Grid investment capability prediction based on path analysis and BP neural network

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Abstract. With the more complex investment environment of China's power grid, the accurate prediction of the investment ability of power grid enterprises has become an important prerequisite for managers to make precise investment decisions. This paper first selects the factors affecting the investment capacity of the power grid from the internal and external environment, and establishes the index system of the factors affecting the investment capacity. Secondly, the path analysis is used to deeply explore the interaction relationship and influence degree of each index and investment capacity. Finally, the maximum investment capacity of the power network can be predicted based on the BP neural network prediction model. The results show that the BP neural network prediction model can achieve higher prediction accuracy when predicting the power grid investment capability.

Key words: Index system; path analysis; BP neural network; power grid investment capability.

1. Introduction

The environment for grid investment has become increasingly complex in the context of the dual carbon target and new power system transformation. Accurate prediction of the grid's investment capacity is a prerequisite for grid companies to make investment decisions. Therefore, in order to make an accurate investment capacity assessment of the grid in the complex context, a set of simple and comprehensive index system and a scientific prediction model are needed to forecast the grid investment capacity, so that the grid can make a reasonable investment strategy in the new situation.

At present, some literature has made preliminary exploration on the influencing factors of investment capacity from qualitative and quantitative perspectives. Qualitatively, literature [1] analyzed the investment capacity of enterprises from two perspectives of investment efficiency and investment scale of grid enterprises, and summarized the main influencing factors. The literature [2] investigates the influence of management power on corporate investment, and the results show that power intensity is significantly and positively related to the level of corporate investment. Quantitatively, the literature [3] used the TOPSIS method to analyze the excellent level of investment capacity of grid companies in each year. The literature [4], on the other hand, investigates the dynamic feedback relationship between the amount of grid investment and investment efficiency based on system dynamics. The literature [5] verified the influence mechanism between grid investment and macro-environmental factors based on co-integration theory and vector error correction model. In order to accurately grasp the investment capacity of grid enterprises, some studies forecast the grid investment capacity. The literature [6] proposed a multi-region grid investment capacity measurement method based on asset-liability ratio, which provides a basis for the investment plan of grid enterprises. The literature [7] constructs an investment capacity measurement model adapted to the power system reform through comprehensive plan balance optimization, and reasonably allocates the investment of each project.

Compared with the above traditional forecasting model, the intelligent forecasting algorithm can avoid the errors caused by subjectivity. The literature [8] constructed a provincial grid investment scale prediction model based on MLR and REF neural network, and the model prediction error is small. The literature [9], on the other hand, used an improved support vector machine model to forecast and analyze the investment capacity of a power grid company. The literature [10] performs a variational modal decomposition and forecasts it using multiple support vector machine models. A small part of the literature predicts the grid investment capacity based on two and more models. The literature [11] proposed a LSTNET-ship2 network model for grid investment capacity prediction by applying a combination of convolutional networks, CRU networks, and autoregressive models. The literature [12] proposed a combined forecasting model combining gray forecasting model, BP neural network and multiple regression model, thus combining the advantages of various methods to forecast the grid investment scale and further improving the forecasting accuracy.

From the above literature analysis, it can be obtained that there may be serious coupling relationship among the factors of grid investment capacity. Therefore, when selecting the influencing factors, the original information is retained as much as possible, so that the simplified influencing factors truly reflect the level of grid investment capacity. And a suitable intelligent prediction model is selected to improve the accuracy of grid investment capacity prediction. Therefore, this paper firstly selects the factors affecting the grid investment capacity from the internal and external environment, and analyzes the mutual influence relationship and the degree of influence between each index and the investment capacity. Finally, the maximum investment capacity of the grid is predicted based on the BP neural network prediction model. The prediction results show that the proposed prediction method can predict the grid investment capacity more accurately.

2. Construction of index system

The main purpose of the analysis of investment ability influencing factors is to screen and identify the main influencing factors and lay the foundation for the investment ability measurement model. This paper identifies the main influencing factors of investment capacity by combining qualitative and quantitative methods.

2.1 Analysis of the influencing factors

This paper comprehensively constructs the influencing factor index system of power grid investment capacity from both internal factors and external factors. Internal factors are divided into business status and management status. External factors are divided into market environment, economic environment and policy environment. The index system of the factors influencing the investment capacity is shown in Table 1.

Table 1 Index system of influencing factors of investment capacity

Power grid invest-ment capacity impact factor index system	State of opera-tion	Nonbusiness income
		Main business income
		Electricity purchasing cost
		Financing cost
		Construction in process
		Original value of fixed assets
		Current liabilities
		Net margin
		Cost of transmission and distribution
Power grid invest-ment capacity impact factor index system	Management level	Corporate culture level
		Manager experience
	Market circumstances	Sales electricity price
		Power supply population
		Selling electricity
	Economy environment	Interest rate
		GDP
	Policy environment	Policy subsidies
		Environmental protection policy
		Tax policy

2.2 Bivariate correlation analysis

Using SPSS software, calculate the correlation coefficient between each influencing factor and the historical investment ability. If the Pearson coefficient is greater than 0.8, it indicates that the factor affects the investment ability greatly. Factors with a Pearson coefficient greater than 0.8 are shown in Table 2.

