Journal of Applied Science and Engineering, Vol. 22, No. 1, pp. 171–178 (2019) *DOI: 10.6180/jase.201903_22(1).0017*

Enterprise Financial Risk Early Warning Method Based on Hybrid PSO-SVM Model

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Abstract

In order to ensure the healthy and orderly development of enterprises, it is of great importance to effectively predict enterprise financial risk in advance, and then provide early warning information to enterprise's managers. Firstly, we design an index system for enterprise financial risk early warning, which contains five aspects: 1) Profitability, 2) Debt paying ability, 3) Operation ability, 4) Growth ability, and 5) Non-financial indicators. Secondly, we propose a novel hybrid PSO-SVM model based enterprise financial risk early warning algorithm by converting the proposed problem to a classification problem. As the performance of SVM classifier highly relies on parameter selection, we introduce the PSO algorithm to estimate optimal parameters for SVM. Thirdly, we choose several ST companies of the listed companies in China as financial crisis enterprises, and compare their running states with Non-ST companies. Main contributions of this paper lie in that we propose a hybrid PSO-SVM model based enterprise financial risk early warning algorithm by solving a classification problem. Experimental results show that the proposed algorithm is able to effectively provide early warning information for enterprise financial risk, and performs better than BP neural network and SVM without parameter optimization.

Key Words: Enterprise Financial Risk, Risk Early Warning, Particle Swarm Optimization, Support Vector Machine

1. Introduction

In recent years, with the rapid development of economic globalization, there are many opportunities and challenges for modern enterprises to face [1]. Moreover, the risks in enterprise management have increased under this complex background and uncertain conditions. Hence, how to effectively exploit this changing environment can obtain the superiority status in the competition, and then ensure healthy and orderly market environment [2–4].

Each enterprise faces financial risk in the period of its production and management in the market economy. However, many enterprises cannot realize the importance of financial risk management and in time warning [5,6]. In the development of the market economy, it is possible for enterprises to consider bankruptcy and financial problems in advance. It is of great importance to seek a suitable way to manage and early warn financial risks [7–9].

Particularly, enterprise financial risk refers to enterprise to lose debt paying ability perhaps and uncertainty, shareholder of income [10]. In addition, financial risk early warning denotes that measuring and controlling the financial risk, and then reducing different types of losses. The happening of financial crisis requires a period of time duration, and then quantitative varying may greatly influence the qualitative change with warning index of financial risk [11,12]. If the enterprise manager make warning as early as possible, potential risks can be effectively prevented in advance, and then and effective measures can be made to enhance enterprise management le-

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vel [13,14]. That is to say that enterprise's financial risk accurately should be predicted in advance, and then take the effective measures to control financial risks [15–17].

The paper is organized as follows. In the next section, related works about PSO-SVM model are given. In section 3, we introduce the index system construction method. Section 4 proposes a novel hybrid PSO-SVM model based enterprise financial risk early warning method. Afterwards, experiments are conducted in section 5 to make performance evaluation, and the whole paper is concluded in section 6.

2. Related Works

In this section, we illustrate related works about hybrid PSO-SVM model, which is able to solve classification problems in many areas. As is well known that SVM refers to a non-linear regression forecasting approach, in which the input variables are mapped into a high dimensional linear feature space via a non-linear transformation function. To enhance the performance of parameter selection, The particle swarm optimization (PSO) algorithm denotes a population-based search algorithm with the simulation of the bird flocking. Afterwards, PSO is revised with a population of random solutions [18]. Just like to evolutionary computation algorithms, PSO is a population-based search algorithm which can utilize the model of social sharing of information. In the following part, related works about hybrid PSO-SVM model is given.

Zhou et al. exploited PSO-SVM coupling model based on the response of the induced factors to forecast the landslide displacement. The moving, average approach was used to separate the total displacement into trend term and periodic term. The trend displacement is managed by the geological conditions and forecasted via a polynomial function [19].

