Application of BP neural network technology on dynamic financial risk prediction

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Abstract. This work mainly studied the application of BP neural network technology. Based on the crisis early warning of listed real estate companies at home and abroad, this study used BP neural network method to determine the corporate governance indicators of crisis enterprises from eight aspects, such as profitability, solvency, operation ability, development ability, cash flow, risk, etc. This work took the real estate listed companies as the research object and put forward eight early warning indicators. Traditional early warning models have low fault tolerance, and most of them are static early warning. In this study, the innovation point is that the BP neural network model has the ability of self-learning and adjustment, strong risk identification and fault tolerance, and can cope with the changeable financial risk environment of real estate enterprises. BP neural network model can analyze problems through self-learning and training, and has strong nonlinear mapping ability. It is feasible to construct financial risk early warning model of real estate listed enterprises.

1. Introduction

In recent years, the development of China's capital market has been gradually accelerated, which is largely due to the continuous expansion of economic globalization. Compared with the past, the company's management and financial environment are more complicated. All companies need to suffer huge economic pressure and survival pressure in the process of operation and development. The global economic crisis has a great impact on the operation and development of Chinese companies. The reason for the crisis may be any link in the financial activities such as operation, investment, financing, etc. Therefore, the company managers are faced with the inevitable serious problem is to improve the company's ability to resist risks, thus adapting to the changes of the economic and social environment. In this context, the urgency of financial risk early warning research is increasingly obvious.

Financial risk is one of the most harmful risks. If enterprises can’t effectively prevent and resolve financial risks, they will fall into business difficulties or even competition. The financial risk is characterized by objectivity and variability. Therefore, enterprises should carry out early warning, identification, evaluation and control of factors that may affect the financial risk of enterprises according to their own financial situation, and take effective preventive and resolving measures; otherwise it will lead to financial crisis.

At present, domestic and foreign research on financial risk early warning theory mainly includes single factor judgment model, multi-factor judgment model, multi-factor judgment analysis technology, logistic model test model, Probit model, BP neural network analysis model, etc.
Based on the simulated neural network proposed by Yang Baoan et al. (2001), a financial analysis early warning model using input layer, output layer and hidden layer was established. The results show that the model has good prediction effect. According to the financial data of 20 listed companies, Yang Shue and Huang Li (2005) established a financial early warning model using BP neural network. The results show that the model is more accurate than the principal component analysis model. Li Jianhua (2011) established the financial early warning analysis model of expressway company, and analyzed the company's financial data by using MATLAB software. Feng jiao (2019) believes that it is difficult for traditional statistical methods to predict future changes due to the limitation of data invariance in traditional computing models. However, BP artificial neural network is easy to deal with incomplete and unclear data, and thus the application of artificial neural network in economics is a more scientific basis for the evaluation and prediction of future price and risk.

### 2. Model Construction

#### 2.1. Financial risk early warning index primary election

Based on the financial analysis indicators, this study intends to separate the indicators that are most directly related to cash flow. It covers 26 indicators in four aspects of "profitability", "repayment ability", "development ability" and "operation ability" of the enterprise, thus comprehensively and truly reflecting the financial risk status of the enterprise. Details are shown in Table 1.

**Table 1. Financial warning index system**

| Name            | Code | Index name                                                 |
|-----------------|------|------------------------------------------------------------|
| Profitability   | X1   | Basic earnings per share                                   |
|                 | X2   | Total asset margin                                         |
|                 | X3   | Cost profit margin                                         |
|                 | X4   | Operating profit margin                                    |
|                 | X5   | Return on equity                                           |
|                 | X6   | Return on net assets                                       |
|                 | X7   | Current ratio                                              |
|                 | X8   | Quick ratio                                                |
|                 | X9   | Cash ratio                                                 |
|                 | X10  | Interest coverage ratio                                    |
| Repayment ability| X11  | Asset liability ratio                                      |
|                 | X12  | Long term debt to working capital ratio (%)                |
|                 | X13  | Long term debt ratio (%)                                   |
|                 | X14  | Ratio of long-term assets to long-term funds (%)           |
|                 | X15  | Equity ratio (%)                                           |
|                 | X16  | Growth rate of main business income (%)                    |
| Growth ability  | X17  | Net profit growth rate (%)                                 |
|                 | X18  | Growth rate of net assets                                  |
|                 | X19  | Growth rate of total assets                                |
|                 | X20  | Turnover rate of accounts receivable (Times)               |
| Operation capacity| X21  | Inventory turnover (Times)                                 |
|                 | X22  | Turnover rate of total assets (Times)                      |
|                 | X23  | Turnover rate of current assets (Times)                    |
|                 | X24  | Return on operating cash flow of assets (%)                |
|                 | X25  | Ratio of net operating cash flow to liabilities (%)        |
|                 | X26  | Cash flow ratio (%)                                        |
2.2. Financial risk prediction model selection

2.2.1. Research hypothesis. In this study, BP neural network is used to build a financial risk early warning model based on cash flow, and the following assumptions are proposed.

