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Malfunction Diagnosis of Microgrid Devices Based on Optimized Graph Neural Network

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Abstract

Malfunction diagnosis based on deep learning ensures the stable operation of microgrid. However, the microgrid system with new energy access appears to be increasingly complex and changeable, and its frequently changing topology brings challenges to the training of traditional neural network models. A method for malfunction diagnosis of microgrid devices based on optimized Graph Neural Network is proposed in the paper. Firstly, data reconstruction is completed through the mapping of nodes, edges and graphs in order to standardize changeable data. Secondly, abnormal data is processed to improve the quality of database. In that way, device misoperation caused by extreme data loss can be avoided, thus improving the training efficiency. Then, aiming at fully capturing the characteristics of time and space dimensions of data at different latitudes, the graph-convolution network under Multi-head Attention mechanism is adopted in the process. Finally, a microgrid simulation model is built to prove that the proposed scheme has the advantages of good robustness, strong adaptability, high reliability and accurate diagnosis.

Keywords: Graph neural network; Malfunction diagnosis; Data repairing; Multi-head attention

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1. Introduction

With the proportion of new energy in power system growing, the multi-energy microgrid system has been developed vigorously over the last few years. Its high flexibility and reliability can reduce the impact of fluctuating clean energy and ensure the safe and stable operation of the power system [1]. And its own cleaning characteristics can also reduce carbon emissions and environmental pollution. However, in engineering practice, the diversity of energy and the increasing complexity of network structure pose threat to the operation of microgrid devices [2-3].

Malfunction monitoring and diagnosis of devices are the necessary guarantees for the proper functioning of microgrid devices. The traditional method used to monitor the operation of industrial devices directly through external electronic instruments and meters to analyze and judge whether there is a malfunction, and at the same time determine the location, type and cause of the malfunction by technical means [4]. Specifically, signals such as current, voltage, sound wave are collected and processed to complete signal filtering and feature engineering. The features are constructed, extracted and selected by time domain, frequency domain or time-frequency analysis [5-6]. Then mathematical analysis and malfunction diagnosis are carried out [7]. This method, with poor robustness, requires high signal processing ability, finding itself hard to be applicable to the flexible new energy microgrid system [8].

With the rapid development of artificial intelligence, combining deep learning with malfunction diagnosis has become a hot research topic at home and abroad. Taking neural network as an example, deep learning has strong data mining and feature learning capabilities, and can capture the highly abstract internal features and external correlation of signals, which has great potential in the field of malfunction diagnosis of complex microgrid devices [9-10]. Thesis [11] propose a convolution neural network diagnosis model based on random diagonal algorithm training, which can deal with single

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or composite faults. Thesis [12] combines discrete wavelet transform and convolution neural network to better capture the characteristics of discrete waveform data. Thesis [13] uses the correlation between the time series data of non-stationary signals to add a Distribute Layer to the one-dimensional convolution neural network, so that it can learn deeper features. Thesis [14] proposes a fault diagnosis method of multi-channel one-dimensional convolution neural network. The advantage of this method is that the network model can effectively fuse multi-channel signals and achieve key feature extraction, and connect SDAE after the full connection layer to reduce dimension and further extract features, so as to improve the fault tolerance and diagnosis accuracy of the model.

Yet in practical engineering, microgrid may frequently change its topology, data structure and internal correlation according to the changes of user load and the actual needs of peak and frequency regulation. Due to the complexity and variability of microgrid, the traditional deep learning model can not be directly applied, and structural optimization is in need. Considering the flexibility and variability of Graph Neural Network (GNN) model for topological structure, this paper proposes a neural network structure based on optimized GNN. Firstly, the devices of microgrid are mapped as nodes, the connection of different devices as edges and the microgird topological structures as graphs to reconstruct the dataset. Then abnormal data prediction, repairing and locking are added to improve data quality and avoid misoperation of devices. The multi-head self-attention mechanism is integrated to capture the time and space feature information respectively, so as to improve the accuracy of malfunction identification. Finally, through the simulation experiment, it is proved that the scheme can improve the robustness and reliability of malfunction diagnosis.

