Research Article

Design of Financial Crisis Early Warning Model Based on PSO-SVM Algorithm

Wan Li
Zhengzhou University of Economics and Business, Zhengzhou 450000, Henan, China
Correspondence should be addressed to Wan Li; liliwan952@outlook.com
Received 12 July 2022; Revised 26 August 2022; Accepted 16 September 2022; Published 30 September 2022
Academic Editor: Wenlong Hang

Copyright © 2022 Wan Li. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

To address the problem that the accuracy of the SVM algorithm is affected by random parameters at the input end, a financial crisis early warning model (FCEWM) based on PSO-SVM is constructed based on the nonequilibrium sample characteristics of different financial conditions of listed companies in China’s gem. The model uses the PSO algorithm to optimize the parameters of SVM and selects 24 financial risk evaluation indexes as the input to predict the financial crisis. The results show that the proposed model is superior to other models in prediction accuracy and robustness.

1. Introduction

With the acceleration of the process of economic globalization, the development scale of China’s companies is expanding, and enterprises are facing unprecedented opportunities and challenges. Especially as an important part of China’s national economy, manufacturing enterprises seize the opportunity to introduce technology, talents, and equipment, and inevitably fall into the predicament of the high cost of human resources and assets, and even break the capital chain, leading to financial risks and company’s imminent bankruptcy. If the potential financial risk cannot be found by the company’s managers in time, the company will have a financial crisis [1], which will involve the interests of the chain of people, that is, enterprise investors and creditors, and the company is manifested as capital turnover difficulties, profits suddenly reduced, daily working capital cannot maintain the normal operation of the enterprise, and finally, the listed enterprises produce inestimable economic losses [2]. Before the outbreak of a financial crisis, it is very important to identify the financial risk quickly, control and deal with the risk in time, transform the irreversible financial crisis into the reversible crisis, and avoid the occurrence of greater risks inadvertently.

At present, FCEW is generally studied through examples. The classification method in mathematical statistics learning is used to analyze the relevant financial data of enterprises in financial crisis and in normal operation to build a FCEWM, and then, the model is used to predict whether the enterprise will have a financial crisis [3]. Since the 21st century, machine learning technology has been developing vigorously, and researchers have begun to use these emerging technologies for financial crisis warning. Scholars have published rich academic achievements on FCEW. The early warning index system of the financial crisis has developed from a single index to a multidimensional index system, and the model has also developed from a unitary linear model to a machine learning model. With the deepening of theoretical research, the FCEWM is constantly practiced in real life, and the accuracy of the model is higher, which has been widely used. However, in the selection of indicators, most of the literature takes financial indicators as early warning indicators, only a small number of studies have added nonfinancial indicators, and the introduction of nonfinancial indicators into FCEW research is still in its infancy. Whether in the field of medicine, information, or finance, the sample set tends to show the characteristics of skewness; that is, the number of two types of samples is often unequal. The classification results of the model trained by
this kind of unbalanced samples will have obvious bias; that is, the prediction accuracy of most samples is higher than that of minority samples. The good prediction performance of traditional SVM often requires that the two types of samples are balanced [4], but after all, there are only a few listed companies with the financial crisis and the majority of listed companies with normal finance, which will inevitably lead to the imbalance of the two types of samples, thus making the classification hyperplane constructed by SVM biased to the financial crisis samples, and then, the prediction effect of the model is unsatisfactory.

Therefore, in view of the unbalanced sample characteristics of different financial conditions, this paper uses the PSO-SVM algorithm to construct the FCEWM. SVM has the problem that the randomness of weight and threshold parameters affects its early warning effect. Particle Swarm Optimization (PSO) can find the best particle position to make up for the defects of random solution to improve the accuracy.