Hypothesis 1: there is a significant negative correlation between the company's profitability and development ability and financial risk;

Hypothesis 2: there is a positive correlation between asset liability ratio, long-term asset to long-term capital ratio and financial risk;

Hypothesis 3: there is a negative correlation between repayment ability and financial risk;

Hypothesis 4: there is a negative correlation between the company's operating capacity and financial risk;

Hypothesis 5: the closer the financial data is to the current time node, the higher the accuracy of financial risk identification.

2.2.2. Basic model. Traditional early warning models have low fault tolerance, and most of them are static early warning. BP neural network model has the ability of self-learning and adjustment, strong risk identification ability and fault tolerance, and can deal with the changeable financial risk environment of real estate enterprises. The calculation process of BP neural network model is composed of forward calculation process and reverse calculation process, which is composed of three layers: input layer, hidden layer and output layer. After training, the weights of each neuron are modified to reduce the error and approach the expected output. Its structure is shown in Figure 1.

![BP neural network structure diagram](image)

**Figure 1.** BP neural network structure diagram

3. Empirical Analysis

3.1. Sample collection and processing

This work selected the listed companies in the real estate industry as the research object. As of February 21, 2021, there were 135 listed real estate enterprises in Shanghai and Shenzhen. In this study, financial data of all 135 real estate enterprises from 2017 to 2019 were collected and sorted based on the annual reports of enterprises in the Shanghai and Shenzhen stock markets. Through screening, enterprises with incomplete data were deleted, and the data of 122 enterprises were finally selected as the research samples. Among them, there are 10 ST and *ST companies and 2 delisting companies.
3.2. Financial risk early warning index processing
In this work, the factor analysis method is used to deal with the early warning index of financial risk. Factor analysis method describes the relationship between multiple indicators or factors according to a few factors, and reflects most information through a few factors. The most commonly used method is principal component analysis, which uses fewer indicators to carry the information of more indicators. It has strong objectivity and can avoid the analysis deviation caused by human empowerment. The index factors selected in this model are processed, mainly including variable standardization, KMO test, Bartlett sphericity test, rotation factor load matrix. The 26 financial indicators of 122 selected enterprises are analyzed.

3.2.1. KMO test and Bartlett sphericity test. KMO test and Bartlett sphericity test mainly judge the correlation between the variables in the data, and test whether the variables are independent. KMO is used to test the correlation and partial correlation between variables. The value of KMO is between 0 and 1. The closer its value is to 1, the stronger the correlation between variables and the better the effect of factor analysis. When KMO is less than 0.5, it is not suitable for factor analysis. Bartlett sphericity test is used to judge whether the correlation matrix is a unit matrix. If the variables are independent of each other and cannot extract the common factor, it is not suitable to use factor analysis. Sig. < 0.05 (i.e., P < 0.05), indicates that there is correlation among the variables, and it is suitable to use factor analysis. In this study, KMO test and Bartlett sphericity test are performed on the data, and the test results are shown in Table 2. The results show that the KMO value is 0.553, which is greater than 0.5, indicating that the data is suitable for factor analysis.

Table 2. KMO and Bartlett sphericity test results

| KMO test and Bartlett test | Sampling the Kaiser-Meyer-Olkin measure of adequacy | Bartlett sphericity test |
|---------------------------|-----------------------------------------------|-------------------------|
|                           | Approximate chi-square | df | Sig. |
|                           |                             |   |    |
| KMO test                  | .553                        | 9082.569 | .000 |
| Bartlett sphericity test  |                             | 325 |  |

3.2.2. Total variance explanation. The total variance explanation table of factors is shown in Table 3. The test results show that there are 9 factors with the eigenvalue of 1. When the number of extracted main factors reaches 9, the cumulative contribution rate of extracted main factors reaches 76.394%. Therefore, the number of main factors is determined to be 9, which are set as Y1, Y2, Y3, Y4, Y5, Y6, Y7, Y8 and Y9 respectively.

