

Electric Power Engineering Cost Predicting Model Based on the PCA-GA-BP

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Abstract. In this paper a hybrid prediction algorithm: PCA-GA-BP model is proposed. PCA algorithm is established to reduce the correlation between indicators of original data and decrease difficulty of BP neural network in complex dimensional calculation. The BP neural network is established to estimate the cost of power transmission project. The results show that PCA-GA-BP algorithm can improve result of prediction of electric power engineering cost.

1.Introduction

Since the 21st century, China's economic level has been rapid development, power construction project investment put forward higher requirements for power engineering cost management. It is the significant work that the prediction of power engineering cost to improve the management of electric power engineering project. The accurate engineering cost prediction can reduce the waste of money and is the embodiment of scientific development.

In this paper, an hybrid artificial neural network algorithm: PCA-GA-BP model are proposed by combining Principal Component Analysis, Genetic Algorithm and the BP (Back Propagation) neural networks.

In this algorithm, the PCA algorithm is established to reduce the correlation between data indicators and decrease the difficulty of forecasting model in the high dimensional calculation. The Back Propagation neural network is used to predict electric power engineering cost, and Genetic model are used to optimize the initial parameters of Back Propagation neural network to prevent it into over-fit.

2. Material and Methods

2.1 Principal Component Analysis

PCA is a statistical analysis technology proposed by Scientist Pearson in 1901 and developed by Scientist Hotelling later. PCA utilizes an orthogonal transformation to convert multiple indicators into a few comprehensive indicators called principal components. these principal components can reflect the most information of original indicators . they are usually expressed as a linear combination of the original indicators.

In the theory of PCA, original data is transformed to a new coordinate system. Consider a process with input data set matrix $X \in \mathbb{R}^{n \times p}$, where each of the n rows represents observations and each of p columns represents process indicators. The role of PCA is to reduce the difficulty in the high dimensional calculation and eliminate the multicollinearity between the variables.

The standard PCA algorithm can be explained as follows:



Step 1: Standardize the process indicators and indicators of each column becomes equal to 0 and 1 respectively.

Step2: Find out the correlation between standardized indicators. The covariance matrix Λ by following expression.

$$\Lambda = \frac{1}{n-1} X^T X = V \Lambda V^T \quad (1)$$

where $\Lambda = \text{diag}(\lambda_1 \geq \lambda_2 \dots \geq \lambda_m)$.

Step3: Determine the number of principal component by parallel analysis method.

Step4: Determine the expression of principal component

$$F_i = \lambda_i Z_i \quad (2)$$

where Z is Standardized value of process indicator.

2.2 Standard BP Neural Network

The BP neural network is one of the most widely used neural network models, which is put forward by Rumelhart and McCelland in 1986. The back propagation neural network is a multilayer feed-forward model trained by the principle of error inverse propagation algorithm. The standard topology of BP neural network includes input layer, hidden layer and output layer.

three-layers BP neural network is established in this paper. The main parameters of standard BP model can be seen as follows:

- (a) Network Training Algorithm: gradient descent algorithm
- (b) The Number of Neurons in the Input Layer :10
- (c) The Number of Neurons in the Hidden layer:15
- (d) The Number of Neurons in the Output layer:1
- (e) Maximum Number of iterations:50

2.3 BP Model Optimized by GA

The GA is a randomized search method that evolves from the evolution of the biological world which is proposed by Holland in 1962. GA is used to generate useful solutions for optimization and search problems. Genetic algorithms provide a general framework for solving complex system problems. In this paper, the Genetic algorithms is established to optimized the initial parameters of BP model in order to improve the accuracy of the forecast results.

The GA-BP algorithm can be described as follows:

Step1: Use GA to find the optimal initial weights and threshold value of BP neural network.

The following equation is utilized to decide the length of a chromosome :

$$N_c = N_k + N_i \times N_j + N_j \times N_k + N_j \quad (3)$$

where N_c is the length of a chromosome, N_k is the number of neurons in output layer of BP model, N_i is the number of neurons in input layer of BP model, N_j is the number of neurons in hidden layer of BP model.

The fitness function is calculated as:

$$F(i) = k \left(\sum_{i=1}^n (\text{abs}(y_i - o_i)) \right) \quad (4)$$

where i is the number of the whole chromosomes, n is the number of neurons in output layer of BP model, y_i is the forecasting electric power engineering cost signals, o_i is the guiding electric power engineering signals. k is the coefficient of fitness function.

In this paper, the main parameters of GA are selected as:

- (a) Size of chromosomes:50
- (b) Probability of Crossover :0.2
- (c) Probability of Mutation:0.15
- (d) Algorithm of Selection Operation: Roulette Wheel Algorithm
- (e) Number of Iterations:500

Step2: Complete the electric power engineering cost predicting by utilizing the BP neural network whose initial weights and thresholds have been optimized by GA.

3. The Proposed Method

Use the PCA algorithm to convert 30 original indicators into 10 principal components. The purpose of doing so is to reduce the difficulty of BP model in the high dimensional calculation and eliminate the multicollinearity between the variables.

Establish the BP neural network optimized by the GA and MEA respectively. MEA and GA are used to optimized the initial parameters of BP model. The purposed of this step is to make BP model predict more accurately.

Calculate the predictions by using the BP model, PCA-GA-BP model and PCA-MEA-BP model. Making comparisons between predicted and actual values. three error criterions and three percentage error criterions were used in this paper.

Make comparisons between different prediction models of the forecasting accuracy. The involved models include the PCA-GA-BP model, the PCA-MEA-BP model and the single PCA-BP model.

4.Result

The Root Mean Square Error(RMSE), the Mean Absolute Percentage Error(MAPE) , the Mean Absolute Error(MAE) of these three indexes are selected in this paper to test the prediction accuracy of the proposed PCA-GA-BP model and PCA-MEA-BP model. The equation of three indexes are adopted as:

$$MAPE = \frac{1}{N} \sum_{t=1}^N \left| \frac{X(t) - \hat{X}(t)}{\hat{X}(t)} \right| \quad (5)$$

where $X(t)$ is the raw data of electric power engineering cost, $\hat{X}(t)$ is the forecasted data series of electric power engineering cost and N is the number of the sample in the data series.

$$MAE = \frac{1}{N} \sum_{t=1}^N |X(t) - \hat{X}(t)| \quad (6)$$

$$RMSE = \sqrt{\frac{1}{N-1} \sum_{t=1}^N [X(t) - \hat{X}(t)]^2} \quad (7)$$

Table 1. Result

Indexes	PCA-GA-BP	PCA-BP
MAE(%)	3.858	5.975
MAPE(%)	7.721	11.906
RMSE(%)	3.668	5.66

5.Discussion

From the result, We can draw the following conclusions:

When comparing the hybrid GA-BP neural networks with the standard BP neural networks, the hybrid GA-BP neural networks performs better than the latter in all indexes obviously.

Since the PCA algorithm is established to reduce the correlation between data indicators and the MEA/GA algorithms select the best parameters for standard BP neural networks, the optimized BP neural networks can achieve high accuracy prediction results.

6. Conclusion

Above all, the hybrid artificial neural network algorithm PCA-GA-BP model are proposed for the electric power engineering cost by combining Principal Component Analysis, Genetic Algorithm and the Back Propagation model. The contribution rate of the Principal Component Analysis and Genetic model to promote the standard BP model are investigated based on electric power engineering cost forecasting experiment. The results in the experiment show the GA algorithm also can improve the predictive performance of BP neural network and are suitable for the electric power engineering cost predictions for the cost management.

7. References

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