Multiple Faults Diagnosis of Distribution Network Lines Based on Convolution Neural Network with Fuzzy Optimization

Huanxin Guan, Bo Yang, Herong Wang, Di Wu, Baixiang Zhao, Jingbo Liu, Tong Wu

***Abstract*—With the continuous expansion of power grid, the system structure becomes more and more complex, and multiple faults occur frequently. And multiple faults are the key and difficulty of fault diagnosis. Due to the huge and complex power grid structure and the large data size of fault processing, it is necessary to diagnose the power grid fault quickly and accurately. In this paper, based on convolutional neural network, a multi-fault diagnosis model of distribution network based on fuzzy optimal convolutional neural network is proposed. Firstly, fault line and fault type judgment based on two soft maximum classifiers are analyzed. Membership functions of distribution network faults are established by using fuzzy theory. Secondly, the influence of convolution kernel number and sample width on the accuracy of model diagnosis is studied and analyzed. Simulation results show that, under the same conditions, the accuracy of fuzzy optimized convolutional neural network for multiple fault diagnosis is higher than that of convolutional neural network. The time of fault diagnosis and training is less than that of convolutional neural network.**

***Index Terms*—Distribution network; Multiple faults; Convolution neural network; Fuzzy optimization;**

I. Introduction

With the rapid development of China's economy and the improvement of public infrastructure, the living standard of the people has been constantly improved. multiple faults show the characteristics of coupling and fuzziness.Multiple fault diagnosis of missile system is used by expert system and neural networks [1]. Researchers try to use the intelligent algorithm as it takes a long time to diagnose by expert system. Multi-fault diagnosis of turbo generator vibration is applied to genetic algorithm combined with fuzzy C partition and probabilistic causality model [2].Zhang Wei et al .[3] used parallel BP neural network to study the method of multi-fault diagnosis and classification. A method of neural network and Dempster-Shafer theory(D-S) fusion diagnosis of faults in turbine generator set is researched [4].Ma Jing et al. [5] proposed a novel wide-area multiple fault location algorithm based on fault confirming degree. The new method is easy to calculate and thus a low computational complexity. Wang Yumei et al. [6] constructed a concise method for fault location in distribution networks based on the matrix algorithm. Fu Fangzhou et al. [7] considered a new method based on a bank of Kalman filters to detect and isolate faults in sensors and actuators. Lan Hua et al. [8] proposed faulty line detection method for distribution network based on fuzzy rough sets and GA-BP neural network.

The combination of neural network and expert system improves the accuracy of expert system diagnosis and reduces the training time. The combination of neural network and D-S theory improves the diagnosis speed and the diagnosis range. Liu Kun[9] et al. proposed remote sensing aircraft recognition based on blur-invariant convolution neural network. The accuracy of convolution neural network for fuzzy target recognition is improved. Wei Dong [10]et al. constructed research on internal and external fault diagnosis and fault-selection of transmission line based on convoluional neural network. This paper is proposed multiple faults diagnosis of distribution network lines based on convolution neural network with fuzzy optimization. It has the advantages of fast diagnosis speed, strong learning generalization ability, strong robustness, accurately and rapidly judging of fault types and fault lines.

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II. Fuzzy Theory and Convolution Neural Network

There are different pros and cons in different neural networks and thus many scholars used other theoretical methods to optimize neural networks for improving the efficiency of neural networks. For instance, fuzzy theory, immune theory and genetic algorithm[12].

A. Fuzzy Theory

A fuzzy set is a pair *(X,A(x))* where X is a set an $A(\chi): \chi \to [0,1]$ a membership function.The reference set X is called universe of discourse, and for each $\chi \in X$,the value $A(\chi)$ is called the grade of membership of χ in .The function (U, m) is called the membership function of the fuzzy set $A = (U, m)$.