Table 3. Total variance explanation table

| Composition | Total | Initial eigenvalue | Extraction squared load | Rotation squared load |
|------------|-------|-------------------|------------------------|----------------------|
|            | 5.596 | 21.524 | 5.596 | 21.524 | 4.897 | 18.836 | 18.836 |
| 2          | 3.787 | 14.566 | 36.090 | 3.787 | 4.566 | 36.090 | 3.360 | 12.922 | 31.759 |
| 3          | 2.278 | 8.760 | 44.851 | 2.278 | 8.760 | 44.851 | 2.109 | 8.110 | 39.869 |
| 4          | 1.797 | 6.913 | 51.764 | 1.797 | 6.913 | 51.764 | 2.046 | 7.868 | 47.737 |
| 5          | 1.616 | 6.217 | 57.980 | 1.616 | 6.217 | 57.980 | 1.812 | 6.970 | 54.707 |
| 6          | 1.353 | 5.205 | 63.186 | 1.353 | 5.205 | 63.186 | 1.803 | 6.934 | 61.641 |
| 7          | 1.269 | 4.882 | 68.068 | 1.269 | 4.882 | 68.068 | 1.446 | 5.563 | 67.204 |
| 8          | 1.150 | 4.422 | 72.490 | 1.150 | 4.422 | 72.490 | 1.317 | 5.065 | 72.269 |
| 9          | 1.015 | 3.904 | 76.394 | 1.015 | 3.904 | 76.394 | 1.073 | 4.126 | 76.394 |
| 10         | .969  | 3.728 | 80.122 | | | | | |
| 11         | .911  | 3.506 | 83.628 | | | | | |
| 12         | .737  | 2.835 | 86.464 | | | | | |
| 13         | .688  | 2.645 | 89.108 | | | | | |
3.2.3. Factor load after rotation. The main component analysis method and the maximum variance method are used to generate the table of the rotating component matrix, as shown in table 4. After 6 iterations, 9 main factors are divided into convergence region. According to the table of rotating component matrix and the total variance explanation table, it can be seen that:

The variance contribution rate of the first main factor Y1 is 21.524%, which indicates that Y1 is the key factor to determine the financial risk of enterprises. According to the rotating component matrix table, Y1 factor has a very high load on the profit rate of total assets, the profit rate of cost and expense, the return rate of net assets and the growth rate of net assets. In the financial analysis, the above indicators mainly reflect the profitability and development ability of the enterprise, and are named as profit development factor.

The variance contribution rate of the second main factor Y2 is 14.566%, which indicates that Y2 is the second key factor to determine the financial risk of enterprises. According to the rotating component matrix, Y2 factor has a very high load on current ratio, quick ratio and cash ratio. In financial analysis, the above indicators reflect the enterprise's solvency, and are named as solvency factor.

The variance contribution rate of the third main factor Y3 is 8.76%, which indicates that Y3 is the secondary key factor to determine the financial risk of enterprises. According to the rotating component matrix table, Y3 factor has a very high load on the turnover rate of total assets and the turnover rate of current assets. In the financial analysis, the above indicators reflect the operating capacity of the enterprise, and are named as operating capacity factor.

The variance contribution rate of the fourth main factor Y4 is 6.913%, which indicates that Y4 is the secondary key factor to determine the financial risk of enterprises. According to the rotating component matrix table, Y4 factor has a higher load on earnings per share, return on equity and turnover of total assets. In the financial analysis, the above indicators mainly reflect the profitability of the enterprise, and are named as profit factor.

According to the load of the main factors of the rotation component matrix on each index, the scoring equation of each factor can be obtained as follows:

\[ Y_1 = 0.411X_1 + 0.901X_2 + 0.894X_3 + 0.779X_4 + 0.335X_5 + 0.879X_6 + 0.074X_7 - 0.026X_8 - 0.037X_9 + 0.03X_{10} - 0.433X_{11} + 0.002X_{12} + 0.031X_{13} - 0.741X_{14} + 0.048X_{15} - 0.001X_{16} + 0.247X_{17} + 0.897X_{18} + 0.097X_{19} + 0.04X_{20} + 0.002X_{21} - 0.009X_{22} - 0.011X_{23} + 0.034X_{25} \]