Zhang et al. proposed a new analog circuit fault diagnosis method exploiting using generalized multiple kernel learning-support vector machine method and particle swarm optimization algorithm. Particularly, the wavelet coefficients' energies of impulse responses are extracted as features. Next, a diagnosis model is established via utilizing GMKL-SVM approach with the above features [20].

Xu et al. proposed a novel approach by integrating both Multiscale Base-Scale Entropy and Support Vector Machine with Particle Swarm Optimization algorithm to detect roller bearings fault. Afterwards, SVM optimized by PSO hybrid model is used to classify the fault type and fault severity [21].

To forecast the resonant frequency of the compact microstrip antenna by artificial neural network, Sun et al. utilized a hybrid SVM-PSO model to model the resonant frequencies of the compact microstrip antenna to reduce the number of samples and simplify the structure. Particularly, in this work, parameters of SVM classifier and weight coefficients of the HKF are optimized using particle swarm optimization [22].

Zhan et al. used a hybrid PSO-SVM-based model to forecast the friction coefficient between aircraft tire and coating. The proposed method integrates a support vector machine with particle swarm optimization algorithm. However, the friction coefficient which is forecasted based on SVM should to be found between aircraft tire and coating [23].

Apart from the above works, PSO-SVM model has been successfully used in other areas, such as predicting a successful growth cycle of the Spirulina platensis [24], predicting the filtered volume and outlet parameters in micro-irrigation sand filters fed [25], gender recognition [26], rotation-invariant image texture classification [27], intrusion detection system [28], forecasting of the remaining useful life for aircraft engines [29], predicting of the cyanotoxin content from experimental cyanobacteria concentrations [30], internal and external defect identification of pipelines [31], hyperspectral image classification [32], forecasting monthly streamflow [33], short-term load forecasting [34], long-term forecasting of turbidity in the Nalon river basin [35]. Motivated by the above works, in this paper, we utilize the PSO-SVM model to predict the degree of enterprise financial risk.

Apart from the above works, optimization algorithms have been widely used in many areas, such as Industrial system performance optimization [36], constrained optimization problem [37], structural engineering design optimization [38], performance analysis of an industrial system [39], generation scheduling of pumped storage hydrothermal system [40], reliability optimization [41], Stock Market Prices Prediction [42].

Different from the above works, in this paper, we propose a new hybrid PSO-SVM model based enterprise financial risk early warning algorithm through converting the proposed problem to a classification problem.

3. Index System Construction

In this paper, we regard the enterprise financial risk early warning problem as a classification problem, and utilize the SVM classifier to solve it. Furthermore, vector space should be constructed in advance. Therefore, in this section, we illustrate how to construct the feature vector to tackle the enterprise financial risk early warning problem. The proposed index system for enterprise financial risk early warning is made up of five aspects, that is, 1) profitability, 2) debt paying ability, 3) operation ability, 4) growth ability, and 5) non-financial indicators.

As is shown in Figure 1 that the proposed index system of the enterprise financial risk early warning is able to cover main influencing factors in the issue of enterprise financial risk early warning. However, we still cannot know which indicators are more important. Hence, in the experiment section, we will discuss indicator weight and then choose important indicators to predict enterprise financial risk.

4. The Proposed Hybrid PSO-SVM Model Based Enterprise Financial Risk Early Warning Method

In this section, we propose a novel hybrid PSO-SVM model based enterprise financial risk early warning method. Particularly, we regard enterprise financial risk early warning as a classification problem, and a SVM classifier is optimized by PSO algorithm.

