International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 17 (2025) pp. 1-19

https://doi.org/10.70917/ijcisim-2025-0309
Article

Intelligent Financial Risk Identification System Supported by Enterprise Financial Data Mining in Big Data Environment

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Abstract: In this paper, 27 corporate financial risk indicators are first selected in the big data environment, and 8 non-significant indicators are screened out from the 27 indicators by using K-W test and T-test; and then further condensed into 6 factors by combining with the factor analysis method and constructing the financial risk early warning indicator system. Then, PSO-BP neural network based on particle swarm optimization algorithm is constructed, and the identification effect of this network in enterprise financial risk is simulated and tested. The results show that: after screening, this paper finally selected 19 indicators as the early warning indicators of the model; after factor analysis identification of the 19 indicators, six main factors are obtained, such as dominated by the net equity interest rate and dominated by the balance sheet ratio, whose response rate to the financial characteristics of the sample enterprise is more than 75%. The training number of PSO-BP neural network reaches 21 times, then it can reach the prediction accuracy set by this paper, and then the overall fitting effect of the model is tested in simulation. Accuracy, at this time, the overall fit R value of the model is as high as 0.9871, the network prediction error range is between -0.39-0.31, the accuracy of the expected value and the predicted value of the financial risk identification is more than 95%; the accuracy of the identification of the enterprise's financial data in the big data environment reaches 98.15%, which efficiently completes the intelligent identification of the enterprise's financial risk.

Keywords: financial risk identification; factor analysis; PSO-BP neural network; K-W test

1. Introduction

In recent years, the term big data has been mentioned more and more, and with the development of society and the wide application of the Internet, big data came into being. Because of its variety, fast acquisition speed, low cost of acquisition and storage, and wide source channels, it can be applied to various fields, and the research on big data has become increasingly in-depth [1-3]. Big data makes it possible for enterprises to realize efficient and high-quality financial management, and big data can not only improve the use value of financial data, but also enhance the processing efficiency of financial data, providing managers with useful information for decision-making [4-5].

In the big data environment, a series of changes have occurred in the financial risk management of enterprises, the access to information has become wider so that enterprises can have more reference bases for decision-making, the speed of access to information has become faster so that enterprises can pay attention to the real-time information that has an impact on the financial risk, the application of cloud computing, mobile computing and other technologies to improve the efficiency of financial analysis [6-8]. At the same time, the application of big data is of great significance to the early warning work of enterprise financial risk. Enterprises use data mining technology to select valuable information for the enterprise in the massive amount of data, and analyze this information, and predict the potential risks of the enterprise according to the analysis results, this method is increasingly being applied to the financial management of the enterprise, to help business managers more accurately grasp the current situation of the enterprise, and take timely countermeasures to reduce the likelihood of the occurrence of financial risks, and minimize the loss [9-10].

With the increasingly fierce competition between enterprises, in order to obtain competitive advantage in the future market, enterprises must pay attention to the management of financial risk, do a good job in the identification and evaluation of risk factors, and to be able to effectively avoid and control the relevant risk factors of the strategy [11-13]. Enterprises need to have a high degree of sensitivity to financial risk and a deep understanding of the Russian and Ukrainian war as a turning point, due to the United States of America's foreign trade policy changes, the domestic and foreign macroeconomic environment to the national environment changes are also occurring in the complexity of the changes in the various types of risks faced by the enterprise is also increasing, and a lot of hidden risks will be exposed subsequently [14-15]. Due to the changes in the international situation, resulting in a variety of energy structure and price changes, reflected in the enterprise's raw material costs and expenses continue to rise, the original traditional advantages are gradually lost, the enterprise's various hidden contradictions gradually began to focus on the emergence of the enterprise, which makes the enterprise's financial risk management and prevention and control work is particularly urgent.

The influencing factors of financial risk are categorized into micro and macro, starting with micro factors, which have been richly studied by scholars at home and abroad. Kavassalis et al. carried out a corresponding study on the relationship between financial risk and corporate management, after analyzing a number of industries and the size of the enterprise, the large-scale enterprises as the object of the study, to explore whether the governance capacity of corporate management will affect the level of financial risk faced by the enterprise, and finally concluded that there is a correlation between the two [16]. For the enterprise financial risk identification perspective, Skoglund and Chen believe that the capital flow leads to the emergence of the enterprise's risk is the enterprise's own control, risk control from the perspective of capital flow, the need to closely integrate the financing and investment links, and the need to pay extra attention to the capital flow [17]. Ajao and Oluwadamilola believe that the influence of financial risk is caused by not one but many factors, they studied the relationship between internal control and financial risk, and concluded that the strength of internal control directly affects the severity of financial risk, in addition to proposing that the enterprise should pay attention to the internal control environment, control activities, detection of the quality of internal control, and so on, and through the management of internal control of the corresponding level of management of the enterprise's financial risk [18]. In addition to the above reasons, Helwege, J also analyzed the systemic and insolvency of the financial risk of the enterprise, and he attributed the two characteristics to the enterprise information infection and correlation infection [19].

Macro-factor approach, McNulty et al. explored the association between financial risk and external factors through extensive investigation and research, and found that market factors, bank exchange rates, and economic development will all have a certain impact on corporate financial risk, and changes in macro-national policies make the market unstable, which also further increases the probability of corporate financial risk [20]. Liu and Shehzad analyzed the financial data of A-share listed companies in Shanghai Stock Exchange in China from 2010 to 2019 in depth, and tried to analyze whether the uncertainty of the macroeconomic environment will have an impact on corporate financial risk. China's financial data of A-share-listed enterprises on the Shanghai Stock Exchange from 2010 to 2019, and try to analyze whether the uncertainty of the macroeconomic environment will have an impact on corporate financial risk, and the study found that the macroeconomic environment can potentially affect corporate financial risk through the dual channels of economic growth and monetary liquidity [21]. Ren et al.'s study found that the level of market economic development will also affect the enterprise financial risk to a certain extent, specifically, when the economic growth trend is better, corporate earnings will increase, debt risk and bankruptcy risk will be synchronized to reduce; and when the economic growth rate is slowing down, macroeconomic downturn, the financial burden of enterprises will be aggravated will lead to an increase in the financial risk [22]. Calvez and Lugovskyy in order to identify the financial risk of small and medium-sized enterprises faced with business activities, investigated the business activities of small and medium-sized enterprises faced with financial risks, the financial risks of small and medium-sized enterprises faced with business activities. Calvez and Lugovskyy, in order to identify the financial risks faced by SMEs in their business activities, investigated whether the financial risks associated with business activities are related to the investor's personal and family factors, and the results of the study confirmed the correlation between the two, suggesting the need to develop risk-prevention measures in conjunction with external factors [23].

