Disentangled Table-Graph Representation for Interpretable Transmission Line Fault Location

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Abstract

The fault location task in power grids is crucial for maintaining social order and ensuring public safety. However, existing methods that rely on tabular state records often neglect the intrinsic topological influences of transmission lines, resulting in a segmented approach to fault location that consists of multiple stages. In this paper, we propose an Disentangled Table-Graph representation framework, termed DTG, which integrates fault location tasks at coarse-grained line levels and fine-grained point levels within an end-to-end learning paradigm. Our innovative disentanglement strategy produces interpretable attribution coefficients that connect tabular records and transmission line topology, thereby facilitating fault location at both line- and point-levels. The joint prediction tasks designed around our disentangled tabular graph representation promote mutual information exchange between features and topology of transmission lines in an interpretable manner. Experimental results on the 7-bus system, 36-bus system and a realistic 325-bus system in China demonstrate that the proposed method adapt to different topological structures and handle different types of faults. Compared to traditional methods, DTG4Power achieves high accuracy in both fault lines and fault points.

Introduction

The power transmission system often faces problems such as power outages and equipment damage due to line faults, which not only affect the reliability and stability of the power grid system but also pose a threat to social order and public safety. Therefore, it is necessary to detect, classify, and locate faults in the power grid as early as possible to avoid long-term power interruptions and cascading failures. This not only ensures the operational quality of the power grid system but also reduces revenue losses caused by power failures and saves labor costs when manually locating faults.

The fault diagnosis of power grid is divided into three steps: fault detection, fault classification, and fault location(FL) (Fahim et al. 2021). The current methods for fault location in power grid can be categorized into those based on mathematical physical models and those based on statistical analysis of measurement data. The methods based on mathematical physical models mainly use methods based on traveling waves (Li et al. 2020; Jafarian and Sanaye-Pasand 2010; Ngwenyama, Le Roux, and Ngoma 2021) and impedance (Rafinia and Moshtagh 2014; Esmaeilian, Popovic, and Kezunovic 2015; Bíscaro et al. 2015; Liu et al. 2011; Orozco-Henao et al. 2019; Majidi and Etezadi-Amoli 2018), requiring the establishment of mathematical models based on prior knowledge, with poor generality and complex calculations; the statistical analysis methods based on measurement data mainly use traditional machine learning methods (Okumus and Nuroglu 2021; Thukaram, Khincha, and Vijaynarasimha 2005; Majidi, Arabali, and Etezadi-Amoli 2014), deep learning (Tong et al. 2021; Shi and Xu 2021), and reinforcement learning methods (Li et al. 2022), requiring sufficient historical data to train and adjust the computational models, thus demanding high quality of the dataset.

However, with the continuous application of emerging complex architectures such as microgrids, new generation loads, and equipment in the existing power system network, traditional protection schemes are no longer sufficient to meet new challenges. In addition, with the increasing amount of available measurement data, traditional fault location methods mainly face two problems (Liao et al. 2021): firstly, these methods cannot flexibly merge measurement data from different buses but instead specify fault lines and process fault data; secondly, traditional machine learning methods struggle to model the topology of power system, let alone the possibility of topology changes. These limitations result in insufficient accuracy and precision in predicting results when dealing with complex power grid systems. Therefore, the introduction of graph neural networks is crucial. They can effectively handle graph data, model nodes and lines of the power grid, and utilize the topological relationships between nodes for information transmission and learning, thus better reflecting the actual operational status of the power grid (Liu et al. 2024a,b).

This study aims to utilize the feature disentangled graph convolutional network to address the issue of fault location in power grids. By leveraging both data features and spatial features of buses, the goal is to enhance the accuracy of predicting power grid fault locations. The proposed method in-

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volves modeling the nodes and lines of the power grid using graph convolutional networks, followed by the application of feature disentangled technology to extract hidden features and structures from the power grid data. This approach is expected to improve the precision of power grid fault location, bolster the security of the power grid, advance smart grid development, and offer novel insights for research and practical applications in the realm of power system fault location. Our main contributions can be summarized as follows:

- We innovatively construct line graphs to model transmission lines under various faults in the power grid, effectively utilizing multiple measurements from both ends of power system branches.
- We propose an interpretable method, DTG4Power, based on disentangled graph representations to effectively extract the representation of tabular data in power systems. This method is designed to facilitate the identification of fault locations in both a coarse-grained manner, pinpointing fault lines, and a fine-grained manner, determining the exact point of a fault along a transmission branch.
- Experiments on three different specifications of real network topologies demonstrate excellent performance in locating fault transmission lines and fault points.

