State Evaluation Method of Relay Protection Device Based on Fuzzy Neural Network

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Abstract

In order to evaluate the operation status of relay protection devices more scientifically and effectively, and to arrange the maintenance plan rationally, the existing state evaluation methods of relay protection devices are studied and compared, and a comprehensive evaluation method based on fuzzy neural network is proposed. Firstly, the state evaluation index system is improved according to the evaluation guidelines. Secondly, the index fuzzy matrix is established by using the fuzzy membership function. Then, the dimension of the eigenvector is reduced by using KPCA algorithm. Finally, the state evaluation is completed by using BP neural network. The experimental results show that the method can effectively improve the accuracy of state evaluation.

Keywords

Relay protection device; State evaluation; KPCA dimensionality reduction; BP neural network.

1. Introduction

For the state evaluation of relay protection devices, Chinese State Grid Corporation issued the Guidelines for the State Evaluation of Relay Protection from QGDW11285 to 2014 in 15 years. Although the Guidelines determine certain state variables and their respective weights, the division and evaluation of the weights are only calculated by simple formulas. In the increasingly complex environment of smart substation, the limitations of this scheme will become more and more serious. In order to make the state evaluation more scientific and accurate, scholars have put forward many solutions[1, 2]. However, the state index system established by scholars has a relatively large number of entry and exit, which will inevitably lead to some contradictions when it is popularized. It is very important to determine a general, comprehensive and scientific index system.

After the establishment of the index system, it is generally necessary to divide the weights of state variables. For this reason, scholars at home and abroad have proposed expert experience method[3], entropy method[4], analytic hierarchy process[5]. Among them, expert experience method and analytic hierarchy process are subjective, and the entropy method is too objective. In order to solve the above contradiction, scholars put forward a simple multiplication combination of expert experience method and entropy method to synthesize the evaluation index[6]. Literature [7] uses moment estimation theory for subjective and objective optimal combination weighting, and Literature [8] uses Bayesian theory for weight updating. These are all good variable weighting methods, and the effect is obvious.

At present, the state evaluation of relay protection device is mainly based on the fuzzy membership function[9-11]. Some scholars have proposed the state evaluation of intelligent substation based on cloud theory, which takes into account the fuzziness and randomness of the system, and puts forward a new idea for the state evaluation of relay protection device[12].

Aiming at the problems of unreasonable weight distribution, incomplete information and ambiguity in the evaluation of safety status of relay protection devices, this paper adopts fuzzy neural network analysis method with fuzzy reasoning and good fault tolerance. The method is based on fuzzy membership function. On the basis of the above, the KPCA algorithm is used to obtain the optimal eigenvector matrix. Finally, the reduced dimension feature vector is used as the input of the BP neural network, and the output is the evaluation set label standard value of the training data. The method utilizes the variable weight and self-learning of the neural network, avoids the complex calculation of the weight, and enhances the adaptability of the fuzzy system.

2. Theory of Fuzzy Neural Network

2.1 Fuzzy Evaluation Matrix

Fuzzy evaluation matrix is a method based on fuzzy mathematics[13]. Applying the principle of fuzziness, some factors that are not easy to quantify are quantitatively evaluated, which has the characteristics of clear results and strong systematicness. The general steps of the establishment of the fuzzy evaluation matrix are: to construct the index system of the fuzzy comprehensive evaluation, to construct the evaluation set, and finally to construct the evaluation matrix through the fuzzy membership function.

Firstly, the evaluation factor set U of relay protection device is established.

$$U = [u_j] = \{u_1, \ldots, u_n\} \tag{1}$$

Formula u_j includes operating environment, infrared temperature measurement, insulation status and other state indicators.

Establishing a relay protection state evaluation set V according to the guide code specification:

$$V = [v_j] = \{v_1, \ldots, v_j\} \tag{2}$$

Determine the appropriate membership function f (U) and get the set of membership degree $[r_{ij}]$ corresponding to $[u_j]$ and $[v_j]$, that is, the fuzzy evaluation matrix R.

$$f(U) = R = [r_{ij}] \tag{3}$$

If it is the rule of fuzzy membership comprehensive evaluation, the weight matrix w should be established. The weight matrix is usually obtained by analytic hierarchy process, entropy method and variable weight theory. However, the division of weights itself has a certain degree of ambiguity and uncertainty, and the calculation is relatively complex. Different weights have a very direct impact on the results. Moreover, if the evaluation factors need to be increased or reduced after the weight is established, the weight needs to be re-divided, which leads to the limitation of the adaptability of the system.

