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Research of Bus Protection Based on Artificial Neural Network

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***Abstract* - Bus is one of the most important parts in power plants and transformer substations. The research on the high-reliability and high-intelligence bus protection will be quite important both in theory and practice. An ANN(artificial neural network) is set up to replace the physical object of bus protection in this paper, which presents a new bus protection method based on approximation ability of function on ANN. Various types of fault results collected in practice are used as sample data. Applying this model, bus protection failures are analyzed and compared in two different improved algorithms of neural networks. And two simulation results are acquired. The result shows that the trained ANN model could not only approximates the normal bus operation precisely and reflects all types of the inner failures but also satisfies precision of protection.**

Index Terms - artificial intelligence, neural network, RBF, bus protection

I. INTRODUCTION

Bus Protection is the one of the most important parts in power plants and transformer substations. The failure frequency of the bus is usually very low but it could be one of the worst failures. When failure happens, a large area of electric elements which are connected to the bus will be invalidated. The power cut in large scale will happen and the stability of the power grid system will be affected. Then it will lead to more serious failures. Therefore, it is important and significant for research on bus protection devices with high reliability, good selectivity, fast response and enhancing operation ability of the bus.

At present, the commonly used bus protections such as mid-impedance bus differential protection and micro–computer bus differential protection have their own characteristics on resolving the problems of CT saturation nearly without being affected by CT saturation. When CT transformation ratio is inconsistent, the mid-impedance bus differential protection device may be over-complex and the micro-computer bus differential protection device may have some defects. However, when the bus operation mode is changed or CT is broken-line, the mid-impedance bus differential protection and micro-computer bus differential protection lack of adaptive faculty. So the major orientation of the bus protection research is to search a bus protection device with high-performance, powerful function, high-reliability and high-intelligence. Employing new theories and technologies in the research will be quite important in practice.

Artificial neural network is a network composed of a large number of simple interconnected neuron [1]. This network is a hyper-complex and non-liner dynamic system, can automatically study the uncertain system with high fault tolerance and strong robustness. And it can reflect many basic functions of human brain to a certain extent. This paper is to discuss the achievement of bus protection by artificial neural network [3]. According to the simulation of various system faults, the artificial neural network for bus protection could distinguish the fault inside from the fault outside automatically and estimate the fault phase and fault type correctly.

II. DESIGN OF ANN BUS PROTECTION

A. The diagnosis of bus protection faults based on BP and RBF neural networks

1) The principle and algorithm of BP network

The BP(Back Propagation) neural network is multilayer feed forward network. One BP network is divided into n layers, with the first layer defined as input layer, the last layer defined as the output layer and other layers between them defined as the hidden layers. The input data is transferred from the input layer to the output layer step by step. The mapping relationship of every neuron is f and the link weight of neurons from the j neuron in k-1 layer to the i neuron in k layer is , so the input and output sample is $\{x_{si}, y_i\}$, i=1, 2,…,n. At the same time, the input sum of i neuron in k layer is defined as u_i^k and the output sum is y_i^k , so the relationships among those variables are

$$y_i^k = f\left(u_i^k\right) \quad (1)$$

$$u_i^k = \sum_j w_{ij} y_j^{k-1} \qquad \text{k=1, 2,…,n} \quad (2)$$

for the p_{th} sample, the error is :

$$E_p = \frac{1}{2}\sum_i (t_{pi} - y_{pi})^2 \tag{3}$$

t_{pi} is the expectant output and the y_{pi} is the network computing output.

the total target function of network is：

$$J = \sum_p E_p \tag{4}$$

According to the grads descent, the weights are adjusted by J through output layer. Suppose step size is η, the learning rule of weight from the neuron j to the neuron i is

$$w_{ij}(t+1) = w_{ij}(t) - \eta\frac{\partial J(t)}{\partial w_{ij}(t)} = w_{ij}(t) - \eta\sum_p \frac{\partial E_p(t)}{\partial w_{ij}(t)} = w_{ij}(t) + \Delta w_{ij}(t) \tag{5}$$

if f is Sigmoid function, we define

$$d_{ki} = \frac{\partial J}{\partial u_{ki}} \tag{6}$$

This can be written as:

$$d_{ki} = y_{ki}(1 - y_{ki})\frac{\partial J}{\partial y_{ki}} \tag{7}$$

If i is the neuron of output layer, i.e. $k = n$,

$$d_{ni} = y_{ni}(1 - y_{ni})(y_{ni} - y_i) \tag{8}$$

If i is the neuron of hidden layer,

$$d_{ki} = y_{ki}(1 - y_{ki})\sum_l w_{li} d_{(k+1)l} \tag{9}$$

2) The principle and algorithm of RBF network

Since the missions of the output layer and hidden layer are different in RBF(Radial Basis Function) network, their learning strategies are different too. The learning speed of output is faster, because it used the linear optimized strategy to adjust the linear weight. In contrast, the learning speed of hidden layer is slower because it adjusts the function parameters using nonlinear optimized strategy [2]. Since the learning time and process are different in the two layers, the learning is usually divided into two steps.