2. Literature Review

The research of financial crisis prediction mainly includes the construction of prediction model and prediction index. Many researchers have proposed many financial forecasting methods: one is based on statistical theory, and the other is machine learning method represented by artificial intelligence. Martin et al. [5] used logistic regression analysis to predict the financial situation of enterprises. The model based on statistics has higher requirements for samples. With large samples, the prediction effect may be poor, and the generalization ability is weak. Xiao and Yang [6] constructed the L1/2 regularized logistic regression model, which avoided the defect of sensitivity of multicollinearity interference between financial indicators and improved the accuracy of FCEW and the generalization ability of the model. As far as the performance of the logistic model is concerned, the performance of the logistic model is better than that of the BP neural network. In addition, the performance of the combined model combined with variable selection technology is significantly better than that of the single model [7–9]. In the aspect of machine learning, Lapedes and Farbe [10] selected a neural network method for early warning of the bank credit crisis. Chen [11] effectively measured the quality and business performance of listed enterprises based on the BP financial crisis warning model and gave financial crisis warning to listed enterprises. Wu et al. [12] constructed the twin SVM model to study the FCEW of China’s GEM-listed companies based on the unbalanced sample characteristics of different financial conditions. Zhang et al. [13] studied the relationship between default probability and financial early warning indicators of Chinese manufacturing listed companies and established Aalen additive model to predict financial distress. Zheng [14] proposed a financial early warning method based on rough set theory and least squares support vector machine for manufacturing listed companies. Zhu [15] used the nonlinear SVM method for FCEW of high-tech enterprises. From these studies, we can find that the FCEWM based on machine learning represented by artificial intelligence has been widely concerned, but at present, the selection of financial crisis prediction indicators mainly stays on pure financial indicators, and nontraditional financial information has not been given enough attention. In the field of financial crisis prediction, most of them adopt the neural network learning method, but the learning time of these methods is not accurate enough.

Li et al. [16] applied linear discriminant analysis and SVM support vector machine model to FCEW and added index screening technology to the model. In the combination model, the SVM model is mainly combined with the parameter optimization model and data dimension reduction model, and the model effect is significantly enhanced. Shi [17] used financial data as an early warning index, processed indicators with the principal component analysis (PCA) method, and built FCEWM with support vector organization optimized by parameters. The results showed that PCA-SVM was suitable for FCEW, and the model showed good performance in processing small sample data, which can be used for the unbalanced sample characteristics of different financial conditions of the company. PSO-SVM solves the problem of unbalanced samples fundamentally. It does not need to increase or reduce the original samples but constructs a classification hyperplane for the financial normal samples and financial crisis samples of listed companies. Meanwhile, its classification flexibility and computational performance will be greatly improved, thus effectively overcoming the fundamental shortcomings of traditional SVM. Therefore, this paper uses the PSO-SVM algorithm to construct FCEWM.

3. FCEWM Based on SVM

3.1. Index Construction. The establishment of SVM-based early warning model requires state indicators and characteristic indicators. The state indicators used in this paper are \( y_i^t \in \{-1, +1\} \), which represent the financial status of listed company \( i \) at time \( t \), where “-1” means that the company belongs to the financial normal category, and “+1” means that the company belongs to the financial crisis category. \( x_i^{d,t} = (x_{i,1}^t, x_{i,2}^t, \ldots, x_{i,m}^t) (d = 1, 2, \ldots, m) \) represents the characteristic index variable of the \( m \) dimension. By using the characteristic index variable at time \( t \) to predict the state index variable at time \( t + 1 \), then each research sample can be constructed as \( (x_i^{d,t}, y_i^{t+1}) \) data set.

On the basis of constructing the total data set, this paper divides some sample data \( (x_{k,t}^i, y_{k,t}^{t+1}) (k = 1, 2, \ldots, \text{with time length of } h \text{ into training samples}) \). Another part of the sample data \( (x_{h+1, u}^i, y_{h+1}^{t+1}) (u = h + 1, n) \) as the test sample. The essence of the FCEW problem of listed companies is to fit the training samples to find the optimal classification hyperplane, so as to determine the optimal kernel function and parameters and to obtain the classification decision function. Then, the test samples are fitted with the established model to test its accuracy. In addition, a classification hyperplane is constructed for financial crisis samples and financial normal samples, respectively, so that one classification hyperplane is as close to the financial crisis samples as possible and far away from the financial normal samples, and the other classification hyperplane
is as close to the financial normal samples as possible and far away from the financial crisis samples. SVM is to use two parallel hyperplanes to fit two kinds of samples, respectively. The inequality constraint in the original problem description of SVM reduces the problem to the solution of linear equations. Specifically, the goal of SVM is to solve two nonparallel hyperplanes, as shown in the following equations:

\[
\begin{align*}
  f_1(x) &= K(x^T, D^T)w_1 + b_1 = 0, \\
  f_2(x) &= K(x^T, D^T)w_2 + b_2 = 0,
\end{align*}
\]  

where \( D = [X_1 X_2]^T \), and the Kernel Function is expressed as \( K \), which is to map the two kinds of points that are linearly indivisible in two-dimensional space to become separable in higher-dimensional space, so as to achieve the purpose of separating the two kinds of samples.

