

State Evaluation of HVDC Core Equipment Based on BP Neural Network

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Abstract: The damage of core power equipment will cause serious losses to the power grid, and the evaluation and diagnosis of power equipment status can effectively avoid the economic loss of the power grid. In this paper, combining the operating characteristics of the DC transmission system and the impact of related core equipment on the stability of the system, the set value iteration method and BP neural network are used to determine the time-varying weight of the evaluation index of the core equipment of the DC transmission. Ideal samples and negative ideal samples, calculate the gray correlation degree between each sample and the positive and negative ideal samples and calculate the closeness of the core equipment status to realize the real-time status evaluation of the core equipment. Finally, take the voltage source converter as an example to establish an evaluation index system for real-time evaluation of equipment status.

Keywords: Transmission core equipment; State evaluation; BP neural network; Time-varying weight; TOPSIS analysis.

1. Introduction

Accurate evaluation of the operation status of key power transmission and transformation equipment is of great significance to ensure the safe, reliable and economic operation of power system. The evaluation of the operation status of power transmission and transformation equipment is an important means to ensure the safe and stable operation of power system [1-2].

Due to the special operating conditions of power transmission and transformation equipment, it is impossible to carry out power outage maintenance in time when the equipment status tends to deteriorate. Therefore, it is the main means to ensure the safe and reliable operation of the equipment to install various sensing devices in the transmission and transformation equipment, obtain various state quantities used to reflect the operation of the equipment in real time, and establish the evaluation model of the transmission and transformation equipment based on this, and grasp the operation status of the equipment in time [3]. Cao Lei proposed a fault warning for commutation failure of HVDC converter valves, and on this basis, a topology optimization method was proposed [4]. Gong Hao proposed a transformer condition assessment model based on hierarchical weighting and discrete fuzzy number [5]. Xue Wei built an effective monitoring system for the condition of power grid equipment based on the state evaluation model of power grid equipment that can realize state detection [6]. Li Erxia proposed an optimization model of distribution network maintenance plan based on equipment state evaluation and power grid loss risk calculation [7]. Aiming at the problems of low efficiency of periodic maintenance of secondary equipment in power grid and excessive dependence of evaluation results on subjective experience of experts, Nan Dongliang proposed a risk assessment method of secondary equipment operation status based on association rule mining and combination weighting-cloud model [8]. Wang Shanshan proposed to evaluate the operation status of primary equipment in smart grid based on TOPSIS method [9]. Chen

Jiahui proposed a new fault diagnosis method for microgrid based on maximum overlap discrete wavelet transform (MODWT) and back propagation (BP) neural network [10]. By introducing the pole selection reliability coefficient in the fault scenario, Wang Yangguang established a sensitive detection criterion for unipolar and inter-pole short-circuit faults of DC feeders, and realized accurate isolation of fault components and accurate positioning of fault sections [11]. Vandermaer A J reviewed the diagnosis and monitoring tests that can be used to evaluate the condition of transformers and provide early warning of potential faults [12]. Hao Kai has made an in-depth discussion on the common problems of power equipment failure in the process of power equipment condition maintenance in power equipment system [13]. Guo Tao designed the overall framework of technical support system construction, and expounded the state evaluation method of DC transmission equipment [14]. Tan Jinhua introduced the basic principle of equipment condition monitoring, and combed the state quantity and health index system of filters, converter valves, converter transformers and other equipment [15]. Ji Panpan proposed a power system fault prediction method based on expert database, which can predict the operation risk and abnormal development trend in advance by monitoring the operation parameters of the converter valve [16]. Xiao Fei used artificial intelligence method to correct the power grid fault diagnosis method of error remote communication, mapped the standard remote communication data of various devices to the fault diagnosis space, obtained the optimal coding set, and compared and classified the fault space coding value of fault remote communication with the optimal coding value of fault space to find the fault type and realize the fault diagnosis of power grid [17].

The basic idea of equipment condition evaluation based on monitoring data is to integrate multi-index monitoring data into a comprehensive evaluation result. The traditional equipment condition evaluation generally adopts the fixed weight method, but in fact, the importance of each index may be different under different working conditions and different

monitoring values of the equipment. In view of the above problems, this paper designs to use the variable weight theory, based on the BP neural network to determine the time-varying weight of the equipment monitoring value. Based on the analysis of the importance of the main index parameters of each core equipment at each time, the monitoring results of the index are integrated to reduce the evaluation deviation and improve the accuracy of the state evaluation model. The grey correlation-TOPSIS method is used to evaluate the running state of the core equipment at each time, which avoids the subjectivity of the monitoring data evaluation. Better describe the comprehensive impact of multiple impact indicators.