SVM refers to a particular type of linear model, which aims to seek the maximum margin hyperplane. Suppose that we divide a set of training vector to two classes, and we let $G = \{(x_i, y_i)\}$, $i \in \{1, 2, \ldots, N\}$ with a hyperplane $w^T x + b = 0$, where $w \in R^d$ denotes a normal d dimensional vector, and $x_i \in R^d$ refers to the i^{th} input vector and $y_i \in \{+1, -1\}$. SVM should follow the following condition:

$$Y_i (w^T x_i + b) \geq 1, i \in \{1, 2, \ldots, N\} \quad (1)$$

The maximum distance between two hyperplances is the optimal goal, and hyperplane 1 and 2 are represented as $w^T x_i + b = 1$ and $w^T x_i + b = -1$ respectively. Therefore, it can be seen that the best hyperplane can be gained through tackling the following equation.

$$\min_{b,w} \frac{1}{2} \|w\|^2 \quad (2)$$

Based on the above definitions, the proposed problem can be solved by calculating the saddle point of a Lagrange function as follows.

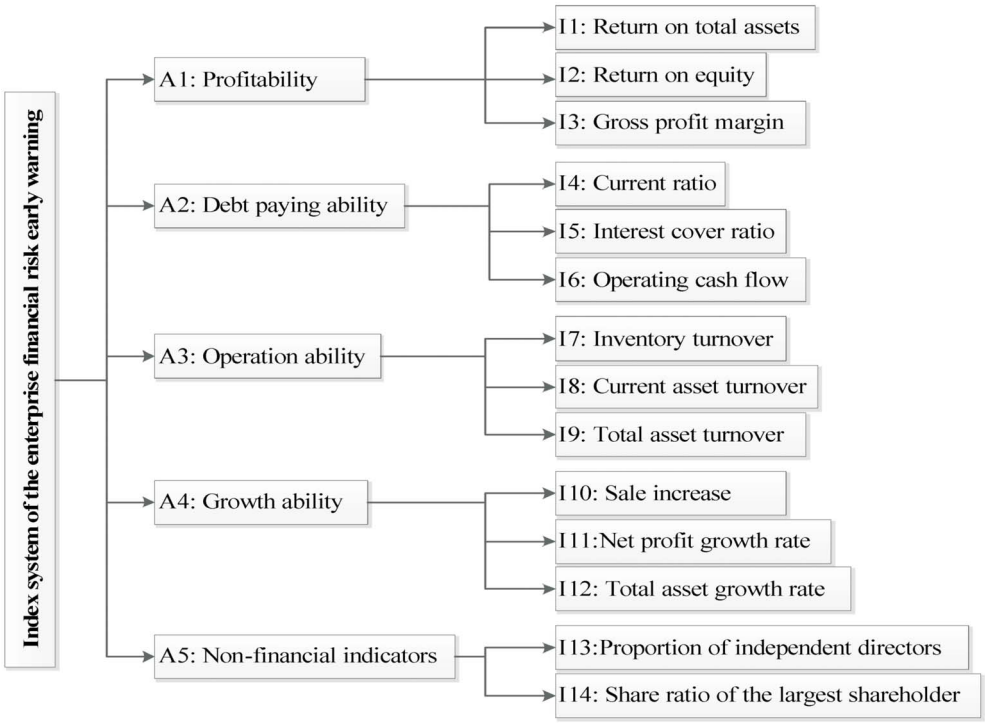

Figure 1. Index system for the enterprise financial risk early warning.

$$\min L = \min\left\{\frac{1}{2}\|w\|^2 - \sum_{i=1}^{N}\alpha_i\left[y_i(w^T x_i + b) - 1\right]\right\} \quad (3)$$

To achieve optimal parameters of SVM, the particle swarm optimization method is used through modifying each particle's velocity to its pbest and gbest. PSO updates each particle's velocity and position as follows.