2. Basic Theory of GNN and Microgrid Topology Structure

2.1 Graph Neural Network Theory

With the rapid development of computing resources and the acquisition of massive training data, it has been proved by scholars that it is effective to extract potential features from European spatial data by using deep learning algorithm. The rise and successful application of neural network has also greatly promoted pattern recognition and data mining. The traditional method of information processing and feature extraction based on artificial experience has been replaced by various end-to-end artificial intelligence models (such as Convolutional Neural Networks (CNN), Recurrent Neural Network (RNN), etc.). Among them, GNN is able to directly learn the frame of graph structure data. Regarding complex and changeable data, we only need to define the expressions and internal relations of nodes and edges from the data space characteristics, so as to ensure the unity and regularity of network computing. This method can effectively capture the interdependence between data samples without being affected by the irregular data structure. With a high receptive field, it can meet the requirements of tasks such as classification and prediction.

To further explain the point, a GN block is taken as an example. It is a graph-to-graph module. We input a graph, and after the calculation of GNN is completed, a graph is output. (Note that the graph mentioned here refers to a data set with a graph structure, not specifically a picture). A graph can be defined as a triplet $\mathrm{G} = (u, V, E)$. Where u denotes the general representation of the graph, V and E represent all the node sets and all the edge sets. In the edge set E, a pair of nodes u and v are connected, indicating that the two nodes are related as $E_i = (u, v)$. If the reaction is symmetrical, the relationship is undirected. If the reaction is asymmetric, their relationship should be directed. In microgrid, because the current flow is directional, the edges in the graph are directional. Each Block contains three update functions ϕ and three aggregate functions ρ . The update function updates the data of each edge, each node and the whole graph respectively. The aggregate function integrates and processes the input data respectively. The calculation formula is as follows.

$$\mathrm{H}^{l+1} = \sigma((D+I)^{-0.5}(A+I)(D+I)^{-0.5}H^{l}W^{l}) \qquad (1)$$

Where, H^{l} stands for the l-th layer of the network. For nonlinear activation function σ , ReLu is used here. D , A , I represent a degree metrix, an adjaceny matrix and an identity matrix respecively. The W^{l} is the weight of the network layer.

2.2 Microgrid Topology Structure

Due to the access of new energy sources, the structure of microgrid is becoming more and more complicated. In order to fix the fluctuation of photovoltaic and wind energy and ensure the stability of system voltage and frequency, microgrid have to adjust its topology frequently. In the system, each device can be regarded as a node with a large amount of data. Different devices are not independent of each other, and the correlation is constantly changing according to different topological structures. Therefore, this microgrid model with frequent structural changes is suitable for data mining based on GNN. Fig. 1 shows a mapping diagram of a simple microgrid topology in GNN.

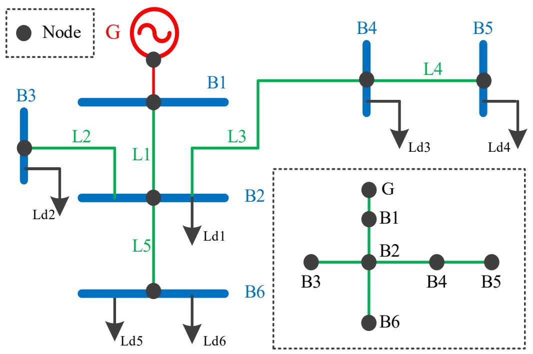

Fig. 1. Mapping diagram of a simple microgrid topology in GNN

The simple microgrid model structure of IEEE 7 nodes is shown in Fig. 1. It consists of six buses (B1-B6), one generator (G), six load points (Ld1-Ld6) and five transmission lines (L1-L5). According to the definition of GNN, the topological structure can be mapped into a graph structure with 7 nodes and 6 edges. Each point represents different types of data sets that can be collected at the location, and the edge symbolizes the directed correlation between nodes. Let geneartor G be Node 0 and buses B1-B6 be Node 1-6, and the related adjacency matrix can be calculated as follows. Note that the topology is a single power supply structure, and the current direction is unidirectional and fixed. In the system with multi-energy structure, the current is generally bidirectional.