B. Concept and structure of convolution neural network

The difference between convolution neural network (CNN) and ordinary neural network is that CNN has an additional feature extractor composed of convolution layer and sub-sampling layer. Convolution and sub-sampling greatly simplify the complexity of the model and reduce the parameters of the model. The structure of convolution neural network is shown in figure 1:

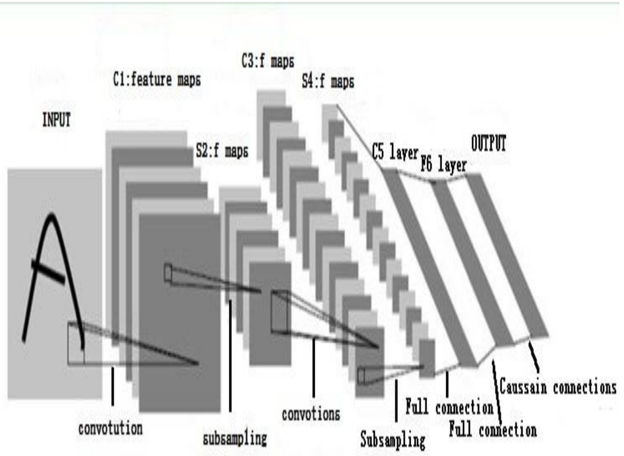

Fig.1. The structure of convolution neural network.

The convolution neural network consists of three parts. The first part is the input layer. The second part is composed of n convolution layers and pooling layers. The third part consists of a fully connected multilayer perceptron classifier.

The task of convolution kernel is to find the output node matrix from input to output. The ith node value in the node matrix is proposed:

$$S(i)=f(\sum_{\chi=1}^{A}\sum_{y=1}^{B}\sum_{z=1}^{D}\alpha_{\chi,y,z}\times\varphi^{i}_{\chi,y,z}+\beta^{i}) \quad (1)$$

where $S(i)$, A, B and D are the size and feature number of input data; $\alpha_{x,y,z}$ is the value of the convolution kernel node; $f(x)$is the excitation function, $\varphi^{i}_{x,y,z}$ is the ith node weight in output node matrix; β^{i} is the ith node biases.

III. Multiple Fault Diagnosis Model

Multiple faults of the distribution network line require voltage data at both ends of the transmission line, current at each node and voltage signal. Convolution neural network is a supervised depth model architecture, which is especially suitable for two-dimensional data structure, and voltage data can easily constitute two-dimensional data samples.

A. Multiple fault diagnosis model of convolution neural network

The multiple fault diagnosis model is shown in figure 2.Firstly, voltage data at each node are collected to generate test sample set and training sample set. Training sample set trains convolution neural network parameters of fuzzy optimization, and test sample set to test the accuracy of fuzzy optimization convolution neural network in multiple fault diagnosis results.When the error rate of detection results is reduced to the allowable range, the trained fuzzy optimized convolution neural network is saved and Voltage.And current, zero sequence current fundamental component and fifth harmonic component are selected as characteristic data.Suppose the sample set is $\mathrm{X}=\{\mathrm{x}_1,\mathrm{x}_2,\ldots,\mathrm{x}_\mathrm{n}\}$,including $\mathrm{x}_\mathrm{i}\in\mathrm{R}^{2\times5}$.

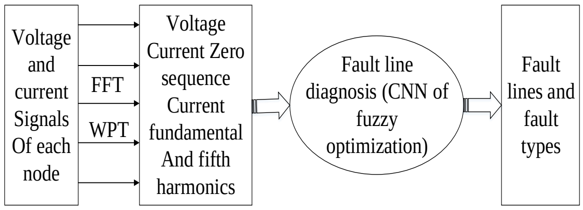

Fig.2. Multiple fault diagnosis model of convolution neural network with fuzzy optimization

B. Fuzzy Optimization

In order to avoid data over-fitting, a fuzzy layer is added to the down-sampling layer of convolution neural network to optimize the convolution neural network, and get the new objective function :

$$J(W,Z)=min\left[V(\gamma)+G(\gamma)+\frac{1}{2}\|W\|_2^2\right] \quad (2)$$

Where $\mathrm{V}(\gamma)$ is cost function of softmax; Wis weight of fcbi layer network; B is biasing of fcn layer network; $\mathrm{G}(\gamma)$is the fuzzy constraint invariant.