In order to explore the causes of financial risk, as well as ways to reduce the probability of financial risk, there are many other scholars through empirical research to create the identification model of financial risk, which provides a good theoretical basis for financial risk identification [24-25]. Cherry and Asebedo believe that in financial risk identification, managers should take into account the entire process of business activities, and carry out all-round and multi-angle identification of fundraising, investment, operation and other activities of the enterprise, with a view to investigating what financial risks exist in the enterprise [26]. Krüger et al. selected some small and medium-sized enterprises (SMEs) and investigated the identification of financial risks hindering the normal functioning of SMEs through quantitative analysis methods, and then helped the enterprises to formulate countermeasures, with the aim of reducing the failure rate of SMEs and improving the ability to cope with risks [27]. Kharlanov et al. suggest that corporate social responsibility contributes to the creation of a favorable social image, which in turn can help companies to mitigate the negative impact of financial risks, and that this positive effect is particularly prominent in times of economic crisis [28]. In terms of methodology, Wu, P et al. proposed that it is crucial to establish an objective financial risk early warning mechanism and constructed a set of risk early warning models operating in the context of financial risk prevention and earnings risk management, which is a multivariate phenomenon prediction model based on non-correlation analysis, which can effectively identify the financial risks [29]. Gospodinov et al. introduced machine learning methods such as Support Vector Machines (SVM) in risk modeling for identifying financial risks throughout the business operations and found that the financial risk estimation results under the SVM method were more accurate [30].

With the rapid development of information technology, emerging technologies such as big data, cloud computing, artificial intelligence and so on have gradually come into the vision of enterprise management, injecting new vitality into financial risk identification. In particular, big data technology, through the real-time collection, storage, calculation and analysis of massive data, can portray the financial operation of the enterprise from a global perspective, reveal potential risk factors from multiple dimensions, and capture the risk occurrence law from dynamic changes, which greatly improves the breadth, depth and precision of financial risk identification [31-32]. Kang used market-to-book ratio, gearing ratio, cash flow ratio and financing structure model as constraint parameters, combined with adaptive fuzzy weighted control and big data technology to construct a big data analysis model for enterprise financial risk assessment, and found that it has good application value in the prevention and control of financial risk [33]. Regin and Rajest constructed an optimization model for corporate financial risk identification based on big data mining techniques and neural networks and found that it can improve organizational structure, increase management efficiency, and significantly reduce financial risk [34]. Kumar et al. explored the potential applications of BDA (Big Data Analytics based technology) for enterprise financial risk management, real-time decision making, predictive analytics, and risk assessment, stating that companies maximizing the use of BDA can somewhat reduce financial risk, plan ahead, and seize opportunities in emerging markets [35]. Elumilade et al. argue that big data analytics has emerged as a transformative tool to identify, assess, and mitigate financial risks more accurately and efficiently through the use of big data, machine learning, and predictive modeling [36].

Data mining, also known as Knowledge Discovery in Databases (KDD), is the process of extracting implicit, yet potentially useful information and knowledge from large, noisy, and stochastic real-world application data using various analytical tools [37-39]. Regarding the application of data mining technology in enterprise financial risk, Jin et al. pointed out that enterprise financial risk analysis and assessment are affected by various internal and external factors, and the use of data mining's powerful analytical ability is applicable to enterprise financial risk analysis and crisis early warning [40]. Gao constructed a set of financial risk early warning model based on deep learning and data mining techniques, and combined it with a financial risk assessment index system covering four dimensions: solvency, operational capacity, profitability, growth capacity and cash flow capacity, which effectively reduced the financial risk of the enterprise [41]. Koyuncugil et al. utilized a data mining-based technology to construct a financial risk detection Early Warning System (EWS), and found that the EWS system is able to provide financial analysis services for SMEs in the decision-making process like a tailor-made financial advisor [42]. Feng and Qu combined data mining technology with deep learning to provide Internet financial enterprises with a financial market risk identification and analysis method, which is able to effectively warn the market of potential risks and provide targeted risk management measures [43]. The above scholars summarize the drawbacks of traditional financial risk management, identify and measure financial risks from different angles and using different methods, while focusing on the impact of non-financial indicators on enterprise financial risk, and also apply data mining technology in the study of enterprise financial risk early warning.

In this study, the data sources and selection principles of financial risk early warning were first outlined, after which the normality K-W test, T-test and non-normality Mann-Whitney U test were used to screen the financial risk early warning indicators of enterprises, and only those financial risk early warning indicators that were significantly different were retained. Then using factor analysis, further dimensionality reduction to get six characteristic factors that can reflect most of the enterprise finance. Finally, the particle swarm algorithm is used to optimize the BP neural network model to construct the financial risk early warning model of PSO-BP neural network, and simulation experiments are carried out.

2. Mining corporate financial risk indicators in a big data environment

2.1. Early Warning Data Sources and Selection Principles for Corporate Financial Crisis

2.1.1. Research data sources

The main source of data in this paper is the financial data published by the organization using the Cathay Pacific Data Service Center (CSMAR database), which is the financial data of enterprises for five years from 2020 to 2024. This paper has certain criteria for the selection of the research sample, which requires the screening of data.

This paper has screened the enterprise samples obtained, and finally this paper selects 100 enterprises for early warning research, of which 20 have financial crisis (8 ST stocks, 12 significant losses), and 80 enterprises with normal financial.

2.1.2. Principles for the selection of indicators

(1) The principle of comprehensiveness

The selection of early warning indicators must be able to comprehensively respond to the financial status of the enterprise. When selecting indicators, we should comprehensively consider the possible non-financial indicators, so that the model can be more comprehensive and accurate.

(2) Principle of accessibility

In the acquisition of data must be taken into account the availability of relevant data and information, generally speaking, enterprises will publicly release the company's financial reports, so through the financial statements to obtain the financial data of the enterprise's operations is the most commonly used method.

(3) Predictive principle

In this paper, when selecting financial indicators, we need to utilize statistical means to screen the indicators, so that when these indicators are abnormal, they can be instantly observed and effectively predict the occurrence of financial crises.

(4) Importance principle

In the selection of financial early warning indicators, it is necessary to select the most important, most responsive to the financial crisis of the relevant indicators.

(5) Comparability principle

In the selection of indicators must be in the calculation method, calculation caliber, calculation time and space can be horizontally comparable and vertically comparable.

2.2. Screening of financial early warning indicators for enterprises

2.2.1. Preliminary selection of early warning indicators

According to the above index selection principles, this paper obtains enterprise financial early warning indicators as shown in Table 1. The results show that this paper mainly selects six primary indicators and 27 secondary indicators of “profitability, solvency, operational capacity, development capacity, cash flow capacity and non-financial indicators”. After that, the K-W test, T-test and Mann-Whitney U-test of normality were used to further screen the initial selection of indicators. See below for details.

Table 1. Financial early warning indicators of listed companies.

