Research on Financial Risk Prediction and Prevention for Small and Medium-Sized Enterprises - Based on a Neural Network

Xiaohui Wang
School of Accounting and Finance, Wuxi Vocational Institute of Commerce, Wuxi, Jiangsu 214153, China
E-mail: aoxihui728824@yeah.net

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For companies, timely and accurate risk prediction plays an an essential role in sustaining business growth. In this paper, firstly, the financial risk of small and medium-sized enterprises (SMEs) was simply analyzed. Some financial indicators were selected, and then some of the indicators were eliminated by Mann-Whitney U test and Pearson test. For risk prediction, an improved sparrow search algorithm-back-propagation neural network (ISSA-BPNN) method was designed by optimizing the BPNN with the piecewise linear chaotic map (PWLCM)-improved SSA. Experiments were performed on 82 special treatment (ST) enterprises and 164 non-ST enterprises. The results showed that the BPNN had higher accuracy in risk prediction than methods such as Fisher discriminant analysis; the optimization of the ISSA for the BPNN was reliable as the accuracy and F1 value of the ISSA-BPNN method were 0.9834 and 0.9425, respectively; the prediction was wrong for only one sample out of 20 randomly selected samples. The results demonstrate the reliability and practical applicability of the ISSA-BPNN method.

Povzetek: Prispevek analizira finančne nevarnosti za mala in srednja podjetja z uporabo nevronskih mrež. ISSA-BPNN metoda, optimizirana z PWLCM, je v testih pokazala visoko zanesljivost in natančnost.

1 Introduction

With the fast advancement of the economy and the continuous improvement of the capital market, it brings opportunities for the development of enterprises, but also new risks and difficulties. For business managers, how to ensure the survival of their enterprises has become a primary issue. Financial risks have a significant impact on the survival of enterprises [1]. The emergence of financial risks will not only seriously affect the future development and survival of enterprises, but also affect the stakeholders of enterprises and even the entire capital market. Therefore, it is particularly important to predict and prevent corporate risks. With the advancement of computers and big data, many new methods for predicting and preventing financial risks have been developed [2]. In this paper, a back-propagation neural network (BPNN)-based prediction method was designed for the financial risk of SMEs, and the effectiveness of the method was proved by experimental analysis. This work provides theoretical support to further improve the management of financial risks and promote the smooth development of enterprises.

2 Related works

Studies on the prediction and prevention of financial risks are listed in the following table.

Table 1: Literature list of related work

Literature	Indicators	Methods	Results
Ptak-Chmielewska et al. [3]	Share of net financial surplus in total liabilities, capital ratio, inventory turnover, etc.	Gradient boosting, logistic regression, decision trees and neural networks	The logistic regression model works best for bankruptcy risk prediction; the use of non-financial indicators has an improving effect on the results of all models.
Jaki et al. [4]	Relative market value added, cash flow return on sale, etc.	Discriminant function	The market measures were characterized by the highest usefulness level in explaining the bankruptcy risks of the studied companies; a change in the proportion of the division of objects to the learning and testing

			community at the stage of building and verifying the predictive effectiveness of the discriminant models affects both the general and partial predictive effectiveness of the constructed models
Chi et al. [5]	None	Four traditional and sixteen hybrid models by combining conventional and modern artificial intelligence methods	In the LR/MLP hybrid model, the inclusion of LR develops the interpretability and cross-validation capacity of the approach, whereas the use of MLP boosts the prediction ability of the planned method.
Ragab et al. [6]	Five financial variables and thirteen non-financial variables related to governance	Logistic regression	The results showed that the model with financial variables had a prediction accuracy of 91.7%, whereas models with a combination of financial and non-financial variables related to governance predict with comparatively better accuracy of 92.7 and 93.6%.

3 Financial risk forecast indicators for SMEs

3.1 SME financial risk

In order to encourage the development of SMEs, the Shenzhen Stock Exchange has established the SME gathering board. These enterprises have good profitability, high revenue growth rate, and active trading, so they are an important part of the capital market. As of April 2021, the number of listed companies in the SME gathering board reached 1,004, and the total turnover reached 160.187 billion yuan.