Related Work

Fault Location in Power Grid

According to the measurement characteristics, existing fault location of transmission lines in power system can be mainly divided into three families (Personal et al. 2016): based on traveling waves , based on high frequency, and based on phasor based methods. Traveling waves methods (Li et al. 2020; Ngwenyama, Le Roux, and Ngoma 2021; Jafarian and Sanaye-Pasand 2010) are based on the analysis of propagation time associated with fault effects. In addition, fault locations are determined based on high-frequency (Rafinia and Moshtagh 2014; Esmaeilian, Popovic, and Kezunovic 2015) and phase-based methods (Bíscaro et al. 2015; Liu et al. 2011), which respectively use the high-frequency information and phase relationship of voltage and current. Specially, the most traditional implementations of phasor based methods are commonly known as impedance methods (Girgis, Hart, and Peterson 1992). However, the majority of references rely on voltage and current measurements as inputs, disregarding other measurable information of transmission lines. These methods are primarily founded on physical meanings, lacking efforts to fully comprehend the hidden relationships among multiple measured values. The advancement of artificial intelligence, including support vector machines (Thukaram, Khincha, and Vijaynarasimha 2005), decision trees (Okumus and Nuroglu 2021), neural networks (Usman, Ospina, and Faruque 2018) and others(Jin and Ju 2012; Majidi, Arabali, and Etezadi-Amoli 2014; Ghaemi et al. 2022), has provided new perspectives for many tasks in the power system. Machine learning methods, despite their higher accuracy compared to traditional approaches, face challenges in capturing the relationships among the inherent bus nodes in the power grid. This limitation leads to significant performance degradation when changes happen in the topology.

Deep Learning Methods in Power Grid

The integration of renewable energy sources, such as photovoltaic plants and wind farms, introduces fluctuations and intermittency to the power system. This poses challenges for traditional model-based methods in adequately fulfilling the control and analysis needs of the power system due to the inherent uncertainty and complexity involved. Deep neural networks (Fahim et al. 2021; Chen et al. 2025, 2023) are commonly employed in sophisticated modern smart grid because of their exceptional ability to extract representations effectively across diverse domains. Several studies have examined various types of fault data inputs in the power grid, including voltage and current (Yu et al. 2021), signal sequences (Shi and Xu 2021), and transformed signal images (Shi and Xu 2021). These studies have utilized convolutional networks (Tao et al. 2018), recurrent neural networks (Belagoune et al. 2021; Wang et al. 2022), and other techniques to enhance fault location performance. However, these approaches often neglect the intrinsic non-euclidean properties of the power grid, the stable interconnections between buses, leading to a lack of robustness in addressing issues related to alterations in the scale or topology.

In order to solve these problems, Tong et al. (2021) employed bus voltage signals within a single sampling period following a transient fault, along with the network topology, to incorporate additional prior knowledge using graph convolutional networks (GCN) . This approach led to enhanced performance in classifying transient stability faults. Chen et al. introduced a GCN framework that utilizes data collected by voltage and current phase detectors as input. They incorporated data augmentation techniques to enhance the robustness against noise and data loss. Ukwuoma et al. employed a Graph Attention Convolutional Neural Network to represent the topology of power system, bus estimations, branch variables, and error points, thereby improving the detection of anomalous data. Li et al. proposed a fault detection approach based on deep reinforcement learning, where various faults are treated as model parameters to broaden the range of fault identification. However, these methods primarily rely on the measurement data from the buses, neglecting the potential insights that could be gained at both ends of the transmission branch. Furthermore, they tend to concentrate solely on one aspect, failing to address the simultaneous identification of faulty lines and faulty points.

Problem Formulation

We focuses on the fault location method of power system transmission lines, aiming to include coarse-grained fault branch location and fine-grained fault point location. In contrast to conventional methods, which usually only consider the voltage and current of the bus as inputs, our approach involves gathering measurement data from both ends of the transmission line. In the event of a fault, we collect 9-dimensional features at both ends of each transmission line, resulting in a total of 18 features(F) for each line.