Indicator type	Name of index	Indicator code
Profitability	Total assets net profit margin	X1
	Return on invested capital	X2
	Return on Equity	X3
	Operating Profit Margin	X4
	Earnings per share	X5
Debt paying ability	Current ratio	X6
	Quick ratio	X7
	Asset-liability ratio	X8

	Cash ratio	X9
	Equity ratio	X10
Service power	Inventory turnover ratio	X11
	Fixed asset turnover	X12
	Average accounts receivable turnover ratio	X13
	Turnover of total capital	X14
	Turnover of current assets	X15
Development capability	Asset Growth	X16
	Net profit growth rate	X17
	Increase rate of business revenue	X18
	Owner's equity growth rate	X19
	Sustainable Growth Rate	X20
Cash flow capability	Cash flow ratio	X21
	Net Cash Ratio	X22
	Cash-to-sales ratio	X23
	Cash return on assets	X24
Non-financial indicators	Audit opinion	X25
	Equity Concentration	X26
	Business circumstance	X27

2.2.2. Indicator normality test based on K-W

Kruskal-Wallis test [44], the Kruskal-Wallis test, is also known as the K-W test.The K-W test is mainly used for the comparison of multiple independent samples of the continuous type, and is used as a nonparametric method to compare whether multiple independent samples are likely to be distributed with the same probability distribution.The K-W test does not require that the sample data satisfy a normal distribution, which is very friendly. In this paper, we intend to use this test to verify whether there is a significant difference between the financial and non-financial indicators of enterprises. The test steps are as follows:

Suppose there are m mutually independent simple random samples $\left(X_1,\cdots,X_{ni}\right)(i=1,2,\cdots,m)$;

In the first step, the $N=\sum_{i=1}^{m} n_i$ observations of all the samples are arranged in increasing order in a column;

In the second step, use R_i as the sum of the ranks of the n_i observations of the i th sample under the arrangement $X_1,\cdots,X_{ni}$;

In the third step, the statistic is computed:

$$H=\frac{12}{N(N+1)}\sum_{i=1}^{m}\frac{R_i^2}{n_i}-3(N+1) \tag{1}$$

Assuming that each sample has r identical data, and letting t_1 be the number of times the common observation of each sample's first is present in all N observations, then compute the following modified statistic:

$$H^* = H\frac{N\left(N^2-1\right)}{\sum_{i=1}^{r}\left(t_i^3-t_i\right)} \tag{2}$$

At a sufficiently large N, both H^* and H are close to obeying the χ^2 distribution and it has a degree of freedom formula of $v = m-1$;

In the fourth step, for a given level of significance α and degree of freedom v, it is assumed that $H^* \geq x^2{}_{\alpha,v}$ (or $H \geq x^2{}_{\alpha,v}$) then it can be assumed that m samples participating in the test will not be from the same total population exactly. If the hypothesis is valid, the fit will be verified by probability integration of x^2.

The results of the test of normal distribution of financial indicators of enterprises are shown in Table 2. It can be seen that, among the 27 indicators, 9 indicators obey the normal distribution, which are X8, X12, X14, X15, X18, X21, X23, X24, X26, and most of the indicators do not conform to the normal distribution. Because of this, this paper firstly conducts T-test to censor the indicators that conform to normal distribution, and then adopts Mann-Whitney U-test of non-parametric method to censor the rest of the indicators, in which the latter test is actually a kind of rank-sum test, and the statistic of the testing process has no relation to the size of the sample value, and the null hypothesis of its testing method is: two independent samples come from the overall without significant difference.

Table 2. Financial index normal distribution test results of listed companies.

Variable	Zhengtai parameters		Kruskal-Wallis test	P price	Is it normally distributed
	Average value	Standard deviation			
X1	0.0088	0.076	0.2238	0.0298	Deny
X2	0.0197	0.0852	0.1867	0.0000	Deny
X3	-0.0491	0.3056	0.3009	0.0000	Deny
X4	0.018	0.2177	0.2423	0.0139	Deny
X5	0.4622	1.3116	0.3034	0.0000	Deny
X6	2.4169	3.0192	0.2511	0.0000	Deny
X7	1.5962	2.5121	0.3008	0.0000	Deny
X8	0.4321	0.2114	0.0983	0.7001	Yes
X9	0.6623	1.0779	0.3033	0.0000	Deny
X10	1.3989	2.2313	0.2962	0.0000	Deny
X11	2.8021	2.397	0.1985	0.0301	Deny
X12	2.7521	2.4837	0.181	0.1397	Yes
X13	28.328	56.142	0.2972	0.0000	Deny
X14	0.5189	0.335	0.1425	0.2995	Yes
X15	1.1603	0.8887	0.1501	0.2793	Yes
X16	0.0907	0.2509	0.1893	0.0098	Deny
X17	3.1411	18.3441	0.4497	0.0000	Deny
X18	0.06	0.3171	0.0997	0.7768	Yes
X19	0.0685	0.3389	0.2813	0.0000	Deny
X20	-0.0311	0.1755	0.2989	0.0000	Deny
X21	0.1767	0.3138	0.1505	0.2054	Yes

X22	-0.254	5.8193	0.2981	0.0000	Deny
X23	0.0767	0.2371	0.1205	0.4891	Yes
X24	0.033	0.0748	0.0576	0.8957	Yes
X25	0.1204	0.3294	0.5045	0.0000	Deny
X26	0.3302	0.1558	0.088	0.8002	Yes
X27	11.824	21.2294	0.302	0.0000	Deny

2.2.3. T-test for normal distribution indicators

The results of the t-test for normally distributed early warning indicators are shown in Table 3. The results show that X12 and X26 did not pass the mean test, so it was determined that these two variables do not differ much in different groups of enterprises, i.e., they have a weak function in early warning of financial crises, so these two indicators were deleted.

Table 3. T-test results for the normal distribution warning index.

Variable	Mean		T-test value	Is the difference significant
	Normal group	Crisis Group		
X8	0.3992	0.6259	-2.5028**	Yes
X12	2.87	2.0957	0.694	Deny
X14	0.5691	0.2265	2.4053**	Yes
X15	1.2725	0.4743	2.0955**	Yes
X18	0.1119	-0.2172	2.4688**	Yes
X21	0.2113	-0.0204	1.8887*	Yes
X23	0.1088	-0.0812	1.9144*	Yes
X24	0.4096	-0.019	1.7822*	Yes
X26	0.3382	0.2672	0.8384	Deny

2.2.4. Mann-Whitney U test for non-normally distributed indicators

The results of Mann-Whitney U test [45] for non-normally distributed early warning indicators are shown in Table 4. The results show that X2, X6, X7, X13, X19, and X22 did not pass the test, which means that there is no significant difference between the above six early warning indicators, indicating that the function of these indicators for early warning of financial crises is weak, and therefore need to be deleted.

According to the results of the above tests, the final selection is based on the results of the T-test with Mann-Whitney U. The final selection is made:

Table 4. Mann-Whitney U test results for warning indicators.

