

Power Grid Fault Diagnosis Based on Deep Pyramid Convolutional Neural Network

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Abstract—Existing power grid fault diagnosis methods rely on manual experience to design diagnosis models, lack the ability to extract fault knowledge, and are difficult to adapt to complex and changeable engineering sites. Considering this situation, this paper proposes a power grid fault diagnosis method based on a deep pyramid convolutional neural network for the alarm information set. This approach uses the deep feature extraction ability of the network to extract fault feature knowledge from alarm information texts and achieve end-to-end fault classification and fault device identification. First, a deep pyramid convolutional neural network model for extracting the overall characteristics of fault events is constructed to identify fault types. Second, a deep pyramidal convolutional neural network model for alarm information text is constructed, the text description characteristics associated with alarm information texts are extracted, the key information corresponding to faults in the alarm information set is identified, and suspicious faulty devices are selected. Then, a fault device identification strategy that integrates fault-type and time sequence priorities is proposed to identify faulty devices. Finally, the actual fault cases and the fault cases generated by the simulation are studied, and the results verify the effectiveness and practicability of the method presented in this paper.

Index Terms—Alarm information, deep pyramid convolutional neural network, fault classification, fault device identification, feature extraction, key information.

I. INTRODUCTION

FAST and accurate power grid fault diagnosis plays an important role in accelerating the processes of accident management and system recovery and ensures the safe and stable operation of the power system. With the continuous expansion of the scale of the power grid, the scale of real-time alarm information collected at each plant and station in electric energy management systems (EMSs) has become increasingly large, and the logic relationships among alarm information texts have become increasingly complicated. When the power grid fails, especially when relay protection and circuit breakers

are inoperable or malfunctioning, it is difficult, in a short period, for dispatchers to determine key alarm information, accurately analyze the fault process, or identify faulty devices. Research on power grid fault diagnosis methods that can quickly and accurately identify faulty devices, in a complex data environment, is of great significance for assisting dispatchers in assessing faults and realizing intelligent dispatching [1].

Power grid fault diagnosis methods primarily involve expert systems [2]–[5], Bayesian networks [6] and analytical models [7], [8]. Expert systems were the earliest artificial intelligence tools applied for fault diagnosis. In [4], based on expert experience, rules were established to express the relationship among protection, circuit breakers and devices, and a knowledge base for fault diagnosis was built. Then, the faulty device could be identified by matching alarm information with the knowledge base. In [5], data mining technology was applied to expert systems to mine abundant alarm information and improve the rule base, thus increasing the speed and accuracy of expert system fault diagnosis. To solve the problem of incomplete or uncertain alarm information, a Bayesian network that combined graphics and conditional probabilities was used to express uncertain alarm information in [6]. Then, a component-oriented Bayesian network model for line, transformer and bus fault diagnosis was established, and it solved the fault diagnosis problem of uncertain alarm information. In [7], an artificial neural network was used to model a protection system and overcome the uncertainty issue with alarm information; this approach was combined with an expert system to determine specific faulty devices. In [8], the problem of fault diagnosis was transformed into a 0–1 integer programming problem considering the possibility of protection and circuit breaker refusal or misoperations, and an analytical fault diagnosis model was developed to evaluate the uncertainty of protection and circuit breaker issues. On the basis of [8], the time series attribute of alarm information was introduced in [9], and a diagnosis model containing a time series attribute was established to improve the speed and accuracy of fault diagnosis.

The above methods have achieved valuable results, but there are still some problems with these methods in practical applications; notably, they rely on logic rules to establish diagnostic models. In the modeling process, many alarm information screening and classification tasks are generally performed. Most models do not directly correspond to the alarm information, and it is difficult to automatically extract

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the characteristic differences among different power grids in various fault cases. Thus, these approaches cannot support the increasingly urgent development of intelligent power grid dispatch schemes based on data-driven models.

In recent years, artificial intelligence methods, such as deep learning [10]–[14], have been continuously developing. Deep learning methods can automatically extract and learn the features of an original dataset, have strong self-learning ability, and can effectively solve the above problems. Therefore, such methods have been widely used in the field of power grid fault diagnosis based on electrical data [15]–[18], but there have been few studies on fault diagnosis directly based on alarm information.

To achieve fault feature extraction for online alarm information, this paper proposes a power grid fault diagnosis method based on a deep pyramid convolutional neural network (DPCNN) [19]. Based on the ability of the DPCNN to extract in-depth knowledge from alarm information, two fault classification models and a key information extraction model are established for the alarm information set and alarm information text, respectively, to perform fault classification and key information extraction. On this basis, the set of suspicious faulty devices is determined according to the output results of the above models, and a faulty device is identified based on a fault device identification strategy that integrates fault-type and time sequence priorities. To verify the effectiveness of the above method, this paper performs fault diagnosis with an alarm information set from actual fault cases in Zhejiang, China, and the alarm information set is generated by the faulty simulation system. The results show that the proposed method can effectively achieve fault classification and identify faulty devices.

The main contributions of this paper are as follows:

- 1) The proposed method is directly oriented to the alarm information texts, without the need to establish a complex topology model, which is helpful to realize end-to-end fault diagnosis.
- 2) The proposed method is implemented based on the DPCNN model, which can complete the fault identification of the alarm information texts of different fault types. A fault device identification strategy that integrates fault-type and time sequence priorities is proposed to realize the identification of faulty devices in a complex data environment.

- 3) The proposed method has been tested on a simulated fault case and an actual fault case. The results show that the proposed method can adapt to different power grid environments and has high application value.

II. ALARM INFORMATION FEATURE EXTRACTION BASED ON THE DPCNN

A. Text Representation of Alarm Information

After a power grid fails, the protection and circuit breaker action information related to the faulty device is uploaded to the supervisory control and data acquisition (SCADA) system in real time. Additionally, the SCADA system receives some alarm information, such as information about device failure or a switch mechanism spring not storing energy, which is recorded in chronological order to generate an alarm information set for the failure event. Table I shows an example of an alarm information set for Zhejiang, China.

To facilitate computer processing, the texts formed by the alarm information set must be expressed numerically. There are many ways for text representation, primarily including discrete representation methods based on one-hot, bag-of-words models [20], TF-IDF [21], and distributed representation methods based on n-gram [22], Word2vec [23], and GloVe [24] models. Among them, the Word2vec model can map words from high-dimensional space to low-dimensional space and retain the association relationship between words, which effectively solves the problems of vector sparseness and semantic connection in text representation.

Therefore, this paper uses the Word2vec model to vectorize the alarm information texts. The vectorization process is as follows.

- 1) Remove the time column in the alarm information texts.
- 2) Segment the alarm information texts. Cut each alarm information text according to the station, device, device description and action description.
- 3) Word vectors are generated by the Word2vec model. The model can use the contextual information for words to generate low-dimensional word vectors that can represent the relationships between words. The more similar the semantics of the words are, the closer the corresponding word vectors are in the vector space.

TABLE I
ALARM INFORMATION SET EXAMPLE

Time	Station	Device	Device description	Action description
2019-07-08 07:20:21:01	Hetian Substation	Full Site	Total accident signal	Action
2019-07-08 07:20:21:02	Hetian Substation	Xufeng Y150	Protect	Action
2019-07-08 07:20:21:03	Hetian Substation	Xufeng Y150	Circuit breaker	Trip
2019-07-08 07:20:22:01	Hetian Substation	Xufeng Y150	Protect the recloser	Action
2019-07-08 07:20:22:02	Hetian Substation	Xufeng Y150	Switch mechanism spring is not charged	Action
2019-07-08 07:20:22:03	Hetian Substation	Xufeng Y150	Circuit breaker	Close
2019-07-08 07:20:24:01	Xitiao Substation	110 kV fault recorder	Protection device fault	Reset
2019-07-08 07:20:27:01	Hetian Substation	Xufeng Y150	Switch mechanism spring is not charged	Reset
2019-07-08 07:20:28:01	Jinshan Substation	#2 capacitor	Switch mechanism spring is not charged	Reset
2019-07-08 07:20:31:01	Antang Substation	#2 transformer	Online oil filter device start	Reset
2019-07-08 07:20:32:01	Hetian Substation	Xufeng Y150	Protect the recloser	Reset
2019-07-08 07:20:34:01	Hetian Substation	Xufeng Y150	Protect	Reset
2019-07-08 07:20:54:01	Hetian Substation	Full site	Total accident signal	Reset

4) Generate sentence vectors based on word vectors. With the average word vector method [25], the sentence vector can be obtained for the alarm information text.

5) Generate a sentence vector representation of texts. By concatenating the vectors corresponding to the alarm information text, the sentence vector representation matrix of the texts can be obtained:

$$x_{1:n} = x_1 \oplus x_2 \oplus \cdots \oplus x_i \oplus \cdots \oplus x_n \quad (1)$$

where $\oplus$ represents a vector connection, corresponding to the sentence vector matrix in Fig. 1, and x_i represents the sentence vector of the i th alarm information text.

$$x_i = x_i^1 \oplus x_i^2 \oplus \cdots \oplus x_i^j \oplus \cdots \oplus x_i^k \quad (2)$$

where k is the dimension of the sentence vector, and x_i^j represents the j -dimensional component of the i th alarm information sentence vector.