In the process of attribute reduction, fuzzy set method can be used to classify the internal elements through fuzzy membership function, so as to obtain the reduction with small information loss. The membership function of extracting feature vectors from zero sequence current is:

$$\mu_i^j=\exp\left[-\left(x_i-c_{ij}\right)^2\Big/\sigma_{ij}^2\right] \quad (3)$$
$$\left(i=1,2,\ldots,m;\ j=1,2,\ldots,n\right)$$

The membership function of fault measure of fundamental wave component of zero sequence current is defined, and Q is element set.

$$\mu_L=\begin{cases}1 & A(L)\le -0.5Q\\ [0.5Q-A(L)]/Q & -0.5Q<A(L)<0.5Q\\ 0 & A(L)\ge 0.5Q\end{cases} \quad (4)$$

The membership function of fault measure of fifth harmonic component of zero sequence current is defined,

$$\mu_{5L}=\begin{cases}1-max(\varphi'_{5L})/180^0 & L=0\\ \varphi'_{5L}/180^0 & L=1,2,\ldots,n\end{cases} \quad (5)$$

Each node of the fuzzy layer represents a fuzzy rule. Formula (5) calculates the applicability τ_j of each fuzzy rule:

$$\tau_j=min\left(\mu_j^{i_1},\mu_j^{i_2},\mu_j^{i_3},\ldots,\mu_j^{i_n}\right)(j=1,2,\ldots,n),i_n\epsilon\{1,2,\ldots,n\} \quad (6)$$

Fuzzy optimization reduces the computation amount of softmax and the data volume required by convolution neural network training, and improves the accuracy of fault identification and generalization ability of convolution neural network.

C. Softmax Classifier Determines the Fault Line and Fault Type

The number of hidden layers of convolution neural network is controlled according to the actual requirements. In this paper, the minimum number of elements in all dimensions is 90, and convolution and pooling have the effect of dimensionality reduction. Therefore, the number of network layers cannot be too many.

Softmax is the output classification method of convolution neural network. Its principle is to set the output number of n independent classifications as n, the corresponding index number as 1 to n, and the index number corresponds to a category. The maximum output value of n outputs (normalized between 0 and 1) is set to 1, and the remaining output values are set to 0. The index number with output of 1 is the ideal classification. So W{True}=1,W{False}=0. And cost function:

$$V(\gamma)=-\frac{1}{n}\left[\sum_{i=1}^{n}\sum_{j=1}^{k}W\{y^{(i)}=j\}log\frac{e^{\gamma_j^T x^{(i)}}}{\sum_{j=1}^{k}e^{\gamma_j^T x^{(i)}}}\right] \quad (7)$$

The probability of category j events in the sample is expressed as:

$$P\left(y^i=j\middle|x^{(i)}:\gamma\right)=\frac{e^{\gamma_j^T x^{(i)}}}{\sum_{j=1}^{k}e^{\gamma_j^T x^{(i)}}} \quad (8)$$

Now there's no good way to minimize the cost function. Most researchers use iterative optimization algorithm to find its gradient expression.

$$G=\frac{\lambda}{2}\sum_{i=1}^{k}\sum_{j=0}^{d}\gamma_{ij}^2 \quad (9)$$

Substitute (8) into (9) to obtain the cost function for rapid optimization:

$$V(\gamma)=-\frac{1}{n}\left[\sum_{i=1}^{n}\sum_{j=1}^{k}W\{y^{(i)}=j\}log\frac{e^{\gamma_j^T x^{(i)}}}{\sum_{j=1}^{k}e^{\gamma_j^T x^{(i)}}}\right]+G$$

(10)

Where G is the attenuation term, accelerating the global optimization processing speed of the parameter model.Since equation (10) is convex function, the optimal parameter γ of the model can be calculated.

Offset parameters and iteration update weights:

$$\nabla_{\gamma_j}V(\gamma)=-\frac{1}{n}\sum_{i=1}^{n}\left[x^i\left(1\{y^{(i)}=j\}-p(y^i=j|x^i;\gamma)\right)\right]+\lambda\gamma_j \quad (11)$$

$$\gamma_j=\gamma_j-\varepsilon\nabla_{\gamma_j}V(\gamma) \quad (j=1,2,3,\dots,k) \quad (12)$$

Where ε is the learn rate and ε ∈ [0,1].

