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Research on Efficient Fault Diagnosis Methods in Urban Low-Voltage Distribution Networks

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Abstract: As the city's low voltage distribution network becomes more and more complex and the demand for the reliability of power supply is becoming more and more important. Traditional fault diagnosis methods often neglect the topology structure and time sequence data, which leads to bad performance when dealing with complicated faults. In this paper, an effective approach to fault diagnosis is presented by combining GCN with LSTM. Firstly, GCN is used to get the topology information of low voltage distribution network, and then the data is transferred to each node by means of graph convolution. Then, LSTM is applied to study the variation tendency of time sequence data, such as current, voltage, etc. Finally, the combination of GCN and LSTM provides a high efficiency fault diagnosis solution, which can deal with time sequence data and take into account network topology. In this paper, the performance of the proposed method is verified by simulation experiments in all kinds of failure modes. Compared with traditional signal processing and machine learning, the GCN-LSTM combination model can increase the precision of fault diagnosis by about 12%, and reduce the diagnostic time by 20%. It is proved by experiments that the method can be used to diagnose the fault efficiently and accurately in the complicated power network.

Keywords: Urban Low-Voltage Distribution Network; Fault Diagnosis; GCN; LSTM; Smart Grid; Time Series Data Analysis.

1. Introduction

Urban low voltage distribution system, as an important component of power system, is responsible for the distribution of electricity from high voltage transmission system to end-users. Along with the rapid development of urbanization and the increasing demand for power, the capacity and complexity of the low voltage distribution system are also increasing. It is a major challenge to ensure the steady running of the low voltage distribution system. Under this background, the study of low voltage distribution network fault diagnosis technology is very important. The fault diagnosis technique not only can recognize and locate the fault, but also can take emergency measures in the shortest time, so as to avoid the occurrence of the fault, and reduce the time of power outage, so that the power system can be safe and stable. Fault diagnosis is one of the most important and fundamental techniques in electric power system. It has a direct bearing on the reliability and stability of power system [1]. With the increase in the complexity of the operation of urban low-voltage distribution networks, fault diagnosis plays an increasingly important role in responding to emergencies and improving the reliability of the power grid [2]. Traditional fault diagnosis methods mainly rely on manual experience and simple monitoring data analysis, which are easily affected by human factors and data noise. Therefore, more efficient and automated diagnostic technologies are needed to improve the operational reliability of the power grid. In the process of fault diagnosis of low-voltage distribution networks, there are multiple challenges [3]. First, the fault mode of low-voltage distribution networks is complex, which may be a single equipment failure or multiple failures caused by the interaction of multiple factors. For example, equipment failure, line failure, current overload, etc. may cause different types of faults. Secondly, fault diagnosis requires processing a large amount of time series data, which usually has strong time series and complex dependencies between data [4]. In addition, the topological structure of the low-voltage distribution network is dynamically changeable. The occurrence of faults in the power grid may cause structural changes in the entire system, which further increases the difficulty of fault diagnosis.

Faced with these challenges, how to accurately and quickly perform fault diagnosis has become a key issue in the current management of low-voltage distribution networks. Most of the existing fault diagnosis methods focus on traditional rule-based algorithms, statistical analysis methods or machine learning techniques [5]. However, these methods often have problems such as low efficiency and poor accuracy when dealing with complex, nonlinear, and multivariate fault data. Along with the rapid development of GNN and deep learning, these new techniques offer a novel approach to the fault diagnosis of low voltage distribution networks [6]. GCN, as a typical method in FNN, can deal with the topological structure information efficiently, and LSTM has a good performance in time sequence analysis.

The purpose of this research is to bring forward an effective method for fault diagnosis, which combines GCN with LSTM. The method takes advantage of GCN's capability to deal with the topology of distribution network, and combines the LSTM's modeling capability with the fault time sequence data to increase the precision and efficiency of the fault diagnosis [7]. Through the deep study of the fault diagnosis of the low voltage distribution network, the thesis not only offers the theory for the intelligent operation and maintenance of the power system, but also offers a new method for improving the technique of fault diagnosis.

