Hindawi
Wireless Communications and Mobile Computing
Volume 2022, Article ID 9650934, 10 pages
https://doi.org/10.1155/2022/9650934

Research Article

A Self-Learning BP Neural Network Assessment Algorithm for Credit Risk of Commercial Bank

Lulu Liu [1,2]

[1]Wuhan University of Technology, Wuhan 430070, China
[2]Xinyang Agriculture and Forestry University, Xinyang 464000, China

Correspondence should be addressed to Lulu Liu; 2012220003@xyafu.edu.cn

Received 16 November 2021; Revised 15 December 2021; Accepted 17 December 2021; Published 17 January 2022

Academic Editor: Xin Ning

Commercial banks play an important role in the financial system, and their role in the processes of capital circulation, capital integration, capital resource allocation, and total social demand and supply adjustment is irreplaceable. This paper proposes the idea of constructing a credit risk evaluation system for commercial banks based on BPNN by combining qualitative and quantitative analysis, based on computer technology and management theory. Its main goal is to use a neural network's self-learning ability to perform complex loan risk assessment. BPNN is capable of self-learning, self-adaptation, and knowledge acquisition, as well as dealing well with uncertainty. It is a nonlinear method that eliminates obvious subjective and artificial factors, resulting in a more objective and effective evaluation result. Experiments show that the established model is effective in regulating personal credit management and reducing investment risks for commercial banks, as well as providing a new decision-making framework for banks' personal credit business.

1. Introduction

The credit risk management of commercial banks has always been the focus of attention. After introducing engineering methods to measure credit risk, the back propagation neural network (BPNN) credit risk model stands out from many methods because of its strong advantage of approximating nonlinear function, and its ability to simulate and predict historical data also shows unique advantages [1, 2]. Commercial banks play an important role in a country's financial system, and their role is irreplaceable, such as the financing of funds, the optimal allocation of resources, and the balance regulation of total social demand and supply [3]. Credit is a basic element of modern market economy. In some developed countries, a perfect personal credit system is a solid foundation for the normal operation of national market economy [4]. Credit risk is one of the oldest and most important forms of financial risk in the financial market [5]. The primary link of credit risk management of commercial banks is credit risk assessment, which is also the most key link in the management process [6]. For a long time, financial markets at home and abroad have devoted a lot of human and material resources to its research. The reason is that accurate evaluation of the credit risk of commercial bank loan enterprises can help commercial banks effectively avoid credit risk and make better loan decisions [7].

Credit risk is an issue that affects people all over the world. All countries have paid close attention to the prevention and management of commercial bank credit risk. According to an investigation and research on commercial banks, a large number of commercial banks with good operations failed due to poor credit risk management [8]. Some of the most important decisions made by bank credit practitioners are based on the business intuition of the approvers of the bank credit management department or the interest orientation of marketing indicators, rather than stock business or customer information data. The massive amount of data in the bank information database has turned into a "data grave," and figuring out how to make effective use of it has become a top priority [9]. Data mining is based on the accumulation of specific data. People will be able to query and use [10] once they have accumulated some useful data. Neural network technology has the characteristics of parallel processing and nonlinear mapping. It can fully approach any complex nonlinear relationship by self-learning and adaptive unknown or uncertain system and has strong robustness and fault tolerance [11]. By introducing BPNN into credit risk evaluation of commercial banks, this paper constructs a credit risk evaluation model by using its self-learning ability and adaptive ability, realizes the learning and testing of the model, and obtains a high accuracy, so as to effectively reduce the impact of human factors, so as to provide some reference for commercial banks to prevent credit risk.

Despite the fact that investment banking, equity investment, cash management services, and other banking businesses have grown rapidly in recent years, public shares and real bonds remain relatively common [12]. The asset business of absorbing deposits, issuing on balance sheet and off-balance sheet financing, and earning interest difference by expanding its own assets has the most weight in terms of profit distribution indicators and risk appetite [13]. Due to the high uncertainty and complexity of credit risk, a new technology is urgently needed in current credit risk evaluation work to compensate for the flaws and shortcomings of the old methods [14]. Data mining technology is widely used in all walks of life, especially in finance, insurance, e-commerce, and telecommunications. Neural network technology is one of the most widely used methods in data mining technology [15]. The development of credit business will inevitably face the risk of default, which will affect the asset quality of commercial banks. Once there are nonperforming loans or overdue loans, the bank's economic capital occupation and provision will be improved, which will directly affect the bank's operating efficiency [16]. BPNN has the ability of self-learning, self-adaptive, and acquiring knowledge. It can deal with uncertainty well. It is a nonlinear method without obvious subjective components and human factors, which makes the evaluation results more objective and effective. Firstly, this paper expounds the definition of credit risk management and the significance of studying new methods of credit risk assessment, then puts forward a credit risk assessment model of commercial banks based on BPNN, and verifies the effectiveness of BPNN in credit risk assessment of commercial banks. The results show that the credit risk assessment model of commercial banks based on the BPNN algorithm improves the efficiency of risk identification on the premise of ensuring accuracy.

