Computer Life (CPL) ISSN: 1819-4818
DELIVERING QUALITY SCIENCE TO THE WORLD

Research on Fault-selection of Double Circuit Transmission Lines on the Same Tower Based on Convolutional Neural Network

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Abstract: Based on the structure of convolutional neural network (CNN), a new method for judging the fault phase of double-circuit transmission lines on the same pole is proposed. The six independent CNN classifiers are used to judge the current of the six-phase line of the double-circuit transmission line of the same pole to judge whether the phase is faulty. Through simulation verification, the classifier can accurately identify the fault phase, with high accuracy and quick action, and is not affected by the fault location, fault initial angle and transition resistance.
Keywords: Convolutional Neural Network, Fault-selection, Double-circuit Transmission Lines on the Same Tower, Deep Learning.

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1. INTRODUCTION

The double-circuit transmission line on the same pole has been widely used in power grids all over the world due to its small footprint and large capacity. In the protection of the double-circuit line of the same pole, it is necessary to identify and select the fault phase. Due to the complicated coupling situation of the double-circuit transmission line on the same pole, the fault phase selection of the traditional three-phase line is no longer applicable to the double-circuit line on the same pole. Therefore, many scholars are committed to the fault phase selection of the same-circuit double-circuit line[1-6].

In [7], a new phase selection component is proposed, which uses a single-sided double-loop phase current. The six-sequence component method can be used to obtain the phase current abrupt change, and then the correlation of the phase name is obtained by the phase current mutation. Degree, according to the correlation between the phase of the same name and the magnitude of the sudden change of the current, the phase selection component can determine which phase of the fault phase of the same phase is the phase or both phases are fault phases, and the three groups of the same name phase are faulty. By selecting the phase, you can get the fault phase that appears on the double-circuit line on the same pole. In [8], the six-sequence component is also used to decouple the electrical quantity on the line, and then the amplitude and phase of the current sudden change amount are

obtained. By comparing the current sudden change amount and the voltage amplitude, it can be judged that the fault phase is a certain A single phase, in the cross-line fault, adding the phase comparison of the sudden change, can determine the fault phase of the initial phase in the cross-line fault. Reference [9] proposes a method of phase selection using a single-ended current on a parallel double-return line with narrow line spacing. The method determines whether the same-name phase is faulty by judging whether the phase current of the same name exceeds a preset value, and if the fault occurs, compares the mean value of the sudden change of the current, and determines whether the phase is faulty or both phases are fault phases.

At present, the fault phase selection of the double-circuit transmission line on the same pole mainly uses the power frequency to perform fault phase selection. Although the fault phase selection using the power frequency is high, the accuracy is slightly low, and the complex cross-line fault cannot be selected in time. The expansion of the fault may cause the area to be powered off. Based on the literature [10], this paper studies the structure of Convolutional Neural Network (CNN), and proposes a fault phasing method based on convolutional neural network for double-circuit transmission lines on the same pole. The CNN uses these six CNNs to identify the amount of current on the six-phase line to determine whether the line is faulty. Through simulation verification, the classifier can accurately identify the fault phase, with high accuracy and quick action, and is not affected by the fault location, fault initial angle and transition resistance.

2. CONVOLUTION NEURAL NETWORK

The Convolutional Neural Network (CNN) is an efficient identification method that has developed in recent years and has attracted widespread attention. CNN can directly input the original image, avoiding the complicated preprocessing of the image in the early stage. At the same time, CNN is highly invariant to image information in translation, scaling, tilting or other forms of deformation, and thus is more widely used. CNN stacks multiple single-layer convolutional neural networks. The output of the previous layer is used as the input of the next layer, and the full-connection layer and classifier are connected to the output feature map of the last layer, which is used for identification on somethings, such as image, voice, etc. [11].

2.1 CNN structure and principle

The typical structure of CNN is shown in Figure 1. Each sample data is input in two dimensions and then mapped to a hidden layer by a convolution kernel (a weight matrix of neurons). The hidden layer is mainly composed of a convolutional layer (C layer) and a down-sampling layer (S layer), C The layer and the S layer are alternately repeated, and the output of the layer is used as an input of the next layer, so that the network structure has high distortion tolerance to the input samples, and the hierarchical expression of the data is more accurately realized.

The main function of the C layer in CNN is to extract the local features of the neuron data. Each C layer is composed of several feature matrices, each of which is a plane, the same as the convolution kernel on the same plane, with rotation The characteristics of displacement, invariant and weight sharing can learn features in parallel, greatly reducing the number of free parameters. Different convolution kernels are different for different planes, and multi-convolution kernels make feature extraction more complete. The C-layer convolution process is shown in Figure 2.