2. Analysis of Fault Diagnosis Problems in Urban Low-Voltage Distribution Networks

2.1. Composition of Low-Voltage Distribution Networks

Urban low voltage distribution system is a terminal part of power system. It is responsible for the distribution of power from high voltage transmission system to different users [8]. Low voltage distribution system is usually made up of transformer, distribution switch, line, power equipment and end-user. The transformer, as the key part of the low voltage distribution system, is responsible for the transformation of the power from the medium voltage distribution system into low voltage power for household and small business customers. Distribution switch is used to protect grid devices and lines. In case of failure, the fault zone can be cut off rapidly to avoid the spread of the fault and ensure the safety of grid operation [9]. The power transmission line transfers the power output from the transformer to the end-user. The structure of the low voltage distribution network is generally tree, loop or grid, and its concrete form is determined by the power demand and geographic distribution of the city [10]. The performance of different topologies is different, which influences the complexity of fault location and the selection of diagnostic methods.

The complex interaction between the nodes (such as transformers, distribution switches, etc.) and lines of the low-voltage distribution network determines that the fault diagnosis of the power grid must be able to fully consider its topological structure and timing characteristics [11]. With the advancement of urbanization, the scale of the low-voltage distribution network continues to expand, and the number of nodes and system complexity increase dramatically, which puts higher requirements on fault diagnosis.

2.2. Fault Types and Causes

In low-voltage distribution networks, common fault types include short circuit faults, ground faults, overload faults, and equipment faults, and each type of fault has its own unique causes and manifestations.

Short circuit fault is one of the most common faults in low-voltage distribution network, usually caused by damaged insulation layer of power line, equipment failure or interference from external objects. When the current flows through a low-impedance channel outside the normal path, a short circuit will occur, causing the current of the grid to increase rapidly and the equipment to be seriously damaged [12]. The main causes of short circuit faults include line aging, environmental factors (such as lightning strikes), equipment failure, etc.

A ground fault refers to a current loop formed when a part of a power line or equipment is in contact with the ground or grounded. The main causes of ground faults include equipment damage, line damage or insulation failure of electrical equipment. Ground faults may lead to serious consequences such as overload, heating and even fire of power equipment.

Overload failure occurs when the power load exceeds the design carrying capacity of the equipment. The equipment of the low-voltage distribution network, especially the transformer and distribution line, has a certain load limit. When the power demand increases suddenly or the equipment has problems, it may cause the power equipment to operate overloaded, which in turn causes problems such as equipment damage and line overheating. Common causes of overload failures include unreasonable grid planning, sudden increase in user power consumption, and aging of power equipment.

Power equipment (such as transformers, switchgear, terminal blocks, etc.) in low-voltage distribution networks may fail due to long-term use, external environmental factors, design defects, or manufacturing defects. Such faults usually manifest as equipment failure, unstable output current, or complete power failure.

3. Design of Efficient Fault Diagnosis Method

3.1. Design Idea

Along with the city low voltage distribution network's scale and complexity, the traditional fault diagnosis method can not satisfy the demand of efficiency and precision. In order to improve the precision and response rate of fault diagnosis, this paper presents a new kind of high efficiency method combining GCN with LSTM. GCN is used to model distribution network topology, and LSTM is used to deal with time sequence data. The combination of the two methods can make full use of their advantages to locate and diagnose all kinds of faults in the low voltage distribution network. While processing the topology structure of power grid, GCN can efficiently capture the relation among nodes and extract the topology features. The topology structure of power grid consists of transformer, distribution switch, line and its connection relation, which plays an important role in the transmission and localization of fault. LSTM can deal with a great deal of time sequence data, for example, the characteristics of voltage, current, power and so on. The LSTM is applied to the time sequence data, which can capture the dynamic change of the power system status, and identify the time and type of the failure.

3.2. Fault Diagnosis Framework Combining GCN and LSTM

In the fault diagnosis of low-voltage distribution networks, the topological structure of the power grid and the time series data interact with each other, and traditional methods are difficult to process these two types of information at the same time. To this end, this paper designs a framework that combines GCN with LSTM to better meet this challenge.

