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Fault location method for overhead line-cable hybrid line based on the LSTM network

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Abstract: The intelligent algorithm has attracted broad attention in recent research of fault location method for the overhead line-cable hybrid line. To aim at the problems of high computational complexity and poor fault tolerance in existing hybrid line intelligent fault location algorithms, a new fault location method based on Long Short-term Memory (LSTM) network is proposed. Firstly, a 220kV hybrid line is built to collect line-mode voltage signals on the bus side of the line under different fault types. Secondly, discrete wavelet transform is used to decompose the line-mode voltage signal to extract fault features, and the data is preprocessed to obtain a sample set. Finally, the LSTM network performs adaptive learning on the input and output samples to obtain the LSTM fault location model. PSCAD/Matlab simulation results show that the fault location algorithm is simple to implement and has high fault tolerance. It is not affected by the transition resistance and the initial phase angle of the fault. It meets the requirements of engineering practice that the positioning accuracy is within 200 meters.

1. INTRODUCTION

When there is a fault in the transmission line, accurate fault location is conducive to quickly finding the line's fault point, eliminating the fault, and reducing the economic loss caused by power failure. At present, overhead line cable hybrid transmission lines are widely used in urban power supply in China. Such transmission lines usually have an enormous span and complex impedance composition, so it is difficult to find fault points [1-2].

For hybrid transmission lines, the fault location methods mainly include fault analysis method [3], traveling wave method [4-6], spectrum analysis method [7-8], and intelligent algorithm [9-10]. The fault analysis method mainly uses the power frequency voltage and current values collected when the line fails, combined with the line parameters for analysis and calculation to realize the fault location. The principle of the fault analysis method is simple, but there is a problem that the parameters of the hybrid line are not single, resulting in a complex calculation process and being prone to pseudo roots. The traveling wave method mainly uses the transmission law of transient traveling wave signals for fault location. Due to multiple impedance discontinuities in the hybrid line, the traveling wave will have multiple refraction and reflection in the propagation process, which makes it challenging to identify the traveling wave head. The spectrum analysis method is to extract the frequency characteristics of transient signal for fault location without identifying traveling wave head; Due to the discontinuous impedance of hybrid lines, the natural frequencies of fault traveling waves are easy to overlap, so it is difficult to extract the principal frequency components of fault traveling waves. Firstly, the intelligent algorithm is collected the fault voltage and current signals. Then, it extracts the features of the fault signals by using discrete wavelet transform, fast Fourier transform, empirical mode decomposition, and other algorithms, and finally establishes a sample set from the feature quantity and fault distance, which is input into the neural network for learning and training to obtain the ranging model.

The application of the intelligent algorithm to fault location of overhead line cable hybrid line is one of the current research hotspots. The intelligent algorithm has strong reliability, but it needs to collect many data samples, and the implementation of the algorithm is complex. Literature selects the polarity and time difference of the first three wave heads of the detection points as the input characteristics of artificial neural network (ANN) establishes the ranging network model to complete the preliminary ranging. However, the neural network ranging results can only calibrate the range of the fault point, and the final fault distance can be obtained only after further verification. Based on the spectral characteristics of line current, the document analyzes the mapping relationship between spectral resonance frequency and fault distance and establishes a BP neural network ranging model. However, the algorithm in this paper needs to calculate the equivalent admittance of upstream and downstream faults, respectively, and the positioning accuracy is greatly affected by line parameters.

In 1997, Hochreiter and schmidhuber first proposed a long-term and short-term memory artificial neural network (LSTM), which is very suitable for processing and predicting events with long spans and delayed in time series. As an improved model of RNN, LSTM replaces the hidden layer neurons in RNN with memory units and changes the partial derivative of backpropagation from continuous multiplication to continuous addition. Aiming at complex implementation problems and poor fault tolerance of existing hybrid line intelligent fault location algorithms, a new fault location method based on the LSTM network is proposed in this paper. Firstly, a 220kV hybrid transmission line is built to collect the line mode voltage signals on the bus side of the line under different fault types; Secondly, the discrete wavelet transform is used to decompose the line mode voltage signal to extract the fault characteristics and the data is preprocessed to obtain the sample set; Finally, the LSTM network is used to adaptively learn the input samples and output samples to obtain the LSTM ranging model. PSCAD / Matlab simulation is used to verify and analyze the effectiveness of the algorithm

2. LONG SHORT MEMORY NEURAL NETWORK

2.1 Basic structure and principle of LSTM network

Figure 1 shows the structural model of the LSTM network. LSTM memory unit controls the input and output of signals through three "gate" structures: forgetting, input, and output [17]. The output of the sigmoid activation function inside the "door" determines the opening or closing of the door. The output of "0" represents the closed state and does not allow the information to pass. The output of "1" represents the open state and allows the information to pass.

