

Chapter 2

The Research on Fault Diagnosis of Building Electrical System Based on RBF Neural Network

Qian Wu, Yahui Wang, Long Zhang and Li Shen

Abstract Building electrical system fault diagnosis is the blank in the fault diagnosis field at home and abroad. The main reason is that the building electrical systems have many complex and huge subsystems; meanwhile, it is very hard to establish the mathematical model of system. By using the neural networks which is not depending on the model and using its advantage of convergence speed, the difficulties of building electrical system fault diagnosis can be well solved. This paper puts forward a method of fault diagnosis based on radial basis function neural network (hereinafter referred to as the RBF network) and applied it to building electrical system fault diagnosis. Beijing institute of civil engineering and architecture building intelligent experiment center provides building electrical test platform which can collect actual fault samples for RBF network training. After experiments and verification, RBF network's accuracy and speed on fault diagnosis of building electrical system is significantly better than BP network. The effective RBF network in building electric system fault diagnosis field will have good engineering application prospect in the future.

Keywords Fault diagnosis · Building electrical system · RBF neural network

Q. Wu (✉) · Y. Wang · L. Shen
Department of Electrical and Information Engineering, Beijing University
of Civil Engineering and Architecture, 100044 Xi Cheng District, Beijing, China
e-mail: wq05dianzi@126.com

Y. Wang
e-mail: yahui-wang@vip.sina.com

L. Shen
e-mail: Shenligood1988@sina.com

L. Zhang
Department of Electrical and Information Engineering, Beijing Forestry University,
Hai Dian District, Beijing, China
e-mail: long1988iacf@yahoo.com.cn

2.1 Introduction

With the acceleration of urbanization, the number of high-rise and super high-rise buildings is increasing; meanwhile, there is a growing pursuit of building functionality and comfort in the residence and office. Due to the rapid development of electronic communication and network technology, building electrical system is moving in the development of large-scale, complex structure, including lighting, power, and control in one large intelligent system, so that building electrical system failure will bring great inconvenience to people's work and lives. Even some serious accident of electricity would threaten property and personal safety, therefore security and reliability have become a major issue in the current building electrical.

Building electrical system failure can be divided into two categories: electrical equipment faults and the line faults. Traditional building electrical system failures were most manually detected by the electrician to identify the location of the faults, and then replace the line or components. Manual detection often rely on personal experience of maintenance electrician, but for the increasingly complex coupling relationship exists between the various subsystems, modern building electrical system need to put forward a new intelligent fault diagnosis method.

The neural network is an important way to solve the fault diagnosis problem, through the effective training of the neural network can remember the process of knowledge, learn directly from the historical data, and make it suitable for online detection and fault diagnosis. It has the ability to distinguish the cause of the malfunction and the type of fault. In fact, the neural network technology has become a valid means of fault diagnosis. Radial basis function neural network (RBFNN) which rely on its simple network structure and fast training procedure, received extensive attention in many areas. This paper presents a fault diagnosis method for complex building electrical system based on RBF network. This method can quickly identify and determine the type of failure, and can diagnose the same category of the new faults. From engineering point of view, it has a good practical application value and bright prospect.

2.2 Basic Principles of RBF Neural Network Algorithm

2.2.1 *The Basic Concepts of the RBF Network*

Radial Basis Function (RBF) is a kind of neural network function whose independent variables are the distance to a fixed point. In the two-dimensional Euclidean space, the distance is:

$$r_k = r_k(x, y, x^{(k)}, y^{(k)}) = \sqrt{(x - x^{(k)})^2 + (y - y^{(k)})^2} \quad (2.1)$$

r_k is the independent variable of radial basis function, denoted $\phi^{(k)}(r_k)$, (x, y) is arbitrary coordinates of the Euclidean space, $(x^{(k)}, y^{(k)})$ is the coordinates of the fixing points k , known as the center of the radial basis function, radial basis function $\phi(r)$ is generally divided into two categories: local and overall. If $\lim_{r \rightarrow \infty} \phi(r)$ is zero, called a local radial basis function, otherwise it is called the overall radial basis function. Local radial basis function interpolate in the center of the input data area, while the overall radial basis function can interpolate globally.

