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Research Article

The Cable Fault Diagnosis for XLPE Cable Based on 1DCNNs-BiLSTM Network

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Diagnosing the fault type accurately from a variety of faults is very essential to ensure a stable electricity supply when a short-circuit fault occurs. In this paper, a hybrid classification model combining the one-dimensional convolutional neural network (1D-CNN) and the bidirectional long short-term memory network (BiLSTM) is proposed for the classification of cable short-circuit faults to improve the accuracy of fault diagnosis. Sample sets of the current signal for single-phase grounding short circuit, two-phase grounding short circuit, two-phase to phase short circuit, and three-phase grounding short-circuit are obtained by the simulink model, and the signal is input to this network model. The local features of the cable fault signals are extracted using 1D-CNN and the fault signal timing information is captured using BiLSTM, which enables the diagnosis of cable faults based on the automatically extracted features. The experimental results of the simulation show that the model can obtain a good recognition performance and can achieve an overall accuracy of 99.45% in classifying the four short-circuit faults with 500 iterations. In addition, the analysis of loss function curves and accuracy curves shows that the method performs better than networks with only temporal feature extraction, such as 1D-CNN and LSTM.

1. Introduction

Because of the advantages of better insulation and electrical characteristics, cross-linked polyethylene (XLPE) cables are widely used [1, 2]. In the process of power transmission, cables may be affected by many factors, which may lead to short-circuit faults in cables and even make the supply grid paralyzed if the faults cannot be removed in time. Therefore, it is important to fully understand the characteristics of cable short-circuit faults and accurately determine the type of cable short-circuit faults, which can guarantee the power grid's safe operation.

With the development of power cable fault diagnosis technology, various technologies have been gradually applied to cable fault diagnosis. Traditional cable fault diagnosis methods are centered on machine learning and artificial intelligence algorithms, including artificial neural networks (ANN) [3], wavelet analysis [4], and other methods. These methods can be used in combination [5], for example, Ren built a cable simulation model by Simulink, then extracted the features of the normal voltage signals and fault voltage signals, respectively, and finally used ANN to diagnose cable faults and identify the cable fault signal [6]. These methods show greater advantages in the processing and classification of signals but have problems such as poor prediction stability and ineffective processing of large-scale data. Therefore, deep learning models are introduced into the field of fault diagnosis of cables, such as the deep neural network (DNN) [7], the random forest algorithm [8], the deep belief network (DBN) [9], and convolutional neural network (CNN) [10], and other methods. These deep neural network models improve the performance and have higher recognition accuracy than the traditional algorithms [11]. Compared with other deep learning models, CNN has a unique structure, with subsampling operations reducing the dimensionality of the data and weight sharing reducing the complexity of the network [12]. It has effective training methods and a special network structure, which can better

extract the effective features that are conducive to recognize in the data. The 1D-CNN model is used to learn high-level features, which can be applied to various cable types, and has an excellent performance in terms of recognition accuracy [13, 14]. A previous study [15] used convolutional neural networks for pattern recognition of partial discharges to identify insulation defects in cables. A previous study [16] used optimized convolutional neural networks for the identification and classification of early faults in cables with high accuracy.

However, there are still problems such as cumbersome methods, low efficiency, and insufficient recognition accuracy. Most of the present research has focused on the voltage characteristics of short circuits, but it is also crucial to monitor the current during the electricity grid operation [17]. The age of cable insulation can be judged by the change in current. In addition, since the higher the short-circuit current, the greater the damage to the faulty equipment, the measurement of short-circuit current can also help us to judge the degree of urgency. Therefore, the phase current signal is collected in this paper to facilitate other analyses.

According to the above analysis, for the high accuracy requirements of cable fault diagnosis and the problems in existing models, a fault diagnosis method for electric power cables based on 1D-CNN and BiLSTM is proposed in this paper. With the structural features and actual parameters of the cable, a 10 kV cable short-circuit fault model was established by adding noise to simulate the actual operating environment, and the phase current sample data of the cable short-circuit fault was generated using Simulink. The local features of the cable fault signal are extracted using 1DCNN, and the fault signal timing information is considered using BiLSTM so that the cable fault diagnosis is realized. The significant contributions of this paper are shown as follows:

(1) A reference basis is provided for future research on online monitoring of cables. A cable fault simulation model is built to simulate the dynamic changes in the current when a short-circuit fault occurs in the cable, and the cable fault sample data is generated.

(2) The timing of the current signal is considered. A BiLSTM network model is introduced to extract the relationship between the output of the current time and the past and future states, which is the first time, to our knowledge, to be applied to the field of cable fault detection.

(3) An effective cable fault identification method is proposed. The advantages of the 1D-CNN model and the BiLSTM network model are fused to construct an improved 1DCNN-BiLSTM model, so that the accuracy of cable fault diagnosis and the performance of the algorithm is improved.