For the alarm information text, omit step 4) and step 5) and directly splice the word vectors in the text to form a word vector matrix, as shown in Fig. 2.

B. Deep Pyramid Convolutional Neural Network Model

The structure of the DPCNN model is shown in Fig. 3,

and it consists of a region embedding layer, two convolutional blocks, two pooling layers and a fully connected layer. Among them, the region embedding layer is the embedding generated after the convolution operation on the text; the convolution blocks are composed of two convolution layers and a residual module; the convolution blocks are connected by a pooling layer with a step size of 2, referred to as the 1/2 pooling layer.

The superposition of the convolution blocks and the 1/2 pooling layer forms a pyramid convolution module, as shown in Fig. 4.

In Fig. 4, the convolutional layer adopts equal-length convolution to make the output sequence length equal to the input sequence length. If the size of the convolution kernel is n , the embedding of each position of the output sequence is the context information of the word or sentence at the corresponding position in the input sequence and that of the left and right $(n-1)/2$ words or sentences; with this approach, the semantic description is richer and more accurate. In addition, the convolution block introduces a residual module to avoid the gradient dispersion problem caused by the increase in network depth.

After the output result of the region embedding layer is

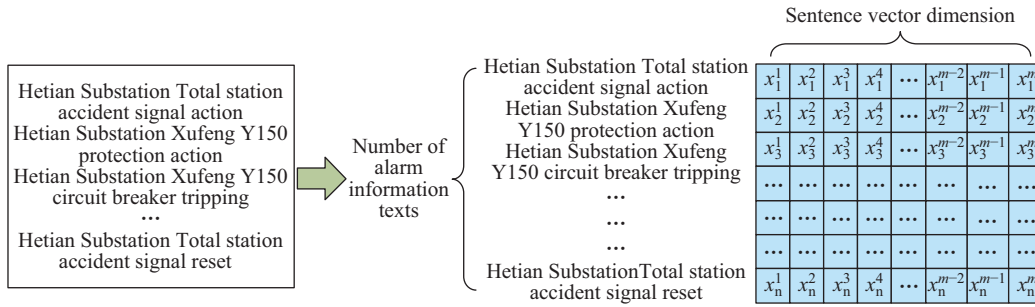


Fig. 1. Sentence vector representation of alarm information texts.

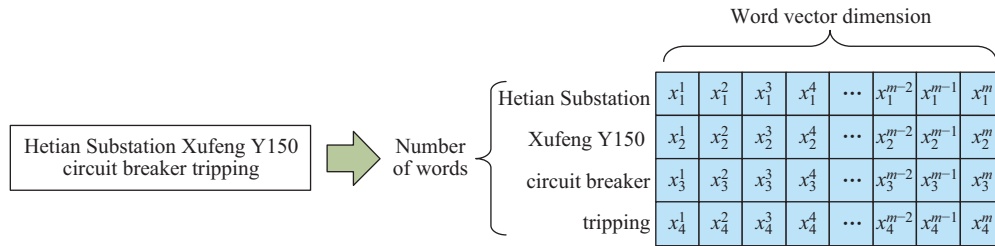


Fig. 2. Word vector representation of alarm information text.

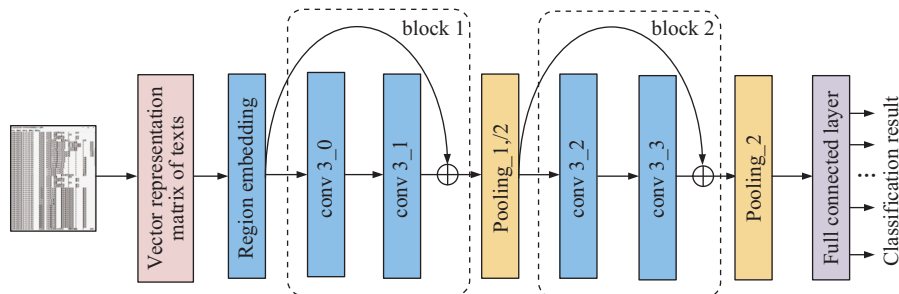


Fig. 3. DPCNN model.

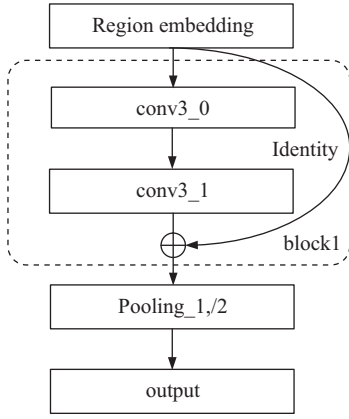


Fig. 4. Pyramid convolution module.

subjected to the convolutional block operation, the 1/2 pooling layer with a step size of 2 is used for downsampling. At this time, the output sequence length is reduced by half, and the number of perceived text segments is doubled. If the model is equipped with multiple pyramid convolution modules, the text sequence length will be exponentially reduced through the alternation of the convolution block and the 1/2 pooling layer, resulting in a “pyramid” shape as the modules increase. The pyramid convolution module of the DPCNN model enables the model to perceive long-distance text information and enhances the ability to extract the global features of the text.

C. Feature Extraction Based on the DPCNN

Based on the above characteristics of the DPCNN model, the text features of the alarm information are extracted by the DPCNN. For the alarm information texts $A \in R^{n \times k}$, where n is the length of the texts and k is the dimension of the sentence vector, the text region features are extracted through the region embedding layer. Then, a convolution kernel parameterized by the weight matrix $w \in R^{h \times k}$ is established, and convolution operations are performed in the length direction of the texts. The convolution process is as follows:

$$c_i = f(w \cdot x_{i:i+h-1} + b) \quad (3)$$

where $x_{i:i+h-1}$ is the h -th sentence vector included in the convolution kernel window, $b \in R$ is the bias vector, f is the nonlinear activation function, and c_i is the eigenvalue. Texts of length n contain $n - h + 1$ windows $\{x_{1:h}, x_{2:h+1}, \dots, x_{n-h+1}\}$, and each window is convolved to generate corresponding features. All the features are spliced to obtain a feature vector of the alarm information texts, as shown in (4).

$$c_{\text{region}} = [c_1, c_2, \dots, c_{n-h+1}] \quad (4)$$

After the feature vector is input into the first convolution block for equal-length convolution and identity mapping, the output feature vector is:

$$c_{\text{conv}} = [c'_1, c'_2, \dots, c'_{n-h+1}] \quad (5)$$

where the dimension of c_{conv} is the same as that of c_{region} .

Then, the 1/2 pooling layer is used for downsampling, and the sampling results are input into the next convolution block.

The final pooling layer performs maximum pooling on the feature vector output by the convolution block to obtain the text features of the global alarm information texts.

Figure 5 is a feature vector diagram for alarm information texts extracted from each convolutional layer and pooling layer after alarm information texts with a text sequence length of 20 ($\text{seq_length} = 20$) are input into the DPCNN model ($\text{kernel_size} = 3$). In the figure, different color areas represent eigenvalues of different sizes. The closer the color is to white, the larger the eigenvalue, and the greater the impact on text classification.

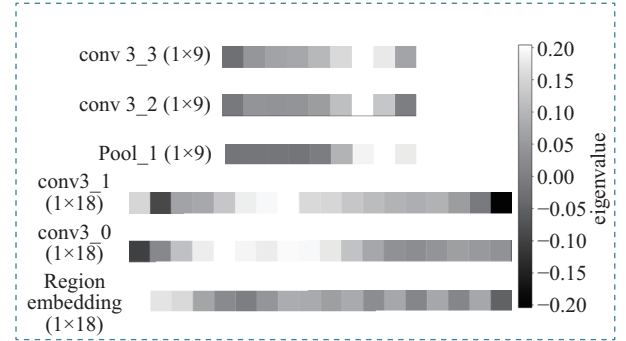


Fig. 5. Visualization of feature maps of each network layer of DPCNN.

Notably, due to the use of the pyramid convolution module, the change in the length of the feature vector is in the shape of a pyramid. The feature vector length of the region embedding layer at the bottom is 18 ($\text{seq_length} - \text{kernel_size} + 1$); the vector lengths of the conv3_0 and conv3_1 layers in the first convolution block remain unchanged; the Pool_1 layer performs 1/2 pooling on the feature vector output by the conv3_1 layer, and the length of the vector is reduced to 9. This result is input into the second convolution block; the conv3_2 and conv3_3 layers perform equal-length convolution operations, and a feature vector of length 9 is output.

III. POWER GRID FAULT DIAGNOSIS MODEL BASED ON THE DPCNN

The deep network structure of the DPCNN model can extract long-distance text dependencies and is suitable for scene classification for long texts. Therefore, this paper proposes to establish two fault classification models based on the DPCNN to classify alarm information sets with different complexities and different types of faulty devices. To further identify the faulty devices, a key information extraction model based on the DPCNN is designed to extract the key alarm information text in the alarm information set and combine the classification results of faulty device types to obtain the set of suspicious faulty devices. Then, based on the fault classification results for different complexity levels and the set of suspicious faulty devices, a faulty device identification strategy, that integrates fault types and time sequence priority, is proposed to realize the identification of faulty devices.

A. Fault Classification Models

This paper designs two DPCNN-based fault classification models for the alarm information set, and the model structure

is shown in Fig. 6.

