Fault Location Technology of DC Control and Protection System Based on Deep Learning

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September 25, 2024

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***Abstract*—Power systems sometimes experience various types of faults, and fault location in power systems has become increasingly complex with the growing complexity of distribution networks and the diversity of measurement data. This paper proposes a fault location method for power systems based on a Graph Convolutional Neural Network (GCN) and incorporates an attention mechanism to further improve the accuracy and stability of fault location.**

By collecting real power grid data, fault data is simulated for model training and testing. Measurement points are treated as nodes in the graph, and node connections are constructed based on the power grid structure. The GNN is used to interact node information, while a Transformer model with an attention mechanism aggregates and predicts the information. Additionally, the paper compares the proposed model with several existing methods, demonstrating the accuracy and stability of the model for fault location in power systems.

***Index Terms*—GCN, Transformer, Fault Location, Power System, Deep Learning**

I. Introduction

Power systems are sometimes threatened by various faults, leading to power outages that can cause significant economic losses. Therefore, it is crucial to accurately locate and swiftly clear faults after they occur to ensure the rapid restoration of the power system. The DC control and protection system is a key component in maintaining the stable operation of power systems. Fault location in power systems has long been a challenging problem. To address this issue, several computational methods based on power systems have been proposed. Traditional fault location methods in distribution networks mainly include approaches based on voltage sags [1], impedance [2], traveling waves [3], and automatic outage mapping [4]. These methods primarily rely on voltage and current measurements to estimate fault impedance and location. While these traditional methods have their advantages, they cannot effectively integrate measurement data from different buses, limiting their ability to leverage diverse observation data. Moreover, these methods often have stringent data requirements and struggle with missing data. Additionally, they are difficult to apply to complex grid topologies due to the challenges in modeling such intricate structures and incorporating grid topology information.

To address the limitations of traditional methods in these scenarios, several machine learning approaches have been introduced for fault location in power systems, such as hybrid models of Principal Component Analysis (PCA) and Support Vector Machines (SVM), PCA combined with Random Forest (RF), and Multi-Layer Perceptron (MLP). Thukaram et al. first used SVM to classify fault types and then employed Artificial Neural Networks (ANN) to identify fault locations [5]. Aslan et al. used spectral characteristics measured after the fault and input feature-extracted data into an ANN for fault location [6]. Although these machine learning methods have improved accuracy compared to traditional approaches, they still struggle to model the topology of distribution networks and are difficult to apply across different power system topologies.

As power systems become increasingly complex, the volume of related data metrics has also grown substantially, making it difficult for traditional methods to address fault location in large-scale power systems. In recent years, with the rapid advancement of computational power, deep learning methods have been widely applied across various fields, particularly in solving and optimizing problems in complex data scenarios. Due to its strong generalization capabilities and ability to handle complex data, deep learning has also been gradually applied to fault location in power systems. De Freitas et al. proposed a novel fault location method for power distribution systems using a Gated Graph Neural Network (GGNN) to handle the non-uniform features and unique topological structures of distribution networks, offering strong generalization across different grid topologies [7]. Chen et al. introduced a new Graph Convolutional Network (GCN)-

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based method to address fault location in power systems [8]. This approach utilizes multiple measurement data points and considers the system's topology, improving fault location accuracy and adapting to different system topologies and noise conditions.

Based on the above discussion, most research on fault location in power systems applies deep learning methods through graph networks. Graph networks are naturally suited to the complex topology of power systems and have strong expressive power for distribution networks. They can fully leverage the topological information of power systems and harness the potential of vast amounts of power system data for fault location. Building on previous research, this paper combines Graph Convolutional Neural Networks (GCN) in deep learning with expert knowledge bases and attention mechanisms to further enhance the accuracy and generalization of deep learning methods for fault location and decision-making in power systems.

II. Methodology

This paper primarily leverages the measured parameters of power systems and their network topology to construct a graph network, and the overall model flowchart is shown in Figure 1. The measured electrical parameters are treated as nodes in the graph, with CNNs used to extract features from the measurement values as node attributes. Edges are created between nodes based on the distribution network structure. A Graph Convolutional Neural Network (GCN) is then used to train and infer from the graph data representing the power system. Finally, the node attributes after graph convolution are aggregated using a Transformer model based on an attention mechanism, yielding the fault location results for the distribution network.