2. Methodology

2.1. Types of Faults. Short-circuit faults have the highest probability of occurrence among all faults in power cables. It usually refers to a fault in the cable due to the lowering of the insulation layer, when the insulation resistance of one or more phases of the cable to ground is small, generally tens of ohms to hundreds of ohms. It is necessary to study the differences between different faults in cables to be able to deal with them quickly, which is essential to ensure the reliability and safety of grid operation. The types of short-circuit faults are shown in Table 1.

For the line grounded by the arc extinguishing coil, when a single-phase ground fault occurs, the ground fault and the arc extinguishing coil constitute another circuit. An inductive current is added to the grounding current; they are in opposite directions and compensate each other, making the fault current at the grounding point smaller compared to the case of direct neutral grounding.

When a single-phase grounded fault occurs, the current of the fault phase will increase; when a two-phase grounded short-circuit fault occurs, the current of the nonfault phase remains unchanged, and the current of the fault phase rises sharply; when a two-phase short-circuit fault occurs, the current of the fault phase increases rapidly, and the current of the nonfault phase remains basically unchanged; when a three-phase short-circuit fault occurs, the three phases remain symmetrical, and the three-phase short-circuit current rises sharply with equal amplitude and phase angle difference of 120°.

2.2. Feature Extraction with 1D-CNN. The essence of cable fault classification is to distinguish the fault current from the normal current signal. The key to getting high accuracy from the network is the extraction of features. If the method is not chosen properly, the feature will be redundant and unfavorable to the classification results.

CNN can effectively extract structural features of one-dimensional complex signals, and it can extract temporal features excellently with fewer network parameters, thus improving the speed of model detection and preventing overfitting [18].

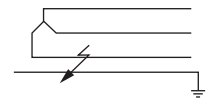
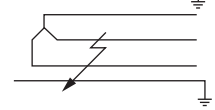
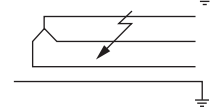
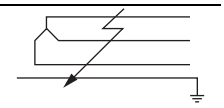
Considering that the spatial dimension of the current signal is not as informative as the temporal dimension, 1D-CNN is used to improve the recognition rate of the signal, and its structure consists of a convolutional layer, a pooling layer and a fully connected layer [19]. The role of the convolution layer is to perform an effective feature extraction of the input specific signal, which is to perform a local convolution operation on the target input.

In the case of one spatial dimension, the convolution process is formulated as follows:

$$X_j^l = f\left(\sum_{i\in \mathbf{N}} X_i^{l-1} W_{ij}^l + b_j\right), \tag{1}$$

where f is the activation function, M_j is the target of the input operation, is the length of the input, X_i^{l-1} is the region of the target input to be convolved, W_{ij}^l is the convolution kernel, also known as the weights, and b_j is the bias parameter. Since the Tanh function is an output zero mean function, it can achieve better practical results and converge faster than the Sigmoid function.

Table 1: Short-circuit fault type.

Type	Name	Schematic
Asymmetric short-circuit	Single-phase grounding fault	
	Two-phase grounding fault	
	Two-phase to phase short-circuit	
Symmetrical short-circuit	Three-phase grounding fault	

The pooling layer generally follows the convolutional layer. The pooling operation is similar to the convolutional operation in that it also moves over the operation target. By sampling the convolutional layer, the dimensionality of the input data is reduced, and the computational speed of the network is increased. The expressions are shown as follows.

$$X_j^l = f\left(\beta_j^l \operatorname{down}\left(x_j^{l-1}\right) + b_j^l\right), \tag{2}$$

where l is the current layer of the network, down 0 is the pooling function, and β is the weight.

The formula for the fully connected layer is given as follows:

$$h\left(x^l\right) = f\left(\omega_1 x^{l-1} + b_1\right), \tag{3}$$

where $h(x^l)$ is the fully connected output of layer L, Ω_1 and b_1 are the weight parameters and offsets of the neuron nodes.

Softmax is usually used as the activation function to solve problems with multiple classifications and the output is

$$Y = S\left(\omega_2 h + b_2\right), \tag{4}$$

where Y is the output and S is the Softmax function, which is expressed as follows:

$$S_j = \frac{e^{a^j}}{\sum_{p=1}^{k} e^{a_p}}, \tag{5}$$

where a_j indicates the result of the jth output of the fully connected layer, and S_j indicates the probability that the classification result is the jth class.

2.3. Capture of Fault Signal Timing Information with BiLSTM. Recurrent Neural Network (RNN) has the structural feature of nodes connected in a loop, which makes it suitable for the processing of time series data, but often faces the problem of gradient disappearance. The long- and short-term memory (LSTM) and gated recurrent unit (GRU) improve on RNN by adding multiple threshold gates to alleviate the gradient disappearance problem and improve the accuracy of classification. Since the LSTM model contains memory units, it prevents the network from experiencing gradient explosion. In the LSTM, input gates, output gates, and forgetting gates control the flow of information in the memory cell.

