Financial Model Based on Principle Component Analysis and Support Vector Machine

Zhuo Zhang, Jia Wang

***Abstract*—**Financial pre-warning model plays a vital role in the financial monitoring of one business. It can help management to predict, prevent and control enterprise financial risks. This paper builds up a new financal model based on the integration of principle component analysis (PCA) and support vector machine (SVM) model at a standpoint view. The model indicates higher accuracy than some prevailing financial monitoring model by comparing and analyzing some samples under China's special economic environment. The model algorithm takes core information of all samples into consideration as to the feature extraction process of sample data. The redundant index information undergoes compression-based extraction. Under the prerequisite of maintaining key index information, disturbing factors in sample indexes are eliminated to optimize the training performance of the follow-up monitoring and diagnose model. At a result of the empirical study, this paper proves new integration model can more efficiently help enterprise to predict, prevent and control financial risks of the enterprise.

***Keywords*—**Financial monitoring, Model integration, compression-based extraction.

I. INTRODUCTION

SINCE 2000, more and more Chinese enterprises have joined into the capital market and play important role in the international capital market[1]. However, their financial management status of these Chinese enterprise groups don't express their scale advantage as they should do[2]. Internal management mechanism and system corresponding to the organization's structure have been not completely built up[3]. The major reason is that their management lack ideas of setting an advanced set of financial management system[4]. For instance, they have no intention to settle up a pre-warning method for hedging potential financial risks[5]. In fact, some businesses worse performances in 2008 financial crises are impeding their development, which exerts a high influence on globe economy. So enterprise groups must learn financial crisis pre-warning methods; otherwise it is hard for them to efficiently control and manage their financial risks once happen.

There are many risks identified in pre-warning method, especial to credit risk[6-7]. Credit risks of enterprises are related not only to an enterprise, but to a total group of enterprises[8]. An enterprise group is a complicated system, which features a complex equity structure and related transaction. Financial crisis and credit risks of an enterprise group are much more complex due to such features. Therefore, building up methods including credit risks to financial crisis is an important key for enterprise group financial monitoring their crisis[9].

Based on a summary of traditional recognition models, this paper compares and analyzes the prevailing enterprise group financial pre-warning models on China's special economic environment[10]. An enterprise group financial monitoring model based on integration of PCA and SVM is built up. Simulation test of practical data verifies the efficiency of the model. The research findings in this paper can provide theoretical basis for further improvement of financial monitoring[11].

The financial crisis of listed enterprises is a period concept with a start and ending, that is, starting from the moment that a financial crisis appears to the moment that an enterprise bankrupts. Besides, the financial crisis of listed enterprises is divided into different degrees. To sum up, their financial crisis can be divided into following circumstances: 1) Technical failure, meaning enterprises cannot repay capitals with interest according to their debt contracts; 2) Accounting failure, meaning that enterprises' book net assets are negative and that enterprises become insolvent; 3) Enterprise failures, meaning that enterprises are insolvent to pay due debts after liquidation; 4) Statutory bankruptcy, meaning that enterprises or creditors cannot perform their obligations under debt contracts in time, and the situation continues, forcing them to apply for bankruptcy to the court. Those "specially-handled" enterprises in China's stock market all have "abnormal financial situations", meaning that they keep on losing for the recent two years or that their net asset value per share in the recent one year is lower than the face value per share or these two situations happen at the same time.

At present, there are different financial pre-warning model algorithms and modeling methods. Since prerequisites and hypotheses of data and statistical

Zhuo Zhang thanks Macau University of Science and Technology Faculty Research Grant (Project Code: FRG-17-007-MSB) for the support of the Mini Research.

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principles are not fully consistent with the reality, some models have limitations during the practical use process. For example, the multi-element linear discriminant analysis, the principal component model and the Logistic regression model all belong to a recognition and pre-warning system built on statistics; while the neural network model is a simulation of biological intelligence based on advances of computer application techniques, so it shows a high robustness and expansibility. Analysis of advantages and disadvantages of a financial monitoring model mainly proceeds from model's prerequisites and assumptions of samples and the model's method, promotion ability, prediction accuracy and explaining ability of results. To be specific:

1) Model selection methods: All the above financial monitoring models predict enterprises' financial crises through quantitative research methods and based on financial indexes or quantization of non-financial data. As the quantitative pre-warning techniques keep on developing and changing, financial pre-warning research has made great progress.

