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Research Article

Enterprise Financing Risk Analysis and Internal Accounting Management Based on BP Neural Network Model

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A BP neural network-based model is proposed to study corporate financial risk analysis and internal accounting management. Using MATLAB software and the BP neural network model, it is possible to obtain enterprise financing risk situations over a period by simulating and predicting enterprise financing risks by creating an early warning model for enterprise financing risks. Finally, from the point of view of the company's internal and external operations, the company's financial risk prevention measures and proposals are proposed to improve the financing efficiency of the companies and to prevent financial risks. This study predicts the financing risk of companies listed on the Mongolian Stock Exchange and analyzes the causes of the risk status. According to the test results, the learning speeds for successive substitutions are as follows: 0.005, 0.01, 0.02, 0.03, and 0.04. Finally, it was found that the error was minimal and the stability was best when the learning speed was exactly 0.01. The error is 0.0031011, and the step size is 157, which is only slightly lower than the target error value, which indicates that the learning speed is good. In addition, the novelty of this study is the use of the BP neural network model to conduct an early warning study of corporate financial risks. The BP neural network assessment model for corporate lending risk in this document is highly accurate. In addition to providing theoretical insights to researchers, it can be a good tool for banks to realistically assess the credit risk of SME supply chain financing.

1. Introduction

The SMEs are a product of economic reform and have contributed to economic development and social progress. However, traditional small- and medium-sized enterprises have been overwhelmed and unable to resist the external environment and fierce market competition that has become increasingly complex during development. In addition, their enterprises lack viability and are poorly managed [1]. During this period, small and medium enterprises have collapsed one after another, and several negative cases and adverse effects have occurred. It should be noted that the driving force behind the transition of enterprises is no longer simple elements but soft forces such as technological innovation. In contrast, China's traditional economic path of high consumption and low energy not only wastes a lot of manpower and material resources but also misses out on good development opportunities. With China's accession to the WTO, it must face the general pattern of globalization, improve its national strength, and prioritize technological innovation to further improve the living standards of its people. The development of an innovative economy and the creation of an innovative social system have become a priority. As the backbone of small and medium enterprises, it is clear that innovative small and medium enterprises play a positive role. In this context,

modern small and medium enterprises have emerged, joined the economic wave, and walked the forefront of the time [2].

The influx of international champions, the fierce competition of domestic companies under the middle bag, and the lack of funding for the development of innovative small- and medium-sized enterprises have not been resolved. Although foreign scholars have contributed to the challenges and proposals for financing SMEs, there are very few analytical studies using the financing capacity of the new era of SMEs, especially the BP neural network method. The laws of a market economy are unstable. The allocation of scientifically sound and efficient resources depends on the development prospects of enterprises. Therefore, it is necessary to be closely related to the current basic conditions of development of the market economy, to direct private capital to local conditions, and to implement legal and rational capital operations (Figure 1). These issues are the theoretical basis for the system for assessing the financing capacity of innovative small and medium enterprises, and the requirements for multichannel and innovative financing of enterprises. At present, technological research and industrial innovation are the main content of research in innovative enterprises, but the financing capacity of innovative enterprises is rarely considered in terms of financing structure. This study examines innovative financing for small and medium enterprises as an integrated system. This document, which is at the peak of the sustainable development strategy of enterprises, systematically proposes a comprehensive evaluation index system appropriate to the financing capacity of innovative small and medium enterprises, which is important to guide innovation small and medium enterprises' financial risk assessment and program optimization [3].

2. Literature Review

Lan and Li pointed out, in the process of organizational cooperation or alliance cooperation, that mutual trust among members can effectively reduce the risk of failure, which is very important for the whole cooperative enterprise [4]. Aiqun et al. specially studied the important impact of trust on R & D through empirical experiments and pointed out that the higher the degree of trust between members, the easier it is to promote R & D. On the contrary, the lower the degree of trust, the easier it is to bring risks to cooperation [5]. Li et al. believe that a cooperation lacking trust cannot last for a long time. To establish a long-term cooperative relationship, members must strengthen mutual trust [6]. Zhao and Lv believe that the intellectual property risk caused by bad credit has become a shackle hindering cooperative R & D, explore the causes of such risks, and give corresponding prevention and control measures [7]. Li and Quan take fast trust as the research perspective and believe that fast trust plays a positive role in solving intellectual property risks and forming performance of innovation alliance [8]. For example, Wu and Lu established a conceptual model of risk transmission among enterprises participating in cooperative innovation and pointed out that inhibiting risk transmission should be carried out from the two dimensions of prevention and process control to weaken the negative effect of risk transmission. They also believe that building a corresponding risk early warning system, improving the enterprise's understanding of risk transmission, and the ability to deal with risks are the three aspects of enterprise prevention and control; the three aspects of process control are to monitor the interaction of risks, reduce the speed of risk transmission among enterprises, and hinder the transmission path of risks [9]. Xuesong et al. calculated the index risk value of each partner in the cooperative alliance from the perspective of the third party, constructed the early warning system of information sharing risk, and gave different early warning information according to different degrees of risk, so as to curb the risk caused by information sharing [10]. Nayak et al. constructed a technological innovation risk early warning model integrating functions, early warning index system, and risk response strategies, which pointed out the direction for the response and strategy research of enterprise technological innovation risks [11]. Shen et al. established a risk early warning system for enterprise technological innovation projects using a rough neural network, which is both effective and feasible, pointing out the direction for the risk early warning management of enterprise technological innovation projects [12]. Zou analyzed the characteristics of risks in the process of joint innovation from the perspective of financial management and constructed a new financial early warning system. The system has the functions of monitoring, early warning, incentive, and reward and can effectively avoid the risks [13].

Based on the current research, a BP neural network model is proposed. Using the MATLAB software and the BP neural network model to build the enterprise financing risk early warning model, the enterprise financing risk simulation forecast gets a certain period in the future enterprise financing risk status. Finally, for the company's internal activities and external activities, to ensure that enterprises achieve the purpose of improving financing efficiency and preventing financing risk, this must be considered from the two perspectives of corporate financing risk prevention countermeasures and suggestions. This study predicts the financing risk of listed companies and analyzes the causes of the risk.