The LSTM network can improve the shortcomings of the RNN network, but it can only obtain the information about the sequence from front to back, not from back to front. In many cases, the output of the current time is related not only to the state information of the past time, but also to the state information of the future time. In response to the problem, the BiLSTM network was established [20], which combines past and future information by connecting two LSTMs. The internal structure of the BiLSTM network consists of two main parts, the front-to-back LSTM layer, and the back-to-forth LSTM layer. The forward and backward layers compute the input data separately, and finally, the structure of the two computed layers is combined to obtain the output of the BiLSTM network. The BiLSTM network is calculated as follows:

$$\begin{aligned} o_t &= g\left(\omega_1 i_t + \omega_2 o_{t-1}\right), \\ o_t' &= g\left(\omega_3 i_t + \omega_5 o_{t-1}'\right), \\ y_t &= f\left(\omega_4 o_t + \omega_6 o_t'\right), \end{aligned} \tag{6}$$

where ω is the weight parameter in the BiLSTM network, i_t is the input at the time of t, o_t is the output of the forward hidden layer at the time t, o_t' is the output of the backward hidden layer at the time t, and y_t is the final output of the network.

3. 1DCNN-BiLSTM Network Model

1D-CNN can well adapt to the one-dimensional characteristics of the cable fault signal and can effectively extract the local features of the cable fault signal. However, 1DCNN does not consider the timing of fault signals and cannot solve the long-term dependence problem of fault signals. BiLSTM can solve the problem of long-term dependence, but the feature extraction ability is relatively weak [21]. Therefore, a 1DCNN-BiLSTM cable fault diagnosis model is designed in this paper, and the features extracted by 1D-CNN are transmitted to the BiLSTM network, which can make the

network diagnose the cable fault more accurately. The constructed CNN-BiLSTM is shown in Figure 1.

1D-CNN and Maxpooling layers are used for parameter sharing, spatial layout and local sensing. The parameter sharing allows reducing a set of parameter sets and free variables, thus performing feature extraction with reduced use of processing resources. Spatial layout allows the alignment of a sparse matrix of identified features to better identify the correlations of features. Finally, local perception allows reducing the number of parameters to substantially shorten the training time. The maxpooling layer follows 1D-CNN layers, which allow sample-based discretization of parameters to identify relevant features, thus reducing training time and preventing overfitting.

The BiLSTM layer is used to learn forward and backward time series data. The hidden layer uses two units with the same input and connected to the same output, one unit processing the forward time series and the other processing the backward time series. This approach can shorten the training time and achieve better feature learning, thus improving the recognition accuracy for large span time series data.

The specific process of the cable fault diagnosis using 1DCNN-BiLSTM is shown below:

(1) Generate cable insulation aging current samples. Build a 10 kV distribution network simulation model by Simulink, collect the phase current signals of cable faults, make a set of cable fault samples, and set the code of the corresponding type for each type of sample.

(2) Construct a network model with 1D-CNN and BiLSTM fusion. The structural parameters and data shape of the CNN-BiLSTM model in the paper are shown in Table 2. The best characteristics of the network were determined through several experiments. Five convolutional layers and three pooling layers are used in the CNN network, and two BiLSTMs are used in the BiLSTM network. In the first two convolution layers, a $3 * 16$ filter kernel is used for extracting the local detailed structure, in the second two convolution layers, the filter kernel is $3 * 32$, and in the last one convolution layer, the filter kernel is $3 * 64$. As the number of layers increases, more and more global and complex properties of the input signal are captured. One max pooling layer is added after every two convolution layers to retain the main features and reduce the computation. The max pooling layer is connected to a dropout layer with a probability of 0.5. The hyperbolic tangent function (Tanh) is used to improve the ability of the neural network to express the model in each convolutional layer. Finally, a softmax classifier of $1 * 4$ is used to classify the four event targets.

(3) Generate training samples and test samples. The samples are randomly divided into training samples and test samples in a ratio of 7 : 3.

(4) Training process. The training sample is used as the input of the model, and 500 iterations of training are performed to optimize the parameters through repeated updates of the parameters and to establish the mapping relationship between the input and output.

(5) Testing process. The trained network is tested with the test sample to test the accuracy of the neural network recognition.

4. Experiments

4.1. Construction of Simulation Model. In this paper, Simulink is used to build a simulation model of a 10 kV distribution network. According to the real conditions of the grid operation, the grounding method of the model is set to ground the neutral point via the arc extinguishing coil.

The power supply is a 10 kV three-phase AC power supply, and the frequency is set to 50 Hz at industrial frequency. A three-phase PI-type equivalent circuit module is used, referencing the actual XLPE cable parameters. The positive sequence parameters are set to $R_1 = 0.64\,\Omega/\text{km}$, $L_1 = 0.1223\,\text{mH/km}$, and $C_1 = 0.0094\,\mu\text{F/km}$. The zero sequence parameters are set to $R_0 = 0.921\,\Omega/\text{km}$, $L_0 = 6.116\,\text{mH/km}$, and $L_0 = 0.0031\,\mu\text{F/km}$. Three-phase series resistors and inductor modules are selected for the load module to achieve a three-phase balanced load through a series combination of resistors and inductors, and the load exhibits a constant impedance at the rated frequency.