2) Model's prerequisites and assumptions of samples: Different financial monitoring models have different application prerequisites. During the application process of financial monitoring models, their application prerequisites are especially emphasized. Most of them have strict hypotheses, but these hypotheses are just good wishes of researches to get rid of the influence of disturbing factors.

3) Model's promotion: Since most models have strict hypotheses, such hypotheses are often not satisfied. The existence of these hypotheses might limit practicability of models during the application process. Besides, financial monitoring models are still development, so models adapting to the new environment should be explored constantly. There is not a constant financial monitoring model. Therefore, financial pre-warning researchers should pay attention to not only prediction accuracy, but also operability of the models. Besides, more efforts should be made to promote applications of financial monitoring techniques.

4) Prediction accuracy and explaining ability: Model applications are often based on approximate processing or hypothesis processing. Research conclusions might deviate from real conditions to some extent, thus driving down prediction accuracy of a model. In a word, there has not yet been an agreement about advantages and disadvantages of various multivariate financial monitoring models. The statistical methods are simple in calculation, convenient in application and easy in explaining, but the models featuring the parameter methods, based on traditional statistical methods, are often restricted by hypotheses and prerequisites, so they are unsuitable for the current complex and changing enterprise operation environment and the increasingly high requirement of precision. Non-statistical methods have an edge in terms of sample distribution limits and nonlinear modeling, but they have shortages, including over-fitting, poor promotion ability and difficulty of being explained. These shortages have become bottlenecks of their further development.

II. Review of Literature

Defines the financial crisis as a process, which includes less serious financial difficulties, bankruptcy liquidations and situations between the two extremes. The financial crisis of listed enterprises is a period concept with a start and ending, that is, starting from the moment that a financial crisis appears to the moment that an enterprise bankrupts. Besides, the financial crisis of listed enterprises is divided into different degrees. To sum up, their financial crisis can be divided into following circumstances: 1) Technical failure, meaning enterprises cannot repay capitals with interest according to their debt contracts; 2) Accounting failure, meaning that enterprises' book net assets are negative and that enterprises become insolvent; 3) Enterprise failures, meaning that enterprises are insolvent to pay due debts after liquidation; 4) Statutory bankruptcy, meaning that enterprises or creditors cannot perform their obligations under debt contracts in time, and the situation continues, forcing them to apply for bankruptcy to the court. Those "specially-handled" enterprises in China's stock market all have "abnormal financial situations", meaning that they keep on losing for the recent two years or that their net asset value per share in the recent one year is lower than the face value per share or these two situation happen at the same time.

Indicates there are different financial pre-warning model algorithms and modeling methods. Since prerequisites and hypotheses of data and statistical principles are not fully consistent with the reality, some models have limitations during the practical use process. For example, the multi-element linear discriminant analysis, the principal component model and the Logistic regression model all belong to a recognition and pre-warning system built on statistics; while the neural network model is a simulation of biological intelligence based on advances of computer application techniques, so it shows a high robustness and expansibility. Analysis of advantages and disadvantages of a financial monitoring model mainly proceeds from model's prerequisites and assumptions of samples and the model's method, promotion ability, prediction accuracy and explaining ability of results. To be specific:

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III. Research Methods

A. Principle of the PCA model

Principal component analysis (PCA) is a statistical method which transforms multiple variables into several principal components through the dimensionality reduction technique. There are many indexes influencing the development potential not yet been utilized, and different index are correlated with each other to some extent, thus increasing complexity of benefit evaluation. Therefore, it is necessary to combine multiple indexes and replace them with several mutually independent indexes, which can reflect the original data information at most. PCA is to find a way to recombine original indexes into a new set of mutually independent and comprehensive indexes, which can reflect the information of original indexes. Below is a brief introduction of the basic principle of the principal component model and its application steps:

Here, it is summed that the original analysis index data constitutes the matrix: $X=(x_{ij})_{n\times m}$ ($0\le i\le n$, $0\le j\le m$).

$$X=\begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{pmatrix} \tag{1}$$

Where, n stands for the number of objects to be evaluated; m stands for the number of indexes to be analyzed; x_{ij} stands for the value of the j index of the i evaluation object.

