Analysis of the Power of Predicting Financial Distress of Companies Listed in Tehran Stock Exchange using Artificial Neural Networks

Saeideh Hedayati Shahedi
Department of Accounting, Science and Research Branch, Islamic Azad University, Yazd, Iran
Safaieeh, Shoahadegomnam Road, Zip code: 89195/155, Yazd, Iran

Corresponding Author: Ali Morovati Sharifabadi
Department of Industrial Management, Yazd University, Yazd, Iran
Safaieeh, daneshgah Road, pajouhesh street, Yazd, Iran

Mahmoud Moeinadin
Department of Accounting, Yazd Branch, Islamic Azad University, Yazd, Iran
Safaieeh, Shoahadegomnam Road, Zip code: 89195/155, Yazd, Iran

Abstract
Financial ratios and fundamental analysis method are among one of the most common methods of bankruptcy prediction. In most previous studies, statistical techniques have been used for predicting bankruptcy and less attention has been paid to the application of Artificial Intelligence (AI)-based approaches. Artificial Neural Networks are among ideal tools in which mental aspects are considered in addition to application of the statistics. In these networks, specific patterns and trends can be learned without any formula or method. Therefore, the present study was designed and conducted to predict bankruptcy of companies listed in Tehran Stock Exchange using Artificial Neural Networks. The study sample consisted of 167 firms (47 bankrupts and 120 non-bankrupts) and a 6-years period for the years 2006 to 2011 was considered. Thus the observation rises to 6 * 167(year-companies). In the present study, practical, descriptive correlation and ex post facto methods were used in terms of objective, implementation and data status, respectively. Results of the study indicate the approval of the appropriate power of artificial neural network in explaining bankruptcy of the sample listed companies.

Keywords: bankruptcy, financial health, Artificial Neural Networks, financial ratios

1. Introduction
Providing models with better predictions about the overall prospects of the company, according to environmental conditions, can make predictions closer to reality and provide a more accurate basis for investors. There are also many software programs in which mathematical techniques such as linear regression, and the like may be used as prediction engines. Financial distress prediction has long been an important and widely studied topic in the financial area. Since in these models, the dependent variable of categorical type (bankrupt or healthy firms) is used, the problem of classification will be raised. So it is clear that in such studies the traditional statistical models like Multiple discriminant analysis, Logit analysis, Probit analysis or new techniques in the field of artificial neural networks are used. Neural networks are powerful tools for model identification and classification due to their nonlinear, nonparametric and adaptive learning features. Using artificial neural network models in predicting some variables led some economists to pay attention to this method and use it to solve some financial problems including bankruptcy prediction (Lee, 1996).

The most common reason for using neural networks is that there are many problems that cannot be solved by algorithms for solving nonlinear models. Moreover, researchers need not to know the type of relationship between independent and dependent variables. Bankruptcy is the time of death of a company. Death of a company has a lot of implications that will affect different people in the community. Bankruptcy of a company can impose huge losses to investors, creditors, managers, suppliers, employees, customers and even government. Therefore, conducting a research helping to solve this problem will become
necessary. Indeed, if we can use a model to predicts the possible occurrence of bankruptcy and then improve the company affairs by troubleshooting and problem solving techniques. In this way, it would be possible to prevent wasting the national wealth in the form of physical and human capital and its effects. Moreover, such a model can be considered as an appropriate guidance for decision makers, such as investment firms, banks and government. Also, managers and even the government can come up with the knowledge that a firm is on the verge of bankruptcy and perform preventive measures and every effort to rescue the company from death. All these cases are positive points associated with bankruptcy prediction. Therefore, being aware of the financial status of a company by the company financial ratios representing status and location of the company or its bankruptcy or non bankruptcy in the form of a model can help us to predict the state of a company. Considering what mentioned above, the purpose of this study is to answer the question whether the artificial neural networks model can appropriately predict financial distress for companies listed in the Tehran Stock Exchange?

2. Literature review and basic research background

2-1. Financial distress

In the Oxford dictionary, the word "Distress means pain, lack of funds and poor. There are also different definitions of financial distress in the financial literature. Gordon, in one of the first academic studies on the theory of financial distress, defined the word "distress" as reduced earning power which increases the probability of inability to repay the interest and original debt (Gordon, 1971). Whitaker considered the financial distress as a situation where the company's cash flows is less than the total interest costs of long-term debt (Whitaker, 1999). Economically, financial distress can be defined as the company losing state in which no success will be obtained. In fact, in this case the company's rate of return is lower than the cost of capital (Weston et al., 1992). Financial distress occurs when a firm cannot pay for its financial commitments (Pyarat, 2006).

