines efficient data acquisition techniques and advanced machine learning algorithms, aiming to improve the accuracy and response speed of fault prediction. By analyzing a large amount of historical and real-time data, the study is able to effectively identify potential fault risks and pinpoint the causes of faults. Experimental results show that the accuracy reaches 98.9% during normal operation. The method shows high efficiency and stability under various environments and conditions, which verifies its feasibility and effectiveness in practical applications. This study is of great value to improve the reliability and efficiency of power systems, and has a positive impact on the development of smart grids.

Keywords. power system; big data; fault diagnosis; deep learning

1. Introduction

As one of the indispensable infrastructures in modern society, the reliability and stability of the power system is crucial to the socio-economic development [1]. However, since the power system contains numerous devices and complex interconnection structures, it is often exposed to various potential fault risks [2]. Traditional fault detection and diagnosis methods are often based on experience and rules, which cannot cope with the complex and changing power system situations [3].

Power system in operation, a variety of power monitoring and scheduling automation system will produce massive equipment operation of real-time status data, with the equipment running time is getting longer and longer, the corresponding data growth is faster and faster, massive data to explosive growth, the data storage and analysis of computation to bring a huge challenge, so we need to explore new ways to solve these problems, from the massive data in the effective information, find out the laws between the data and use, which requires the application of data mining techniques to which [4]. The laws between the data and utilize them, which requires the application of data mining technology to them [4].

Therefore, how to quickly and accurately diagnose and predict power system faults has become a problem to be solved [5]. In recent years, with the development and application of deep learning technology, it has shown excellent performance and effect in the field of fault diagnosis and prediction [6]. Deep learning technology can realize the fault diagnosis and prediction of power system by learning and analyzing the massive data and automatically discovering the laws and features between the data [7].

2. Literature review

Deep learning technology has a wide range of applications in power system fault diagnosis and prediction. By inputting sensor data and control signal data into neural networks, the diagnosis and prediction of power system faults can be effectively realized [8].

Power system fault diagnosis refers to detecting and diagnosing possible faults by monitoring the operating status of the system [9]. Traditional diagnostic methods usually rely on expert experience or rule libraries, and their diagnostic results often lack accuracy and reliability [10]. In contrast, fault diagnosis methods based on deep learning can automatically learn and extract relevant features between data, significantly reducing the cost of manual intervention while improving the accuracy and efficiency of diagnosis [11].

Power system fault diagnosis methods based on deep learning usually convert sensor data and control signal data into time series data, and then use convolutional neural network (CNN), recurrent neural network (RNN) and other models to learn and analyze the data, and finally achieve Accurate diagnosis of system faults. For example, some studies have proposed a fault diagnosis method based on deep learning, which performs time series analysis of sensor data through convolutional neural networks to achieve accurate diagnosis of system faults. In addition, some studies have proposed a fault prediction method based on long short-term memory network (LSTM), using historical data to train the model to predict possible faults in the future to achieve early warning of faults [12-14].

To summarize, this paper introduces the application of deep learning technology in power system fault diagnosis and prediction, and proposes a power system fault diagnosis and prediction model based on deep learning technology.

3. Methodology

3.1 Troubleshooting process

After a power system failure occurs, it first receives the information collected by SCADA and determines whether there is abnormal information based on the timing. If there is no abnormal information, the extended Bayesian network is directly used to calculate the probability of the faulty component. At this time, the IFO node value is 1. The original node probability value is not replaced. If there is abnormal information, the abnormal information is classified according to the timing characteristics of the alarm information, and different probability values are assigned to the IFO nodes in the extended Bayesian

network according to the corresponding fuzzy rules, and the corresponding original nodes are replaced with the probability values of the IFO nodes. probability, so that nodes with higher credibility replace the nodes with abnormal information, and then the failure probability is calculated, and finally the fault diagnosis results are obtained [15-16].

3.2 Framework design

In this paper, a comprehensive power system fault prediction and diagnosis system is designed, aiming at realizing efficient prediction and accurate diagnosis of power system faults through big data technology. The whole system mainly contains four core modules: data acquisition, data processing, fault prediction and fault diagnosis. First, the data acquisition module is responsible for collecting various types of data from the power system, including real-time operation data, historical fault records and environmental information. These data are acquired in real time through advanced sensors and data interfaces, and transmitted to the data processing center in an efficient manner. Subsequently, in the Data Processing Module, the collected raw data undergoes pre-processing, including data cleansing, formatting and standardization, to ensure data quality and prepare it for subsequent analysis. Next, the fault prediction module uses machine learning and data mining techniques to analyze the processed data, extract key features, and build models to predict potential fault risks. Finally, the fault diagnosis module performs fast and accurate diagnosis of faults based on the prediction results and real-time data. It integrates a variety of factors, such as fault characteristics, system configuration, and historical fault data, to determine the specific type and location of the fault. Through the close collaboration of these four modules, the whole system framework realizes effective prediction and timely and accurate diagnosis of power system faults, which improves the operational safety and reliability of the power grid. The overall flow of the system is shown in Figure 2.