\[ Y_2 = -0.019X_1 + 0.139X_2 + 0.129X_3 + 0.019X_4 - 0.085X_5 + 0.073X_6 + 0.858X_7 + 0.945X_8 + 0.932X_9 + 0.018X_{10} + 0.693X_{11} + 0.118X_{12} + 0.189X_{13} + 0.311X_{14} + 0.05X_{15} + 0.207X_{16} + 0.046X_{17} + 0.057X_{18} + 0.145X_{19} - 0.089X_{20} + 0.152X_{21} + 0.062X_{22} + 0.091X_{23} + 0.13X_{24} + 0.206X_{25} - 0.115X_{26} \]
\[ Y_3 = -0.032X_1 - 0.027X_2 - 0.013X_3 + 0.003X_4 - 0.038X_5 + 0.007X_6 + 0.076X_7 + 0.04X_8 + 0.075X_9 + 0.002X_{10} \\
-0.01X_{11} + 0.029X_{12} + 0.135X_{13} - 0.16X_{14} + 0.048X_{15} - 0.048X_{16} - 0.036X_{17} + 0.014X_{18} + 0.034X_{19} - 0.01X_{20} \\
-0.006X_{21} + 0.982X_{22} + 0.974X_{23} + 0.361X_{24} + 0.152X_{25} + 0.003X_{26} \\
Y_4 = +0.856X_1 + 0.264X_2 + 0.196X_3 + 0.079X_4 + 0.873X_5 + 0.171X_6 - 0.078X_7 + 0.026X_9 - 0.026X_{10} + 0.248 \\
X_{11} + 0.149X_{12} + 0.042X_{13} - 0.044X_{14} + 0.041X_{15} + 0.021X_{16} + 0.247X_{17} + 0.077X_{18} + 0.472X_{19} - 0.044X_{20} + 0.056X_{21} - 0.009X_{22} - 0.022X_{23} - 0.095X_{24} - 0.06X_{25} - 0.046X_{26} \\
Y_5 = +0.053X_1 + 0.089X_2 - 0.039X_3 - 0.041X_4 + 0.038X_5 - 0.013X_6 - 0.102X_7 + 0.137X_8 - 0.034X_9 - 0.197 \\
X_{10} - 0.133X_{11} + 0.106X_{12} - 0.194X_{13} - 0.015X_{14} + 0.06X_{15} + 0.168X_{16} - 0.07X_{17} - 0.01X_{18} + 0.203X_{19} - 0.011X_{20} \\
+0.824X_{21} - 0.012X_{22} - 0.003X_{23} + 0.328X_{24} + 0.005X_{25} + 0.892X_{26} \\
Y_6 = +0.05X_1 + 0.041X_2 + 0.094X_3 + 0.086X_4 + 0.044X_5 - 0.03X_6 + 0.173X_7 + 0.066X_8 + 0.138X_9 - 0.008X_{10} \\
+0.054X_{11} + 0.041X_{12} + 0.08X_{13} - 0.137X_{14} + 0.087X_{15} + 0.031X_{16} + 0.732X_{17} - 0.064X_{18} - 0.082X_{19} + 0.028 \\
X_{20} - 0.058X_{21} + 0.062X_{22} + 0.178X_{23} + 0.572X_{24} + 0.871X_{25} + 0.129X_{26} \\
Y_7 = -0.023X_1 + 0.013X_2 + 0.023X_3 + 0.079X_4 - 0.053X_5 - 0.004X_6 + 0.066X_7 + 0.005X_8 + 0.027X_9 + 0.065 \\
X_{10} - 0.089X_{11} + 0.042X_{12} + 0.177X_{13} + 0.054X_{14} + 0.094X_{15} + 0.754X_{16} + 0.15X_{17} + 0.07X_{18} + 0.437X_{19} + 0.75 \\
55X_{20} + 0.103X_{21} - 0.012X_{22} - 0.022X_{23} - 0.072X_{24} - 0.021X_{25} + 0.002X_{26} \\
Y_8 = +0.028X_1 + 0.045X_2 + 0.139X_3 + 0.321X_4 + 0.032X_5 - 0.129X_6 - 0.063X_7 + 0.029X_8 + 0.017X_9 + 0.027 \\
X_{10} - 0.175X_{11} - 0.083X_{12} - 0.619X_{13} + 0.179X_{14} + 0.79X_{15} - 0.018X_{16} + 0.265X_{17} - 0.059X_{18} - 0.048X_{19} + 0.036 \\
X_{20} + 0.006X_{21} - 0.001X_{22} - 0.018X_{23} - 0.087X_{24} - 0.068X_{25} + 0.036X_{26} \\
Y_9 = +0.13X_1 + 0.076X_2 + 0.013X_3 - 0.097X_4 + 0.136X_5 + 0.014X_6 - 0.162X_7 - 0.027X_8 - 0.018X_9 + 0.698X_{10} \\
-0.158X_{11} + 0.502X_{12} - 0.367X_{13} - 0.043X_{14} - 0.214X_{15} + 0.031X_{16} - 0.02X_{17} - 0.012X_{18} - 0.159X_{19} + 0.104X_{20} \\
-0.081X_{21} + 0.006X_{22} + 0.012X_{23} + 0.055X_{24} + 0.021X_{25} + 0.012X_{26} \\

