

A Method of Information Fusion Based on Fuzzy Neural Network and Its Application

Ji-Pu GAO¹, Chang-Bao XU¹, Li ZHANG¹, Jun-Lin ZHENG², Huai SHU² and Xi YUAN²

¹Guizhou Electric Power Research Institute of Guizhou Power Grid Co., Ltd., Guiyang, 550002, Guizhou, China

²Wuhan Zhongyuan Huadian Science & Technology Co., Ltd, Wuhan 430074, China

Abstract. In view of the limitation of fault diagnosis methods in substation intelligent patrol system, a fault diagnosis method based on multi-sensors information fusion is proposed. In the field of fault diagnosis, this method can deal with uncertain and imprecise information by using fuzzy theory, and has a high self-study capability based on neural network. Collecting samples of data through establishing many sensors in the scene of the intelligent patrol system, and then through the BP algorithm of fuzzy neural network training to achieve accurate fault diagnosis function of the intelligent patrol system. By comparing the result of an example, it shows that, compared with using single information, using multi-sensors information as the diagnosis method is more accurate and reliable in the intelligent patrol system.

1 Foreword

With the expansion of the system scale, the complexity of the increase, and the huge investment, it is urgent to improve the reliability and security of the system. Therefore, the establishment of a monitoring system to monitor the running of the whole system is necessary, constantly testing system changes and failures, and take the necessary measures to prevent damage and accidents. But because the system dynamic behaviour, function and the complex structure, nonlinear and uncertainty, a single information source fault diagnosis theory based on conventional or traditional methods, judging the fault by several major fault features, is difficult to achieve the corresponding goal [1-3]. So it is necessary to make full use of the detection method and status information obtained to form intelligent integration of intelligent diagnosis strategy.

Though the parallel processing network structure and strong learning function, neural network cannot make full use of the inspiring knowledge summarized by the domain expert [4, 5]. Fuzzy logic can better use the language knowledge, and knowledge of the form is easier to understand. But in fact, it has a weak learning ability and is difficult to use the value information.

Therefore, this paper combines neural network with fuzzy logic [6, 7], and puts forward a fault diagnosis method by using fuzzy neural network, which is more close to the human thinking [8-10]. The intelligent patrol system in the substation equipment in the resettlement of more than three different sources of the transformer sensors to detect the characteristics of the substation system, and using fuzzy neural network as the implementing agencies of information fusion to achieve substation intelligent patrol system fault diagnosis. At the same time, by comparing the result of fault diagnosis, it is demonstrated that using multi-sensors information fusion is more accurate and reliable in comparison to using single information.

2 Fuzzy neural network structure

FNN fault diagnosis is a combination of fuzzy logic and neural network technology. Through processing the tradition artificial neural networks by fuzzy method, retaining its results, the carrying on fuzzy processing in the neuron, fuzzy neural network can cause the neuron to evolve from processing the pure processing value data to can process the fuzzy information data.

2.1 FNN architecture

According to the actual situation of intelligent patrol system, the paper use a four-story fuzzy neural network structure, and the network consists of three parts: the first part is a fuzzy quantify function; the second part is the neural network; the third part is to get rid of the fuzzy. Its structure is shown in Figure 1.

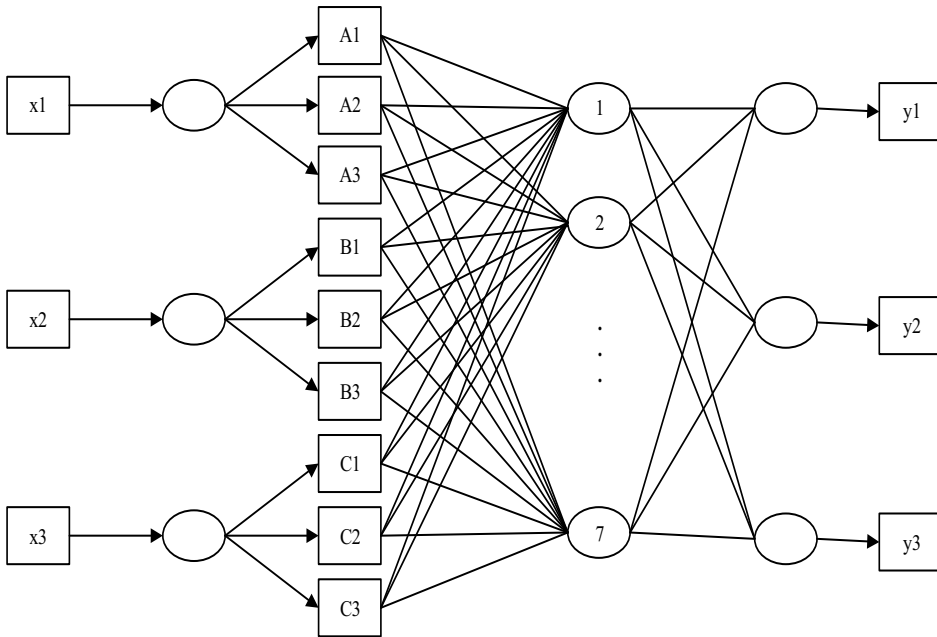


Figure 1. FNN architecture.