Selecting PBF center by supervised learning is adopted in this paper, and the detailed algorithm is as follow.

First let's define the instantaneous value of the cost function

$$\varepsilon = \frac{1}{2}\sum_{j=1}^{N} e_j^2 \tag{10}$$

Where N is the sample number of training, and e_j which is error signal is defined as:

$$e_j = d_j - \sum_{i=1}^{N} w_i G\left(\left\| X_j - t_i \right\|_{c_i}\right) \tag{11}$$

Find the free parameter w_i, t_i and $\sum_i^{-1}$ (the latter one is related with weighted norm matrix) to make the ε get minimum. The minimizing result is as followed.

a、linear weight (output layer)

$$\frac{\partial \varepsilon(n)}{\partial w_i(n)} = \sum_{j=1}^{N} e_j(n) G\left(\left\| X_j - t_i(n) \right\|_{c_i}\right) \tag{12}$$

$$w_i(n+1) = w_i(n) - \eta_1 \frac{\partial \varepsilon(n)}{\partial w_i(n)}$$, where i=1, 2,…, m (13)

b、center (hidden layer)

$$\frac{\partial \varepsilon(n)}{\partial t_i(n)} = 2 w_i(n) G'\left(\left\| X_j - t_i(n) \right\|_{c_i}\right)\sum_i^{-1}\left[X_j - t_i(n)\right] \tag{14}$$

$$t_i(n+1) = t_i(n) - \eta_2 \frac{\partial \varepsilon(n)}{\partial t_i(n)}$$, where i=1, 2,…, m (15)

c、center spread（hidden layer）

$$\frac{\partial \varepsilon(n)}{\partial \sum_i^{-1}(n)} = -w_i(n)\sum_{j=1}^{N} e_j(n) G'\left(\left\| X_j - t_i(n) \right\|_{c_i}\right) Q_{ji}(n) \tag{16}$$

$$Q_{ji}(n) = \left[X_j - t_i(n)\right]\left[X_j - t_i(n)\right]^T \tag{17}$$

$$\sum_i^{-1}(n+1) = \sum_i^{-1}(n) - \eta_3 \frac{\partial \varepsilon(n)}{\partial \sum_i^{-1}(n)} \tag{18}$$

B. The model of Artificial Neural Network for Bus Protection

1) The functional relation for the physical object of Bus Protection

A power system bus could be regarded as a certain physical object. The input of the physical object is the synchronous secondary inspect current $\hat{i}_n$ (n is from 1 to N, N is the maximum number of the loops on the bus), which is transferred by TA from each loop on the bus. The primary side synchronous current for each loop on the bus is i_n, so the output of the physical object is $\sum_{n=1}^{N} i_n$. According to the Kirchhoff law of current, the sum of the primary side synchronous currents on each loop of the bus is 0, and therefore, $\sum_{n=1}^{N} i_n = 0$.

The transform error is induced by $\hat{i}_n$ after TA transferred and let $\sum_{n=1}^{N} \hat{i}_n \neq 0$. Considering $\hat{i}_n$ is the function of i_n, because $\hat{i}_n = f_n(i_n)$ and this function is monotonic, the inverse function is $i_n = F_n(\hat{i}_n)$ for function $\hat{i}_n = f_n(i_n)$. Let

$$g(\hat{i}_1, \hat{i}_2, \cdots, \hat{i}_N) = \sum_{n=1}^{N} F_n(\hat{i}_n) = \sum_{n=1}^{N} i_n = 0 . \qquad (19)$$

Obviously, $g(\hat{i}_1, \hat{i}_2, \cdots, \hat{i}_N)$ is the function of the secondary side synchronous current $\hat{i}_n$ and the value is 0.

According to ANN(Artificial neural network) mathematic model function approximation theory, if only the ANN transfer function is monotonic increasing bounded nonlinear function, such as sigmoid function, $g(\hat{i}_1, \hat{i}_2, \cdots, \hat{i}_N)$ can be approximated by the ANN with hidden units. In addition, it can also be approximated if the ANN transfer function is piecewise linear function with hidden units (PWL function). Since $\hat{i}_n$ is detected current when bus is error-free running, $g(\hat{i}_1, \hat{i}_2, \cdots, \hat{i}_N)$ could be thought as linear function. So, $g(\hat{i}_1, \hat{i}_2, \cdots, \hat{i}_N)$ can be considered approximately by the ANN math model with liner transfer function [4].