Indicator code	Mann-Whitney U	Wilcoxon W	Z	Is the difference significant
Total Asset Net Profit Margin (X1)	51	69	-1.9864**	Yes
Return on invested capital (X2)	72	90	-1.2703	Deny
Return on Equity (X3)	47	63	-2.2013**	Yes
Operating margin (X4)	60	81	-1.7616*	Yes
Earnings per share (X5)	56	76	-1.7888*	Yes

Current Ratio (X6)	81	101	-0.9116	Deny
Quick Ratio (X7)	68	87	-1.3684	Deny
Cash Ratio (X9)	64	88	-1.9237*	Yes
Equity ratio (X10)	43	677	-2.1427**	Yes
Inventory Turnover (X11)	41	64	-2.2949**	Yes
Accounts Receivable Turnover (X13)	68	88	-1.4525	Deny
Asset Growth Rate (X16)	37	56	-2.6097***	Yes
Net profit growth rate (X17)	62	85	-2.1463**	Yes
Owner's Equity Growth Rate (X19)	78	96	-1.0308	Deny
Sustainable Growth Rate (X20)	60	82	-1.9542**	Yes
Net Cash Ratio (X22)	81	103	-0.7923	Deny
Audit Opinion (X25)	77	710	-1.6592*	Yes
Rural Business (X27)	72	95	-1.7927*	Yes

According to the results of K-W test, T-test with Mann-Whitney U, finally “X1, X3, X4, X5, X8, X9, X10, X11, X14, X15, X16, X17, X18, X20, X21, X23, X24, X25, X27” 19 indicators are used as early warning indicators for the model.

2.3. Identification of Financial Early Warning Indicators Based on the Factor Analysis Method

2.3.1. Factor analysis

Factor analysis is a dimensionality reduction processing method proposed for high-dimensional data, and the basic idea is to replace multi-dimensional complex variables (indicators) with common factors, group variables with the same attributes into one category, and use a few composite indicators to represent the vast majority of the information of the original variables.

(1) Factor model

Let $\mathbf{X}=\left(X_1,X_2,\cdots,X_p\right)^{\mathrm{T}}$ be the common factor random variable, and the factor mathematical model is as follows:

$$X_i=\alpha_{i1}F_1+\alpha_{i2}F_2+\cdots+\alpha_{im}F_m+\varepsilon_i i=1,2,\cdots,p \tag{3}$$

Where: F_m is the common factor; ε , is the special factor.

The factor model matrix is of the following form:

$$\mathbf{X}=\mathbf{AF}+\boldsymbol{\varepsilon} \tag{4}$$

Among them:

$$\mathbf{X}=\begin{bmatrix} X_1 \\ \vdots \\ X_p \end{bmatrix},\mathbf{A}=\begin{bmatrix} \alpha_{11} & \cdots & \alpha_{1m} \\ \vdots & \ddots & \vdots \\ \alpha_{p1} & \cdots & \alpha_{pm} \end{bmatrix},\mathbf{F}=\begin{bmatrix} F_1 \\ \vdots \\ F_p \end{bmatrix},\boldsymbol{\varepsilon}=\begin{bmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_p \end{bmatrix} \tag{5}$$

(2) Solving factor loading matrix

Usually, principal component analysis, maximum likelihood and other methods can be used to solve the factor loading matrix, in this paper, the factor loading matrix is obtained through the principal component method, the solution process is as follows:

① Calculate the covariance matrix $\mathbf{\Sigma}$ of the original variables, the covariance of the variable X , with F , is as follows:

$$Cov\left(X_i,F_j\right)=Cov\left(\sum_{k=1}^{m}a_{ik}F_k+\varepsilon_i,F_j\right)=Cov\left(\sum_{k=1}^{m}a_{ik}F_k,F_j\right)+Cov\left(\varepsilon_i,F_j\right)=a_{ij} \tag{6}$$

② Calculate the eigenroots of the covariance matrix $\mathbf{\Sigma}$ as $\lambda_1 \geqslant \cdots \geqslant \lambda_p \geqslant 0$, and the corresponding unit eigenvectors as $\mathbf{T}_1, \mathbf{T}_2, \cdots, \mathbf{T}_p$;

③ Using the covariance matrix $\mathbf{\Sigma}$ corresponding to $\mathbf{T}_i$ and λ_i, solve the matrix $\mathbf{A}$, i.e.:

$$\mathbf{A} = \left(\sqrt{\lambda_1}\mathbf{T}_1, \sqrt{\lambda_2}\mathbf{T}_2, \cdots, \sqrt{\lambda_p}\mathbf{T}_p\right) \tag{7}$$

(3) Factor rotation

The factor loading matrix obtained by the principal component method is not unique, and the variables may not be well differentiated on the common factor loading, which will not be conducive to the interpretation of the meaning of the common factor. At this time, the load matrix needs to be factor rotation, factor rotation can be orthogonal rotation or oblique rotation and other methods to make the load matrix values to 0 and 1 level of differentiation, so that it is easy to name the common factor.

(4) Factor score

The factor model matrix is of the form $\mathbf{X} = \mathbf{AF} + \boldsymbol{\varepsilon}$, and if the effect of the factor $\boldsymbol{\varepsilon}$ on the model is neglected, when $m = p$ and $\mathbf{A}$ is invertible, the score of the sample $\mathbf{X}$ on the corresponding common factor $\mathbf{F}$ can be calculated. However, m is usually smaller than p, and the exact value of $\mathbf{X}$ cannot be obtained, at this time, the estimated value of the factor scores can be obtained by the parameter estimation method. In this paper, Thompson regression method is applied to estimate the factor scores, and the Thompson factor scores are biased but with small errors, and the expressions are as follows:

$$\hat{\mathbf{F}} = \mathbf{B}^{\mathrm{T}}\mathbf{\Sigma}^{-1}\mathbf{X} \tag{8}$$

Where: $\mathbf{W}$ is the matrix of factor score coefficients; $\mathbf{W} = \mathbf{B}^{\mathrm{T}}\mathbf{\Sigma}^{-1}$.

2.3.2. Identification results of early warning indicators based on factor analysis

The chi-square (KMO) is a method to test whether the data is suitable for factorization, taking the value between 0 and 1. The closer the KMO value is to 1, the better the correlation is, the more suitable for factorization of variable research.The purpose of Bartlett's spherical test is to test whether the variables conform to the normal distribution, generally the Sig value is less than 0.005, it indicates that the variables conform to the normal distribution between them, and can be used for factor analysis.

The sample KMO test value is 0.6324, indicating that there is a good correlation between the indicator variables; in the Bartlett spherical test, the Sig value of 0.000 is less than 0.005, indicating that these variables are consistent with the normal distribution among them, and factor analysis can be used to optimize the selected indicators.

The total variance explained results of the early warning model indicator data are shown in Table 5. It can be seen that there are six eigenvalues greater than 1 in the total variance explained matrix, which are 4.5622, 2.9014, 2.3598, 1.8887, 1.3976, and 1.2313, and the cumulative variance of these six factors reaches 75.48%, which can reflect most of the financial characteristics of the sample enterprises.

Table 5. Explanatory results of total variance of early warning model index data.

