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Neural Network Prediction Model of Transmission Line Icing Considering Terrain

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Abstract. In order to reduce the impact of transmission line icing accidents on the safe production of the power grid, the power grid operation and maintenance department guides the deicing and melting work of the power grid by estimating the thickness of the line icing. This paper proposes to predict the ice thickness based on the entropy weight method and BP neural network learning method. First, the entropy weight method is used to select the main influencing factors of line icing. Then a BP neural network prediction model of ice coating is constructed with weather and terrain as input and ice thickness as output. Finally, performance evaluation is performed using artificial ice observation data. The goodness of fit between the test data and the artificial ice observation data is 0.76805. The error is 5.33mm, which is far lower than 6.51 mm compared with the stepwise regression model. This verifies the validity of the model and has certain significance for the research on transmission line icing prediction.

Keywords. Transmission Line, BP neural network prediction model, Ice thickness, Terrain

1. Introduction

The Guizhou area is affected by the "quasi-stationary front" and terrain, resulting in unique terrain conditions and three-dimensional microclimate, which makes the icing of transmission lines extremely complex and diverse, seriously threatening the stable operation of the power system[1]. At present, research online icing prediction technology mainly includes the following. Hou and Wang[2] used icing-related meteorological factors and considered different state characteristics of line icing. They established a regression model using meteorological factors to predict line icing conditions and pointed out that the prediction error was 6.62%. Zhuang et al.[3] used SVM to fit the historical data of natural icing. At the same time, they considered the time accumulation effect of meteorological factors, as well as the optimization of the initial value of network parameters. The overall prediction error can be controlled at 30%. Chen et al. [4] aimed at the current situation that the accuracy of the existing icing prediction is insufficient, using the micro-meteorological monitoring data of the Yunnan power grid line ice disaster in the same period and using the LS-SVM model to predict the line icing thickness with a feedback mechanism. Wu et al.[5] used the projection tracking algorithm

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to comprehensively consider micro-topographic and micro-meteorological factors such as altitude, slope, and temperature. They optimized the weight of each factor index and established terrain and meteorological conditions to evaluate the icing risk of the line. It can be seen that most of the existing studies are from the perspective of meteorological conditions and use the empirical model method and the physical model method to establish the relationship model between meteorological factors and ice thickness while ignoring the influence of different terrain characteristics on the line icing. With the continuous expansion of the scale of the power grid, the advantages of artificial intelligence technology in the production, operation, and maintenance of the power grid have gradually become prominent, resulting in a model construction method that combines the traditional empirical model method and the physical model method. Based on the advantages of the empirical model method, the physical mechanism and complexity of the physical model method are also considered. The icing situation of transmission lines is predicted by comprehensive modeling through neural networks, fuzzy reasoning, and other methods [6]. The advantage of this method is that it can make full use of various factors to express complex nonlinear relationships, has high prediction accuracy, and has certain reliability and practicability. Therefore, this paper comprehensively considers the influence of meteorology and terrain. It first uses the entropy weight method to select the main influencing factors of line icing. It then simulates and implements an icing prediction model based on BP neural network and finally uses artificial ice observation data to perform performance analysis.

2. Influencing Factors of Line Icing

Icing is a physical process in which liquid supercooled water droplets hit the surface of the wire and release latent heat to solidify. It is closely related to heat exchange and transfer. It is not only affected by terrain but also by weather. According to previous research results [7], this paper summarizes the impact of ten easy-to-obtain factors for ice thickness, namely, temperature, elevation, vertical span, the horizontal distance from the water body, relative humidity, windward slope, slope, the height difference between towers on both sides, undulation, and wind speed. In order to dig out the main influencing factors of line icing and improve the accuracy of model construction, it is necessary to calculate the weight value of each index. Conventional methods include the analytic hierarchy process, fuzzy mathematics, and other methods. These methods have a lot of human subjectivity in the process of constructing the judgment matrix factors. The resulting evaluation results lack a certain scientific basis. Therefore, this study mainly adopts the entropy weight method to determine the index weight value through the sensitivity of each factor data fluctuation degree to the ice thickness. It defines the entropy and defines the entropy weight calculation process as the following [8].