After the bus protection's functional relation between input and output was determined, Fig.1 gives the ANN model of bus protection physical object [5].

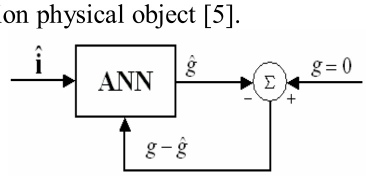
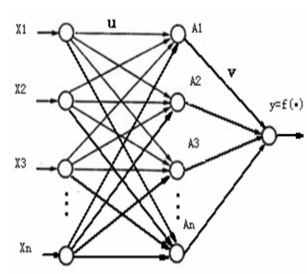


Fig. 1 ANN model of bus protection physics object

In Fig.1, $\hat{\mathbf{i}}$ is the synchronous secondary detected current $(\hat{i}_1, \hat{i}_2, \cdots, \hat{i}_N)$ which is transferred by TA from each loop on the bus. g is the function expressed by (19).

2) Network model construction

To build up the model of ANN bus protection is the base of ANN bus protection, which is using mathematic model instead of physical model and use the model to approximate the relation between the input and output of physical object. The built ANN network model is shown as Fig.2, which is the liner model with multiple input and single output. A hidden unit is also included, which is to accelerate the convergent speed of the system. In the figure, X_i is the synchronous sample current from TA. U is the weight from input unit to hidden unit and V is the weight from hidden unit to input unit. y is the output.



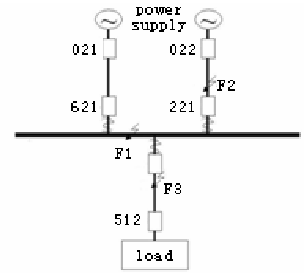


Fig. 2 Bus protection ANN model Fig. 3 Physical testing circuit of bus relay

3) The training and simulation of ANN Bus Protection

Fig.3 is the data collection model for motion experiment. Fault-free running data and several kinds of inner and outer fault data from simulating the fault of monophase grounding, disphase grounding short-circuit, disphase short-circuit, three-phase short-circuit and outer. The data is trained with MATLAB and 3 layers ANN. Under normal condition, the data is used to simulate the function relation of actual physical model and reflect the relation of input and output. When system has a fault, the relation of input and output could not satisfy the normal relationship of function. Therefore, the relation of input and output which the network reflects will change a lot. According to the changes, the fault could be estimated.

The training content of phase A (shown in Fig. 4) in fault-free running are acquired when CT ratio on each loop of the bus is 300/5. And the training result of phase A under linear transfer function ANN model is acquired in fault-free running. Input data is on the left, and the output is on the right.

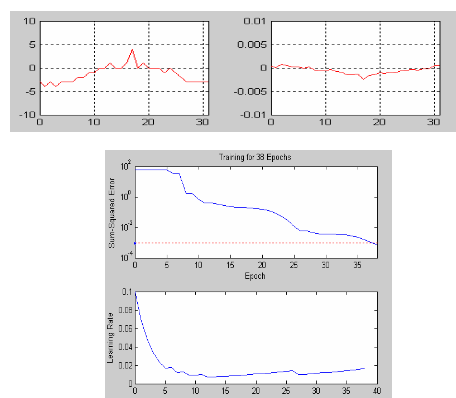


Fig. 4 training results of phase A in normal operating conditions

After 38 times of training, phase A of the ANN bus protection model using linear transfer function converged, and the simulation output was approximated to zero meeting with the expected error (Fig.4).

The simulation of the three-phase short-circuit is shown in Fig. 5. The left is the input data and the right is the output.

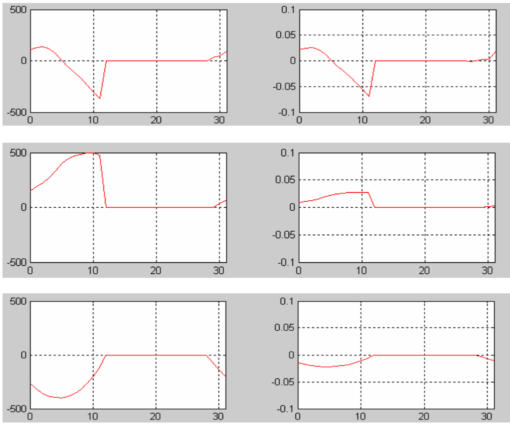


Fig.5 Testing result of inner three-phase short-circuit

As shown in Fig.5, ANN bus protection model can truly reflect the characteristics of changes in three-phase short-circuit, so the model can successfully reflect the practical faults.