2.2.2 Principle of RBF Network

RBF network is a three-layer network structure, as shown in Fig. 2.1, the three layers include the input layer, hidden layer and output layer. The input layer to the hidden layer is nonlinear mapping and output layer is linear weight sum of the hidden layer unit, so it is a linear mapping.

The hidden layer of RBF network takes radial basis function as the activation function, and this function is usually Gaussian function, when the input sample is x , the output of the i unit of the hidden layer is as follows:

$$R_i(x) = e^{-\frac{\|x-c_i\|^2}{2\sigma_i^2}} \quad i = 1, 2, \dots, L \tag{2.2}$$

Wherein, c_i is a base function center, σ_i is the width of the Gaussian function in hidden layer unit i , the output of the corresponding output node is:

$$Y = \sum_{i=1}^L W_i R_i(x) \tag{2.3}$$

W_i represent hidden layer i to the output layer weights. When the input sample is at the farther distance from the center, the lower degree of neurons is activating,

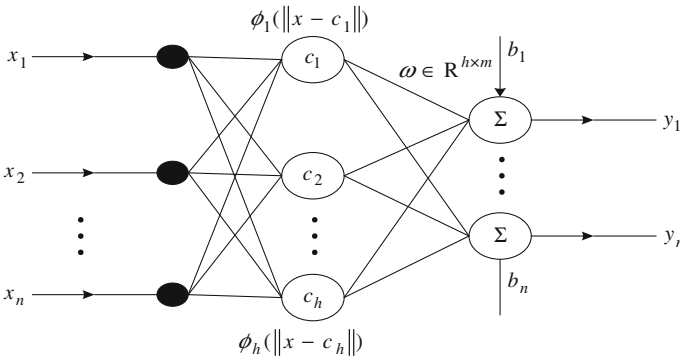


Fig. 2.1 RBF neural network diagram

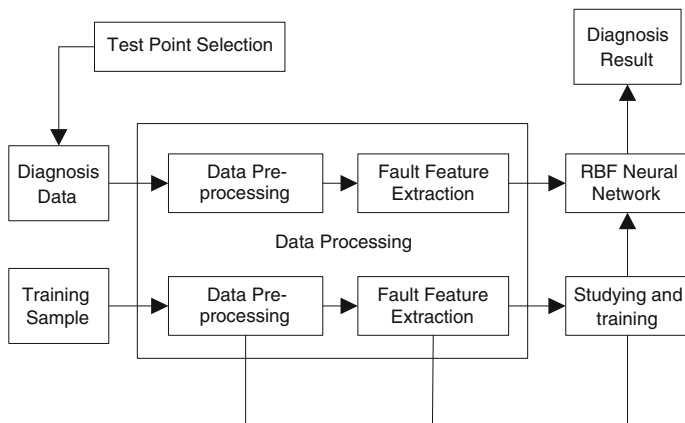


Fig. 2.2 Standard model of fault diagnosis system

and when it more than a certain distance, the neurons will not be activated. Therefore, for the RBF neural network, each hidden layer node has a data center.

In the neural network fault diagnosis algorithm, the input general is corresponding to the fault features, and the output node are the causes and reasons of the fault. The fault samples are used to network training, so as to make sure the structure of network, and reference value, such as neuron weights and threshold value. After training, the process of setting nonlinear mapping between fault features and fault set is complete. Standard model of fault diagnosis system is shown as Fig. 2.2. Testing point selection is very important to the fault diagnosis result, especially to large and complex system which includes electric circuit; this topic will be discussed in another paper.

2.3 In the Application of the Building Electrical Fault Diagnosis

2.3.1 Introduction of Building Electrical Test Platform

The METREL Building Electrical Testing Experimental Systems is original made in German. It is actually an integration of constructions electrical elements which are concentrated in a test platform. It has brought great convenience to the construction of electrical test experiment. The physical model of electrical test platform is shown as Fig. 2.3.