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2. A BP Neural Network-Based Method for Dynamic Assignment of Indicators

2.1. Weighting of Indicators

Variable weights can improve the evaluation of equipment status well, but determine the indicator weights based on different monitoring values but rely on the initial weights of experts, this paper uses the set-value iterative method to give the weights directly from experts based on the subjective importance of the indicators, and the steps of the set-value iterative method are as follows:

(1) Let the set of indicators be $X = \{x_1, x_2, \dots, x_m\}$, m is the number of indicators, and L ($L \geq 1$) experts are selected, so that each expert selects the s ($1 \leq s \leq m$) indicators that he considers most important in the set of m indicators. Then the k th expert selects a subset $X(k) = \{x_1(k), x_2(k), \dots, x_n(k)\}$ ($k = 1, 2, \dots, L$) of the indicator set X .

(2) As a schematic function

$$u_k(x_j) = \begin{cases} 1 & x_j \in X(k) \\ 0 & x_j \notin X(k) \end{cases} \quad (1)$$

(3) Denote $g(x_j) = \sum_{k=1}^L u_k(x_j)$, ($j = 1, 2, \dots, m$), normalize $g(x_j)$ and use this ratio $g(x_j)/\sum g(x_j)$ as the weight coefficient w_j corresponding to the indicator x_j , that is

$$w_j = \frac{g(x_j)}{\sum_{j=1}^m g(x_j)} \quad (2)$$

If it is considered possible that some indicators have been unselected, the weight coefficients can be recalculated by referring to equation (3) to avoid the case of zero weight.

$$w_j = \frac{g(x_j) + \frac{1}{2m}}{\sum_{j=1}^m [g(x_j) + \frac{1}{2m}]} \quad (j = 1, 2, \dots, m) \quad (3)$$

2.2. Weight Prediction Based on BP Neural Network

BP neural network is a multilayer forward neural network based on error back-propagation algorithm studied and designed by Remenlhart, McClelland et al [18]. Since the neurons of BP neural networks are usually Sigmoid-type differentiable functions, they can achieve arbitrary nonlinear mapping between input and output, and therefore have the

most widespread applications in pattern recognition, risk evaluation, and adaptive control [19]. BP neural networks consist of four main components:

2.2.1. Input Mode Cis-Propagation

This process mainly uses the input pattern to find the corresponding actual output.

Let the input quantity be $X_i = [x_1, x_2, \dots, x_d]$, and d be the number of cells in the input layer. The corresponding output quantity is $Y_i = [y_1, y_2, \dots, y_l]$, and l is the number of units in the output layer. According to the principle of M-P neuron model, the activation value of each neuron in the hidden layer can be calculated as follows:

$$s_j = \sum_{i=1}^n \omega_{ih} \cdot a_i - \theta_j \quad (j = 1, 2, \dots, q) \quad (4)$$

Where: ω_{ih} is the connection right from the input layer to the hidden layer; θ_j is the threshold of the intermediate layer unit; q is the number of intermediate layer units.

Since the S-type function is closer to the signal output curve of biological neurons, the activation function uses the S-type function, that is:

$$f(x) = \frac{1}{1 + \exp(-x)} \quad (5)$$

Bringing the above activation values into the activation function yields the output value of cell j of the hidden layer as:

$$b_j = f(s_j) = \frac{1}{1 + \exp(-\sum_{i=1}^n \omega_{ih} \cdot a_i + \theta_j)}, \quad (j = 1, 2, \dots, q) \quad (6)$$

During the learning process, the threshold θ_j is continuously adjusted, as are the weights, and the effect of the threshold is equivalent to shifting the output value by θ units.

Similarly, the activation and output values of the output layer can be obtained as follows:

$$l_j = \sum_{j=1}^p v_{ih} \cdot b_j - \gamma_h \quad (7)$$

Let the activation value of the j th cell of the output layer be l , then

$$c_j = f(l_j), \quad (j = 1, 2, \dots, q) \quad (8)$$

Where v_{ih} is the connection power from the hidden layer to the output layer and γ_h is the output layer cell threshold.

Using the above equation, the correlation coefficient of the BP neural network input pattern in the process of down propagation can be calculated.