### 3.2. Sample Solution

The original problem of nonlinear PSO-SVM can be transformed into solving the following two optimal problems for financial normal samples and financial normal samples, respectively.

\[
\begin{align*}
\min_{w_1, b_1, \xi} & \quad \frac{1}{2} K(X_1, D^T)w_1 + e_1 b_1^2 + c_1 e_1^2 \xi \\
\text{s.t.} & \quad -[K(X_2, D^T)w_1 + e_2 b_1] + \xi \geq e_2 \\
& \quad \xi \geq 0, \\
\min_{w_2, b_2, \eta} & \quad \frac{1}{2} K(X_2, D^T)w_2 + e_2 b_2^2 + c_2 e_2^2 \eta \\
\text{s.t.} & \quad -[K(X_1, D^T)w_2 + e_1 b_2] + \eta \geq e_1 \\
& \quad \eta \geq 0,
\end{align*}
\]

where \( c_1, c_2 > 0 \) and are the penalty parameters; \( e_1, e_2 \) represent column vectors of units of appropriate dimensions; \( \xi \) and \( \eta \) are nonnegative slack variables.

In order to solve the optimal problem of (2), the Lagrange multiplier (LM) is introduced, and the Lagrangian function (LF) is obtained as follows:

\[
L(w_1, b_1, \xi, \alpha, \beta) = \frac{1}{2} K(X_1, D^T)w_1 + e_1 b_1^2 + c_1 e_1^2 \xi + \alpha^T[K(X_2, D^T)w_1 + e_2 b_1 - \xi - e_2] - \beta^T \xi.
\]

Thus, a classification hyperplane can be obtained. In the same way, we can solve the optimal problem of (3) and obtain another hyperplane \( z_2 \). Then, each class corresponds to a hyperplane, and the class of each sample point is determined by the following equation:

\[
y_i = f(x) = \arg \max_k \left| w_k K(x^T, D^T) + b_k \right|, \quad k = 1, 2.
\]

### 4. FCEWM Based on PSO Optimization

#### 4.1. PSO Algorithm

PSO is usually used to find the optimal value of a function. The potential solution of the optimization problem is regarded as the particles in the p-dimensional search space. In the process of continuous iteration, the particles follow the individual extreme value \( P_{best} \) and the global extreme value \( G_{best} \) to update their position as shown in the following formulas:

\[
\begin{align*}
X_i &= x_{i1}, x_{i2}, \ldots, x_{ip} \quad i = 1, 2, 3, 4, \ldots, n, \\
V_i &= v_{i1}, v_{i2}, \ldots, v_{ip} \quad i = 1, 2, 3, 4, \ldots, n, \\
V_{i+1} &= \omega V_i + c_1 n Rand (P_i - X_i) + c_2 n Rand (P_{G_i} - X_i) = X_i^{i+1} = X_i + V_i^{i+1},
\end{align*}
\]

where \( \omega \) is the inertial weight, \( c_1 \) and \( c_2 \) are the acceleration constants, and Rand () is a random function with a value range of [0, 1].

PSO algorithm is used to find the optimal weight and deviation, and combined with SVM classification to early warning enterprise financial crisis. The early warning process is shown in Figure 1.

#### 4.2. Model Construction

##### 4.2.1. Indicator Selection

It is an important step to construct an early warning model of financial crisis to accurately extract the characteristic indexes that cause financial crisis. As the input variables of the model, i.e., the selection of financial indicators has not been determined yet. Therefore, this paper selects 24 financial indicators from six aspects: innovation and development ability, cash flow ability, profitability, operating ability, solvency, and equity structure, as shown in Table 1.