Ingredient	Starting eigenvalue			Extract and load		
	Amount to	Variance (%)	Accumulation (%)	Amount to	Variance (%)	Accumulation (%)
1	4.5622	24.01	24.01	4.5622	24.01	24.01
2	2.9014	39.28	39.28	2.9014	39.28	39.28
3	2.3598	51.70	51.70	2.3598	51.70	51.70
4	1.8887	61.64	61.64	1.8887	61.64	61.64
5	1.3976	69.00	69.00	1.3976	69.00	69.00
6	1.2313	75.48	75.48	1.2313	75.48	75.48
7	0.9637	80.55				
8	0.8441	84.99				

9	0.8345	89.39				
10	0.6907	93.02				
11	0.4098	95.18				
12	0.2752	96.63				
13	0.1757	97.55				
14	0.1427	98.30				
15	0.1371	99.02				
16	0.0866	99.48				
17	0.043	99.71				
18	0.0251	99.87				
19	0.0308	100.00				

In order to be more convenient for the interpretation of the factors, the above six principal component factors are transformed using the variance maximization method in the orthogonal rotation method, and then the rotated factor loadings are obtained, and the rotated component matrix of the early warning data is shown in Table 6. The results show that: principal component F1 is dominated by the net equity interest rate, which represents the profitability of the enterprise; principal component F2 is dominated by the gearing ratio, which represents the solvency analysis of the enterprise; principal component F3 is dominated by the growth rate of operating income, which represents the development ability of the enterprise; principal component F4 is dominated by the proportion of supervisors, which represents the governance structure of the enterprise; principal component F5 is dominated by the proportion of independent directors, which represents the governance structure of the enterprise; principal component F5 is dominated by the proportion of independent directors, which represents the governance structure of the enterprise; principal component F5 is dominated by the proportion of independent directors, which represents the governance structure of the enterprise. F5 is governed by the proportion of independent directors, which represents the governance structure of the enterprise; principal component F6 is governed by the interest coverage multiple, which represents the solvency of the enterprise. In summary, this paper selects 6 metrics from 19 indicators as the final indicators of early warning research, which can reflect the financial status of Internet enterprises in a more comprehensive way.

Table 6. Rotate early warning data component matrix.

Metric	Element					
	F1	F2	F3	F4	F5	F6
X1	0.2681	-0.2318	0.1388	-0.6254	0.0434	-0.2831
X3	-0.4393	0.6779	0.0328	0.4184	-0.1129	0.1927
X4	-0.6553	0.6565	0.1859	0.1059	-0.0788	0.1355
X5	-0.355	-0.3076	-0.2791	0.1783	0.1063	0.5089
X8	0.8408	0.296	0.0326	-0.0811	0.2588	-0.1355
X9	0.9149	0.1642	-0.0039	0.2018	0.0374	0.015
X10	0.8072	0.17	-0.1138	-0.0577	0.1475	0.4425
X11	0.7233	0.4137	0.2744	-0.2794	-0.1734	0.1561
X14	0.6134	0.4563	0.2376	-0.1468	-0.1329	0.1912
X15	-0.6548	0.5106	0.3383	-0.3675	0.1126	0.0074
X16	0.0142	0.2928	0.0989	-0.1932	0.5969	-0.119
X17	-0.7397	0.4113	0.3311	-0.3717	0.0225	0.0752
X18	0.0623	0.2234	0.6142	0.3282	0.0114	-0.3545

X20	0.6367	0.1123	0.3042	0.3618	-0.2805	-0.3745
X21	0.0021	-0.4518	0.5965	0.3616	0.298	0.2822
X23	0.0562	-0.3415	0.5953	0.2989	0.3339	0.0215
X24	0.6759	0.2931	-0.1537	-0.0147	0.1093	0.3629
X25	-0.0868	0.2531	-0.4284	0.3146	-0.3535	-0.1436
X27	-0.0834	0.3433	-0.434	0.0611	0.634	-0.2751

The 6 principal component factors are not correlated and are orthogonal to each other. According to the results of running the principal component analysis method of factor analysis in SPSS software to get the score matrix of the six principal component factors, the factor score matrix is shown in Table 7. The scores of each principal component factor are automatically calculated according to the factor expression, and these data are the input variables for establishing the financial early warning model in the second year.

Table 7. Factor Score Matrix.

Metric	Element					
	F1	F2	F3	F4	F5	F6
X1	0.0442	-0.0851	0.0607	-0.3279	0.026	-0.2344
X3	-0.076	0.2328	0.0149	0.2199	-0.074	0.1523
X4	-0.1156	0.2201	0.0744	0.0586	-0.053	0.1244
X5	-0.0613	-0.111	-0.119	0.1023	0.0882	0.4079
X8	0.1426	0.1068	0.0063	-0.0512	0.1779	-0.1104
X9	0.164	0.0627	0.006	0.1011	0.0336	-0.007
X10	0.1425	0.0574	-0.0388	-0.0219	0.1147	0.3411
X11	0.1267	0.1372	0.1108	-0.1457	-0.1381	0.1251
X14	0.1106	0.1943	0.1011	-0.081	-0.1024	0.1625
X15	-0.1223	0.1802	0.1463	-0.1904	0.0724	-0.0048
X16	0.0107	0.0836	0.0491	-0.1087	0.4236	-0.087
X17	-0.1246	0.1439	0.1404	-0.2	0.0181	0.0697
X18	0.0098	0.1214	0.2672	0.1752	0.0143	-0.2918
X20	0.1073	0.0314	0.131	0.1948	-0.2018	-0.2967
X21	0.001	-0.1567	0.2506	0.1942	0.2186	0.2031
X23	0.0084	-0.1147	0.2522	0.1558	0.2313	0.0171
X24	0.1241	0.0894	-0.0705	-0.0042	0.0697	0.2931
X25	-0.0132	0.1013	-0.1838	0.163	-0.2563	-0.1115
X27	-0.0142	0.1245	-0.1879	0.0366	0.4423	-0.2186

3. Enterprise financial risk early warning model construction based on PSO-BP neural network

3.1. BP Neural Network

3.1.1. Principles of BP Neural Networks

The learning process of BP neural network consists of two processes: forward propagation of the signal and back propagation of the error. In forward propagation, the input samples are passed in from the input layer, processed layer by layer by each hidden layer, and then passed to the output layer. If the actual output of the output layer does not match with the desired output, it will be transferred to the reverse propagation stage of the error; when the reverse propagation is performed, the output will be back-propagated to the input layer layer by layer through the hidden layers in a certain form, and the error will be shared to all the units of each layer, so as to obtain the error signals of the units of each layer, which is used as the basis for the correction of the weights of each unit.

3.1.2. BP Neural Network Characterization

BP neural network consists of three elements i.e. network topology, transfer function and learning algorithm.

(1) Network Topology

A BP network is actually a multilayer perceptron, so its topology is the same as that of a multilayer perceptron. Since the single hidden layer (three-layer) perceptron has been able to solve simple nonlinear problems, it is most commonly used. In this paper, the single hidden layer BP neural network is chosen. It mainly consists of three layers i.e. input layer, hidden layer and output layer.