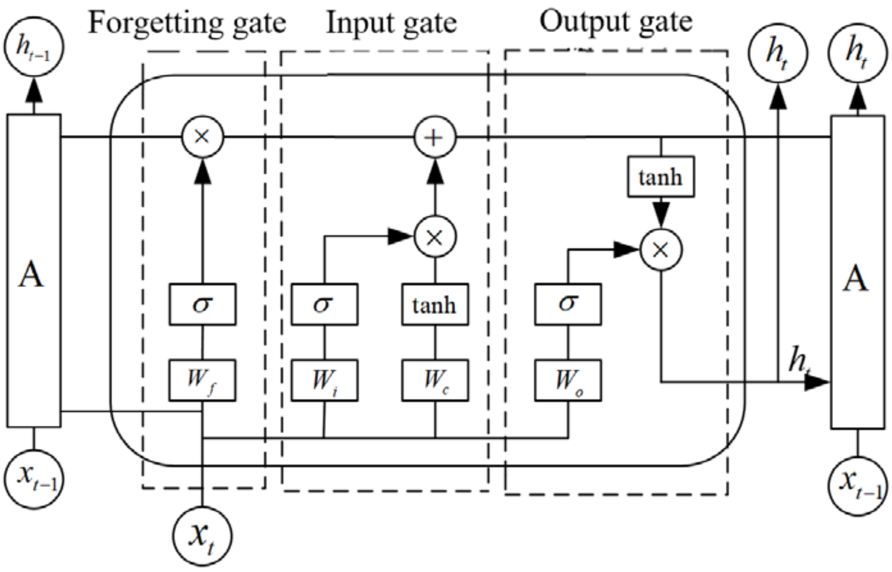

Figure 1. LSTM structure model

Calculation formula of forgetting door:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{1}$$

The formula is the output of f_t forgetting gate, h_{t-1} is the hidden state of the memory unit at the previous time, x_t is the input vector at the current time, W_f is the weight matrix of forgetting gate, b_f is the offset term, $[h_{t-1}, x_t]$ □ represents the combination of the two vectors to form a long vector, and Ω represents a sigmoid operation. When the ft output is 1, the neuron will retain the previous memory information.

The input gate calculation is divided into two parts. The first part is to calculate the forgetting gate ft's product and the previous time's cell state. The second part calculates the product of the degree i_t of the input at the current time to be saved to the memory cell and the cell state C_t after the input is transformed. Finally, the two parts sum to obtain the current memory cell state

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{2}$$

$$\tilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \tag{3}$$

$$C_t = f_t C_{t-1} + i_t \tilde{C}_t \tag{4}$$

The input xt jointly determines the output gate at the current time t and the output t-1 of the hidden layer at the time h_{t-1}. The calculation formula of the output gate is

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = o_t \tanh(C_t) \tag{6}$$

2.2 Adam adaptive algorithm

Adam is an adaptive algorithm that dynamically adjusts each parameter's learning rate by using the first-order moment estimation and second-order moment estimation of the gradient. After bias correction, the learning rate of each iteration is only adjusted in a fixed interval so that the parameter update tends to be stable [18]. This paper introduces Adam's adaptive algorithm to update the network parameters and find the best and minimum loss function points globally to improve the model's convergence speed and accuracy. The process of Adam adaptive algorithm is as follows: initialize the parameters and calculate the gradient of t time step:

$$g_t = \nabla_\theta J(\theta_{t-1}) \tag{7}$$

Calculate the exponential average of the gradient component and $\hat{m}_t$ is approximately the unbiased estimation of the first-order moment of the gradient.

$$\hat{m}_t = \frac{\beta_1 m_{t-1} + (1-\beta_1) g_t}{1-\beta_1^t} \tag{8}$$

Calculate the exponential weighted average of the square g_t^2 of the gradient component, $\hat{v}_t$ is the unbiased estimation of the second moment of the gradient, and v_0 is initialized to 0.

$$\hat{v}_t = \frac{\beta_2 v_{t-1} + (1-\beta_2) g_t^2}{1-\beta_2} \tag{9}$$

Update the network parameters according to the learning rate :

$$\theta_t = \theta_{t-1} - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \varepsilon} \tag{10}$$

β_1 and β_2 are the exponential decay rates of the two moving averages respectively, and β_1 is taken as 0.9, β_2 is 0.999.