Table 2 Correlation coefficient between various factors and historical investment capacity

Each factor	Pearson correlation
Operating income	0.962
Power purchase cost	0.801
Operation income	1.000
Depreciation	0.957
Net profit	0.945
Short Term Loans	0.997
Construction project	0.996

2.3 Diameter analysis

Make the model correction using SPSS Amos, and finally get the investment capacity model path map as shown in Figure 1.

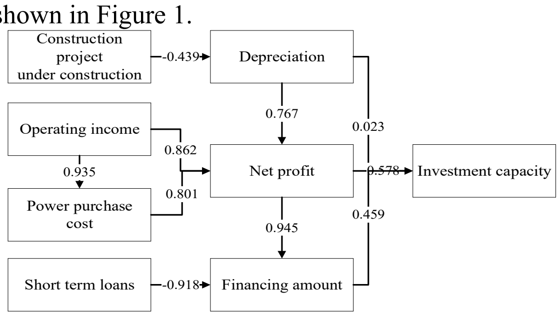

Figure 1 Path analysis of key indicators of investment

The total effect of the factors on the investment capacity should be the sum of the direct diameter coefficient and the indirect diameter coefficient, and only consider the direct diameter coefficient is not comprehensive. Therefore, in order to make the results more reasonable and reliable, the investment ability modeling should be composed of internal financial indicators and external factor correction coefficient.

3. BP neural network prediction model

The relevant factors affecting the grid investment capacity are used as input elements to forecast the grid investment capacity. the learning of BP neural network consists of two main parts.

(1) Forward propagation of the input signal

According to the BP neural network structure, the various unit input and output functions in the implied layer are as follows:

$$\begin{cases} net_j^{in} = \sum_{i=1}^{m} w_{ij} x_i + b_j \\ net_j^{out} = \varphi(net_j^{in}) \quad i=1,2,\cdots,\text{m};\ j=1,2,\cdots,n \end{cases} \tag{1}$$

In formula: w_{ij} b_j is the weight between the i-th neurons in the input layer and the j-th neurons in the hidden layer;

b_j represents the output threshold of the neurons in the hidden layer; $\varphi(\bullet)$ is a transfer function representing the hidden layer.

By processing the multi-layer neurons, the output results of the output layer can be calculated:

$$\begin{cases} Net_k^{in} = \sum_{k=1}^{r} w_{jk} net_j^{out} \\ o_k = \psi(Net_k^{in} + a_k) \quad j=1,2,\cdots,n;\ k=1,2,\cdots,r \end{cases} \tag{2}$$

In formula: w_{jk} is the weights between the j-th neuron in the hidden layer and the k-th neuron in the output layer;

(2) Reverse propagation of error information

The error of the BP network is calculated as follows:

$$e_s = \frac{1}{2}\sum_{q=1}^{s}\sum_{k=1}^{r}(t_k^q - o_k^q)^2 \tag{3}$$

The reverse optimization process is to correct the network parameters, and the output layer correction algorithm is as follows:

$$\begin{cases} \Delta w_{ki} = -\eta \frac{\partial e_s}{\partial w_{ki}} = -\eta \frac{\partial e_s}{\partial Net_k^{in}} \frac{\partial Net_k^{in}}{\partial w_{ki}} = -\eta \frac{\partial e_s}{\partial o_k} \frac{\partial o_k}{\partial Net_k^{in}} \frac{\partial Net_k^{in}}{\partial w_{ki}} \\ \Delta a_k = -\eta \frac{\partial e_s}{\partial a_k} = -\eta \frac{\partial e_s}{\partial Net_k^{in}} \frac{\partial Net_k^{in}}{\partial a_k} = -\eta \frac{\partial e_s}{\partial o_k} \frac{\partial o_k}{\partial Net_k^{in}} \frac{\partial Net_k^{in}}{\partial a_k} \end{cases} \tag{4}$$

In formula: t_k^q and o_k^q represent the target and output values of the k-th neurons in the q-th sample output layer.

4. Case study

This paper takes the investment data of a municipal power grid as an example. First, key indicators are screened based on path analysis, and the interaction relationship between indicators is analyzed. Secondly, BP neural network model is used to predict the investment ability of power grid. Finally, and the prediction results are compared with the actual value of investment ability.

4.1 Sample selection and division

Data on factors affecting investment capacity from 2011-2020 were used as a training set sample, and data in 2021 were used as a test set sample.

4.2 Investment capacity forecast

(1) Analysis of the model prediction effect

After multiple training sessions, training set predicted values and training set scatter fitting results, as shown in Figures 2 and 3, respectively. The predicted value of investment ability almost coincides with the expected value. The strong correlation between the predicted value and the true value, and the correlation coefficient is reaching 1.0000.