SMEs are relatively large in number and play an important role in promoting employment and stabilizing society, so it is important for SMEs to predict and prevent financial risks. An effective prediction model is helpful for enterprise managers to identify risks early and avoid financial crises, and it can also help market regulators to monitor enterprise risks and stabilize capital markets.

The financial risk of an enterprise can be caused by internal mismanagement, personnel changes, uneven distribution, etc. It may also be affected by market turmoil, natural disasters, etc. When an enterprise has financial risk, there are three specific manifestations: (1) loss, the enterprise's poor operating conditions, reduced profitability, to a loss; (2) repayment: the enterprise's inability to repay its debts; (3) bankruptcy: the execution of bankruptcy liquidation.

Financial risk prediction means selecting some financial indicators with the help of technologies such as big data to understand whether there is a possibility of financial risk by analyzing the financial data of enterprises, helping enterprise managers to improve their risk perception and minimize the loss caused by financial risk. For enterprises with abnormal financial status, the Securities and Exchange Commission will add special treatment (ST) or ST* before the stock code; therefore, enterprises marked with ST can be studied as enterprises with financial risks. The research data of this paper was obtained from the GTA database. Eighty-two ST enterprises were selected, and 164 normal enterprises (non-financial industry) were randomly selected as non-ST samples. The financial statements of these samples were collected as the experimental data of this paper. Some ST and non-ST enterprises are shown in Table 2.

Table 2: Some sample companies.

Stock code	
002042	Huafu Fashion
002048	Ningbo Huaxiang
002271	Oriental Yuhong
002299	Sunner Development
002352	SF Holding
002422	Kelun Pharmaceutical
002563	Semir Garment
002739	Wanda Film
002788	Luyan Pharmaceutical
002841	CVTE
002052	*ST Coship
002076	*ST CNlight
002089	*ST Xinhai
002113	ST Tianrun
002200	ST Jiaotou
002259	ST Shengda
002499	*ST Kelin
002535	ST Linzhou Heavy
002569	ST Busen

002700	ST Haoyuan

3.2 Indicator selection

Before forecasting financial risk, it is first necessary to select appropriate indicators. Based on the existing literature, the following aspects are considered in this paper.

(1) Debt service level: An enterprise that is able to repay principal and interest on time indicates that it is in good health and can give creditors the confidence to continue to invest.

(2) Profit level: It refers to the profit level of an enterprise by selling products over a period of time; the higher the profit level, the better the efficiency of the enterprise;

(3) Cash flow level: It can reflect the actual income of an enterprise.

(4) Operating level: It can reflect the efficiency of an enterprise's capital use and its re-production capacity.

(5) Development level: It refers to the future development potential of an enterprise. A higher development level of an enterprise indicates that there are fewer problems within the enterprise and lower possibility of risks.

Based on the above content, the financial indicators selected for this paper are as follows.

Table 3: Financial indicators.

Category	Number	Indicator
Debt service level	X1	Current ratio
	X2	Quick ratio
	X3	Asset-liability ratio
	X4	Equity ratio
	X5	Times-interest-earned ratio
Profit level	X6	Earnings per share
	X7	Return on assets
	X8	Operating profit ratio
	X9	Return on total assets
	X10	Ratio of profits to cost
	X11	Net interest rate on total assets
	X12	Net interest rate on fixed assets
Cash flow level	X13	Cash content of operating income
	X14	Cash content of net profit
Operating level	X15	Business cycle
	X16	Inventory turnover rate
	X17	Accounts receivable turnover ratio
	X18	Total assets turnover ratio
Development level	X19	Total assets growth rate
	X20	Growth rate of fixed assets
	X21	Operating income growth rate

3.3 Indicator processing

Table 2 contains 21 indicators that need to be screened again in order to improve the effectiveness of the subsequent prediction. First, the Mann-Whitney U test [7] was performed on the data of ST and non-ST enterprises, and the results are shown in Table 4.

Table 4: Results of the Mann-Whitney U test (bolded: $p > 0.05$).