2. Related Work

The purpose of taking the credit risk management of commercial banks as the source of topic selection is to make positive and beneficial exploration for improving the credit risk management level of commercial banks by revealing the formation mechanism of customer credit risk of commercial banks on the basis of domestic and foreign research results. Literature [17] in the research process of enterprise credit risk, different neural network models are proposed for different research topics. Literature [18] shows that when multiple investors finance multiple projects, an intermediary bank is introduced, investors deposit funds in the bank, and the bank lends to multiple enterprises separately, which can save the cost of supervision and information. Literature [19] studies the influence of entrepreneur's human capital on enterprise debt repayment and holds that the combination of entrepreneur's unique talents and assets can generate cash flow, and the assets owned by banks do not necessarily enable enterprises to generate cash flow, so the threat that banks can obtain enterprise assets is conditional, precisely because entrepreneur's talents are difficult to be controlled from outside. Banks cannot restrict entrepreneurs' freedom to leave enterprises, so some good projects may not get financing, or loans cannot be paid off according to the contract [20]. Literature [21] puts forward the incomplete contract method to analyze debt and holds that a project can not only generate observable monetary benefits but also generate private benefits owned by some entrepreneurs. Literature [22] discusses the issue of sovereign debt, and they think that the debtor has the motivation to repay the debt because of the convenience of financing in the future. Literature [23] studies the motivation of enterprises to repay loans and holds that the threat of bank terminating loans will provide an incentive for enterprises to repay loans. Literature [24] applies their model to multistage dynamic environment, which also proves the existence of this mechanism of terminating loans.

In this paper, the idea of constructing a credit risk evaluation system for commercial banks based on BPNN is put forward to address the problems that exist in the current analysis and evaluation of commercial banks' credit risk and to overcome the shortcomings of the traditional pure management mode or pure mathematical method, based on computer technology and management theory, adopting the research method of combining qualitative analysis with quantitative analysis and using the research method of combining qualitative analysis with quantitative analysis, to overcome the shortcomings of the traditional pure management mode or pure mathematical method.

3. Credit Risk Assessment Theory of Commercial Banks

3.1. Definition of Credit Risk Management. In the definition of risk, people usually divide risk into two categories: broad risk and narrow risk. The generalized risk refers to the uncertainty of the results due to various external or internal uncertainties. This result may be in line with expectations and bring benefits, but it may also be contrary to expectations and bring losses. In short, although there is only one result of generalized risk, there are two possibilities. A narrow sense of risk refers to the loss caused by various external or internal uncertain factors in life. Credit risk refers to the risks encountered by commercial banks in the whole process of implementing their own credit products, such as loan issuance, loan management, and loan recovery. From the aspect of lenders, it includes due diligence risk, operational risk, credit examination and approval risk, legal risk, country risk, loan management risk, and loan recovery risk. From the borrower's point of view, there are business risks, policy risks, industry risks, exchange rate risks, and related risks, which can be collectively referred to as financing risks or credit risks.

3.2. The Significance of Studying New Methods of Credit Risk Assessment. Commercial banks are influenced by the external environment, policies, and customers, as well as internal management policies, systems, and employees, in the course of their daily operations, making their operating results uncertain. When external and internal conditions are favourable, commercial banks will reap the expected benefits; however, when external and internal conditions are unfavourable, commercial banks will suffer losses. Commercial bank credit risk refers to the possibility that the bank will not be able to recover the loan's principal and interest from customers within the time frame specified after the loan has been released. If the credit risk does not occur, management measures can be used to conclude that the greater the credit risk of a customer, that is, the greater the likelihood that the customer will cause losses in the future. If a credit risk exists, the greater the customer's credit risk, the greater the loss caused by the customer [25]. Different from operational risk, credit risk is irreversible in nature, because credit risk is often controlled by law, which is simply understood as being restricted by credit contract, so the losses caused by credit risk can not be predicted, and it will also have a direct impact on commercial banks. For financial institutions and regulatory authorities, risk prevention is the main object and core content. With the development of financial globalization and the fluctuation of global regional economy, banks and investment institutions in various countries have been challenged by unprecedented credit risks. The biggest cause of bank bankruptcy also comes from the collapse of credit risk.

Compared with market risk, an important feature of credit risk lies in its probability distribution. For unsecured loans, the risk feature is that the lender can get normal interest income when the loan is safely recovered, but once the risk is converted into actual loss, this loss is much larger than the interest income. The probability distribution characteristics of credit risk are shown in Figure 1.

While commercial banks profit from the credit business, they must also deal with the risks that come with it, and credit risks cannot be completely avoided, but they do come with profits. Only appropriate management methods or advanced management theories can reduce commercial banks' credit risk. Credit risk must be reduced through management theory or measures, whether for domestic or foreign commercial banks, as this is the foundation for commercial banks' stable operation and long-term development. Despite the fact that commercial banks generally have objective or competent credit risks, we cannot ignore the fact that credit risks exist. Simply put, commercial banks will not stop lending due to the risks. On the contrary, we should take proactive risk management measures and employ more advanced and effective credit management techniques. The selection of indicators used by commercial banks to evaluate customers does not appear to be objective. Customers are typically judged subjectively based on account managers' experience or information, making the evaluation results unreliable. Business risk managers for the bank, a business entity with equal risks and benefits, should not only identify the degree of risk but also maximise profits. To accomplish this, they must first collect all of the data within the target range, then analyze and identify the data that is available for risk classification management.