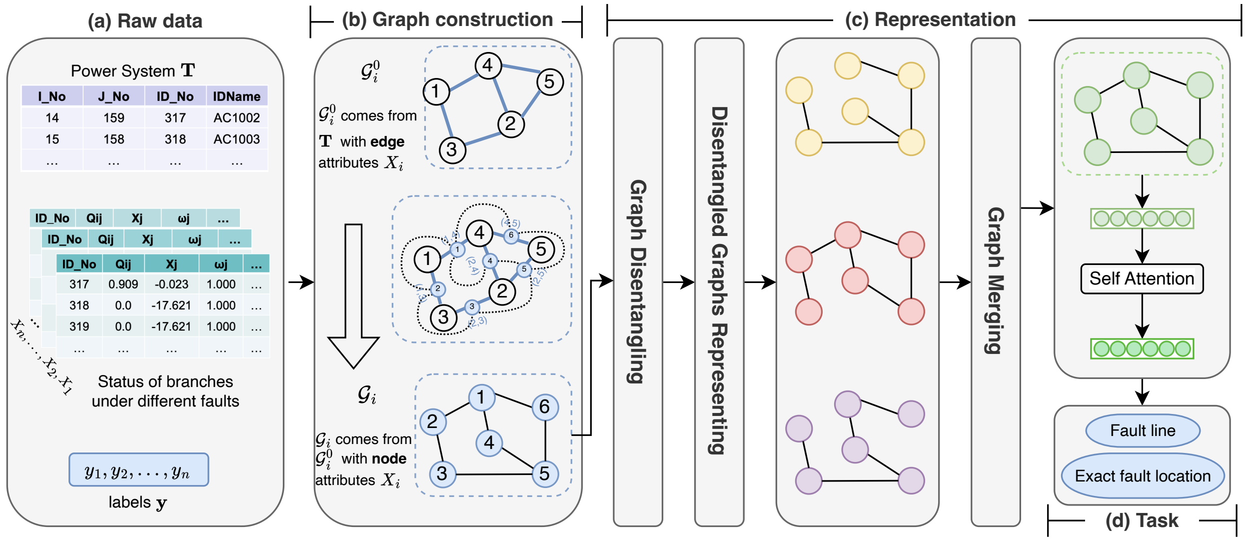


Figure 1: The overall architecture of our proposed method (DTG4Power).

When a fault, denoted $\xi_i \in \Xi$, occurs in a transmission branch at location y_i, a data sample i of measurement from the power system can be represented as $\mathbf{X}_i \in \mathbb{R}^{m \times F}$, where m is the number of transmission lines in the power system. Furthermore, for the specific operational scenario, the topology $\mathbf{T}$ of the power grid, which refers to the interconnection of lines, remains unchanged. As shown in Figure 1(a), we have access to the raw data $\mathcal{D} = \{\mathcal{X}, \mathbf{y}, \mathbf{T}\}$, where $\mathcal{X} = \{\mathbf{X}_1, \mathbf{X}_2, \ldots, \mathbf{X}_n\}, \mathbf{X}_i \in \mathbb{R}^{m \times F}, \mathbf{y} = \{y_1, y_2, \ldots, y_n\}$ and n indicates the number of samples. In the fault branch location task, the variable y_i denotes the branch containing a fault, while in the fault point location task, y_i signifies the percentage position along the line, ranging from 1 to 99.

Method

In what follows, we will elaborate on the interpretable graph representation method (DTG4Power) proposed for locating faults in transmission lines. As shown in Figure. 1, the process commences with converting raw data into graph data, utilizing both the topological structure and the measurement values of the transmission lines. Next, a graph disentangling network is utilized to obtain the representation of transmission lines within the power system. This involves restructuring subgraphs to eliminate redundant information and derive efficient representations of all transmission lines. To improve accuracy, irrelevant branches are filtered out using a self-attention mechanism, ensuring that the resulting effective representation is applied to fault location tasks.

Transmission Line Graph from Tabular Data

When a fault ξ_i occurs in the power grid, denoted as $\mathcal{G}_i^0$, the bus is typically considered the node in the graph, with the transmission lines acting as the connecting relationships represented as edges. As a result, the attributes $\mathbf{X}_i$ of the transmission lines are treated as edge data. Since graph neural networks mainly focus on node in feature representation, inspired by line graphs (Cai et al. 2021), we reorganize the relationship between buses and transmission lines to convert edge data into node data.

As shown in Fig 1(b), we denote the original graph as $\mathcal{G}_i^0$ and the transformed graph as $\mathcal{G}_i = \{\mathcal{U}, \mathcal{E}\}$. In $\mathcal{G}_i$, each edge in $\mathcal{G}_i^0$ is represented as a node, and if two edges in $\mathcal{G}_i^0$ share a node, they are transformed into an edge in $\mathcal{G}_i$.