2.2.2. Back Propagation of Output Errors

After the above calculations, the actual output values of the BP neural network are obtained, but if these actual output values do not match the expected output values, or if the error is greater than the limit value, the network needs to be repaired. The correction error of the output layer is:

$$d_j = (y_j - c_j) f'(l_j) \quad (9)$$

Where y_j is the desired output, c_j is the actual output, and $f'(l_j)$ is the derivative of the output layer function.

The correction error of each cell in the hidden layer is:

$$e_h = (\sum_{t=1}^l v_{ih} \cdot d_j) f'(s_h) \quad (10)$$

Where the correction error of each implied layer cell is generated by passing the correction error from the l output layer cells. Once the correction error is found, then the weights of the implied layer to the input layer can be adjusted

layer by layer along the inverse direction using d_j and e_h .

2.2.3. Circular Memory Training

In order to make the training error of each BP neural network tend to be minimum, so for each set of training patterns of BP neural network input, thousands of cycles of memory training are usually required. This circular memory training is actually the above-mentioned input and output pattern error back-propagation process.

Discernment of learning outcomes

After each training, it is necessary to determine the neural network learning results and check whether the errors are small enough. If it passes the check, the whole learning and training process can be completed.

3. Literature References

TOPSIS is an effective method for solving multi-objective problems. Using TOPSIS, a measure is defined in the objective space to measure how close a solution is to the ideal solution and how far it is from the negative ideal solution [20]. The state evaluation of HVDC transmission core equipment using TOPSIS based on gray correlation can determine the positive and negative ideal samples in real time according to the historical operation status of the equipment, which can reflect the operating conditions of the core equipment, and for the possible situation that the positive and negative ideal samples are no longer applicable due to the advancement of technology, a period of time can be set as the sampling period to update the positive and negative ideal samples in time, and TOPSIS method is more suitable for making judgments, which can reflect more intuitively whether the core equipment is early warning and whether the grid system needs to be dispatched for operation.

3.1. Initial Processing of Data

There are more parameters to be considered when evaluating the state of core equipment, which can increase the complexity of the model. In addition, there are also complex nonlinear relationships between the parameters, which can affect the final evaluation [21-22]. Therefore, this paper uses gray correlation analysis to preprocess the model input variables separately.

The gray correlation analysis uses the similarity of the geometry of the change curves of different variables to calculate the degree of association between the variables. The process of determining the degree of association between two series using gray correlation analysis is as follows.

3.1.1. The Setting of Reference Sequence and Comparison Sequence

Let X be the set of factors of the gray system and X_i be the elements of the system, then $X_i \in X$. Let the reference sequence be X_0 , $X_0 = \{x_0(1), x_0(2), \dots, x_0(n)\}$, and the comparison sequence be X_i , $X_i = \{x_i(1), x_i(2), \dots, x_i(n)\}$. Where: n sequence length; $i = 1, 2, 3, \dots, m$ (m is the number of elements of the system).

$$R^+ = (r_{ij}^+)_{m \times n}, R^- = (r_{ij}^-)_{m \times n} \quad r_{ij}^+ = \frac{\min_i \min_j |z_j^+ - z_{ij}| + \theta \max_i \max_j |z_j^+ - z_{ij}|}{|z_j^+ - z_{ij}| + \theta \max_i \max_j |z_j^+ - z_{ij}|} \quad r_{ij}^- = \frac{\min_i \min_j |z_j^- - z_{ij}| + \theta \max_i \max_j |z_j^- - z_{ij}|}{|z_j^- - z_{ij}| + \theta \max_i \max_j |z_j^- - z_{ij}|} \quad (16)$$

Calculate the gray correlation between the state of the core equipment and the positive and negative ideal solutions at each moment:

3.1.2. Normalization Process

In order to eliminate the influence of the inconsistency in the magnitude of each series on the results of gray correlation analysis, the input data of each series need to be pre-processed. The singular and incomplete data are removed and the remaining data are normalized. The expression of the normalization treatment equation is

$$\bar{x}_i = (x_i - x_{\min}) / (x_{\max} - x_{\min}) \quad (11)$$

Where: x_i is the i th value in the sequence; $\bar{x}_i$ is the normalized result of x_i ; $x_{\max}$, $x_{\min}$ are the maximum and minimum values in the specified sequence, respectively.

Since the input data are normalized to within $[0, 1]$, the model output y' should also be the normalized value, and the inverse normalization gives the actual value y .