2.2 Principal Component Analysis and Kernel Principal Component Analysis

Principal Component Analysis (PCA) is the most commonly used data dimension reduction method. Its main function is to transform a group of variables which may have linear correlation into a group of variables which are not linear correlation through linear transformation. The transformed variables are the main components. That is to find the most important aspect of the data, which is used to replace the original data, so as to achieve the effect of projecting from high-dimensional data to low-dimensional data. Its basic algorithm flow is as follows:

Centralization of samples

$$x^{(i)} = x^{(i)} - \frac{1}{m}\sum_{j=1}^{m} x^{(j)} \tag{4}$$

Computing Covariance Matrix XX^T ;

Eigenvalue decomposition of covariance matrix;

The eigenvector $\{w_1,\ldots,w_{n'}\}$ corresponding to the n' largest eigenvalues is extracted and normalized to form eigenvector matrix W;

Convert each sample set $x^{(i)}$ into

$$z^{(i)} = W^T x^{(i)} \tag{5}$$

Get the output sample set

$$D' = \{z^{(1)},\ldots,z^{(m)}\} \tag{6}$$

However, PCA can't solve the non-linear relationship. Kernel Principal Component Analysis (KPCA) can map the input vector into a high-dimensional linear feature space by adding a kernel function, and then use PCA to calculate the principal components in this space. The commonly used kernels are linear kernels, radial basis function (rbf), polynomial kernels, cosine kernels and sigmoid kernels. Different kernels have different effects, so choosing appropriate kernels is the focus of KPCA. KPCA algorithm steps:

Data standardization like PCA;

The kernel matrix K is computed, and the original data is mapped to the high-dimensional feature space by using the kernel function. Taking the radial basis function as an example, the formula is as follows:

$$K(x_i, x_j) = (b * s(x_i, x_j) + c)^d\ ; \tag{7}$$

Centralized Kernel Matrix K_c:

$$Kc = K - l_N K - K l_N + l_N K l_N \tag{8}$$

Computing PCA subsequently.

2.3 BP Neural Network

Back Propagation Error (BP) algorithm is the most widely used and representative neural network. Its structure is relatively simple, see Fig. 1.

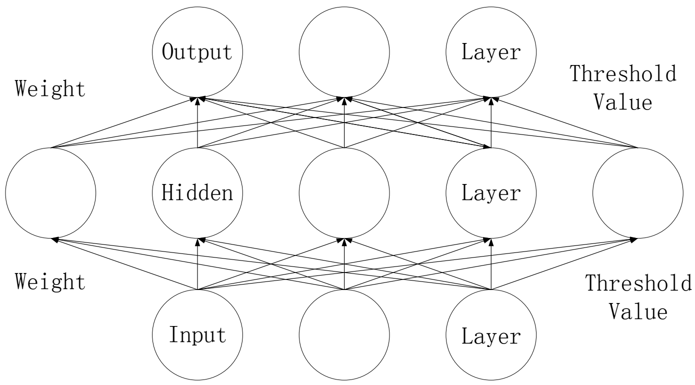

Fig. 1 Structure of BP Neural Network

The basic BP algorithm includes two processes: forward propagation of signals and reverse propagation of errors. By constantly adjusting the weights and thresholds, it can train the ability of approaching the input values of samples to the standard output values, so that it has a strong self-learning ability. The input layer of the BP neural network of the system is the reduced dimension fuzzy evaluation matrix. Taking it as the last link of the state evaluation can effectively increase the adaptive ability of the system, avoid complex and uncertain weight calculation, and reduce the influence of human factors on the evaluation results.