Step 1: Conduct normalization of the original data: Since the dimensionality representation forms of the value of various indexes collected are different, the original data are all normalized to eliminate the influence of dimensionality. In this paper, the standard deviation normalization method is adopted. See Eq. 2 below:

$$x'_{ij}=\frac{x_{ij}}{S_j} \tag{2}$$

Where, $\bar{x}_j=\frac{1}{n}\sum_{i=1}^{n}x_i$, $S_j=\frac{1}{n-1}\sum_{i=1}^{n}(x_{ij}-\bar{x}_j)^2$; $\bar{x}_j$ stands for the average value of the j index; Sj stands for the standard deviation of the j index.

Step 2: Build the correlation coefficient matrix, work out the eigenvalue of the correlation coefficient matrix, and confirm the number of principal components, namely the number of new indexes, k. Calculate the eigenvalue of the correlation coefficient matrix, R, and the variance contribution rate. Rank the eigenvalue, R, in the following order, $\lambda_1>\lambda_2>\cdots>\lambda_p\ge 0$. Then, choose a proper number of principal components to replace the

original variables. In this paper, the principle of accumulated variance contribution rate is adopted to determine the number of principal components, k. See Eq. 3 below:

$$CPV(k)=\sum_{j=1}^{k}\lambda_j \Big/ \sum_{j=1}^{m}\lambda_j \tag{3}$$

Where, λ_j stands for the j eigenvalue. Generally speaking, the principle of $CPV(k)\ge 90\%$ is adopted to determine the number of principal components.

Step 3: Work out the corresponding eigenvector of every eigenvalue, P, and the eigenmatrix can be worked out through calculation of the covariance matrix of $\bar{X}$. See Eq. 4 below:

$$p_i^T p_j = 0\,(i \neq j),\ p_i^T p_j = 1\,(i = j) \quad (4)$$

Step 4: Work out the corresponding number of principal component coefficient, q_j, of every eigenvector, pi, and conduct weighting according to the principal component coefficient and the indexes after normalization to obtain the score of every principal component, namely the compression index value. See Eq. 5 below:

$$F_{ik} = \sum_{j=1}^{m} q_j x_{ij} \quad (5)$$

Where, F_{ik} stands for the score of the k principal component of the i object; q_j stands for the principal component coefficient of the corresponding j index of the eigenvector, pi; x_{ij} stands for the index value after normalization

B. Financial monitoring based on integration of PCA and SVM.

Based on the above introduction of PCA, it is applied to extracting various financial indexes. The index value obtained through compression-based extraction is calculated, and adopted as the analysis data for the next step. The selected data undergo PCA. By solving the index matrix eigenvalue after normalization, the contribution rate of every eigenvalue can be worked out. Results are shown in Table 1 below. Changing results of the accumulated contribution rate along with the number of principal components are shown in Fig. 2 below:

Tab. 1 Eigenvalue and accumulated contribution rate

Eigenvalue	Contribution rate%	Accumulated contribution rate%
5.4288	33.9303	33.9303
2.4058	15.0363	48.9666
1.7206	10.7535	59.7201
1.4417	9.0107	68.7308
1.2432	7.7697	76.5005
1.0183	6.3644	82.8649
0.6852	4.2825	87.1474
0.6342	3.9635	91.1110
0.4987	3.1168	94.2278
0.3671	2.2944	96.5223
0.2022	1.2636	97.7858
0.1532	0.9575	98.7434
0.0946	0.5910	99.3344
0.0630	0.3940	99.7284
0.0369	0.2304	99.9587
0.0066	0.0413	100.000

Support vector model is built based on the VC dimension theory and the SRM principal to seek the optimal compromise and obtain the best generalization ability according to the learning ability of limited sample information and the model's complexity. Its basic idea can be explained by the optimal classification plane shown in Fig. 1. In Fig. 1, the solid and empty points stand for different data samples. H stands for the optimal classification hyperplane, $\omega^T x + b = 0$; H1 and H2 stand for the data sample straight lines paralleled to the classification line and nearest to the classification line; the distance between H1 and H2 is called classification interval.