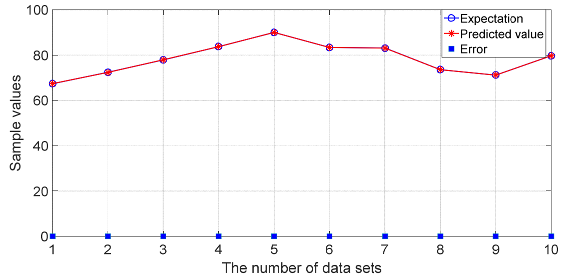

Figure 2 The predicted and actual values of the training set are compared

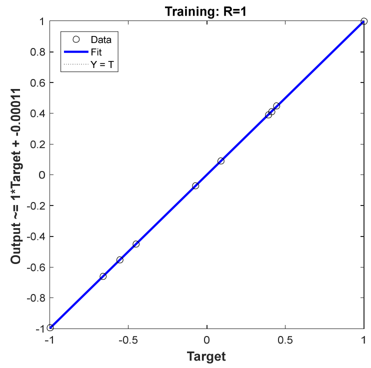

Figure 3 training set scatter fitting results

(2) Analysis of investment ability prediction results

The investment capacity prediction results are shown in Table 3, and the actual investment pair is shown in Figure 4. Before 2016, Chongqing Electric Power Company's investment capacity showed a rapid growth trend and peaked in 2016; from 2017-2020, the investment capacity gradually decreased; in 2021 and 2022, the investment capacity gradually increased and then leveled off; from 2011-2024, the investment capacity can meet the investment demand.

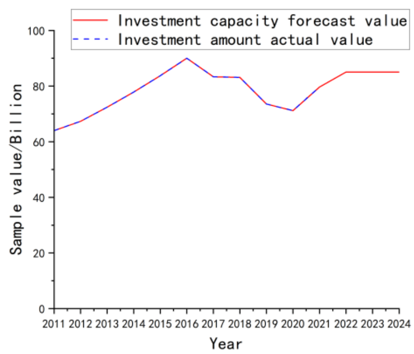

Figure 4 Comparison of actual investment amount and maximum investment capacity value

Table 3 Investment capacity value between 2022-2024

Year	Investment ability forecast value
2022	85.0736
2023	85.0742
2024	85.0721

5. Conclusion

This paper first selects the factors affecting the investment capacity of the power grid from the internal and external environment, and establishes the index system of the factors affecting the investment capacity. On this basis, the path analysis is used to analyze the interaction relationship between various indicators and investment capacity. Finally, the power grid maximum investment capacity is predicted based on the BP neural network prediction model. The results show that:
(1) The actual investment of the power grid in each region is within the investment capacity, and the prediction method is practical and feasible.
(2) In recent years, power grid investment remains high but the overall downward trend.

References

1. Design and realization of the investment capability analysis system of Dai Wenbo power grid enterprises [D]. North China Electric Power University, 2012.
2. Lu Xin, Wu Ting, Zhang Xiaofen. The Impact of Management Power on Corporate Investment [J] Management Review, 2014,26 (08): 168-180..
3. Pan Liqiang, Sheng Kun, He Hongbin, et al. Evaluation of 220kV Power Grid Investment Capacity Based on TOPSIS Method[J]. Modern Economic Information, 2016 (07): 380-383.
4. He Kelei, Zeng Ming, Qiao Hong. Research on Power Grid Investment Optimization Model Based on System Dynamics [J]. Shaanxi Electric Power, 2015,43 (12): 62-65.
5. Xia Huali, Ye shu. Power grid investment influencing factors and growth effect[C]. Power grid engineering cost management excellent paper, 2011: 20-28.
6. Zhang Pengfei, Liu Lu, Yang Weihong, et al. Multi-region power grid investment capacity measurement method based on asset-liability ratio [J]. Journal of Electric Power System and Its Automation, 2018, 30(06): 85-89.
7. Qi Yongwei, Yang Chunhui, Zhang Yingcai, et al. Research on investment allocation model and investment capacity measurement model adapted to power transmission and distribution price reform[J]. Power and Energy, 2017, 38 (04): 424-427.
8. Pan E, Peng D, Long W, et al. Provincial Grid Investment Scale Forecasting Based on MLR and RBF Neural Network[J]. Mathematical Problems in Engineering, 2019, 2019: 1-12.
9. Wang Ling, Wu Hongliang, Peng Daoxin. Prediction of grid investment scale under the new round of transmission and distribution price supervision cycle-is based on optimized support vector machine model[J]. Technical Economy, 2020, 39 (10): 45-53.
10. Wang Mianbin, Qi Xia, An Lei, et al. Investment prediction of VMD-SVM under small samples[J]. Science and Technology Management Research, 2020, 40(16): 231-235.
11. Chen Guanlan. Power Grid Investment Prediction Algorithm based on Deep Learning[D]. North China Electric Power University (Beijing), 2021.
12. Liu Wei, Li Meng, Li Qiuyan, et al. Grid portfolio prediction method based on improved genetic algorithms[J]. Power System protection and Control, 2020, 48 (08): 78-85.
13. Li Kangping. The Application of Entropy Method in Wind Power Combined Prediction[J]. Applied Mechanics and Materials, 2014, 3365: 602-605.