Research on Enterprise Financial Risk Prediction of BP Neural Network

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Abstract: Some problems have gradually emerged in the process of enterprise operation with the rapid development of the economy, which causes the financial sector of modern enterprises to face greater risks. To actively respond to financial risks and further improve enterprises' risk response and prevention capabilities, enterprises should establish a forecasting mechanism that can the enterprises' financial risks based on the actual financial operation. This paper discusses the application of BP neural network in financial risk forecasting, starts with selecting financial risk information indicators, studies the theory of risk identification, and designs and optimizes the risk assessment model by constructing BP neural network and using the idea of combined forecasting. Finally, to eliminate the negative influence of the local optimum, the particle swarm algorithm is used to improve the convergence ability of the model, thereby improving the algorithm's robustness.

1. Introduction

With the rapid development of my country's economy, the number of enterprises of various sizes in my country is increasing. The business activities of enterprises affect the development of this industry and promote the progress of society. However, since Chinese reform and opening up, although the economic development trend is good, for enterprises themselves, their internal risk management and control capabilities need to be improved [1]. In many corporate affairs, the financial status can give clearer feedback on the current situation of the company's development. It can also more accurately display the problems faced by the company. Therefore, data analysis based on financial data is always key business management and evaluation activity. The assessment of financial risk is at the heart of business assessments. For modern enterprises, the enterprise's financial risk has been difficult to see due to the many indicators involved, which requires establishing a more intelligent and accurate enterprise financial risk and forecasting framework to further adapt to the needs of enterprises and investors for real-time monitoring and evaluation of the business status of enterprises. Through literature search and research, it can be found that there are many studies on financial risk prediction. Starting from the characteristics of the enterprise financial crisis itself, some scholars have designed an evaluation model of related factors to screen the core factors that affect the financial status of enterprises [2]. Some scholars have also established a univariate model, expecting to predict the financial risk at a certain time point in the future. With the development of artificial intelligence technology, research on the application of artificial intelligence in financial risk prediction has gradually emerged, and financial risk prediction methods and theories based on decision trees and BP neural networks have been formed. In addition, there are studies on the use of statistical methods to build forecasting systems, but simply using statistical methods requires high data requirements, and its practicability is difficult to fully guarantee [2]. This paper constructs a financial risk prediction model suitable for enterprises by studying the enterprise financial risk assessment method and combining it with BP neural network. The research is expected to provide specific help to enterprise financial risk management.

2. Overview of BP Neural Network

BP neural network is a feedforward neural network processing method that simulates the work of the human brain. This type of neural network contains one or more layers of hidden layer networks and can handle linear inseparable problems. Since the emergence of the neural network, the problem of multi-layer network weight processing has been encountered, which greatly limits the application of neural networks. In the 1980s, BP neural network was proposed by Rumelhart, McClelland, et al., which optimized the weights of the multi-layer neural network through parallel distributed processing and greatly improved the applicability of the neural network [3]. The BP neural network model with the simplest structure has a three-layer structure: the input, hidden, and output layers. Specifically, the hidden layer is usually a multi-layer structure. Figure 1 shows a basic BP neural network topology.

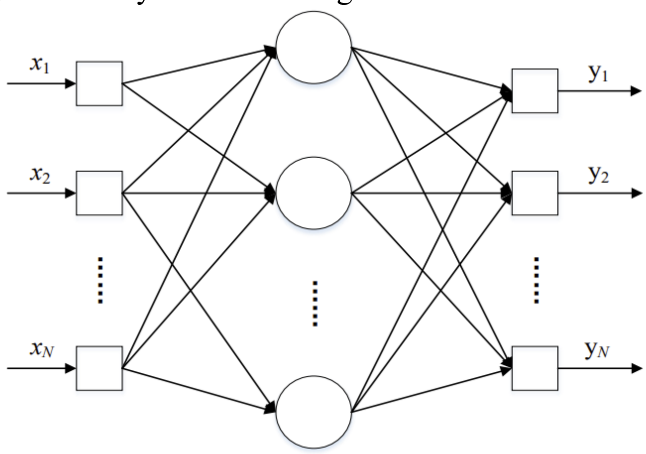

Figure 1 Schematic diagram of BP neural network structure

BP neural network has the following typical characteristics:

First of all, the BP neural network has a multi-layer structure, the neurons in the same layer are independent of each other, and the sexual neurons between layers are related to each other in the form of full connection. This network structure enables it to capture various features of the input signal and express the importance of each feature through weights. The weights are continuously revised through the training process, and some links are randomly discarded through loss to avoid overfitting [3].

