Risk Assessment of Power Communication Network Based on LM-BP Neural Network

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ABSTRACT: In order to predict the operational risk of the power communication network more comprehensively and accurately, this paper presents a BP neural network model based on Levenberg-Marquardt (LM) algorithm. Firstly, establishing a set of indicators that reflect the operational characteristics of the power communication network. These indicator data are used as input to the model. Then, the operating efficiency of the traditional BP neural network is improved by the LM algorithm. The research results show that the model is simple, the forecast performance is stable and the accuracy is high, which provides an effective theoretical basis and modeling method for the prediction of power communication network risk.

1. Introduction

The power communication network is connected with all links of the power system. It is an important infrastructure for power grid dispatching automation, network operation marketization and management informationization. And it is an important guarantee for safe, reliable, economical and efficient operation of the power grid. Therefore, the risk assessment of the power communication network is conducive to improving the operation level of the power communication network and ensuring safe, reliable and stable operation of the power communication network[1].

At present, the more mature risk assessment methods mainly include analytic hierarchy process, fuzzy evaluation method and neural network, etc. However, due to the complexity of the power communication network and the uncertainty of the influencing factors, these methods are difficult to achieve satisfactory results in the accuracy of risk assessment. Moreover, the phenomenon of indicator design redundancy is common in the risk assessment of power communication networks, which increases the complexity of the algorithm to some extent. This paper proposes an evaluation method based on LM-BP neural network for these problems. Firstly, a set of risk assessment indicators for power communication networks was established. Then, using principal component analysis method, the redundant condition attribute in the index system is deleted, the input dimension is reduced, and then the BP neural network improved by LM algorithm is used for training and testing, and the weights of various factors of the risk network are obtained. Finally, the method is simulated, and the simulation results are compared with the evaluation values of the traditional BP neural network algorithm and the actual evaluation values[2]. The final results show that the new method has simple input, short training time and high precision.
2. Method principle

2.1. Principle of BP neural network algorithm

Neural networks can learn from a large amount of discrete data and extract domain knowledge. And express this knowledge as network connection weights and thresholds to reflect the structure of complex systems. The error back propagation (BP) neural network’s model is simple and algorithm is mature, so it is one of the most widely used neural network models[3]. BP neural network model is a multilayer feed-forward neural network. Its network topological structure includes: input layer, hidden layer and output layer. BP neural network has a high degree of nonlinear mapping capability that can be used to solve complex problems in internal mechanisms. The topological structure of the BP neural network is shown in figure 1.

![BP neural network diagram](image)

Figure 1. BP neural network diagram

The BP neural network can learn the input samples, and the data flows into the neurons through the input layer. After the calculation of the hidden layer and the output layer, data will flow out from the neural network[4]. The output value of the output layer corresponds to the predicted value of the network. If the error between the predicted value and the expected value does not meet the accuracy requirement, then enter the reverse transfer error phase. Each layer of neural network adjusts the weights and thresholds of each layer according to the gradient descent method.[5] The process of forward and backward information transmission and the reverse of error is actually the process of continuously adjusting the weight and threshold of each layer of neural network. This process last until the output value of the output layer meets the accuracy requirement, or the number of iterations reaches the preset number of learning times. The output signal for each activated hidden layer neuron is:

\[ I_j = \sum_{i=1}^{n} u_{ij} x_i - a_j \quad j = 1, 2, ..., n \]  \hspace{1cm} (1)
\[ y_j = f(I_j) \quad j = 1, 2, ..., n \]  \hspace{1cm} (2)

Where \( u_{ij} \) is the connection weight between the input layer neuron \( i \) and the hidden layer neuron \( j \), \( a_j \) is the threshold of the hidden layer neuron \( j \), \( f(x) \) is the activation function of the hidden layer neuron. This paper uses the Sigmoid function which is \( f(x) = \frac{1}{1 + e^{-x}} \).[6]

Similarly, the output signal of the neural network output layer can be obtained as:

\[ l_j = \sum_{j=1}^{m} v_{ij} l_j - \beta_j \quad j = 1, 2, ..., m \]  \hspace{1cm} (3)
\[ y_{kj} = f(l_j) \quad j = 1, 2, ..., m \]  \hspace{1cm} (4)

Where \( v_{ij} \) represents the connection weight of the \( i \)-th hidden layer neuron and the \( j \)-th output layer neuron, \( \beta_j \) is the threshold of the output layer neuron; \( f(x) \) is the activation function of the output layer neuron.