3. HYBRID TRANSMISSION LINE FAULT LOCATION ALGORITHM

Unlike the fault location algorithm of a single transmission line, the hybrid line fault location algorithm is divided into two parts: fault interval identification and accurate fault location. Firstly, the wavelet energy ratio is used to identify the fault interval accurately, then the line mode voltage data on the bus side of the fault line is used as the initial data set, and then the sample set is obtained through data preprocessing. Finally, the fault location model is obtained by inputting LSTM network training.

3.1 Fault interval identification based on the wavelet energy ratio

Figure 2 shows the overhead line cable hybrid transmission line, with the total length of L, in which the length of the cable line is L_C and the length of the overhead line is L_C.

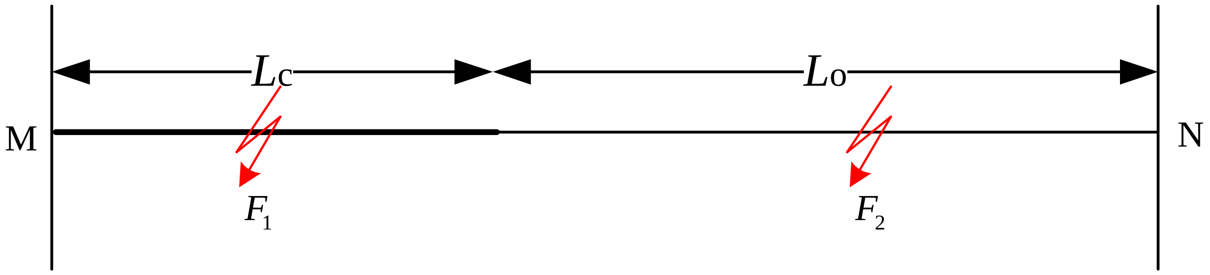

Figure 2. Structure diagram of overhead line cable hybrid transmission line

After the line fault occurs, the voltage signals of the bus side are collected for discrete wavelet decomposition, which is at both ends of the line before and after the fault. Due to the high energy concentration and good frequency characteristics of the DB6 wavelet, this paper selects the Db6 wavelet as the basis function, uses the Db6 wavelet to decompose 6 layers, and obtains the wavelet coefficient $C_j(k)$ at each scale. According to the wavelet multi-resolution theory, when a wavelet basis function is a group of orthogonal basis functions, the wavelet transform will meet the energy conservation theorem [19]. Wavelet energy in a single scale is the sum of squares of wavelet coefficients in that scale.

$$E_j = \sum_k \left| C_j(k) \right|^2 \tag{11}$$

The total energy of the signal is the sum of the wavelet energy of each scale. Therefore, the total energy E_{sum} of the discrete signal is expressed as:

$$E_{sum} = \sum_j \sum_k E_{j,k} \tag{12}$$

The wavelet energy at both ends of the line is obtained from formula (12). Assuming that the fault occurs at the line connection, the wavelet energy ratio at both ends at this time is used as the judgment threshold δ. When the ratio of wavelet energy at both ends is more remarkable than δ When, the fault occurs in the cable section; On the contrary, the fault occurs in the overhead line section.

3.2 Ranging principle based on LSTM neural network

The specific process of hybrid transmission line ranging based on LSTM network is as follows:

Step 1: sample set construction. The 220kV hybrid transmission line is simulated, and the fault line model voltage signals under different fault types, different fault locations, and different bus voltages are simulated to construct the sample set;

Step 2: sample pretreatment. In order to reduce the number of network iterations and improve the accuracy of model fitting, the input samples are compressed and normalized;

Step 3: parameter initialization. Set the number of network hidden layer nodes, and the initial network learning rate is 0 005. The maximum number of iterations is determined to be 250. After 125 rounds of training, the learning rate is reduced to 0.5% 001；

Step 4: sample training. Build the LSTM model in the MATLAB deep learning toolbox, input the normalized training samples into the LSTM model for training, after several training iterations, and then use the test data to verify the ranging accuracy of the model;

Step 5: To obtain the fault location results, input the online measured fault data into the trained LSTM model. The model's output is analog and needs to be converted into actual fault distance through inverse normalization.