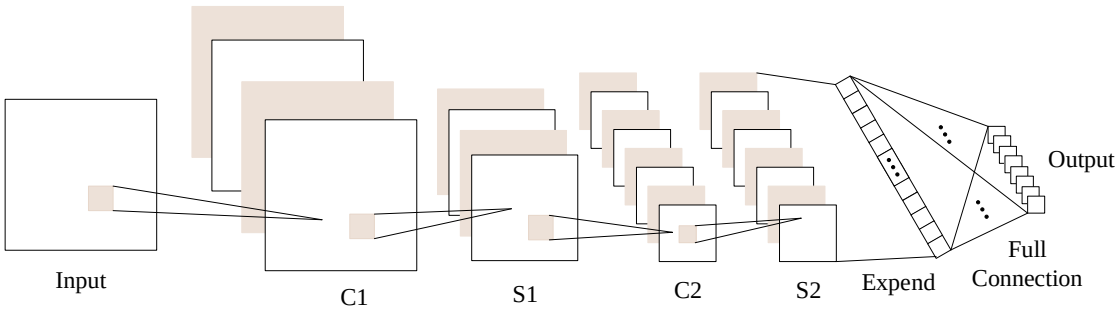

Figure 1 structure of CNN

The input feature matrix ($n \times n$) of the previous layer is two-dimensionally convolved with the learnable convolution kernel ($k \times k$), and the convolved data is subjected to the activation function to obtain the output feature matrix ($m \times m$) of the layer, and the dimensions of the three are satisfied $m = n - k + 1$. The calculation formula is as shown in equation (1):

$$X_o^l = f\left(\sum_{i \in m} X_i^{l-1} \times K_{io}^l + B^l\right) \tag{1}$$

In Equation 1, l represents the first few layers of the network., K represents the convolution kernel, B represents the offset, X_o^l represents the layer output, and X_i^{l-1} represents the layer l input.

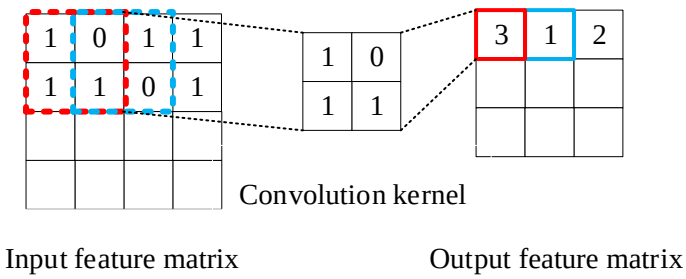

Figure 2 C-layer Convolution Process

The S layer of CNN is used to scale and map the data of the upper layer to reduce the data dimension. The extracted features have scale invariance, and can also prevent over-fitting. Generally, the downsampling (pooling) method such as averaging pooling is adopted. .Sub-sampling input, output, and pooling matrix dimensions are satisfied m=n/k. The S layer can be regarded as a fuzzy filter, which plays the role of quadratic feature extraction. The neuron calculation method is shown in formula (2):

$$X_o^l = f\left(\frac{1}{k}\sum_{i \in m} X_i^{l-1} + B^l\right) \tag{2}$$

The essence of CNN is to learn a plurality of filters capable of extracting the characteristics of input data, and perform layer-by-layer convolution and pooling on the input data to extract the topological features hidden in the data step by step. As the network structure is deeper, the extracted features are gradually abstracted, and finally the feature representation of the translation, rotation and scaling invariance of the input data is obtained.

2.2 Paramenters training of CNN

The parameter training process of CNN is similar to the traditional artificial neural network. The back propagation algorithm is adopted. The training process is as follows:

Forward Propagation: Extract a sample from the sample set $\left(X, X_p\right)$, input X to the network, and transfer the information from the input layer to the output layer through a step-by-step transformation to calculate the corresponding actual output O_P:

$$O_P = F_n\left(\cdots\left\{F_2\left[F_1\left(XW_1\right)W_2\right]\cdots\right\}W_n\right) \tag{3}$$

Backpropagation: Also known as the error propagation phase. Calculate the difference E_P between the actual output O_P and the ideal output Y_P:

$$E_P = \frac{1}{2}\sum_j\left(y_{Pj} - o_{Pj}\right)^2 \tag{4}$$

Weight adjustment: Adjust the weight matrix according to the method of minimizing the error.

CNN learns through training data, implicitly learns features from training data, and avoids explicit feature extraction, which is also an advantage of convolutional neural networks over other neural networks.

3. PRINCIPLE OF FAULT PHASE SELECTION FOR DOUBLE-CIRCUIT TRANSMISSION LINES ON THE SAME TOWER BASED ON CNN

CNN is a supervised depth model architecture that can be used to obtain the data samples needed to train CNN by obtaining current information on the same-circuit double-return line.