##### 4.2.2. Data Processing

Before the data are trained, the data normalization method map minimax is used to change the data into [0, 1]. Therefore, the magnitude difference is eliminated to ensure the effect of the PSO-SVM model. In view of the missing values in the data set, the missing data are predicted through the relationship between variables, and the Monte Carlo method is used to generate several complete data sets, which are analyzed, and finally, the analysis results are summarized.

##### 4.2.3. Construction of PSO

The population size was given randomly, and the mean square error (MSE) function was used as an adaptive function:

\[
\text{Fitness} = E = \frac{1}{N} \sum_{i=1}^{N} (y_{\text{real}} - y_i)^2,
\]

where \( N \) is the number of data, \( y_{\text{real}} \) is the expected output, and \( y_i \) is the actual predicted value of the model. After several rounds of updating, the output value of the model is the optimal solution. Moreover, the best value experienced by all particles themselves is according to their respective adaptive function values, and from these best values to determine the overall best value. If \( P_{\text{recent}} < P_{\text{best}}, P_{\text{best}} = P_{\text{recent}}, P_{\text{best}} = x_i \),
otherwise, \( P_{\text{best}} \) unchanged. If \( P_{\text{r}, \text{best}} < g_{\text{best}} \),
\( g_{\text{best}} = P_{\text{r}, \text{best}} \); otherwise, \( g_{\text{best}} \) unchanged.

The optimized connection weights and thresholds are the optimal solutions of this problem, and the optimized SVM model can be trained.

5. Experiment and Analysis

5.1. Sample Selection. Because of the time lag of the listed companies in the recent three years, the early warning model can be designed to reduce the losses of the companies listed on the gem for three consecutive years. In order to ensure the foresight and timeliness of the financial crisis warning of listed companies, this paper studies the warning degree from 2016 to 2018, so we should select the data from 2015 to 2017. After eliminating the samples with missing data, a total of 600 sample companies are obtained. From the three-year data samples, we randomly select an equal proportion of data to form training set and test set. Through statistics, it is found that the proportion of financial normal samples and financial crisis samples exceeds 10 : 1, which constitutes a serious unbalanced sample. All the data in this paper are from wind database.

5.2. Evaluation Index. In the past, scholars used to take net profit and net asset as the standard when identifying the financial crisis of GEM listed companies, but only defined the negative net profit as the standard, which lacked certain rationality. Although some enterprises are difficult to operate and fall into financial crisis, they can survive because of government or bank subsidies. Therefore, in this paper, net profit after deducting nonrecurring gains and losses is used instead. Net profit after deducting nonrecurring gains and losses = Operating income—operating expenses—operating taxes and surcharges—selling expenses—administrative expenses—financial expenses—loss of asset impairment ± Change in fair value profit or loss ± net investment profit or loss. Finally, this paper defines the identification criteria of the financial crisis as follows: first, the net profit deducting nonrecurring profit and loss in the latest fiscal year is negative; second, the net profit...
asset growth rate at the end of the most recent fiscal year is negative. For a listed company, once the two thresholds are reached at the same time, it is identified as a sample of the financial crisis. Otherwise, it is identified as the financial normal sample.

The prediction accuracy is evaluated by using the evaluation index for unbalanced samples, and the evaluation indexes for the classification of unbalanced samples are geometric average accuracy rate $G$ and minority class measure $F$.

Let TP and TN represent the number of correct predictions of financial crisis sample and financial normal sample, respectively, while FN and FP represent the number of wrong predictions of financial crisis sample and financial normal sample, respectively. The confusion matrix represents the results of the predictive classification of the test set, as shown in Table 2.

According to the results of the confusion matrix in Table 2, classification accuracy, $G$ value, and $F$ value can be calculated as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$G = \sqrt{\frac{TP}{TP + FN} \times \frac{TN}{TN + FP}}$$

$$F = \frac{2 \times TP/TP + FN \times TN/TN + FP}{TP/TP + FN + TP/TP + FP} \quad (10)$$

### 5.3. Training Results

Among the 600 sample companies, 450 samples are randomly selected as training set modeling. The experimental results are shown in Figures 2 and 3.