Fault classification model 1 can be used to distinguish non-faulty, simple faults, complete-protection failed action faults, incomplete-protection failed action faults, circuit breaker failed action faults, and developmental faults.

Fault classification model 2 can distinguish line, bus and transformer faults.

The definitions of these types of faults are as follows:

1) Simple faults: There is only one faulty device in the fault event, and the protection and circuit breaker operates correctly.

2) Complete-protection failed action faults: All sets of protection for the faulty device refuse to operate, then the backup protection of adjacent equipment operates, and the scope of failure is expanded.

3) Incomplete-protection failed action faults: When a device equipped with dual protections fails, one or part of the protection refuses to operate, but other protections operate to cut off the circuit breaker, and the fault range is not expanded.

4) Circuit breaker failed action faults: There is only one faulty device in the fault event, and the protection operates correctly, but the circuit breaker refuses to operate, which causes the backup protection action of adjacent equipment.

5) Developmental faults: In this paper, these refer to the protective action of other devices within the scope of the fault due to a device failure, and the nonfaulty devices, such as 10 kV or 35 kV capacitors, are removed.

The structure of the two classification models is the same, and only the input and output results are different, as shown in Fig. 6. The input layer of the model is the sentence vector matrix $A \in R^{n \times k}$ corresponding to the alarm information texts to be classified, where n is the number of sentences in the alarm information texts, and k is the sentence vector dimension corresponding to each alarm information text. The convolution kernel size of the region embedding and convolution layers is set to 3, the correlation features between three adjacent alarm information texts in the alarm information set are extracted, and 200 matrix windows with different weight values are set at the same time to obtain a complete feature

expression. After the alarm information texts are extracted with the feature extraction approach described in Section II-C, the fully connected layer calculates the probability of each classification label. The label with the highest probability is the fault classification result corresponding to the alarm information texts.

B. Key Information Extraction Model

In this section, for an alarm information text in the alarm information set, a key information extraction model based on the DPCNN is designed to extract the key information from the alarm information set—namely, the alarm information for protection and circuit breaker actions. Here, the structure of the key information extraction model is the same as the fault classification model shown in Fig. 6, which uses the DPCNN model structure. The difference is that the key information extraction model takes a single alarm information as the input, and the input layer of the model is the word vector matrix $A' \in R^{m \times k}$ corresponding to the alarm information text to be classified, where m is the number of words contained in the text, and k is the word vector dimension. The output of the model is the classification result of the alarm information text and denotes whether the text is key information or noncritical information.

C. Determination of the Suspicious Faulty Device Set

The alarm information set is input into the key information extraction model, and the classification result for each alarm information text is output. If the alarm information text is key information, the device associated with this text is defined as a suspicious faulty device. The devices linked to all the key information in the alarm information set are represented by a suspicious faulty device set D .

$$D = \{d_1, d_2, \dots, d_i, \dots, d_n\} \quad (6)$$

where d_i is the device associated with the i th instance of key information in the alarm information set, and n is the number of suspicious faulty devices.

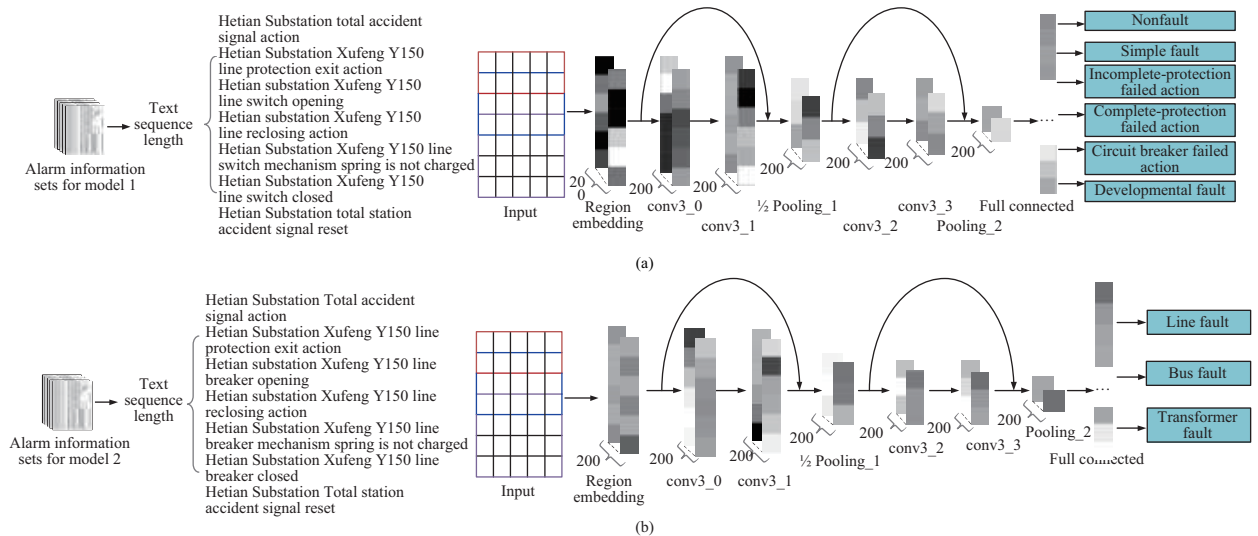


Fig. 6. Fault classification models. (a) Fault classification model 1. (b) Fault classification model 2.

To improve the accuracy of identifying faulty devices, according to the classification results of fault classification model 2, the scope of the suspicious faulty device set is further narrowed, and the final suspicious faulty device set D' is obtained.

$$D' = \{d_1, d_2, \dots, d_m\} \quad (7)$$

where $m \leq n$. According to the classification result of fault classification model 2, D' may be a suspicious fault line set, a suspicious fault bus set or a suspicious fault transformer set.

D. A Faulty Device Identification Strategy that Integrates Fault-type and Time Sequence Priorities

After determining the set of suspicious faulty devices from the key information and fault classification model 2, faulty devices need to be identified. According to the time sequence distribution characteristics of alarm information for different fault types, this paper proposes a fault device identification strategy that integrates fault types and time sequence priorities.

Figures 7 and 8 show the time sequence distribution of alarm information for simple and complex fault events (referring to a device fault with circuit breaker or protection failed action and developmental faults) that occurred in Zhejiang, China. The

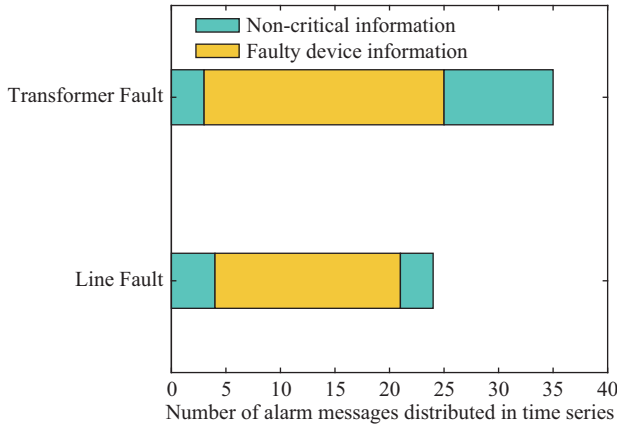


Fig. 7. Time sequence distribution characteristics of alarm information for simple fault events.

protection failed action events in Fig. 8 are all incomplete-protection failed action events, and the complete-protection failed action events have no faulty device information. Notably, the time distribution characteristics of the faulty device information for simple faults and complex faults are different. Regardless of noncritical information, the information for faulty devices with a simple fault is provided throughout the event, so the devices in the suspicious faulty device set D' are faulty devices; the information for a faulty device with a complex fault is scattered, but its occurrence time is earlier than that of nonfaulty devices. Therefore, the first device in D' can be determined as the faulty device based on the timing priority strategy. The faulty device identification strategy is shown in Fig. 9.

1) When the classification result of fault classification model 1 is a simple fault, the devices in the suspicious faulty device set are identified as faulty devices.

2) When the classification result of fault classification model 1 is a circuit breaker failed action, developmental fault, or incomplete-protection failed action fault, the first device in the set of suspicious faulty devices is identified as the faulty device.

3) When the classification result of fault classification model 1 is a complete-protection failed action, the faulty device needs to be determined according to the network topology.

E. Fault Diagnosis Process Based on the DPCNN

The power grid fault diagnosis framework based on the DPCNN is shown in Fig. 10, and it consists of two parts: a model training and test, and online diagnosis.

The model training and testing process is as follows.

1) Obtain the alarm information sets for historical fault events collected by the SCADA system as sample sets and use the Word2vec model to vectorize the alarm information sample sets and alarm information text.

2) Divide the sample sets according to the two fault classification models described in Section III-A to form two sets of fault samples, each of which is labeled with a corresponding fault event label to construct a fault sample set for model learning.