4. Credit Risk Assessment of Commercial Banks Based on BPNN

4.1. BPNN Principle. In the past evaluation methods, there are always various limitations. For example, it is required that explanatory variables are uninterrupted in a certain time period or interval, and some even have to obey a certain mathematical distribution, such as chi-square distribution. In reality, the data that meet these requirements are rare. If researchers cannot find the data that fully meet the requirements, they will use some flawed data for empirical analysis. For the research based on this assumption as the theoretical premise, there will inevitably be deviations from the actual results. In contrast, artificial neural network (ANN) does not have to be based on assumptions, and there are not so many hard and fast rules. Basically, the collected data can be used. Compared with traditional methods, ANN has a wider application range and good universality [26]. The learning process of the BPNN model includes forward propagation and error back propagation. Because of its good self-learning and self-correlation functions, it has been widely used in nonlinear modeling, function approximation, signal processing, and other aspects and has become the most widely used neural network. BPNN is a kind of multilayer feedforward neural network, which uses error back propagation, as shown in Figure 2.

Let the structure of BPNN be $n \times q \times m\, m$. The network includes the weight $w_{ij}^{I}(i = 1, 2, \cdots, n\,; j = 1, 2, \cdots, q)$ from the Ith neuron of the input layer to the Jth cell of the hidden layer, the weight $w_{jk}^{H}(j = 1, 2, \cdots, n\,; k = 1, 2, \cdots, q)$ from the Jth neuron of the hidden layer to the Kth neuron of the output layer, the threshold θ_j^H of the Jth neuron of the hidden layer, and the threshold θ_k^O of the Kth neuron of the output layer. The nonlinear activation function, sigmoid function, is

$$f(u) = \frac{1}{(1 + e^{-u})}. \tag{1}$$

Set the initial values of the network weights and thresholds to values in the interval [0, 1]. Suppose the input of the pth group of data samples is

$$x_p = \left(x_{1p}, x_{2p}, \cdots, x_{np}\right). \tag{2}$$

The expected output is

$$t_p = \left(t_{1p}, t_{2p}, \cdots, t_{mp}\right). \tag{3}$$

L represents the total number of samples, and the output

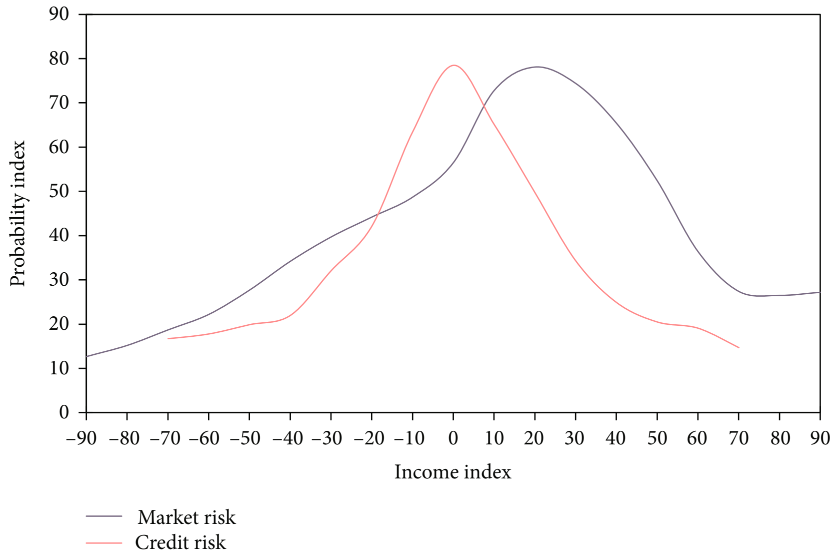

Figure 1: The probability distribution characteristics of credit risk.

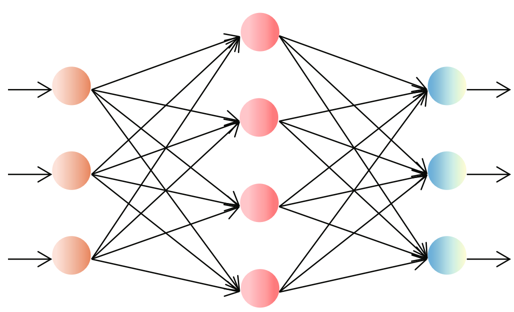

Figure 2: BPNN.

information of the jth neuron in the hidden layer is

$$H_{ip} = f\left(\sum_{i=1}^{n} w_{ij}^{I} x_{ip} - \theta_j^H\right), \quad j = 1, 2, \cdots, q, \quad p = 1, 2, \cdots, L. \tag{4}$$

The hidden layer passes the output information to the output layer, and the final output is

$$y_{kp} = f\left(\sum_{j=1}^{q} w_{jk}^{H} H_{jp} - \theta_k^O\right), \quad k = 1, 2, \cdots, m, \quad p = 1, 2, \cdots, L. \tag{5}$$

Suppose the actual output of the pth group of samples is

$$y_p = \left(y_{1p}, y_{2p}, \cdots, y_{mp}\right). \tag{6}$$

Then, the network error square sum E can be expressed as

$$E = \frac{1}{2}\sum_{p=1}^{L}\sum_{k=1}^{m}\left(y_{kp} - t_{kp}\right)^2. \tag{7}$$

Judge whether the error sum of squares E converges to the given learning accuracy ε, if $E \le \varepsilon$, the algorithm ends and the network stops training; otherwise, it continues with the following steps.