In this manner, the transient state of the power grid when a fault ξ_i occurs at position y_i is denoted as $\mathcal{G}_i = \{\mathcal{U}, \mathcal{E}\}$. Here, $\mathcal{U} = \{u_1, u_2, \ldots, u_m\}$ signifies the set of nodes corresponding to the lines of the power grid, $\mathcal{E} = \{e_1, e_2, \ldots, e_k\}$ represents the shared bus between lines in $\mathcal{U}$. Thereby, we formulate the fault location task as a graph prediction.

Disentangled Representation for Fault Location

In light of the task, we explore the concept of graph-level feature disentangling, which involves creating multiple subgraphs through untangling. As illustrated in Figure 1 (c), during the feature untangling phase, the initial graph is broken down into several factor graphs, determined by the hyperparameter specifying the number of factor graphs κ. The effectiveness and interpretability of graph representation hinge on three main components: disentangling, subgraph representing, and graph merging.

Graph Disentanglement. To further extract information from graph-based data, the input feature matrix $\mathbf{X}$ undergoes a linear transformation by multiplying it with a transformation matrix $\mathbf{W} \in \mathbb{R}^{F' \times F}$ to yield a new hidden space denoted as $\mathbf{H}$. This transformation is represented as $\mathbf{H} = \mathbf{W}\mathbf{X}^T$, where $\mathbf{H} = \{h_1, \ldots, h_m\} \in \mathbb{R}^{F' \times m}$. Such a procedure is a fundamental operation in many Graph Convolutional Network (GCN) models and serves to enhance the model's expressive capacity.

In the disentangled step of the graph, DTG4Power employs a mechanism akin to Graph Attention Networks (GATs) (Velickovic et al. 2017) to compute attention scores for edges, denoted as $s_{ij} = \Psi(\mathbf{W}h_i, \mathbf{W}h_j)$, where $\Psi : \mathbb{R}^{F'} \times \mathbb{R}^{F'} \rightarrow \mathbb{R}$ represents a shared attention mechanism responsible for determining the attention score s_{ij} of edge e in the factor graph by utilizing the features of nodes i and j as inputs. This mechanism is implemented as a single-layer perceptron. The attention score s_{ij} signifies the significance of node j with respect to node i. A score of 0 implies that other nodes do not influence this particular node.

All nodes can participate in the convolution process of node i, but we incorporates the graph structure using a masked attention mechanism. Specifically, only nodes j within the neighborhood $\mathcal{N}_i$ are utilized to the calculation for node i. In the algorithm setting , we set this neighborhood to be first-order, that is, the set of all points directly connected to node i.

The difference is that, GAT normalizes attention coefficients between adjacent nodes using the softmax function to facilitate comparison across nodes, whereas the model proposed in this study generates new factor graphs by directly computing edge coefficients. By setting a threshold, nodes i and j are deemed weakly connected if the scores of the edges between them fall below this threshold. Subsequently, the transformed features are utilized to calculate the ensuing factor coefficients:

$$E_{ije} = 1/(1 + \mathbf{e}^{-s_{ij}}). \tag{1}$$

In order to disentangle the graph into independent structures as much as possible, DTG4Power transforms the optimization problem into a graph classification problem by simply setting factor graph labels, aiming to approximate the solution. That is, different topological structures are generated by guiding factor graph generation through label differences. Therefore, the head is defined as the discriminator.

$$G_e = \text{Softmax}\left(f\Big(\mathit{Readout}\big(\mathcal{A}(\mathbf{E_e}, \mathbf{H})\big)\Big)\right), \tag{2}$$

where $\mathcal{A}$ is a three-layer graph autoencoder that utilizes the transformed feature $\mathbf{H}$ and the factor graph $\mathbf{E_e}$ as inputs to produce new node features. These features are then mapped to simple labels using a fully connected layer. The *Readout* function aggregates the node features in the graph through averaging, yielding a graph-level feature representation.

$$\mathcal{L}_d = -\frac{1}{n}\sum_{i}^{n}\big(\sum_{c=1}^{\kappa}\mathbb{I}_{e=c}\log(G_i^e[c])\big), \tag{3}$$

where κ represents the number of factor graphs, while n denotes the total number of training samples. Here, G_i^e signifies the distribution of sample i, with $G_i^e[c]$ indicating the probability associated with the label c for the generated factor graph. The function $\mathbb{I}_{e=c}$ serves as an indicator, taking the value of $\mathbb{I}$ when the predicted label is correct and 0 otherwise. Equation 3 involves computing the logarithm of the sum of probabilities of all factor graphs predicting correctly for a single sample, followed by determining the negative average of the logarithmic sum across all samples to derive the loss value generated in one training iteration.