Number	Indicator	P value
X1	Current ratio	0.000
X2	Quick ratio	0.000
X3	Asset-liability ratio	0.000
X4	Equity ratio	0.000
X5	Times-interest-earned ratio	0.000
X6	Earnings per share	0.000
X7	Return on assets	**0.312**
X8	Operating profit ratio	0.000
X9	Return on total assets	**0.267**
X10	Ratio of profits to cost	0.000
X11	Net interest rate on total assets	0.000
X12	Net interest rate on fixed assets	**0.378**
X13	Cash content of operating income	**0.055**
X14	Cash content of net profit	0.000
X15	Business cycle	**0.314**
X16	Inventory turnover rate	0.000
X17	Accounts receivable turnover ratio	**0.411**
X18	Total assets turnover ratio	0.002
X19	Total assets growth rate	**0.217**
X20	Growth rate of fixed assets	**0.126**
X21	Operating income growth rate	**0.075**

According to Table 3, $p > 0.05$ was used as the criterion to exclude the indicators that did not differ significantly between ST and non-ST enterprises, and the indicators with $p < 0.05$ were retained, totaling 12. Then, the Pearson correlation coefficient test [8] was performed on these 12 indicators, and the results are shown in Table 5.

Table 5: Pearson correlation coefficient test results (bolded: small correlation coefficient).

Number	Indicator	P value
X1	Current ratio	**0.007**
X2	Quick ratio	**0.009**
X3	Asset-liability ratio	0.055
X4	Equity ratio	**0.006**
X5	Times-interest-earned ratio	-0.116
X6	Earnings per share	-0.222
X8	Operating profit ratio	-0.125
X10	Ratio of profits to cost	**0.002**
X11	Net interest rate on total assets	-0.123

X14	Cash content of net profit	-0.068
X16	Inventory turnover rate	0.312
X18	Total assets turnover ratio	**0.008**

According to Table 4, the correlation coefficients of X1, X2, X4, X10, and X18 were small, and these indicators were considered as less relevant to the existence of financial risk in the enterprise, so they were eliminated. The final indicators obtained for forecasting are shown in Table 6.

Table 6: Financial indicators used for risk forecasting.

Category	Number	Indicators
Debt service level	X1	Asset-liability ratio
	X2	Times-interest-earned ratio
Profit level	X3	Earnings per share
	X4	Operating profit ratio
	X5	Return on total assets
Cash flow kevel	X6	Cash content of net profit
Operating level	X7	Inventory turnover rate

4 Neural network-based prediction methods

The neural network method with good self-learning ability and fault tolerance can effectively process a large amount of data, and has mature applications in industrial control and medical health [9]. Therefore, this paper designed a financial risk prediction of SMEs based on neural networks.

BPNN is one of the most widely used neural network methods [10]. Taking a simple three-layer network as an example, the model parameters are assumed to be as follows.

Input layer vector: $X_i = (x_1, x_2, \cdots, x_n)$

Hidden-layer output vector: $Y_j = (y_1, y_2, \cdots, y_m)$

Output-layer vector: $O_k = (o_1, o_2, \cdots, o_l)$

Input-layer and hidden-layer weights: w_{ij}

Hidden-layer and output-layer weights: v_{jk}

Then, the output of the implicit layer is written as: $Y_j = f\left(\sum_{i=1}^{n} w_{ij} X_i - b_j\right)$, where b_j is the hidden-layer threshold. The output of the BPNN is written as: $O_k = f\left(\sum_{j=1}^{m} v_{jk} Y_j - b_k\right)$, where b_k is the output-layer threshold. Let the expected output vector be d_k, then the error of the model is written as: $E_k = \frac{1}{2}\sum_{k=1}^{l}(d_k - o_k)^2$. The goal of training is to make the error satisfy the accuracy. The BPNN trains the model by back-propagating the error and continuously adjusting the weights and thresholds.

However, the BPNN has the characteristics of slow convergence and easy to fall into local optimum. In this paper, an improved sparrow search algorithm (ISSA) was designed to optimize it, and the ISSA-BPNN method is obtained.