$$v_i(t+1) = \gamma\left\lfloor v_i(t) + c_1 r_1(p_{besti} - x_i(t)) + c_2 r_2(g_{best} - x_i(t))\right\rfloor \quad (4)$$

$$x_i(t+1) = x_i(t) + v_i(t+1)$$

$$\text{s.t. } \gamma = \frac{2}{\left|\sqrt{2 - \chi - \sqrt{\chi^2 - 4\chi}}\right|},\ \chi = c_1 + c_2,\ \chi > 4 \quad (5)$$

where $x_i = [x_{i1}, x_{i2}, \ldots, x_{in}]$ refers to the position of the i^{th} particle in the whole searching space, $v_i = [v_{i1}, v_{i2}, \ldots, v_{in}]$ denotes the velocity of the i^{th} particle. Furthermore, p_{besti} and g_{best} refer to the best former the position of the i^{th} particle and the best particle in the whole searching space. Parameter γ is a weight, c_1, c_2 mean positive constants, and r_1, r_2 are random numbers.

Based on the above analysis, the PSO algorithm can be described as follows.

(1) Initialization process: Randomly producing initial particles.
(2) Fitness: Estimating the fitness of each particle from the population.
(3) Updating process: Calculating the velocity of each particle.
(4) Construction process: For each particle, let it move to its next position.
(5) Ending process: If the ending condition is satisfied, ends, otherwise, goto (2).

Flowchart of the hybrid PSO-SVM model is shown in Figure 2.

For example, we provide a sample to make performance, and the vector of this sample is (-4.046, -3.487, -0.027, -2.074, -2.984, -2.217, -2.041, 0.457, -2.046, 0.314, 0.533, 0.125, 1.056, 0.852). Using the proposed SVM classifier, this sample is regarded as high probability for the financial risk.

5. Experiment

As is well known that, the ST companies of the listed companies in China are identified as financial crisis enterprises. ST means "special treatment", and the target of the policy is an abnormal financial situation or other situation. According to published information of China's Securities Regulatory Commission on listed companies, in 2006, there are a total number of 59 new types of ST companies, which can be divided into two categories: 1) manufacturing enterprises, and 2) non-manufacturing enterprises. We randomly select 5 manufacturing enterprises and 5 non-manufacturing enterprises as ST samples (denoted as $\{S_1, S_2, \ldots, S_{10}\}$). On the other hand, another 10 non-ST enterprises (denoted as $\{N_1, N_2, \ldots, N_{10}\}$) are chosen to make performance comparison. In addition, we also build a training dataset which is made up 100 ST enterprises and 100 Non-ST enterprises.

Particularly, parameters of SVM are listed as follows. C is equal to 1.0, Kernel we used is RBF, and Gamma is set to 0.1.

To choose most significant indicators, we compute T value of all indicators, and experimental results are shown in Table 1.

It can be observed from Table 1 that based on the T test results, the significance probability of two-tailed T test about I1, I2, I4, I5, I6, I7, I9 are lower than 0.05. That is to say, these indicators can effectively discriminate ST from non-ST enterprise. However, the significance probability of the rest indicators cannot be suitable to be used in enterprise financial risk early warning.

To make performance comparison, BP neural network and standard SVM are chosen to be compared with

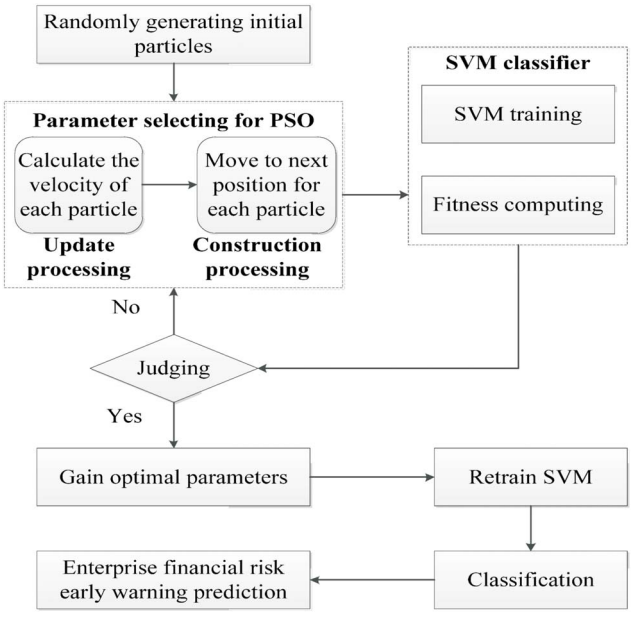

Figure 2. Flowchart of the hybrid PSO-SVM model.