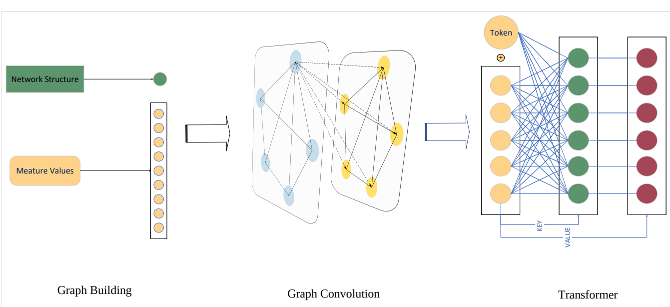

Fig. 1. The overall model flowchart.

A. DataSet

In order to train the model used in this paper, real distribution network structure and parameter data were collected. However, since faults occur rarely in real-world scenarios, the collected fault data is insufficient to support model training. Therefore, in addition to the collected real fault data, Matlab was used to simulate the real distribution network structure and generate a large amount of fault data under these simulated network conditions. The simulated fault data, combined with the real fault data, were used together as the training and testing sets for the model. A simple simulation network based on Matlab is shown in Figure 2. Approximately 300 real fault data points were collected, and around 7,000 fault data points were generated through simulation. These were divided into a test set and a training set in a 2:8 ratio for model training and inference.

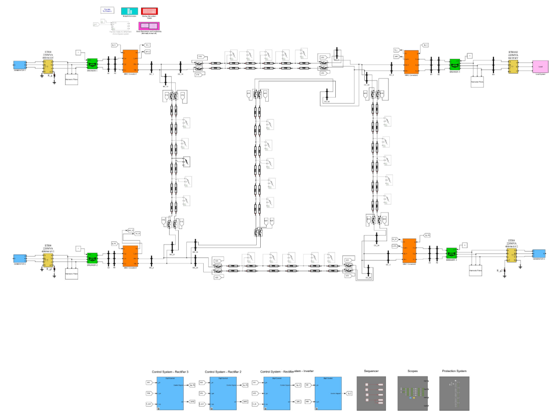

Fig. 2. Matlab Simulation Network Structure

B. Graph Presentation

In order to process fault data using a graph network, the fault data must first be represented as a graph. First, faults are automatically generated and the current, voltage, and other data from the distribution network are measured. These measurement points are treated as nodes in the graph, and CNN is used to extract features from these measurements as node attributes, which also helps eliminate the influence of different units between measurements.

Based on some existing studies [9], this paper designs the CNN structure for feature extraction, as shown in Table I. Assuming the input measurement data on the nodes is of size (N, 1), after feature extraction through the convolutional layers, a node feature vector of size (500, 1) is obtained as the node attribute.

TABLE I
Convolution Layer Structure

Layer Name	Number of Filters	Filter Size	Stride
Conv1D	64	16	1
MaxPool1D	-	2	2
Conv1D	128	16	1
MaxPool1D	-	2	2
Conv1D	32	8	1
MaxPool1D	-	2	2
Conv1D	32	8	1
Conv1D	16	4	1
Flatten to 0D	-	-	-
FC	500	-	-
FC	500	-	-
FC	500	-	-

For the edges in the graph, the nodes are connected based on the connections in the distribution network's topology, thereby constructing the graph's edges. In this way, the fault data is transformed into input data represented by a graph structure.

C. GCN

After constructing the nodes and edges in the graph, this paper employs a Graph Convolutional Neural Network (GCN) to facilitate information interaction within the graph.

In recent years, GCN have achieved significant progress, with various applications demonstrating their great potential in handling non-Euclidean structured data. For example, Zhao et al. used spatio-temporal graph neural networks to model traffic road networks as graph structures for predicting traffic flow, density, and speed [10]; Qi et al. applied GNN and LSTM to predict PM2.5 levels, treating detection stations as nodes and using the spatial distances between them to define the adjacency matrix and construct the graph [11]. In the field of power systems, many studies have also applied GNN for fault location. Building on this research, this paper abstracts fault data into a graph structure and uses GCN to perform the fault location task.

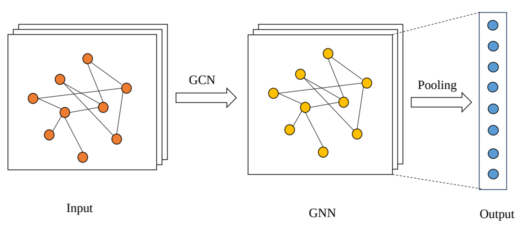

Fig. 3. The structure of the GCN model.