3. Financing Risk Analysis Based on BP Neural Network

3.1. Establishment of 1bp Neural Network Model. The establishment of the BP neural network model is divided into six stages. The first stage is to find and process the financing risk early warning index data required by the BP network model. The second stage is to determine the training input data, training target data, test input data, test target data, and prediction input data of the BP network model. The third stage is to divide the early warning and warning

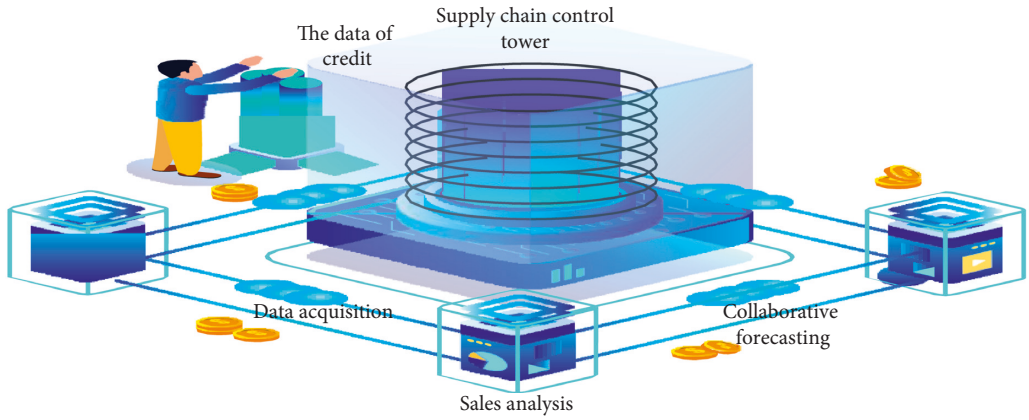

Figure 1: Enterprise financing risk analysis.

interval of financing risk. In the fourth stage, the training input data and training target data of the BP network model are input, the parameters of the model are set, and sample training is conducted. In the fifth stage, the test input data and test target data selected by the early warning model are input for the sample test. In the sixth stage, the prediction input data selected by the early warning model are input for sample prediction.

The algorithm flow of the BP neural network model is shown in Figure 2, including starting, determining data, calculating the node output value of the hidden layer and output layer, calculating the deviation value, comparing and meeting the deviation, adjusting parameters, and obtaining the model.

The algorithm flow of the BP neural network model is shown in Figure 2. The flow is simple, including starting, determining the input data and target data, calculating the node output value of the hidden layer and output layer, calculating the deviation value between the target value and actual output, comparing and meeting the deviation, adjusting parameters, and obtaining the model [14].

First, the input data and target data of the model are determined, and then, the output values of each hidden layer and output layer node of the model are obtained. Through the comparison of the target value and output value, the deviation between the target value and the actual output is obtained. When the error fluctuation is within a certain range, the algorithm is ended, so as to obtain the established BP network model; if the error fluctuation exceeds the limited range, the error of hidden layer nodes should be calculated, the error gradient should be calculated, then, the parameters of the number of hidden layers and nodes should be set, and then, the target value and actual output error are calculated until the obtained error meets the set error range, so as to establish the BP network model and obtain the parameters, threshold, and weight of the model.

The learning process of the BP neural network model is to minimize the error. The training process of the model needs to provide input vectors.

X and target vector y can adjust the weight and threshold of the network according to the error performance of the adjustment model, with the purpose of making the model achieve the process of learning and imitation.

Let the model have n layers of the neural network, the input independent variable of the model is x, and let the sum of the input information of the i-th neuron of the m-th layer of the BP network model be S_i^m and R_i^m as the output information of the i-th neural node, A_{ij} is the connection weight between the i-th neural node of this layer and the j-th neural element output of the upper layer, and f is the functional relationship between the input data and the output data. The relationship between input and output is shown as follows:

$$\begin{aligned} R_i^m &= f\left(S_i^m\right), \\ S_i^m &= \sum A_{ij} R^{m-1}. \end{aligned} \tag{1}$$

The C_j is set as the target output value of the model. R_i^n is the actual output result calculated by the system network. It is a function obtained by connecting weight and input mode [15]. The error function is represented by error E, which is the sum of squares of the difference between the actual output value and the target output value, and its expression is as follows:

$$e = \frac{1}{2} \sum \left(R_i^n - c_j\right)^2. \tag{2}$$

The meaning of this function is to make the actual output value close to the target output value by calculating the minimum value of the error function. In order to achieve the purpose of error, nonlinear programming method can be used to reduce the error function along the gradient direction. The updated amount ΔA_{ij} of its weight A_{ij} can be expressed by the following formula:

$$\Delta A_{ij} \infty - \varepsilon \frac{\partial d}{\partial A_{ij}}. \tag{3}$$

Therefore, the following formula can be listed:

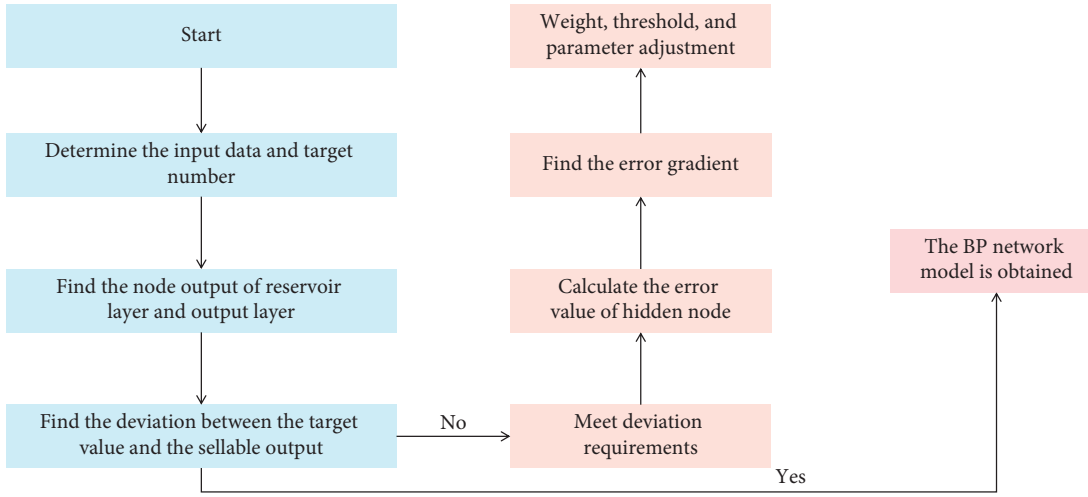

Figure 2: Flowchart of the BP network model.

$$\frac{\partial S_i^m}{\partial A_{ij}} = \frac{\partial}{\partial A_{ij}}\left(A_{ij}R_j^{m-1}\right) = R_j^{m-1},$$

$$\frac{\partial e}{\partial A_{ij}} = \frac{\partial e}{\partial S_j^m}\frac{\partial S_j^m}{\partial A_{ij}} = \frac{\partial e}{\partial S_j^m}R_j^{m-1},$$

$$\Delta A_{ij} = -\varepsilon\frac{\partial e}{\partial S_j^m}R_j^{m-1}, \tag{4}$$

$$d_j^m = \frac{\partial e}{\partial S_j^m},$$

$$\Delta A_{ij} = -\varepsilon d_j^m R_j^m.$$

In equation (2), ε represents the parameter of learning rate.

$$R_i^m = f\left(S_i^m\right),$$

$$\frac{\partial R_i^m}{\partial S_j^m} = f\prime\left(S_j^m\right). \tag{5}$$

If $f(S_j^m)$ is a nonlinear sigmoid function,

$$f\left(S_j^m\right) = \frac{1}{1+\exp\left(-S_j^m\right)},$$

$$f'\left(S_j^m\right) = R_j^m\left(1-R_j^m\right). \tag{6}$$

If I is the node in the output layer, then, $M = n$, and then, CJ is the target ax value preset by the system.

