http://ansinet.com/itj

ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSInet
Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Information Technology Journal 11 (2): 294-300, 2012
ISSN 1812-5638 / DOI: 10.3923/itj.2012.294.300

Financial Distress Prediction Based on Cost Sensitive Learning

[1,2]Wang Hong-Bao, [1]Wang Fu-Sheng and [3]Yang Xian-Fei
[1]School of Management, Harbin Institute of Technology,
Harbin 150001, China
[2]College of Applied English, Heilongjiang University, Harbin 150080, China
[3]College of Economics and Management, Dalian 116021, China

Abstract: When companies' FDP models have prediction errors, company owners and investors will suffer a great economic loss. Most researches in FDP take the prediction accuracy as the only standard of assessing the quality of financial distress prediction models (FDP). However, these researches ignore the different economic losses of market participants which result from the different costs between type I error and type II error of the model. Therefore, this study proposed companies' FDP model based on Cost-Sensitive Support Vector Machine (CS-SVM). The model was established from the perspective of minimizing the cost of prediction error so that it could reduce the loss of users of the model. An empirical research was carried out, taking 86 Chinese listed companies as sample data and adopting 8 times of random sampling to assess the cost of prediction error and prediction accuracy. The result demonstrated that the total cost of prediction error of FDP model based on CS-SVM was only 15.59 which was markedly less than that based on SVM, 23.07.

Key words: Financial distress prediction, cost sensitive learning, support vector machine, cost of prediction error, cost-sensitive support vector machine

INTRODUCTION

In China, stock market is one of the most widely accepted channels for public to make an investment. However, capital markets are volatile and most investors only know whether a company is financially distressed or not after the financial statement of the company has been made public. Therefore, financial distress prediction (FDP) has played an important role in today's society (Bose and Pal, 2006; Hu, 2008; Li and Sun, 2009, 2010), since it has a significant impact on different market participants. For stockholders, FDP can help them diagnose the company financial condition in advance and withdraw capital before suffering huge economic loss. For creditors, such as banks, FDP can help them know precisely the credit rating of enterprises so as to timely reduce their bad debts (Ko and Lin, 2006).

The earliest researches in FDP were mainly focused on the classic statistical techniques, such as univariate analysis, risk index models, multivariate discriminant analysis (MDA) and logistic regression (Logit) (Hui *et al*., 2010). In the 1990s, neural networks (NNs) were employed in FDP and its performance was often compared with that of MDA and Logit. Many researchers argued that NNs model was superior to statistical ones in the aspect of prediction accuracy (Pendharkar, 2005; Yang *et al*., 1999). Besides NNs, other intelligent approaches were also employed in FDP. Shin and Lee (2002) applied Genetic Algorithm (GA) to draw quantitative and qualitative rules for FDP. A hybrid intelligent system by combining a rough set approach and NNs model was applied in FDP based on the past financial performance data (Ahn *et al*., 2000). The empirical result showed that the prediction accuracy of proposed hybrid model was higher than that of neural network model. Support vector machine (SVM) is widely applied in many fields such as classification, data mining and time series forecasting (Samsudin *et al*., 2010; Shahrabi *et al*., 2009; Wang *et al*., 2010). In (Fan and Palaniswami, 2000), FDP model based on SVM was established and it took advantage of the characteristic of minimization of structural risk to resolve the classification problem of small sample companies. Min *et al*. (2006) integrated GA with SVM to improve the prediction accuracy of SVM for FDP. The result showed that GA optimized input features and model parameters in the construction of FDP model.

In China, the research in FDP began late. Zhou *et al*. (1996) constructed F-Score FDP model based on Altman's Z-Score model after considering Chinese companies' characteristics and taking cash flow as predictor variables.