The expression of the inverse normalized treatment equation is

$$y = y' (y_{\max} - y_{\min}) + y_{\min} \quad (12)$$

Where: $y_{\max}$, $y_{\min}$ are the maximum and minimum values in the actual value sequence, respectively.

Number of grey contacts

The equation for the correlation coefficient of each indicator in the reference series is

$$\xi_i(k) = \frac{\min_i \min_n |x_0(k) - x_i(k)| + \rho \max_i \max_n |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \rho \max_i \max_n |x_0(k) - x_i(k)|} \quad (13)$$

Where: k is the k th value of the correlation coefficient sequence; ρ is the resolution coefficient, which is taken as 0.5 in this paper.

3.1.3. Calculation of Gray Correlation Degree

In order to compare the correlation coefficients between the indicators, the correlation coefficients between X_i and each data point in X_0 are weighted and averaged to obtain the weighted average between the different data points of the two series, i.e., the gray correlation degree r_i of the two series. r_i is calculated as

$$r_i = \frac{1}{n} \sum_{k=1}^n \xi_i(k) \quad (14)$$

Usually, the gray correlation degree r_i is from 0 to 1. The closer its value is to 1, the greater the influence of the comparison series on the reference series.

3.2. Core Equipment Status Evaluation

Weights are assigned to the normalized matrix to obtain the weighted decision matrix $Z = (z_{ij})_{m \times n}$, which determines the positive ideal solution Z^+ and the negative ideal solution Z^- of the weighted decision matrix:

$$Z^+ = (z_1^+, z_2^+, \dots, z_j^+), Z^- = (z_1^-, z_2^-, \dots, z_j^-) \quad (15)$$

Where, $z_j^+ = \max_i z_{ij}$, $z_j^- = \min_i z_{ij}$

Calculate the gray correlation coefficient matrices R^+ and R^- between each solution and the positive and negative ideal solutions.

$$r_i^+ = \frac{1}{n} \sum_{j=1}^n r_{ij}^+, r_i^- = \frac{1}{n} \sum_{j=1}^n r_{ij}^- \quad (17)$$

The gray correlation coefficients r_i^+ and r_i^- are normalized separately:

$$R_i^+ = \frac{r_i^+}{\max r_i^+}, R_i^- = \frac{r_i^-}{\max r_i^-} \quad (18)$$

The final closeness of the core equipment condition evaluation obtained in this paper:

$$Q_i^+ = \frac{R_i^+}{R_i^+ + R_i^-} \quad (19)$$

The larger the closeness indicates the better state of the core equipment, and conversely, the smaller the closeness, the worse the state.

In this paper, we use BP neural network to predict the time-varying weights of core equipment indicators and evaluate the state of DC transmission core equipment as shown in Figure 1.

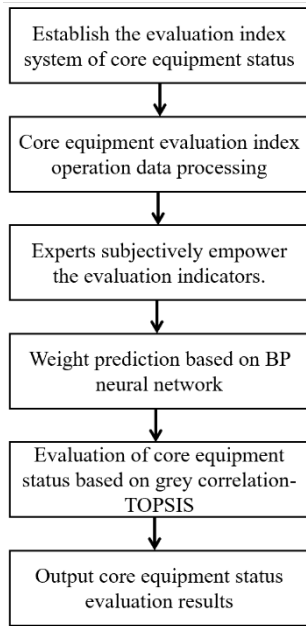


Figure 1. State Evaluation Process of HVDC Transmission Core Equipment Based on BP Neural Network

4. Simulation and Analysis of Algorithms

4.1. Evaluation Index Data Processing

In order to verify the validity of the model, this paper evaluates the state of voltage source converter in DC transmission core equipment based on 250 sets of data in a regional DC transmission system, including 234 sets of valid data, from eight aspects of voltage source converter parameters including collector current, collector-emitter voltage, peak collector current, gate-emitter voltage, short-circuit withstand time, junction temperature, operating junction and storage temperature, and the state evaluation index system of voltage source converter is shown in Table 1.

According to the voltage source converter operation data, the state evaluation of the equipment is carried out. For the convenience of calculation, 10 groups of data are selected for analysis, and the data of eight indicators are normalized according to the data processing method above, and the normalized data are obtained as shown in Table 2.