The SSA is an algorithm based on the foraging behavior of sparrows [11], which has strong local search ability and fast convergence. Suppose that in a D-dimensional space, there are n sparrows, their initial positions is written as: $X = \{x_{1,1}, x_{1,2}, \cdots, x_{n,d}\}$. In the population, the sparrow searching for food is called the discoverer. At time t, its position update is written as:

$$x_{i,j}(t+1) = \begin{cases} x_{i,j}(t) \cdot exp\left(-\frac{i}{\alpha t_{max}}\right), if\ R < ST \\ x_{i,j}(t) + QL, if\ R \geq ST \end{cases}, \quad (1)$$

where:

α: a random number in [0,1],

R: an alert value in [0,1],

ST: a safety value in [0.5,1],

Q: a random number satisfying a normal distribution,

L: a $1 \times d$ matrix.

The followers will follow the discover to compete for food, and if they cannot compete for enough food, they will move to other regions to search. The process is written as:

$$x_{i,j}(t+1) = \begin{cases} Qexp\left(\frac{x_w - x_{i,j}(t)}{i^2}\right), if\ i > \frac{n}{2} \\ x_{i,j}(t) + \left|x_{i,j}(t) - x_p(t)\right| \cdot A^+ \cdot L, otherwise \end{cases},$$

where:

x_w: the location with the worst fitness,

x_p: the location with the best fitness,

A^+: $A^+ = A^T(A^{AT})^{-1}$ (A is a $1 \times d$ matrix, and A^T is the transposition of A).

When danger is detected, individuals on the outside of the population will move closer to the inside, and individuals on the inside will move closer to their peers. The process is written as:

$$x_{i,j}(t+1) = \begin{cases} x_b(t) + \beta \cdot \left|x_{i,j}(t) - x_b(t)\right|, if\ f_i \neq f_b \\ x_{i,j}(t) + K \cdot \frac{\left|x_{i,j}(t) - x_b(t)\right|}{(f_i - f_w)}, if\ f_i = f_b \end{cases}, \quad (2)$$

where:

x_b: the globally optimal position

f_i: the fitness of sparrow i,

f_b: current best fitness,

f_w: current worst fitness,

β: a random number satisfying a normal distribution,

K: a random number in [-1,1] to control the direction of the sparrow's movement.

When $f_i \neq f_b$, it is the process of sparrow approaching from outside to inside, and when $f_i = f_b$, it is the process of sparrows approaching from the inside to their companions. The SSA obtains the optimal solution by continuously updating the sparrow positions. However, the SSA uses random generation for population initialization, which is not conducive to the diversity of the population, so the SSA was improved by combining chaos mapping. PWLCM [12] was used to achieve the initialization of the population. The formula is:

$$x_i = \begin{cases} \frac{x_{i-1}}{\delta}, 0 \leq x_{i-1} < \delta \\ \frac{(x_{i-1} - \delta)}{0.5 - \delta}, \delta \leq x_{i-1} < 0.5 \\ 0, x_{i-1} = 0.5 \\ F(1 - x_{i-1}, \delta), 0.5 < x_{i-1} < 1 \end{cases}, \quad (3)$$

where δ is the control parameter.

The steps of the ISSA-BPNN method were: ① initialize the BPNN; ② initialize the sparrow population by PWLCM; ③ calculate the individual fitness and update the sparrow position according to the rules of the SSA; ④ judge whether the maximum number of iterations is reached; if it is, the optimal weight and threshold are output; ⑤ finish the training of the BPNN and get the predicted results.

5 Experimental results

To verify the effectiveness of the ISSA-BPNN method in predicting financial risk, experiments were conducted in the MATLAB environment. The population size of the ISSA was 25. The maximum number of iterations was 100. The maximum safety value was taken as 0.7. The number of input layer nodes of the BPNN was 7, which were the seven financial indicators in Table 5. The number of output layer nodes was 1, which meant whether there was a financial risk in the enterprise; if there was, the output result was "1"; if not, the output result was "0". The number of hidden layer nodes was determined based on the empirical formula: $m=\sqrt{n+l}+a$, where a is an integer between 0 and 10; through trial and error, the number was determined to be 9. The final BPNN structure was 7-10-1, the maximum number of training was 500, the learning rate was 0.01, and the accuracy requirement was 0.05. In accordance with the treatment of financial indicators in Section 2, experiments were conducted using these samples. The division of these samples is shown in Table 7.