Corresponding Author: Wang Hong-Bao, School of Management, Harbin Institute of Technology,
97 Xidazhi Street, 150001, Harbin, Heilongjiang, China Tel: +86 13654667905

Zhang (2000) did an empirical research on companies' FDP by employing linear discriminant analysis method. The result showed that it could predict companies' financial distress 4 years in advance. Wu and Lu (2001) compared the prediction performance among MDA, multiple linear regression and multivariate logistic regression. They concluded that the three models had a high prediction performance 3 years before the financial distress and prediction error probability of multivariate logistic regression model was the lowest. Yang and Huang (2005) employed back-propagation neural network (BPNNs) method to construct FDP model. Its empirical research result showed that the model had higher prediction accuracy than principal components analysis model. Yang and Wang (2007) further proposed a FDP model based on panel data and did a research on long-term FDP. Song *et al.* (2009) improved the prediction performance of SVM by using GA to optimize not only model parameters but also financial index system.

These previous researches play an important role in FDP field and almost all of them focus on how to improve the prediction accuracy. However, these researches ignore one important matter that prediction accuracy isn't the only standard to evaluate models. Because in the real world stakeholders pay markedly different costs when FDP model has different error, namely type I error or type II error. In the former situation, it classifies financially distressed company as financially healthy one which results in the cost of losing principal and interest. However, in the latter situation, it classifies financially healthy company as financially distressed one, which results in the cost of losing profit (Chen *et al.*, 2011). Compared with type I error, the cost of type II error is cheaper to company owners, debt-holders, investors and so on. Therefore, when constructing the companies' FDP model, it does not reflect the reality that type I error and type II error are treated equally.

As a result, the main motivation of this paper was to employ CS-SVM to establish companies' FDP model in order to minimize the cost of prediction error. The main objectives of this study were to (1) adopt cost-sensitive learning and SVM to construct a FDP model, (2) eliminate the missing and outlier data in the data preprocessing stage and employ statistical methods to select financial ratios in order to enhance the accuracy of FDP model, (3) compare CS-SVM approach with SVM approach in the aspect of cost of misclassification and (4) expand this FDP model based on cost-sensitive learning so that it will provide further information to different market participants in the FDP field.

RESEARCH BACKGROUND

Support vector machine: Support vector machine (SVM) is one of typical artificial intelligent classifiers based on maximum margin strategy (Vapnik, 1995) which has been widely used in the field of companies' FDP due to its excellent classification generalization ability. Given the training sample:

$$D=\{(x_1\cdot y_1),\cdots,(x_l\cdot y_l)\},\ (x_i\in R^n,\ y_i\in\{1,-1\}\ \ i=1,2,\cdots,l)$$

SVM uses the training sample D to find an optimal hyperplane H, denoted as w.x+b = 0, which correctly separates the positive and negative training examples and has maximum margin which is the distance between two hyperplanes w.x+b≥1 and w.x+b≤-1, as shown Fig. 1. The optimal hyperplane can be obtained by the following quadratic programming:

$$\begin{cases}\min\ \ \frac{1}{2}\|w\|^2+C\sum_{i=1}^{l}\xi_i\\ \text{s.t.}\ \ y_i((w\cdot x_i)+b)\ge 1-\xi_i\\ \xi_i\ge 0,\ \ i=1,2,\cdots,l\end{cases}\tag{1}$$

where, $1/\|w\|$ is the minimum distance between correctly classified data and the hyperplane w.x+b = 0. ξ_i is called a slack variable, denoting the distance misclassified data deviating from the correctly classified area. With the increasing value of $1/\|w\|$, SVM is becoming stronger to classify the two groups of data. With the value of:

$$\sum_{i=1}^{l}\xi_i$$

decreasing, SVM is becoming more precise to classify the training data. C is penalty coefficient. The larger value of C denotes that SVM penalizes misclassified data more and trained SVM misclassifies the training data less.