Second, the transfer function of BP neural network is differentiable. BP neural network smoothly uses sigmoid or linear function as a transfer function. When selecting the S-function, it is mainly to judge whether it outputs a negative value. The S-function is smooth and differentiable, so its accuracy is higher than that of linear functions in classification applications, and it has better fault tolerance. Among them, the linear function is usually used as the transfer function of the output layer to avoid excessive restriction of the output value, and the sigmoid function is usually used as the transfer function of the hidden layer [4].

Third, the BP neural network uses the method of backpropagation to provide feedback on the error. In the BP neural network, the data is propagated layer by layer, and the weights of each neuron in each layer are continuously updated. After reaching the output layer, the training error is evaluated, the error correction signal is gradually passed forward to decrease error, and the weights are continuously optimized. With the continuous progress of the learning behavior, the final error will converge to a certain range, at which point the training can be terminated, and the model can be output.

3. Analysis on the Forecasting Methods of Enterprise Financial Risk

3.1 Enterprise Financial Risk Prediction Ideas

The financial risks of the enterprise mainly come from the daily operation and management activities. Among them, many factors affect the financial risk of enterprises, including the ability of enterprise management, solvency, profitability, future growth expectations, etc., all of which directly affect the estimation of enterprise financial risk. Based on this, it can be seen that various financial indicators of an enterprise are very important for evaluating and predicting financial risks. Considering the feasibility of obtaining financial indicators and the convenience of operation, screening financial data to a certain extent and selecting appropriate financial indicators as the basis for risk assessment is usually necessary. Based on these data, using the BP neural network, a neural network model for predicting financial risks can be established, and the selected enterprise operation indicators are input into the neural network model as parameters so that the financial risks in the process of the enterprise operation can be fuzzily identified for enterprise management decision-making [5]. Table 1 presents some typical financial information risk indicators according to the enterprise financial information management model's research theory.

Table 1 Financial Information Risk Indicators

Category	Index
Short-term solvency	X1 flow rate ratio
	X2 flow rate ratio
	X3 working capital asset ratio
Long-term solvency	Assets and liabilities
	Debt to equity ratio
	Long-term debt-to-equity ratio
Operational capability	Inventory turnover
	Total asset turnover
	Accounts Receivable Turnover
Profitability	Main business ratio
	Return on total assets
	Return on equity
	Loss ratio
Growth ability	Growth rate of the leading business
	Total Assets Expansion Rate

3.2 Enterprise Financial Risk Prediction Method

Subject to the company's technical conditions and other constraints and restrictions, the company's financial information will always show a certain limited and non-equilibrium. This makes it difficult to use traditional financial analysis methods to conduct comprehensive analysis and evaluation through financial data. With the advent of the information age, there are more data sources and higher dimensions, which makes it possible to use comprehensive financial data for risk assessment and prediction. In the market economy, financial risks will always exist. Only by discovering and warning risks as soon as possible can we provide more objective and scientific suggestions for the production and operation of enterprises. Among them, the design of the financial risk forecasting method is particularly critical. This paper proposes a comprehensive forecasting method based on combined forecasting. The core purpose of combined forecasting is to integrate the obtained single forecast information and use the integrated data to make an overall forecast, weakening the excessive influence of individual indicators on the results and reducing the subjectivity of the forecast results [6].

When predicting a problem, there are m pieces single-item unbiased prediction methods. Using y_{it} to represent the result of the prediction performed by the i-th method at the t-th time, the prediction error can be expressed as $e_{it} = (y_t - y_{it})$. At the same time, let the combined weight be w_i, which should satisfy Equation 1. At the same time, let e_t be the error expectation of the t period, then there is formula 2, where $\hat{y_t}$ is the predicted value of the t period, and y_t is the actual value of the t period. Finally, the sum of squared errors of combined prediction can be obtained as shown in Equation 3.

$$w_1 + w_2 + \ldots + w_m = 1 \tag{1}$$

$$e_t = y_t - \hat{y_t} = \sum_{i=1}^{m} w_i e_{it} \tag{2}$$

$$W = \sum_{t=1}^{T} e_t^2 = \sum_{t=1}^{T} \sum_{i=1}^{m} \sum_{j=1}^{m} w_i\, w_j e_{it} e_{jt} \tag{3}$$