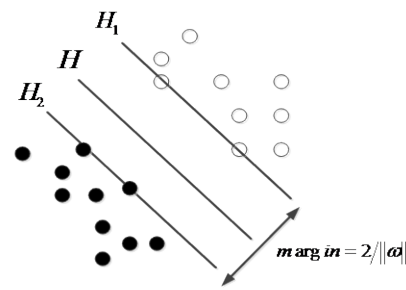


Fig. 1 Schematic diagram of the optimal classification hyperplane

The above optimal classification hyperplane, H , can maximize the classification interval when the two types of data samples are clearly divided. Therefore, Eq. 6 can be obtained:

$$\begin{cases} \omega^T x_i + b \geq 1, & y_i = +1 \\ \omega^T x_i + b \leq -1, & y_i = -1 \end{cases} \quad (6)$$

Then,

$$y_i(\omega^T x_i + b) \geq 1, i = 1, 2, ..., N \quad (7)$$

The corresponding classification decision-making function is shown in Fig. 8 below:

$$f(x) = sign[\omega^T x + b] \quad (8)$$

It is easy to prove that the optimal classification plane is actually the minimized hyperplane meeting conditions of Eq. 9:

$$\Phi(\omega) = \| \omega \|^2 \quad (9)$$

When the data are linearly indivisible, the above model can compromise the least wrongly divided samples and the maximum classification internal. Therefore, ξ is introduced to the model, and the model is transformed into a quadratic programming problem with constraint conditions. See Eq. 10 below:

$$\min \Phi(\omega, \xi) = \frac{1}{2} \| \omega \|^2 + C\sum_{i=1}^{N} \xi_i$$
$$st. \begin{cases} y_i(\omega^T x_i + b) \geq 1 - \xi_i \\ \xi_i \geq 0, i = 1, 2..., N \end{cases} \quad (10)$$

Where, ξ_i stands for the slack variable, which can control the wrong classification rate to some extent; C stands for the model's penalty factor, which can control the degree of penalty on wrong samples.

C. Steps to build the enterprise financial monitoring model based on integration of PCA and SVM.

Based on the above calculation process of the PCA and SVM model, it can be seen that the former just considers correlation among indexes, thus properly realizing dimensionality reduction and simplification of the index system. Under the prerequisite of not losing a large amount of key index information, the disturbing information in sample indexes is eliminated. Therefore, as sample data enter the core model training process, they can undergo compression-based extraction in advance to efficiently increase validity of various sample indexes and increase the prediction accuracy of the recognition model as well. Based on the above model algorithm analysis, below are steps to build the enterprise financial monitoring model based on integration of PCA and SVM:

1) Conduct maximin normalization of data and eliminate dimensionality differences among data;

2) Conduct PCA of data after normalization and obtain the accumulated contribution rate, which meets the condition of the component matrix coefficient, $CPV(k) \geq 90\%$

3) Conduct weighting of the component matrix coefficient extracted above and the data after normalization to obtain the compression value of indexes after extraction. See Eq. 11 below:

$$F_{ij} = \sum_{i=1}^{n} p(i,j) \cdot x_j \tag{11}$$

Where, F_{ij} stands for the index value of the j principal component of the i object; $p(i,j)$ stands for the principal component coefficient of the j index value of the i object; x_j stands for the j index of the object.

4) Build the SVM model, adopt the sample index value after compression as the training samples of the model, train the model already built and build a complete financial monitoring model system.

IV. MODEL APPLICATION AND RESULT ANALYSIS

A. Selection of sample indexes and samples

Selection of financial indexes has a huge influence on accurate financial monitoring. Therefore, to build a complete evaluation index system must adhere to the following principles: 1) Comprehensiveness: The index system should be comprehensive and can objectively, directly or indirectly reflect evaluation objects. Besides, indexes should not be overlapped with each other in terms of their concepts; 2) Indirectness: Index selection should be simple and layered. The evaluation should be multi-aspect and multi-dimensional; 3) Quantization: Indexes chosen should be quantizable, easy to collect and understand during the practical process. Quantitative and quantitative principles should also be adhered to during index selection; 4) Targetedness: Evaluation indexes are used to directly evaluate targets. They can be materialized and are highly targeted.