Starting from the output layer, back propagation layer by layer, using the steepest descent method in nonlinear programming:

$$w_{ij}(n+1) = w_{ij}(n) - \eta \frac{\partial E(n)}{\partial w_{ij}(n)}. \tag{8}$$

In the formula, η represents the step value or the network learning rate. The introduction of η is to accelerate the convergence rate of the network. Usually, a momentum parameter a is added to the weight correction formula. The modified formula for the nth learning weight is

$$\Delta w_{ij}(n+1) = -\eta \frac{\partial E(n)}{\partial w_{ij}(n)} + \alpha \Delta w(n). \tag{9}$$

Until the output error of the sample meets the predetermined condition, the network training is ended.

4.2. Selection of Credit Risk Evaluation Index System and Neural Network Parameters of Commercial Banks. The

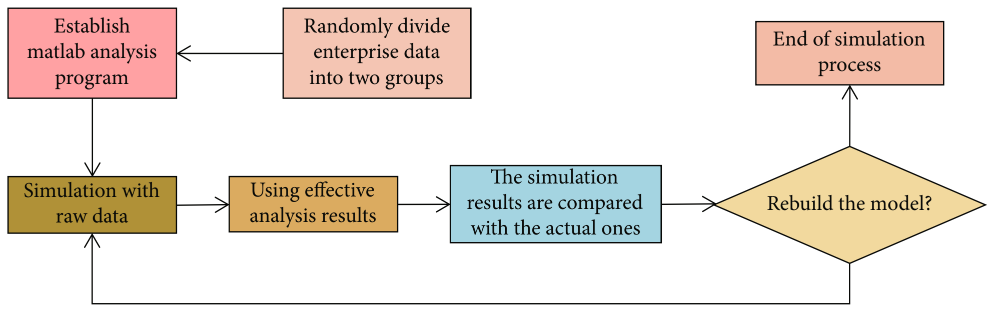

Figure 3: BPNN simulation process.

repayment efficiency of commercial bank loan enterprises is influenced by a number of factors. Many different types of influencing factors exist, each with a different influence weight, and they are interconnected rather than independent. It is necessary to build a scientific and reasonable evaluation index system in order to improve the accuracy and stability of credit risk assessment, and partial consideration of the influence of individual factors cannot accurately assess credit risk. A scientific and reasonable index system, rather than a random combination and simple stacking of multiple indexes, can truly and comprehensively reflect the credit risk status of enterprises. There are many different types of factors that influence credit risk in commercial bank loan enterprises, and they cover a wide range. The selection of indicators should take into account comprehensiveness and comprehensiveness, so as to ensure the accuracy of the evaluation results. BPNN simulation process design is shown in Figure 3.

In order to avoid the overlapping of indicators due to too many and too few indicators, which will lead to serious correlation of indicators and affect the evaluation results, while insisting on the completeness of the index system, we should reduce unnecessary evaluation indicators and make the constructed evaluation index system as concise as possible. Under the existing technical means, cost constraints, and policy environment, in order to ensure that data is easier in practical work, the selection of acquisition indicators should be compatible with enterprise financial statements and statistical data as much as possible. At the same time, the selected evaluation indicators should be credible, and the purpose of credit risk assessment of commercial banks is to objectively and accurately predict and evaluate the credit risk of loan enterprises and to assist banks to make credit approval. The credit risk evaluation index system of commercial banks established in this paper is shown in Figure 4.

The sigmoid activation function sigmoid has a value range of [0,1]. Therefore, the output value of the output neuron of the general neural network should be normalized. Clean the dirty data in the database, that is, remove empty values and noisy data. The activation function is an important function to control the final output of the network. The choice of the activation function is more important. The sigmoid function is a more commonly used and effective activation function, including the sigmoid function with a range of (0,1) and a range of (-1, 1) the tangent function. The expression is as follows:

$$f(x) = \left(1 + e^{-ax}\right)^{-1}, \tag{10}$$

$$f(x) = \frac{1 - e^{-x}}{1 + e^{-x}}, (-1 < f(x) < 1). \tag{11}$$

Among them, an is a constant, and its value affects BPNN's training speed. As a rises, the initial network convergence speed accelerates. By adjusting the value of a, a sigmoid function with the best shape can be found to minimise the number of learning times of the network under the same initial conditions. Because a problem with the size of the initial value can cause the network to linger around a local minimum, the initial value is more important for neural network training. As a result, it is generally hoped that after initial weighting, each neuron's output value will be close to 0 and that the input samples will be normalized.

The neural network learning rate η is also called the learning step size, which is a crucial factor in determining the size of the weight adjustment $\Delta w_{ij}(n)$.

$$\Delta w_{ij}(n) = -\eta \frac{\partial E(n)}{\partial w_{ij}(n)}. \tag{12}$$

If the selection of learning rate is too small, the convergence speed of the network will slow down, and if the selection of learning rate is too large, the adjustment of weights will be larger each time. Generally, the learning rate is selected between 0.01 and 0.8.