Then, the formula $(\partial e/\partial x)$ is found; if i is a node in the output layer, then, $m = n$, and then, C_j is the target ax value preset by the system, that is,

$$\frac{\partial e}{\partial S_j^m}\left(R_j^n - c_j\right),$$

$$d_j^n = R_j^n\left(1-R_j^n\right). \tag{7}$$

If i is not the node of the output layer, but the node of the hidden layer, then,

$$\begin{aligned}\frac{\partial e}{\partial R_j^m} &= \sum_i \frac{\partial e}{S_i^{m+1}}\frac{\partial S_i^{m+1}}{\partial R_j^m}\\ &= \sum A_{ij}d_i^{m+1},\\ d_j^m &= R_j^m\left(1-R_j^m\right)\sum A_{ij}d_i^{m+1}.\end{aligned} \tag{8}$$

Through the repeated operation of the model, it can be concluded that the error signal d_j^m of layer m is directly proportional to the error signal of layer m-1, and it can be adjusted according to the direction of consistency. In addition, the above calculation processes can prove that the principle of signal transmission of the BP neural network is the error function obtained by comparing the actual output value RJ obtained from the forward transmission of the input data of independent variables with the target output value and finally reducing the error value to a certain range through a series of parameter adjustments such as weight and threshold.

The weight adjustment can be reflected by the following formula:

$$\begin{aligned}\Delta A_{ij} &= -\varepsilon\frac{\partial e}{\partial S_j^m}R_j^{m-1},\\ d_j^n &= R_j^n\left(1-R_j^n\right)\left(R_j^n - C_j\right),\\ d_j^m &= R_j^m\left(1-R_j^m\right)\sum A_{ij}d_i^{m+1}.\end{aligned} \tag{9}$$

The above formula proves that the error signal d_j^m of m layer has strong correlation with the error signal d_i^{m+1} of $m+1$ and proves that the error signal is transmitted from the input layer to the output layer. After adjusting the weight, threshold, and other parameters of the BP neural network system for many times, the output value within the error range is finally reached. At this time, the system will

automatically stop learning and complete the construction of the BP network model [16].

3.2. Selection of Relevant Indicators. The early warning indicators of this study include 17 indicators in two aspects: capital integration and capital financing. The integration of funds includes financing scale, financing cost, financing structure, fund availability, and so on. In particular, as shown in Table 1, the financing scale selects two indicators: asset equity ratio and debt financing ratio; the financing cost includes debt financing cost and equity financing cost; the financing structure is reflected by the equity debt ratio, and the degree of funds in place is reflected by the speed of financing. The ability of financing includes profitability, operation ability, solvency, and growth ability. It is an important reference to measure the financing status of enterprises and analyze financing risks.

Profitability includes return on total assets and return on equity; operational capacity is assessed by three indicators: total capital turnover, inventory turnover, and receivables turnover; solvency is reflected in the following two indicators: current ratio, capital turnover, debt ratio, and growth capacity. Four financial indicators are as follows: total capital turnover ratio, fixed asset growth rate, operating income growth rate, and earnings per share growth rate.

Asset-to-equity ratio. The ratio of assets to equity is the ratio of owners' equity to total assets. This ratio reflects the share of the owner's investment, liabilities, and the relative amount of total equity in the firm's financing. In general, the higher the capital-to-capital ratio, the lower the financing risk and the lower the financing risk for the entity. The index formula is as follows:

$$\text{Asset equity ratio} = \frac{\text{owner}'\text{s equity}}{\text{total assets}}. \tag{10}$$

Debt financing ratio. The debt financing ratio refers to the ratio of debt financing through short-term borrowing, long-term borrowing, issuance of bonds, and other debt financing to the total financing of the company. The greater the value of debt financing cost, the greater the financing risk, and the greater the possibility of financing risk. On the contrary, the smaller the financing risk, the less likely the enterprise will have financing risk. The enterprise occurrence index formula is as follows:

$$\text{Debt financing ratio} = \frac{\text{total debt financing}}{\text{total assets}}. \tag{11}$$

Debt financing costs. Debt financing cost refers to the proportion of expenses incurred in the process of raising funds by listed coal companies through short-term loans, long-term loans, issuance of bonds, and other loan relationships. In particular, this expense is the financial expense on the balance sheet of each enterprise. The greater the value of debt financing cost, the greater the financing risk, and the greater the possibility of financing risk. On the contrary, the smaller the debt financing cost, the smaller the financing risk, and the smaller the possibility of financing risk [17]. The index formula is as follows:

Table 1: Financing early warning indicators' table.

Index selection	Financing ability	Indicators
Money into	Financing scale	Asset equity ratio
		Debt financing ratio
	The cost of financing	Debt financing cost
		Equity financing cost
	Financing structure	Equity to debt ratio
	Degree of funding	Raising speed
	Profitability	Return on total assets
		Return on equity
Money RongChu	Ability to operate	Total asset turnover
		Inventory turnover
		Accounts receivable turnover
	Debt paying ability	Current ratio
		Asset-liability ratio
	Growth ability	Growth rate of total assets
		Growth rate of fixed assets
		Growth rate of operating income
		Growth rate of earnings per share

$$\text{Debt financing cost} = \frac{\text{financial expense}}{(\text{short} - \text{term loan} + \text{long} - \text{term loan} + \text{bonds payable})}. \tag{12}$$

Equity financing cost refers to the proportion of expenses incurred by enterprises through equity financing channels such as IPO, share allotment, and additional issuance. In this study, the equity financing cost is estimated by calculating the sum of the risk return rate and risk-free return rate through the capital asset pricing method (CAPM). The greater the value of equity financing cost, the greater the financing risk, and the greater the possibility of financing risk. The smaller the value of equity financing cost, the smaller the financing risk, and the smaller the possibility of financing risk of the enterprise. The index formula is as follows:

$$\text{CAPM} = R_F + \beta(R_M + R_F). \tag{13}$$

In the formula, R_I is the risk-free rate of return, and the interest rate of the three-year treasury bill is selected, which is about 6%. R_I is the average profit margin of the coal listed company industry.