Cost-sensitive support vector machine: CS-SVM solves the difficult classification problem where there are different costs associated with different misclassified data. Most of classification methods focus on minimizing the total number of errors while CS-SVM aims to minimize the total cost of errors. For example, given the training data set $D_1=\{(x_1,y_1,z_1),\cdots,(x_l,y_l,z_l)\}$, where, z_i denotes the cost of x_i being misclassified, D_1 is used to train SVM. The position of the optimal hyperplane is shown in Fig. 1 which has the highest classification accuracy. But x_i is misclassified by SVM. Then we use D_1 to train CS-SVM.

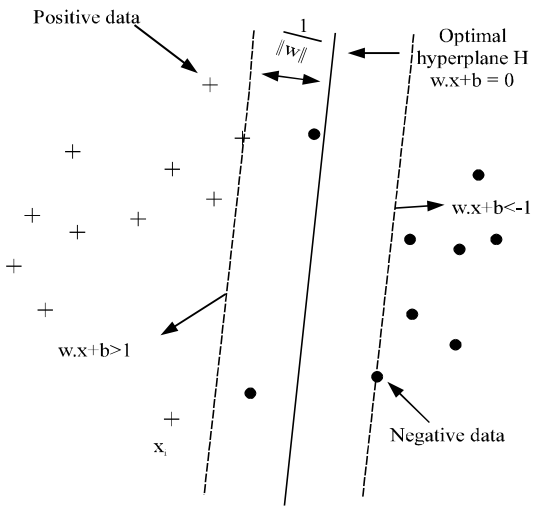

Fig. 1: Overview of SVM

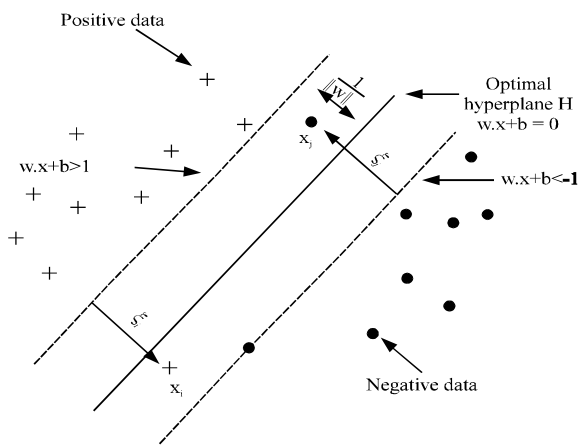

Fig. 2: Overview of CS-SVM

If the value of z_i is large, the position of the optimal hyperplane deviates, as shown in Fig. 2. As a result, x_i is correctly classified by CS-SVM and the total cost of misclassified data is the minimum.

The optimal hyperplane of CS-SVM can be obtained by the following formula:

$$\begin{cases} \min \ \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l} z_i\xi_i \\ \text{s.t.} \ \ y_i((w\cdot x_i)+b) \ge 1-\xi_i \\ \xi_i \ge 0, \ \ i=1,2,\cdots,l \end{cases} \tag{2}$$

The solution procedure of the optimal hyperplane of CS-SVM is similar to SVM. Firstly, by means of Lagrange method formula 2 is transformed as the following formula:

$$L(w,r,u) = \frac{1}{2}w\cdot w + C\sum_{i=1}^{l} z_i\xi_i - \sum_{i=1}^{l} r_i\{y_i((w\cdot x_i)+b)-1+\xi_i\} - \sum_{i=1}^{l} u_i\xi_i \tag{3}$$

where, r_i and u_i are Lagrange coefficient and $r_i \ge 0$ and $u_i \ge 0$. The following formula is derived from formula 3:

$$\begin{aligned} &\frac{\partial L(w,r,u)}{\partial w} = w - \sum_{i=1}^{l} r_i y_i x_i = 0 \\ &\frac{\partial L(w,r,u)}{\partial \xi_i} = Cz_i - r_i - u_i = 0 \\ &\frac{\partial L(w,r,u)}{\partial b} = -\sum_{i=1}^{l} r_i y_i = 0 \end{aligned} \tag{4}$$