Table 1. State Evaluation Index System of HVDC Transmission Core Equipment

Equipment name	First grade indexes	Sign	Unit
Voltage source converter	Collector current	R1	A
	Collector-emitter voltage	R2	V
	Peak collector current	R3	A
	Gate-emitter voltage	R4	V
	Short circuit tolerance time	R5	μs
	Junction temperature	R6	°C
	Operating junction temperature	R7	°C
	Storage temperature	R8	°C

Table 2. Normalized data of voltage source converter operation

Index	1	2	3	4	5
R1	1.000	0.636	0.091	0.318	0.773
R2	0.889	0.278	0.056	1.000	0.889
R3	0.450	0.800	0.650	0.000	0.350
R4	0.750	1.000	0.833	0.583	0.250
R5	0.000	0.389	0.470	0.941	1.000
R6	0.091	0.364	0.000	0.818	0.636
R7	0.929	1.000	0.286	0.929	0.857
R8	1.000	0.692	0.769	0.846	1.000
Index	6	7	8	9	10
R1	0.909	0.727	0.227	0.045	0.818
R2	0.000	0.111	0.389	0.944	0.833
R3	0.150	1.000	0.250	0.200	0.350
R4	0.333	0.000	0.750	1.000	0.833
R5	0.733	0.441	0.767	0.607	0.396
R6	0.545	0.727	1.000	0.364	0.273
R7	0.714	0.786	0.857	0.429	0.500
R8	0.231	0.000	0.154	0.308	0.462

4.2. Determining Indicator Weights

Variable weights can improve the model effect well, but determining the indicator weights based on different monitoring values relies on expert evaluation, and it is difficult and complicated to integrate variable weights. For this reason, this paper collects several groups of monitoring values under typical working conditions of core equipment, and builds a training data set based on the set-value iteration method, inviting experts to score the index weights of different groups of monitoring data to determine the index weights. Then, a BP neural network is used for machine learning to train a neural network model that can simulate the expert opinion to judge the index monitoring values and give the corresponding variable weights quickly.

The core equipment indicator variable weight BP neural network is designed as follows:

4.2.1. Input and Output Layer Design

The number of neuron nodes in the input layer of BP neural network is very important for neural network, too few nodes will cause insufficient prediction accuracy, too many nodes will easily cause too much model calculation, but the accuracy improvement is not obvious, so it needs to be determined according to the actual situation, the input variables selected in this paper are eight parameters of voltage source converter: collector current, collector-emitter voltage, peak collector current, gate-emitter voltage, short circuit tolerance time, junction temperature, operating junction

temperature and storage temperature. The output variables of the output layer are the time-varying weights of the eight parameters of the voltage source converter at the next moment, so the number of neuron nodes is 8.

4.2.2. Implicit Layer Design

The BP neural network in this paper consists of a three-layer topology with an input layer, a hidden layer and an output layer. The number of nodes in the input and output layers can be determined according to the above. And the number of nodes in the hidden layer should generally be determined based on practical experience. The range of values for the number of nodes is usually determined empirically, and all nodes are validated once based on the same training samples, and the optimal number of nodes is determined based on the accuracy of the validation results. The node with a small relative error in the validation result

corresponds to the optimal number of nodes in the hidden layer of the model [23]. This method is called the trial-and-error method, and the empirical formula is as follows:

$$p = \sqrt{n + q} + \alpha \quad (20)$$

Where p denotes the number of neuron nodes in the hidden layer, n denotes the number of neuron nodes in the input layer, and q denotes the number of neuron nodes in the output layer, which is an integer between 1 and 10. From the above analysis, it can be seen that the number of nodes in both the input and output layers of the BP neural network designed for the experiments in this paper is 8. The neuron nodes in the hidden layer of the BP neural network can be calculated from 5 to 14 by the above formula, and then the experimental results of the trial patchwork are shown in Table 3.

Table 3. Statistics of prediction results of the number of neurons in different hidden layers

Node number	5	6	7	8	9
Mean square deviation	0.00097	0.00089	0.00083	0.00083	0.00079
Correlation coefficient	0.62522	0.66554	0.68906	0.69143	0.70861
Node number	10	11	12	13	14
Mean square deviation	0.00079	0.00081	0.00085	0.00078	0.00084
Correlation coefficient	0.71154	0.69819	0.68162	0.71248	0.68866

According to the results in the table, the statistical chart of the prediction results of the number of neuron nodes is shown in Figure 2. By comparing the mean square deviation and correlation coefficient corresponding to different node numbers, it can be seen that node 11 has the smallest mean square deviation of 0.00062 and the largest correlation coefficient of 0.86819, so the network model has the best performance at node number 11, so there are 11 neuron nodes in the hidden layer designed in this paper.