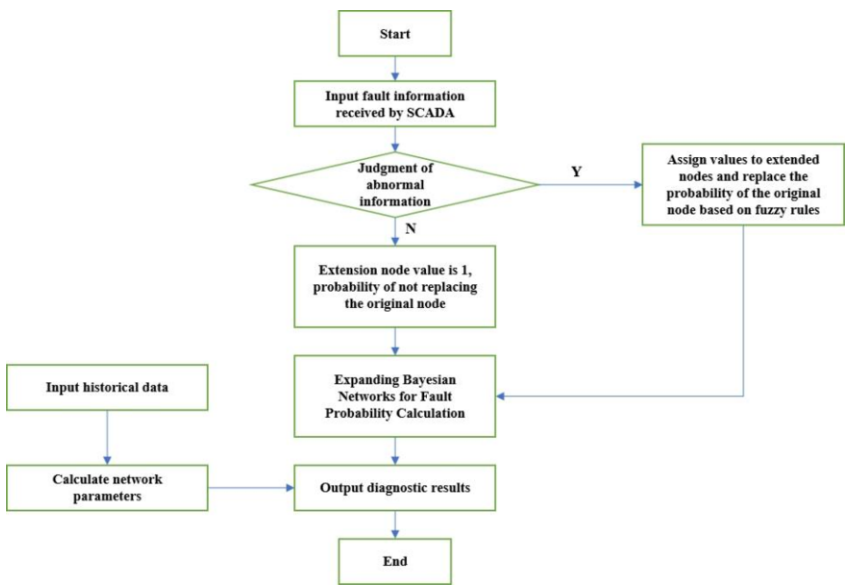


Figure 1. Troubleshooting flowchart

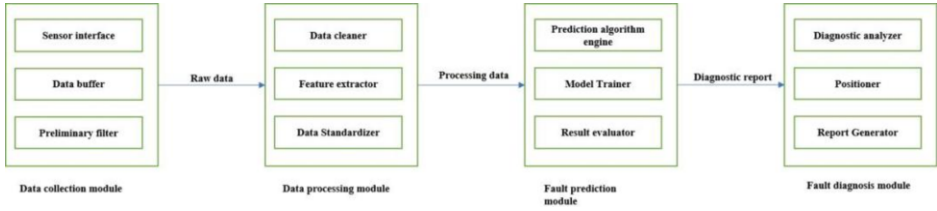


Figure 2. Overall system framework

In summary, the deep learning-based power system fault prediction and diagnosis system designed in this paper realizes the comprehensive monitoring and in-depth analysis of power system operation status. In addition, the efficient data processing capability and advanced machine learning algorithms of the system provide powerful data support and intelligent decision-making tools for grid operation and maintenance, which help to reduce the operation and maintenance costs and improve the overall efficiency of the grid.

3.3 Data Acquisition Module

The main function of the data acquisition module is to collect all kinds of data from the power system in real time, including but not limited to voltage, current, frequency and environmental factors.

The data acquisition module must first measure voltage and current. The measurement of voltage V and current I is crucial for monitoring the status of the power grid. They are usually measured with voltage transformers (VT) and current transformers (CT). The measured value can be expressed as:

$$\begin{aligned} V &= V_m \sin (2\pi f t + \phi_v) \\ I &= I_m \sin (2\pi f t + \phi_I) \end{aligned} \tag{1}$$

In the formula, the V_m and I_m are the amplitudes of the voltage and current, respectively. f is the grid frequency. t is time. ϕ_v and ϕ_I are the phase angles of voltage and current, respectively.

Next, the module needs to perform power calculation. The real-time power P can be calculated from the instantaneous values of voltage and current. For AC systems, the calculation formula of power P is:

$$P = \frac{1}{T} \int_0^T V(t) \cdot I(t) dt \tag{2}$$

In the formula, T is the cycle time.