2.2. LM algorithm

Traditional BP neural network algorithm uses the steepest descent algorithm for learning. This is an iterative algorithm for the least squares estimation of nonlinear regression model parameters. This method has the disadvantages of slow training speed and weak global search ability[7]. Therefore, this paper uses the Levenberg-Marquardt (LM) algorithm to improve it. LM algorithm is an algorithm combining gradient descent algorithm with Gauss-Newton algorithm. The LM algorithm is a fast algorithm that utilizes standard numerical optimization techniques. This method has the local
convergence characteristics of the Gauss-Newton method and the global characteristics of the gradient descent algorithm\[8\]. Since the LM algorithm utilizes approximate second-order derivative information, the efficiency of the algorithm is better than that of the gradient algorithm. The following is a brief description of the LM algorithm optimization neural network weights. Generally, the BP neural network uses the mean square error as a performance evaluation method, and compares the neural network output value $y_i$ with the target value $y_{real}$ for adjusting the weight and the threshold.

$$E(x) = \frac{1}{2} e_i^2(x) = \frac{1}{2} \sum_{i=1}^{n} (y_{real} - y_i)^2$$ (5)

Among them, $y_{real}$ is the expected output value of the neural network, $y_i$ is the actual output value of the BP neural network, and $E(x)$ is the error.

Suppose $x^k$ represents the vector consisting of the connection weight between neurons and the threshold of neurons at the k-th iteration. The vector $x^{(k+1)}$ consisting of the new weight and threshold can be obtained by the following method:

$$x^{(k+1)} = x^k + \Delta x$$ (6)

Where $\Delta x$ is the amount of change in the weight and threshold. According to the Gauss-Newton method, $\Delta x$ can be obtained:

$$\Delta x = -[J^T(x)J(x)]^{-1}J^T(x)e(x)$$ (7)

The LM algorithm is an improvement on the Gauss-Newton algorithm. The weight and threshold adjustment methods are as follows:

$$\Delta x = -[J^T(x)J(x) + \alpha I]^{-1}J^T(x)e(x)$$ (8)

Where $J$ is the Jacobian matrix, $J = \left(\frac{\partial e_i(x)}{\partial x_j}\right)_{i\times j}$. It can be seen from equation (8) that when $\alpha=0$, it is the Gauss-Newton algorithm. When the value of $\alpha$ is large, it is close to the gradient descent algorithm. At each iteration of the algorithm, the value of $\alpha$ will also become smaller, so that it is similar to the Gauss-Newton method when approaching the error target\[9\]. Because the LM algorithm utilizes approximate second-order derivative information, it is much faster than the gradient descent method. And $[J^T(x)J(x) + \alpha I]$ is positive definite, so the solution of equation (8) always exists. $\alpha$ is a tentative parameter in actual calculation. For a given $\alpha$, if the $\Delta x$ obtained can reduce the error function, the value of $\alpha$ is decreased; if the error function is increased, the value of $\alpha$ is increased.

3. Instance analysis

3.1 The risk indicator system of power communication network

The power communication network is a dynamic and complex network, and its operating state is affected by many factors. The operational risk assessment of power communication networks is a vital technology in routine maintenance. In this paper, considering the difficulty of obtaining various indicators, combining with the actual situation of the power communication network, fully satisfies the principles of comprehensive, scientific and practicality of the indicator design, from the four aspects of equipment failure rate, business operation, operation and maintenance, management and environmental to establish a risk assessment indicator system for power communication networks.

| First level indicator               | Second level indicator(A1)               |
|------------------------------------|------------------------------------------|
| Equipment failure factor(A)        | Cable failure rate(A2)                    |
|                                    | SDH Equipment failure rate(A3)            |
|                                    | PCM Equipment failure rate(A4)            |
|                                    | Switch device failure rate(A5)            |
|                                    | Carrier failure rate(A6)                  |
|                                    | Power failure rate(A7)                    |
|                                    | Average service life of equipment(A8)     |
Serious equipment failures (A9)
Business affected quantity (B1)
Business dual channel rate (B2)
Average business interruption time (B3)
Number of faults (C1)
Failure mean time to repair (C2)
Maintenance not completed (C3)
Thunder (D1)
Wind power (D2)
Human Factors (D3)
Other factors (D4)