Equity debt ratio. The equity debt ratio is an indicator that reflects the financing structure of a company and is the ratio of the company's total liabilities to total shareholders' equity. The greater the value ratio of equity to liabilities, the greater the financing risk of the enterprise, and the greater the possibility of financing risk of the enterprise. Conversely, the smaller the financing risk of the enterprise, the smaller the possibility of financing risk. The index formula is as follows:

$$\text{Equity to debt ratio} = \frac{\text{total debt}}{\text{total shareholders' equity}}. \quad (14)$$

Financing speed. The financing rate is an index of an entity's capital adequacy, which is the ratio of the entity's core business income to its total cash flow from financing activities. In general, the faster the financing rate, the lower the financing risk, and the lower the financing risk for the entity. Conversely, the larger the scope of enterprise financing, the greater the opportunity to finance risk. The index formula is as follows:

$$\text{Financing rate} = \frac{\text{total cash flow from business income}}{\text{financing activities}}. \quad (15)$$

Return on total assets. Return on total assets is an important indicator of the profitability of the formula and an important reference in choosing whether to conduct debt financing activities. This is equal to the ratio of the firm's average net profit to total assets. In general, the higher the financing value of the total return on an asset, the lower the financing risk, and the lower the probability that the entity will be exposed to the financing risk. Conversely, the higher the risk of corporate financing, the greater the opportunity to finance the risk. The index formula is as follows:

$$\text{Return on total assets} = \frac{\text{net profit}}{\text{average of total assets}}. \quad (16)$$

ROE. Return on equity, or the return on equity, also known as ROE, is an important indicator of the ratio of a company's profitability and net profit to the average shareholder's equity. In general, the higher the return on equity, the higher the profitability of mining companies, the better the operating efficiency, the lower the financing risk, and the lower the risk of financing. Conversely, the higher the financing risk, the higher the probability that the entity will be at financial risk. The index formula is as follows:

$$\text{Return on net assets} = \frac{\text{net profit}}{\text{total average shareholders' equity}}. \quad (17)$$

Total capital turnover. The ratio of total assets to turnover is an important basis for assessing the operational capacity of an enterprise. It can measure the distribution between the extent of an enterprise's capital investment and the level of activity. It represents the ratio of average sales to total assets. In general, the higher the share of total capital turnover, the higher the return on assets, the higher the level of asset management of the entity, the lower the financing risk, and the lower the financing risk. Conversely, the higher the risk of financing an entity, the higher the risk of financing that entity. The index formula is as follows:

$$\begin{aligned} \text{Total capital turnover} &= \frac{\text{sales revenue}}{\text{average total assets}}, \\ \text{Average total assets} &= \frac{(\text{total assets at the end of the period} + \text{total assets at the beginning of the period})}{2}. \end{aligned} \quad (18)$$

Inventory turnover. Inventory turnover rates are an important basis for reflecting an entity's operational capacity at the same rate as total asset turnover. It also compensates for the turnover ratio of current assets. In particular, the inventory turnover ratio reflects the management of the enterprise in the three stages of sales of goods purchased, put into production, and recycled, and the cost of sales is equal to the ratio of average inventory. In general, the higher the inventory turnover rate, the faster the entity's inventory disposal rate, the stronger its liquidity, and the lower its financing risk. Conversely, the higher the risk of financing an entity, the higher the risk of financing that entity. The index formula is as follows:

$$\begin{aligned} \text{Inventory turnover} &= \frac{\text{Sales costs}}{\text{Average inventory}}, \\ \text{Average inventory size} &= \frac{(\text{Starting Inventory} + \text{Ending Inventory})}{2}. \end{aligned} \quad (19)$$

Accounts receivable turnover rate. The turnover rate of accounts receivable reflects the turnover rate of accounts receivable and the financial management efficiency of the enterprise and reflects the operation ability of the enterprise. It is the ratio of net sales revenue to the average

balance of accounts receivable. The higher the turnover rate of accounts receivable, the faster the recovery rate of accounts receivable, which means that the average collection period is shorter, and this shows that the listed coal companies have strong asset liquidity and short-term solvency. The smaller the financing risk of the enterprise, the less likely it is to have a financing crisis. On the contrary, the financing risk of the enterprise is greater, and the possibility of a financing crisis is greater [18]. The specific formula is as follows:

$$\text{Turnover rate of accounts receivable} = \frac{\text{net sales revenue}}{\text{average balance of accounts receivable}},$$

$$\text{Average balance of accounts receivable} = \frac{(\text{balance of accounts receivable at the beginning of the period} + \text{balance of accounts receivable at the end of the period})}{2}. \tag{20}$$

Current ratio. The current ratio can explain and explain the liquidity of enterprise assets and the solvency of enterprises. It is the ratio of current assets to current liabilities. The larger the current ratio, the stronger the short-term solvency of the enterprise, and the less likely the enterprise a financing crisis is. On the contrary, the weaker the solvency of enterprises, the greater the possibility of financing crisis. The specific formula is as follows:

$$\text{Turnover ratio} = \frac{\text{current assets}}{\text{current liabilities}}. \tag{21}$$

Gear ratio. The ratio of assets to liabilities may reflect the liquidity of the entity's current assets before the maturity of short-term liabilities and is equal to the ratio of total liabilities to total assets. In general, the lower the capital-to-debt ratio, the stronger the long-term solvency of an entity and the less likely it is to enter a financial crisis, and conversely, the lower the solvency of an entity, the higher the probability of a financial crisis. The specific formula is as follows:

$$\text{Debt ratio} = \frac{\text{total liabilities}}{\text{total assets}}. \tag{22}$$

Gross asset growth rate. The growth rate of total assets is an important indicator of an enterprise's ability to accumulate and develop capital, and it is a measure of the ability to protect against changes in the scale of total assets. This is the ratio of value added to total assets at the beginning of the reporting period. In general, a growth rate in total assets indicates that the business is expanding. The higher the growth rate of total assets, the faster the amount of capital will grow, and the lower the risk of financing of enterprises, the higher the financing risk will be. If the growth rate of a company's assets is negative, there is a very high probability that the company will face a financial crisis. The specific formula is as follows:

$$\text{Asset growth rate} = \frac{(\text{total assets at the end of the period} - \text{total assets at the beginning of the period})}{\text{total assets at the beginning of the period}}. \tag{23}$$