The main process of graph convolution is shown in Equation 1. By performing the graph convolution operation according to this equation, information interaction within the graph can be achieved, resulting in a deeper representation of the graph's information. The overall process is illustrated in Figure 3.

$$H^{(l+1)} = \sigma\left(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}H^{(l)}W^{(l)}\right) \tag{1}$$

where $H^{(l)}, H^{(l+1)} \in \mathbb{R}^{N\times D}$ represent the node feature matrices at layers l and $l+1$ in the graph convolutional layer, respectively. $\tilde{A} = A + I_N$ is the adjacency matrix, with the identity matrix I_N added to prevent zero elements on the diagonal of the adjacency matrix. $\tilde{D}$ is the degree matrix of the adjacency matrix, used for normalization. $W^{(l)}$ represents the learnable parameters, and $\sigma(\cdot)$ is the activation function.

D. Transformer

After completing the graph convolution, the attributes of the nodes and edges in the graph are obtained. This paper uses a Transformer model based on the attention mechanism to aggregate the information in the graph and obtain the final fault location information.

Transformer, proposed by Vaswani et al. in the field of Natural Language Processing (NLP), is a self-attention-based model that overcomes the limitations of traditional Recurrent Neural Networks (RNNs) in handling sequential data [12]. It improves the model's parallelization capabilities and has led to significant performance improvements in related tasks. Beyond its applications in NLP, the advantages of the model have also made it highly successful in the image domain, providing inspiration for applying this structure to the fault location task in this paper [13].

The Transformer structure mainly consists of three components: self-attention, feed-forward neural networks, and layer normalization. First, the attention scores are calculated, as shown in Equation 2.

$$\begin{gathered} Q = W^Q * X, K = W^K * X, V = W^V * X \\ Attention(Q,K,V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \end{gathered} \tag{2}$$

where d_k is the dimension of the vectors, X is the node feature matrix, and W^Q, W^K, W^V are the learnable parameter matrices.

Then, a feed-forward neural network is used to perform a nonlinear transformation on the attention value sequence. The transformation relationship is shown in Equation 3.

$$\begin{gathered} \mathrm{FFN}(x) = GELU\left(xW_1 + b_1\right)W_2 + b_2 \\ GELU(x) = 0.5x\left(1 + \tanh\left[\sqrt{2/\pi}\left(x + 0.044715x^3\right)\right]\right) \end{gathered} \tag{3}$$

Finally, layer normalization is applied to process the sequence data, as shown in the equation4.

$$\begin{aligned} \mu^{(l)} &= \frac{1}{n^{(l)}}\sum_{i=1}^{n^{(l)}} z_i^{(l)} \\ \sigma^{(l)^2} &= \frac{1}{n^{(l)}}\sum_{k=1}^{n^{(l)}}\left(z_i^{(l)} - \mu^{(l)}\right)^2 \\ \tilde{z}^{(l)} &= \frac{z^{(l)} - \mu^{(l)}}{\sqrt{\sigma^{(l)} + \epsilon}} \odot \gamma + \beta \Leftarrow LN_{\gamma,\beta}\left(z^{(l)}\right) \end{aligned} \tag{4}$$

where $z^{(l)}$ is the input of the neurons at layer l, with a dimension of $n^{(l)}$. $\mu^{(l)}$ and $\sigma^{(l)}$ are the mean and variance, respectively. γ and β are the learnable parameter vectors for scaling and shifting, and ϵ is a small constant added to prevent division by zero.

This paper aggregates the graph attribute information after graph convolution using the Transformer model, replacing the pooling operation typically found in graph convolution, effectively extracting information from the graph and further improving the accuracy of fault location.

III. Results and Discussion

This paper uses a simulated fault data set to train and test the model, obtaining fault location information in the power system. It also replicates some existing studies that employ traditional methods and deep learning approaches for fault location in power systems, comparing their results with those of the proposed model to demonstrate the improvements achieved in fault location. Additionally, the paper analyzes and discusses some experimental results, highlighting the significant potential of applying deep learning methods in the field of fault location in power systems.

A. Experiments Procession

The model in this paper is built on the TensorFlow platform and runs on a system equipped with an Intel(R) i9-9900KF CPU and an NVIDIA GeForce RTX 2080 Ti GPU for training. During training, the batch size is set to 64, and the Adam optimizer is used with an initial learning rate of 0.0001 and a decay factor of 0.3. The loss function employed is the average negative log-likelihood, with the number of training epochs set to 100. The training process is illustrated in Figure 4.