5. Result Analysis and Discussion

Adding BPNN to the original evaluation system is not a simple replacement of the original model, but an organic whole and an applicable evaluation system. In view of this system, certain policy and environmental support are needed to ensure its effective promotion and implementation. The ST system is aimed at listed companies with abnormal financial or other conditions. The model sets the output of 0.5 as the critical point for judging the probability of default. When the output value is less than 0.5, it is judged as ST enterprise. If the output value is greater than 0.5, it is judged as a non-ST enterprise. The network model parameters are initialized,

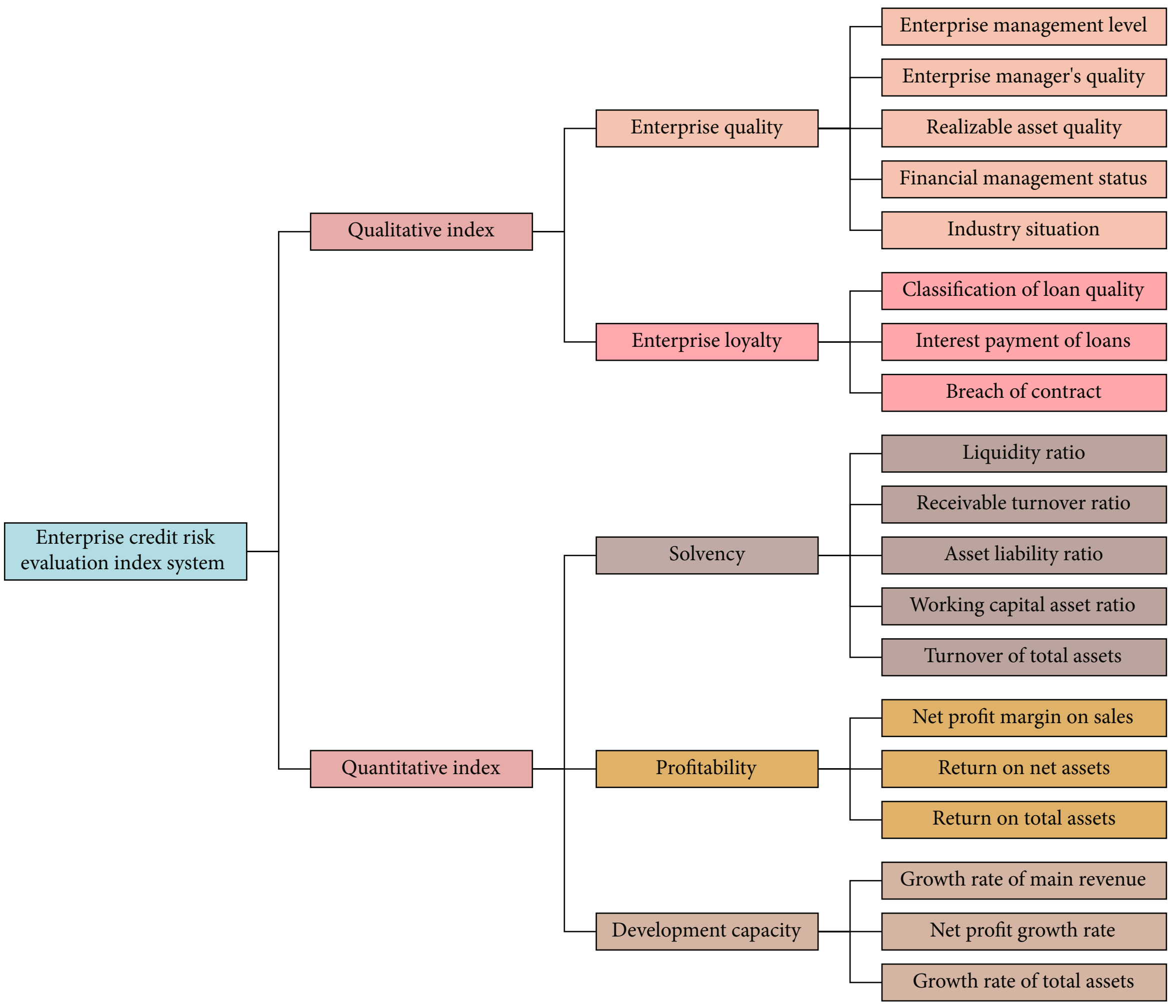

FIGURE 4: Credit risk evaluation index system of commercial banks.

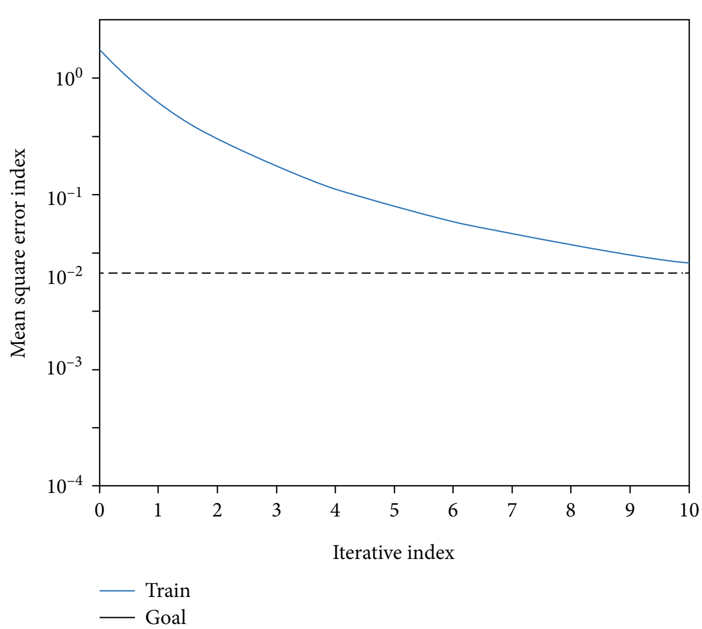

FIGURE 5: Training error curve.