3. Comprehensive Evaluation of Relay Protection Equipment

3.1 Constructing State Evaluation System

In the evaluation guideline, two kinds of evaluation indicators are given, i.e. device body and secondary circuit indicators. They include several detection state variables, reliability state variables, failure risk state variables and improved state variables. The index system is obtained by many experts. It is more scientific and comprehensive, and can accurately represent the state of equipment. It has a good reference value. After adding alarm information index and CPU temperature index on the basis of the above, this paper establishes the following index system, in which the reciprocal of positive index is unified as negative index, see see Fig. 2

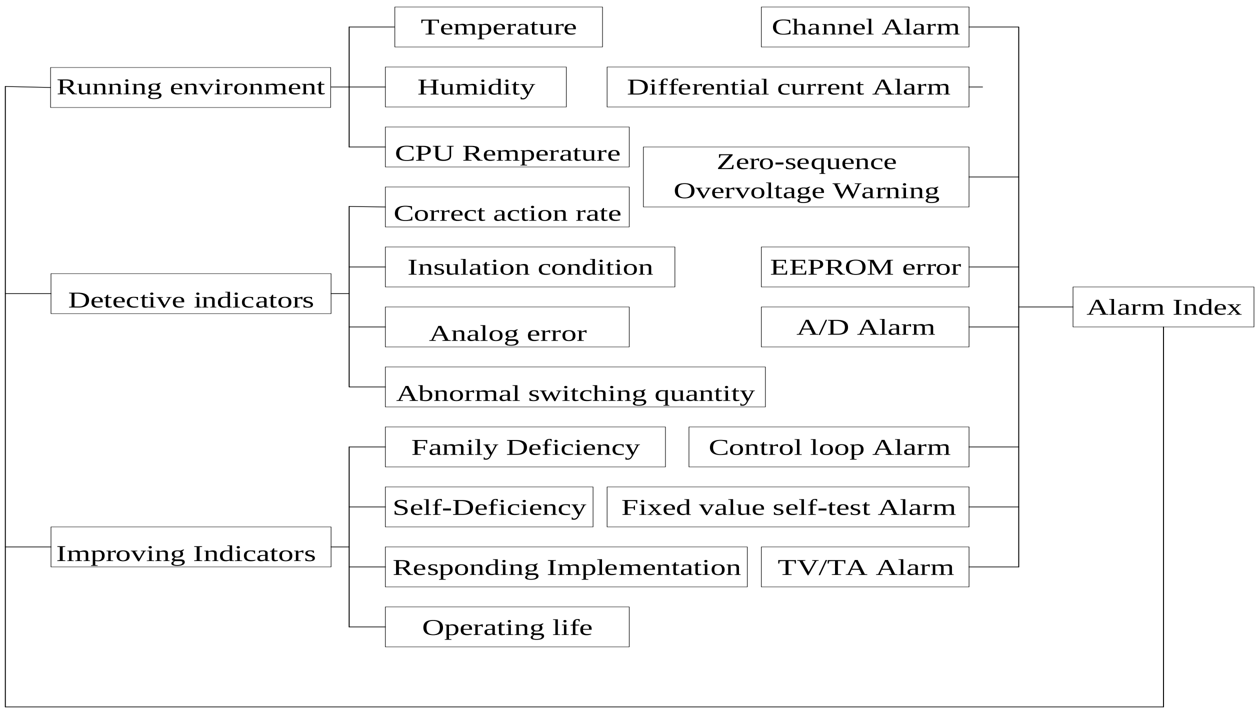

Fig. 2 Structure of BP Neural Network

3.2 Constructing State Assessment Set and Standard Value

In order to represent the health status scientifically and intuitively, according to the Guidelines for Assessment of Relay Protection Status from QGDW11285 to 2014, four kinds of relay protection equipment states are determined as evaluation sets (v) and standard values of each state (μ_j), see Table 1

Table 1 Evaluation Index System and Critical Values of Each State

Index	State quantity	Normal μ_0	Warning μ_1	Abnormal μ_2	Serious μ_3
Running environment	temperature(℃)	40.00	42.00	44.00	46.00
	humidity	70.00	75.00	85.00	95.00
	CPU temperature(℃)	40.00	50.00	70.00	90.00
Detective indicators	1/ Correct action rate(%)	1.00	1.005	1.01	1.02
	1/ Insulation condition(MΩ)	0.05	0.07	0.1	0.15
	Analog error(%)	3	4	5	6
	Abnormal switching quantity	0	/	/	1
Continued Table 1					
Improving Indicators	1/Family Deficiency Score	1	1.25	1.67	2.0
	1/Self-Deficiency Score	1	1.11	1.43	1.67
	Responding Implementation Score	1	1.25	1.67	2.0

	Operating life (year)	6	8	10	12
Alarm index (times / years)	Channel alarm	0	1	2	3
	Differential current alarm	0	1	2	3
	Zero-sequence Overvoltage Warning	0	1	2	3
	EEPROM error	0	1	2	3
	A/D alarm	0	1	2	3
	Control loop alarm	0	/	/	1
	Fixed value self-test alarm	0	1	2	3
	TV alarm	0	/	/	1
	TA alarm	0	/	/	1