Network level 1 is the input layer, which the value of the neurons is 1, and the neurons directly transmit input data to the neurons of level 2. Each node responds to a variety of intelligent patrol system failure instructions. According to the analysis of the actual situation of intelligent patrol system and fault indication relationship, the main transformer fault indication is abnormal breathing light, abnormal cooler and abnormal disconnector and so on, corresponding to fuzzy neural Network x_1 , x_2 , x_3 3 input variables.

Network 2 is a fuzzy quantified layer. According to the membership function defined in the fuzzy subset, it carries on fuzzy processing in the input continuous variable value, and transforms the serial number into the corresponding membership degree, to realize fuzzy processing.

Network level 3 is the implied layer. It maps the fuzzy input variables to the fuzzy output variables. The hidden nodes can be determined by the actual situation, and the general desirability is $2N + 1$ (n is the input layer node), the hidden activation function is Sigmoid function.

Network 4 is the output layer, and the output of each node responds to the substation fault in intelligent patrol system. The fuzzy value size of each output node represents the size of the probability of failure.

The four layer fuzzy neural network can be used to effectively implement the fuzzy input to the fuzzy output mapping, and through the neural network learning algorithm, and can enable the mapping to the method of fuzzy nonlinear function relations.

2.2 Membership function

The introduction of fuzzy mathematics transferred mathematical logic to value logic and shifted absolute "yes" and "no" to the relative "yes" and "no" in the appropriate feature space, thus promoted the logic relation of classical set theory.

The basic idea is that, in the general collection, the membership degree of elements to collection from the original value of the expansion can only take 0,1 to be admitted any value in the range of $[0,1]$, so it is very suitable to describe and process the uncertain sensors information. In the application of multi-sensors data fusion, the fuzzy set theory expresses the uncertainty of various sensors information with the membership function. And in the field of fault diagnosis, the fault membership degree are generally obtained from the fault indication membership degree.

Supposing possible fault sign is $m: x_1, x_2, \dots, x_m$, then the fault indicator fuzzy vector is $X = (\mu_1, \mu_2, \dots, \mu_m)$, where μ_i is the target of the member, which have characteristics of x_i . Supposing the reason for the failure are $n: y_1, y_2, \dots, y_n$, then the fault reason fuzzy vector is $Y = (\mu_1, \mu_2, \dots, \mu_n)$, where μ_j is the membership of the target, which have faults y_j . So the fault diagnosis is function-mapping process, which acquired the reasons fuzzy vector from the corresponding indication fuzzy vector.

When the intelligent patrol system is working, the parameters of the substation should be kept in a stable range. When the substation system is in trouble, the state parameters, which are measured by the sensor, will deviate from the normal range, the larger departure from the normal the larger possibility of failure.

According to the actual situation of intelligent patrol system and the experience of experts establishes the fault indication membership function. The membership function has shown in Figure 2 and Figure 3.

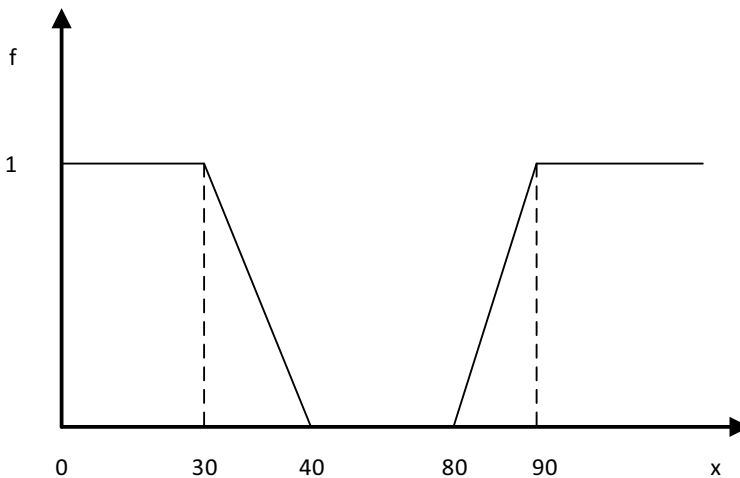


Figure 2. The membership function.

$$f(x) = \begin{cases} 1 & x \in [0, 30] \\ -0.1x + 4 & x \in [30, 40] \\ 0 & x \in [40, 80] \\ 0.1x - 8 & x \in [80, 90] \\ 1 & x \in [90, \infty] \end{cases}$$

Figure 3. The expression of the membership function.