4. Sample pretreatment and model evaluation

Firstly, collect the line double-ended bus's three-phase voltage signal within 20ms after the fault, compress the sampling data by discrete wavelet, and finally normalize the data to obtain the training samples and test samples. The sample dimension is 48, and the total sample capacity is 6750. Add the fault location label in the sample set. In order to make the fault simulation consistent with the reality, the proportion of fault samples is 70% single-phase grounding (LG), 15% two-phase short circuit (LL), 10% two-phase short circuit grounding (LLG), and 5% three-phase short circuit (LLL); Considering the influence of transition resistance, fault distance and fault initial angle on ranging results, the structure of samples for training and testing is shown in Table 1 and Table 2

Table 1 Structure of training samples

Parameter type	Parameter setting	Number of parameters
Fault type	LG、LL、LLG、LLL	10
Fault distance /km	l_1=0.5,step=1	50
Bus voltage /kv	M: 220∠60° 220∠30° 、 220∠0° N: 220∠15°	3
Transition resistance /Ω	0.1、1、100	3

Table 2 Test sample structure table

Parameter type	Parameter setting	Number of parameters
Fault type	LG、LL、LLG、LLL	10
Fault distance /km	l_1'=1,Step=5	10
Bus voltage /kv	M: 220∠60° 、 220∠30° 、 220∠0° N: 220∠15°	3
Transition resistance /Ω	0.1、1、100	3

In order to reduce the amount of network calculation, the wavelet coefficients generated by discrete wavelet transform (DWT) are compressed into feature sets. The characteristics of the generated wavelet coefficients can fully represent the energy entropy, information, and dynamic range of the original coefficients.

5. EXAMPLE SIMULATION

5.1 Hybrid line model

A 220kV hybrid transmission line model is built based on PSCAD simulation software, as shown in Figure 5. The fault is set at F1 and F2. Measuring devices are installed at both ends of the bus. The system reference power is 100mva, the power frequency is 50Hz, the sampling frequency is 10kHz, the time window is 20ms, and 200 wave sampling points per week. Set 0 Short circuit occurs at 1s and lasts for 0.5 minutes 06s. The total simulation time is 0.2s。

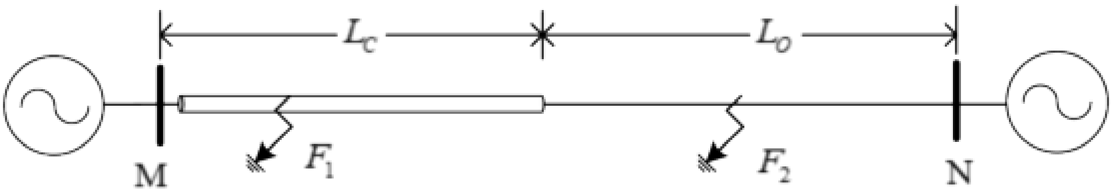

Figure 3. Simulation model of 220kV hybrid transmission line

The cable line is 20km long, and the overhead line is 30km long.

5.2 Factors affecting ranging accuracy

(1) Influence of fault distance on ranging accuracy

When the transition resistance is 1 Ω , and the initial fault angle is 30°, the influence of fault distance on ranging accuracy is studied, and the results are shown in Table 3. It can be seen from table 4 that within the range of cable fault line length of 15km or overhead fault line length of 25km, the absolute error of ranging with LSTM network is less than 0.5% 2km, which shows that the ranging accuracy is not affected by the length of the fault line.

Table 3 LSTM ranging results of different fault distances

Fault distance /km		Calculate distance /km	Absolute error /km
Cable end	1	1.0398	0.04
	5	4.9513	-0.05
	10	10.1325	0.13
	15	15.0223	0.02
Overhead line end	5	5.0586	0.06
	10	9.8869	-0.11
	15	15.1759	0.18
	20	19.9685	-0.03
	25	25.0820	0.08

(2) Influence of fault type on ranging accuracy

Assuming that faults such as single-phase grounding and two-phase short circuit occur 10km away from the M end of the cable and 15km away from the N end of the overhead line, it can be seen from Table 5 that the absolute error of ranging of LSTM network model is less than 0.5 2km, which indicates that the ranging accuracy is not affected by the fault type.

Table 4 LSTM ranging results of different fault distances

Fault distance /km		Calculate distance /km	Absolute error /km
Cable end	Single-phase grounding.	10.1168	0.12
	Two-phase short circuit.	9.9085	-0.09
	Two-phase grounding.	9.9235	-0.08
	Three-phase short circuit	9.8206	-0.18
Overhead line end	Single-phase grounding.	15.0832	0.08
	Two-phase short circuit.	15.1109	0.11
	Two-phase grounding.	15.1577	0.16
	Three-phase short circuit	15.0785	0.08

6. CONCLUSIONS

This paper proposes a hybrid transmission line fault location method based on the LSTM network, and the location effect is verified by PSCAD/Matlab simulation. The line mode voltage signal on the bus side of the overhead line-cable hybrid line is decomposed by discrete wavelet transform to extract fault features, and the data is preprocessed to get a sample set, which can reduce the amount of network calculation. The Adam adaptive algorithm is introduced to optimize the LSTM network parameters, which solves the problems of gradient disappearance and gradient explosion in the RNN training process, and improves the fault tolerance of the ranging model.

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