Table 2 Evaluation Set

Evaluation level(v_i)	Normal(v_0)	Warning(v_1)	Abnormal(v_2)	Severe anomaly(v_3)

Among them, the correct action rate, insulation condition, family defects, self-defects, and countermeasure implementation are positive indicators, which are recorded in the concentration of evaluation factors. Family defect score was 0.5 for critical familial defect, 0.6 for serious familial defect, 0.8 for suspected familial defect, 1 for no defect or defect, and 2/1.67/1.25/1 for negative. Self-defect scoring criteria are: 0.6 points for crisis defect, 0.7 points for serious defect, 0.9 points for general defect, 1 point for no defect or defect, and 1.67/1.43/1.11/1 for reverse; if there are complex defects or multiple defects, the score is the product of each defect score. The scoring criteria for the implementation of countermeasures are as follows: 3 items were not implemented with 0.5 points, 2 items were not implemented with 0.6 points, 1 item was implemented with 0.8 points, and 1 point was fully implemented with 2/1.67/1.25/1.

3.3 Establishment of Fuzzy Evaluation Matrix

The evaluation has fuzziness, so it is necessary to use the fuzzy membership function to fuzzify the evaluation index factors, and then get the fuzzy evaluation matrix. The membership functions can be divided into three categories: small, middle and large. The distribution functions can be divided into rectangular distribution, trapezoidal distribution, k-order parabolic distribution, type Γ distribution, normal distribution and Cauchy distribution[14]. In order to reduce the inappropriateness of choosing membership function, this paper chooses normal function as membership function of state evaluation of relay protection device.

1) j =1:

$$r_{i1}=\begin{cases}1 & x\le\mu_0\\ e^{\frac{-(x-\mu_0)^2}{2(\mu_1-\mu_0)^2}} & \mu_0<x\le\mu_1\\ 0 & x>\mu_1\end{cases} \tag{9}$$

2) j =2:

$$r_{i2}=\begin{cases}0 & x\le\mu_0\\ e^{\frac{-(x-\mu_1)^2}{2(\mu_1-\mu_0)^2}} & \mu_0<x\le\mu_1\\ e^{\frac{-(x-\mu_1)^2}{2(\mu_2-\mu_1)^2}} & \mu_1<x\le\mu_2\\ 0 & x>\mu_2\end{cases} \tag{10}$$

3) j=3:

$$r_{i3}=\begin{cases}0 & x\le \mu_1\\ e^{\frac{-(x-\mu_2)^2}{2(\mu_2-\mu_1)^2}} & \mu_1< x\le \mu_2\\ e^{\frac{-(x-\mu_2)^2}{2(\mu_3-\mu_2)^2}} & \mu_2< x\le \mu_3\\ 0 & x>\mu_3\end{cases} \tag{11}$$

4) j=4:

$$r_{i4}=\begin{cases}0 & x\le \mu_2\\ e^{\frac{-(x-\mu_3)^2}{2(\mu_3-\mu_2)^2}} & \mu_2< x\le \mu_3\\ 1 & x>\mu_3\end{cases} \tag{12}$$

In the formula, $\mu_0\sim\mu_3$ is the standard critical value of each state variable corresponding to the evaluation grade, and x is the actual value. r_{ij} is the membership degree of the first index corresponding to the j-th state, and the state with the largest membership degree is the current state of the index.

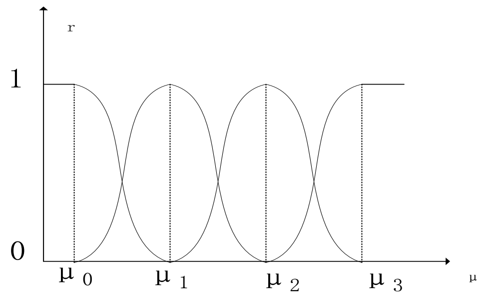

Fig.3 Distribution of normal membership function

3.4 Data dimensionality reduction

The fuzzy evaluation matrix after fuzzification has a high dimension, which will increase the trouble in BP training. Therefore, the Kernel PCA algorithm in Python's sklearn library is used to reduce the generated fuzzy membership function. The dimension matrix after dimensionality reduction is a one-dimensional matrix, which greatly improves the efficiency and accuracy of BP training. The final result is shown below:

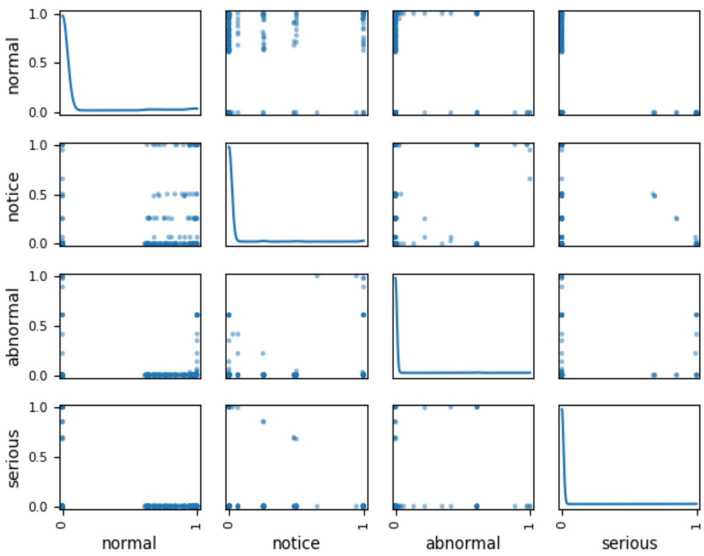

Fig.4 Before dimension reduction

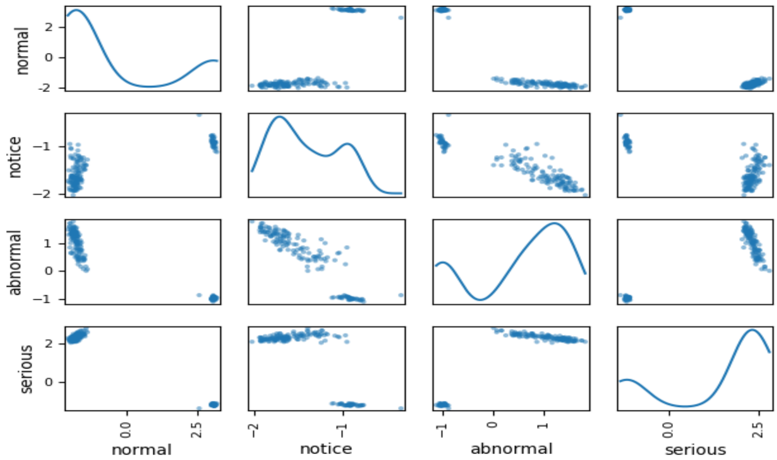

Fig.5 PCA and linear - KPCA

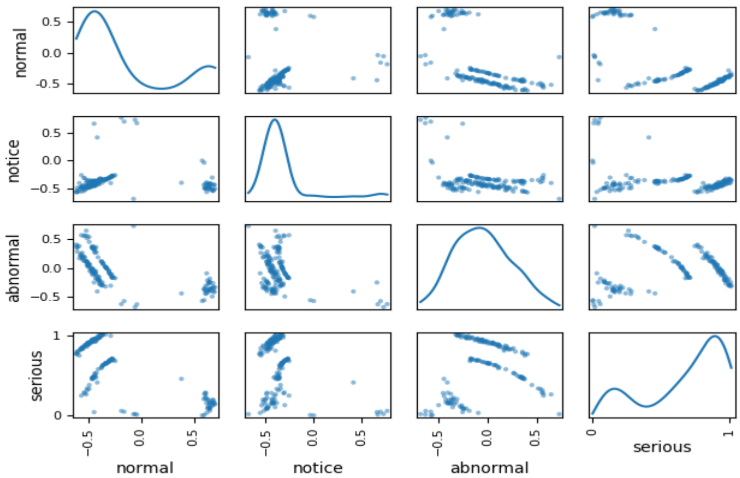

Fig.6 Consine - KPCA

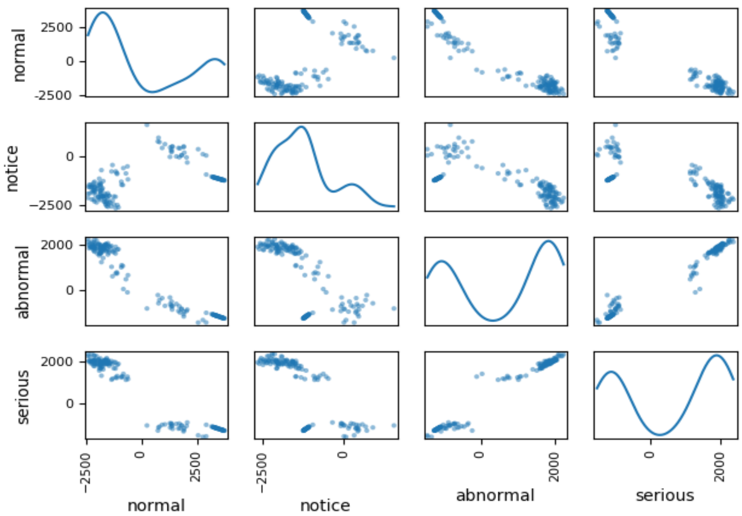

Fig.7 Poly – KPCA

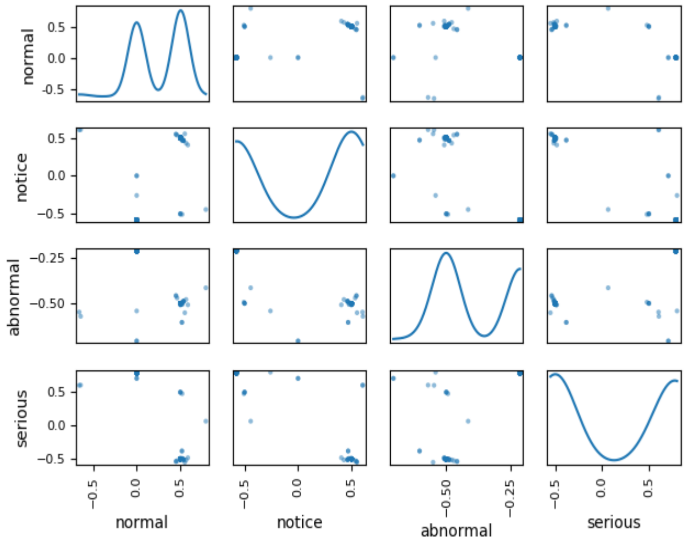

Fig.8 RBF - KPCA

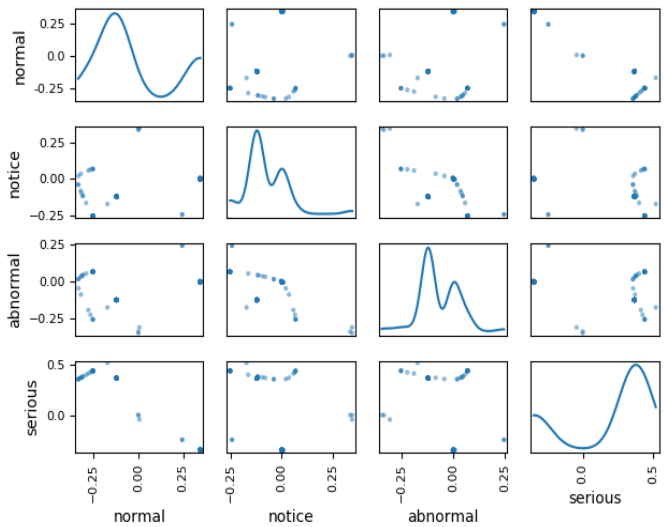

Fig.9 Sigmoid – KPCA

Comparing the above figure, it can be seen that the linear kernel function and PCA obtain the eigenvalue more clearly. Therefore, the linear-KPCA algorithm is used to reduce the data.

3.5 State evaluation of BP neural network

The introduction of BP neural network can enhance the adaptability of the fuzzy system. The feature data after dimension reduction is used as the input of the neural network and output as the maximum membership degree corresponding to each state[15]. Because the simplified feature matrix is relatively simple, the keras library is selected to construct a simple three-layer BP neural network to train and save the trained model. The training times are set to 20,000 times, and the output and input nodes are 4, 1 hidden layer. The initial number of hidden layers is calculated according to formula (13):

$$m = (p + q) * 0.5 + a \tag{13}$$

Where m is the number of hidden layer nodes, p is the number of input layer nodes, q is the number of output layer nodes, a is an integer from 1 to 10, and the calculated initial value of m is 5. After repeated calculations and comparisons, it was found that the training effect at m=10 reached the error requirement, so the final 4-10-4 neural network was determined, and the training error was 0.0002.