In Fig. 2.3, the construction of low-voltage distribution system is composed of a variety of elements, such as circuit breakers, fuses, single-phase sockets and three-phase sockets. Power supply of the electrical test platform is 220 V and 50 Hz mains, and the transformer output 15 V DC to the weak protection part and

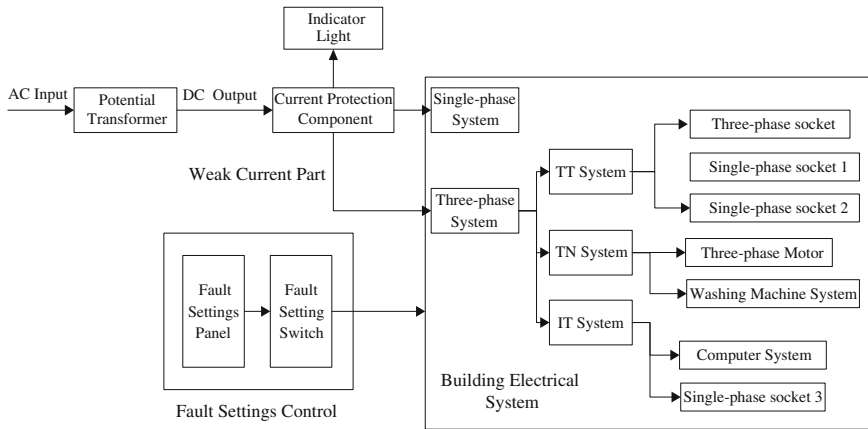


Fig. 2.3 Physical model of electrical test platform

the fault setting control board. The fault setting panel can provide five categories of common household electricity insulation test failures and the 22 faults location button, which completely simulate civilian residential electrical systems and common faults in the real life.

2.3.2 Basic Methods of Diagnosis

The basic idea of fault diagnosis that base on RBF neural network is use fault features as network input and diagnostic result as network output, apply a large amount of historical fault data to network offline training, so that the specific corresponding relationship between the network and the right weight value that remember fault symptoms and corresponding fault type can be set up.

According to the various fault signals collected by the monitoring and data acquisition system, the input layers are fault data, because there are odd data in the collected set, normalization process should be operate according to the formula 3.1 firstly.

$$y = \frac{x - MinValue}{MaxValue - MinValue} \tag{3.1}$$

Fault feature vector is $X = [x_1, x_2, \dots, x_n]$. Intermediate layer input layer get input information and transform into a targeted solution by internal learning to complete the non-linear mapping of input to the output. The output layer is a vector of the failure mode, through comparing with a threshold value; the diagnostic result can be obtained. In this case, the total number of the failed node are 10 and the fault type respectively are the line impedance fault, the continuity fault, the grounding resistance abnormal and ground resistivity insulation resistance is

too small. From the above, five categories failure will occur stochastic at 10 fault location. In every output vector, the judging rule is that number 0 indicating no failure, 1 indicates a failure. So the fault encoding state are Line impedance fault (1,0,0,0,0), Continuity fault (0,1,0,0,0), Grounding resistance anomalies (0,0,1,0,0), Grounding resistivity anomalies (0,0,0,1,0), Insulation resistance too small (0,0,0,0,1).

2.3.3 The RBF Network Design and Training

Firstly, using the algorithm of random selection to select the center of RBF network, and the center of the hidden unit is in the data of the input sample, and fix the center.

There are generally two methods to determine the number of hidden layer neurons of RBF network training, the commonly used method is the input vector elements are equal to the number of neuron, however, when there are more of the input vectors this method will result in excessive number of hidden layer units so that the network structure more complicated. Another method does not need to be determined the number directly, but through the training and optimization to calculate the number of neurons, the way of the second methods is setting the number of nodes of the hidden layer to 0 and then start training by checking the input error, automatically increase the hidden layer neurons. Cumulative iterative loop, so that the network produces the maximum error of the corresponding input vector as a weight vector, resulting in a new hidden layer neuron, then check the error of the new network, repeating this processes until reach the error requirements or maximum hidden layer number of neurons.

The actual collection sample data are 90 groups, also 30 groups of collected data are used to test and there are some excerpts of the collected samples in the Table 2.1. It includes five kinds of failure modes and each sample has 10 position characteristic parameters. So the number of neurons in the input layer is 10, while output neurons number is 5. The number of hidden layer is not fixed, and it will adjust after several constantly training tests. The corresponding network training output and fault diagnosis results is as shown in Table 2.2 (Fig. 2.4).