It can solve two dependent classification problem which is fault diagnosis and fault line in the same convolution neural network[13]. The same convolution neural network is used to solve two dependent classification problems, and the classification principle is shown in table 1.

Table 1 Output classification and corresponding index number

Function	Fault Type								
output	AN	BN	CN	AB	AC	BC	ABN	ACN	BCN
Index number	1	2	3	4	5	6	7	8	9
Function	Fault Type	Fault Line							
output	ABC	1	2	3	4	5	…	44	45
Index number	10	11	12	13	14	15	…	54	55

Among them, there are ten kinds of fault type and 45 kinds of fault line. Set the output port number is 55.The top 10 outputs are used for fault diagnosis. Each fault type corresponds to an index number in output and the index number is from 1 to 10 which is represented AN(A ground short circuit), BN(B ground short circuit), CN(C ground short circuit), AB(AB two - phase short circuit), BC(BC two - phase short circuit), CA(CA two - phase short circuit), ABN(ABN two - phase ground short circuit),BCN(BCN two - phase ground short circuit), CAN(CAN two - phase ground short circuit), ABC(ABC three-phase short circuit. In the 10 outputs, the maximum value of output is set to 1 and to obtain the fault type. It is used for fault line diagnosis from 11 to 55 in the index number. The maximum value is set to 1 and the minimum value is set to 0 in all outputs. For example, If No. 21 means No. 21 line is out of order.

IV. Units The Influence of The Number of Convolution Kernel and Sampling Width on The Accuracy of The Model Diagnosis Results

The network training of convolution neural network requires a large number of sample data. In this paper, BPA is applied to simulate the IEEE39 node system (figure 4) to generate sample data. It is assumed that one part of the generator node is equivalent to a photovoltaic power station, and the other part is equivalent to a power plant with different installed capacity.

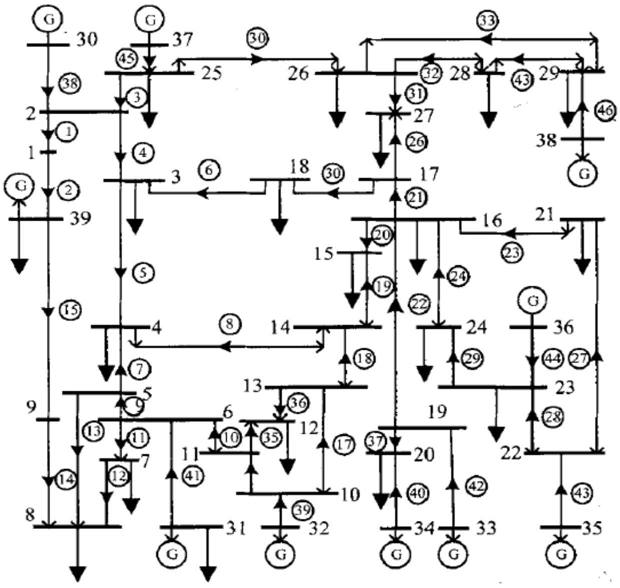

Fig.4. Simulation of the IEEE39 node system

IEEE39 node system is adopted in this paper. Multiple failures occur in the system, so the number of fault types and fault lines is greater than or equal to 2.This paper only considers that the fault type and fault line are equal to 2.The total number of samples was C_10^2 C_46^2 (the total number of samples was 46,575), of which 33,575 were used as training samples and the remaining 13,000 were used as test samples.

The fault diagnosis accuracy of convolution neural network is related to the number of convolution cores and the sampling width. The sampling width is inversely proportional to the accuracy. When the number of convolution kernels exceeds a certain number, it continues to increase, and the accuracy of neural network increases little. The structure of convolution neural network should be determined according to the actual situation.

Table. 2. The influence of the number of convolution kernel on the accuracy of convolution neural network

Convolution kernel	**Error rate/%**	**Error rate of fault type/%**	**Error rate of fault line/%**
11	22.3402	0.5671	21.7731
22	10.5034	0.4302	10.0732
33	3.9444	0.1369	3.8075
45	0.16815	0.02919	0.13896
410	0.14215	0.01536	0.12679

The simulation results are shown in figure 5. When the sampling width is 1, the batch number is 100, the number of convolution kernels is 45, and the number of training times reaches 12, the total error rate is 0%.The neural network can make error-free judgment of fault types and fault lines for 13,000 test samples.