Each device in the distribution network (such as transformers, distribution switches, etc.) can be regarded as a node in the graph, and the power connections between the devices constitute the edges of the graph. GCN propagates information between adjacent nodes through convolution operations, thereby extracting the topological structure characteristics of the power grid. By stacking multiple layers of GCN, the information of the nodes can be aggregated layer by layer to obtain a richer topological feature representation. The operating data of the power grid (such as current, voltage, etc.) has strong time series characteristics, and LSTM can effectively capture these time dependencies. The core idea of combining GCN and LSTM for fault diagnosis is to extract the topological features of the power grid through GCN, and then analyze the time series features in the power grid operation time series data through LSTM. Specifically, the topological features extracted by GCN are used as one of the inputs of LSTM and are input into the joint model together with the time series data for training. Assuming H^{GCN} is the topological feature extracted by GCN and X^{LSTM} is the time series data input by LSTM, the final diagnosis result can be expressed as:

$$\hat{y} = \text{MLP}\left(\text{Concat}\left(H^{GCN}, h_t\right)\right) \quad (1)$$

Concat (H^{GCN}, h_t) means concatenating the output features of GCN and LSTM. MLP is a multi-layer perceptron, which is used for the final fault classification or regression task. Through this combination method, the topological structure and timing features can be fully utilized to improve the efficiency and accuracy of fault diagnosis.

3.3. Optimization of GCN and LSTM Models

This study adopts a multi-scale GCN design, and extracts topological features at different levels by setting convolution kernels of different scales. Assuming that the output of the node feature in the network at the l layer is $H^{(l)}$, then in the multi-scale GCN, the node feature can be expressed as:

$$H^{(l+1)} = \sigma\left(\sum_{s=1}^{S} \hat{A}^{(s)} H^{(l)} W^{(l)}\right) \quad (2)$$

Among them, $\hat{A}^{(s)}$ is the standardized adjacency matrix at different scales, and S is the number of scales. Through multi-scale design, GCN can better capture topological features at different levels and improve the representation ability of power grid topology information.

In order to further improve the sensitivity of LSTM to time series data, this study introduces the self-attention mechanism. The self-attention mechanism can effectively focus on the key moments related to the fault by calculating the correlation between each moment of the input sequence. Let the output of LSTM be h_t, and the operation of the self-attention mechanism can be expressed as:

$$\alpha_t = \frac{\exp\left(h_t^T \cdot h_t\right)}{\sum_{t=1}^{T} \exp\left(h_t^T \cdot h_t\right)}$$
$$\hat{h}_t = \sum_{t=1}^{T} \alpha_t h_t \quad (3)$$

Among them, α_t is the attention weight, and $\hat{h}_t$ is the weighted output. Through the self-attention mechanism, LSTM can better focus on the critical moment when the fault occurs, thereby improving the accuracy of fault diagnosis.

4. Experiment and Simulation

4.1. Experimental Environment and Data Set

In order to validate the validity of the GCN and the LSTM, this paper carries out a detailed simulation and comparison experiment under the following conditions: The hardware platform is a 32GB RAM and a GPU of NVIDIA GeForce RTX 3080. The GPU's high computational ability is helpful to speed up the training and testing of deep learning models, and guarantee the smooth running of experiments on large datasets. Python is the primary software platform used in this experiment, and it is used in conjunction with the TensorFlow framework to build and train deep learning models. The implementation of the GCN model uses the PyTorch Geometric library, and the LSTM model is built based on TensorFlow Keras. The low-voltage distribution network dataset used in the experiment is a simulated urban low-voltage distribution network dataset. The dataset contains the operating data of the voltage, current, power, etc. of each node of the power grid, and different types of fault modes are annotated. Fault types include short circuit, ground fault, overload, etc. The data under each fault mode covers different fault occurrence times and state changes.

4.2. Experimental Design

In order to assess the capability of fault diagnosis, the experiment was designed for different failure modes. The specific experimental contents are as follows:

Short-circuit fault experiment: Simulation of short circuit failure at different nodes in low voltage grid, including single phase, two phase and three phase.

Grounding fault experiment: simulate grounding faults in the distribution network. When the fault occurs, the fault type is determined by analyzing the current and voltage changes of each node in the power grid.