2.4 Comparison and Analysis of the Experimental Test Result

In order to stress the training effect, using BP network as a comparison objective. The process of set up BP network is little complicated than RBF. In order to make the training get best training effect, the parameters of the BP network should be change continually. The number of neurons in the hidden layer of BP network which selected according to multiple test and experience are 15 Figs. 2.7, 2.8.

Table 2.1 RBF neural network training input samples

Number	Fault samples	Set of characteristic parameters																						
		2000	2004	2002	2000	2003	2001	2000	2005	2000	2000	2000	2000	2000	2000	2000	2000	2000	2001					
1	Line impedance fault	10.77	10.74	10.72	10.79	10.75	10.77	10.71	10.73	10.72	10.73	10.71	10.73	10.72	10.78	10.79	10.77	10.71	10.73	10.72	10.79	10.78	10.75	
2		10.74	10.71	10.73	10.75	10.74	10.73	10.79	10.74	10.73	10.72	10.73	10.79	10.73	10.72	10.79	10.77	10.73	10.79	10.72	10.79	10.78	10.75	
3		9.89	9.91	9.86	9.81	9.81	9.83	9.81	9.81	9.83	9.81	9.83	9.81	9.81	9.87	9.89	9.87	9.89	9.81	9.87	9.87	9.89	9.87	9.87
4	Continuity fault	2000	2004	2002	2000	2003	2001	2000	2003	2001	2001	2000	2000	2005	2000	2000	2001	2000	2000	2005	2000	2000	2000	2001
5		3.68	3.76	3.45	3.56	3.45	3.65	3.64	3.45	3.65	3.65	3.64	3.64	3.61	3.69	3.58	3.61	3.64	3.61	3.61	3.61	3.69	3.58	
6		2.78	2.71	2.34	2.77	2.21	2.45	2.56	2.21	2.45	2.45	2.56	2.56	2.64	2.57	2.54	2.64	2.56	2.64	2.64	2.64	2.57	2.54	
7	Grounding resistance Anomaly	3.45	3.65	3.76	3.56	3.54	3.85	3.25	3.54	3.85	3.42	3.25	3.25	3.42	3.62	3.52	3.42	3.25	3.42	3.42	3.62	3.62	3.52	
8		3.66	3.68	3.67	3.89	3.67	3.45	3.44	3.67	3.45	3.76	3.44	3.44	3.76	3.25	3.78	3.76	3.44	3.76	3.76	3.25	3.25	3.78	
9		6.01	6.19	6.05	6.07	6.12	6.11	6.09	6.12	6.11	6.03	6.09	6.09	6.03	6.07	6.11	6.03	6.09	6.03	6.03	6.03	6.07	6.11	
10	Ground resistivity Anomaly	0.32	0.33	0.31	0.36	0.34	0.33	0.36	0.34	0.33	0.33	0.36	0.36	0.35	0.33	0.34	0.33	0.36	0.35	0.35	0.33	0.33	0.34	
11		9.21	9.32	9.24	9.2	9.27	9.25	9.29	9.2	9.25	9.25	9.29	9.29	9.31	9.34	9.42	9.31	9.29	9.31	9.31	9.34	9.34	9.42	
12		0.143	0.141	0.139	0.142	0.144	0.147	0.148	0.144	0.144	0.147	0.147	0.148	0.143	0.141	0.145	0.143	0.148	0.143	0.143	0.143	0.141	0.145	
13	Insulation resistance Too small	0.32	0.33	0.31	0.36	0.34	0.33	0.36	0.34	0.33	0.33	0.36	0.36	0.35	0.33	0.34	0.33	0.36	0.35	0.35	0.33	0.33	0.34	
14		9.21	9.32	9.24	9.21	9.27	9.25	9.29	9.21	9.25	9.25	9.29	9.29	9.31	9.34	9.42	9.31	9.29	9.31	9.31	9.34	9.34	9.42	
15		0.143	0.141	0.139	0.142	0.144	0.147	0.148	0.144	0.144	0.147	0.147	0.148	0.143	0.141	0.145	0.143	0.148	0.143	0.143	0.143	0.141	0.145	
16	Trouble-free	1.21	1.11	1.15	0.23	0.58	0.63	0.25	0.58	0.63	0.63	0.25	0.25	0.27	0.36	0.68	0.27	0.25	0.27	0.27	0.36	0.36	0.68	
17		1.23	1.13	1.18	0.22	0.49	0.60	0.22	0.49	0.60	0.60	0.22	0.22	0.29	0.33	0.68	0.29	0.22	0.29	0.29	0.33	0.33	0.68	
18		1.23	1.13	1.18	0.22	0.49	0.60	0.22	0.49	0.60	0.60	0.22	0.22	0.29	0.33	0.68	0.29	0.22	0.29	0.29	0.33	0.33	0.68	