When there are n samples, and each sample has m indicators to be evaluated, the entropy of the i-th evaluation indicator is calculated as follows:

$$H_i = -k\sum_{j=1}^{n} f_{ij} \ln f_{ij},\ i=1,2,3,...,m \tag{1}$$

in the formula, $f_{ij} = r_{ij} / \sum_{j=1}^{n} r_{ij}$, $k = \dfrac{1}{\ln n}$; when $f_{ij} = 0$, $f_{ij} \ln f_{ij} = 0$.

After calculating the entropy value of the i-th evaluation index through the above formula, its entropy weight is calculated as follows:

$$z_i = \frac{1 - H_i}{m - \sum_{i=1}^{m} H_i} \tag{2}$$

in the formula, $0 \le z_i \le 1, \sum_{i=1}^{m} z_i = 1 \cdot$

In order to obtain the objective weight value of each impact index calculated by the entropy weight method more accurately, the data of these 10 main influencing factors are firstly pre-processed. This project combines the actual situation from the two aspects of "the largest is the best" and "the smallest is the best". The main processing principles are undulation, elevation, vertical span, relative humidity, windward slope, slope, the height difference between towers on both sides and wind speed. The larger the data value of these 8 factors is, the greater the coverage of the line will be. The greater the degree of influence of the ice thickness is, and the greater the value of the remaining two factor indicators is, the smaller the degree of influence on the ice thickness of the line will be. Secondly, Formulas (1) and (2) are used to calculate the entropy weight method weights for 10 factors, as follows:

Table 1. Weight statistics of factor entropy weight method

Factor	Weight	Ranking
Windward slope	0.0837	6
Vertical span	0.1143	3
Slope	0.0764	7
Elevation	0.1602	2
Height difference between towers on both sides	0.0735	8
Wind speed	0.0632	10
Undulation	0.0668	9
Horizontal distance from water body	0.0938	4
Temperature	0.1746	1
Relative humidity	0.0935	5
Windward slope	0.0837	6

According to the calculation results of the above entropy weight method, From Table 1, it can be seen that the weight order of factors affecting icing is: temperature>elevation>vertical span>horizontal distance from the water body>relative humidity>windward slope>slope>height difference between towers on both sides>fluctuation >wind speed. The temperature, elevation, vertical span, horizontal distance from the water body, relative humidity, windward slope, and slope are calculated by the entropy weight method. The weight of these seven indicators accounts for 79.65% of the total weight and is the main influencing factor. Factors to build a model will improve the accuracy of the model.

3. The Establishment of the Neural Network Model

BP neural network is a typical machine learning model, which has a great range of applications in the field of artificial intelligence[9]. In smart grid icing prediction, research on icing prediction based on BP neural network has achieved great results[10]. In this paper, according to the 7 main icing factors and the prediction accuracy requirements, a 3-layer BP neural network is selected as the prediction model[11]; that is, 7 indicators are used as the input layer data (index 1: relative humidity, index 2: elevation, index 3: distance from the water body, index 4: height difference between towers on both sides, index 5: vertical span, index 6: windward slope, index 7: temperature), 1 output layer data (artificial ice observation), 1 hidden layer, ice-coated neural network The model structure is shown in Figure 1.

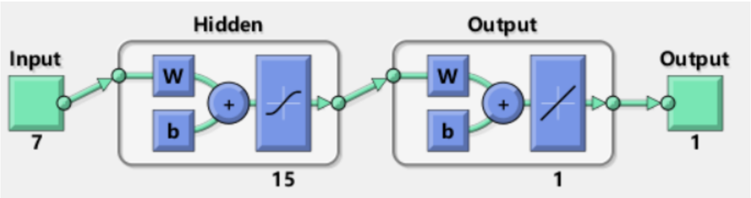

Figure 1. Structure of ice-covered neural network model

The input layer is the data of 7 index factors, and the output layer is the input value of the hidden layer node. The calculation method is shown in formula (3):

$$y_j = f_1(\sum_{i}^{N} x_i \omega_{ij} + b_j) \tag{3}$$

in the formula, y_j is the output value of the *j-th* node in the hidden layer, x_i is the input data of the index factor of the *i-th* node, b_j is the threshold value of the *j-th* node in the hidden layer, and w_{ij} is the *i-th* index of the input layer to the hidden layer The weight of the *j-th* node, *N* is the number of nodes in the hidden layer, and $f_1()$ is the S-type activation function (non-linear tansig function).