Dual formula of the formula 2 can be obtained by putting formula 4 to it:

$$\begin{cases} \min \ \ \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} r_i r_j (x_i\cdot x_j) - \sum_{i=1}^{l} r_i \\ \text{s.t.} \ \ \sum_{i=1}^{l} r_i y_i = 0 \\ \qquad 0 \le r_i \le Cz_i, \ \ i=1,2,\cdots,l \end{cases} \tag{5}$$

The quadratic programming is employed to solve the formula above and the value of Lagrange coefficient $\hat{r}_i$ can be computed. Then the value is put to formula 6:

$$\hat{w} = \sum_{i=1}^{l} \hat{r}_i y_i x_i \tag{6}$$

In compliance with KKT condition, the value of bias b, denoted as $\hat{b}$, can be obtained by the following formula:

$$\begin{aligned} &\hat{r}_i\{y_i((\hat{w}\cdot x_i)+\hat{b})-1+\hat{\xi}_i\} = 0 \\ &u_i\hat{\xi}_i = 0, \ \ i=1,2,\cdots,l \end{aligned} \tag{7}$$

Therefore, the optimal hyperplane of CS-SVM $\hat{w}\cdot x + \hat{b} = 0$ can be obtained.

EMPIRICAL EXPERIMENT

Experiment data

Collection of initial data: Companies in this empirical research were categorized into two classes, financially distressed and healthy companies. Financially distressed companies refer to those who have had negative net profit in consecutive two years, or its net capital per share is lower than the face value per share for the reason of one year's substantive loss. They are also the criteria whether the listed companies are specially treated (ST) by Chinese Stock Exchange. Healthy companies refer to those who have never been specially treated.

When companies are defined as ST ones, their financial ratios have already been obviously deteriorating. If financial data one year before ST is used to build FDP model, the prediction performance of the model will be overestimated. Therefore, the financial data two years before ST was selected in this paper. The data used in this research was obtained from RESSET Financial Database. Forty three pairs of companies listed in Shenzhen Stock Exchange and Shanghai Stock Exchange were selected as initial data set. Twenty three financial ratios were selected as initial features, covering debt ability, growth ability, activity ability, profitability and indicators per share.

Data preprocessing: In the data preprocessing, missing and outlier data were eliminated: (1) Missing data refers to those, which miss at least one financial ratio. (2) Outlier data refers to those which deviates from the mean value as much as four times of standard deviation. The final number of sample data was 80 after the elimination of missing and outlier data.

Experimental data sets: The empirical experiment aims to validate whether FDP model based on CS-SVM can minimize the cost of prediction error. Fifty two financially distressed companies and healthy companies were selected to form training data set and the rest 28 were used to form testing data set.

Feature selection: In the field of FDP, a large number of financial ratios are collected in order to reflect a complete financial condition of companies. However, some financial ratios cannot effectively distinguish financially distressed companies from healthy ones. Therefore, the purpose of feature selection is to remove irrelevant and redundant features so as to improve the accuracy of the model, decrease the computational effort and facilitate the use of the model.

Statistical analysis: In this study, statistical methods were employed to select financial ratios. The selection procedure was as follows: Shaprio-Wilks test was used to examine whether each financial ratio met normal distribution. If financial ratios met normal distribution, T test was used to examine whether the financial ratios were significant. If financial ratios didn't meet normal distribution, Kolmogorov-Smirnov test was used to examine whether the financial ratios were significant, as shown in Table 1.