The growth rate of fixed assets. The growth rate of fixed assets reflects the growth of fixed assets of enterprises. This is an important indicator of an enterprise's ability to develop and protect against risk. This is the ratio of the value added of fixed assets to total fixed assets at the beginning of the period. In general, the growth rate of fixed assets is positive and the scope of enterprise development is expanding. The higher the rate of growth of fixed assets, the faster the size of the enterprise's assets, and the lower the rate of financing, the lower the rate of growth of fixed assets. If the growth rate of fixed assets is negative, the probability of a financial crisis is very high. The specific formula is as follows:

$$\text{Growth rate of fixed assets} = \frac{(\text{end} - \text{time fixed assets} - \text{early fixed assets})}{\text{early fixed assets}}. \tag{24}$$

Operating income growth rate. The rate of growth of operating income is an important indicator of the growth and development of an enterprise. This is a key indicator of enterprise development. This is the ratio of operating income growth to operating income. In general, the growth rate of operating income is positive and the scope of enterprise development is expanding. If operating income growth is negative, the company is more likely to finance the crisis. The specific formula is as follows:

$$\text{Operating growth rate} = \frac{(\text{current operating income} - \text{operating income at the beginning of the period})}{\text{operating income at the beginning of the period}}. \quad (25)$$

Percentage growth rate per share. The rate of increase in earnings per share can be expressed as the ratio of a company's performance growth and development capacity, i.e., the rate of earnings per share, to earnings per share at the beginning of the period. In general, the higher the growth rate of EPS, the lower the risk of corporate financing and the higher the probability of a financial crisis; conversely, the lower the EPS growth rate, the higher the financing risk and opportunity. opportunity, and the smaller the financing risk. If the increase in earnings per share is negative, the company will have a great opportunity to finance the crisis. The specific formula is as follows:

$$\text{Percentage increase in earnings per share} = \frac{(\text{earnings per share at the end of the period, earnings per share at the beginning of the reporting period})}{\text{earnings per share at the beginning of the period}}. \quad (26)$$

3.3. Strategies for Improving the Internal Accounting Management System of Enterprises

3.3.1. Establishing Internal Accounting Management System. Managers are fully responsible for the accounting work of the enterprise and improving the accounting management system. Enterprises shall supervise and supervise the behavior of accounting staff, accounting institutions, and other personnel. Reward accountants are loyal to their duties and make remarkable achievements. Enterprise staff shall strictly implement accounting rules and laws, ensure that accounting materials are legal, true, accurate, and complete, and implement enterprise accounting management rules and regulations. An internal accounting management system is built, and supervision and assessment are improved. According to the actual situation of the enterprise, reasonable planning is made and the responsibilities of the accounting supervisor and the person in charge of the accounting organization are clarified. The working relationship and responsibilities of enterprise accounting are clarified, and it is ensured that accounting staff exercise their functions and powers according to the law.

3.3.2. Establishing a High-Quality Accounting Team. Accountants are managers and supervisors of enterprise business activities. The quality of accounting managers is closely related to the level of financial management. After the implementation of the new accounting system, higher requirements are put forward for the overall quality of enterprise financial accounting managers. Business management and accounting work need a group of qualified accountants. Accountants should constantly learn advanced financial management methods and new financial professional skills, master professional knowledge and financial system, and ensure the standardization of enterprise financial accounting work. At the same time, we should fully understand the actual development requirements of the market economy, constantly improve our ability, and skillfully apply the knowledge of financial management. At present, the quality of the enterprise accounting team is generally low. Enterprises should strengthen training and optimize the accounting team. Through formal training and learning, the professional quality of enterprise accounting staff should be improved, and the knowledge structure should be constantly improved, so that the staff can adhere to the principles, strictly exercise self-discipline, and be loyal to their duties. The quality of accountants has a direct impact on the quality of accounting work and is related to the implementation of the accounting management system. Enterprise accountants must have a strong ability to analyze and solve problems, a high-quality professional level, extensive knowledge, and good adaptability. Enterprise accountants should actively learn the contents of the new accounting system and relevant knowledge of financial accounting to improve their ability [19].

3.3.3. Establishing the Internal Management System of Accounting Computerization. Computerized accounting is conducive to the formulation of modern enterprise system and the improvement of accounting work quality. It is of great significance to the improvement of financial work efficiency and work quality. It is an important development direction of accounting. Full-time personnel should be used to manage accounting

Table 2: Relationship between hidden layer unit number and training step number.

Number of nodes in hidden layer	4	5	6	7	8	9	10	11	12	13	14	15	16
The training steps	167	268	163	255	152	233	241	255	156	230	179	236	160

computerization and carry out relevant training. The internal management system of accounting computerization should be established, given a full play to the role of accounting computerization, and improve the efficiency and quality of accounting work. Enterprises should regularly check the implementation of financial and accounting indicators, conduct financial and accounting analysis, find problems in time actively and improve, and improve the internal accounting management level of enterprises.

3.3.4. Establishing Internal Containment System. The establishment of a long-term and effective internal containment system in enterprises can strengthen the supervision and restraint of internal personnel, prevent favoritism, fraud, and serious mistakes and ensure the quality of accounting management. Reasonable division of labor and full implementation of the internal accounting system of enterprises need to build an internal containment system. The establishment of an internal containment system is conducive to the implementation of a modern enterprise internal accounting system. During the period of asset reorganization and a major investment, the enthusiasm of accountants should be brought into full play to ensure the stable operation of various economic activities. Enterprise managers should pay attention to correction, control, inspection, supervision, and other methods, carry out targeted enterprise management, and adhere to legal compliance. Internal control is of great value to ensure the safety of assets, the legitimate rights and interests of investors, and the quality of accounting information. Based on internal containment, the system should be constantly adjusted, and the internal control of the enterprise should be strengthened. Accounting control should be standardized, and the work of each link within the constraints of laws and regulations should be carried out. It should be insisted on stopping and exposing noncompliance, illegality, and other accounting to ensure the legitimacy and quality of accounting work.