The output value calculation formula of the *k-th* node in the output layer is:

$$Z_k = f_2(\sum_{j}^{M} y_j \omega_{jk} + b_k) \tag{4}$$

in the formula (4), Z_k is the output value of the *k-th* node in the output layer, b_k is the threshold value from the hidden layer to the *k-th* node in the output layer, w_{jk} is the weight value from the *j-th* index in the hidden layer to the *k-th* node in the output layer, and *M* is The number of nodes in the hidden layer, *j* is the number of nodes in the output layer (this item is set to 1), and $f_2()$ is the linear activation function (purelin step function).

In addition, in order to speed up the training and convergence speed, a learning method that does not need to calculate the Hessian matrix after the improvement of the Newton algorithm is adopted: the Levenberg-Marquardt training method. The core idea of the LM algorithm is to use the Jacobian matrix (easy to calculate) to replace the calculation of the H matrix, which improves the optimization efficiency.

4. Model Simulation and Evaluation

4.1. Data Preprocessing

A total of 110 towers in Guizhou Province, with data collected by the online ice monitoring system, were selected as samples. Since the range of data before training has an important impact on the convergence speed of network training, the sample data is normalized, and denormalization is performed again when the data is output to the network.The normalization processing method is shown in formula (5) as follows:

$$X' = X - Xmin/Xmax - Xmin \tag{5}$$

where X = {a, b, c, ...} is the original input data, Xmin and Xmax are the minimum and maximum values in the input data {a, b, c, ...}, and X' is the normalized data.

4.2. Simulation of the Model

In order to prevent the model from falling into local convergence or overfitting, the samples should be divided into training data, verification data, and test data [12]. Among them, 75% of the sample data is used to train the network (83 sets of training data), 15% of the data is used to verify the samples (16 sets of verification data), and the remaining 10% of the data is used to test the trained network (11 test data). The number of input nodes is 7, the number of output nodes is 1, the number of hidden layer nodes is 15, and the hidden layer adopts the nonlinear tansig function. The output layer adopts linear purelin function so that the training model error can be minimized. The learning rule adopts LM The training algorithm of the method, the number of training iterations <1000, the error <0.001, modeling and simulation in the Matlab2020 environment. The simulation results are as follows:

It can be seen from the trend graph of the fitting error of the neural network model in Figure 2 that the error of the trained network model is the smallest when the model is iterated to the 14th generation.

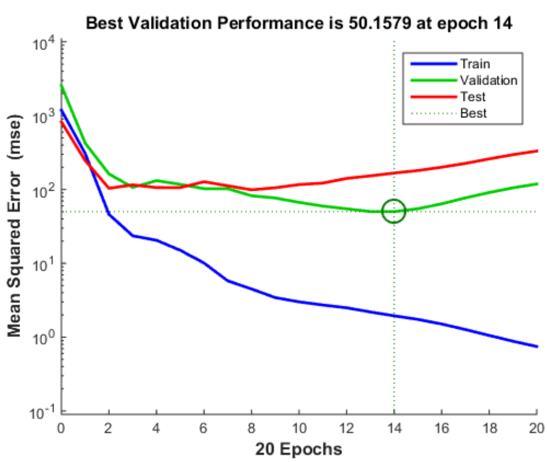

Figure 2. Trend chart of fitting error of neural network model

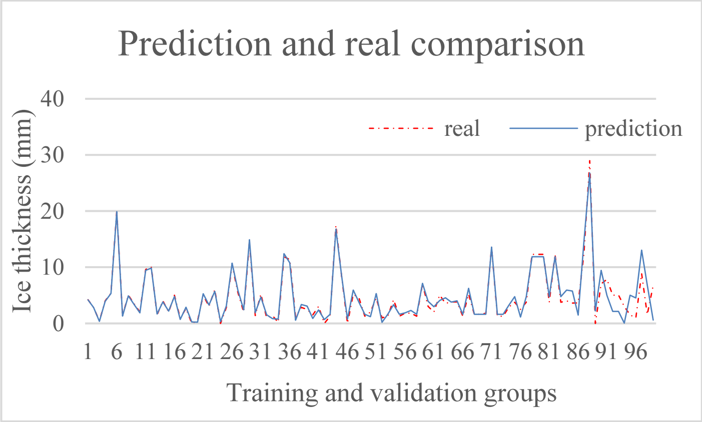

Figure 3. Training simulation diagram

Figure 3 shows the simulation implementation of the training process of 83 training groups and 16 verification groups. It can be seen that the degree of convergence of the training is very good, basically completely fitting with the training samples. At the same time, linear regression analysis is carried out on the output training prediction value and real value to test the predictive ability of model [13]. The simulation results of predicted output and real value linear regression analysis are shown in Figure 4. The linear regression fit coefficient of the training group reached 0.9807, and the verification group also reached 0.7105, which is close to 1, and the fitting degree is very high. The two sets of training data outputs track the real value better.