Analysis on significance test of financial ratios: From Table 1, it could be shown that only debt to asset ratio and operating income growth rate passed Shaprio-Wilk test. It showed that the two financial ratios met normal distribution and were consistent with the previous research result that most financial ratios do not meet normal distribution. Additionally operating income growth rate, net profit growth rate, turnover rate of accounts receivable, turnover rate of current assets and turnover rate of equity did not pass the significance test, by which distressed companies could not be distinguished from

Table 1: Significance test of financial ratios

	t-test		Kolmogorov-Smirnov test		Shaprio-Wilks test	
Variables	t-Statistic	Prob.	KS-Statistic	Prob.	SW-Statistic	Prob.
Return on Equity			2.138	0.000**	0.643	0.000
Return on Assets			2.405	0.000**	0.624	0.000
Return on Invested Capital			1.871	0.002**	0.649	0.000
Net Profit Margin			2.272	0.000**	0.542	0.000
Cost Profit Margin			2.405	0.000**	0.703	0.000
Current Ratio			2.405	0.000**	0.685	0.000
Quick Ratio			2.138	0.000**	0.645	0.000
Equity Ratio			2.138	0.000**	0.352	0.000
Debt to Asset Ratio	4.100	**0.000			0.973	0.231***
Debt to Tangible Asset Ratio			1.737	0.005**	0.420	0.000
Operating Cash Flow/Total Liability			1.604	0.012*	0.905	0.000
Operating Income Growth Rate	-1.079	0.285			0.965	0.107***
Net Profit Growth Rate			1.336	0.056	0.422	0.000
Total Asset Growth Rate			2.004	0.001**	0.597	0.000
Turnover Rate of Accounts Receivable			0.668	0.763	0.147	0.000
Turnover Rate of Accounts Payable			1.604	0.012*	0.155	0.000
Turnover Rate of Current Assets			0.935	0.346	0.674	0.000
Turnover Rate of Fixed Assets			2.004	0.001**	0.644	0.000
Turnover Rate of Equity			1.069	0.203	0.396	0.000
Turnover Rate of Total Assets			2.004	0.001**	0.839	0.000
Earning Per Share			2.806	0.000**	0.800	0.000
Net Asset Value Per Share			2.940	0.000**	0.694	0.000
Operating Revenue Per Share			2.272	0.000**	0.832	0.000

*Significant at 5%; **Significant at 1%; ***The financial ratios meeting normal distribution

healthy companies. Therefore, these ratios were discarded.

Parameter setting

Setting of cost of misclassification: When a company is misclassified by FDP model, the costs of misclassification of different market participants are different. For example, company owners' loss is hugely different from debt-holders' one when a financial distressed company is misclassified as a healthy company. Therefore, before setting the value of cost of misclassification, the user of the model should be identified firstly. Then Delphi method was used to determine the value of cost.

In the empirical research we supposed that the user of FDP model was shareholders in the stock market. Shareholders can use the prediction result of FDP model to make a decision of buying or not. Therefore, when the model has type I error, the cost of error of shareholders is share price of the stock. When the model has type II error, the cost of error of shareholders is earnings per share of the stock.

Setting of parameters of CS-SVM: RBF kernel function was used to train CS-SVM, whose classification performance was affected seriously by parameter pairs, (C, r). C is the penalty coefficient and r is the parameter of FBF kernel function. We used different value of parameter pairs to train CS-SVM, whose classification performance was shown in Table 2.

From Table 2, we can see that with the increasing value of C and r, misclassification rate and cost of misclassification were deceasing. The minimum value of the cost of misclassification was 0.1 and the corresponding numbers of support vector were respectively 20 and 30. In order to reduce workload in FDP, the value of parameter pair was selected as CS-SVM parameter, which had smaller number of support vector.

Experiment results and analysis: In the experimental stage, multiple experimental data sets were constructed to get multiple performance statistics. The data were from Shanghai Stock Exchange and Shenzhen Stock Exchange. Therefore it was difficult to collect multiple experimental data sets with certain kind of sample scale. By repetitively and randomly classifying training sample and testing sample, this research obtained multiple experimental data sets. By simple random sampling without replacement, 52 financial distressed companies and healthy companies were selected to form training data set and the rest 28 were used to form testing data set each time. After 8 times of random sampling, 8 experimental data sets were obtained.