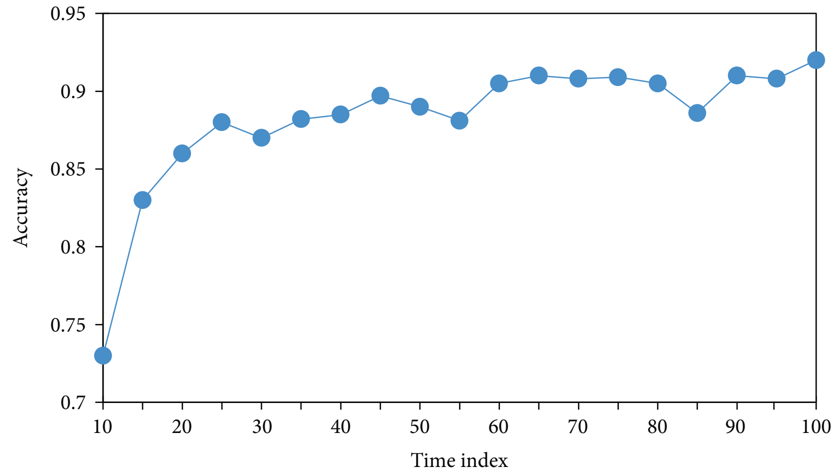

Figure 6: The accuracy trend chart of the deep convolutional neural network verification set.

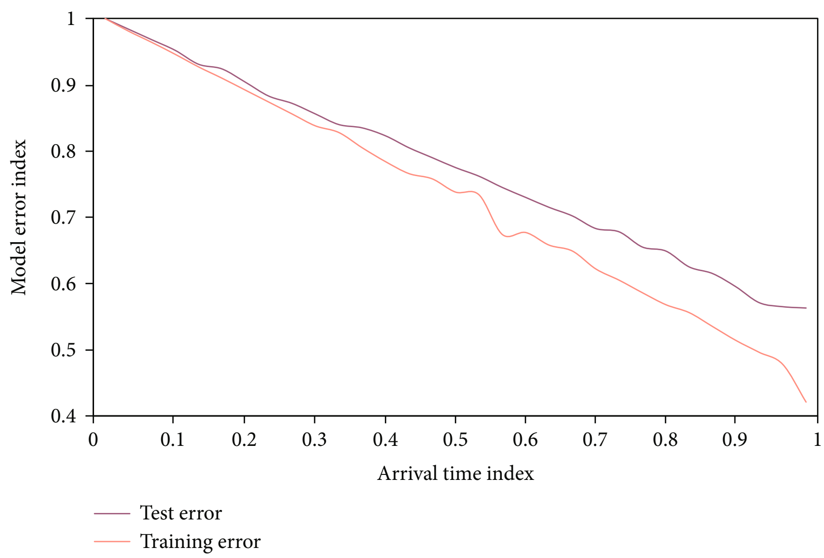

Figure 7: The relationship between the number of iterations and normal training and overfitting training.

and the sample data are input into the BPNN model for training. The error curve obtained by training is shown in Figure 5.

During the training phase of the model, tests will be conducted on the verification set at regular intervals. Figure 6 shows the trend chart of the accuracy rate on the verification set with the training process. It can be seen that the accuracy of the verification set of the network is increasing with the convergence of the model, which verifies the correctness of the network convergence and the effectiveness of the network in feature extraction.

Different index data have different dimensions. If the data are not standardized before use, the neural network model may not achieve the expected convergence effect in the training process. Therefore, before building the credit risk evaluation model of commercial banks, we should first standardize the data and then eliminate the adverse effects of different dimensions on the model. When training, the loss function reflected by verification is gradually increasing rather than decreasing, which indicates that network training has entered the trap of local optimization. Figure 7 is a graph showing the relationship between the number of iterations and normal training and overfitting training.

On the whole, the behavior of each economic entity is carried out in the macro credit environment. Whether this credit environment is good or not can affect the credit status of organizations, especially the risk management of commercial banks, by affecting the credit status of individuals. But conversely, the credit risk management of commercial banks can also affect the macro credit environment of the whole country. The difference in the expected rate of return may lead to the difference in the time discount rate of financial institutions, as shown in Figure 8.

Bank loan officers need to check and analyze the changes of the borrower's operating conditions, financial indicators, and other related contents and set the inspection frequency

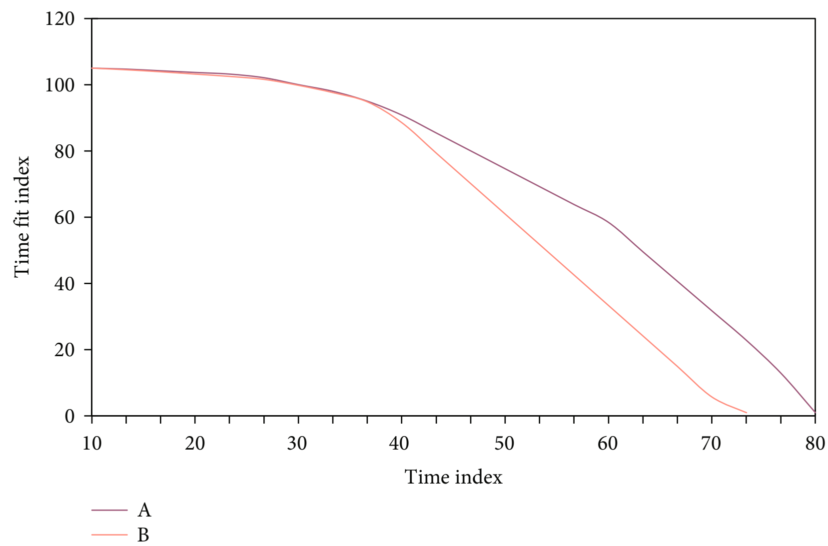

FIGURE 8: Time difference curve.