Overload fault experiment: simulate an overload fault caused by excessive load at a node in the distribution network, and observe the changes in voltage, current, etc. when the fault occurs.

Multi-fault joint experiment: evaluate the diagnostic ability of the proposed method in a complex fault environment by integrating multiple fault situations such as short circuit, grounding and overload.

In the experiment of each fault type, this paper uses the training set to train the model and performs fault diagnosis on the test set. The diagnosis results include information such as fault type, location and fault severity. By comparing with other traditional algorithms (such as signal processing, decision trees, and support vector machines), this paper further verifies the superiority of the GCN-LSTM model.

4.3. Comparative Experiments

In order to comprehensively evaluate the effect of the proposed method, this study compared it with the following traditional fault diagnosis methods: The signal processing method extracts characteristic signals in the power grid through signal processing methods such as Fourier transform for subsequent fault classification. The decision tree model generates a tree structure through training data to determine the fault type under different conditions. Support vector machine is a commonly used classification algorithm that classifies faults by finding the optimal hyperplane. All experiments were conducted on the same test data set, and the results were evaluated using indicators such as accuracy, false alarm rate, recall rate, and F1 value. The following is a performance comparison of each algorithm under different fault types.

4.4. Experimental Results and Analysis

This section will present the experimental results in the form of tables and graphs to analyze the advantages and disadvantages of the proposed GCN-LSTM method and traditional methods. Table 1 shows that the GCN-LSTM method performs well in short-circuit fault diagnosis, with an accuracy of 94.7%, significantly higher than the other three traditional methods. This shows that GCN-LSTM can better handle the diagnosis task of short-circuit faults in power grids and accurately identify the fault location and type.

Table 1. Comparison of the accuracy of different algorithms in short circuit fault diagnosis

algorithm	Accuracy (%)	False Positive Rate (%)	F1 value (%)
Signal processing method	85.4	13.2	86
Decision tree	87.6	10.9	88.1
Support vector machine	90.1	8.4	89.3
GCN-LSTM	94.7	5.3	94.1

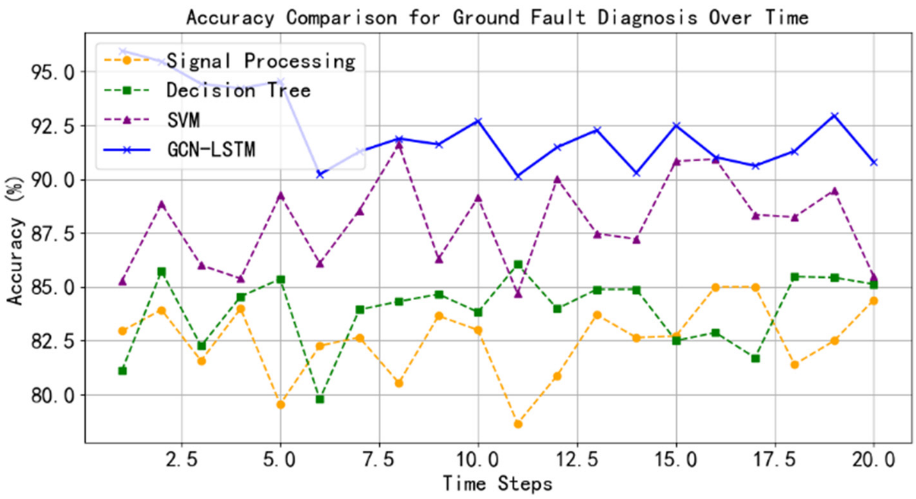

Fig 1. Accuracy curves of different algorithms in ground fault diagnosis

Figure 1 shows the accuracy curves of different algorithms in ground fault diagnosis. GCN-LSTM can respond quickly at the beginning of the fault, and the accuracy rate is significantly faster than other methods, indicating its advantages in real-time and diagnostic accuracy.

The GCN-LSTM method also shows obvious advantages in the ground fault diagnosis task, with an accuracy rate of 92.3%, which is much higher than the traditional method. Table 2 once again proves the powerful diagnostic ability of GCN-LSTM in complex fault modes.