Total costs of prediction error and prediction accuracy on 8 testing data sets were listed in Table 3. The number of experimental data sets on which FDP model based on SVM got higher testing accuracy was more than that of FDP model based on CS-SVM. The average prediction accuracy on 8 data sets of FDP model based on SVM was 87.95 which was slightly higher than that of FDP model based on CS-SVM, 86.16. The reason was that when FDP model based on CS-SVM was established, the costs of different prediction errors were integrated into the model. Therefore, the position of optimal hyperplane of CS-SVM was deviated from the original position

Table 2: Classification performance of CS-SVM

	R					
C	0.0001	0.001	0.01	0.1	1	10
1	50/11.28/29	50/11.28/28	50/11.28/28	28.85/4.74/31	19.23/1.64/38	26.92/2.41/49
10	50/11.28/27	50/11.28/28	28.84/4.74/26	15.38/1.38/20	11.54/0.85/39	5.77/0.1/49
100	28.85/11.28/28	28.84/4.74/26	13.46/0.99/18	11.54/0.85/19	3.85/0.1/30	5.77/0.1/49
1000	28.84/4.74/25	13.46/0.99/18	9.62/0.52/17	5.77/0.42/19	3.85/0.1/30	5.77/0.1/49
10000	13.46/0.99/18	9.62/0.52/17	9.62/0.52/15	3.85/0.1/20	3.85/0.1/30	5.77/0.1/49

Data in the table respectively represents misclassification rate, cost of misclassification and number of support vector

Table 3: Experimental results on testing data set

	SVM				CS-SVM			
Data	Number of type I error	Number of type II error	Prediction accuracy	Total cost of prediction error	Number of type I error	Number of type II error	Prediction accuracy	Total cost of prediction error
set 1	2	2	85.71	22.80	1	4	82.14	15.62
set 2	0	1	96.43	9.17	0	1	96.43	9.17
set 3	3	2	82.14	27.62	1	4	82.14	12.99
set 4	2	2	85.71	22.28	2	4	78.57	21.03
set 5	2	0	92.86	22.84	1	1	92.86	14.30
set 6	1	0	96.43	8.67	0	1	96.43	0.04
set 7	4	2	78.57	41.35	2	5	75.00	30.33
set 8	3	1	85.71	29.80	2	2	85.71	21.27
Average	2.13	1.25	87.95	23.07	1.13	2.75	86.16	15.59

compared with the position of SVM, as shown in Fig. 1 and 2. It could be seen that the average total cost of prediction error of FDP model based on CS-SVM was 15.59, markedly lower that based on SVM, 23.07. The reason was that the number of type I error of CS-SVM was less than that of SVM and the cost of type I error was hugely larger than that of type II error.

On the basis of above experimental results and analysis, the prediction accuracy of FDP model based on SVM slightly outperformed that based on CS-SVM. But the total cost of prediction error of FDP model based on CS-SVM markedly outperformed that of SVM. Therefore, the research demonstrated that the model integrating total cost of prediction error makes shareholders, company owners, suppliers and etc. suffer economic losses less.

CONCLUSION

FDP takes an increasingly important role in the corporate governance field. Previous researches have made comprehensive investigation on FDP but most of them take the prediction accuracy as the only way to evaluate the quality of FDP models. Few consider the different losses of market participants resulted from the different costs between type I error and type II error of the model. This paper explored to integrate the cost of misclassification into the establishment of FDP model and make an empirical comparison. This research took 43 financial healthy companies and matched them with 43 financially distressed companies. Fifty two companies were selected as training data set and the rest were selected as testing data set. The result demonstrated that the total cost of prediction error of FDP model was markedly reduced by CS-SVM approach compared to the traditional SVM approach.

ACKNOWLEDGMENT

This research is partially supported by the National Natural Science Foundation of China (Grant No. 70972097).

REFERENCES

Ahn, B.S., S.S. Cho and C.Y. Kim, 2000. The integrated methodology of rough set theory and artificial neural network for business failure prediction. Expert Syst. Appl., 18: 65-74.