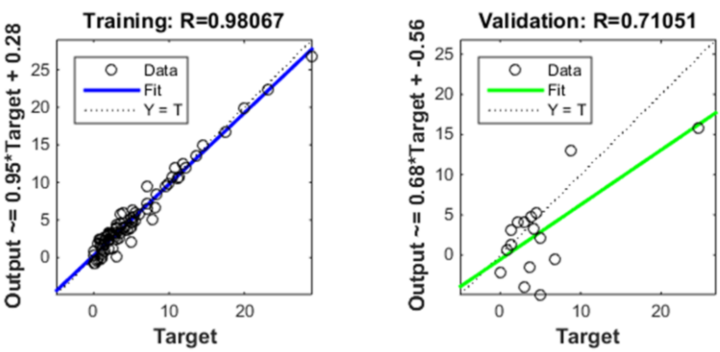

Figure 4. Neural network model fitting results

4.3. *Prediction Performance Evaluation*

After the training, in order to test the accuracy of the model, the remaining 11 sets of test data were used as test inputs for simulation prediction. Linear regression analysis was performed on the ice thickness value predicted based on the neural network and the corresponding artificial ice observation value to detect. The predictive ability of the model, the predicted simulation results, and the linear regression analysis of the artificial ice observation value are shown in Figure 5, and the goodness of fit is 0.76805.

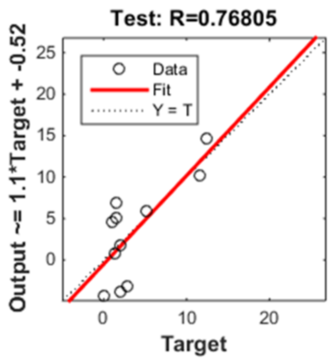

Figure 5. Test data fitting result graph

Then the same set of data is predicted by the traditional stepwise regression method, and its predicted value is listed in Table 2 with the predicted value of this paper. The maximum errors between the two algorithms and the actual ice thickness is 5.33mm and 6.51 mm, respectively. It can be seen that the neural network training results are far superior to traditional mathematical models.

Table 2. Comparison statistics of the calculation results of the two algorithms

No	Real	Neural network	Stepwise regression	Error Neural network	Error Stepwise regression
1	19.45	19.45	18.5	0	0.95
2	2.86	2.86	9.37	0	-6.51
3	6.85	6.85	10.46	0	-3.61
4	12.57	14.34	12.69	-1.77	-0.12
5	15.2	14.79	13.11	0.41	2.09
6	4.34	4.22	8.59	0.12	-4.25
7	4.91	3.94	7.81	0.97	-2.9
8	3.79	6.56	8.03	-2.77	-4.24
9	1.28	6.61	2.24	-5.33	-0.96
10	5.59	5.59	2.42	0	3.17
11	0.91	5.26	5.64	-4.35	-4.73

5. Conclusion

The ice thickness prediction model is based on the entropy weight method and BP neural network learning method proposed in this paper. Firstly, the entropy weight method is used to select 7 main factors affecting the line icing, namely temperature, elevation, vertical span, water body level distance, relative humidity, windward slope, and slope. The weight of these indicators accounts for 79.65% of the total weight. We then build an ice-covered BP neural network prediction model with meteorology and terrain as input and ice-covered thickness as output. Finally, we use artificial ice observation. The performance evaluation of the data shows that the goodness of fit between the test data and the artificial ice observation data is 0.76805. The error is 5.33mm, which is far lower than 6.51 mm compared with the traditional stepwise regression model. The research results can effectively solve the problem that the traditional mathematical model is difficult to adapt. This kind of random and non-linear factor problem can better solve the calculation and simulation problems of conductor icing thickness prediction. The application of this model can improve the safety performance of transmission lines, improve the prediction, deicing, and risk assessment of transmission line icing, and has a certain reference value for transmission line icing prediction research.

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