The simulation model is shown in Figure 2. There are three cable lines in the simulation model, all of which are set to 5 km in length, and the loads on the cable lines are equal. Each line consists of two PI-type modules to simulate the actual cable, and the fault location is set in the middle of the two cable lines.

In this paper, the fault current signals were collected on the cable line. The fault point was added at 0.05 s after the start of the cable operation and continued to the end of 0.2 s.

Considering the uneven distribution of the power cable signal, white noise is added to the collected fault current signal to simulate the noise interference of the field environment, which has a Gaussian distribution of amplitude and a uniform distribution of power spectral density. The cable noise characteristic is shown in Figure 3.

The above noise source is added to the current obtained from the simulation, and the result is shown in Figure 4.

It is clear that there is a visible signal loss in the phase current signal with the addition of noise, where, *A_G* means the ground fault occurred in phase A, *AB_G* means the ground fault occurred in phase A and phase B, *ABC_G* means the ground fault occurred in phase A, phase B, and phase C, *A_B* means a short-circuit fault occurred between phase A and phase B.

4.2. Denoising with Wavelet Transform. In order to gain a higher recognition accuracy, the current signal of the cable needs to be denoised to minimize the external interference.

The wavelet transform is a modified form of the Fourier transform. Compared with the Fourier transform, it has the ability to judge the local signal characteristic changes and

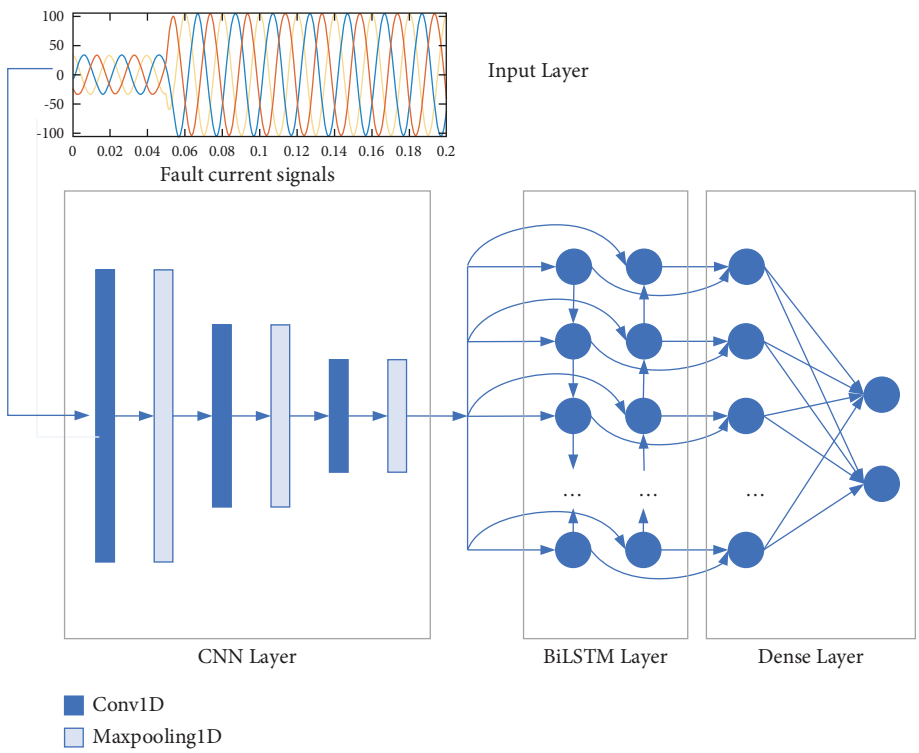


Figure 1: The 1DCNNs-BiLSTM algorithm.

Table 2: The structural parameters of the 1DCNN-BiLSTM network.

Layers	Parameters	Data shape
Input		(8004, 1)
Conv1 Conv2	Fitters = 16, kernel size = 3, stride = 1, activation = "tanh"	(8002, 16) (8000, 16)
MaxPooling1	Pool size = 3	(2666, 16)
Conv3 Conv4	Fitters = 32, kernel size = 3, stride = 1, activation = "tanh"	(2662, 32) (2660, 32)
MaxPooling2	Pool size = 3	(888, 3)
Conv5	Fitters = 64, kernel size = 3, stride = 1, activation = "tanh"	(886, 64)
MaxPooling1	Pool size = 3	(295, 64)
BiLSTM1 BiLSTM2	Hidden = 128, activation = "tanh"	(256) (256)
Softmax	Classifier	(4)

automatically change the time window according to the frequency characteristics of the signal, thus characterizing the singularity of the measured signal.

After several attempts, the wavelet transform with the decomposition layer of 5 and wavelet base of db4 is selected in this paper.

As shown in Figure 5, where I is the original signal of the five-layer wavelet decomposition, A_1, A_2, A_3, A_4, and A_5 are the approximation, and D_1, D_2, D_3, D_4, and D_5 are the detail. In the process, the approximation of each level will participate in the next level of decomposition, while the detail will not.