Bose, I. and R. Pal, 2006. Predicting the survival or failure of click-and-mortar corporations: A knowledge discovery approach. Eur. J. Operat. Res., 174: 959-982.

Chen, N., B. Ribeiro, A.S. Vieira, J. Duarte and J.C. Neves, 2011. A genetic algorithm-based approach to cost-sensitive bankruptcy prediction. Expert Syst. Appl., 38: 12939-12945.

Fan, A. and M. Palaniswami, 2000. Selecting bankruptcy predictors using a support vector machine approach. Proc. Int. Joint Conf. Neural Networks, 6: 354-359.

Hu, Y.C., 2008. Incorporating a non-additive decision making method into multilayer neural networks and its application to financial distress analysis. Knowledge-Based Syst., 21: 383-390.

Hui, L., J. Sun and J. Wu, 2010. Predicting business failure using classification and regression tree: An empirical comparison with popular classical statistical methods and top classification mining methods. Expert Syst. Appl., 37: 5895-5904.

Ko, P.C. and P.C. Lin, 2006. An evolution-based approach with modularized evaluations to forecast financial distress. Knowledge-Based Syst., 19: 84-91.

Li, H. and J. Sun, 2009. Hybridizing principles of the Electre method with case-based reasoning for data mining: Electre-CBR-I and Electre-CBR-II. Eur. J. Operat. Res., 197: 214-224.

Li, H. and J. Sun, 2010. Business failure prediction using hybrid^2 case-based reasoning (H^2CBR). Comput. Operat. Res., 37: 137-151.

Min, S.H., J. Lee and I. Han, 2006. Hybrid genetic algorithms and support vector machines for bankruptcy prediction. Expert Syst. Appl., 31: 652-660.

Pendharkar, P.C., 2005. A threshold-varying artificial neural network approach for classification and its application to bankruptcy prediction problem. Comput. Operations Res., 32: 2561-2582.

Sanisudin, R., A. Shabri and P. Saad, 2010. A comparison of time series forecasting using support vector machine and artificial neural network model. J. Applied Sci., 10: 950-958.

Shahrabi, J., S.S. Mousavi and M. Heydar, 2009. Supply chain demand forecasting; A comparison of machine learning techniques and traditional methods. J. Applied Sci., 9: 521-527.

Shin, K.S. and Y.J. Lee, 2002. A genetic algorithm application in bankruptcy prediction modeling. Expert Syst. Appl., 23: 321-328.

Song, X.P., Y.S. Ding and Y.M. Zeng, 2009. Application of a GA-based simultaneous optimization method in financial crisis prediction. Forecasting, 28: 48-55.

Vapnik, V.N., 1995. The Nature of Statistical Learning Theory. 1st Edn., Springer-Verlag, New York, ISBN: 0-387-94559-8.

Wang, Y.H., D.A. Chiang, S.W. Lai and C.J. Lin, 2010. Applying data mining techniques to WIFLY in customer relationship management. Inform. Technol. J., 9: 488-493.

Wu, S.N. and X.Y. Lu, 2001. A study of models for predicting financial distress in China's listed companies. Econ. Res. J., 6: 46-55.

Yang, S.E. and L. Huang, 2005. Financial crisis warning model based on BP neural network. Syst. Engin. Theory Practice, 1: 12-18.

Yang, S.E. and L.P. Wang, 2007. Research on financial warning for listed companies by using BP neural networks and panel data. Syst. Eng. Theory Practice, 2: 62-66.

Yang, Z.R., M.B. Platt and H.D. Platt, 1999. Probabilistic neural networks in bankruptcy prediction. J. Bus. Res., 44: 67-74.

Zhang, L., 2000. Financial distress discriminant analysis model and its application. Forecasting, 6: 38-40.

Zhou, S.H., J.H. Yang and P. Wang, 1996. A study on financial distress prediction-F-score model. Account. Res., 8: 8-11.