3.1 Model of double-circuit transmission lines on the same tower

Figure 3 shows the line model of the same-circuit double-circuit line. The M and N terminals are busbars connected to the line, MN is inside the double-circuit line protection zone, PM and NO are outside the protection zone, and R_1~R_6 are corresponding. The traveling wave protection unit of the position stipulates that the traveling wave flows from the busbar to the line in a positive direction. Taking the traveling wave protection unit R_1 as an example, the current traveling wave Δi detected by the protection unit R_1 is set[12].

If the traveling wave Δi arrives at the bus M for the first time t_0 from the fault point, and the sampling point of the half cycle after the fault is extracted as the starting point of t_0. The sampling frequency used in this paper is 50 kHz, so 500 samples are extracted per phase after the fault. The sample point is used as the input to the CNN.

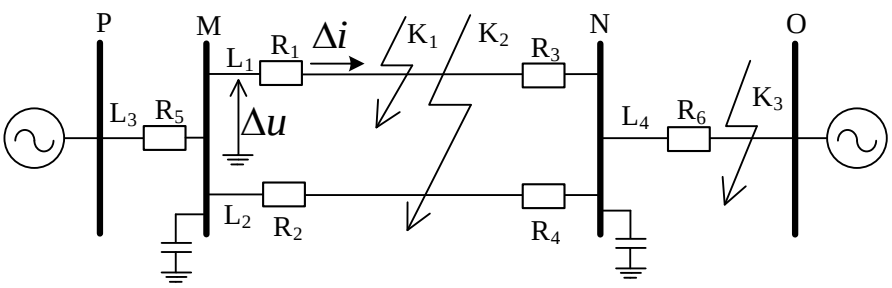

Fig.3 Simplified model of the double lines on same tower

3.2 Fault-selection flow based on CNN

The construction phase selection model is shown in Figure 4. Firstly, the six-phase current sampling data on the same side of the same-circuit double-return transmission line is 6×500 matrix, and the fault data in the case of different parameter variables are obtained as N_R and N_T, so that the training sample set is $6\times500\times N_R$ and the test sample set is $6\times500\times N_T$.

Secondly, the current sampling points after the initial traveling wave of the fault are extracted by phase separation. This paper constructs six CNN networks to determine whether the six-phase transmission line is faulty. So the input per network is 1×500.

The training sample set is used to train CNN network parameters, and the six CNN networks are trained with $1\times500\times N_R$ training samples respectively; the test sample set is used to test the accuracy of the training completed CNN for fault phase selection, and each CNN network is $1\times500\times N_T$ samples were tested. If the error rate in the test is too high, return to the training session for CNN network training.

After the test result error rate is reduced to the allowable range, the training completed CNN network is saved. During use, after obtaining a set of fault data, the saved CNN is called to directly output the fault phase.

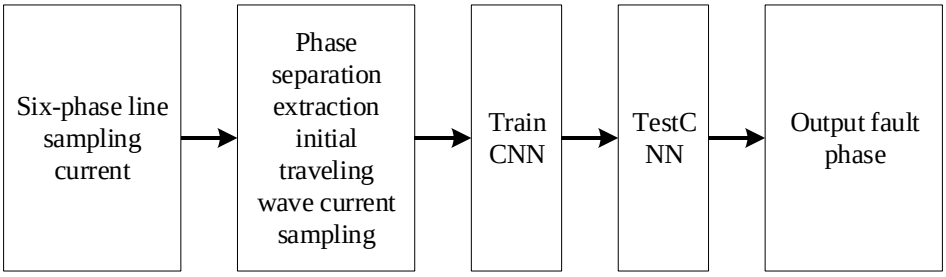

Figure 4 Fault-selection flow based on CNN

For the six different CNN networks, the corresponding independent classification is set. The CNN network classification is shown in Table 1.:

For the same-circuit double-return transmission line, there are 120 fault types, all of which are arranged by six-phase line faults. Therefore, for different fault types, six CNN networks are used to identify six phases respectively, which can achieve optimal effect of fault-selection. Use different index numbers for different phases to clearly distinguish different phase sequence faults.

Table 1 output classification and index numbers

output	1A	1B	1C	2A	2B	2C
index numbers	1	2	3	4	5	6

4. SIMULATION AND EXPERIMENTS

This paper uses PSCAD to build a simulation model of the same-pole double-circuit transmission line. The schematic diagram of the simulation model is shown in Figure 1. The length of the line in the model is 300km, the voltage at the M and N terminals is 500kV, 50Hz. The protection unit is set as shown in Figure 1. The line parameters of the same-circuit double-circuit line are Tower: 3L12,

and the line parameters used for the single-circuit line are Tower. : 3H5, the sampling frequency is set to 200kHz.