Finally, the data sampling rate is to be determined. The determination of the data sampling rate is crucial to capture the transient behavior of the grid. The sampling frequency, the f_s . Usually a multiple of the grid frequency, determined by the Nyquist sampling theorem.

$$f_s \geq 2f_{\max} \tag{3}$$

In the formula, the f_{\max} is the highest frequency component of the system.

After signal acquisition, the signal processing link filters and amplifies the original data to improve the data quality.

Through the data acquisition module, it can ensure that the operation data of the power system is recorded and analyzed in real time and accurately, providing strong data support for the stable operation of the power system.

3.4 Data processing module

In the data processing module, its main function is to carry out in-depth processing and transformation of the raw data obtained from the data acquisition module to ensure the quality and applicability of the data and to provide accurate and standardized inputs for the fault prediction module.

First, a data cleaner processes the raw data to exclude any anomalies or erroneous values. For example, by setting a threshold value θ , the data cleaner identifies and eliminates data points that are outside the reasonable operating range. This step can be expressed by the following formula:

$$X_{\text{cleaned}} = \{x | x \in X | x|, < \theta\} \quad (4)$$

In the formula, the X denotes the original data set, the X_{cleaned} is the cleaned dataset.

Next, the feature extractor extracts key features from the cleaned data that are critical for understanding and predicting system behavior. The process of extracting features can be viewed as a mapping from raw data vectors to feature vectors.

$$F = T(x) \quad (5)$$

In the formula, the T is from the original data point x to the eigenvectors F .

Finally, the data normalizer normalizes the extracted features to eliminate the effects of differences in scale and magnitude on the results of the analysis. Data normalization usually consists of subtracting the mean value of each feature and dividing by its standard deviation. The mathematical representation of standardization is as follows.

$$Z_i = \frac{(X_i - \mu_i)}{\sigma_i} \quad (6)$$

In the formula, the X_i is the raw values of the individual features, the μ_i and σ_i are the mean and standard deviation of the feature, respectively, and, the Z_i is then the normalized eigenvalue.

Through these processing steps, the data processing module ensures the quality and consistency of the data, and provides a solid data basis for the fault prediction and diagnosis of the power system.

4. Results and discussion

In order to ensure the accuracy and reliability of the test results, this paper simulates different degrees of power system faults. This paper uses a series of predefined fault

scenarios, including mild, moderate, severe faults, as well as faults in extreme environments. These fault scenarios are realized by changing parameters such as current, voltage, frequency, and environmental conditions (such as temperature, humidity) of the transmission line. For example, a minor fault might be simulated as a slight voltage fluctuation, while a severe fault might be simulated as a severe line short or open circuit. Failures in extreme environments are achieved by simulating power grid operation under high temperature, high humidity or other harsh environmental conditions. We tested the above five different scenarios under the same hardware and software configuration. The main hardware includes a Dell PowerEdge R740 server equipped with Intel Xeon Gold 6130 processor and 128GB RAM, as well as 4TB SSD storage. In terms of software, the system is deployed on the Ubuntu 20.04 LTS operating system, using Apache Hadoop and Spark for big data processing, while using TensorFlow and PyTorch to implement and train machine learning models. The test results are shown in Table 1.

Table 1. Results of the system tests

performance indicators	normal operation	Mild malfunctions	Moderate failure	Heavy failure	Extreme environments
Accuracy (%)	98.9	97.5	95.2	92.3	89.7
Response time (s)	4	4.5	5	5.2	5.4
System stability (%)	99	98.6	98.2	97.8	95

In summary, the accuracy rate can reach 98.9% during normal operation. The test results demonstrate the efficient performance and stability of the system under various environments and conditions, and verify its feasibility and effectiveness in practical applications.

5. Conclusion

This article proposes research on power system fault diagnosis and prediction methods based on deep learning. In this study, we successfully developed and verified a power system fault prediction and diagnosis system based on big data analysis. Its performance is excellent and in line with the complexity of modern power grids. need. By integrating advanced data processing technology and machine learning algorithms, the system demonstrates its powerful capabilities in identifying and solving potential faults in the power system. This not only improves the speed and accuracy of fault response, but also significantly improves the overall operating efficiency and safety of the power grid. The stability and robustness of the system ensure reliability in long-term operation, which is crucial for grid security and continuous power supply. All in all, this system not only improves the efficiency and effectiveness of power system fault management, but also provides strong support for the realization of smart grids and the modernization of the power industry, demonstrating the huge potential and application value of big data technology in the field of power systems.

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