Table 7: Experimental samples

	Training set	Test set	Total
ST enterprises	61	21	82
Non-ST enterprises	123	41	164
Total	184	62	246

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The evaluation of the algorithm was performed based on the confusion matrix (Table 8).

Table 8: Confusion matrix.

Confusion matrix		True value	
		Positive	Negative
Predicted value	Positive	True positive (TP)	False positive (FP)
	Negative	False negative (FN)	True negative (TN)

For classification algorithms, the commonly used evaluation indicators were as follows. ① Accuracy: $Accuracy=(TP+TN)/(TP+FP+FN+TN)$; ② precision: $Precision=TP/(TP+FP)$; ③ recall rate: $Recall=TP/(TP+FN)$. The F1 value was used to

First, to understand the performance of the BPNN on financial risk prediction, it was compared with other methods: fisher discriminant analysis [13], random forest (RF) [14], and support vector machine (SVM) [15]. The results are presented in Table 9.

Table 9: Results of comparison of the BPNN with other prediction methods.

	Fisher discriminant analysis	RF	SVM	BPNN
Accuracy	0.8872	0.9136	0.9377	0.9616
Precision	0.9012	0.9233	0.9456	0.9716
Recall rate	0.7764	0.7856	0.7921	0.8012
F1 value	0.8342	0.8489	0.8621	0.8782

From Table 9, it was found that, among the four forecasting methods compared, Fisher discriminant analysis was less effective in forecasting financial risk, with an accuracy of 0.8872 and an F1 value of 0.8342, while the RF and SVM methods were slightly better than Fisher discriminant analysis, with an accuracy of over 90%. The accuracy of the BPNN method reached 0.9676, which was 0.0744, 0.048, and 0.0239 higher than the Fisher discriminant analysis, RF, and SVM methods. The F1 value of the BPNN method also reached 0.8782, which was 0.044, 0.0293, and 0.0161 higher than the previous three approaches. These results proved the reliability of the BPNN as a financial risk prediction method for SMEs.

Then, the effectiveness of the BPNN optimization was analyzed by comparing the effectiveness of the BPNN, SSA-BPNN, and ISSA-BPNN methods on financial risk prediction, and the results are shown in Figure 1.

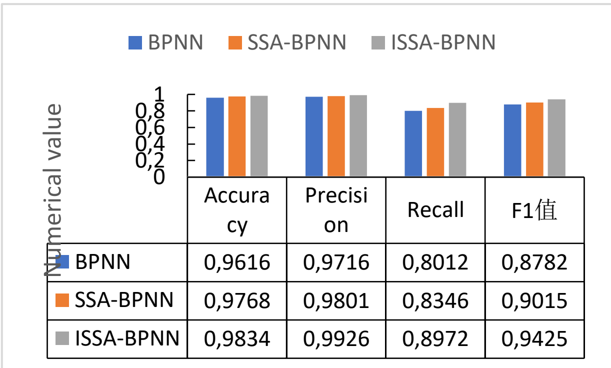

Figure 1: Prediction performance analysis of the ISSA-BPNN method.

It was observed in Figure 1 that the ISSA-BPNN prediction method performed the best. In terms of accuracy, the ISSA-BPNN approach was 0.0218 higher than the BPNN method and 0.0066 higher than the SSA-BPNN method; in terms of F1 value, the ISSA-BPNN method was 0.0643 higher than the BPNN method and 0.041 higher than the SSA-BPNN method. First, according to the comparison between the SSA-BPNN and

BPNN methods, it was found that the introduction of the SSA into the BPNN was effective. Then, after comparing the ISSA-BPNN method with the SSA-BPNN method, it was found that the SSA combined with chaos mapping was better for the BPNN, which can provide reliable prediction for the financial risk of SMEs.

Twenty samples were randomly selected from the test set, and the prediction results of the ISSA-BPNN method are shown in Table 10.