Table 4. Rotation component matrix table

| Code | Index name | Component 1 | Component 2 | Component 3 | Component 4 | Component 5 | Component 6 | Component 7 | Component 8 | Component 9 |
|------|------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| X1   | Basic earnings per share | .411 | -.019 | -.032 | .856 | .053 | .050 | -.023 | .028 | .130 |
| X2   | Total asset margin (%) | .901 | .139 | -.027 | .264 | .089 | .041 | .013 | .045 | .076 |
| X3   | Cost profit margin (%) | .894 | .129 | -.013 | .196 | -.039 | .094 | .023 | .139 | .013 |
| X4   | Operating profit margin (%) | .779 | .019 | .003 | .079 | -.041 | .086 | .079 | .321 | -.097 |
| X5   | Return on equity (%) | .335 | -.085 | -.038 | .873 | .038 | .044 | -.053 | .032 | .136 |
| X6   | Return on net assets (%) | .879 | .073 | .007 | .171 | .013 | -.030 | -.004 | -.129 | .014 |
| X7   | Current ratio (%) | .074 | .858 | .076 | -.078 | -.102 | .173 | .066 | -.063 | -.162 |
| X8   | Quick ratio (%) | -.026 | .945 | .040 | .000 | .137 | .066 | .005 | .029 | -.027 |
| X9   | Cash ratio (%) | -.037 | .932 | .075 | .026 | -.034 | .138 | .027 | .017 | -.018 |
### 3.3. Result and analysis

**3.3.1. Model determination.** In order to build a financial risk model based on BP neural network, the input vector X and target vector A need to be determined first. Due to time limitation, the single-layer neural structure was selected to construct BP neural network model in this study. According to the data processing results, vector X composed of 18 elements was selected as input vector in this study. The target vector is divided into two categories: normal and crisis. The output value of 1 represents that the enterprise's financial situation is normal and the financial risk is low. The output value of 0 represents that the enterprise's financial situation is abnormal and the financial risk is high.

| X1 | Interest coverage ratio (%) | .030 | .018 | .002 | -.026 | -.197 | -.008 | .065 | .027 | .698 |
| X11 | Asset liability ratio (%) | -.433 | -.693 | -.010 | .248 | -.133 | .054 | .089 | -.175 | -.158 |
| X12 | Long term debt to working capital ratio (%) | .002 | -.118 | .029 | .149 | .106 | .041 | .042 | -.083 | .502 |
| X13 | Long term debt ratio (%) | .031 | -.189 | .135 | .042 | -.194 | .080 | .177 | -.619 | -.367 |
| X14 | Ratio of long-term assets to long-term funds (%) | -.741 | .311 | -.016 | -.044 | -.015 | -.137 | .054 | .179 | -.043 |
| X15 | Equity ratio (%) | .048 | -.050 | .048 | .041 | -.060 | .087 | .094 | .790 | -.214 |
| X16 | Growth rate of main business income (%) | -.001 | .207 | -.048 | .021 | .168 | .031 | .754 | -.018 | .031 |
| X17 | Net profit growth rate (%) | .247 | .046 | -.036 | .247 | -.070 | .732 | .150 | .265 | -.020 |
| X18 | Growth rate of net assets | .897 | .057 | .014 | .077 | -.010 | -.064 | .070 | -.059 | -.012 |
| X19 | Growth rate of total assets | .097 | -.145 | .034 | .472 | -.203 | -.082 | .437 | -.048 | -.159 |
| X20 | Turnover rate of accounts receivable (Times) | .040 | -.089 | -.001 | -.044 | -.011 | .028 | .755 | .036 | .104 |
| X21 | Inventory turnover (Times) | .000 | .152 | -.006 | .056 | .824 | -.058 | .103 | .006 | -.081 |
| X22 | Turnover rate of total assets (Times) | .002 | .062 | .982 | -.009 | -.012 | .062 | -.012 | -.001 | .006 |
| X23 | Turnover rate of current assets (Times) | .000 | .091 | .974 | -.022 | -.003 | .178 | -.020 | -.018 | .012 |
| X24 | Return on operating cash flow of assets (%) | -.009 | .130 | .361 | -.095 | .328 | .572 | -.072 | -.087 | .055 |
| X25 | Ratio of net operating cash flow to liabilities (%) | -.011 | .206 | .152 | -.060 | .005 | .871 | -.021 | -.068 | .021 |
| X26 | Cash flow ratio (%) | .034 | -.115 | .003 | -.046 | .892 | .129 | .002 | .036 | .012 |