Disentangled Graphs Representation. After completing the initial step of identifying the structure of the graph, the next task is to aggregate the features of the factor graph. This aggregation process occurs independently for each factor graph and aims to boost the expressive capabilities of the features. During aggregation, new node features are created by calculating the weighted sum of their neighboring nodes as follows:

$$z_i^{(l+1)e} = \sigma(\sum_{j\in\mathcal{N}_i} E_{ije}/c_{ij}v_j^{(l)}\mathbf{W}^{(l)}), c_{ij} = (|\mathcal{N}_i||\mathcal{N}_j|)^{1/2}, \tag{4}$$

where $z_i^{(l+1)e}$ represents the new feature of node i obtained by aggregating from factor graph e in layer $l+1$, and $\mathbf{W}^{(l)}$ is trainable parameter in the feature disentangled step. Different decoupled subgraphs are beneficial for explaining different types of feature subsets in the power grid, facilitating the discovery of critical local information on power grid faults. They possess a certain level of interpretability while eliminating redundant information, thereby enhancing the representational capacity of model.

Graph Merging. Finally, we merge the decoupled subgraphs to effectively represent the power grid fault lines for subsequent tasks. Finally, we merge the features derived from various factor graphs to effectively represent the power grid fault lines for subsequent tasks by applying:

$$z_i^{(l+1)} = \|_{e=1}^{\kappa} z_i^{(l+1)e}, \tag{5}$$

where $z_i^{(l+1)}$ is the output feature of node i; $\|$ denotes concatenation.

Fault Location Prediction

After a power grid failure, all buses will be impacted to different extents. It is not efficient to locate the fault position by equally utilizing all transmission lines features representation $\mathbf{Z} = \{z_1, z_2, \dots, z_m\}$ for fault location. Hence, upon obtaining the feature representation of all transmission lines, we utilize a self-attention mechanism to assign weights as Equation 6 to various nodes in the feature map, prioritizing the lines most affected by the fault.

$$\begin{aligned} z' &= \alpha * \mathit{Sigmoid}\big(\mathit{SelfAttention}(\mathbf{Z})\big), \\ \mathit{SelfAttention}(\mathbf{Z}) &= \mathit{Sigmoid}(\frac{\mathbf{Z}\mathbf{Z}^T}{\sqrt{d_k}}\mathbf{Z}). \end{aligned} \tag{6}$$

In this manner, we can automatically learn the importance of node features and fault locations, thus better reflecting the actual situation in the power network. At the same time, the computational cost of the self-attention mechanism is smaller, the training speed is faster, and it can better handle the fault location problem in large-scale power networks.

The overall framework loss is defined as:

$$\mathcal{L} = \mathcal{L}_d + \lambda * \mathcal{L}_{task}, \tag{7}$$

where $\mathcal{L}_d$ and $\mathcal{L}_{task}$ represent the disentangled layer loss and task loss, respectively. λ is the weight to balance these

	Fault Point Location					Fault Line Location				
	GCN	MLP	RF	KNN	**DGT4Power**	GCN	MLP	RF	KNN	**DGT4Power**
7-bus	0.967	0.998	0.937	0.883	**0.990**	0.534	1.000	1.000	1.000	**1.000**
36-bus	0.995	**0.998**	0.841	0.786	<u>0.996</u>	0.973	1.000	1.000	1.000	**1.000**
325-bus	0.884	0.975	0.706	0.214	**0.988**	0.792	0.776	1.000	0.782	**0.998**

Table 1: Accuracy comparison of different models on three scales of datasets. The data presented in bold denotes the highest accuracy, whereas the underlined data signifies the second highest accuracy.

two losses. Specially, for fault line location, we consider it as a graph classification task, using cross-entropy loss. In contrast, fault point location is a numerical value ranging from 1 to 99, which we consider as a regression task and use Mean Square Error loss.

Experiment

To demonstrate the effectiveness of the proposed method, case studies are conducted based on the 7-bus system, 36-bus system and a real 325-bus system using the PSASP simulation. In this section, the scenario generation methods are first introduced, and the detailed parameter setting of our method is provided. Then the comparison results, ablation study and visualization analysis are reported to evaluate the performance of the proposed method.