Table 2.2 RBF actual output of the neural network diagnostic results

Number	Diagnostic results		The type of fault				
	Ideal output	Diagnostic results					
1	1, 0, 0, 0, 0	1.0321	0.0005	0.0000	0.0002	0.0006	0.0006
2	1, 0, 0, 0, 0	1.0331	0.0006	0.0005	0.0007	0.0005	0.0005
3	1, 0, 0, 0, 0	1.0331	0.0005	0.0000	0.0005	0.0004	0.0004
4	0, 1, 0, 0, 0	0.0002	0.9984	0.0002	0.0001	0.0012	0.0012
5	0, 1, 0, 0, 0	0.0001	0.9998	0.0000	0.0004	0.0015	0.0015
6	0, 1, 0, 0, 0	0.0001	1.0005	0.0000	0.0005	0.0004	0.0004
7	0, 0, 1, 0, 0	0.0001	0.0006	1.0012	0.0019	0.0009	0.0009
8	0, 0, 1, 0, 0	0.0001	0.0002	1.0000	0.0000	0.0009	0.0009
9	0, 0, 1, 0, 0	0.0001	0.0002	0.0000	0.0003	0.0005	0.0005
10	0, 0, 0, 1, 0	0.0002	0.0005	0.0001	1.0009	0.0006	0.0006
11	0, 0, 0, 1, 0	0.0001	0.0002	0.0000	1.0000	0.0004	0.0004
12	0, 0, 0, 1, 0	0.0001	0.0000	0.0005	1.0001	0.0009	0.0009
13	0, 0, 0, 0, 1	0.0000	0.0002	0.0004	0.0001	1.0006	1.0006
14	0, 0, 0, 0, 1	0.0001	0.0002	0.0000	0.0008	1.0006	1.0006
15	0, 0, 0, 0, 1	0.0001	0.0000	0.0006	0.0002	1.0004	1.0004