Extraction method: main component  Rotation method: orthogonal rotation method with Kaiser normalization  
a: the rotation converges after 6 iterations
3.3.2. Model training and testing. This work collected and collated the financial data of 122 listed real estate enterprises in 2017-2019. As of March 2021, there are 10 ST and *ST enterprises, 2 enterprises for delisting and finishing, and 110 normal enterprises. In this study, 70% of the random enterprises are used as training samples, and the other 30% are used as test samples for neural network training. The five hypothesis tests are established.

1) Three-year comprehensive training and test of financial data

Comprehensive training and testing are conducted on the financial data from 2017 to 2019 to judge the financial risk status in 2020. The training and testing results are shown in Table 5 and Table 6. The model test results show that the correct rate of training sample model is 93.8%, and the correct rate of test sample model is 93.6%. It shows that this model has high accuracy in financial risk early warning of real estate listed enterprises. However, the accuracy of financial risk prediction for enterprises in abnormal state in March 2021 is not high from the perspective of classification prediction. The training accuracy rate is 48.0%, and the test accuracy rate is 54.5%. Consequently, the applicability is insufficient. The reason is that the sample number of abnormal enterprises is too small.

Table 5. Model training and test results summary

| Model summary | | |
|----------------|----------------------|
| Cross entropy error | 57.971 |
| Percentage error prediction | 6.3% |
| Rules for discontinuation of use | Error not reduced 1 continuous step |
| Training time | 00:00:00.173 |
| Cross entropy error | 19.449 |
| Percentage error prediction | 6.4% |

Dependent variable: ST state (1 normal, 2ST or *ST or delisted sorted)

a: miscalculation based on test samples

Table 6. Model training and test results classification

| Classification | | |
|----------------|----------------------|
| Sample | Observed | Projected | Correct percentage |
| Training | Normal | ST | |
| Normal | 243 | 4 | 98.4% |
| ST | 13 | 12 | 48.0% |
| Total percentage | 94.1% | 5.9% | 93.8% |
| Test | ST | Normal | |
| Normal | 82 | 1 | 98.8% |
| ST | 5 | 6 | 54.5% |
| Total percentage | 92.6% | 7.4% | 93.6% |

Dependent variable: ST state (1 normal, 2ST or *ST or delisted sorted)

2) Comprehensive training and test of financial data in 2017

The financial data of 2017 is trained and tested comprehensively to judge the financial risk status in 2020. The training and test results are shown in Table 7 and Table 8. The model test results show that the correct rate of training sample model is 94.0%, and the correct rate of test sample model is 92.3%. It shows that this model has high accuracy in financial risk early warning of real estate listed enterprises. However, the accuracy of financial risk prediction for enterprises in abnormal state in March 2021 is not high from the perspective of classification prediction. The training accuracy rate is 44.4%, and the test accuracy rate is 0%. Consequently, the applicability is insufficient. The reason is that the sample number of abnormal enterprises is too small. At the same time, 2017 is too long from 2020, and the correlation degree of cash flow is weakened.

Table 7. Model training and test results summary

| Model summary | | |
|----------------|----------------------|
| Cross entropy error | 57.971 |
| Percentage error prediction | 6.3% |
| Rules for discontinuation of use | Error not reduced 1 continuous step |
| Training time | 00:00:00.173 |
| Cross entropy error | 19.449 |
| Percentage error prediction | 6.4% |
Training

Cross entropy error: 20.470
Percentage error prediction: 6.0%
Rules for discontinuation of use: Error not reduced 1 continuous step
Training time: 00:00:00.047

Test

Cross entropy error: 6.963
Percentage error prediction: 7.7%

Dependent variable: ST state (1 normal, 2ST or *ST or delisted sorted)
a: miscalculation based on test samples

