State Evaluation of Intelligent Substation Communication Network Based on Clustering and Fuzzy Neural Network

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Abstract

With the development of intelligent substation, the communication network that replaces the traditional cable by optical fiber determines whether the intelligent substation can be safely and stably operated. Aiming at the complexity of intelligent substation communication system and the fuzzy correlation between evaluation indexes, this paper analyzes the process of fuzzy neural network learning, and then uses clustering method to classify the network anomaly state into five categories, and uses the classification result as a neural network model training sample. The ideal output basis, followed by the state evaluation process, the state evaluation method. Finally, a neural network model based on nine evaluation indicators is built, and the state evaluation of the intelligent substation communication network is carried out. The results show that the neural network evaluation results are consistent with the classification results. The evaluation model combined with clustering and fuzzy neural network can effectively evaluate the state and describe the interaction between various influencing factors. The research in this paper is to solve the problem. Substation communication network status evaluation provides a new idea.

Keywords

Intelligent substation, Network, Status evaluation, Neural Networks, Clustering.

1. Introduction

Equipment status assessment is based on the current working conditions of the equipment, relying on advanced condition monitoring means to identify early signs of failure, and to judge the specific location, severity and development trend of the fault, and then to determine the optimal maintenance time for each component. With the application of the unified process layer network in the intelligent substation, it provides great convenience for the sharing of substation data information. All the devices accessing the unified communication network can obtain the information of the whole station, which makes the implementation of the substation function happen greatly. Change [1]. Since the safe and reliable operation of the power station is affected by the network performance, its reliability is directly related to the safety of the substation. Secondly, the various information transmitted in the optical fiber cannot be fully reflected in the design drawings, which causes a lot of daily maintenance for the staff. inconvenient. Therefore, it is important to conduct a comprehensive safety assessment of the substation communication network system.

This paper analyzes the process of fuzzy neural network learning, and then studies the evaluation index and value standard of intelligent substation communication network. The weight obtained by the analytic hierarchy process is introduced into the standard Euclidean distance space algorithm for data dimensionality reduction. The clustering method is used to classify the network anomaly state into five operational states (attention, heaviness, seriousness, especially seriousness, Shutdown) as the type set, and the classification result is used as the ideal output basis of the neural network model training sample, followed by the state evaluation process. A state evaluation method is obtained.

Finally, a neural network model based on nine evaluation indicators is built, and the state evaluation of the intelligent substation communication network is carried out. The results show that cluster analysis combined with fuzzy neural network method is effective for comprehensive evaluation of substation communication network operation status, and has engineering application value.

2. Evaluation method

2.1 Fuzzy Neural Network

Fuzzy Neural Network (FNN) combines fuzzy systems and neural networks, fully considering the complementarity of the two, integrated logical reasoning, language computing, and nonlinear dynamics. It has learning, association, recognition, and Adaptive and fuzzy information processing capabilities and other functions The essence is to input the fuzzy input signal and the fuzzy weight into the neural network network, the input and output nodes of the neural network are used to represent the input and output signals of the fuzzy system The implicit (intermediate) nodes of the neural network are used to represent the membership functions and fuzzy rules, and the parallel processing capability of the neural network is utilized. The reasoning ability of the fuzzy system is greatly improved [2].

Fuzzy mathematics is a mathematics used to describe, study, and deal with the fuzzy features of things. "Fuzzy" refers to its research object, and "mathematics" refers to its research method. The most basic concepts in fuzzy mathematics are membership degrees and fuzzy membership functions. Among them, the degree of membership refers to the degree to which the element u belongs to the fuzzy subset f, represented by $\mu f(u)$, which is a number between [0, 1]. The closer $\mu f(u)$ is to 0, the smaller the degree to which u belongs to the fuzzy subset f; the closer to 1, the greater the degree to which u belongs to f. The fuzzy membership function is a function for quantitatively calculating the membership degree of an element. The fuzzy membership function generally includes a trigonometric function, a trapezoidal function, a normal function, and the like.

The T-S fuzzy system is a fuzzy system with strong adaptive ability. The model can not only update automatically, but also continuously modify the membership function of the fuzzy subset. The T-S fuzzy system is defined by the following "if-then" rule form. In the case of the rule R^i, the fuzzy reasoning is as follows:

$$R^i\text{: If } x_i \ is\ A_1^i, x_2\ is\ A_2^i, \dots, x_k\ is\ A_k^i \text{ then } y_i = p_0^i + p_1^i x_1 + \cdots + p_k^i x_k$$

Where A_j^i is the fuzzy set of the fuzzy system; $p_j^i (j = 1,2,\dots,k)$ is the fuzzy system parameter; y_i is the output according to the fuzzy rule, the input part (ie the if part) It is ambiguous, and the output part (ie the then part) is deterministic, which represents the output as a linear combination of inputs.