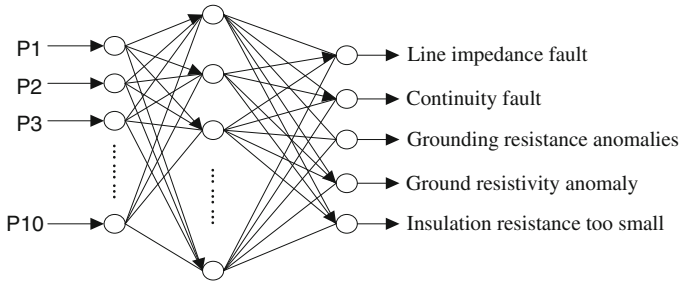


Fig. 2.4 Structure of RBF fault diagnosis model of building electrical system

Fig. 2.5 RBF training result

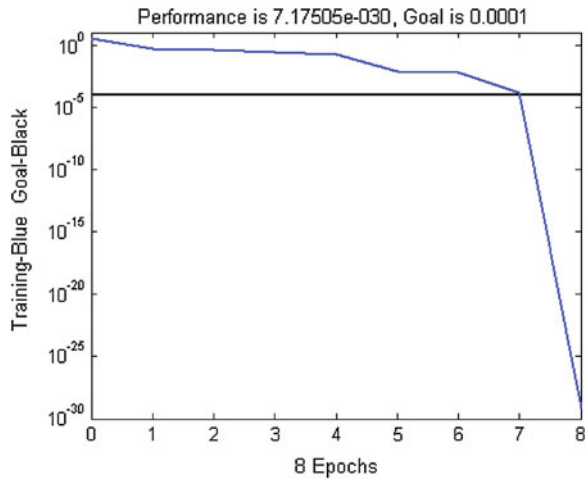


Fig. 2.6 BP training result

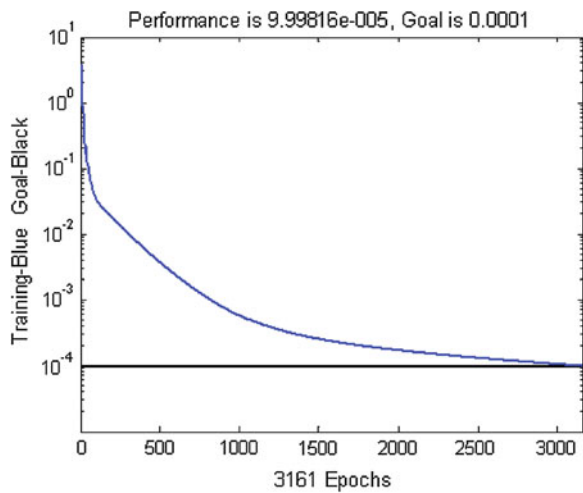


Fig. 2.7 RBF network fault identification

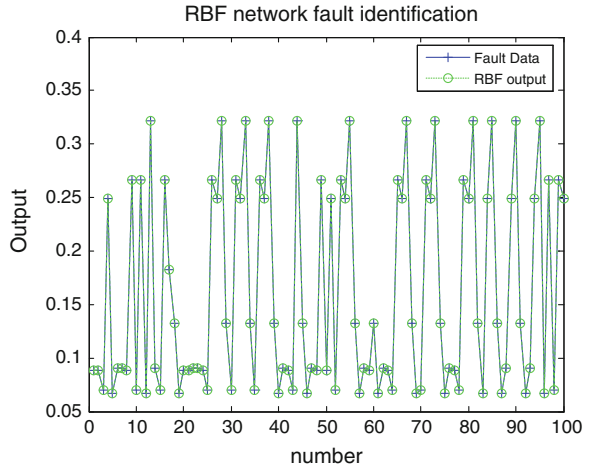
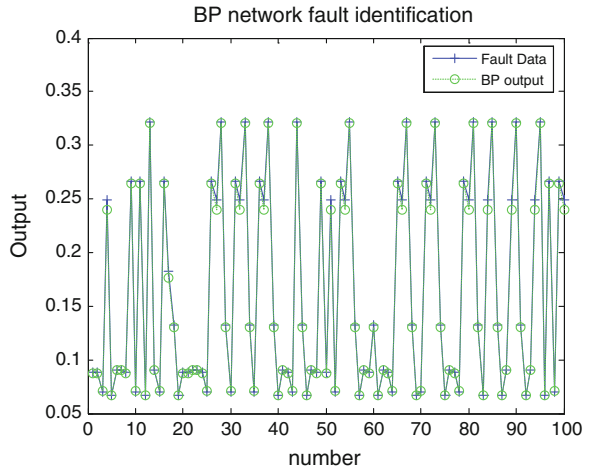


Fig. 2.8 BP network fault identification



The Figs. 2.5 and 2.6 are the training curve of RBF and BP network. In the figures, X axis is training epochs, Y axis is system error. In order to compare effectiveness, set error goal is $10e-4$. According to the simulation results shown in Figs. 2.5 and 2.6, it can be seen that when the error of BP network is $10e-4$, training epochs are 3,161, while RBF network just takes 8 epochs. During the training, even if the entire parameters of BP network have been determined, every training result is different, while the result of RBF network is more stable and not easy to fall into local minimum, when all the parameters are determined.

In addition, RBF network compared with BP network, the output layer is linear weight sum of hidden units and its learning speed is faster than the BP network, however, due to its generally radial basis function using a Gaussian function as the

activation function, the input space area is small, so it need set more radial basis neurons. On the whole, RBF network structure is easier to build, and training speed is fast and stable. In the case of building electrical system fault diagnosis, the RBF neural network is superior to BP neural network.

2.5 Conclusion and Outlook

The application of artificial neural network in building electrical system fault diagnosis, the RBF neural network is able to determine the fault type accurately and quickly. This approach verified by building electrical data acquisition and test platform which was research and development by Electrical and intelligent Experimental Center of Beijing University of Civil Engineering and Architecture. Especially, this equipment cooperate the method of RBF fault diagnosis can monitor the real-time status of critical node. Believe in the near future, this method's advantages, such as early detection and troubleshooting can play a good role, and it will have broad application prospects.