4.1 Training sample set and test sample set generation

The training sample set and the test sample set need fault data under different parameter variables. The different parameter variables are shown in Table 2. Considering all combinations can obtain $C_3^1 C_{18}^1 C_3^1 C_3^1 = 486$ combinations, extracting data at both ends of the line, and obtaining two sets of data in one fault simulation. A total of 972 sets of data can be obtained. The current sample data of the same end can be obtained as $6 \times 500 \times 486$ of the training sample set, and the current sample data of the other end can be obtained by the test sample set $6 \times 500 \times 486$.

4.2 Simulation experiment test results and analysis

This paper uses MATALB for sample data extraction and CNN network training. The training and test platform parameters are shown in Table 3. The error rate and training time of CNN networks with different fault parameters are shown in Table 4. Since the input amount of each CNN is a one-dimensional matrix, the lower one core is used as the number of convolution kernels of the CNN.

Analysis Table 4 shows that as the number of training increases, the error rate of fault identification can be reduced. When the number of training reaches ten times under the 6C-1S-12C-1S network structure, the phase selection error rate can be approximately zero. If the number of features in the network structure is taken as 1, the CNN network is equivalent to the BP network. Under the BP network, the phase selection error rate is significantly higher than that of the CNN network, but as the number of training increases, the phase selection accuracy rate gradually improve.

It can be known from the experiment that CNN can still accurately judge the fault phase in the case where the test sample is different from the training sample. This is because the training sample data traverses the fault type, fault location, fault initial angle, transition resistance and other parameters. CNN has strong generalization ability and learning ability, so it is not affected by factors such as fault location, initial fault angle, transition resistance, etc., and no tuning of any parameters is required. Based on the above analysis, when the number of samples is sufficient, CNN is used for fault phase selection judgment with extremely high accuracy.

Table 2 Different fault parameter traversal table

Parameter Type	Value of Parameter	Number of paramenter
Fault location /km (based on the distance N end)	50,150,250	3
Fault type	Ⅰ A Ⅱ BG, Ⅰ A Ⅱ BCG, Ⅰ AB Ⅱ BCG, Ⅰ ABCG, Ⅰ ABC Ⅱ AG, Ⅰ ABC Ⅱ ABCG, Ⅰ ABC Ⅱ BCG, Ⅰ B Ⅱ CG, Ⅰ BC Ⅱ BG, Ⅰ B Ⅱ BCG, Ⅰ BC Ⅱ CG, Ⅰ BCG, Ⅰ AG, Ⅰ BG, Ⅰ CG, Ⅱ AG, Ⅱ BG, Ⅱ CG,	18
Initial fault angle /°	5,60,120	3
Transition resistance /Ω	10,50,100	

Table 3 Training and testing platform

Project	Paramenters
System version	Windows 10 Professional 64 位
Model of CPU	Inter(R) Core(TM) i7-4720HQ
Speed of processing	2.60 GHz
Memory	16 GB

Table 4 Simulation results of fault phase selection method based on CNN

Serial number	Network structure	Number of training	Rate of error/%						Training time/S
			1A	1B	1C	2A	2B	2C	
1	6C-1S-12C-1S	1	0	6.17	2.74	0	6.17	4.73	20.16
2	6C-1S-12C-1S	5	0	3.09	0.21	0	0.21	3.09	96.78
3	6C-1S-12C-1S	10	0	0.21	0.21	0	0.21	0.21	190.13
4	1C-1S-1C-1S	1	3.09	6.79	3.29	3.09	7.41	4.32	2.35
5	1C-1S-1C-1S	5	0	4.73	3.09	0.41	3.09	3.49	9.28
6	1C-1S-1C-1S	10	0	0.21	0.21	0	0.21	0.21	17.89

5. CONCLUSION

This paper proposes a fault phase selection method for the same-pole double-circuit transmission line based on convolutional neural network. The convolutional neural network is applied to solve the fault phase selection of the same-pole double-circuit transmission line, and six different CNN networks are constructed. The complex coupling of the return transmission line is decomposed into six independent cases. The simulation results show that the method is not affected by factors such as fault location, initial fault angle and transition resistance, and has high reliability.

With the development of computer hardware in the future, the training speed of the CNN network will be greatly improved, and the fault data under different fault parameters will be more conveniently obtained as a training sample, relying on CNN's powerful learning. The generalization ability is expected to accurately identify faults in the future, and there is a broad prospect for smart grids in the future.

ACKNOWLEDGEMENTS

This research was supported by the artificial intelligence key laboratory of Sichuan province Foundation (2014RYY05,2015RYY01,2017RYY02), and the Graduate innovation Foundation of Sichuan University of Technology (y2017032,y2017033).

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