Table 1. Results of significant indicators choosing

Indicator ID	T value	Two-tailed T test
I1	-4.046	0.000
I2	-3.487	0.001
I3	-0.027	0.975
I4	-2.074	0.045
I5	-2.984	0.004
I6	-2.217	0.026
I7	-2.041	0.043
I8	0.457	0.647
I9	-2.046	0.042
I10	0.314	0.751
I11	0.533	0.567
I12	0.125	0.857
I13	1.056	0.284
I14	0.852	0.383

the proposed algorithm. In BP neural network, Back propagation is a method used in artificial neural networks to calculate a gradient that is needed in the calculation of the weights to be used in the network. Moreover, standard SVM means the SVM classifier without parameter optimization. Enterprise financial risk early warning degrees for all ST samples are shown in Figure 3 as follows.

Next, enterprise financial risk early warning degrees for all Non-ST samples are shown in Figure 4 as follows.

Integrating experimental results of Figure 3 and Figure 4, we can see that the proposed algorithm can predict enterprise financial risk early warning degree more accuracy than BP neural network and SVM, and enterprise financial risk early warning degree of ST samples are all higher than Non-ST samples.

Next, to show the enterprise financial risk early warning prediction performance with time varying, we test the performance of different methods in a period of time (from 2005-2008). Moreover, a year is divided to four quarters, which are denoted as Q_1, Q_2, Q_3, Q_4. Firstly, enterprise financial risk early warning prediction results of sample S_1 is shown in Figure 5 as follows.

Secondly, enterprise financial risk early warning prediction results of sample N_1 is shown in Figure 6 as follows.

As is shown in Figure 5 and Figure 6, time period 1-16 are corresponding to 2005Q1 to 2008Q4 respectively. Furthermore, Figure 5 and Figure 6 demonstrate that the proposed algorithm can achieve higher accuracy for enterprise financial risk early warning prediction with time cnging than other methods. Afterwards, we can observe that the proposed algorithm is able to effectively provide early warning information for enterprise financial risk. Our algorithm performs better than others, because the PSO-SVM model is able to effective the classification problem.

6. Conclusion

The goal of this paper is to forecast enterprise financial risk in advance, and then provide early warning information to enterprise's managers. An index system for enterprise financial risk early warning is designed, which consists of five aspects: 1) Profitability, 2) Debt paying ability, 3) Operation ability, 4) Growth ability, and 5) Non-financial indicators. Main innovation of this paper lies in that we propose a novel hybrid PSO-SVM model based enterprise financial risk early warning algorithm

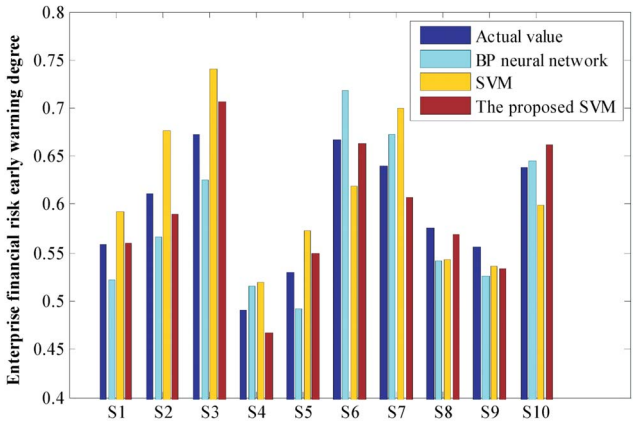

Figure 3. Enterprise financial risk early warning degrees for all ST samples.