Data Description

The dataset utilized in this study is derived from real data and generated through fault simulation using PSASP (Zhongxi and Xiaoxin 1998). It is constructed by incorporating various elements such as different numbers of nodes, branch connection scenarios, fault lines, and types of faults. The dataset includes three sizes: two small power systems composed of 7 and 36 buses, and a real regional power system in China composed of 325 buses. The power systems with 7 and 36 buses operate under a single scenario without changing the topology, while the dataset with 325 buses includes three different branch connection scenarios, establishing 417, 412, and 406 lines respectively.

In addition, each fault line generates power system state data under four fault types, including single-phase short circuit(Single-SC), two-phase short circuit(Two-SC), two-phase-to-ground(Two-TG), and three-phase-to-ground(Three-TG). With a minimum experimental sample size of 1000 lines per category unit, all sample data were classified into a total of 144 categories, amounting to 144,000 samples based on the combination of node count, generation method, faulty line, and fault type.

Compared Methods and Parameter Settings

The experiment employed a batch size of 16 and a learning rate of 1e-3, ensuring the convergence of all models within 300 epochs. The training process utilized the Adam optimizer and cross-entropy for task loss calculation. The model architecture comprises five layers: a decoupling layer, a batch normalization layer, a fully connected layer, and the predicted output is generated through joint training with the mapping layer.

Fault Location Performance

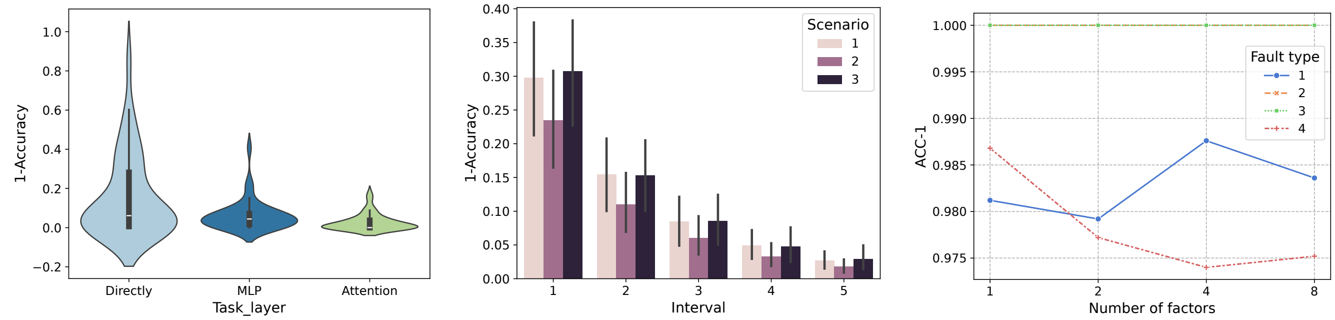
Comparison with Baselines. To compare with our method, we adopt K-Nearest Neighbors (KNN) (Cover and Hart 1967), Random Forest (Breiman 2001), Multi-Layer Perceptron (MLP) (von der Malsburg 1986) and Graph Convolutional Network (GCN) (Kipf and Welling 2016) as baseline models. Among these baselines, both MLP and GCN share the same network architecture as our approach, enabling them to learn the structural information inherent in the datasets. We define the actual fault location using labels ranging from 1 to 100. Specifically, a prediction is considered to be correct within the error range of 5%.

In contrast to previous methods (Zhang et al. 2024; Vaish et al. 2021) that could only locate fault lines or points individually, DTG4Power demonstrates superior performance in fault line and fault point localization, as illustrated in the Table 1. The DTG4Power method consistently demonstrates superior accuracy in detecting four distinct fault types. Among the compared methods, MLP shows strong performance, followed by RF and GCN, while the KNN method exhibits the lowest effectiveness.

Experimental evaluations on fault location in various networks were conducted, where 4, 8, and 10 fault lines were classified, respectively, each corresponding to 1000 samples. The results presented in the final column of Table 1 demonstrate the high performance of our model, achieving an accuracy close to 1.0 in the fault line recognition task.

Performance on Different Scales of Power System. To verify the scalability of the proposed method in power systems of different scales, we first simulated two small-scale systems, including a 7-bus and a 36-bus system, and then we applied a large 325-bus system from a real project scenario in China. The performance of power systems of different scales is shown in the Table 1.