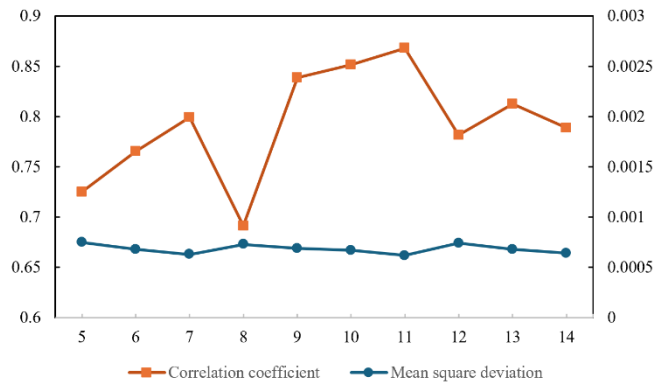


Figure 2. Statistics of prediction results of the number of neurons in different hidden layers

4.2.3. Output of BP Neural Network

In order to make the subjective assignment in this paper more convincing, the set-value iteration method is used to give the weights directly from the experts based on the subjective importance of the indicators, and the weights of each indicator are scored and assigned by the experts on the operating data of the equipment at each moment, and the BP neural network is trained to obtain the time-varying weights of each indicator at each moment, and the calculation results are shown in Table 4.

Table 4. Time-varying weight of each indicator at different moments

Index	1	2	3	4	5
R1	0.223	0.148	0.044	0.072	0.153
R2	0.159	0.090	0.054	0.150	0.154
R3	0.171	0.189	0.108	0.000	0.063
R4	0.132	0.168	0.224	0.175	0.080
R5	0.000	0.057	0.126	0.143	0.148
R6	0.022	0.096	0.000	0.147	0.118
R7	0.137	0.117	0.213	0.105	0.152
R8	0.094	0.136	0.233	0.099	0.133
Index	6	7	8	9	10
R1	0.131	0.100	0.066	0.044	0.078
R2	0.000	0.018	0.165	0.121	0.112
R3	0.027	0.146	0.104	0.040	0.131
R4	0.135	0.000	0.140	0.261	0.157
R5	0.190	0.224	0.194	0.138	0.131
R6	0.103	0.133	0.077	0.074	0.143
R7	0.228	0.202	0.123	0.221	0.132
R8	0.121	0.000	0.130	0.104	0.117

4.2.4. BP Neural Network Model Training

In this section, 234 sets of equipment monitoring data are used as the training data for the BP neural network, and the following training results are shown in Figure 3. The analysis shows that the error value of the minimum output of the BP neural network is 0.000872 and the number of iterations is 8.