Table 8. Model training and test results classification

| Classification | Sample | Observed | Projected | Correct percentage |
|----------------|--------|----------|-----------|--------------------|
|                | Normal | 74       | 0         | 100.0%             |
| Training ST    | 5      | 4        | 44.4%     |
| Total percentage | 95.2% | 4.8%   | 94.0%     |
| Normal         | 36     | 0        | 100.0%    |
| Test ST        | 3      | 0        | 0%        |
| Total percentage | 100.0% | .0%    | 92.3%      |

Dependent variable: ST state (1 normal, 2ST or *ST or delisted sorted)

3) Comprehensive training and test of financial data in 2018

The financial data of 2018 is trained and tested comprehensively to judge the financial risk status in 2020. The training and test results are shown in Table 9 and Table 10. The model test results show that the correct rate of training sample model is 96.5%, and the correct rate of test sample model is 100.0%. It shows that this model has high accuracy in financial risk early warning of real estate listed enterprises. From the perspective of classification prediction, the accuracy of financial risk prediction for enterprises in abnormal state in March 2021 has improved compared with the data forecast in 2018. The training accuracy rate is 75.0%, and the test accuracy rate is 100.0%. Consequently, the applicability is insufficient.

Table 9. Model training and test results summary

| Model summary | Cross entropy error | 10.916 |
|---------------|---------------------|--------|
| Training      | Percentage error prediction | 3.5%   |
| Rules for discontinuation of use | Error not reduced 1 continuous step |
| Training time | 00:00:00.036 |
| Test          | Cross entropy error | 1.022  |
| Percentage error prediction | .0% |

Dependent variable: ST state (1 normal, 2ST or *ST or delisted sorted)
a: miscalculation based on test samples

Table 10. Model training and test results classification

| Classification | Sample | Observed | Projected | Correct percentage |
|----------------|--------|----------|-----------|--------------------|
|                | Normal | 77       | 1         | 98.7%              |
| Training ST    | 2      | 6        | 75.0%     |
| Total percentage | 91.9% | 8.1%   | 96.5%     |
| Normal         | 32     | 0        | 100.0%    |
| Test ST        | 0      | 4        | 100.0%    |
10

Total percentage 88.9% 11.1% 100.0%

Dependent variable: ST state (1 normal, 2ST or *ST or delisted sorted)

4) Comprehensive training and test of financial data in 2019

The financial data of 2019 is trained and tested comprehensively to judge the financial risk status in 2020. The training and test results are shown in Table 11 and Table 12. The model test results show that the correct rate of training sample model is 96.3%, and the correct rate of test sample model is 97.6%. It shows that this model has high accuracy in financial risk early warning of real estate listed enterprises. From the perspective of classification prediction, the accuracy of financial risk prediction for enterprises in abnormal state in March 2021 has improved compared with the data forecast in 2019. The training accuracy rate is 80.0%, and the test accuracy rate is 100.0%. Consequently, the applicability is insufficient.

Table 11. Model training and test results summary

| Model summary         |       |
|-----------------------|-------|
| Cross entropy error   | 5.693 |
| Percentage error prediction | 3.7%  |
| Rules for discontinuation of use | Error not reduced 1 continuous step |
| Training time         | 00:00:00.064 |
| Cross entropy error   | 1.810 |
| Percentage error prediction | 2.4%  |

Dependent variable: ST state (1 normal, 2ST or *ST or delisted sorted)

Table 12. Model training and test results classification

| Classification       |       |
|----------------------|-------|
| Sample               |       |
| Observed             |       |
| Normal               |       |
| 70                   | 1     | 98.6%         |
| ST                   | 2     | 80.0%         |
| Total percentage     |       |
| Normal               | 98.9% | 11.1%         | 96.3% |
| ST                   | 8     | 97.4%         |
| Test                 |       |
| Observed             |       |
| Normal               | 38    | 97.4%         |
| ST                   | 0     | 100.0%        |
| Total percentage     |       |
| ST                   | 92.7% | 7.3%          | 97.6% |

Dependent variable: ST state (1 normal, 2ST or *ST or delisted sorted)

4. Conclusion

This study intends to separate the indicators that are most directly related to cash flow by constructing BP neural network model. It covers 26 indicators in four aspects of "profitability", "repayment ability", "development ability" and "operation ability". This work takes 122 real estate enterprises in 135 listed real estate enterprises in Shanghai and Shenzhen as research samples. Based on the financial data from 2017 to 2019, the conclusion that all the five hypotheses are valid is drawn as follows:

First, there is a significant negative correlation between the company's profitability and development ability and financial risk. The stronger the profitability and development ability of a company, the lower the financial risks. The guarantee of profitability and improvement of development ability have a positive effect on reducing financial risk.