(2) Transfer function

The transfer function used in BP network is a nonlinear transformation function - Sigmoid function (also known as S function). It is characterized by the fact that the function itself and its derivatives are continuous, thus making it very convenient to handle. A simple Sigmoid function is shown below:

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

(3) Learning algorithm

The learning algorithm of the BP network is the core idea of the BP algorithm is to use gradient descent to search the hypothesis space of possible weight vectors to find the best fitting sample of weight vectors. Specifically, that is, using the loss function, each time to move toward the negative gradient direction of the loss function until the loss function obtains the minimum value. Setting: from the input layer data as X, the input layer to the hidden layer parameters as $w, b1$, the hidden layer to the output layer parameters as $v, b2$, the activation function used as $g1, g2$. So the model is set as:

Input layer to hidden layer:

$$\begin{aligned} net_1 &= w^t x + b_1 \\ h &= g_1\left(net_1\right) \end{aligned} \tag{10}$$

Hide layer to output layer:

$$\begin{aligned} net_2 &= v^t h + b_2 \\ haty &= g_2\left(net_2\right) \end{aligned} \tag{11}$$

Model:

$$y = g_2\left(net_2\right) = g_2\left(v^t g_1\left(net_1\right) + b =\right) = g = \left(v^t g_1\left(w^t x + b_1\right)\right. \tag{12}$$

Loss function:

$$E(\theta) = \frac{1}{2}\sum_{i=1}^{2}\left(y_i - \hat{y}_i\right)^2 \tag{13}$$

3.1.3. Advantages of BP Neural Networks

BP neural network has been widely used in medicine, artificial intelligence and other fields, compared with other early warning methods, BP neural network has the following advantages:

(1) Self-learning and adaptive ability: BP neural network can automatically extract “reasonable solution rules” by learning the set of real numbers with correct answers, and adaptively memorize the learning content in the weights of the network.

(2) High accuracy and high speed to find the optimal solution: BP neural network has convergence and can reduce the error and improve the accuracy through continuous automatic training, meanwhile, the computer's powerful arithmetic ability can find the optimal solution of the complex problem quickly.

3.2. PSO-BP Neural Network Corporate Financial Risk Prediction Model

3.2.1. Operational flow of PSO-BP neural network

The basic idea of the financial risk early warning model based on PSO-BP neural network [46] is to first run the particle swarm algorithm to get the initial solution, substitute the results of the particle swarm algorithm into the neural network, and finally train the neural network to warn the enterprise of the risk. The particle swarm algorithm can help the neural network to obtain excellent weights and thresholds, which in turn improves the efficiency and accuracy of the neural network. The process based on PSO-BP neural network is shown in Figure 1.

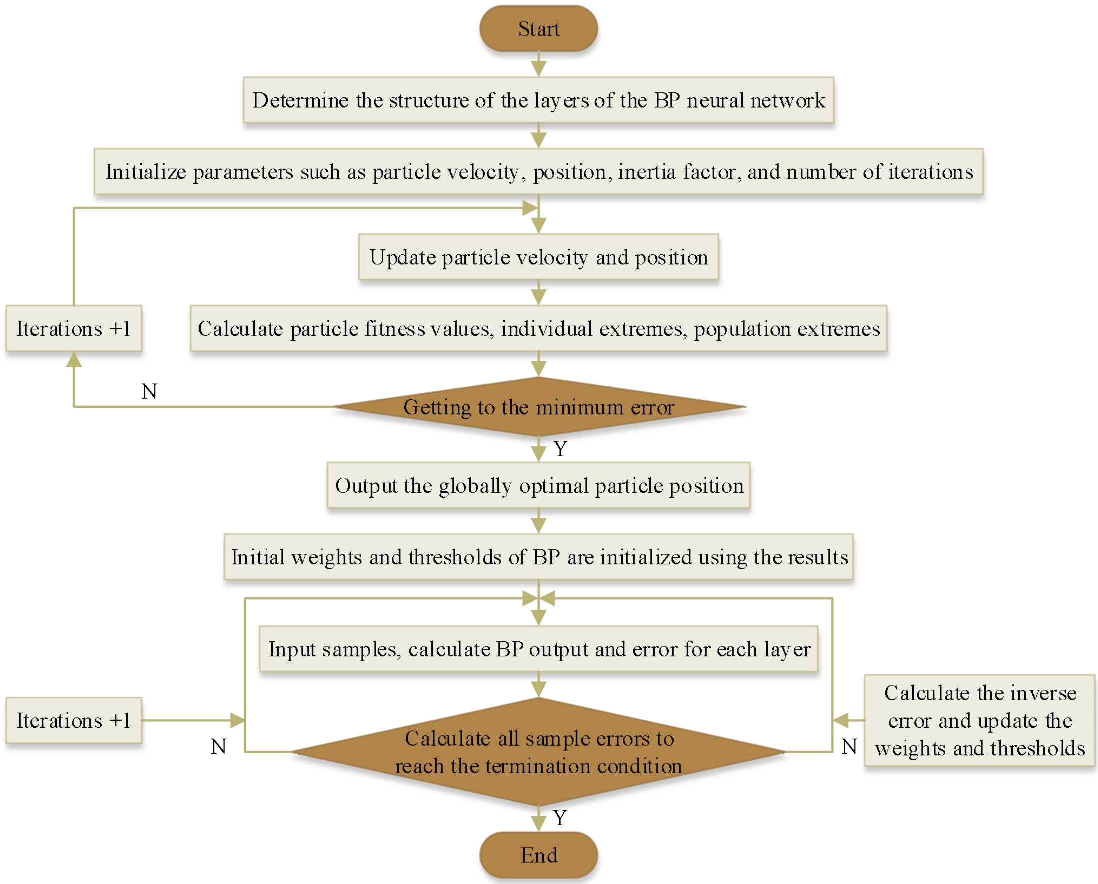

Figure 1. PSO-BP Neural Network Flow Chart.

3.2.2. Design and training of PSO-BP neural network

(1) Data standardization

In this paper, data standardization is carried out through the minmax_scale function, and the standardization formula is:

$$X_{\text{std}} = \frac{X - X \cdot \min}{X \cdot \max - X \cdot \min} \tag{14}$$

(2) Initialize particle swarm parameters

The parameters selected in this paper are as follows:

Iteration number: $\text{iters} = 100$;

Inertia weight: $\omega = 0.9$;

Learning factors: self-cognitive learning factor $c_1 = 0.5$, group conscientious learning factor $c_2 = 0.3$.