To the best of our knowledge, most power grid research utilizes datasets with fewer than 100 nodes (Thomas et al. 2023; Wang et al. 2024c), while the 325-bus configuration used in our experiments represents one of the largest scales among existing studies. For larger scales, experimental validation is often constrained by data availability and the practical needs of fault localization. Large-scale, widespread faults are rare due to the inherent stability mechanisms within power grids, which typically necessitate fault localization at the regional level. Furthermore, very large-scale



(a) Performance of fault location for different task layers.

(b) Performance of fault location for different interval under different scenarios.

(c) The effect on the number of factors.

Figure 2: Ablation and sensitivity results for fault location.

grid data is often restricted due to confidentiality concerns, which limits opportunities for standardized testing.

Performance on Multiple Fault Types. Power system faults in transmission lines can be classified into many types based on the phase and nature of occurrence. The most common (70%) and least severe type of fault is single-phase-to-ground fault, while the least common (5%) and most severe is three-phase fault (Stefanidou-Voziki et al. 2022). This article divides faults into four different severity levels, and the performance of DTG4Power single branches and all branches under different fault types is shown in the Table 2.

Notably, lines with fault on two-phase exhibit easy-to-learn features under different scenarios, with model prediction accuracy achieving 1.0 within a 5% error range. Fault types on single-phase and three-phase also achieves high performance, with average accuracies above 0.9. Therefore, our method remains applicable in power system with different topological structures formed under various scenarios.

Performance on Multiple Connection Scenarios of Branches. The operation of the power system is influenced by a variety of factors. Adjustments to the network configuration, which pertains to the topological connections within the power system, are essential for minimizing losses and balancing loads. To evaluate the effectiveness of the proposed model under different network topologies, three distinct scenarios (Scenario 1, Scenario 2, and Scenario 3) were developed based on the 325-bus system by altering the open and closed states of select motors and loads. As illustrated in Figure 2, DTG4Power demonstrates fault location accuracy exceeding 90% across different scenarios, indicating robust performance under diverse network configurations.

Ablation and Sensitivity Analysis

Separate and Mixed Training Approaches for Fault Location. This section investigates the impact of hybrid lines on model performance. Previous experiments categorized fault location datasets according to scales, scenarios, fault lines, and types. However, in practical applications, the utilization of training resources and storage costs make it nearly unfeasible to train separate models for each line, especially in large-scale power systems. Therefore, training on hybrid fault lines is of considerable practical importance.

	Separate			Mixed		
	S-1	S-2	S-3	S-1	S-2	S-3
Single-SC	0.944	0.970	0.927	0.988	0.988	0.974
Two-SC	1.000	1.000	1.000	1.000	1.000	1.000
Two-TG	1.000	1.000	1.000	1.000	1.000	1.000
Three-TG	0.934	0.960	0.956	0.974	0.988	0.982

Table 2: The performance of separate and mixed training approaches for fault location under different scenarios and various fault types in the 325-bus power system. S-1, S-2, and S-3 represent different scenarios.

We merge datasets from different lines of the power system and randomly shuffle and regenerate labels for training. To explore whether learning the features of other fault lines can improve the model's performance, we compare the average accuracy of the model trained on mixed lines with the model trained separately for predicting lines. The experimental results are shown in Table 2.

According to the data presented in the table, the model trained on mixed fault line outperforms the models trained solely on individual fault lines. This improvement may be attributed to the similarity of data features associated with the same fault types, which enhances the model's ability to extract robust feature representations. This experiment highlights two key advantages of training on mixed fault lines: it reduces training resource costs and model storage requirements, making the training process more practical, and enhances model performance, leading to higher accuracy in predicting fault locations.

The impact of different mapping methods. We evaluated three algorithms for mapping graph networks to fault locations to compare their performance. The first method directly extracts the features of the known faulty lines for mapping. The second method utilizes a fully connected network to map all node features to a one-dimensional fault location. The third method employs a self-attention mechanism to achieve a similar mapping. The network parameters