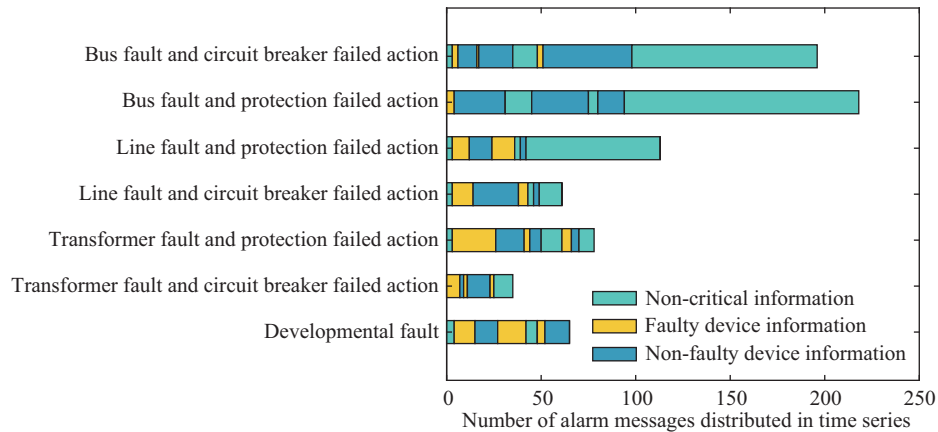


Fig. 8. Time sequence distribution characteristics of alarm information for complex fault events.

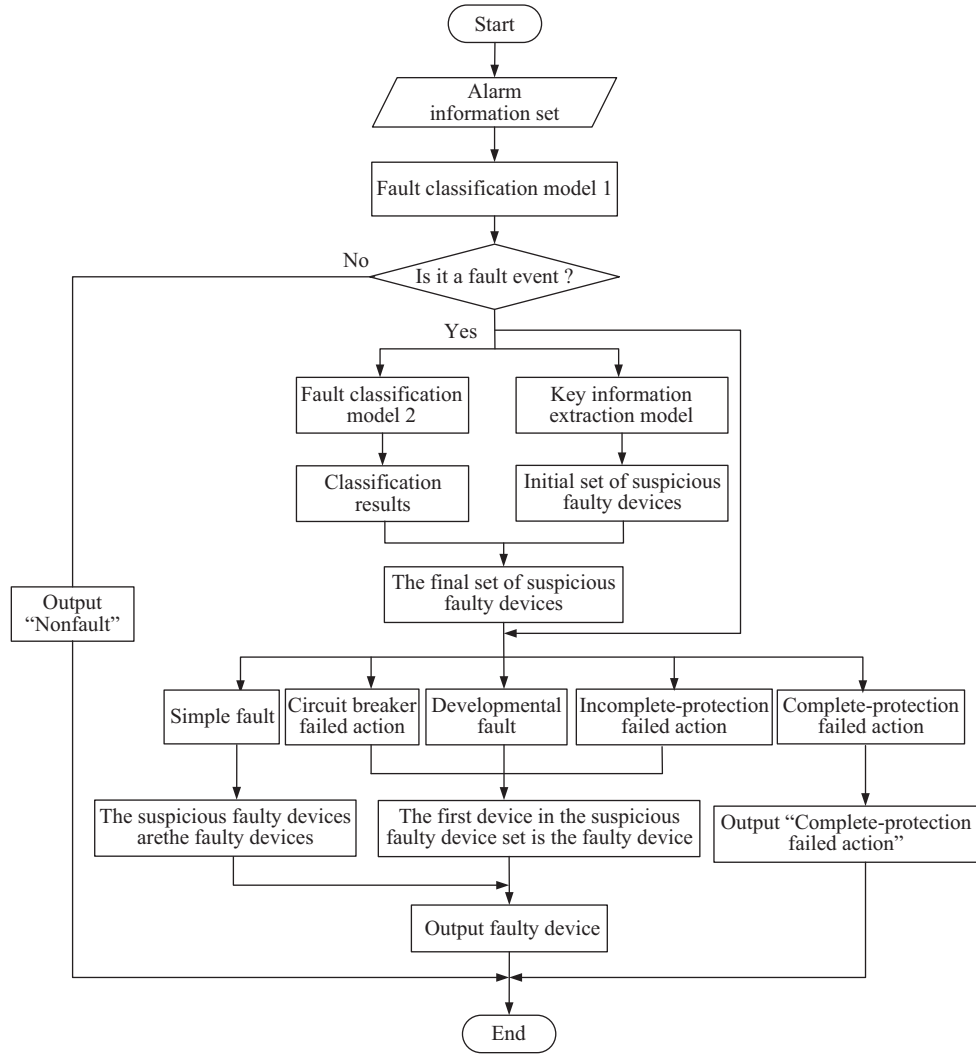


Fig. 9. Flowchart of the faulty device identification strategy.

3) Label the key information or noncritical information for an alarm information text in the alarm information sample sets to construct alarm information text sets.

4) Build two fault classification models and key information extraction models.

5) Divide the fault sample sets and the alarm information text sets into a training set and a test set, train the fault classification model and the key information extraction model, and test the model classification effect on the test set.

6) Add the samples with incorrect classification results to the training set and perform retraining to improve the accuracy of model classification until the online diagnosis requirements are met.

Use the trained model for online fault diagnosis. The diagnosis process is as follows.

1) A sliding time window with a step size of 5 s and a window size of 10 s is used to intercept the real-time alarm information in the SCADA system and perform vectorized representation, as described in Section II-A.

2) Input the vectorized alarm information texts into the diagnosis model, output the fault classification results, and determine the faulty device based on the faulty device identification strategy.

If the result of fault classification is a complete-protection failed action, the faulty device should be determined according to the network topology.

3) The dispatcher assesses the diagnosis result. If the diagnosis result is correct, it will be directly added to the sample library for training and learning; if the diagnosis result is incorrect, the dispatcher will add the correct fault label to the alarm information sample and add it to the sample library to increase the sample library capacity.

IV. EXAMPLE VERIFICATION

A. Sample Data

To reflect the applicability of the proposed model to different descriptions of alarm information, this paper selects the actual power grid in Zhejiang, China, and the TS2000 simulation system used to simulate the D5000, which is the Chinese smart grid dispatching technical support system, as the data sources for obtaining samples. The actual power grid includes 731 plant stations, 5382 lines and 13 voltage levels from 0.22 kV to 500 kV, and the TS2000 simulation system includes 60 plant stations, 825 lines and 5 voltage levels from

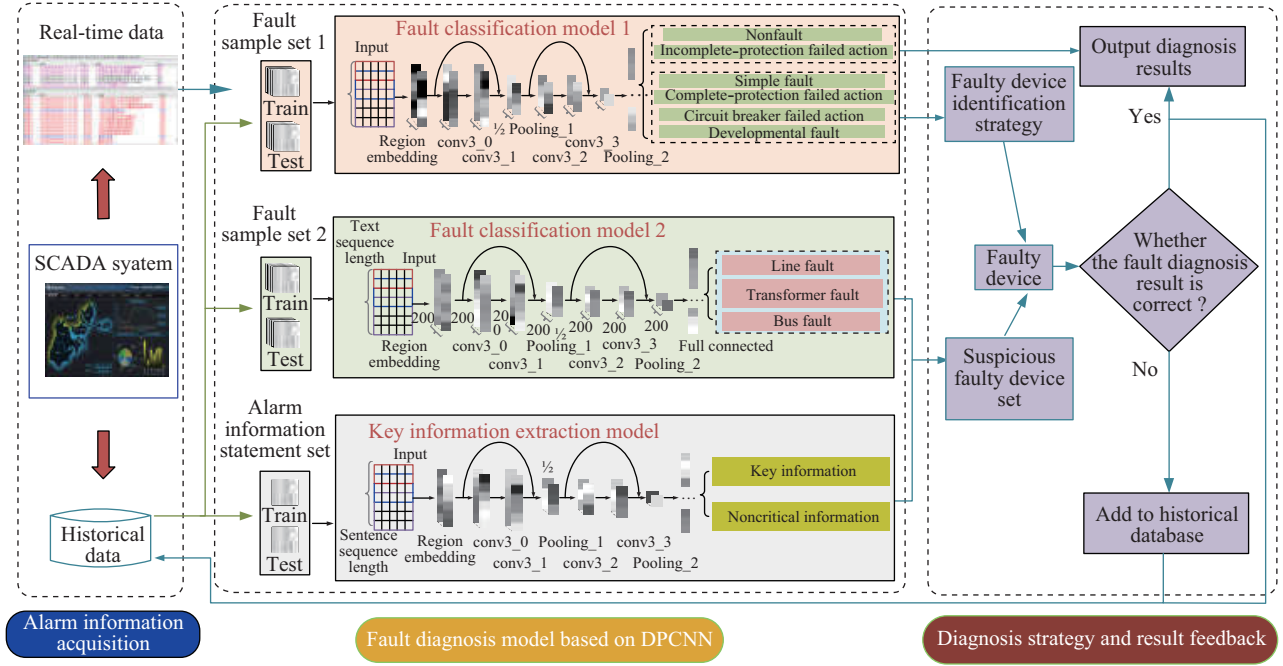


Fig. 10. Frame diagram of power grid fault diagnosis based on the DPCNN.

10 kV to 500 kV. The alarm information samples generated by two different power grids have the following characteristics.

1) The alarm information generated by the actual power grid is general-level information and contains a large amount of nonfaulty information. The alarm information is characterized by high noise and simplified descriptions. For details, see Table AI in Appendix A.

2) The alarm information generated by the TS2000 simulation system provides detailed descriptions of faults, contains limited nonfaulty information, has a low noise level and is highly descriptive. For details, see Table BI in Appendix B.