Suppose that for the input quantity $x = [x_1, x_2, \dots, x_k]$, the membership degree of each input variable x_j is first calculated according to the fuzzy rule:

$$\mu A_j^i = \exp\left(-(x_j - c_j^i)^2 / b_j^i\right) \quad j = 1,2,\dots,k; i = 1,2,\dots,n \qquad (2-1)$$

Where c_j^i, b_j^i are the center and width of the membership function, respectively; k is the input parameter; n is the number of fuzzy subsets.

The fuzzy degree is calculated for each membership degree, and the fuzzy operator is used as the multiplication operator:

$$\omega^i = uA_j^1(x_1) * uA_j^2(x_2) * \dots * uA_j^k(x_k) \quad i = 1,2,\dots,n \qquad (2-2)$$

Calculate the output value y_i of the fuzzy model based on the fuzzy calculation results:

$$y_i = \sum_{i=1}^n \omega^i \left(p_0^i + p_1^i x_1 + \cdots + p_k^i x_k\right) / \sum_{i=1}^n \omega^i \qquad (2-3)$$

The T-S fuzzy neural network is divided into four layers: input layer, fuzzy layer, inference layer and defuzzification layer, as shown in Fig. 1. The input layer is connected to the input vector x_i, and the number of nodes is the same as the dimension of the input vector. The fuzzification layer uses the membership function (2 - 1) to blur the input value to obtain the fuzzy membership value μ. The reasoning layer uses the fuzzy multiplication formula (2 - 2) to calculate ω. The defuzzification layer uses the formula (2 - 3) to calculate the output of the fuzzy neural network.

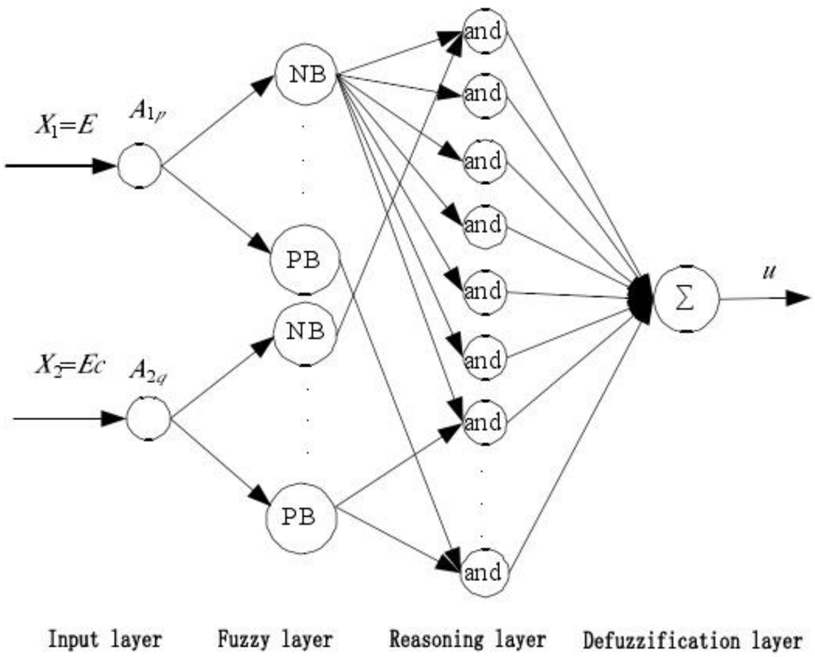

Fig. 1 Fuzzy neural network schematic

2.2 Fuzzy clustering

Since the fuzzy cluster has no initial center point, clustering is performed by calculating the distance between each data and the best data. In many classification problems, there is no clear boundary between the classification objects, and they often have the same performance. For example, there is no clear boundary between good and bad. I think that someone is a good person. Others may not think so. There is no clear boundary between the short and the short. The high talent is a high person. Maybe everyone has the judgment of everyone. . Such problems, if the traditional clustering method (system clustering method or K-means clustering method, etc.) is used for classification, and each object to be classified is strictly classified into a certain class, there is also some irrationality. Sex. To this end, with the help of the fuzzy set theory proposed by L.A.Zadeh, people began to use the fuzzy method to deal with the clustering problem, which is called fuzzy clustering analysis.

3. Operational status evaluation

References [3, 4] This article will be based on nine indicators: availability, response time, packet loss rate, throughput, accuracy, utilization, conflict rate, broadcast rate, multicast rate. Because there is no unified standard for the abnormal operation status of intelligent substation communication network, this paper combines the previous research results and the operating characteristics of the intelligent substation communication network, the data percentage system, the parameter range demarcation point and the maximum and minimum percentage system, and the equal interval value as the data value. The specification of the percentage system is defined as 0 or 100. The non-percentage system such as response time, broadcast rate (frame/s), and multicast rate (frame/s) is taken as the analog data. As shown in Table 1:

Table 1 Intelligent substation communication system operating abnormal state

Ideal boundary	classification	I	II	III	IV	V
100%	Availability ≥	99.9	74.925	49.95	24.975	0
0ms	Response time (ms) ≤	4	28	52	76	100