$$A=\begin{pmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \tag{2}$$

2.3 Malfunction Diagnosis of Devices

Microgrid devices mainly refer to new energy generator sets, power transformers, buses, transmission lines, circuit breakers and other power devices. The malfunction diagnosis is a comprehensive method of whether the device has internal malfunctions such as overheating and abnormal voltage, and whether the outlet side has external malfunctions such as short circuit or disconnection faults through sensor signals. Due to the scarcity of faults, in order to achieve sufficient data mining and model training, it is necessary to increase the proportion of fault data in the database. In the experiment, the overall fault data accounts for 50% of the total data. And the proportion between different faults should be reasonably set based on actual engineering data statistics. The specific results are shown in Table 1.

Table 1. Classification of malfunctions

Malfunction type (Proportion)	Classification (Proportion)	Malfunction type (Proportion)	Classification (Proportion)
Internal malfunctions (15%)	Overheating (5%)	External malfunctions (35%)	Single phase Short circuit (11%)
	Overvoltage (4%)		Phase-phase Short circuit (7%)
	Undervoltage (2%)		Three-phase Short circuit (12%)
	Overfrequency (2%)		Single phase Disconnection (2%)
	Underfrequency (2%)		Three-phase Disconnection (3%)

As can be seen from the Table, malfunction types of electrical devices are varied. To evaluate the prediction accuracy of deep learning model, this paper adopts the formulas of Accuracy and Weight F1. The calculation formula of Accuracy is shown below.

$$Accu=\frac{\mathrm{TP+TN}}{TP+TN+FP+FN} \tag{3}$$

Where, TP shows the number of samples that are actually positive and judged as positive by the classifier. TN is indicated as the number of samples that are actually negative and judged to be negative. FP means the number of samples that are actually negative and judged to be positive, while FN signifies the number of samples that are actually positive and judged to be negative. The accuracy of prediction can be quantitatively judged by Accu by this means.

However, the above methods do not take the weight between different types of sample data into consideration. For example, the frequency of short circuit malfunction is much higher than that of disconnection malfunction. Therefore, in the training process, even if the prediction accuracy of the model is very high, the prediction rate may be far less than expected in the disconnection malfunction. Using this model, when the external disconnection malfunction occurs, the diagnosis scheme obviously cannot correctly judge, which leads to the failure of device protection processing. To handle the problem of unbalanced samples and realize accurate judgment, weight F1 algorithm is added as a supplement to the model, as shown below.

$$\mathrm{P}_w=\frac{\sum_{i=1}^{L}\frac{TP_i}{TP_i+FP_i}*w_i}{L} \tag{4}$$

$$\mathrm{R}_w=\frac{\sum_{i=1}^{L}\frac{TP_i}{TP_i+FN_i}*w_i}{L} \tag{5}$$

$$\text{scores}=\frac{2*P_w*R_w}{P_w+R_w} \tag{6}$$

Where, P_w denotes Precision. The higher the accuracy, the higher the probability that the classifier predicts positive samples, indicating that the model has strong ability to distinguish negative samples. R_w means Recall. The higher the recall rate, the stronger the ability to distinguish positive samples. W_i stands for the weight coefficient, used to balance sample data.