According to the two fault classification models mentioned in Section III-A, the two corresponding groups of alarm information sample sets and alarm information text sets are obtained from the historical monitoring alarm information for the Zhejiang regional power grid in 2019, and the TS2000 simulation system. The data are then divided into a training set and a test set at a ratio of 7:3. The composition of the two groups of alarm information samples is shown in Table II.

B. Model Parameter Settings

In this paper, DPCNN models based on TensorFlow are built for fault diagnosis, and the classification results of the models are evaluated based on three indexes: precision, recall and the F_1 value.

$$\text{precision} = \frac{n_{TP}}{n_{TP} + n_{FP}} \quad (8)$$

$$\text{recall} = \frac{n_{TP}}{n_{TP} + n_{FN}} \quad (9)$$

$$F_1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} \quad (10)$$

where n_{TP} , n_{FN} , n_{FP} and n_{TN} represent the numbers of samples of true positive (TP), false negative (FN), false positive (FP), and true negative (TN) events, respectively. The relationships among the four types of events are shown in Table III.

To achieve the best classification performance with the models and improve the accuracy of model recognition, this paper changes the main influential model parameters, such as the size of the convolution kernel (kernel_size), the number of convolution kernels (num_filters), and the sequence length of the input model (seq_length) and analyzes the influence of different parameter values on the F_1 value of the model.

The three subgraphs in Fig. 11 are three-dimensional surface graphs of the F_1 value of the fault classification model, which varies with the number of convolution kernels and the sequence length for the specified size of the convolution kernel. Notably, there is a nonlinear relationship between the sequence length, the number of convolution kernels and the F_1 value. The sequence length has the greatest influence on the F_1 value. When the size of the convolution kernel is 3,

TABLE II
SAMPLE COMPOSITION FOR FAULT CLASSIFICATION MODELS

Data source	Fault Classification Model 1						Fault Classification Model 2		
	Non-fault	Simple fault	Complete-protection failed action	Incomplete-protection failed action	Circuit breaker failed action	Developmental fault	Line fault	Bus fault	Transformer fault
TS2000	500	600	230	200	340	300	348	144	240
Regional grid	610	550	0	0	0	30	321	0	30

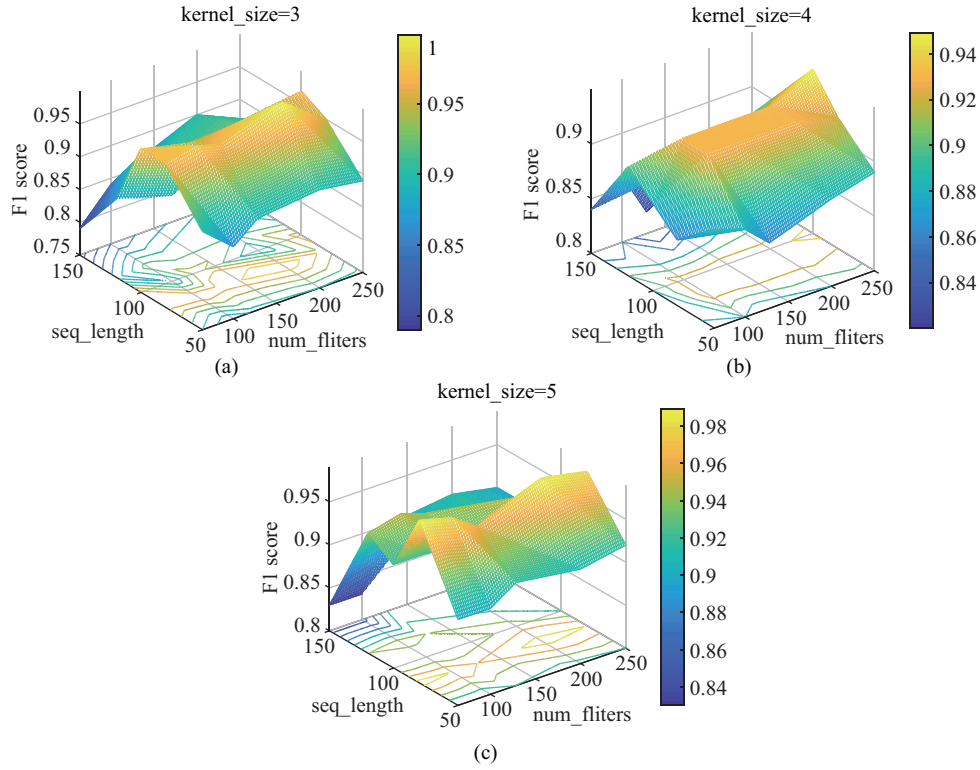


Fig. 11. Influence of hyperparameters on the F_1 score of the fault classification model.

TABLE III
THE RELATIONSHIP BETWEEN TP, FN, FP, AND TN

Type	Actual positive class	Actual negative class
Predicted positive class	TP	FP
Predicted negative class	FN	TN

the number of convolution kernels is 200, and the sequence length is approximately 80, the F_1 value reaches a maximum value of 1.

The two subgraphs in Fig. 12 are three-dimensional surface graphs of the F_1 value of the key information extraction model considering variations in the number and sequence length of convolution kernels for the specified size of the convolution kernels. The size of the convolution kernel and the number of convolution kernels have little influence on the F_1 value, and the sequence length has the largest influence on the F_1 value. The longer the sequence length, the larger the F_1 value. When the sequence length is 6, the F_1 value reaches 1, and when it is greater than 6, the model training speed decreases.

In summary, the size of the convolution kernel, the number of convolution kernels, and the sequence length of the fault classification model are set to 3, 200, and 80, respectively, and the corresponding parameters of the key information extraction models are 3, 150, and 6. The remaining parameters of the model are set according to the performance and calculation speed of the model, as shown in Table IV.

C. Analysis of Results

1) Model test situation:

Each group of training sets is used to train two fault classification models and the key information extraction model

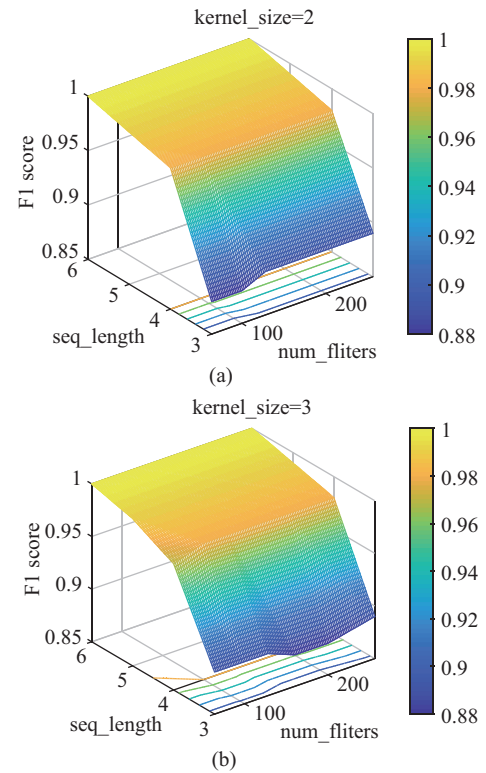


Fig. 12. Influence of hyperparameters on the F_1 score of the key information extraction model.

and evaluate the corresponding test samples. The test results are shown in Table V. The two fault classification models can accurately distinguish the fault types for the respective sam-

TABLE IV
PARAMETERS OF THE FAULT CLASSIFICATION MODEL AND KEY
INFORMATION EXTRACTION MODEL

Model parameters	Fault classification model	Key information extraction model
word vector dimension	128	128
seq_length	80	6
vocabulary size	600	600
num_filters	200	150
kernel_size	3	3
dropout	0.5	0.5
learning rate	0.001	0.001
batch_size	64	128

ples, and the key information extraction model can correctly identify the key information in the alarm information samples.

2) Fault sample diagnosis results:

Select different test sample sets for fault classification and fault device identification; the results are shown in Table VI.

Table VI shows that the method proposed in this paper can accurately distinguish various types of faults, including simple faults, developmental faults, incomplete-protection failed action faults, and circuit breaker failed action faults but cannot identify the faulty device for complete-protection failed action events, which requires the use of the network topology.

D. Comparison With Other Models and Subsequent Analysis

To assess the classification effect of the DPCNN-based fault classification model and the key information extraction model, this paper selects the CNN model and BPNN+TF-IDF model for comparison and verification. The CNN model is widely used in text classification and can directly vectorize and classify the input samples [26]–[28], while the BPNN+TF-IDF model uses the term frequency-inverse document frequency (TF-IDF) method to vectorize the samples, and then the BP neural network (BPNN) [29], [30] classifies the samples.

Figure 13 shows a comparison of the classification results of the three models. The classification accuracy of the DPCNN model is higher than that of the CNN and BPNN+TF-IDF models, and the greater the number of classifications, the lower the accuracy of the CNN model and BPNN+TF-IDF model. This is because the CNN model has fewer network layers, and the model is simpler than the DPCNN model. For the BPNN+TF-IDF model, the BPNN has a simple structure and consists of only a few layers of fully connected neural networks. The ability to capture the contextual information features in the alarm information texts is not strong, and the overall classification performance is weak. Moreover, TF-IDF uses word frequency statistics to represent the alarm information texts. The dictionary generated by the training set forms the TF-IDF representation of test samples. If some words in the test sample set cannot be queried in the dictionary, the sample representation is incomplete, which affects the classification accuracy of the model.

