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Research on Cost Forecasting Model of Power Line Engineering Based on BP Neural Network

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Abstract. In view of the large number of different types of power line engineering projects and the large deviation of cost estimation, how to use a small amount of engineering information to quickly and accurately predict and compare the cost of each project has become a concern. In order to solve this problem, this paper builds a power line engineering cost prediction model based on the BP neural network algorithm of 3 layers 8-12-1 network structure. By analyzing the influencing factors affecting the construction cost of transmission lines, eight indicators are extracted as input factors and the power line engineering cost is used as the output layer factor. In this paper, the BP neural network prediction model is trained and verified by actual engineering data. The experimental results show that the model can estimate the power engineering cost accurately, and can be used for pre-decision phase of the project.

Introduction

The accuracy of grid project cost prediction directly affect the economics of project construction and the effectiveness of resource allocation, and ultimately affect enterprise decision-making[1]. Therefore, it is necessary to make project cost prediction more simple and accurate. In actual power line engineering, the project cost will be affected by factors such as path conditions, meteorological conditions, etc. These influencing factors are difficult to describe with precise formulas, resulting in nonlinearity of power line engineering cost[2].

BP neural network has strong self-organization, adaptive, nonlinear mapping ability and high fault tolerance. BP neural network can grasp the complex nonlinear relationship between engineering cost and its influencing factors through sample learning [3-4]. Therefore, this paper analyzes the main factors affecting the cost of power line engineering, clarifies the main principles of BP neural network algorithm, attempts to use BP neural network to establish a model to predict the cost of power line engineering, provide support for the comparison and optimization of feasibility study schemes, and provide new ideas for the study of transmission line engineering cost

Main Factors affecting the Cost of Power Line Engineering

The main factors affecting the cost of power line engineering [5-8] include:

Path Factor. The choice of path plan needs to comprehensively consider the topography, geological and transportation conditions along the line, try to avoid the demolition of houses, cutting trees, crossing roads, railways, rivers and other obstacles. It is not only related to the type and quantity of components such as line towers and foundations, but also directly affects the cost of the engineering, especially the level of construction site requisition and cleaning fees. Therefore, the reasonable choice of the path plan is a prerequisite for optimizing project cost line.

Wire type Factor. The choice of wire type and split number should be determined according to the planned transmission capacity requirements of the system. Its engineering cost accounts for about 20% of the cost of the main body, but it has a decisive effect on the selection of the tower and indirectly affects the cost of the tower foundation project. Therefore, Reasonable determination of the type of wire and the number of splits have a very important role in optimizing the construction cost.

Meteorological Conditions. The meteorological conditions affecting the design of power line engineering include three factors: wind speed, temperature and ice thickness. It mainly affects the tower material, tower type and tower weight, and is one of the influencing factors of engineering cost.

Tower type and Tower Height Factor. The determination of tower type, nominal height and quantity should consider the route, voltage level, number of loops, cross-over, terrain and meteorological conditions. The cost accounts for a large proportion of the cost of the line body, about 30%. The project is one of the important factors affecting the size of the foundation of the tower.

Geological Conditions. Geological conditions are divided into general soil, hard soil, loose sand, water, mud water, quicksand and rock according to the actual situation. The difference in geological conditions is directly reflected in the difficulty of excavation of the foundation pit and the cost of excavation. It also will indirectly affect the form and size of the foundation of the tower.

The basic Principle of BP Neural Network

The BP neural network is a multi-layer forward feedback neural network. The BP neural network consists of an input unit, a hidden unit and an output unit. The main features of BP neural network are the forward propagation of the input signal and the back propagation of the error. In forward transmission, the input signal is processed layer by layer from the input layer through the hidden layer to the output layer. If the output layer does not get the desired output, it performs backpropagation and adjusts the network weights and thresholds based on the prediction error so that the BP neural network's decision is constantly approaching the desired output [9].

Forward Propagation Process. The input layer has n neurons $x \in R_n, x = (x_1, x_2, \cdots, x_n)$, the hidden layer has d neurons $h \in R_d, h = (h_1, h_2, \cdots, h_d)$, and the output layer has m neurons $y \in R_m, F = (F_1, F_2, \cdots, \mathrm{F_m})$. The weight and threshold between the input layer and the hidden layer are W_{ij} and b_j respectively , and the weight and threshold between the hidden layer and the output layer are W_{jk} and b_k respectively .