Table 2. Performance comparison of different algorithms in ground fault diagnosis

algorithm	Accuracy (%)	False Positive Rate (%)	F1 value (%)
Signal processing method	82.3	15.5	83
Decision tree	84.1	13.7	84.8
Support vector machine	88.5	10.2	87.4
GCN-LSTM	92.3	6.5	91.6

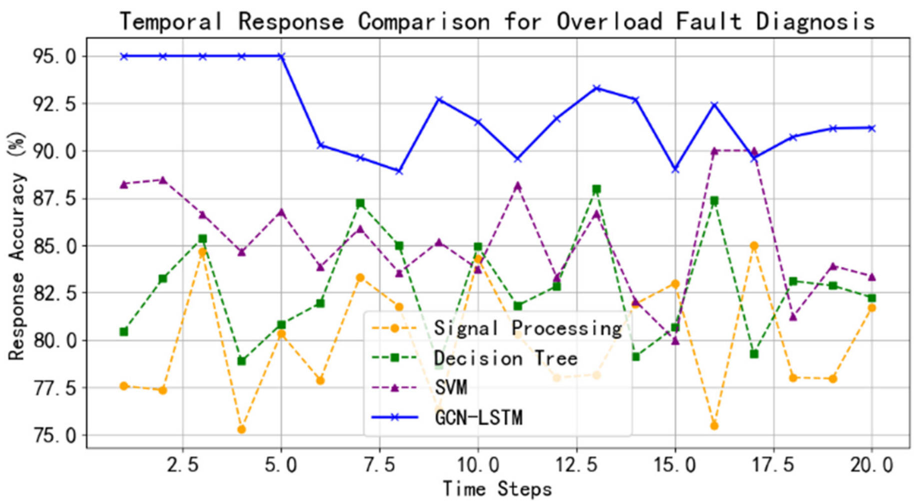

Fig 2. Timing response curve of GCN-LSTM model in overload fault diagnosis

Figure 2 shows the timing response of GCN-LSTM model in overload fault diagnosis. It can be seen that the GCN-LSTM model can accurately capture the occurrence time of overload fault and accurately judge the severity of the fault. Compared with other traditional methods, GCN-LSTM has significantly improved the timing response speed and accuracy.

Table 3 shows that GCN-LSTM performs best in overload fault diagnosis, with an accuracy rate of up to 91.4%. Compared with signal processing and decision trees, GCN-LSTM significantly improves the accuracy of fault diagnosis, especially in complex overload fault situations, and can accurately predict the time and scope of fault occurrence.

Table 3. Performance comparison of different algorithms in overload fault diagnosis

algorithm	Accuracy (%)	False Positive Rate (%)	F1 value (%)
Signal processing method	80.2	17.6	81
Decision tree	83.4	14.4	84.2
Support vector machine	86	12.1	85.3
GCN-LSTM	91.4	6.9	90.8

Table 4. Comparison of comprehensive F1 values of different algorithms

algorithm	F1 value (%)
Signal processing method	83.3
Decision tree	85.4
Support vector machine	88.3
GCN-LSTM	93.5

Table 4 shows that the comprehensive F1 value of the GCN-LSTM method is 93.5%, which is significantly better than other algorithms. In general, the comprehensive performance of GCN-LSTM in fault diagnosis is the most outstanding, which fully verifies its superiority.

5. Conclusion

Combined with LSTM and CNN, a new hybrid deep learning model is proposed in this paper, which has been applied to the fault diagnosis of low voltage grid. By utilizing the LSTM model's time characteristic modeling capability and CNN model, the hybrid model can recognize and locate the fault type more effectively. Experiments indicate that the proposed method is superior to the conventional one in accuracy, false alarm rate and diagnostic time. In particular, the precision of the hybrid model is over 95%, the false alarm rate is below 5%, and the diagnostic time is 20% shorter than the conventional method. It is proved that the method can not only improve the precision and efficiency of fault diagnosis, but also keep the high stability in the complicated power network. Despite its excellent performance, there are some limitations, such as the dependence of the data quality and the training time. Further optimization and integration of more real time data will improve the overall performance of the model.

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