E. Case Analysis

Case 1: An actual fault case for the Wenshan substation in Zhejiang is used for analysis. This case involves a failure of the Luolian D151 line. The wiring diagram of the failure

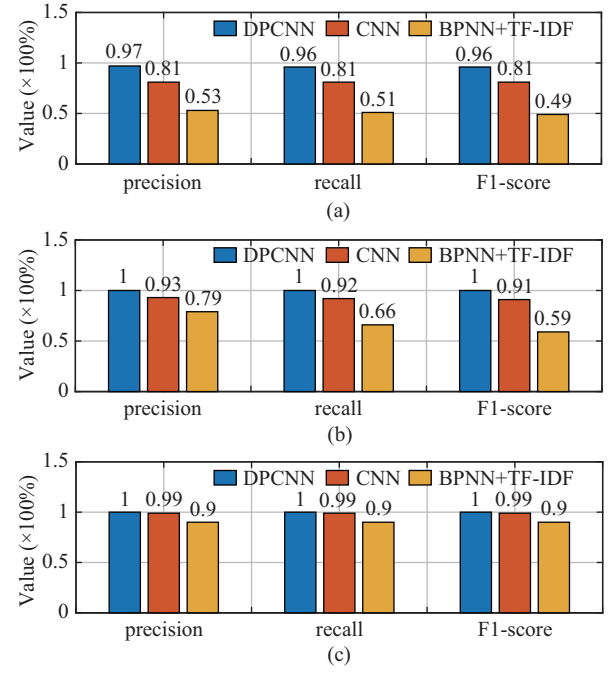


Fig. 13. Comparison of classification results of the DPCNN model, CNN model and BPNN+TF-IDF model. (a) Classification results of non-faulty, simple fault, complete protection failed action, incomplete protection failed action, circuit breaker failed action and developmental fault. (b) Classification results of line, bus and transformer. (c) Classification results of alarm information classification.

area and alarm information set associated with the failure are shown in Fig. A1 and Table AI in Appendix A.

1) Input the alarm information set shown in Appendix A into fault classification model 1 and fault classification model 2 in Fig. 10. The model classification results are shown in the following table, and it can be determined that the system has a simple line fault.

2) The key information extraction model is used to extract the key information sentences of the alarm information set in Appendix A and the key information numbered as 2, 6, 7, 11, 12, and 15 are obtained, from which a set of suspicious faulty devices is obtained:

$$D = \{\text{"Luolian D151 line"}\}$$

3) From the fault classification results in Table VII, the fault sample is a line fault, and the final set of suspicious faulty devices are determined as:

$$D' = D = \{\text{"Luolian Line D151"}\}$$

4) According to the fault classification results in Table VII, the fault sample is a simple fault. According to the faulty device identification strategy in Section III-D, the suspicious faulty device "Luolian D151 Line" is determined to be the faulty device. The diagnosis result is consistent with the actual faulty device. This diagnosis result is correct.

Case 2: In the TS2000 simulation system, an ABC three-phase permanent fault occurs on the Yan'e Line at Emei Station and a CB2254 failed action occurs. The wiring diagram of the fault area and the generated alarm information set are shown in Fig. B1 and Table BI in Appendix B.

TABLE V
CLASSIFICATION RESULTS OF FAULT CLASSIFICATION MODEL 1

	Fault Classification Model 1						Fault Classification Model 2			Key information extraction model	
	Simple fault	Complete-protection failed action	Incomplete-protection failed action	Circuit breaker failed action	Developmental fault	Non-fault	Line fault	Bus fault	Transformer fault	Key Information	Noncritical information
Precision	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Recall	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
F ₁	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

TABLE VI
SAMPLE DIAGNOSIS RESULTS

	Sample composition	Number of samples	Accuracy of classification	Identification accuracy rate for faulty devices
Test set 1	Simple fault	200	100%	100%
Test set 2	Complete- protection failed action	120	100%	0
Test set 3	Incomplete- protection failed action	100	100%	100%
Test set 4	Circuit breaker failed action	120	100%	100%
Test set 5	Developmental fault	110	100%	100%

TABLE VII
CLASSIFICATION RESULTS OF THE FAULT CLASSIFICATION MODELS

Model	Classification result
Fault classification model 1	Simple fault
Fault classification model 2	Line fault

1) Input the alarm information set shown in Appendix B into fault classification model 1 and fault classification model 2 in Fig. 10. The model classification results are shown in Table VIII, and it can be determined that the system has a line fault and a circuit failed action.

TABLE VIII
CLASSIFICATION RESULTS OF FAULT CLASSIFICATION MODELS

Model	Classification result
Fault classification model 1	Circuit breaker failed action fault
Fault classification model 2	Line fault

2) The key information extraction model is used to extract key information from the alarm information set in Appendix B. The key information set is {1, 2, 9–33, 36–38, 41–61, 64–74, 77–81, 83–86, 93–107}, from which a set of suspicious faulty device sets is obtained:

$$D = \{ \text{"Emei Station 220 kV Busbar"}, \\ \text{"Emei Station 220 kV Yan'e Line"}, \\ \text{"Yandang Station 220 kV Yan'e Line"}, \\ \text{"Zhongshan Station 220 kV Zhong'e Line II"}, \\ \text{"Emei Station \# 2 Transformer"}, \\ \text{"Emei Station 220 kV Zhong'e Line II"} \}$$

3) The fault classification results in Table VIII indicate that the fault sample is a line fault, and the scope of the suspected faulty equipment is further reduced to obtain:

$$D' = \{ \text{"Emei Station 220 kV Yan'e Line"}, \\ \text{"Yandang Station 220 kV Yan'e Line"}, \\ \text{"Zhongshan Station 220 kV Zhong'e Line II"}, \}$$

“Emei Station 220 kV Zhong’e Line II”}

4) According to the fault classification results in Table VIII, the fault sample is a circuit breaker failed action fault. According to the faulty device identification strategy in Section III-D, the first suspected faulty device in D' Emei Station 220 kV Yan’e Line is determined as the faulty device. Combined with the network topology, it is determined that a CB2254 failed action occurs. The diagnosis result is consistent with the actual faulty device event, and the diagnosis result is correct.

V. CONCLUSION

This paper proposes a power grid fault diagnosis method based on a DPCNN, and the following results are achieved.

1) A DPCNN-based fault classification model and key information extraction model are established, and a fault device identification strategy that integrates fault-type and time sequence priority information is proposed. The model can be accurately solved for complex grid fault conditions and complex data environments.

2) The DPCNN model can extract the characteristics of fault events in the alarm information set and directly determine whether the fault contains unobservable events, such as circuit breaker failed action and protection failed action. The judgment of these events in the rule system requires complex rule matching and reasoning, and how to set the measurement function calculation has not been well resolved.

3) The diagnosis model directly corresponds to the alarm information, and there is no need to manually analyze the alarm information sequence, information screening and modeling. It is helpful to realize the end-to-end fault diagnosis of a power grid oriented to the alarm information set, which greatly reduces the workload of personnel modeling and maintenance and has high application value.

4) The proposed method still must determine the possible range of the refusal protection and the circuit breaker in the case of complete-protection failed action and circuit breaker failed action by topological analysis, without realizing the end-to-end diagnosis of the entire fault diagnosis process.

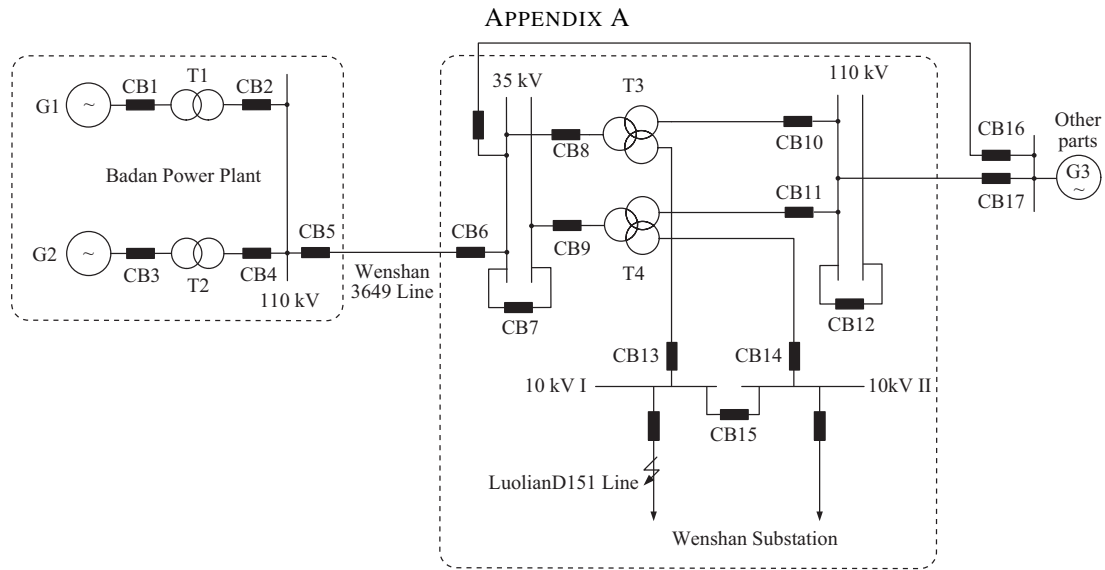


Fig. A1. The electrical wiring diagram of the fault area in case 1.