The process consists of two parts: firstly, the signal containing noise is decomposed to obtain the wavelet coefficients at different scales. At most scales, the amplitudes of the current signal and the noise signal have significant amplitude differences. The amplitude of the current signal is higher, while the amplitude of the noise signal decays rapidly with the scale to converging to zero. Then the wavelet signal is reconstructed, and the approximation is reconstructed to obtain the target signal after removing the noise.

The current waveforms after denoising are shown in Figure 6. It can be seen that the method can achieve effective noise removal of the current signals, and the processed current signals are very close to the original waveforms.

4.3. Acquisition of Experimental Data. The fault signal with denoising is sampled at 13.34 kHz with a sampling time of

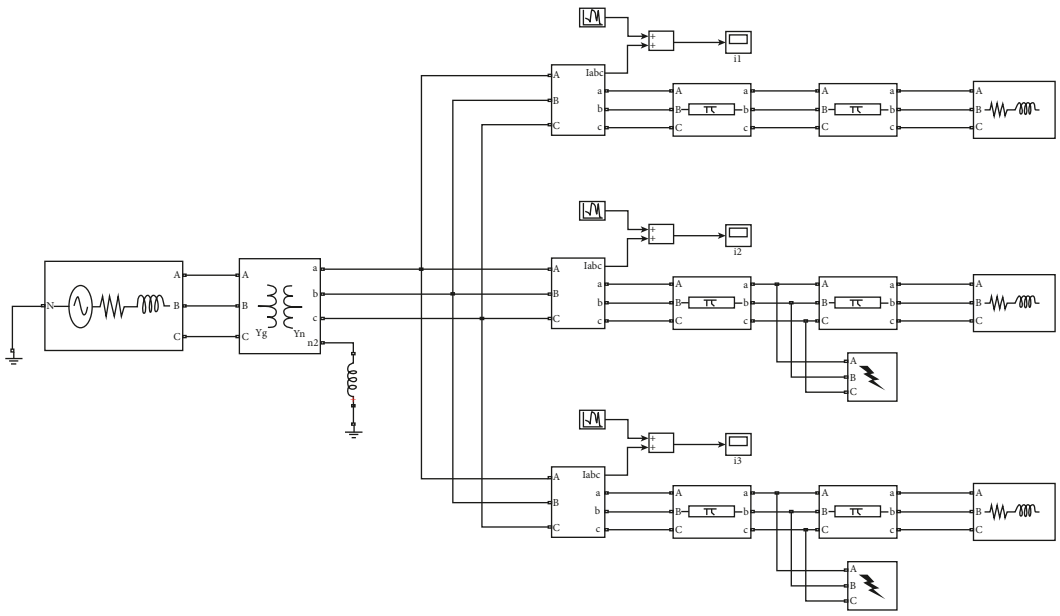


Figure 2: Distribution network simulation model.

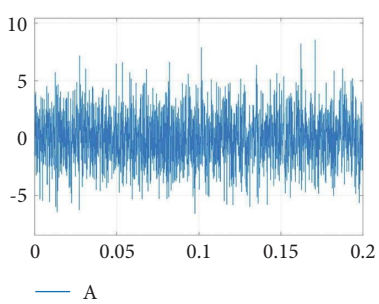


Figure 3: Noise characteristic diagram of a cable.

0.2 s. The single phase contains 2668 points, and each line has three phases with a total of 8004 points, which means the length of each sample is 8004.

In this paper, four types of the cable fault signal are collected, each fault contains 1000 samples, and the total number of samples is 4000. 70% of all are used as training samples, and 30% are used as test samples. The number of samples collected for each type of signal is shown in Table 3.

5. Experimental Results

The network model is built based on Keras. The sample labels in the experiments are processed using one_hot, which is input to the network with a batch size set to 128 and the learning rate set to 0.001.

Loss function curves and accuracy curves are usually used for the evaluation of fault signal recognition capability in neural networks. The loss function calculates the error between the predicted and true values of the network model. The smaller the error, the more accurately the network predicts the target. Accuracy is one of the most common evaluation metrics for network classification, and a higher accuracy rate proves that the network classifies the target more accurately. The 1DCNN-BiLSTM network proposed in this paper is experimentally compared with the 1D-CNN network and the BiLSTM network, respectively. When the number of iterations is 500, the loss function curves are shown in Figure 7, the accuracy curves are shown in Figure 8, and the confusion matrixes are shown in Figure 9.

With the 500 iterations of the network model, the accuracy of the 1DCNN-BiLSTM network for power cable fault diagnosis keeps increasing and the value of the loss function keeps decreasing.

In Figure 7, in terms of the decreasing speed of the loss function curve, the loss function curves of all three networks keep decreasing with the increasing number of iterations, but the 1D-CNN and 1DCNN-BiLSTM networks are significantly faster than the 1DCNN-LSTM network. In terms of the smoothness of the curve, the 1DCNN-BiLSTM network curve is the smoothest, and the value of the final loss function is the smallest and most stable. It can be seen that the performance of 1DCNN-BiLSTM for power cable fault diagnosis is better than that of the other two networks.