(3) Calculate the fitness value of each particle

After initializing the position and velocity of each particle, the adaptation value of the particle is calculated. In this paper, the mean square error function (MSE) is used to calculate the error of the BP network. Namely:

$$f = \frac{1}{n}\sum_{i=1}^{n}\left(y_r - y_i\right)^2 \tag{15}$$

Where n is the number of training samples, y_r is the expected output of the i th sample, and y_i is the actual predicted output of the i th sample. The extreme values are updated by comparing the fitness value of each particle: if the fitness value of the current particle is less than the individual optimal solution, the individual optimal solution is updated, otherwise it is not updated; similarly, if the fitness value of the current particle is less than the population optimal solution, the population optimal solution is updated, otherwise it is not updated.

(4) Update the velocity and position of each particle

Based on the above iteration, the particle updates the position and velocity of the particle itself through the updated individual optimal solution and group optimal solution, according to the updated position and velocity, a new round of fitness value calculation is performed, if it is less than the current value, it is updated, if it is greater than the current value, it is not updated. At the same time, if the desired error has been reached or has been iterated to the maximum number of times, then end the iteration, otherwise return to step (3), calculate the fitness value of each particle and update the individual/population optimal solution to continue to iterate until the end of the iteration to meet the conditions.

(5) Assign BP neural network weights and thresholds and start network training

After the calculation, the optimal value obtained by the particle swarm algorithm is assigned to the initial weights and thresholds of the BP neural network, and then the training of the BP neural network is started by the optimized weights and thresholds of the particle swarm algorithm.

4. Simulation experiment of enterprise financial risk early warning based on PSO-BP neural network

4.1. Sample Selection

In this paper, 100 enterprises in the electronic information industry are selected as the research object, and the data are obtained from CSMAR and Wind database. In this paper, the data of the second year of the enterprises are selected to conduct the experiment. 50 enterprises are randomly selected as training samples and the remaining 50 enterprises are used as prediction samples.

This paper uses MATLABR software to simulate the financial risk early warning model based on PSO-BP neural network for the experiment. According to the divided test samples and prediction samples, the data are imported into MATLABR for training.

4.2. Performance of PSO-BP neural network

4.2.1. Training error variation process of PSO-BP model

The PSO-BP neural network training function is trainlm and the error function is MSE. The error change process of the model is shown in Figure 2. When the number of training times has reached 21 times, the prediction accuracy is 0.0001, which has reached the prediction accuracy of 0.001.

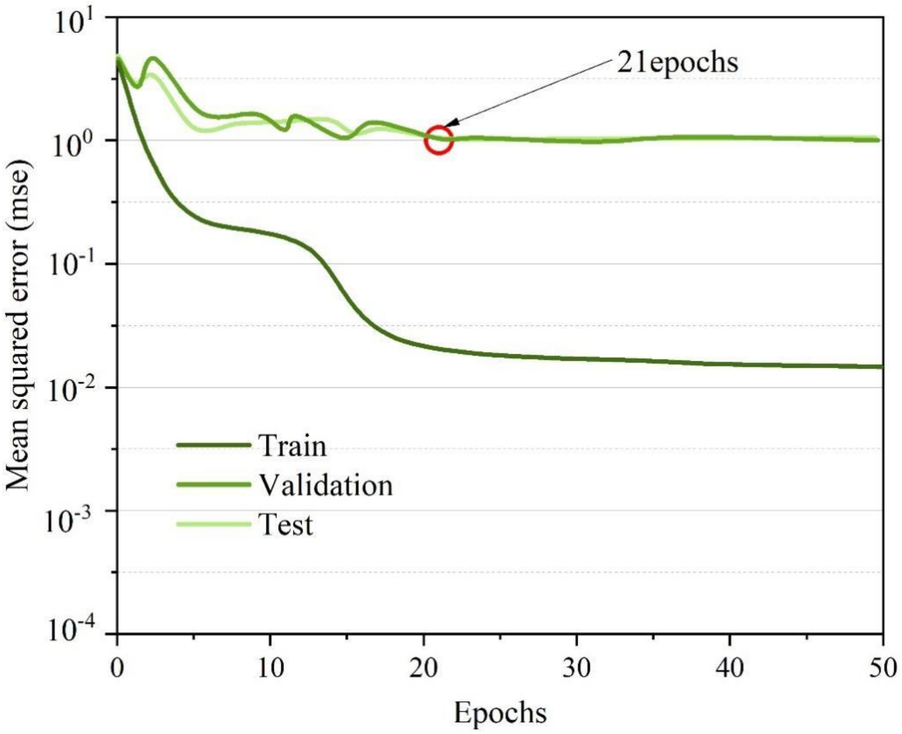

Figure 2. The error variation process of the model.

4.2.2. Network fitting

The fitting results of the PSO-BP neural network model are shown in Figure 3. The fitting results of the model show that its overall R-value reaches 0.9871, which shows that the model's prediction results are extremely accurate.

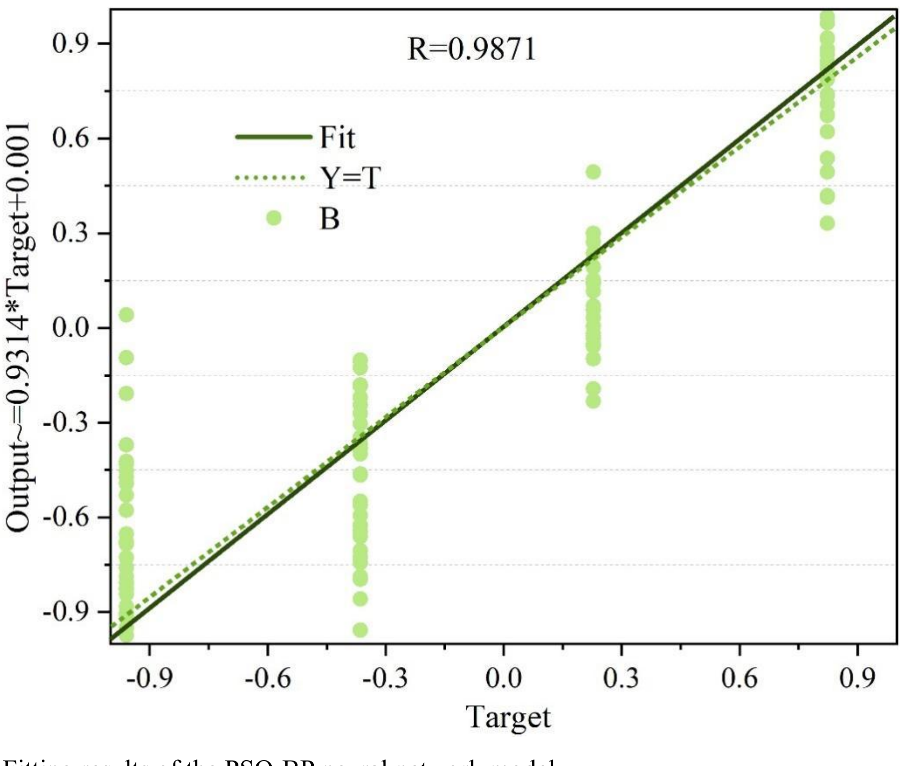

Figure 3. Fitting results of the PSO-BP neural network model.