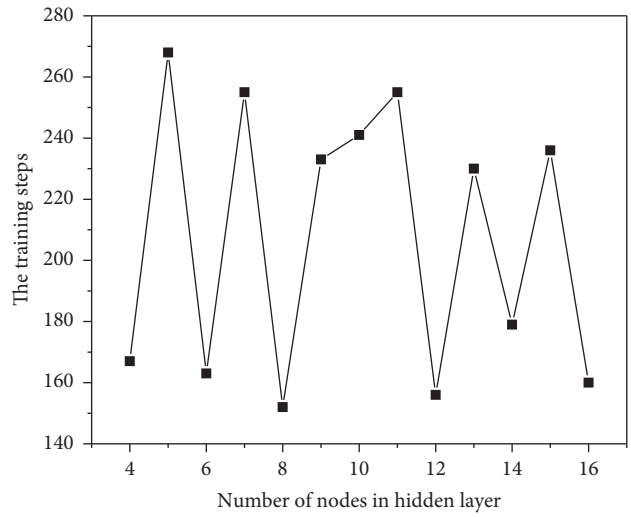

Figure 3: Relationship between the number of hidden layer units and the number of training steps.

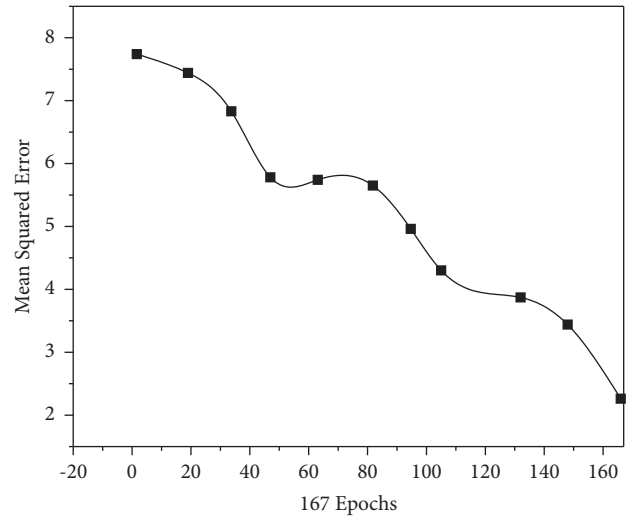

Figure 4: Error curve when hidden layer node is 4.

4. Experimental Results and Analysis

An analysis of the structure of the BP neural network shows that the number of latent nodes in the BP neural network model for risk assessment of SME credit for supply network financing should be between 5 and 14. In the case of setting the same parameters in this chapter, the number of nodes in the hidden layer should be alternated, the systematic errors of the model should be compared, a complete comparison should be made, and the most appropriate number of nodes in the hidden layer should be selected. In the BP neural network model, the latent layer excitation function is tansig, the output layer excitation function is the logsig function, and the training function is the traindm. The network learning era is defined as 2000, and the default value for the model learning speed is 0.01. The target error was set to 0.005 according to the actual output requirement. The number of nodes in the hidden layer is 4–16 each, and the size and convergence of the model errors are observed in the different nodes. By varying the number of nodes in the hidden layer, it is possible to obtain the relationship between the number of units in the hidden layer and the

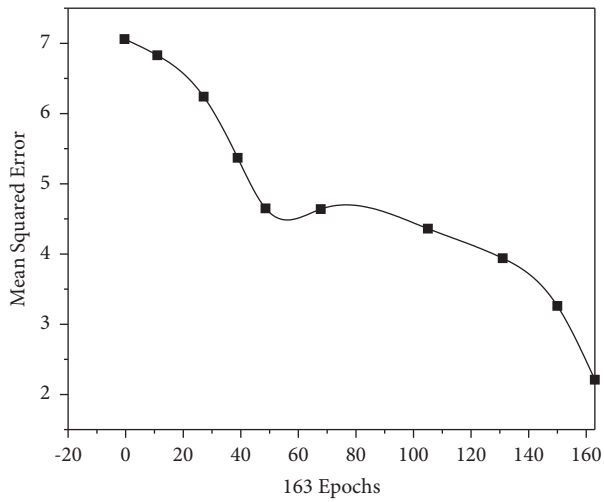

Figure 5: Error curve when hidden layer node is 6.

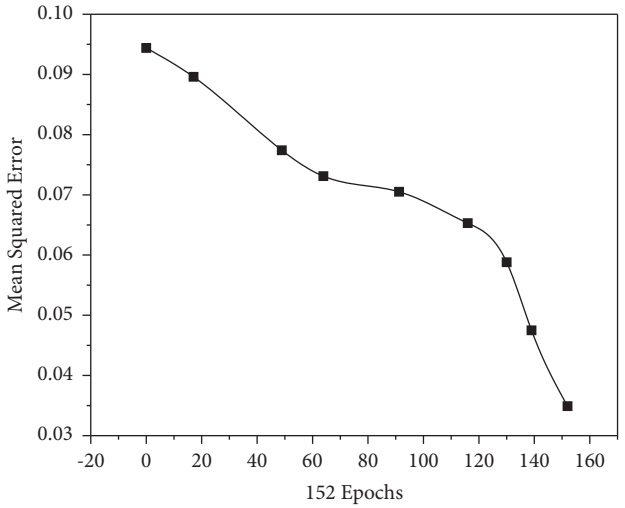

Figure 6: Error curve when hidden layer node is 8.

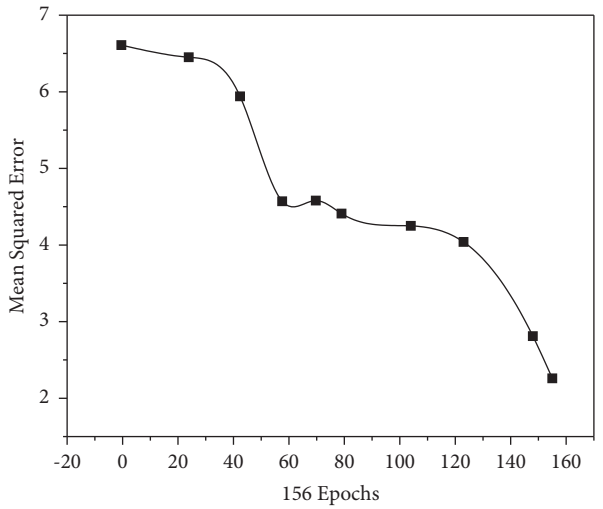

Figure 7: Error curve when hidden layer node is 12.

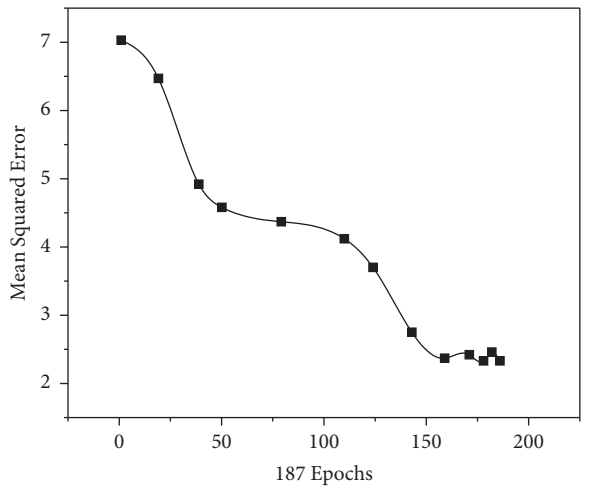

Figure 8: Error curve when hidden layer node is 14.