Table 3 Status Standard Output Values

Evaluation level	Output			
Normal	1	0	0	0
Warning	0	1	0	0
Abnormal	0	0	1	0
Serious	0	0	0	1

4. Example test

Taking the laboratory Xuji WXH-821 line protection device as an example, the above-mentioned fuzzy neural network is used for state evaluation. Through the simulation experiment, the protective device is in four health states, and the index data under four different conditions are collected as the input of the state evaluation. Each state has 40 groups, totally 160 groups of data are trained. Then two groups of data of each state are tested, and the following evaluation results are obtained.

Table 4 Partial Experimental Samples

Status quantity\acquisition serial number	10	30	50	70	90	110	130	150
temperature (℃)	5.78	10.97	8.86	16.16	16.49	5.60	5.59	13.08
humidity	17.00	18.66	76.69	73.40	82.50	78.21	94.74	92.60
CPU temperature (℃)	5.95	27.95	54.18	57.24	61.05	73.90	94.16	89.92
Correct action rate(%)	0.999	0.998	0.997	0.994	0.987	0.992	0.974	0.976
Insulation condition(MΩ)	15.02	15.87	12.95	11.11	9.47	8.51	5.63	5.45
Analog error (%)	0	0	4.06	4.16	4.70	5.05	6.4	6.38
Abnormal switching quantity	0	0	0	0	0	0	1	0
Family Deficiency Score	1	1	0.896	0.823	0.624	0.760	0.592	0.52
Continued Table 4								
Self-Deficiency Score	1	1	0.964	0.933	0.706	0.900	0.530	0.64
Responding Implementation Score	1	1	0.963	0.989	0.606	0.690	0.482	0.499
Operating life (year)	6	6	8	6	10	8	11	11
Channel alarm (time/year)	0	0	0	1	1	0	4	4
Differential current alarm (time/year)	0	0	1	0	0	0	2	4
Zero-sequence Overvoltage Warning (time/year)	0	0	1	0	1	2	3	2

EEPROM error(time/year)	0	0	0	1	1	1	3	4
A/D alarm (time/year)	0	0	1	0	2	2	4	3
Control loop alarm (time/year)	0	0	0	0	0	0	1	1
Fixed value self-test alarm (time/year)	0	0	1	0	2	0	3	2
TV alarm (time/year)	0	0	0	0	0	0	0	1
TA alarm (time/year)	0	0	0	0	0	0	0	1

The corresponding output is:

Table 5 Experimental Results

Serial number	Evaluation Results				Scores calculated according to guidelines	Actual state of equipment
10	1.0100	0.0131	0.0048	0.0029	98	Normal
30	1.0093	0.0145	0.0050	0.0014	95	Normal
50	0.0045	1.0057	0.0012	0.0039	84	Warning
70	0.0040	1.0318	0.0334	0.0073	84	Warning
90	0.0019	0.0037	0.9907	0.0029	65	Abnormal
110	0.0048	0.0020	1.0088	0.0018	63	Abnormal
130	0.0010	0.0006	0.0002	0.9996	55	Serious
150	0.0012	0.0019	0.0019	1.000	47	Serious
Evaluation set	Normal	Warning	Abnormal	Serious	/	/

In the evaluation guidelines, 100-86 were classified as normal, 85-71 as warning, 70-61 as abnormality and below 60 as serious abnormality. By comparison, the fuzzy neural network evaluation model constructed accords with the requirements of state evaluation.

5. Conclusion

The complexity of relay protection device brings a lot of trouble to the state evaluation. Too few index coefficients can not correctly represent the true state of equipment, and too many will bring great difficulties to the establishment of models, such as the allocation of weights. In this paper, after researching and discussing the relay protection device, 20 representative index coefficients are obtained. The normal membership function is used to establish the membership matrix, and then the KPCA algorithm of linear kernel function is used to reduce the dimension. Finally, the evaluation results are output by BP neural network. Through testing, the evaluation results are consistent with the actual health status of the equipment and meet the requirements of condition evaluation. Moreover, the introduction of neural network avoids the weight distribution of a large number of index coefficients, reduces the influence of human factors on state evaluation, makes the updating of evaluation parameters more convenient, makes the evaluation results more accurate, and provides a state basis for state maintenance of relay protection.

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