The two indicators D1 and D2 are determined by the meteorological data of the year, and the rest of the data are obtained based on the actual operational data. The risk value is quantified by experts based on empirical evaluation. Due to the difference in the dimension of the data, normalization is required before the neural network training. The normalization formula is:

\[ I_{ij} = \frac{i_{ij} - \text{min}I_i}{\text{max}I_i - \text{min}I_i} \] (9)

Where \( I_{ij} \) is the normalized processing result of the j-th statistical data of the i-th index; \( \text{min}I_i \) and \( \text{max}I_i \) respectively represent the minimum and maximum values of the i-th index.

3.2. Network structure
In the case where the hidden layer node is sufficient, the three-layer neural network is sufficient to approximate a nonlinear function with arbitrary precision. Therefore, this paper adopts a three-layer network structure, and the number of input nodes and output nodes are 18 and 1 according to actual conditions. Relatively speaking, the number of hidden layer nodes is more difficult to determine. There are fewer hidden nodes, and the learning process may not converge; if there are too many hidden nodes, over-fitting may occur\(^ {10} \). This paper determines the number of hidden layer nodes based on empirical formulas \( k = 2n + 1 \), where \( n \) is the number of input nodes.

3.3. Simulation verification
According to the electricity operation statistics of a province for one year, the probability of occurrence of each indicator in the secondary indicators of table 1 can be calculated. The second level indicators corresponding to the four primary indicators of equipment failure rate, business operation, operation and maintenance management and environmental risk are added together and the mean value is obtained, and the first-level indicator values of the four items are obtained. We input four primary indicators as network data sets into the neural network for training. We can Compare the difference between the traditional BP neural network and the BP neural network improved by the LM algorithm in the training steps, analysing the superiority of using the improved BP algorithm of LM algorithm in the risk assessment of communication network. Set the mean square error of this method to \( \varepsilon = 0.001 \). This paper uses the data collected in the first half of a province as the training set, and the data collected in the second half as the verification set. The simulation results are shown in table 2 and figure 2. According to the simulation statistics, the system error using the LM algorithm reaches \( 10^6 \) for 14 times, while the traditional gradient descent algorithm has used more than 12,000 times when the error is \( 10^4 \). It can be seen that the training speed of the LM-BP neural network is faster.

| Month | 7    | 8    | 9    | 10   | 11   | 12   |
|-------|------|------|------|------|------|------|
| Risk value | 0.4301 | 0.3441 | 0.4486 | 0.1599 | 0.3399 | 0.2056 |

Table 2. Algorithm to estimate risk value and actual risk value
| LM-BP neural network algorithm simulation risk value | 0.4400 | 0.3433 | 0.4509 | 0.1607 | 0.3461 | 0.2144 |
|-----------------------------------------------|--------|--------|--------|--------|--------|--------|
| Actual risk value in the second half of the year | 0.4432 | 0.3430 | 0.4613 | 0.1687 | 0.3521 | 0.2148 |

Figure 2. The estimated of BP, LM-BP and actual values

Moreover, according to the simulation results, using the simulation data and the actual data to find the variance of the two algorithms, the simulation results shown in figure 3 can be obtained. It can be seen from figure 3 that compared with the traditional BP neural network, the LM-BP neural network algorithm has less error in the risk assessment of the power communication network, and the evaluation is more accurate.

Figure 3. Comparison of error values between BP and LM-BP algorithm

4. Conclusion
This paper proposes an improved BP neural network based on LM algorithm to evaluate the risk of power communication network. The new algorithm inherits the strong fitting and fault tolerance of BP neural network. At the same time, since the LM algorithm is an improved form of the quasi-Newton algorithm, the new algorithm has both the local characteristics of the Gauss-Newton algorithm and the global advantages of the gradient algorithm. Finally, experiments show that the improved BP neural network based on LM algorithm is better than the traditional BP neural network, which effectively improves the computational performance and generalization ability of the model.

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