Table 10: ISSA-BPNN prediction results (bolded: the predicted value do not match the true value).

Sample number	True value	Predicted value	Sample number	True value	Predicted value
1	0	0	11	0	0
2	1	1	12	0	0
3	0	0	13	1	1
4	1	1	14	1	1
5	1	1	15	0	0
6	0	0	**16**	**0**	**1**
7	0	0	17	0	0
8	0	0	18	0	0
9	0	0	19	1	1
10	1	1	20	0	0

In Table 10, among the 20 randomly selected samples, the ISSA-BPNN method predicted incorrectly for only one sample. For sample 16, whose real situation was a non-ST enterprise, but the prediction output of the ISSA-BPNN method was an ST enterprise, while for the rest of the samples, the prediction of the ISSA-BPNN method was accurate. This result indicated that using the ISSA-BPNN method could accurately determine whether SMEs have financial risks, thus providing a reliable reference for managers.

6 Discussion

As a very important part of the capital market, SMEs are closely watched by investors and market regulators. For SMEs, in order to maintain a healthy business development, they need to adopt scientific methods to predict and prevent the possible financial risks of enterprises in a timely manner. With the development of machine learning and deep learning, more and more methods have been applied. In this paper, an ISSA-BPNN prediction method based on a neural network was developed.

The experiments on 82 ST enterprises and 164 non-ST enterprises found that the BPNN method performed best in financial risk prediction, with higher accuracy and F1 value than the RF and SVM methods. The comparison between the SSA-BPNN and ISSA-BPNN methods also showed that after the improvement by the ISSA, the BPNN's performance was significantly improved, with an accuracy of 0.9834 and an F1 value of 0.9425. The experimental results proved the predictive performance of the method and its application feasibility for predicting the actual financial risk of SMEs, providing a reference for risk prevention.

From the experimental results, it was found that the ISSA-BPNN method showed better performance in predicting the financial risk of SMEs compared with Fisher discriminant analysis and random forest, and achieved higher accuracy, precision, recall rate, and F1 value in predicting the experimental data. Specifically, BPNN, as a machine learning method, has better performance in dealing with nonlinear, multi-classification problems, and also has strong learning adaptivity, which effectively improves the accuracy in data prediction by back-propagation of errors. To address the shortcomings of BPNN, this paper used an ISSA for improvement and demonstrated the reliability of the improvement by experimental comparison. Therefore, the ISSA-BPNN method is more suitable for SME financial risk prediction.

However, there are still some shortcomings in the methodology of this paper compared with the current research. This paper mainly focused on the forecasting method, and the selection of financial indicators was screened by Mann-Whitney U test and Pearson test, retaining the indicators that are more relevant to financial risk forecasting, but the selection of non-financial indicators was neglected in the initial selection of indicators.

From the current study, it can be seen that there is also a strong relationship between non-financial indicators and financial risk, and the combination of financial and non-financial indicators can often lead to better prediction results. Therefore, in the future work, we will conduct a more in-depth study on the selection of indicators based on the ISSA-BPNN method, consider financial and non-financial indicators together, and further discuss the influence of the selection of indicators on the results, and we will also expand the number of samples to further verify the applicability of the method.

To prevent financial risks, the following suggestions are made:

(1) Raise risk awareness. Financial risks pose a great threat to the survival of enterprises, so enterprises should raise their risk awareness, make early arrangements to deal with risks, and strengthen the supervision and control of risks.

(2) Improve the financial risk management system. Enterprises should establish a sound financial risk management system and equip competent financial risk management personnel to monitor and forecast risks.

(3) Strictly manage the financial activities of enterprises. When making financial decisions in the development of an enterprise, it is important to balance benefits and risks and reduce financial risks.

7 Conclusion

This paper designed an ISSA-BPNN method for the financial risk of SMEs and used the screened financial indicators to achieve the prediction of financial risk. Through experiments, it was found that the proposed method had a high accuracy and F1 value, indicating its effectiveness in accurately determining whether an enterprise has financial risks. The method can be further promoted and applied in practice to improve the prediction level of enterprise financial risk and promote the stability and development of the capital market.

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