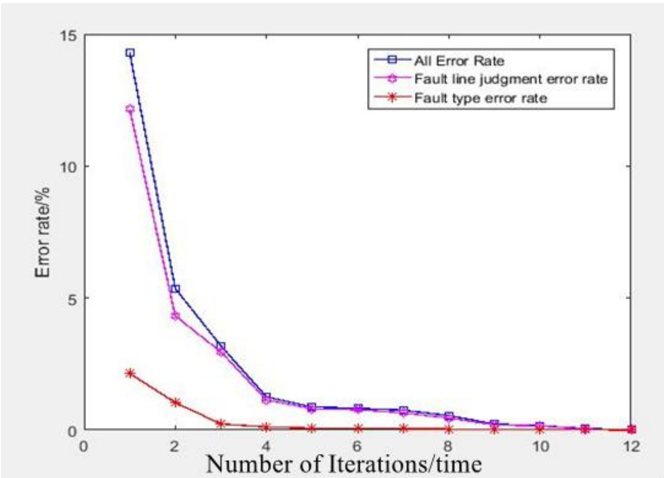

Fig.5. The relationship between error rate and training frequency

V. Simulation

In order to verify the effectiveness, fault tolerance and accuracy of multiple fault diagnosis of convolution neural network based on fuzzy optimization, the distribution network in this paper has been tested under different conditions. The results are compared with the test results of the convolution neural network model. Some test results are shown in table 3:

Table.3. Results of multiple fault diagnosis

Serial number	Abnormal voltage node	CNN		CNN of fuzzy optimization		Actual fault line and fault type	
		Line	Type	Line	Type	Line	Type
1	4、14、25、26	8、30	CN	8、30	CN	8、30	CN
2	19、16、39、1	2、24	AB	2、22	AB	2、22	AB
3	26、29、28	32、43	AC	32、33	ABC	32、33	ABC
4	19、20、34	37、40	BN	37、40	BN	37、40	BN
5	10、13、12、11	10、35	BC	17、36	CA	17、36	CA
6	9、39、3、4	15、5	ACN	15、5	ACN	15、5	ACN

According to table 3, experiment 1 and 6 show that both algorithms can accurately diagnose fault types and fault lines. Experiment 3, 5 and 6 show that when the number of branches connected by a node is greater than or equal to 3, the effect of CNN on the diagnosis of fault lines is lower than that of convolution neural network fuzzy optimization. Experiment 3 and 4 show that when information of abnormal voltage nodes is missing, the effect of CNN on fault type diagnosis is lower than that of convolution neural network fuzzy optimization.

Table.4. Comparison between CNN and fuzzy optimization convolution neural network

Type of fuzzy network	Frequency of training	Error rate/%	Error rate of fault type/%	Error rate of fault line/%	Training time/s
CNN	11	0.775	0.128	0.647	589
CNN of fuzzy optimization	11	0	0	0	426

As can be seen from table 4, the error rate of CNN network training 11 times is still higher than 0.7%. Therefore, compared with CNN neural network, fuzzy optimized convolution neural network has higher accuracy and less training time in line multiple fault diagnosis.

VI. Conclusion

In this paper, multiple fault diagnosis of distribution network based on CNN model with fuzzy optimization is proposed for the first time. Convolution neural network is applied to solve the general problem of power system with multiple faults in distribution network, which provides a basis for the reconstruction of distribution network. Fuzzy optimized convolution neural network uses two softmax classifiers to solve two classification problem of fault type diagnosis and fault line diagnosis. The influence of the number of convolution kernel and sampling width on the accuracy of convolution neural network is studied. It is significant to construct the structure of convolution neural network.By comparing the training results of convolution neural network and fuzzy optimization convolution neural network, in multiple fault diagnosis, fuzzy optimization convolution neural network has stronger learning generalization ability and parallel processing ability than convolution neural network. It has a broad application prospect in the multiple fault diagnosis of power network in the future.

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