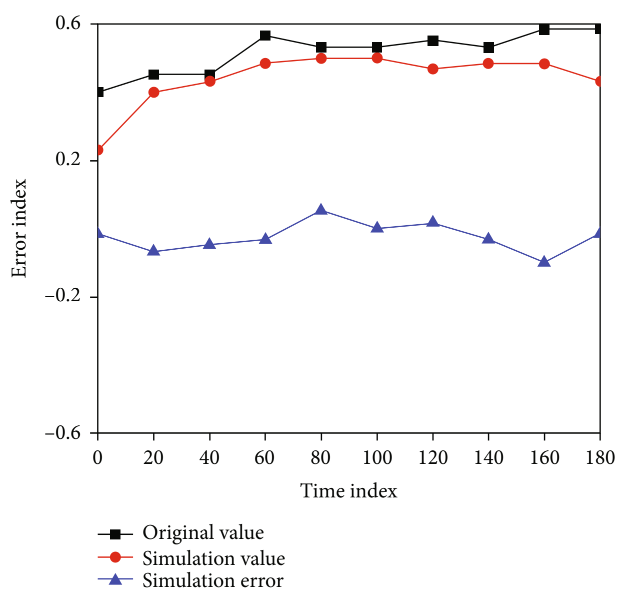

FIGURE 9: Training error and training result.

according to the risk situation of customers and credit granting. With the continuous changes of the borrower's operating conditions, the financial indicators and nonfinancial indicators of the loan are also changing. If the commercial bank collates and analyzes the indicators obtained from the borrower again, it will reduce the overall work efficiency. If BP neural network is introduced into the evaluation model of preloan investigation, it can help loan officers to judge the risk of borrowers. When there are affiliated enterprises that need to provide guarantees, this model can also be introduced into the risk judgment of guarantee enterprises and then combined with the original methods, so as to better identify risks and improve the application effect. When establishing the credit risk evaluation model, we need a lot of real data as the basis. Therefore, a perfect credit risk management information system with abundant data and information is essential for credit risk management. Through the process of self-learning and self-use, the model constantly and automatically adjusts the weights and thresholds, so that the output value approaches the expected target value as much as possible. Except for some points, the relative error is controlled within 0.01%, which shows that the model can effectively simulate the risk assessment of commercial banks. Refer to Figure 9 for training errors and training results.

The empirical results show the accuracy of BPNN in credit risk evaluation, which shows that it is available. After its introduction, it will face some problems, especially the problems of professional research and operation, which requires supporting training of specialized talents. After the introduction of BPNN, a new rating system has been formed. For this new system, policy support is needed from the internal and external environment. Only by constantly innovating the credit risk monitoring model and improving their risk management ability can commercial banks better cope with the changes of the current economic situation.

6. Conclusions

Credit risk in financial institutions, especially in the banking industry, has a long history and is a universal problem in the world. In this paper, combining the theory of credit risk assessment of commercial banks and BPNN technology, an experimental database is prepared, the experimental parameters are rationally selected, and a training model and a testing model are established. Finally, the effectiveness of neural network in the process of credit risk assessment of listed companies is trained and tested, and it is effective to apply the BPNN method to the construction of the credit risk assessment model of commercial banks. Through the collected data of various indicators of enterprises, the existing credit risks can be assessed more accurately, which can provide accurate reference for bank credit decision-making and help commercial banks to approve and price credit. Commercial banks need to use the BPNN credit risk model based on the existing credit risk management model according to the characteristics of commercial banks and their historical data.

The characteristics of the BP neural network model are that it can fully approximate complex nonlinear relationships, has self-learning ability, and can mine hidden information in data. At present, in the field of bank credit risk assessment, based on the development of information technology, the data structure has changed obviously, and the relationship between them has become more vague with the expansion of scale. In this case, the characteristics of the neural network model can be better developed. The credit risk assessment of commercial banks is very complicated. Although this paper has studied this research to a certain extent, there are still many shortcomings to be further studied. How to quickly filter out the linear and nonlinear data rules from the complicated business record data, effectively serve the decision makers, how to distinguish the available data that can identify the credit risk from the massive information, and even provide the weight ratio for diversified risk data, all these may be the problems to be solved urgently in the field of credit management and risk assessment in the future.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The author declares no conflicts of interest.

Acknowledgments

This study was supported by Soft Science Project of Science and Technology Department of Henan Province: "The analysis of the way of financing for small and micro enterprises of science and technology based on Internet" (No. 182400410352).

References

[1] F. Assef, M. T. Steiner, P. J. Steiner Neto, and D. G. . B. Franco, "Classification algorithms in financial application: credit risk analysis on legal entities," *IEEE Latin America Transactions*, vol. 17, no. 10, pp. 1733–1740, 2019.