Hidden layer nodes:

$$h_j = f\left(\sum_{i=1}^{n} W_{ij} x_i - b_j\right) \tag{1}$$

Output layer node:

$$F_k = f\left(\sum_{j=1}^{d} W_{ij} h_j - b_k\right) \tag{2}$$

In the formula, the transfer function:

$$f(x) = \frac{1 - \exp(-x)}{1 + \exp(-x)} \tag{3}$$

The output node error of a sample is:

$$e = \frac{1}{2}\sum_{k}^{m}(t_k - F_k)^2 = \frac{1}{2}\sum_{k}^{m}\left\{t_k - f\left[\sum_{j=1}^{d} W_{jk} f\left(\sum_{i=1}^{n} W_{ij} f\left(\sum_{i=1}^{n} W_{ij} x_i - b_j\right) - b_k\right)\right]\right\}^2 \tag{4}$$

In the formula, expected output and calculated output are t_k and F_k respectively;
error of all samples (p is the number of samples):

$$E = \sum_{i=1}^{p} e_i < \varepsilon \tag{5}$$

Backpropagation Process. The error calculation formula between the output layer node and the hidden layer node is:

$$\delta_k = (t_k - F_k) F_k (1 - F_k) \tag{6}$$

Weight correction:

$$W_{jk}(n_0+1)=W_{ij}(n_0)+\eta\sum_{p_i=1}^{p}\delta_k h_j \tag{7}$$

Threshold correction:

$$b_k(n_0+1)=b_k(n_0)+\eta\sum_{p_i=1}^{p}\delta_k \tag{8}$$

The error calculation formula between the input layer node and the hidden layer node is:

$$\delta_j=h_j(1-h_j)\sum_{k=1}^{m}\delta_k W_{jk} \tag{9}$$

Weight correction:

$$W_{ij}(n_0+1)=W_{ij}(n_0)+\eta\sum_{p=1}^{p}\delta_j x_i \tag{10}$$

Threshold correction:

$$b_j(n_0+1)=b_j(n_0)+\eta\sum_{p_i=1}^{p}\delta_j \tag{11}$$

Establishment of Power Line Engineering Cost Prediction Model

Basic Thoughts on Cost Forecasting of Power Line Engineering. The basic idea of power line project cost prediction is to find out the main factors affecting the cost of power line project as the independent variable X through the accumulated historical project settlement data, and the power line engineering cost as the dependent variable Y, and carry out the simulation experiment in the Matlab7.0 environment. Specific steps are as follows:

(1) According to the results of the analysis, determine the input variable X;

(2) Establish a mathematical model of BP neural network;

(3) After the data is preprocessed, train the network;

(4) Use the obtained network to predict the project cost.

Input Layer Node selection. Since the data used in this paper are all located in the plain area, the terrain does not change much, so the terrain factor is not considered. Considering the above factors affecting the cost of power line engineering, the input layer of the BP network is selected as 8 nodes, including the number of circuits, geology, base number per kilometer, and the amount of towers per kilometer , wire parameters, tensile ratio, tower unit price, wire unit price.

Network Structure Selection. The 3-layer BP neural network has been widely used in many complex nonlinear problems [10], so this paper chooses 3-layer BP neural network as the prediction model. The number of input layer nodes is related to the factors affecting the construction cost. According to the analysis of the factors affecting the cost of power line engineering, the input layer of the BP network is selected as 8 nodes; The output layer of the network is selected as one node, and the output variable is the cost of the power line engineering (the line cost y) under the corresponding input conditions; the number of hidden layer nodes is determined by the empirical formula:

$$d=\sqrt{n+m}+a \tag{12}$$

Where a is a constant between 1 and 10.Since the objective function is a neural network of 8 inputs and 1 output, it can be determined that the number of nodes is 12. The BP neural network model of the network structure of 8-12-1 was finally established. The network structure model is shown in Figure 1.

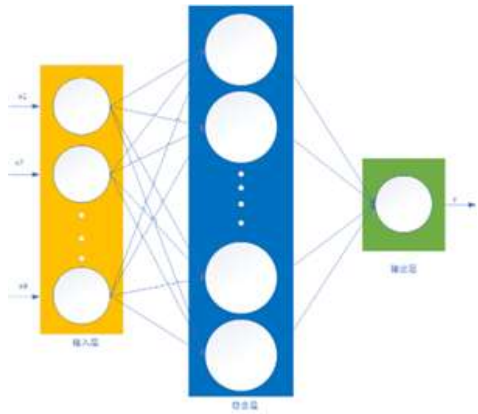

Fig. 1 The BP neural network model

Data Preprocessing and Conversion. In this paper, the original data of 75 sets of 110kV power line projects actually settled in a certain area in 2010-2018 is taken as a sample, and the simulation experiment is carried out in Matlab7.0 environment. The original data is shown in Table 1. The first 65 groups of samples were used to train the network, and then the trained network was used to predict the cost of the last 10 groups of samples, and the deviation rate between the predicted results and the actual settlement cost was compared.