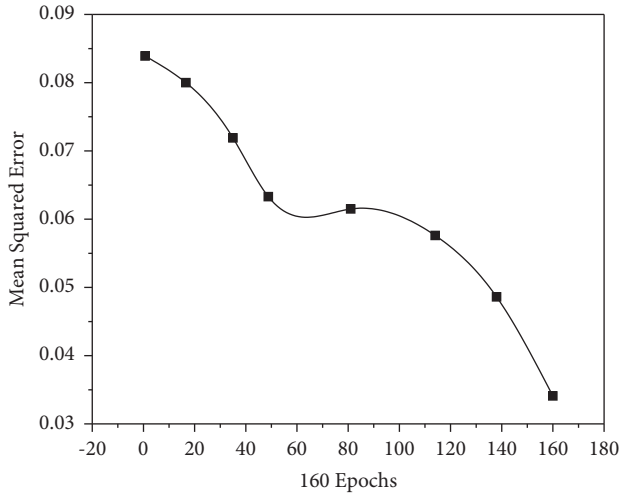

Figure 9: Error curve when hidden layer node is 16.

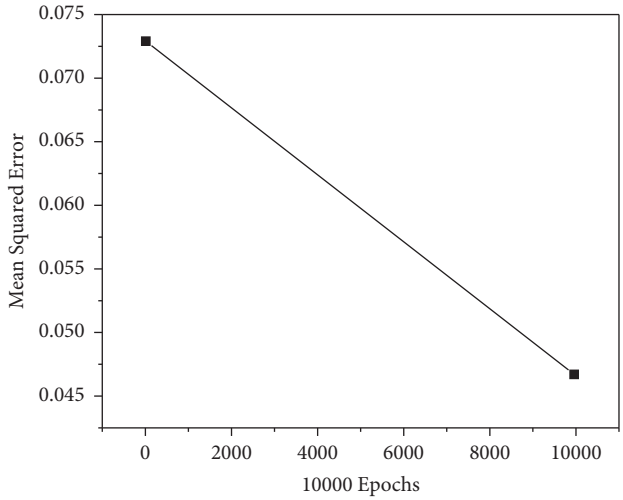

Figure 10: Traingdm is the error curve of the training function.

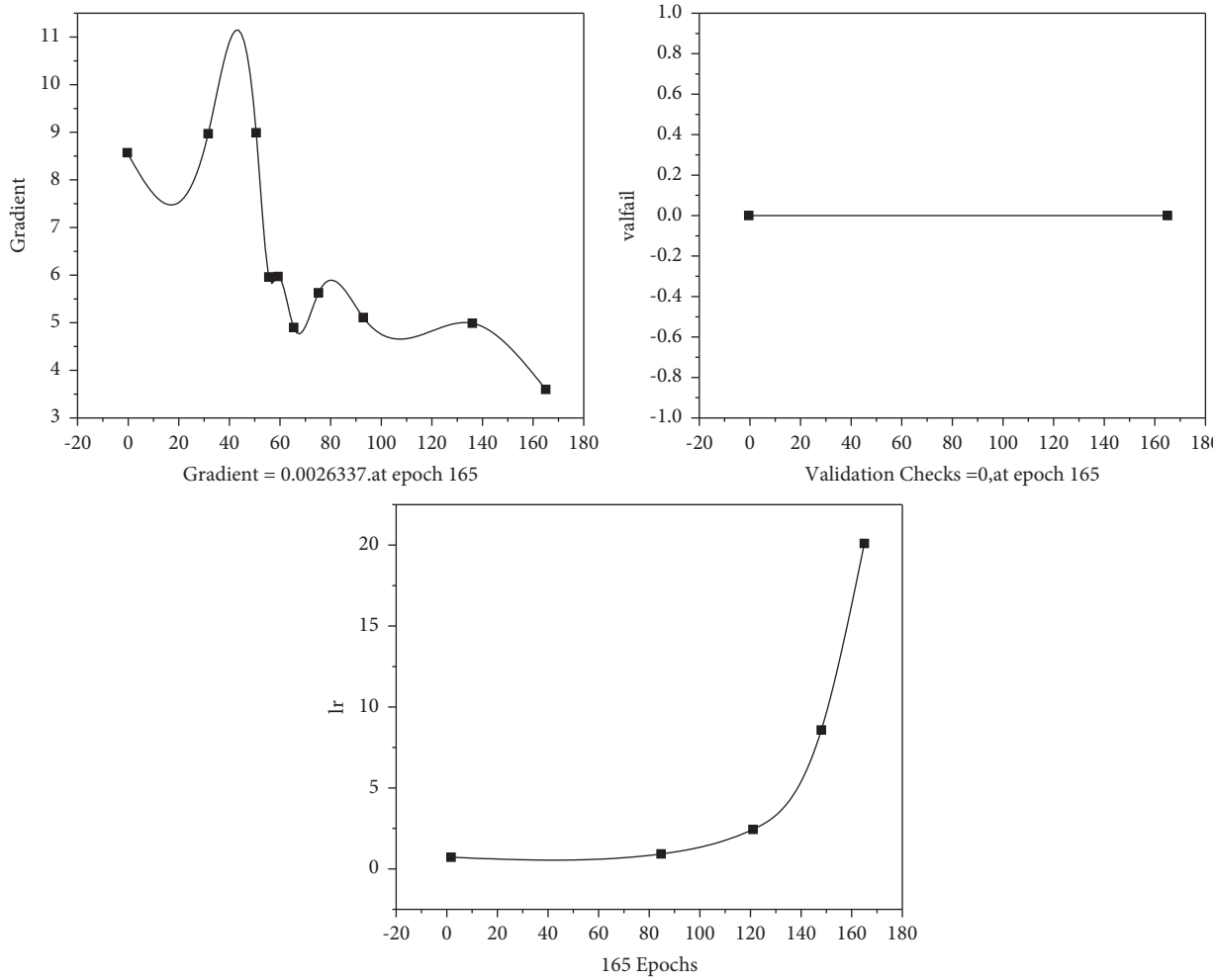

Figure 11: Traingdx is the error curve of the training function.

number of training steps when there are 4–16 nodes, Table 2 and Figure 3.