3. Optimal GNN Malfunction Diagnosis Model

3.1 Pipeline of Proposed Model

The paper proposes an optimized GNN model to further improve the efficiency of malfunction diagnosis of electrical device in microgrid for the purpose of ensuring the proper functioning of the system. In the figure, the main framework of the model consists of data processing, graph neural convolution, attention mechanism and other modules. The data processing module mainly standardizes the collected data. For possible abnormal data, operations such as abnormal identification, repair and locking are carried out to ensure the quality of the data set. Graph neural convolution module is the main calculation module, which performs space-time convolution calculation on the reconstructed data, extracts hidden features and completes malfunction prediction. Because the length of data sequence is often long, feature loss may occur in the convolution process. Therefore, self-attention mechanism is applied. The receptive field is concentrated in the area with high correlation to improve the working efficiency of the model. The specific model pipeline is shown in the Fig. 2.

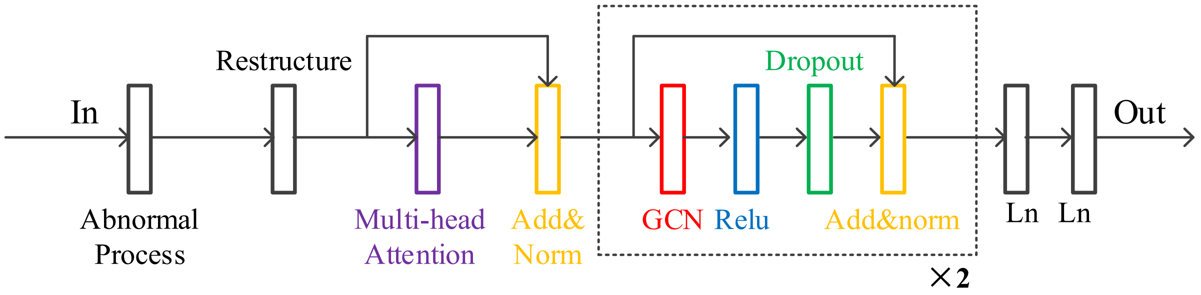

Fig. 2. Pipeline of the proposed model

Here, we utilized the LSTM structure in the Abnormal Process stage. Multiple head attention mechanism and graph convolutional network structure were used in the diagnostic process. These methods achieve spatiotemporal fusion of data and improve the accuracy of diagnosis. At LSTM, we process multidimensional feature data and concatenate the features of each scale in the channel dimension through concatenation, achieving spatial fusion. The input data features are $X \in \mathbb{R}^{N\times L\times F}$, where N is the number of different data features, L is the data length, and F is the data dimension. After completing feature integration, perform convolution analysis using a graph convolution model. And incorporate attention mechanism to automatically learn the importance weights of different feature scales, and achieve attention focusing, thereby improving the accuracy of fault diagnosis.

3.2 Abnormal data prediction, repairing and locking

The input data of the model include voltage, current, frequency, power, power factor, power flow direction, harmonics, device temperature, sound wave and so on. Different data types have different units of measurement. In this model, the feature of data is extracted by graph convolution, and the spatial relationship between different features is analyzed. Different measurement methods will bring errors to the analysis results, so it is necessary to standardize the data. This paper adopts Z-Score standardization method and the formula is as below.

$$\mathrm{X}_{\mathrm{new}} = \frac{\mathrm{X} - \mathrm{X}_{\mathrm{mean}}}{X_{\mathrm{std}}} \tag{7}$$

Where, X stands for the raw data. $\mathrm{X}_{\mathrm{mean}}$ and $\mathrm{X}_{\mathrm{std}}$ are the mean and standard deviation of data X. $\mathrm{X}_{\mathrm{new}}$ represents the data after standardization. This method conducts standardized based on the mean and standard deviation of the original data. The processed data shows normal distribution with a mean of 0 and a variance of 1.

In addition, affected by the factors such as reliability of hardware of microgrid acquisition system, there may be some abnormal points or data loss in the data set. These data anomalies may not only influence the prediction accuracy during model training, but also lead to malfunction misjudgment during testing, which will lead to device misoperation. So it is necessary to identify and handle the outliers in data sets.