Second, there is a positive correlation between asset liability ratio, long-term asset to long-term capital ratio and financial risk. The higher the asset liability ratio and the higher the long-term asset to long-term capital ratio, the higher the financial risk. Reducing the asset liability ratio and the long-term asset to long-term capital ratio has a positive effect on reducing the financial risk.
Third, there is a negative correlation between the company's repayment ability and financial risk. The stronger the company's repayment ability, the lower the financial risk. Improving the company's repayment ability can effectively control the financial risk and has a significant effect on reducing the financial risk.

Fourth, there is a negative correlation between the company's operating capacity and financial risk. The stronger the company's operating capacity, the lower the financial risk. The company can improve the total asset turnover, current asset turnover, inventory turnover and cash flow ratio, which has a positive effect on reducing the financial risk.

Fifth, the financial data of the first three years can be used to identify the current financial risk of the enterprise. The closer the financial data is to the current time node, the higher the accuracy of financial risk identification. It has great reference value for the enterprise to take positive financial risk control measures. Based on enterprise cash flow data, BP neural network model can accurately predict the financial risk of enterprises.

References
[1] Li Yanli.(2020) Research on Early Warning System of Corporate Financial Crisis [J]. Science and Technology Economy Market, (08): 26-28.
[2] Dong Long.(2020) The Establishment of an Early Warning System for Corporate Financial Crisis [J]. China Chief Accountant, (09): 96-98.
[3] Xin Yadi.(2018) Analysis of Corporate Financial Risk Management Strategies [J]. Finance and Economics (Academic Edition), (20): 85-86.
[4] Chen Jie.(2020) The Construction of Modern Enterprise Financial Crisis Early Warning System [J]. Chinese Market, (17): 91-92.
[5] Wang Chunli.(2020) Early Warning System for Corporate Financial Crisis [J]. China Collective Economy, (16): 131-132.
[6] Feng Nannan.(2018) Establishment and Analysis of the Early Warning Model of Corporate Financial Crisis [J]. Friends of Accounting, (09): 113-115.
[7] Wang Zening.(2020) Establishment of Financial Crisis Early Warning System for Construction Enterprises [J]. China Management Information Technology, 23 (05): 44-45.
[8] Xu Hongmei.(2019) Analysis on the Problems and Countermeasures of Financial Crisis Early Warning of Listed Companies [J]. Modern Business, (33): 174-175.
[9] Wang Nanzi, Wu Jifeng, He Yun, Wang Xinyi.(2019) An Empirical Study on Early Warning of Financial Crisis in Real Estate Enterprises [J]. Journal of Engineering Management, 33(03): 154-158.
[10] Chen Hongqi, Li Shiguang.(2020) The Importance of Establishing an Early Warning System for Corporate Financial Crisis [J]. Yunnan Hydropower, 36(06): 180-182.
[11] Zhao Bingyan.(2019) A New Perspective on the Early Warning of Financial Crisis of Small and Medium-sized Enterprises [J]. Modern Economic Information, (08): 224-225.
[12] Qi Xin, Bai Guangcai.(2019) The Construction of an Early Warning Model of Financial Crisis for Small and Medium-sized Enterprises Based on an Innovative Perspective [J]. Business Accounting, (03): 44-46+43.
[13] Cheng Fang, Li Hongli, Shao Danlei.(2018) Construction of Financial Crisis Warning Model for Manufacturing Enterprises [J]. New Finance, (08): 50-51.
[14] Jiang Bingdan.(2018) Analysis on the Early Warning System of Corporate Financial Crisis [J]. Shanxi Agricultural Economics, (12): 81-82.
[15] Li Bin.(2019) Thoughts on Building a Financial Crisis Early Warning Mechanism for Small and Medium-sized Enterprises in China [J]. Light Textile Industry and Technology, 48(10): 91-92.
[16] Yang Yao.(2018) On the Establishment of an Early Warning System for Corporate Financial Crisis [J]. Economic and Trade Practice, (12): 117.
[17] Li Hui, Wen Subin, Li Zhi.(2020) Financial Crisis Early Warning Research: a Literature Review [J]. Finance and Accounting Newsletter, (24): 12-15.