Table 1 Data sample of construction cost for 110-kV transmission lines

Serial number	The number of circuits	Geology	Wire parameters	Base number per kilometer	The amount of towers per kilometer	Tensile ratio	Tower unit price	Wire unit price	Actual cost / (million / km)
1	2	2.23	0.92	3.40	14.56	0.21	1.11	1.36	49.4
2	1	1	0.92	3.40	10.77	0.19	0.61	1.64	35.4
3	1.53	2.90	0.92	3.19	17.01	0.33	0.81	2.1	56.4
…	…	…	…	…	…	…	…	…	…
65	1	1	0.92	3.94	10.64	1.0	0.88	1.32	37.9

Since the number of power circuit loops and geological conditions are textual representations, the two variables need to be represented by numbers: The number of power line circuits is 1, 2, 3, and 4, respectively, indicating single circuit, double circuit, three circuit, and four circuit. When the line meets multiple circuit numbers, the number of circuits included must be weighted and averaged; Geological conditions are classified into 7 grades according to common soil, solid soil, loose sand, water, muddy water, quicksand and rock, and are represented by 1, 2, 3, 4, 5, 6, and 7. For a variety of geology, weighted average processing of the included terrain is required; The wire type and split number are processed according to the following formula: wire parameter = split number × wire nominal single weight.

Because the input layer variables and output layer variables are different in numerical dimension, the data is quite different and cannot be directly used for neural network training. Otherwise, it will affect the learning speed and the convergence of the network. In this paper, the premnmx function is used for normalization. The normalized data values are all in the range of [-1,1], as shown in Table 2.

Table 2 Normalized data of construction cost training samples for 110-kV transmission line

Serial number	the number of circuits	Geology	Wire parameters	Base number per kilometer	The amount of towers per kilometer	Tensile ratio	Tower unit price	Wire unit price	Actual cost / (million / km)
1	1	0.29	0.92	-0.44	0.23	-0.95	1	-0.89	0.33
2	-1	-1	0.92	-0.44	-0.95	-1	-0.89	-0.17	-1
3	0.06	1	0.92	-1	1	-0.65	-0.13	1	1
…	…	…	…	…	…	…	…	…	…
65	-1	-1	0.92	1	-1	1	0.13	-1	-0.76

Analysis of Results

The model adopts the momentum gradient descent algorithm to adjust the parameters in the negative gradient direction of the target, setting the maximum number of cycles to 10000; the target error is 0.01; the initial learning rate is set to 0.02, and the 65 sets of data preprocessed in Table 2 are input. After 7122 trainings, the training error is less than 0.02, the prediction accuracy requirement is met, and the training is over.

The prediction results are shown in Table 3. Comparing the prediction results in Table 3 with the actual settlement cost, it is found that the deviation rate between the prediction result and the actual settlement cost is less than 9% in the predicted 10 groups of data. According to experience, in the comparison and selection process in the previous decision stage, The engineering cost deviation rate is generally controlled within 10%. Therefore, it is feasible to use BP neural network algorithm to e predict the power line engineering cost.

Table 3 Predictive results of construction cost for 110-kV transmission lines

Serial number	Actual cost	Forecast cost	Deviation rate
66	43.7	46.6	-6.64%
67	53.75	55.71	-3.65%
68	36.2	38.4	-6.08%
69	56.4	53.3	5.50%
70	61.3	58.7	4.24%
71	47.4	51.3	-8.23%
72	41.5	41.6	-0.24%
73	51.8	50.2	3.09%
74	55.6	52.8	5.04%
75	46.4	49.9	-7.54%

Conclusion

This paper analyzes the main factors affecting the cost of power line engineering, clarifies the main principles of BP neural network algorithm, and builds a model of BP neural network with 3-layer network structure. After training the network, the cost of power line engineering is estimated and compared with the actual value. The results show that the model not only has simple requirements for engineering information, but also can accurately and quickly predict the engineering cost of the power line, which is suitable for estimating the cost of the project in the comparison and selection stage of the project.

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