III. Failure Diagnosis Of ANN Bus Protection

A. The simulation results of failure diagnosis are defined as follow:

TABLE I
THE DEFINITION OF FAILURE DIAGNOSIS OUTPUT

NO.1	NO.4	NO.5	NO.6
Inner fault	Phase A fault	Phase B fault	Phase C fault
1	1	1	1
0	0	0	0

For example:
The expected output of inner monophase B short-circuit is:
1 0 1 0
The expected output of outer AB diphase grounding fault is:
0 1 1 0

B. The experimental results of BP and RBF networks in various bus protection faults.

TABLE Ⅱ
FAILURE DIAGNOSIS RESULT OF INNER FAULT

BP three-phase short-circuit	0.9928	0.9958	0.9998	0.9997
RBF three-phase short-circuit	1.0000	0.7588	1.0000	1.0000
BP BC diphase short-circuit	0.9981	0.0030	0.9995	0.9973
RBF BC diphase short-circuit	1.0000	0.0000	1.0000	1.0001
BP BC diphase grounding fault	1.0000	0.0000	1.0000	0.9999
RBF BC diphase grounding fault	1.0000	0.0000	1.0000	1.0000
BP monophase A short-circuit	0.9978	0.9977	0.0000	0.0000
RBF monophase A short-circuit	1.0000	0.9022	0.0978	0.0978

TABLE Ⅲ
FAILURE DIAGNOSIS RESULT OF OUTER FAULT

BP three-phase short-circuit	0.0000	0.9983	0.9984	0.9977
RBF three-phase short-circuit	0.0000	0.7885	1.1769	1.3726
BP BC diphase short-circuit	0.0001	0.0013	0.9983	0.9992
RBF BC diphase short-circuit	0.0000	-0.1095	1.0844	1.2175
BP BC diphase grounding fault	0.0006	0.0010	0.9983	0.9995
RBF BC diphase grounding fault	0.0000	-0.2146	1.1724	1.3543
BP monophase A short-circuit	0.0002	0.9957	0.0019	0.0021
RBF monophase A short-circuit	0.0000	0.9721	0.0298	0.0504

Although both of the two networks can correctly show the positions and types of faults, there is a difference from those two networks according analyzing the error between the experimental outputs and the expected outputs. In the inner faults, the maximum error of BP network in monophase grounding and three-phase short-circuit experiments is 0.0072, but the one of RBF is 0.2412; The error of BP network in diphase grounding fault and diphase short-circuit fault was 0.003, whereas the error of RBF network is much smaller (0.0001). In the outer faults, the maximum error of BP network in monophase short-circuit and three-phase short-circuit experiments is 0.0043, but the one of RBF is 0.3726; and the error of BP network in diphase grounding fault and diphase fault was 0.0017, whereas the one of RBF network was much bigger (0.3543). All in all, the results of BP network are much closer to the expected results than RBF network, and the output of BP is stabler and more suitable for the failure diagnosis in bus protection.(Tab.2 and Tab.3)

IV. Conclusion

According to the result of the research, the ANN bus protection has much more advantages than the traditional bus protection. The trained ANN model could not only reflects to normal operation but also to the inside faults, and satisfy the required protection precision. Compared with BP network, RBF network has faster training speed. But BP network has better failure analyzing ability than RBF network.

References

[1] L.K. Roger, "Artificial neural networks and computational intelligence," *IEEE Computer Applications in Power*, vol. 11, no. 4, pp. 14-25, October 1998.

[2] J.W. Hines, "A logarithmic neural network architecture for unbounded non-linear function approximation," Neural Networks, IEEE International Conference on, vol. 2, 3-6, pp. 1245-1250, June 1996.

[3] H.N. Mhaskar and L. Khachikyan, "Neural networks for function approximation," Neural Networks for Signal Processing [1995] V. Proceedings of the 1995 IEEE Workshop, pp. 21–29, August-September 1995.

[4] Y.Q. Duan, J. L. He, "Distance relay protection based on artificial neural network," Proceedings of the CSEE, 19(05), pp. 67-70, 1999.

[5] H.J. Du, F. Deng, W.H. Su, "Adaptive distance relay protection based on artificial neural network," Relay, 30(02), pp. 38-65, 2002.