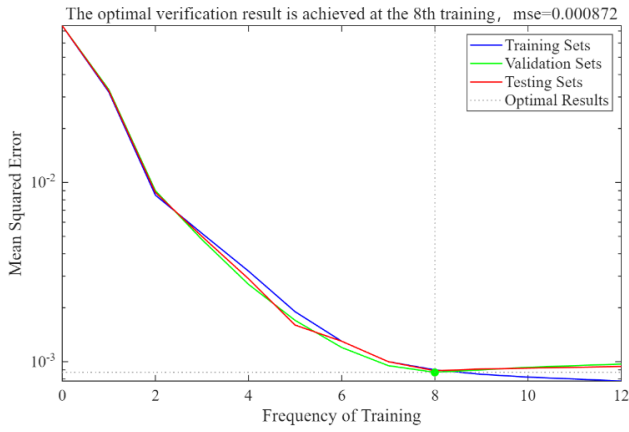


Figure 3. BP neural network error curve

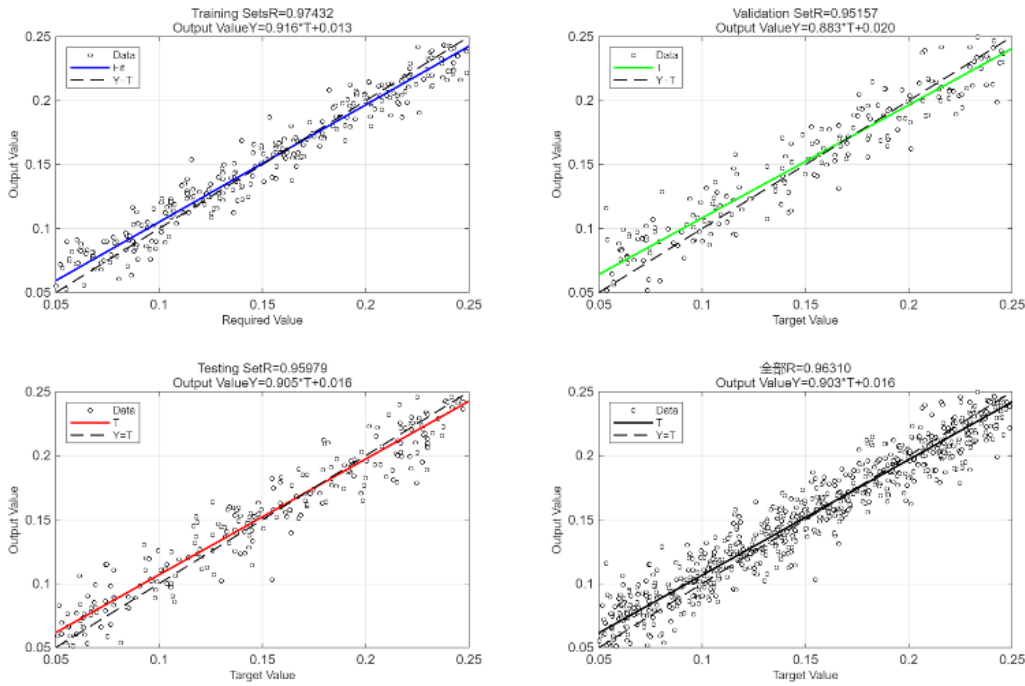


Figure 4. BP neural network regression analysis

From the diagram, it can be seen that the correlation coefficient between the output data of the BP neural network prediction model and the expected data is 0.96310, indicating that the BP neural network model has a high fitting degree to the training data. The training error of BP neural network is shown in Figure 5.

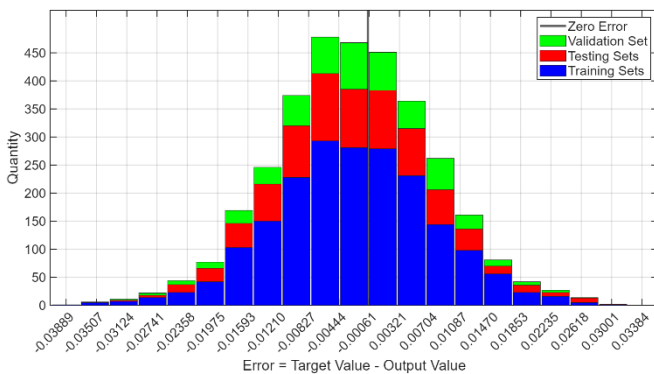


Figure 5. BP neural network training error

4.3. Equipment Running State Evaluation

After normalizing the operation data of the voltage source converter and giving the time-varying weight of each index,

The training samples are used to train the BP neural network model and collect the output data of the model during the training process. Linear regression analysis is performed on the output data and the corresponding expected output data. The regression analysis of the output data of the model is shown in Figure 4.

the time-varying weight is multiplied by the dimensionless matrix to obtain a new weighted decision matrix $Z = (z_{ij})_{m \times n}$, as shown in Table 5.

Table 5. Weighted decision matrix

Index	1	2	3	4	5
R1	0.223	0.094	0.004	0.023	0.118
R2	0.141	0.025	0.003	0.150	0.137
R3	0.077	0.151	0.070	0.000	0.022
R4	0.099	0.168	0.187	0.102	0.020
R5	0.000	0.022	0.059	0.135	0.148
R6	0.002	0.035	0.000	0.120	0.075
R7	0.127	0.117	0.061	0.098	0.130
R8	0.094	0.094	0.179	0.084	0.133
Index	6	7	8	9	10
R1	0.119	0.073	0.015	0.002	0.064
R2	0.000	0.002	0.064	0.114	0.093
R3	0.004	0.146	0.026	0.008	0.046
R4	0.045	0.000	0.105	0.261	0.131
R5	0.139	0.099	0.149	0.084	0.052
R6	0.056	0.097	0.077	0.027	0.039
R7	0.163	0.159	0.105	0.095	0.066
R8	0.028	0.000	0.020	0.032	0.054

By the formula (15), the positive ideal solution Z^+ and the negative ideal solution Z^- are obtained.