According to differences of index types, monitoring indexes include financial indexes, cash flow indexes, market return indexes and other types of indexes. Since financial indexes can be easily obtained from financial statements, many researchers directly adopt financial indexes as monitoring indexes. Based on the above analysis and concerning China's practical situations and accessibility of financial data, this paper chooses the following 16 financial indexes to form the financial crisis monitoring theoretical system. These financial indexes can comprehensively reflect an enterprise's financial status, including its debt-paying ability, profitability, operation ability, cash flow ability, etc. See Appendix Table 2.

Tab. 2 Monitoring indexes of listed enterprises' financial crises

Group	Serial No.	Financial indexes	Calculation formula
Cash flow	X1	Ratio of operating net cash flow to sales revenues	Operating net cash flow/Sales revenues
	X2	Operating net cash flow of assets	Operating net cash flow/Total assets
	X3	Proportion of the cash flow	Operating net cash flow/Total current liabilities
	X4	Operation net cash flow per share	Operating net cash flow/Total equity
Operation ability	X5	Accounts receivable turnover rate	Operating income/Accounts receivable
	X6	Total assets turnover rate	Operating income/Total assets
	X7	Net asset value per share	Stockholders' equity/Total equity
Profitability	X8	Rate of return on equity	Net profits/Stockholders' equity
	X9	Rate of return on total assets	Net profits/Operating profits
	X10	Net profit ratio of operating income	Net profits/(Operating income+Non-operating

			income)
	X11	Earnings per share	Net profits/Total equity
Debt-paying ability	X12	Current ratio	(Total current assets-Inventory)/Total current debts
	X13	Quick ratio	Total current assets/Total current debts
	X14	Stockholders' equity ratio	Stockholders' equity/Total assets
	X15	Debt-to-assets ratio	Total debts/Total assets
	X16	Cash ratio	End of term cash/Total current debts

The samples selected in this paper include enterprises with financial crises and non-financial crises, respectively. According to time differences, the total samples are divided into two groups, namely the estimation sample group and the test sample group. The data of the estimation sample group are used to build the financial monitoring model; while the data of the test sample group are used to test validity of the monitoring model. In order to make the model universal, the annual financial indexes of enterprises and the attributes of samples are needed to divide them into ST enterprises and non-ST enterprises. The time span of the samples selected in this paper lasted from 2014 to 2015. There are 123 non-ST samples and 108 ST samples. The index value of some sample data is shown in Table 3 (Appendix):

Tab. 3 Financial index value of some ST enterprises and non-ST enterprises (2014)

	Non-ST			ST		
Enterprise name	Avic Sanxin	Huasu Holding	Irico	Tianwei Baobian Electric	Beidahuang	Baoding Tianwei Group Tebian Electric
Stock code	C002163	C000509	C600707	C600550	C600598	C600550
X1	-0.12439	-0.44627	-1.86555	0.08207	0.75096	0.08207
X2	-0.02020	-0.11263	-0.00748	0.02009	0.23634	0.02009
X3	-0.03657	-0.13103	-0.02574	0.03866	0.60622	0.03866
X4	-0.17439	-0.09056	-0.07190	0.13237	1.33767	0.13237
X5	1.57885	3.40140	0.26711	1.00081	4.79461	1.00081
X6	0.16239	0.25238	0.00401	0.24479	0.31472	0.24479
X7	1.14910	0.13220	2.72000	0.09600	3.32540	0.09600
X8	-0.09961	0.09548	-0.02710	1.99766	0.16268	1.99766
X9	0.96841	1.19166	0.95063	1.06274	0.98347	1.06274
X10	-0.08128	0.05959	-1.73606	0.11828	0.30258	0.11828
X11	-0.05000	0.01000	-0.06000	0.19000	0.56000	0.19000
X12	0.50613	0.47673	0.22803	0.89480	0.84969	0.89480
X13	0.76533	0.77418	0.29308	1.19664	1.15130	1.19664
X14	0.13311	0.16445	0.28272	0.01457	0.58754	0.01457
X15	0.75116	0.87716	0.73104	0.96090	0.40865	0.96090
X16	0.07588	0.25933	0.16368	0.25780	0.46111	0.25780