0%	Packet loss rate ≤	0.1	25.075	50.05	75.025	100
100%	Throughput rate ≥	70	52.5	35	17.5	0
100%	Accuracy ≥	99	74.25	49.5	24.75	0
0%	Utilization rate (1) ≤	30	47.5	65	82.5	100
0%	Utilization rate (2) ≤	50	62.5	75	87.5	100
0%	Conflict rate ≤	0	25	50	75	100
0帧/s	Broadcast rate (frame / s) ≤	50	62.5	75	87.5	100
0帧/s	Multicast rate (frame / s) ≤	40	55	70	85	100

In this paper, a substation communication system of Shenzhen Power Supply Bureau is taken as an example [5]. The weights of each factor calculated by the analytic hierarchy process are evaluated by the measured values [6]. Availability 99.95%, response time 1ms, packet loss rate 0.05%, throughput rate 80%, accuracy 99.95%, utilization rate (1) 20%, collision rate 0, broadcast rate 38 frames/s, multicast rate 33 frames/s.

According to the judgment conditions, the measured values are all within the normal range of the parameters, so the evaluation result is: the communication network is in good condition and can continue to run.

If it is determined that the data index does not fully satisfy the parameter range, the weight value obtained by the analytic hierarchy process is added to the standard Euclidean space distance formula, the data is brought into the formula, the 9-dimensional data is reduced to one dimension, and then the fuzzy clustering is set. Clustering parameters: the power exponent is 3, the maximum number of iterations is 200, the termination tolerance of the objective function is 1e-6, and the data is clustered into 5 categories. According to the 9-dimensional spatial distance between each data and the best data, 5 types of data are obtained. Labels 1, 2, 3, 4, and 5 from small to large.

Using the fuzzy neural network model, 150 of the 200 samples were used as training data, 40 were used as test data, and 10 were used as evaluation data.

The test results are shown in the figure. It can be seen that the error of the test results is basically controlled between ±1, and the actual output is roughly consistent with the evaluation result curve.

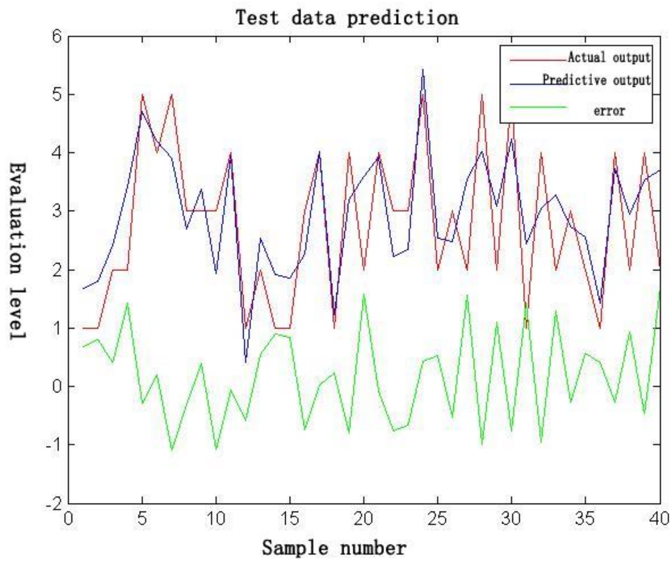

Fig. 1 Test data prediction

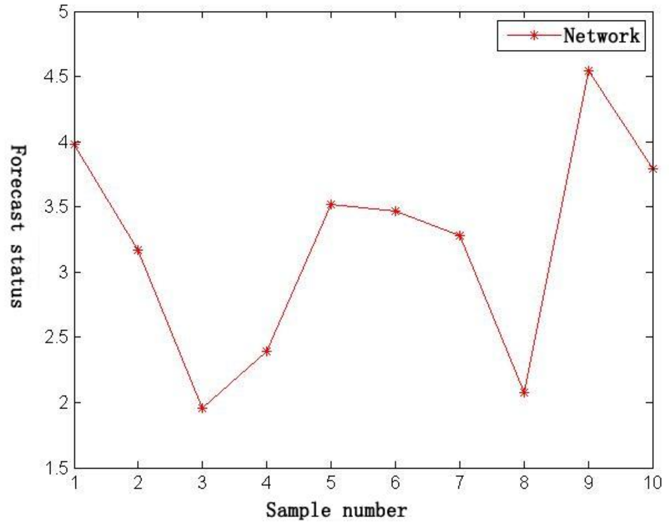

Fig. 3 Status evaluation result

The evaluation results are shown in the figure. From the evaluation conclusion, the neural network results are basically consistent with the fuzzy clustering results. This method can obtain higher accuracy and realize the online evaluation of the intelligent substation communication network status.

4. Conclusion

The example shows that the fuzzy neural network method is effective for comprehensive evaluation of the operation status of substation communication network. This method can evaluate the interaction status of substation communication network and describe the interaction between various influencing factors. Provides a new idea and has certain practical significance. This paper combines the existing results to obtain data standards for testing models, and hopes that the standards will be improved in the future. It is believed that the deepening of fuzzy neural network research will continue to improve the stability of smart substations and even smart grids.

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