Therefore, this paper puts forward a step of abnormal data prediction, repair and locking. Firstly, according to the historical data before this sampling period, the expected data sequence is obtained by LSTM neural network for data prediction. Then compared with the sampled data, the data is identified by three key parameters: allowable error, maximum threshold and minimum threshold. If judged as normal data, there is no need to process it. If judged to be abnormal with a small amount of discontinuous data, the data will be repaired and the abnormal data will be replaced by the predicted data. If judged to be abnormal with large and continuous data points, a locking signal is issued. These abnormal data will affect the accuracy of malfunction diagnosis. Once the electrical device receives the wrong judgment and sends out misoperation actions, the power grid will be damaged severely. Therefore, it is essential to lock the malfunction diagnosis algorithm to ensure the safe and stable operation of the power system. The logic diagram of this step is shown in the Fig. 3.

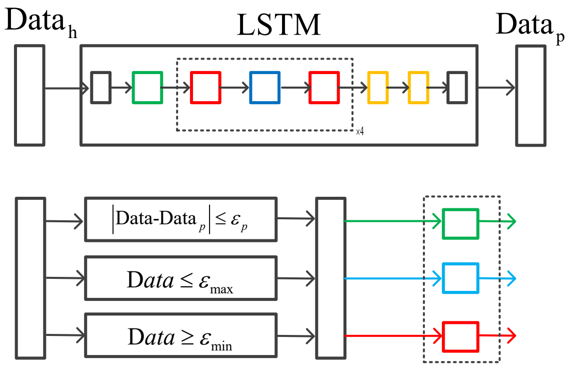

Fig. 3. Diagram of data prediction, repairing and locking

4. Simulation Analysis

Based on a 110kV microgrid model, this paper carries out data acquisition and simulation analysis on a computer with NVIDIA Tesla V100 processor and 32GB of memory. Under the framework of pytorch, the program is written in python language.

4.1 Parameter Setting and Performance Analysis

In order to verify the effectiveness of the proposed scheme, this paper sets different parameters such as model depth, learning rate, training batch, iteration number, neuron loss rate and pooling function to optimize the model. According to the training efficiency, accuracy and memory occupation, the optimal hyper-parameter is determined as shown in Table 2.

Table 2. Hyper-Parameter Setting

Depth of model	3	Training batch	64
Learning rate	0.001	Iteration number	10K
Neuron drop rate	0.2	Activation function	ReLu
Pooling function	Max	Connection layer parameters	(1,128)

In the training process, all data samples are divided into training set, validation set and test set according to 8:1:1. All data need to be scrambled and standardized before being input into the model. Malfunctions are classified into F1-F10 in sequence, and the failure-free condition is set to F0. Altogether there are 11 cases. It should be pointed out that due to the chain reaction when faults occur, external malfunctions may lead to internal ones, and single-phase short-circuit faults may also expand into three-phase short-circuit faults. Therefore, the same batch of data may correspond to multiple fault types, that is, fault types may be repeated.

To verify the effectiveness of this experiment in automatic feature selection, this paper adopts the Shapley Additive explanations method. This is a game theory based approach that calculates the contribution of each feature to the model output, helping us gain a deeper understanding of the model's predictive accuracy and the interactions between features. The specific method is to calculate the difference in predicted output for each feature, including and excluding that feature. These differences reflect the degree of influence of features on model predictions. On the basis of feature selection, we also added key features such as voltage fluctuations, current fluctuations, and other data features to complete the importance analysis. The specific results are shown in the table below. It can be seen that in the original features, current and voltage have the highest importance. And based on these two parameters, analyze the characteristics of voltage fluctuations and current fluctuations within a certain time window, and see that their impact is further improved. That is to say, using selected features as model inputs can improve data utilization and model computational efficiency. The results are shown in Table 3.