4.2.3. Network prediction errors

The network prediction error results of PSO-BP model are shown in Figure 4. From the figure, it can be seen that the network prediction error is more than 0.5 for only four enterprises, and the rest of the errors are smaller, with the error range between [-0.39,0.31].

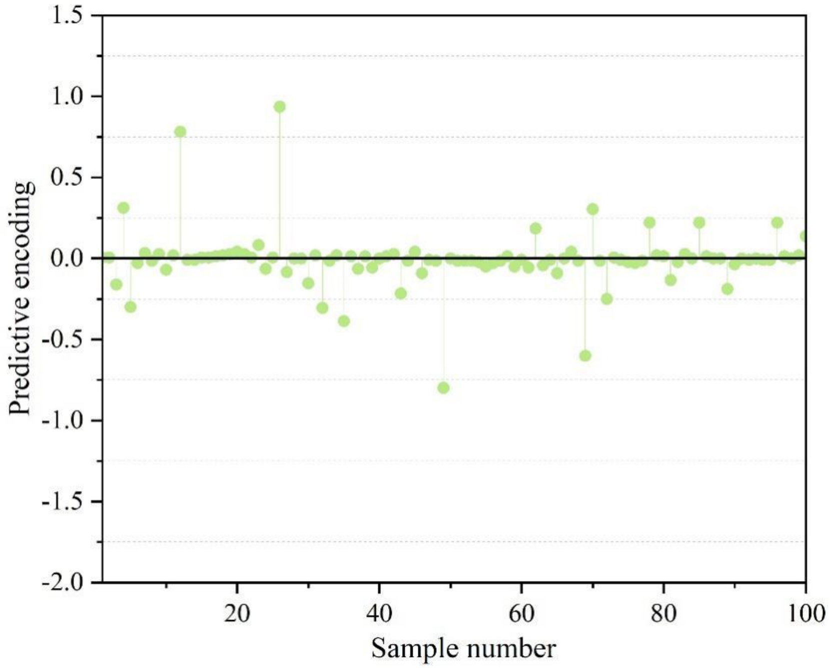

Figure 4. Network prediction error results of the PSO-BP model.

4.2.4. Results of Comparison of Desired and Predicted Values

The results of the comparison between the expected and predicted values of the PSO-BP model are shown in Figure 5. From the figure, it can be seen that only four enterprises have errors in the prediction results, and the prediction outputs of the remaining enterprises are completely consistent with the expected outputs. This shows that the model in this paper has very high accuracy in predicting the results of enterprise financial data in the big data environment.

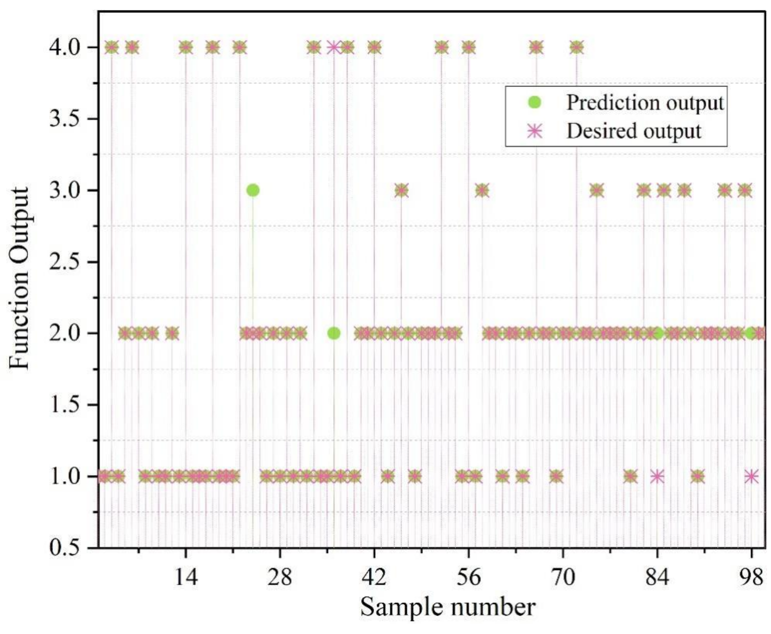

Figure 5. Comparison of Expected and Predicted Values in the PSO-BP Model.

4.3. Analysis of simulation results

The PSO-BP network prediction comparison results are shown in Table 8. The results show that there are a total of 100 prediction samples. Among them, the number of enterprises with no risk, medium risk and serious risk is 63, 6 and 4 respectively, and their judgment error number is 0, and the judgment correct rate is 100%; there are 27 enterprises with smaller risk, and the judgment error is 2, and the correct rate is 92.59%. The comprehensive correct rate of the model reaches 98.15%, indicating that the PSO-BP network prediction model has excellent prediction effect on enterprise financial risk early warning.

In terms of the type of judgment error, it is mainly the misjudgment of class 1 as class 2, class 2 as class 1, and class 4 as class 3. In practice, it is mainly the second type of error that causes the greatest impact. This type of error causes companies to underestimate their financial risk. While the other two types, although misclassified, help to remind managers in time to pre-empt financial risks. As a whole, 63 enterprises are in no risk, 25 enterprises have small risk, and there are 6 and 4 enterprises with medium and high risk respectively.

The synthesis of the above results shows that the financial risk early warning model trained by PSO-BP neural network can play a good role in financial risk early warning for enterprises in the big data environment. It can also be seen that through a series of previous tests on financial and non-financial indicators and factor analysis, the final composition of the financial risk early warning indicator system can establish a financial insurance early warning model with fast computing speed, strong operability and stable performance.

Table 8. PSO-BP network prediction comparison results.

Alert Level	Number of the enterprise	Number of errors	Accuracy (%)
Devoid of risk	63	0	100
Low risk	27	2	92.59
Medium risk	6	0	100
High risk	4	0	100
Amount to	100	9	98.15

5. Conclusion

This paper adopts BP neural network algorithm optimized based on particle swarm algorithm (PSO) to identify financial risks of enterprises, constructs an intelligent identification model of enterprise financial risks under big data environment, and conducts simulation experiments on the warning effect of the model.

The results show that: in this paper, the 27 enterprise financial risk early warning indicators are screened to get 19 evaluation indicators, which are further condensed to get 6 main factors, and their cumulative explanatory variance reaches 75.48%. The overall fit of the financial risk early warning model based on PSO-BP neural network is very high, and its R-value reaches 0.9871; the error range of this paper's model for most of the data is between [-0.39,0.31], and the model's predicted output is basically consistent with the expected output. In addition, the comprehensive correct rate of this paper's model for corporate financial risk early warning reaches 98.15%, and the model's prediction effect is excellent.

However, since this paper does not select non-financial indicators, it cannot better analyze the potential development ability, innovation and strategic layout, etc. for very few special companies. Therefore, in the subsequent research, it is recommended to add non-financial indicators into the early warning model, so as to better and more accurately provide early warning of corporate finance.

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