Table 6. Calculated positive ideal solution Z^+ and negative ideal solution Z^-

Index	R1	R2	R3	R4
Z^+	0.223	0.150	0.151	0.261
Z^-	0.002	0.000	0.000	0.000
Index	R5	R6	R7	R8
Z^+	0.149	0.120	0.163	0.179
Z^-	0.000	0.000	0.061	0.000

It can be seen from the scores of positive and negative ideal solutions that the maximum value in the normalized data table is 1 and the minimum is 0. Therefore, after weighting it, the positive ideal solution is essentially the maximum weight of each index in a period of time, while the negative ideal solution is the minimum weight of each index in a period of time.

After obtaining the positive and negative ideal solutions, the grey correlation degree r_i^+ and r_i^- of each moment with the positive and negative ideal solutions are calculated as shown in Table 7.

Table 7. Calculated gray correlation degree r_i^+ and r_i^-

Time	1	2	3	4	5
r_i^+	0.675	0.632	0.596	0.682	0.699
r_i^-	0.660	0.656	0.767	0.661	0.624
Time	6	7	8	9	10
r_i^+	0.616	0.649	0.606	0.626	0.559
r_i^-	0.726	0.727	0.709	0.730	0.707

Table 8. Calculated normalized gray correlation degree R_i^+ and R_i^-

Time	1	2	3	4	5
R_i^+	0.965	0.904	0.853	0.975	1.000
R_i^-	0.860	0.855	1.000	0.861	0.813
Time	6	7	8	9	10
R_i^+	0.881	0.928	0.867	0.895	0.800
R_i^-	0.946	0.948	0.925	0.951	0.921

The closeness of the operating state of the voltage source converter at each moment is calculated as shown in Table 9.

Table 9. The calculated progress of the equipment status at each moment

Time	1	2	3	4	5
Q_i	0.529	0.514	0.460	0.531	0.552
Time	6	7	8	9	10
Q_i	0.482	0.495	0.484	0.485	0.465

The closer the relative closeness is to 1, the better the running state of the equipment is, and the closer the relative closeness is to 0, the worse the running state of the equipment is. In order to observe the running state of the voltage source converter more intuitively, a line chart of the running state of the equipment is drawn as shown in Figure 6.

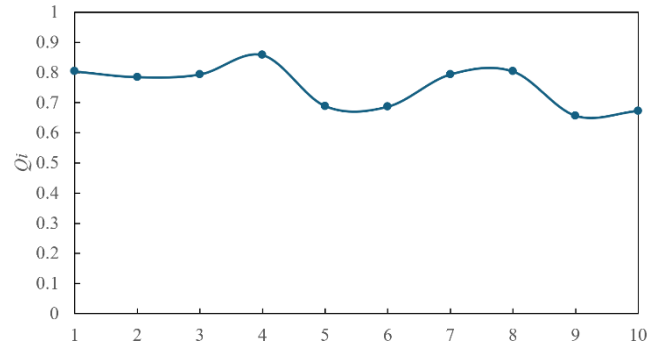


Figure 6. Relative closeness change graph

From the evaluation results of the equipment status obtained from the selected 10 sets of monitoring data, the relative closeness of the test results fluctuates between 0.65 and 0.90, and the overall status of the equipment is relatively stable, but the equipment status is not good. The relevant indicators of the equipment should be paid attention to in time, and the equipment should be repaired and tested if necessary to ensure the safe and stable operation of the power grid.

5. Conclusion

Starting from the core equipment of DC transmission, this paper establishes the evaluation system of core equipment of DC transmission, proposes to use BP neural network to determine the time-varying weight of evaluation index of core equipment of DC transmission, and trains a neural network model that can simulate expert opinions to judge the monitoring value of index and quickly give the corresponding variable weight.

The index variable weight can improve the model effect well. The index weight can be determined according to different monitoring values, and the core equipment status can be monitored in real time to avoid the core equipment failure and power grid risk caused by the equipment index weighting. The grey correlation-TOPSIS method is used to visually display the operation status of the core equipment at each moment, which is convenient for the operation and maintenance personnel to monitor the operation risk of the core equipment in time and effectively, and accurately locate the fault location of the power grid according to the operation status of the core equipment. In addition, the grey correlation-TOPSIS state evaluation method used in this paper has no strict limit on data distribution, sample size and index number. Compared with other evaluation methods, it is more flexible and convenient.

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