Table 3. Numerical analysis of SHAP with different features

Original Features	SHAP	Select Features	SHAP
Current	+0.61	Current	+0.61
Voltage	+0.68	Voltage	+0.68
Frequency	+0.11	Current Fluctuation	+0.83
Temperature	+0.14	Voltage Fluctuation	+0.91
Active Power	+0.31		
Reactive Power	+0.11		
Power Factor	+0.24		

After completing the parameter setting, the model trained and tested the data with 1000 epochs, and the specific loss results are shown in Fig 4. It can be seen that this model achieves the best training effect at 400 epochs. In addition, cluster the data sources, as shown in Fig 5. It can be seen that this model can successfully distinguish different types of data, which also verifies the effectiveness of the model.

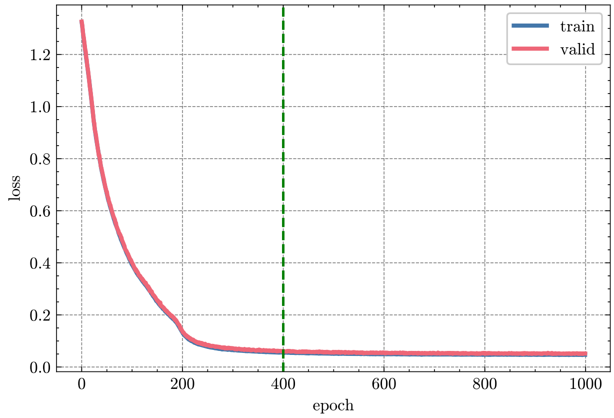

Fig. 4. Loss diagram of model training and validation process

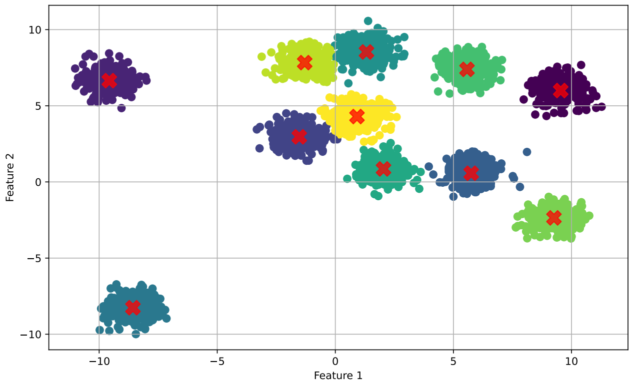

Fig. 5. Clustering diagram of different types of data

4.2 Results Comparison

To ensure the fairness of malfunction diagnosis and evaluation, random seeds are used to in model training. By training multiple seeds, average value can be obtained, achieving the reliability of evaluation. In this paper, three benchmark models, Deep Neural Network(DNN), Long Short Term Memory network(LSTM) and the Vanilla GNN (GNN-V) are selected as tools of comparative experiments to verify the superiority of the proposed scheme in malfunction diagnosis. GNN-O is the proposed optimized model. The specific results are shown in the following Table 4.

Table 4. Diagnostic results of different models. The best results are highlighted in bold with an underline.

Model	Accu	F1-scores
DNN	73.91%	74.49%
LSTM	78.69%	79.02%
GNN-V	86.23%	86.43%
GNN-O	**92.61%**	**92.57%**

The table shows the advantages of GNN graph neural network algorithm. The GNN-O method we proposed has the best diagnostic results, which is better than the Vanilla GNN method. Due to the different data structures, the frequency of faults in the device is much lower than that outside the device, and the disconnection fault is also lower than the short circuit fault. Therefore, the correct rate of malfunction diagnosis in different fault types is not the same. After training, we get the picture as shown in Fig 6.