![Figure 2: Accuracy of PSO-SVM model.](image)

![Figure 3: Accuracy of SVM model.](image)

![Figure 4: Comparison of FCEW effect under different kernel functions.](image)

From the comparison in Figure 4, it is obvious that the accuracy rate of the proposed model is higher than that of the SVM model in both training samples and test samples. With the gradual increase of the penalty factor, the accuracy of the PSO-SVM model is smaller than that of the SVM model, and its accuracy does not decrease after gradually stabilizing. Therefore, the sensitivity is better than that of the SVM model.
in terms of the number of hidden layer nodes. In addition, with the increase in penalty factor, the accuracy of the PSO-SVM model gradually increases to 100%. The number of nodes in the hidden layer of test samples reaches about 16, and the accuracy reaches the highest and starts to be stable. However, when the number of hidden layer nodes of the SVM model is 24, the training accuracy is 80%, and there is a big gap between the accuracy of training samples and that of test samples. The comparison shows that the robustness of the SVM model is worse than that of PSO-SVM. Therefore, the SVM-based FCEWM optimized by the PSO algorithm can not only provide risk assessment for enterprises themselves but also provide a value-based reference for investors.

5.4. Comparison of FCEW Effect

5.4.1. Comparison of Different Kernel Functions. PSO-SVM FCEWM based on different kernel functions has different prediction performances. If the optimal kernel function cannot be determined, the superior early warning

![Figure 5: Comparison of FCEW effect under different models.](image)
model cannot be obtained. In this paper, the optimal kernel function of PSO-SVM FCEWM of GEM listed companies is determined by G value, F value, and classification accuracy under cross-validation. The experimental results are shown in Figure 4.

As can be seen from Figure 5, after combining the five kernel functions with the PSO-SVM model, the g value (0.6681) and F value (0.3586) of the RBF kernel function are significantly higher than those of the other four kernel functions. Although the classification accuracy of the RBF kernel function (0.8616) is slightly lower than that of other kernel functions, the reason is that a large number of financial crisis samples are mistakenly predicted as normal financial samples by the model composed of other kernel functions, and the financial crisis samples only account for a small part. However, the harm caused by the wrong prediction of financial crisis samples as normal financial samples is far greater than that of false prediction of financial crisis samples as financial crisis samples. Therefore, the prediction performance of the combination of RBF kernel function and PSO-SVM is significantly better than other kernel functions.

5.4.2. Comparison of Different Models. To avoid accidental results caused by random selection of data, training sets and test sets with different partition ratios (6:4, 7:3, 8:2, and 9:1) are used for training and prediction, respectively. First, the classification accuracy of the PSO-SVM early warning model is calculated, and then, the geometric average accuracy g and minority measure value f of the PSO-SVM early warning model are calculated under the optimal parameters. It is compared with the improved ODR-ADASYN-SVM model, BP neural network, Bayes model, and KNN model. The results are shown in Figure 5.

As can be seen from Figure 5, regardless of the data partition ratio of 6:4, 7:3, 8:2, or 9:1, the classification accuracy of the PSO-SVM model is slightly lower than BP neural network and KNN method, but slightly higher than the improved ODR-ADASYN-SVM model and significantly higher than Bayes method. This may be due to the fact that the BP neural network and KNN did not consider the characteristics of seriously unbalanced samples formed by financial normal and financial crisis companies, and a large number of financial crisis companies were misjudged as financial normal companies, while the number of normal financial samples only accounted for a small proportion of the total samples, so the overall classification accuracy of them was slightly higher than that of PSO-SVM model. It may be that the fitting effect and prediction performance of the ODR-ADASYN-SVM and the Bayesian model are not as good as the PSO-SVM model, so the accuracy of these two models is lower than that of the PSO-SVM.

### 6. Conclusion

In view of the unbalanced sample characteristics of different financial conditions, this paper uses the PSO-SVM algorithm to construct the FCEWM. Through the analysis of 600 listed companies, 24 financial indicators are selected from six aspects: innovation and development ability, cash flow ability, profitability, operation ability, debt-paying ability, and equity structure. The experimental results show that under different data partitioning ratios, the PSO-SVM model has a better fitting effect and prediction performance than other models for the two types of samples. Therefore, PSO optimized SVM algorithm is an effective method to evaluate enterprise financial crisis combined with enterprise characteristics, which can provide reference and basis for solving FCEW problems of similar enterprises.

### Data Availability

The dataset can be accessed upon request.

### Conflicts of Interest

The authors declare that they have no conflicts of interest.

### References