In the above optimal combination prediction, to minimize the error, the objective function is usually expressed in the form of error to approximate the real situation once. The final constructed weight optimization model is shown in Equation 4, where X is the objective function, w_i is the same as the previous one and is the weight coefficient. The optimal combination model is shown in Equation 5.

$$\begin{cases} minX = X(w_i) \\ s.t. \sum_{i=1}^{m} w_i = 1 \\ \quad w_i \geq 0 \end{cases} \tag{4}$$

$$\hat{y} = w_1 y_1(t) + w_2 y_2(t) + \ldots + w_m y_m(t) \tag{5}$$

4. Enterprise Financial Risk Prediction Model Based on BP Neural Network

This time, BP neural network is selected as the realization method of the enterprise financial risk prediction model. Using BP neural network to construct and apply the network risk prediction model, as shown in Figure 2, it is necessary to prepare appropriate training data first and then input the training data into the network to make the learning signal flow forward through each neural network. Through the hidden layer, it finally reaches the output layer. After that, the training error is calculated and iterated continuously. After the training is completed, the evaluation data is used for backpropagation to correct the network. Finally, the verification data is used to judge the accuracy and determine whether the training is completed to obtain a neural network model that can be used for financial risk estimation [7].

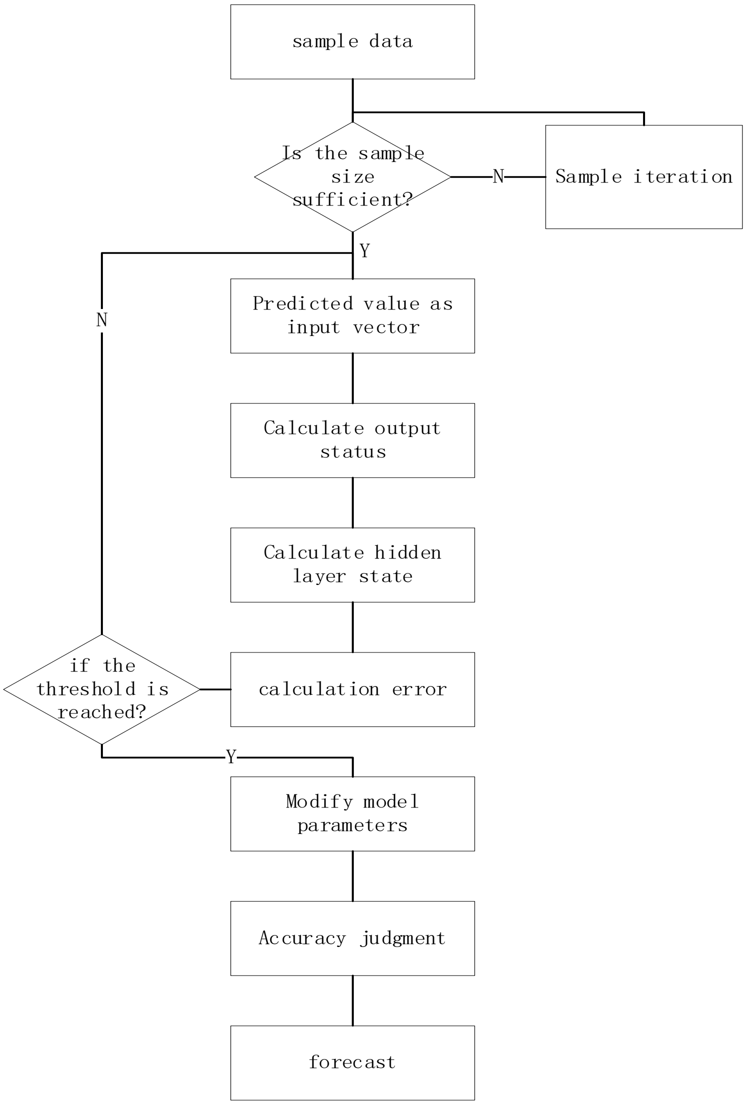

Figure 2 Schematic diagram of enterprise financial risk forecasting process

First, the training data and prediction data need to be prepared. As mentioned above, when predicting the financial risks of an enterprise, there are indicators such as business management ability, debt repayment ability, profitability, and growth ability that can be used in the forecasting process. In the training process, data samples with financial risks and data samples from healthy companies are required. This research can sort out the above-mentioned financial data of ST companies that have published financial reports and select the financial data of high-quality, healthy companies to form training data together. At the same time, the positive and negative training materials are divided into two parts: training data and validation evaluation data, which is used for subsequent model training and validation.