As seen in Figure 8, the accuracy curves of the three network models keep rising with the 500 iterations of training of the three networks. In terms of the rate of increase of the accuracy curves, the three network models are similar, but the curve of the 1DCNN-BiLSTM network is significantly smoother, and the final accuracy is greater than that of the other two networks.

The accuracy of several network models for the cable fault classification is compared, as shown in Table 4.

It can be seen that the 1D-CNN model, which has a strong feature extraction capability but does not consider the timing of the cable fault signal, has the lowest accuracy of only 97.50%. The 1DCNN-LSTM model takes into account

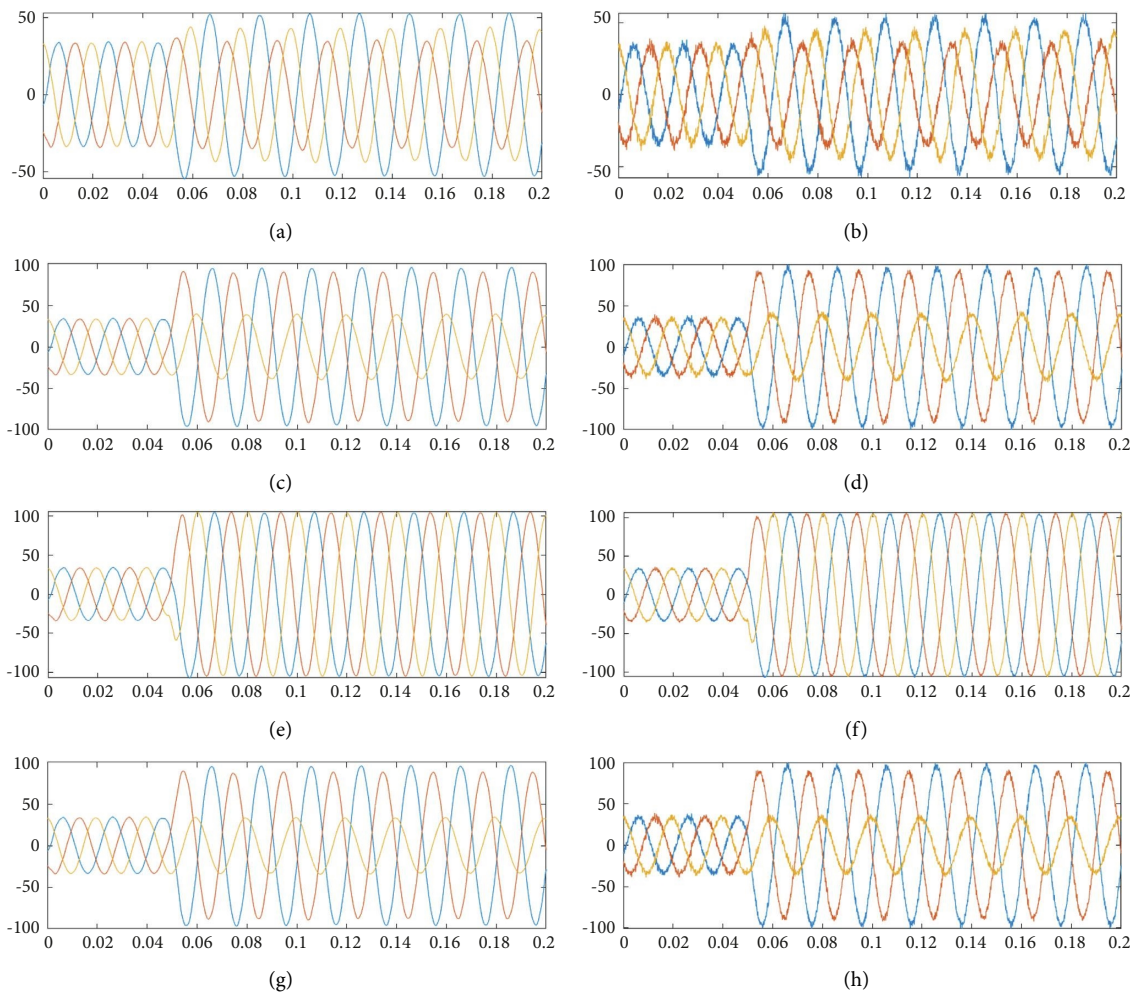


Figure 4: Waveforms of various short-circuit fault current. (a) *A_G* fault. (b) *A_G* fault with noise (SNR = 22.2183). (c) *AB_G* fault. (d) *AB_G* fault with noise (SNR = 26.5354). (e) *ABC_G* fault. (f) *ABC_G* fault with noise (SNR = 32.6782), (g) *A_B* fault. (h) *A_B* fault with noise (SNR = 26.4324).