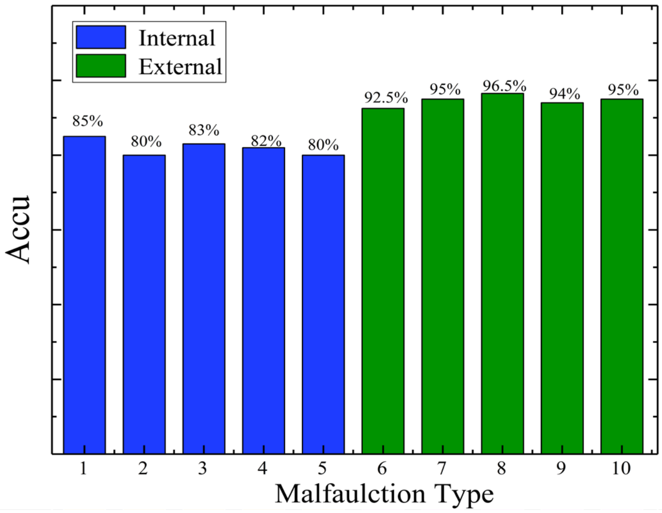

Fig. 6. Comparison diagram of different types of fault diagnosis accuracy

It can be seen from the figure that different types of malfunction diagnosis is charactericed by high recognition rate. The prediction accuracy of external faults of the system is slightly higher than that of internal faults of the device. This is because the variation features of the current and voltage for external faults are easier to identify.

In order to further improve the visualization of model fault diagnosis, this paper randomly selected four sets of data for input and output display. As shown in Fig 7, ithis model can correctly identify the fault type for the input current and voltage signals, and has high reliability.

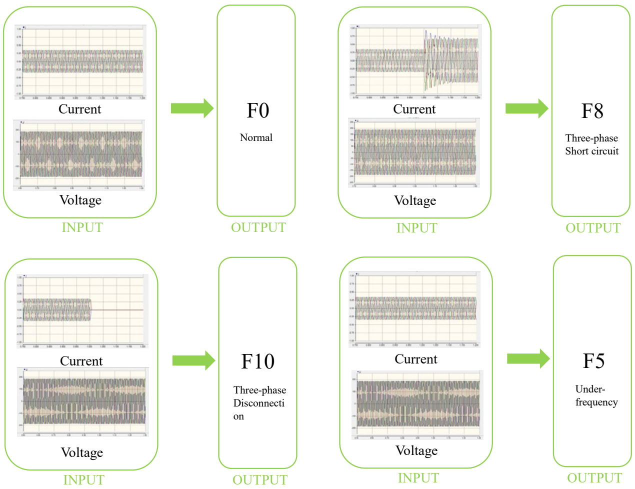

Fig. 7. Model input-output diagrams under different types of faults

4.3 Robustness Analysis

The topology of microgrid with the access of new energy is changeable, which brings challenges to the malfunction diagnosis of traditional models. GNN reconstructs the data of nodes, edges and graphs, and inputs the directed correlation of different data points into the model as the key features, which improves the robustness of diagnosis. For the purpose of testing the adaptability of the model, we adjust the model structure, randomly disconnect specific branches, and simulate the tripping of circuit breaker and topology adjustment of microgrid branches. The diagnostic accuracy can be obtained by testing the trained models respectively as shown in the following Table 5.

Table 5. Diagnostic results of different topologies. The best results are highlighted in bold with an underline

Model	Nodes	Edges	Accu	F1-scores
Topology_1	34	45	92.61%	92.57%
Topology_2	34	48	92.48%	92.51%
Topology_3	22	28	**94.41%**	**94.23%**
Topology_4	22	31	94.02%	93.89%
Topology_5	41	52	90.37%	90.26%
Topology_6	41	55	90.15%	90.01%

It can be noticed that the prediction accuracy achieves nearly 92%, taking the classic 34-bus microgrid topology as an example. When changing the topology by adding or reducing nodes or edges, we can find that the increase in the number will lead to a decline in accuracy. Although the diagnosis accuracy decreases when the structure of the topology becomes more complex, the general accuracy can be maintained more than 90%, which is an ideal result.