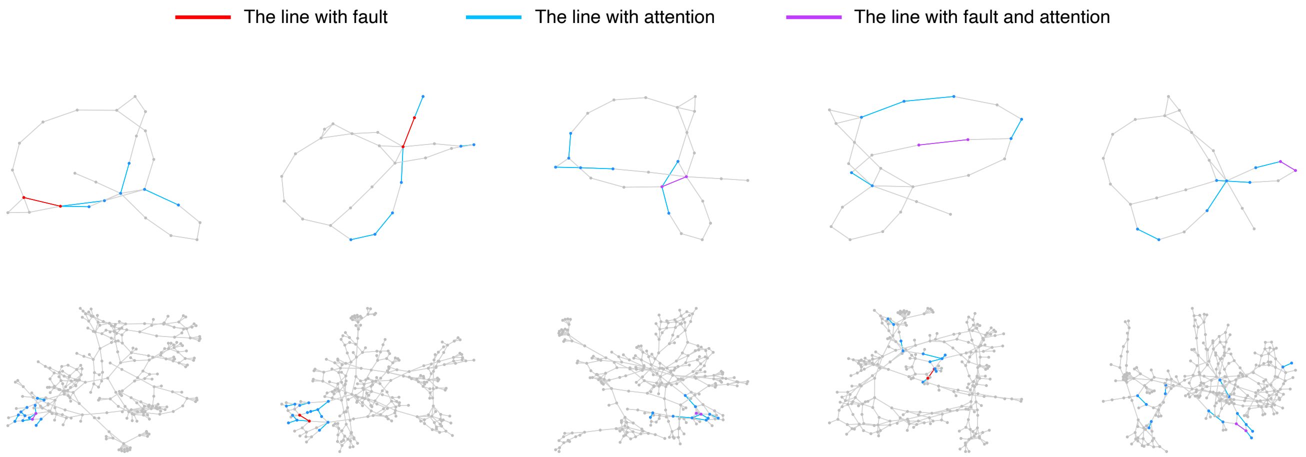


Figure 3: Attention to different topologies when a fault occur on the line. The figures in the first and second rows represent a 36-bus and a 325-bus power system, respectively.

for the latter two methods require joint training with the feature disentangled model. All three methods use the sigmoid activation function for the final transformation. The results are shown in Figure 2(a).

It is evident that the error values from the attention mapping are more concentrated around 0 compared to MLP, whereas the errors under direct mapping are more widely dispersed. In other words, compared to networks employing direct mapping, those utilizing fully connected mappings and self-attention mechanisms demonstrate significantly higher average accuracy in predicting fault locations. This can be attributed to the capability of fully connected layers and self-attention mechanisms to incorporate and effectively learn data features from other lines, in contrast to the direct mapping approach, which relies solely on the features of faulty lines. The integration of features from other lines not only aligns with the intuition that a fault on one line can impact the entire power network but also has been empirically validated to enhance the ability of the DTG4Power model to learn the structural features of the power system more effectively.

Sensitity Analysis. Figure 2(b) illustrates the fault location performance across various intervals under different scenarios. As the error interval widens, the accuracies of the three scenarios also improve, and the distribution of accuracy values becomes more concentrated. The number of factors represents a crucial parameter in the model. As illustrated in Figure 2(c), variations in the number of factors impact the accuracy of datasets associated with fault types 1 and 4. Consequently, in practical applications, it is advisable to adjust the number of factors according to the specific features of the data to obtain optimal experimental outcomes.

Visualization Analysis

In the implementation of the algorithm, the final layer of the DTG4Power architecture maps feature graphs to fault locations using a self-attention layer, where the self-attention parameters represent the attention. Thus, these parameters can be analyzed to explore the relationship between the edges and fault locations of the power system.

We denote faulty lines using red lines, high-attention lines with blue lines, and both faulty and high-attention with purple lines. The remaining unimportant lines are in gray. As shown in Figure 3, the results reveal that high-attention lines mostly cluster around the faulty lines, while the faulty lines themselves are not necessarily classified as high-attention lines. This finding partially explains why the model's final mapping needs to incorporate features from other lines rather than directly extracting features from the faulty lines.

Conclusion

In this paper, we introduce a novel method, termed DTG4Power, which enables the accurate localization of coarse-grained fault lines and fine-grained fault points within the power system. This method is based on interpretable disentangled graphs derived from measurement data recorded in tables. The proposed approach fully utilizes existing prior knowledge to translate transmission line measurement data into graph data. Subsequently, disentangling is employed to achieve a more effective representation of the lines. Moreover, at the task level, precise fault localization is accomplished by varying degrees of attention directed toward the transmission lines. We validated DTG4Power on the IEEE 7-bus system, the IEEE 36-bus system, and a real regional power system in China, demonstrating its superior performance in localizing both fault lines and fault points. Our work is limited by the scarcity of real data. In the future, we will consider reducing the impact of noisy data on models by introducing awareness of uncertainty (Chen, Gao, and Xu 2024; Tao, Dong, and Xu 2023), as well as exploring the spatiotemporal information of existing fault data further through spatiotemporal graph neural networks (Zheng et al. 2023, 2022; Wang et al. 2024a,b).

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