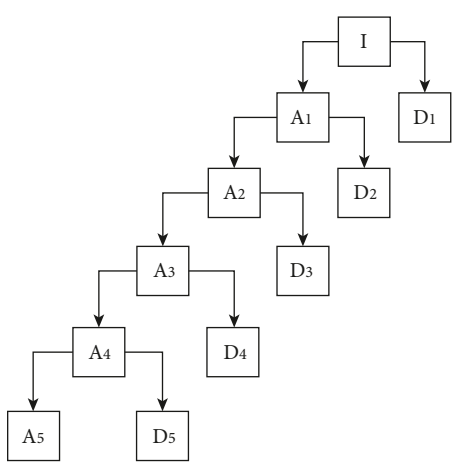


Figure 5: Flow chart of wavelet decomposition.

the temporal information and achieves an accuracy of 98.33%, which is 0.83% better than the 1D-CNN model. BiLSTM considers the past information from the forward layer and future information from the backward layer, which is combined with the powerful feature extraction capability of 1D-CNN, and the accuracy of the 1DCNN-BiLSTM model is further improved to 99.45%.

In Figure 9, the vertical coordinate represents the true categories of cable fault signals, and the horizontal coordinates represent the predicted class of the cable fault signal by the network. The diagonal values on the matrix indicate the probability that the cable fault signal is correctly classified. From the confusion matrices, it can be seen that with 500 iterations, the 1D-CNN model has an accuracy of 96% for the classification of *AB_G* fault and *ABC_G* fault, has an accuracy of 97% for the classification of *A_B* fault, and has an accuracy of 100% for the *A_G* fault. The 1DCNN-LSTM model has an accuracy of 96% for the classification of *AB_G* fault and *ABC_G* fault, and has an accuracy of 100% for the other two faults. The 1DCNN-BiLSTM achieves 100% accuracy for the classification of three faults, just has an accuracy of 97% for the classification of *A_B* fault. It shows that it is fully feasible to use the 1DCNN-BiLSTM network model for cable fault diagnosis.

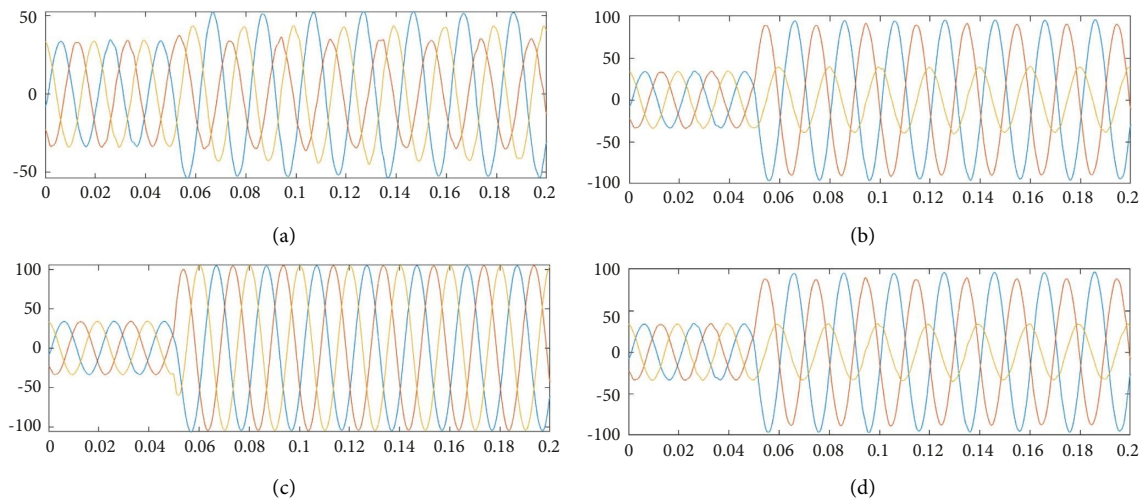


Figure 6: Waveforms of various short-circuit fault current after denoising. (a) *A_G* fault. (b) *AB_G* fault. (c) *ABC_G* fault. (d) *A_B* fault.

Table 3: Collection quantity of various signal samples.

Type of fault	Sample size	Label
A_G fault	1000	1
AB_G fault	1000	2
A_B fault	1000	3
ABC_G fault	1000	4

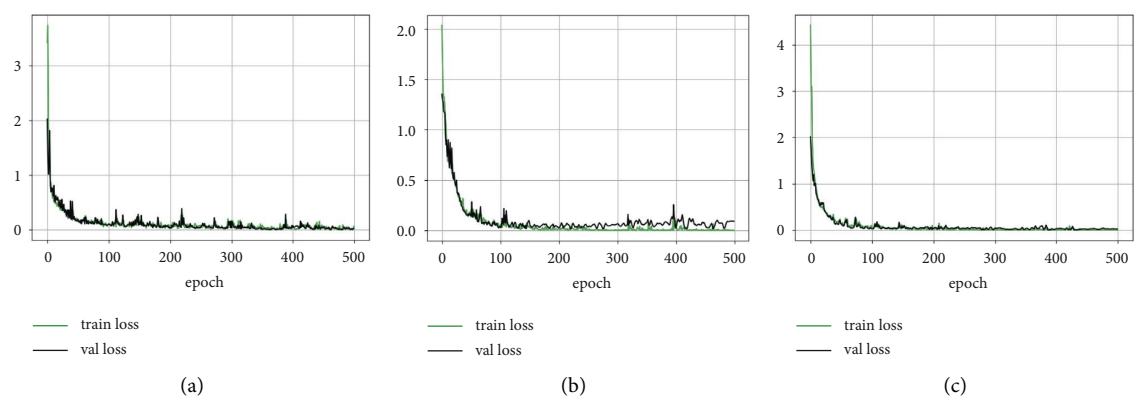


Figure 7: Loss function curves of various network models. (a) 1DCNN network. (b) 1D-LSTM network. (c) 1DCNN-BiLSTM network.