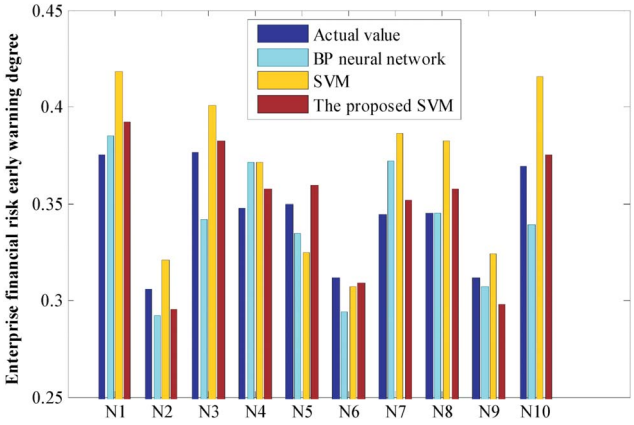

Figure 4. Enterprise financial risk early warning degrees for all non-ST samples.

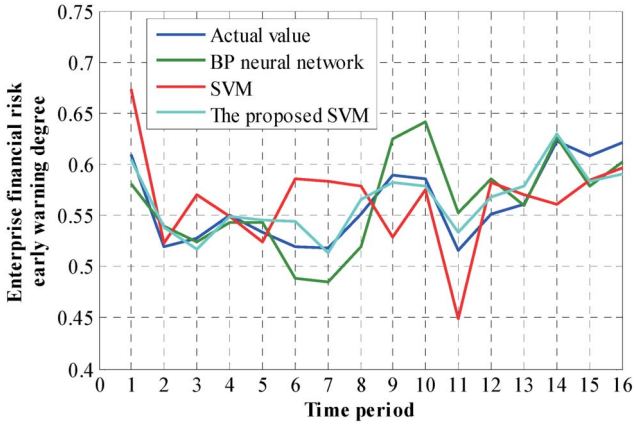

Figure 5. Enterprise financial risk early warning prediction for sample S_1.

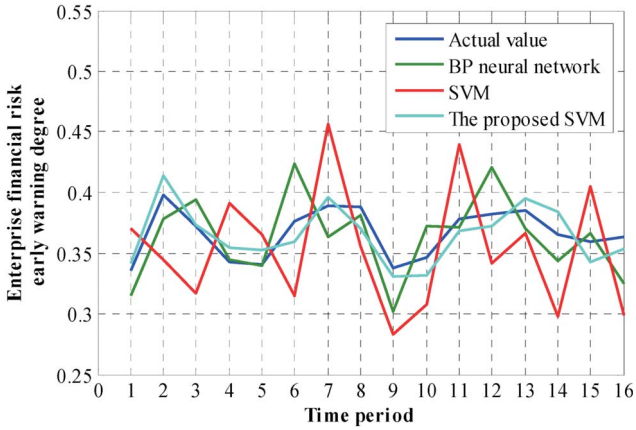

Figure 6. Enterprise financial risk early warning prediction for sample N_1.

and exploit PSO algorithm to optimize parameters for SVM classifier. Experimental results prove the effectiveness of the proposed algorithm.

In the future, we will try to use other types of optimization algorithm to replace the PSO algorithm.

Acknowledgement

This paper is supported by A key program of Humanities and Social Sciences of Anhui Province entitled The O2O Market Research and Development Analysis of Community Service in Anhui Province Based on "Internet +" Technologies (No.: SK2017A0736); A key program of Humanities and Social Sciences of Anhui Province entitled The Integration and Risk Management Research of P2P Online Loan Platforms in Anhui Province (No.: SK2017A0737); and Anhui Provincial Quality Engineering Project entitled An Educational and Training Plan of Excellent Talents in Marketing (No.: 2016zjjh006).

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Manuscript Received: Mar. 28, 2017
Accepted: Oct. 16, 2018