B. Financial monitoring based on integration of PCA and SVM

Based on the above introduction of PCA, it is applied to extracting various financial indexes. The index value obtained through compression-based extraction is calculated, and adopted as the analysis data for the next step. The selected data undergo PCA. By solving the index matrix eigenvalue after normalization, the contribution rate of every eigenvalue can be worked out. Results are shown in Table 4 (Appendix). Changing results of the accumulated contribution rate along with the number of principal components are shown in Fig. 2 below:

From the eigenvalue and the accumulated contribution rate in Fig.2, it can be seen that corresponding contribution rate of the former eight eigenvalue reaches 91.11%. Since the former eight principal components can reflect 91.11% of the information amount of original indexes, they all meet the requirement of the accumulated variance contribution rate, CPV>90%.

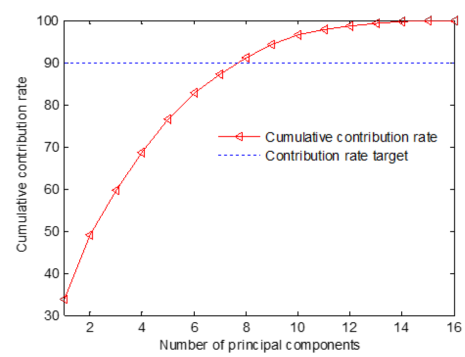
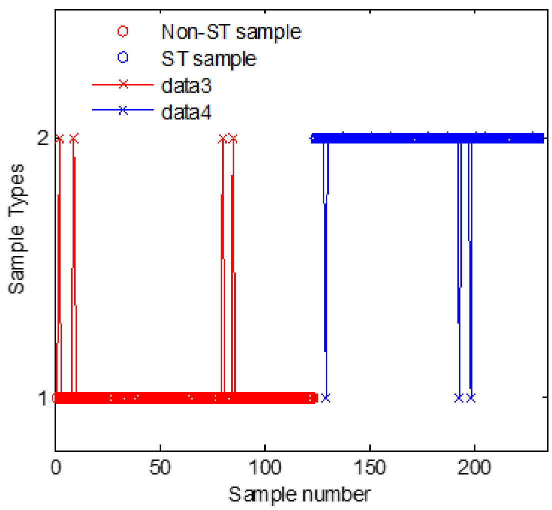


Fig. 2 Changing results of the accumulated contribution rate along with the number of principal components

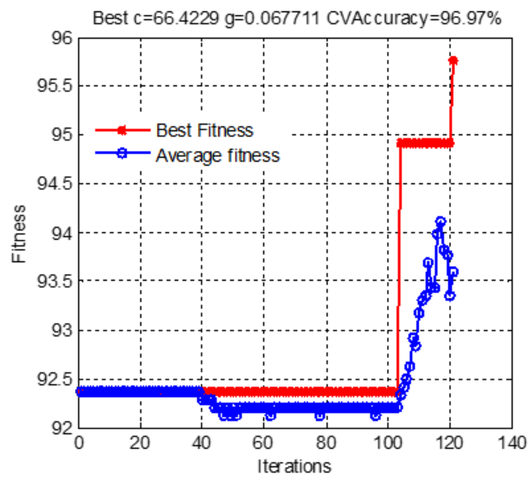
In Table IV (Appendix) , the result of weighting of index data of all non-ST samples and ST samples based on the principal component matrix coefficient is outlined. Adopt the index value of eight principal components as the input information of the SVM model. Encode the ST and non-ST enterprises, respectively. Combine the genetic algorithm (GA) to conduct parameter optimization of the SVM model already built during the training process. The relevant modeling parameters and the convergence parameters are shown in Table 6 below. Recognition of the model's training samples and the model's iterative parameter optimization process are shown in Fig. 3 below:

Tab. 4 Comparison of pre-warning recognition accuracy of various models

Model algorithms	Accuracy of test samples 2014	Accuracy of test samples 2015
Principal components	76.62%	74.59%
Principal component integrated entropy	85.28%	82.25%
Logistic model	80.52%	73.59%
BP neural network model	74.49%	61.47%
SVM model	88.31%	85.71%
Principal component integrated with SVM	96.97%	90.04%



(a)



(b)

Fig. 3 Training sample recognition result and model's parameter optimization process. Fig.3(a) shows recognition results of training samples; Fig.3(b) shows the model's parameter optimization process.