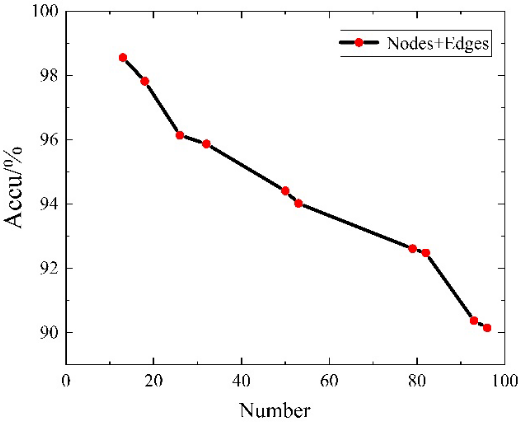

Fig. 8. Comparison diagram of diagnosis accuracy in topologies with different number of nodes and edges

The Fig 8 can be obtained through experiments to compare the performance of different models of topological change. This figure shows the average prediction accuracy under different topological changes of the model. It is also proved that when the number of graph nodes+edges increases, the prediction performance of the model also decreases.

In addition, according to experience, microgrid malfunctions are generally external ones, especially short-circuit faults. And the initial phase angle and grounding resistance of fault point for short circuit are always different. In order to further verify the robustness of the model, the initial phase angle is set to [0,60,120,180] and the grounding resistance is set to [0,1,100,1000] on the simulation model. The diagnostic accuracy of the graph model is tested respectively, and the Table 6 is shown as follows.

Table 6. Diagnostic results of different types of ground faults. The best results are highlighted in bold with an underline

GNN-O	Resistance/Ohm			
	0	1	100	1000

Angle	0°	91.5%	90.5%	87.8%	87.2%
	60°	**91.7%**	90.3%	88.1%	87.6%
	120°	90.7%	90.5%	86.6%	86.9%
	180°	91.0%	89.9%	88.2%	88.3%

It can be seen from the table that the existence of grounding impedance will affect the accuracy of prediction. Especially at high impedance, the prediction accuracy will be significantly reduced. This may be because the current change is not obvious and the feature recognition is difficult when the high impedance is grounded. However, the impact of short circuit phase is relatively insignificant, and it can be defaulted that it will not affect the prediction accuracy.

In addition, different load intensities can actually affect the accuracy of fault diagnosis. On the one hand, load changes may cause normal states to be misjudged as faults, increasing false alarm rates and reducing diagnostic reliability. On the other hand, under different load conditions, diagnostic models may not be able to adapt effectively and have more uncertainty. Therefore, experiments were conducted on fault diagnosis under different load intensities and load fluctuations. The results are shown in the table below.

Table 7. Accurate model recognition under different load conditions

Load	Accu	F1-scores
L- L -L	93.78%	93.61%
M- M -M	92.56%	92.74%
H- H -H	94.62%	94.51%
L- M -H	92.18%	91.89%
H- L -H	91.94%	91.31%
L- H -L	91.65%	91.81%

In the table, L represents Light Load, M represents Middle Load, and H represents Heavy Load. It can be seen that in the first three experiments, the load did not change. The overall diagnostic accuracy is around 93%, achieving the best results. In the following three experiments, the load fluctuated under different conditions. It can be seen that the fluctuation of the load does indeed reduce the diagnostic accuracy by about 1%, but it is still a good effect.

5. Conclusion

In view of the problem that the topological structure of the new microgrid model with multi-energy coupling is changeable, and it is difficult for traditional methods to train a large number of non-standard data, this paper proposes a malfunction diagnosis method for microgrid based on improved GNN.

Firstly, the nodes, edges and graphs of data are reconstructed to ensure the unified interface of all data, which makes it possible for large-scale data training. Then the data is processed to identify the abnormal data caused by human error or device failure. By repairing a small amount of abnormal data, and locking a large number of abnormal data, the data quality and the system stability are ensured without malfunction. After that the malfunction prediction of GNN is carried out, integrated with multi-head self-attention mechanism and convolution module. The characteristics of spatio-temporal data in different dimensions are captured to improve the prediction accuracy. Finally, the microgrid modeling and simulation are completed, and the experiments verify the robustness and effectiveness of the proposed model for malfunction diagnosis.

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