It can be seen from the above table that when the number of hidden layer nodes is 4, 6, 8, 12, 14, and 16, the number of training steps required for network training to reach the preset error is less. The error curve circle of the above node model is shown in Figures 4–9.

As can be seen from the above table and system error diagram, the number of hidden layer nodes is small, and the network performance is poor. The hidden layer has 8 nodes. Although it meets the requirements after 156 times of training, the number of nodes is small and the neural network is unstable. When the number of hidden layer nodes is 12, 14, and 16, the training steps are 156, 187, and 160 times, respectively, and meet the target error requirements of the research. When the number of hidden layer neurons is larger than 12, the error requirements can be met, but the increase in the number of neurons leads to the increase in network burden and the increase in training times, and cannot significantly improve the network performance. Therefore, the hidden layer of the BP neural network model constructed in this study selects 12 neuron nodes [20].

This study has analyzed in detail that the BP neural network model of the credit risk of small- and medium-sized enterprises in supply chain financing should select a new training function. The new training functions of the BP neural network are traingdm and traingdx. When the number of hidden layer nodes and other parameters is the same, the two functions are used to train, respectively, and then, the optimal training function is determined according to the error. When traingdm is selected as the training function, it does not converge to the preset target error value within 10000 steps w (see Figure 10 below). Therefore, this study constructs the BP neural network model and selects traingdx as the training function (Figures 11 and 12).

The learning rate has a great influence on the stability and convergence of the neural network model. According to Figure 12, in the above training process, the learning rate is 0.01 by default. Therefore, this study replaces the following learning rates in turn: 0.005, 0.01, 0.02, 0.03, and 0.04. Finally, it is found that when the learning rate is exactly the default 0.01, the error is the smallest and the stability is the best. The error is 0.0031011, and the step size is 157, which is

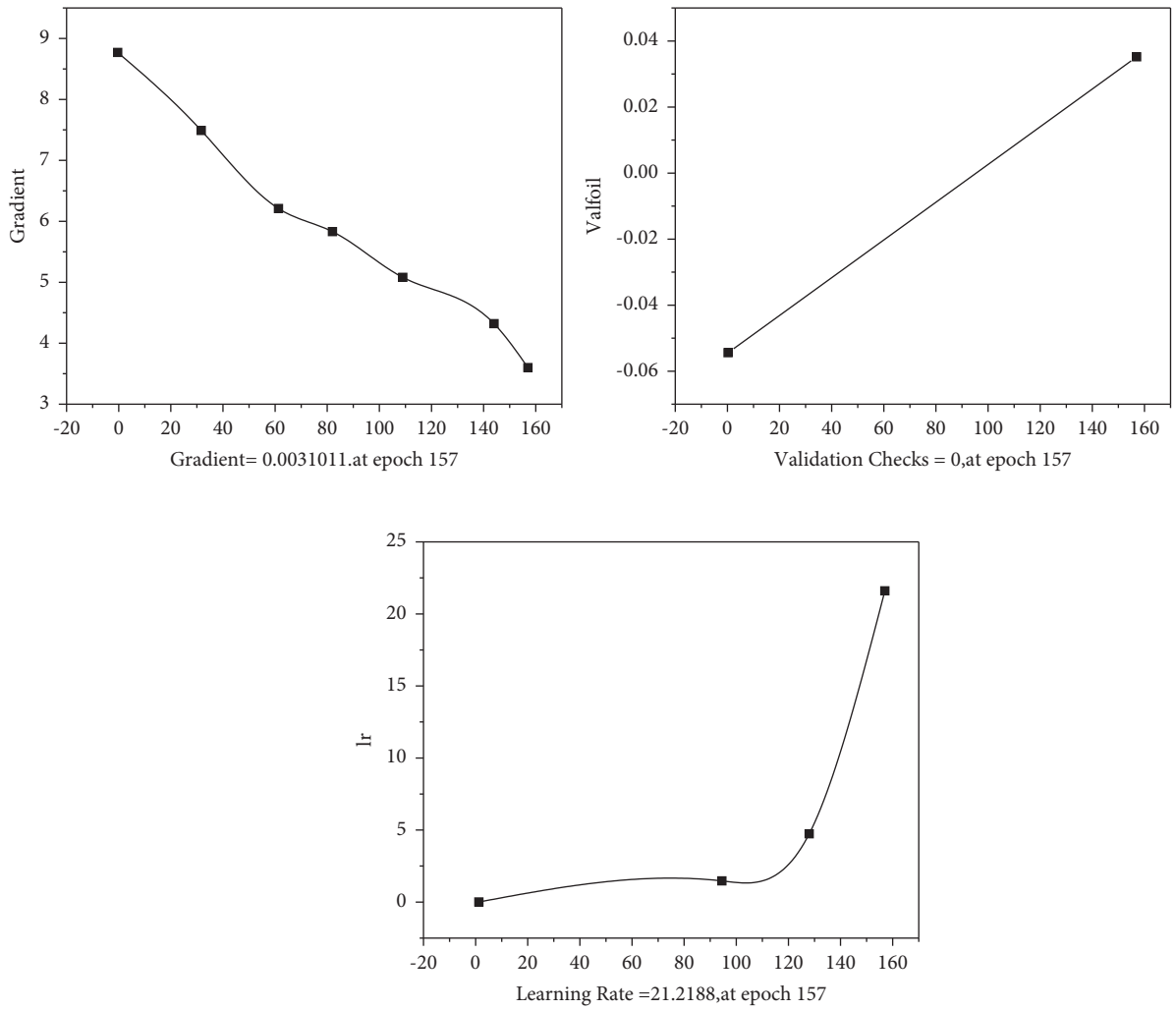

Figure 12: Systematic error diagram at a learning rate of 0.01.

just less than the target error value, indicating that the learning rate is better [21, 22].

5. Conclusions

This study discusses in detail the possibility of using the BP neural network model in the corporate financial risk assessment process. As far as we know, the BP neural network model has been very well researched in the financial sector. Finally, this study selects 19 indicators and provides a concise, scientific, and effective system of indicators. The BP has developed a credit risk assessment model for banking-based banking institutions based on the MATLAB software platform. With the help of wind databases and sample data collected from questionnaires, network design is trained and model accuracy is verified. The BP neural network assessment model for corporate lending risk in this document is highly accurate. In addition to providing theoretical insights to researchers, it can be a good tool for banks to realistically assess the credit risk of SME supply chain financing.

Data Availability

The labeled dataset used to support the findings of this study is available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

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