TABLE AI
THE ALARM INFORMATION SET OF LUOLIAN D151 LINE FAULT IN WENSHAN SUBSTATION

Number	Time	Information	Action description
1	2019-09-18 08:48:13:04	Wenshan Substation total station accident signal	Action
2	2019-09-18 08:48:13:05	Wenshan Substation Luolian D151 interval accident signal	Action
3	2019-09-18 08:48:14:01	Wenshan Substation 10 kV Section I bus grounding	Action
4	2019-09-18 08:48:14:02	Wenshan Substation 10 kV Section I bus grounding	Reset
5	2019-09-18 08:48:14:03	Wenshan Substation Caizhai D156 line zero sequence overcurrent protection alarm	Reset
6	2019-09-18 08:48:14:04	Wenshan Substation Luolian D151 line protection device abnormal	Reset
7	2019-09-18 08:48:14:05	Wenshan Substation Luolian D151 line protection	Action
8	2019-09-18 08:48:17:03	Wenshan Substation Wenshan D154 line zero sequence overcurrent protection alarm	Reset
9	2019-09-18 08:48:17:05	Wenshan Substation Wenshan D154 line protection device is abnormal	Reset
10	2019-09-18 08:48:17:06	Wenshan Substation Total station accident signal	Reset
11	2019-09-18 08:48:18:02	Wenshan Substation Luolian D151 line protection	Reset
12	2019-09-18 08:48:18:03	Wenshan Substation Luo Lian D151 circuit breaker	Trip
13	2019-09-18 08:48:18:04	Wenshan Substation #1 Arc suppression coil control device is abnormal	Reset
14	2019-09-18 08:48:18:05	Wenshan Substation Luolian D151 line zero sequence overcurrent protection alarm	Reset
15	2019-09-18 08:48:18:06	Wenshan Substation Luolian D151 interval accident signal	Reset

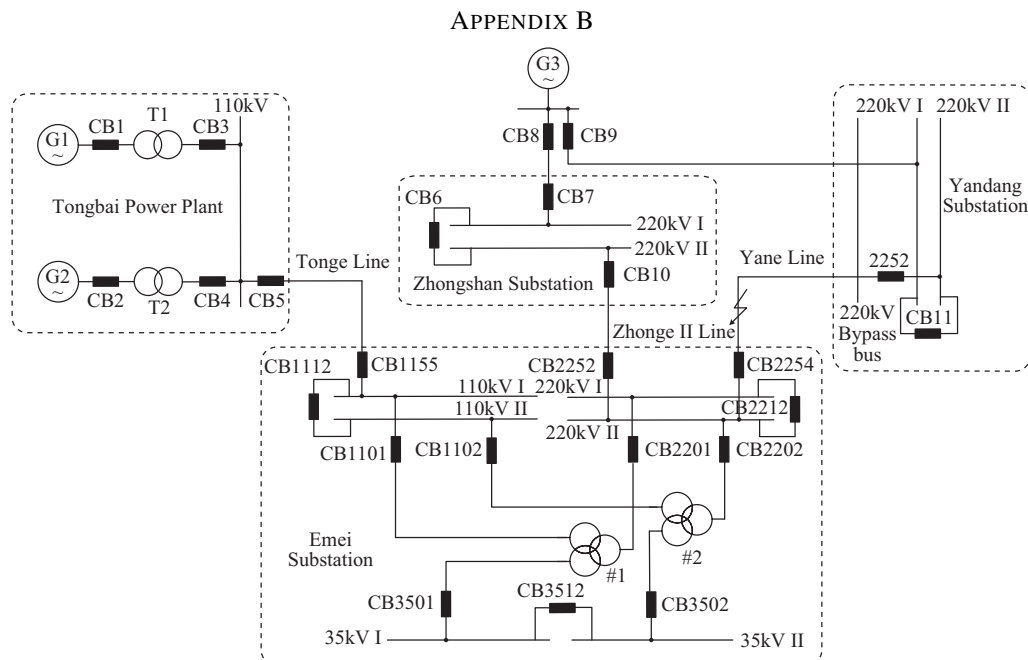


Fig. B1. The electrical wiring diagram of the fault area in case 2.

TABLE BI

THE ALARM INFORMATION SET OF THE PERMANENT FAILURE OF ABC THREE-PHASE OF YAN'E LINE IN EMEI STATION AND CB2254 FAILED ACTION

Number	Time	Information	Action description
1	2020-07-03 16:48:40:462	Emei Substation 220 kV Bus coupler 2212 breaker ABC phase	Trip
2	2020-07-03 16:48:40:462	Emei Substation 220 kV Busbar switch displacement	Action
3	2020-07-03 16:48:50:493	Emei Substation Transformer Fault recorder start	Action
4	2020-07-03 16:48:50:493	Emei Substation 220 kV Fault recorder start	Action
5	2020-07-03 16:48:50:493	Emei Substation 110 kV Fault recorder start	Action
6	2020-07-03 16:48:50:493	Yandang Substation Transformer Fault recorder start	Action
7	2020-07-03 16:48:50:493	Yandang Substation 220 kV Fault recorder Start	Action
8	2020-07-03 16:48:50:493	Yandang Substation 110 kV Fault recorder start	Action
9	2020-07-03 16:48:50:500	Emei Substation 220 kV Yan'e Line protection	Action
10	2020-07-03 16:48:50:500	Emei Substation 220 kV Yan'e Line longitudinal distance	Action
11	2020-07-03 16:48:50:500	Emei Substation 220 kV Yan'e Line A phase tripping	Action
12	2020-07-03 16:48:50:500	Emei station 220 kV Yan'e Line B phase tripping	Action
13	2020-07-03 16:48:50:500	Emei station 220 kV Yan'e Line C phase tripping	Action
14	2020-07-03 16:48:50:500	Emei Substation 220 kV Yan'e Line current differential protection	Action
15	2020-07-03 16:48:50:500	Emei Substation 220 kV Yan'e Line A phase tripping	Action
16	2020-07-03 16:48:50:500	Emei Substation 220 kV Yan'e Line B phase tripping	Action
17	2020-07-03 16:48:50:500	Emei Substation 220 kV Yan'e Line C phase tripping	Action
18	2020-07-03 16:48:50:500	Yandang Substation 220 kV Yan'e Line protection	Action
19	2020-07-03 16:48:50:500	Yandang Substation 220 kV Yan'e Line longitudinal distance	Action
20	2020-07-03 16:48:50:500	Yandang Substation 220 kV Yan'e Line A phase tripping	Action
21	2020-07-03 16:48:50:500	Yandang Substation 220 kV Yan'e Line B phase tripping	Action
22	2020-07-03 16:48:50:500	Yandang Substation 220 kV Yan'e Line C phase tripping	Action
23	2020-07-03 16:48:50:500	Yandang Substation 220 kV Yan'e Line current differential protection	Action
24	2020-07-03 16:48:50:500	Yandang Substation 220 kV Yan'e Line A phase tripping	Action
25	2020-07-03 16:48:50:500	Yandang Substation 220 kV Yan'e Line B phase tripping	Action
26	2020-07-03 16:48:50:500	Yandang Substation 220 kV Yan'e Line C phase tripping	Action
27	2020-07-03 16:48:50:501	Emei Substation 220 kV Yan'e line fast distance	Action
28	2020-07-03 16:48:50:501	Emei Substation 220 kV Yan'e Line phase to phase distance Section I	Action
29	2020-07-03 16:48:50:501	Emei Substation 220 kV Yan'e Line power frequency variation impedance	Action
30	2020-07-03 16:48:50:502	Emei Substation 220 kV Yan'e Line power frequency interphase distance Section I	Action
31	2020-07-03 16:48:50:510	Emei Substation 220 kV Yan'e Line 2254 breaker main outlet tripping	Action
32	2020-07-03 16:48:50:510	Emei Substation 220 kV Yan'e Line 2254 breaker first group outlet tripping	Action
33	2020-07-03 16:48:50:510	Emei Substation 220 kV Yan'e Line 2254 breaker second group outlet tripping	Action
34	2020-07-03 16:48:50:510	Emei Substation 220 kV Yan'e Line reclosing charging completed	Reset
35	2020-07-03 16:48:50:510	Emei Substation 220 kV Yan'e Line blocking autorecloser	Action
36	2020-07-03 16:48:50:510	Yandang Substation 220 kV Yan'e Line 2252 breaker main outlet tripping	Action
37	2020-07-03 16:48:50:510	Yandang Substation 220 kV Yan'e Line 2252 breaker first group outlet tripping	Action
38	2020-07-03 16:48:50:510	Yandang Substation 220 kV Yan'e Line 2252 breaker second group outlet tripping	Action
39	2020-07-03 16:48:50:510	Yandang Substation 220 kV Yan'e Line reclosing charging completed	Reset
40	2020-07-03 16:48:50:510	Yandang Substation 220 kV Yan'e Line blocking autorecloser	Action
41	2020-07-03 16:48:50:520	Yandang Substation 220 kV Yan'e Line 2252 breaker ABC phase	Trip
42	2020-07-03 16:48:50:540	Yandang Substation 220 kV Yan'e Line protection	Reset
43	2020-07-03 16:48:50:540	Yandang Substation 220 kV Yan'e Line longitudinal distance	Reset
44	2020-07-03 16:48:50:540	Yandang Substation 220 kV Yan'e Line A phase tripping	Reset
45	2020-07-03 16:48:50:540	Yandang Substation 220 kV Yan'e Line B phase tripping	Reset
46	2020-07-03 16:48:50:540	Yandang Substation 220 kV Yan'e Line C phase tripping	Reset
47	2020-07-03 16:48:50:540	Yandang Substation 220 kV Yan'e Line current differential protection	Reset
48	2020-07-03 16:48:50:540	Yandang Substation 220 kV Yan'e Line A phase tripping	Reset
49	2020-07-03 16:48:50:540	Yandang Substation 220 kV Yan'e Line B phase tripping	Reset
50	2020-07-03 16:48:50:540	Yandang Substation 220 kV Yan'e Line C phase tripping	Reset
51	2020-07-03 16:48:50:620	Emei Substation 220 kV busbar failure protection	Action
52	2020-07-03 16:48:50:620	Emei Substation 220 kV busbar outlet	Action
53	2020-07-03 16:48:50:620	Emei Substation 220 kV bus II failure protection	Action
54	2020-07-03 16:48:50:620	Emei Substation 220 kV busbar failure	Action
55	2020-07-03 16:48:50:640	Zhongshan Substation 220 kV Zhong'e II Line protection	Action
56	2020-07-03 16:48:50:640	Zhongshan Substation 220 kV Zhong'e II Line A phase tripping	Action
57	2020-07-03 16:48:50:640	Zhongshan Substation 220 kV Zhong'e II Line B phase tripping	Action
58	2020-07-03 16:48:50:640	Zhongshan Substation 220 kV Zhong'e II Line C phase tripping	Action
59	2020-07-03 16:48:50:650	Zhongshan Substation 220 kV Zhong'e II Line 2254 breaker main outlet tripping	Action
60	2020-07-03 16:48:50:650	Zhongshan Substation 220 kV Zhong'e II Line 2254 breaker first group outlet tripping	Action
61	2020-07-03 16:48:50:650	Zhongshan Substation 220 kV Zhong'e II Line 2254 breaker second group outlet tripping	Action
62	2020-07-03 16:48:50:650	Zhongshan Substation 220 kV Zhong'e II Line reclosing charging completed	Reset
63	2020-07-03 16:48:50:650	Zhongshan Substation 220 kV Zhong'e II Line blocking autorecloser	Action
64	2020-07-03 16:48:50:660	Zhongshan Substation 220 kV Zhong'e II Line 2254 breaker ABC phase	Trip
65	2020-07-03 16:48:50:680	Zhongshan Substation 220 kV Zhong'e II Line protection	Reset
66	2020-07-03 16:48:50:680	Zhongshan Substation 220 kV Zhong'e II Line A phase tripping	Reset
67	2020-07-03 16:48:50:680	Zhongshan Substation 220 kV Zhong'e II Line B phase tripping	Reset