Let the input vector set X and the output vector set Y be represented by Equations 6 and 7, respectively.

$$X = \{x_1, x_2, \dots\dots, x_n\}^T \tag{6}$$

$$Y = \{y_1, y_2, \dots\dots, y_n\}^T \tag{7}$$

Let W be the weight from the input layer to the hidden layer, the number of neurons in the hidden layer is denoted as k, and the weight of the hidden layer is denoted as x_i, and the input k_j of each neuron in the hidden layer can be expressed by Equation 8 , where j is a positive integer in the interval

$$[0,\ k].k_j = \sum_{i=1}^{n} w_{ij} - x_j, j = 1,2,\dots\dots,k \tag{8}$$

As mentioned above, when the transfer function is selected, the transfer function of the hidden layer is usually selected as the S-function, and the typical S-functions include the Log-Sigmoid and Tan-Sigmoid functions. In this study, Log-Sigmoid is selected as the transfer function in the enterprise financial risk prediction model, and the function f(x) can be expressed as Equation 9.

$$f(x) = \frac{1}{1+e^{-x}} \tag{9}$$

For the input unit of the hidden layer, it can be expressed by Equation 10.

$$\lambda_i = \frac{1}{1+exp(-\sum_{i=1}^{n} w_{ij} - x_j)} \tag{10}$$

The data is finally passed to the output layer through the arithmetic processing of the input and hidden layers. For the input layer, the input and output can be represented by Equation 11 and Equation 12, respectively. where v_{jt} represents the weight from the hidden layer to the output layer, and ξ_t represents the output threshold.

$$\varsigma_t = \sum_{j=1}^{n} v_{jt}\,\lambda_j - \xi_t \tag{11}$$

$$\eta_i = \frac{1}{1+exp(-\sum_{j=1}^{n} v_{ij}\lambda_j - \xi_t)} \tag{12}$$

The characteristic of the financial risk prediction model based on BP neural network designed this time is that the risk identification error can be calculated and back-propagated. The formula shown in Equation 13 can be used when performing error analysis on single risk data. Based on the error of each risk data, the overall error can be accumulated.

$$\mu_t = \frac{\sum_{t=1}^{n}(y_t - \eta_i)^2}{2} \tag{13}$$

To further control the calculation error of each node in the entire network, the weights and thresholds of each node in the network should be optimized by further reducing the error value of a single sample, as shown in Equation 14. According to the weight vector of the output layer, Δv_{jt} can be expressed as Equation 15, where τ represents the learning rate.

$$\Delta v_{jt} = \frac{-\tau\partial\mu_t}{\partial v_{jt}} \tag{14}$$

$$\Delta v_{jt} = -\tau(y_i - \eta_j)(1 - \eta_j)\kappa_j \tag{15}$$

Accordingly, the modification method of the weights and thresholds of the hidden layer of the finally determined financial risk prediction model can be expressed by Equation 16 and Equation 17.

$$17\begin{cases} \Delta w_{ij} = \lambda e_j^n x_i \\ \Delta x_{ij} = \lambda e_j^n \end{cases} \tag{16}$$

$$e_j^k = \left(\sum_{i=1}^{n} d_t^n v_{ij}\right)\lambda_j(1-\lambda_j) \tag{17}$$

So far, the structure and parameters of the BP neural network for financial risk prediction are completed. By changing the model, the training samples can be input into the model through the input layer, and through multiple layers of hidden layers and output layers, certain weights and thresholds can finally be obtained, and a complete model training can be completed. Repeated learning and training can continuously update the above weights and thresholds. However, similar to other neural networks, this method easily falls into the local optimum, so particle swarm optimization is usually selected to improve the convergence ability of the model, thereby further enhancing the robustness of the entire algorithm [8]. In this process, the particle swarm algorithm calculates the fitness of each calculation process by the fitness algorithm, thereby reducing the training error of the BP neural network constructed this time. To further optimize the network, it can be considered to construct the optimal weights and thresholds and achieve a better model training effect.

5. Conclusion

Analyzing enterprise financial information is the key to enterprise operation status and risk assessment for enterprise development. Traditional financial analysis methods only analyze data by comprehensively calculating a single indicator or using mathematical, statistical methods to analyze data, which is challenging to adapt to the complex trend of enterprise development and has high requirements for the quality and comprehensiveness of sample data. This paper proposes using the BP neural network to solve the problem of enterprise financial risk forecasting and achieve a better financial risk forecasting effect by screening indicators, designing the network, setting parameters, training the network, error correction, and model optimization.

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