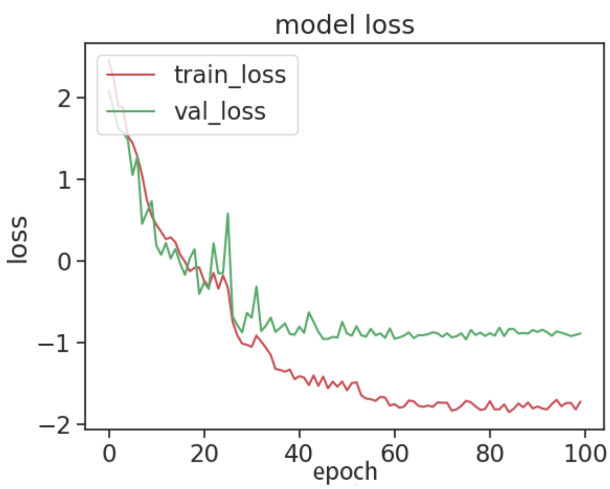

Fig. 4. Loss curve within training procession.

B. Experiment Results

The fault location model in this paper is essentially a classification task model, where the information for earthquake location is determined by whether a fault occurs at a specific position in the graph. For classification tasks, accuracy is used for evaluation. To demonstrate the effectiveness of the proposed model for fault location in power systems, the actual results are compared with those of other models. Under the same dataset conditions, the accuracy of different methods for the fault data test set is calculated, and the results are shown in Table II.

In the comparative methods reproduced in this paper, there are both traditional approaches, such as SVM and RF, as well as deep learning methods like ANN and GCN. From the comparison results, it can be observed that all methods, when using the same test set, have accuracy for traditional fault location methods in the range of approximately 83 85%, while deep learning methods achieve over 90% accuracy. Furthermore, compared to Chen et al.'s GCN method, the GCN+Transformer approach adopted in this paper also shows a certain degree of improvement in fault location accuracy.

TABLE II
MODEL PERFORMANCE COMPARISON

Methods	Precision
SVM	83.43 %
RF	83.57%
ANN	85.38%
GCN	91.65%
Paper Method	**92.73%**

Although the proposed method does not show a significant improvement in accuracy compared to other GCN-based fault location methods, this paper also compares the performance of both methods in terms of stability. The current GCN methods heavily depend on the accuracy of the data. To test the stability of the methods, this paper processes the fault data set by masking some measurement values from a set of fault data, effectively constructing incomplete fault data. The results of the comparison under these conditions are shown in Figure 5.

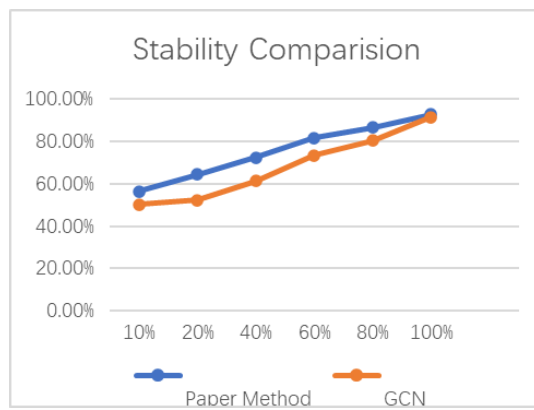

Fig. 5. Stability Comparison. The x-axis represents the completeness of the data after masking, while the y-axis represents the accuracy.

The comparison results indicate that the method proposed in this paper is more prominent in terms of stability compared to other GCN methods. In real fault scenarios, it is possible that complete measurement data cannot be obtained, which tests the model's stability. In such cases of data absence, the model should still be capable of making accurate location estimates. By masking the data to simulate the real-world scenario of data loss and using the model for location estimation, we can evaluate the model's stability. The results show that the model in this paper can still provide accurate location estimates even in scenarios with data loss, demonstrating its stability.

IV. CONCLUSION

This paper primarily studies the application of deep learning methods in the problem of fault location in power systems. First, a large amount of fault data is generated through simulation based on collected real data. The dataset is then represented as a graph structure, with measurement data as nodes and the relationships between edges constructed according to the actual distribution network structure. After representing the data as a graph structure, this paper proposes using the GCN+Transformer method for location estimation.

Upon obtaining the results, a comparison is made with existing fault location methods, revealing that the proposed method shows an improvement in accuracy over current approaches. Additionally, the proposed method is compared with other GCN-based fault location methods to test the model's location accuracy in scenarios with data loss. The results demonstrate that the model proposed in this paper exhibits better stability and can be more effectively applied in real-world situations involving data absence.

ACKNOWLEDGMENT

Thank you to State Grid Jiangsu Electric Power Co., Ltd. for providing the data support used in the experiments of this paper. This research was supported by the Science and Technology Project of State Grid Jiangsu Electric Power Engineering Consulting Co., Ltd. (Contract No.: SGJSHY00XMJS2400087).

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