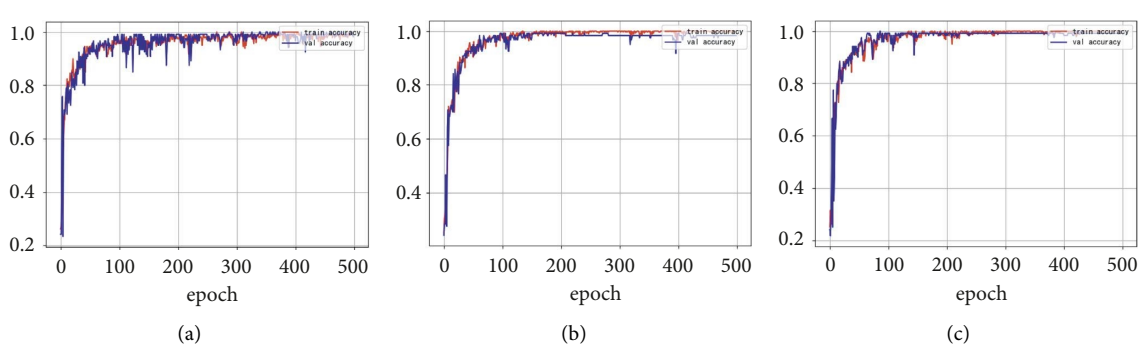


Figure 8: Accuracy curves of various network models. (a) 1DCNN network. (b) 1D-LSTM network. (c) 1DCNN-BiLSTM network.

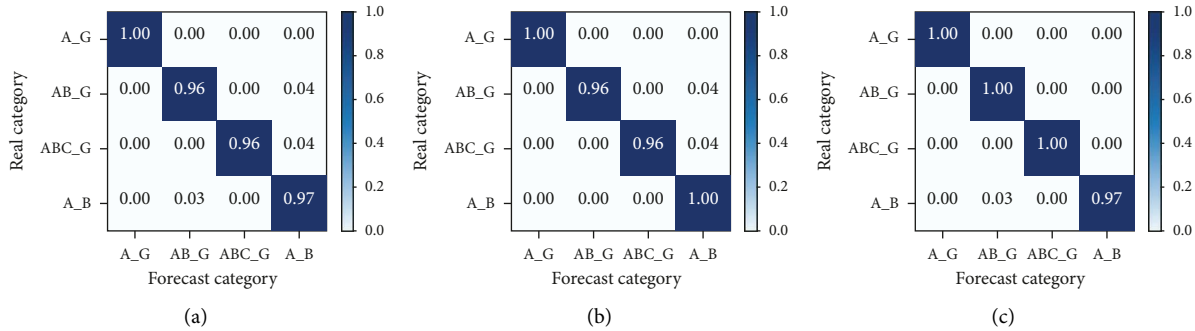


Figure 9: Confusion matrices for the network model. (a) 1DCNN network. (b) 1D-LSTM network. (c) 1DCNN-BiLSTM network.

Table 4: Accuracy comparison of different network models.

Network model	Number of network layers	Accuracy (%)
1D-CNN	4	97.5
1DCNN-LSTM	4 + 2	98.33
1DCNN-BiLSTM	4 + 2	99.45

6. Conclusions

In this paper, a method of cable insulation aging identification based on 1D-CNN and BiLSTM are proposed, which can automatically extract the local features of fault current signals, capture the timing information, and accurately distinguish the short-circuit fault types of cables. The following conclusions are obtained as follows:

(1) In this paper, the background noise during the actual operation of the cable is considered. More realistic cable short-circuit fault phase current signals are obtained through simulation compared with other studies, and the wavelet transform is applied to denoising so that the network model can extract features more effectively.

(2) The algorithm proposed in this paper takes into account the temporal sequence of current signals, and the local features of signals extracted by 1D-CNN are fed into BiLSTM for classification and diagnosis. The fusion of BiLSTM helps to further improve the recognition rate compared with the common models based on 1D-CNN for single temporal feature extraction.

(3) The accuracy, loss function, and confusion matrix are used to compare and verify the performance of the modified model. The results demonstrate the feasibility of the proposed algorithm in this paper for the application of identifying cable short-circuit fault types, and the accuracy of 500 iterations can reach 99.54% with better recognition performance.

To make the proposed method in this paper be applied in practice, a large number of actual measured current signals are still needed for analysis and validation.

Data Availability

The dataset obtained by simulation is used in this study. The Excel data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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