TABLE BI
THE ALARM INFORMATION SET OF THE PERMANENT FAILURE OF ABC THREE-PHASE OF YAN'E LINE IN EMEI STATION AND CB2254 FAILED ACTION
(CONTINUED)

Number	Time	Information	Action description
68	2020-07-03 16:48:50:680	Zhongshan Substation 220 kV Zhong'e II Line C phase tripping	Reset
69	2020-07-03 16:48:50:680	Emei Substation #2 Transformer 220 kV side 2202 breaker main outlet tripping	Action
70	2020-07-03 16:48:50:680	Emei Substation #2 Transformer 220 kV side 2202 breaker first group outlet tripping	Action
71	2020-07-03 16:48:50:680	Emei Substation #2 Transformer 220 kV side 2202 breaker second group outlet tripping	Action
72	2020-07-03 16:48:50:680	Emei Substation 220 kV Zhong'e II Line 2252 breaker main outlet tripping	Action
73	2020-07-03 16:48:50:680	Emei Substation 220 kV Zhong'e II Line 2252 breaker first group outlet tripping	Action
74	2020-07-03 16:48:50:680	Emei Substation 220 kV Zhong'e II Line 2252 breaker second group outlet tripping	Action
75	2020-07-03 16:48:50:680	Emei Substation 220 kV Zhong'e II Line reclosing charging completed	Reset
76	2020-07-03 16:48:50:680	Emei Substation 220 kV Zhong'e II Line blocking autorecloser	Action
77	2020-07-03 16:48:50:690	Emei Substation 220 kV Zhong'e II Line 2252 breaker ABC phase	Trip
78	2020-07-03 16:48:50:690	Emei Substation #2 Transformer 220 kV side 2202 breaker ABC phase	Trip
79	2020-07-03 16:48:50:710	Emei Substation 220 kV Yan'e Line current differential protection	Reset
80	2020-07-03 16:48:50:710	Emei Substation 220 kV Yan'e line fast distance	Reset
81	2020-07-03 16:48:50:710	Emei Substation 220 kV Yan'e Line phase to phase distance Section I	Reset
82	2020-07-03 16:48:50:710	Zhongshan Substation 220 kV Zhong'e II Line reclosing charging completed	Reset
83	2020-07-03 16:48:50:760	Emei Substation 220 kV busbar failure protection	Reset
84	2020-07-03 16:48:50:760	Emei Substation 220 kV busbar outlet	Reset
85	2020-07-03 16:48:50:760	Emei Substation 220 kV bus II failure protection	Reset
86	2020-07-03 16:48:50:760	Emei Substation 220 kV busbar failure	Reset
87	2020-07-03 16:48:55:002	Emei Substation Transformer Fault recorder start	Reset
88	2020-07-03 16:48:55:002	Emei Substation 220 kV Fault recorder start	Reset
89	2020-07-03 16:48:55:002	Emei Substation 110 kV fault recorder start	Reset
90	2020-07-03 16:48:55:002	Yandang Substation Transformer Fault recorder start	Reset
91	2020-07-03 16:48:55:002	Yandang Substation 220 kV Fault recorder Start	Reset
92	2020-07-03 16:48:55:002	Yandang Substation 110 kV Fault recorder start	Reset
93	2020-07-03 16:48:55:022	Emei Substation 220 kV Yan'e Line 2254 breaker first group outlet tripping	Reset
94	2020-07-03 16:48:55:022	Emei Substation 220 kV Yan'e Line 2254 breaker second group outlet tripping	Reset
95	2020-07-03 16:48:55:022	Emei Substation 220 kV Yan'e Line 2254 breaker main outlet tripping	Reset
96	2020-07-03 16:48:55:022	Yandang Substation 220 kV Yan'e Line 2252 breaker first group outlet tripping	Reset
97	2020-07-03 16:48:55:022	Yandang Substation 220 kV Yan'e Line 2252 breaker second group outlet tripping	Reset
98	2020-07-03 16:48:55:022	Yandang Substation 220 kV Yan'e Line 2252 breaker main outlet tripping	Reset
99	2020-07-03 16:48:55:162	Zhongshan Substation 220 kV Zhong'e II Line 2254 breaker first group outlet tripping	Reset
100	2020-07-03 16:48:55:162	Zhongshan Substation 220 kV Zhong'e II Line 2254 breaker second group outlet tripping	Reset
101	2020-07-03 16:48:55:162	Zhongshan Substation 220 kV Zhong'e II Line 2254 breaker main outlet tripping	Reset
102	2020-07-03 16:48:55:192	Emei Substation #2 Transformer 220 kV side 2202 breaker first group outlet tripping	Reset
103	2020-07-03 16:48:55:192	Emei Substation #2 Transformer 220 kV side 2202 breaker second group outlet tripping	Reset
104	2020-07-03 16:48:55:192	Emei Substation #2 Transformer 220 kV side 2202 breaker main outlet tripping	Reset
105	2020-07-03 16:48:55:162	Emei Substation 220 kV Zhong'e II Line 2252 breaker first group outlet tripping	Reset
106	2020-07-03 16:48:55:162	Emei Substation 220 kV Zhong'e II Line 2252 breaker second group outlet tripping	Reset
107	2020-07-03 16:48:55:162	Emei Substation 220 kV Zhong'e II Line 2252 breaker main outlet tripping	Reset
108	2020-07-03 16:48:55:502	Emei Substation #1 Transformer overload	Action
109	2020-07-03 16:48:55:502	Emei Substation #1 Transformer device abnormal	Action
110	2020-07-03 16:49:00:501	Emei Substation 220 kV Yan'e Line TV line-break	Action
111	2020-07-03 16:49:00:501	Emei Substation 220 kV Yan'e Line device failure	Action
112	2020-07-03 16:49:00:501	Emei Substation 220 kV Zhong'e II Line PT line-break	Action
113	2020-07-03 16:49:00:501	Emei Substation 220 kV Zhong'e II Line device failure	Action
114	2020-07-03 16:49:00:501	Emei Substation #2 Transformer TV line-break	Action
115	2020-07-03 16:49:00:501	Emei Substation #2 Transformer device failure	Action
116	2020-07-03 16:49:00:501	Emei Substation 220 kV Busbar TV line-break	Action
117	2020-07-03 16:49:00:501	Emei Substation 220 kV Busbar device failure	Action

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