Based on simulation results in Fig. 3, the SVM model trained by the index value obtained through compression extraction of principal components has a high recognition accuracy. In order to prove validity of the model put forward in this paper, Fig. 7 provides samples of original data trained directly through principal components, principal component integrated entropy, Logistic model, BP neural network model and the SVM model algorithm, and test sample recognition results in 2015.

Tab. 5. Principal component matrix coefficient

	Principal component F1	Principal componen t F2	Principal compone nt F3	Principal componen t F4	Principal compone nt F5	Principal compone nt F6	Principal compone nt F7	Principal component F8
X1	0.2038	-0.2383	-0.2063	0.3650	-0.3693	-0.2677	-0.1913	-0.0467
X2	0.3600	-0.0464	-0.2791	-0.0034	0.0507	0.0930	0.3141	-0.2820
X3	0.3175	-0.2630	0.1868	-0.2070	0.0101	0.0253	0.1447	-0.2878
X4	0.2751	-0.2218	-0.3381	-0.2424	-0.1228	-0.0229	0.3310	0.1813
X5	0.2584	0.0300	0.2889	0.1309	-0.2477	-0.3535	0.4877	0.1790
X6	0.1305	-0.4269	-0.1221	-0.2593	0.0809	-0.1170	-0.3242	0.0432

X7	0.1966	0.2708	-0.3746	-0.3507	-0.0836	-0.0906	-0.2430	0.1921
X8	-0.0714	-0.3544	-0.0413	0.3876	0.3260	0.3230	0.1764	-0.1980
X9	0.0700	-0.0941	-0.1674	0.1599	-0.5151	0.6801	-0.1272	0.1549
X10	0.2404	-0.1375	-0.1096	0.4511	0.1447	-0.3346	-0.3574	-0.0519
X11	0.2090	-0.0808	-0.0707	0.1060	0.5301	0.1367	0.0718	0.6883
X12	0.3050	-0.0250	0.4043	-0.1364	0.0859	0.1231	-0.3800	-0.0612
X13	0.2506	0.2128	0.3534	0.2669	-0.1989	0.0812	-0.0375	0.2914
X14	0.2723	0.4270	-0.1680	0.1477	0.1552	0.0725	-0.0338	-0.1810
X15	-0.2908	-0.4006	0.1174	-0.0721	-0.1616	-0.1232	-0.0098	0.2549
X16	0.3224	-0.1326	0.3384	-0.2245	0.0172	0.1788	-0.0713	-0.0757

From results in Table 5(Appendix) , it can be seen that, the model algorithm put forward in this paper has a higher recognition accuracy of short-term financial pre-warning. The major reason is that, during feature extraction process of sample data, the core principal components of all samples are considered and the redundant index information undergoes compression-based extraction. Therefore, various data samples after extraction have eliminated repeated and disturbing information of various sample indexes to a large extent. After training, the SVM model can have a higher accuracy. Besides, the recognition accuracy results of various samples also show that different models are combined for enterprise financial monitoring. The multi-angle monitoring has a higher accuracy rate than that of a simple model, and is more suitable for practical enterprise financial pre-warning monitoring.

V. Conclusion and Future Studies

In Summary, this paper first introduces the purpose and significance of enterprises' financial monitoring and then analyzes whether one business experiences financial crisis under China's special economic environment. Based on a comparative analysis of the current prevailing enterprise financial pre-warning models, relevant indexes and samples are selected to build a financial monitoring model combining PCA and SVM. At last, the model put forward in this paper undergoes a series of detailed comparative analysis.

Though there are limitations of this study, the result is promising in that the model algorithm put forward in this paper has a higher recognition accuracy than that of prevailing financial monitoring models. The major reason behind this is the model in this paper considers the core principal components of all samples and conduct compression-based extraction of redundant index information. In this way, the key index information is maintained. On the other hand, disturbing factors in sample indexes are eliminated, and the training process of the follow-up recognition model is improved. Therefore, the algorithm in this paper can well realize enterprises' financial monitoring, efficiently prevent and resolve financial risks and crises.

Acknowledgment

Zhuo Zhang thanks Macau University of Science and Technology Faculty Research Grant (Project Code: FRG-17-007-MSB) for the support of the Mini Research.

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