[2] J. Wang, K. Fang, W. Pang, and J. Sun, "Wind power interval prediction based on improved PSO and BP neural network," *Journal of Electrical Engineering and Technology*, vol. 12, no. 3, pp. 989–995, 2017.

[3] A. Beque and S. Lessmann, "Extreme learning machines for credit scoring: an empirical evaluation," *Expert Systems with Applications*, vol. 86, no. 11, pp. 42–53, 2017.

[4] B. Kirubakaran and M. Ilangkumaran, "Selection of optimum maintenance strategy based on FAHP integrated with GRA–TOPSIS," *Annals of Operations Research*, vol. 245, no. 1-2, pp. 285–313, 2016.

[5] K. Li, J. Niskanen, M. Kolehmainen, and M. Niskanen, "Financial innovation: credit default hybrid model for SME lending," *Expert Systems with Applications*, vol. 61, no. 9, pp. 343–355, 2016.

[6] E. Dawood, E. Elfakhrany, and F. A. Maghraby, "Improve profiling bank customer's behavior using machine learning," *IEEE Access*, vol. 7, no. 99, pp. 109320–109327, 2019.

[7] C. Pei, "Commercial bank customer credit risk assessment based on BP neural network," *Financial Management Research*, vol. 2, no. 2, pp. 46–62, 2018.

[8] X. Geng, S. Lu, M. Jiang et al., "Research on FBG-based CFRP structural damage identification using BP neural network," *Photonic Sensors*, vol. 8, no. 2, pp. 168–175, 2018.

[9] R. X. Chen, X. Huang, and L. X. Yang, "Bearing life state recognition using deep sparse auto-encoder neural network with noise adding sample expansion," *Journal of Vibration Engineering*, vol. 30, no. 5, pp. 874–882, 2017.

[10] J. Labriola, "Risky business: institutional logics and risk taking at large U.S. commercial banks∗," *Social Science Quarterly*, vol. 100, no. 1, pp. 389–404, 2019.

[11] T. Buyl, C. Boone, and J. B. Wade, "CEO narcissism, risk-taking, and resilience: an empirical analysis in U.S. commercial banks," *Journal of Management*, vol. 45, no. 4, pp. 1372–1400, 2019.

[12] D. A. Restrepo-Tobon and S. C. Kumbhakar, "A new method to decompose profit efficiency: an application to US commercial banks," *Journal of Productivity Analysis*, vol. 48, no. 2-3, pp. 117–132, 2017.

[13] K. R. Lee and M. S. Pak, "Multi-criteria analysis of decision-making by international commercial banks for providing shipping loans," *Maritime Policy & Management*, vol. 45, no. 7, pp. 850–862, 2018.

[14] T. H. Huang, C. I. Lin, and K. C. Chen, "Evaluating efficiencies of Chinese commercial banks in the context of stochastic multistage technologies," *Pacific-Basin Finance Journal*, vol. 41, pp. 93–110, 2017.

[15] P. Abbassi, R. Iyer, and J. L. Peydro, "Securities trading by banks and credit supply: micro-evidence," *Journal of Financial Economics*, vol. 63, no. 3, pp. 459–471, 2016.

[16] C. Jiafeng, C. Sibin, and H. Xiaoshan, "Quantitative analysis of banks' credit risks of small and medium-sized enterprises and research on credit decisions," *Trade Fair Economics*, vol. 17, no. 9, pp. 74–76, 2020.

[17] A. H. Elsheikh, S. W. Sharshir, M. Abd Elaziz, A. E. Kabeel, W. Guilan, and Z. Haiou, "Modeling of solar energy systems using artificial neural network: a comprehensive review," *Solar Energy*, vol. 180, no. 3, pp. 622–639, 2019.

[18] C. Yanping and S. Xia, "Performance evaluation system of listed commercial banks based on BP neural network," *System Engineering*, vol. 12, pp. 28–34, 2016.

[19] S. L. Chen, C. Yang, J. W. Ma, F. Chen, and X. C. Yin, "Simultaneous end-to-end vehicle and license plate detection with multi-branch attention neural network," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 9, pp. 3686–3695, 2020.

[20] L. Shenxia and X. Xuejun, "Current credit risk identification and management of commercial banks in my country," *Industry and Technology Forum*, vol. 15, no. 9, pp. 251-252, 2016.

[21] S. Feiyan and J. Zeli, "Analysis of commercial bank credit business risks and prevention," *Old District Construction*, vol. 14, pp. 44–47, 2017.

[22] Y. Lili, "Analysis of consumer credit risk and management of commercial banks in my country," *Knowledge Economy*, vol. 10, no. 10, pp. 46-47, 2016.

[23] E. Kayabasi, S. Ozturk, E. Celik, and H. Kurt, "Determination of cutting parameters for silicon wafer with a diamond wire saw using an artificial neural network," *Solar Energy*, vol. 149, no. 6, pp. 285–293, 2017.

[24] Q. Chenglin, "Analysis of the problems and countermeasures in the credit risk management of my country's commercial banks," *Modern Business*, vol. 10, no. 10, pp. 126-127, 2020.

[25] M. Qiang, "New thoughts on credit risk prevention and control of commercial banks in the new situation," *Economic Management Digest*, vol. 741, no. 3, pp. 25-26, 2020.

[26] J. Haoyuan and J. Wenxi, "Analysis of commercial bank credit business risk prevention under the new economic normal," *Liaoning Economics*, vol. 422, no. 5, pp. 82-83, 2019.