2.3 FNN training algorithm

FNN learning algorithm uses a common BP algorithm which is often used in multilayer neural network. The nature of the algorithm modifies the threshold value by the error of the actual neural network output value t_1, t_2, \dots, t_n and the corresponding value of training samples y_1, y_2, \dots, y_n , so the network structure will be more and more close to the real structure of the samples.

Supposing the output of m iterations is $y_i(m)$, and then the unit error will be $e(m)$, $e_i(m) = d_i(m) - y_i(m)$.

The calculation uses the gradient method. The revised value of ω_{ij} linked to the neurons m is: $\Delta\omega_{ij} = \eta\delta_i(m)y_j(m)$. In the formula, η means learning step, and $\delta_i(m)$ is the local gradient, the revised value of which declines in the direction of the gradient.

Because the traditional BP algorithm has the slow convergence rate, and has the local minimum problems in the objective function, a momentum a is increased to enhance the convergence rate, that is: $\Delta\omega_{ij} = a\Delta\omega_{ij}(n-1) + \eta\delta_i(n)y_j(n)$, $a \in [0, 1]$.

3 Applications

Because of the special working environment of substation equipment, safety is essential. According to the frequent fault phenomenon of substation equipment in practical work, three main reasons for failure were: (1) voltage transformer fault; (2) current transformer fault; (3) capacitor fault.

Three indication parameters by is detected by three sensors placed in substation system and the fault indication fuzzy vector is $X = (\mu_1, \mu_2, \mu_3)$, which is derived from the fuzzy sensors data, as fuzzy neural network training samples. And $\mu_i (i = 1 \sim 3)$ is membership of fault indication i , and $Y = (\mu_1, \mu_2, \mu_3)$ is the fault reason fuzzy vector, and $\mu_j (j = 1 \sim 3)$ is the membership of the fault reason j .

When the substation system is failure, the fault indication parameters will change significantly, and the sensors will get the parameters. This parameters are used as training samples, their fault membership degree were calculated by their respective membership functions. In this paper, the FNN has a three input nodes, seven hidden points, three output points, and the expected error is 0.001. Six group samples are selected for the network training, three groups as a network test samples, and the madab7 neural network toolbox was used to make the algorithm of the program, the network convergences after 2120 iterations. After entering the test samples of the three groups, the network can identify the failure of substation system, the fault diagnosis accuracy rate is high.

After the completion of the network training, enter the test samples to verify the accuracy and reliability of the FNN. After entering three groups test samples, the network can identify the failure in

the hydraulic circuit brake system of mining equipment, and fault diagnosis accuracy rate is high, as shown in Table 1.

The output of FNN integration is the value of fault membership. The following principles can be used for the failure of the decision:

(1) The maximum membership principle: the fault component should have the maximum membership value.

(2) The minimum threshold principle: the value of the membership of fault component is greater than a certain threshold, and the threshold value is generally determined in the experiment.

Table 1. The results of single sensors information fault diagnosis and multi-sensors information fault diagnosis.

Fault	Sensors and Information Fusion	Failure membership			The result of Diagnosis
		μ_1	μ_2	μ_3	
1 Brake tank low level	A single sensor	0.650	0.210	0.600	Indefinite
	Multi-sensors fusion	0.956	0.093	0.003	1 Fault
2 Cooling pump failure	A single sensor	0.010	0.850	0.030	2 Fault
	Multi-sensors fusion	0.021	0.945	0.001	2 Fault
3 Brake valve fault	A single sensor	0.310	0.001	0.720	Indefinite
	Multi-sensors fusion	0.021	0.021	0.922	3 Fault

Conclusion

This paper make a full use of the advantages of fuzzy logic and neural network, and proposes the information fusion fault diagnosis method based on fuzzy neural network. This method is closer to human thinking. By using multiple sensors at the scene to collect data, express fuzzy rules and membership functions of fuzzy logic by using the neural network, and through the training of FNN by the BP algorithm, to achieve the precise fault diagnosis of intelligent petrol system. And then through the contrast of multi-sensors data fusion diagnostic identify methods and single sensors identify methods, multi-sensors fault diagnosis can effectively eliminate misjudgement due to lack of information and incomplete and not completely as well as identify the fault occurred reasons more reliably.

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