2-2. Artificial Neural Network

Neural networks are components of dynamic systems in which knowledge or hidden law beyond the data are transferred in to the network structure by processing of experimental data. In these networks, the general principles are obtained by calculations based on numerical data or samples (Russell and Norving, 1995). Artificial Neural Networks can obtain the relationship between networks by data analysis and estimate the corresponding values by applying them for some new data. Therefore, the main application of artificial neural networks is for appropriate and accurate estimation of nonlinear functions.

Every artificial neural network is formed by the processing elements of the artificial neurons. These neurons can be organized in different ways to form a network structure. Each artificial neuron receives and processes the inputs, and delivers an output signal. The input can be raw data or output to other processing elements. The output could be the final product or as input to other neurons. (Dmuth et al., 2004).

2-3. Literature review

The first attempts to use neural network in bankruptcy prediction were carried out by Odom and Sharda (1990). Results showed that the neural-based network has a higher accuracy and prediction power compared with the model based on multivariate diagnostic analysis. Cats and Fanter (1991) investigated the accuracy of the neural networks models and discriminant analysis in predicting the financial crisis. Results showed that the accuracy of the neural network model to predict the bankrupt and financial healthy companies was 91% and 95%, respectively, while the accuracy of the analysis of financial healthy and bankrupt firms by using discriminant analysis was 72% and 89%, respectively. Salchenberger et al (1992) suggested that neural network- based model has a better performance compared with patterns based on Logit analysis.

Tam and Kiang (1992) indicated that neural network- based models had a higher level of prediction and accuracy compared with linear diagnostic models, Logit model and decision tree-based models. Zhang et al(1999) investigated the accuracy of the neural network and logistic regression models. The results showed that the overall accuracy of the predictions of neural networks model is higher than that of logistic regression model. Lin et al (2001) tried to predict corporate bankruptcy using four different methods. Two cases of these methods were related to statistical methods (diagnostic analysis and logistic regression) and two other related to machine learning techniques (Decision trees and neural networks). Results showed that the methods of artificial neural network and decision trees are more acceptable than other methods. Tung et
al (2004) used a hybrid approach by integration of artificial neural networks and fuzzy systems. Researchers, when extracting data from the last financial statements, obtained 93% of the model performance and reported 85% and 75% performance when the data obtained from financial statements of last year and two years ago, respectively. In the study model, about 50 fuzzy rules were produced which represent the interactions between 9 selected input variables and their impact on the financial health of studied banks. Wallace Wanda (2004) designed a network model using neural networks method. In this model, Key Financial Ratios, reported as the best ratios in the previous bankruptcy studies, were used. The overall accuracy value in the Wallace model was 94%. In this model, 65 different financial ratios in the previous studies was investigated. Yim (2005) conducted a comparative study of neural network, Logit and discriminant analysis models in predicting corporate bankruptcy. Results showed that the artificial neural network with data related to one year before bankruptcy prediction had the highest accuracy.

Brockett (2006) compared the capability of two statistical models of Logit and multiple discriminant analysis and neural network using two methods (Learning vector quantization algorithm, back propagation algorithm) to predict the financial crisis. Results showed greater accuracy in both neural network models compared with traditional statistical models. Wu (2008) analyzed the financial crisis of Chinese companies using models of neural network and multiple discriminant analysis. Results showed that neural networks can predict a financial crisis with the high accuracy of 87.5% in the short term and 81.3% in the medium term. Liang Zijang Yang et al (2008) investigated the corporate bankruptcy prediction using multiple discriminant analysis and probabilities of artificial neural network model. Results of this study showed that computational model of neural network is a more suitable tool for bankruptcy prediction . Al-Khatib (2012) investigated the role of a set of financial ratios to predict financial crisis using discriminant analysis and logistic models. Results showed that the two models have the ability to predict companies' bankruptcy using financial ratios, and return on assets and return on capital are two key financial ratios.

3. Methodology
In the present study, practical, descriptive correlation and ex post facto methods were used in terms of objective, implementation and data status, respectively. A 6-years period for the years 2006 to 2011 was considered. In this study, the time scope has been extended to five years before the base year to evaluate the ability of models to predict bankruptcy. Data was collected from companies listed in Tehran Stock Exchange by the end of 2009. Systematic elimination method was used to select a sample with regard to the following restrictions:
1. The companies' financial year to be ended with the end of February each year.
2. The companies should not be a part of intermediate financial companies.
3. Companies information should be available.
4. Companies in which accumulated losses are more than 50 of the company's capital (including Article 141 of the Commercial Code) are considered bankrupt.

With the above restrictions, 167 companies were selected as statistical samples classified in to two financially bankrupt (47) and non-bankrupt (120) companies. In this study, the criteria for selection of bankrupt companies was Article 141 of the Commercial Code. According to this criterion, first a list of companies was prepared which included in this legal code for three consecutive years during 2006-2011. Among this list, those companies with financial data for five previous years were selected for sampling. Finally, this list included 47 bankrupt companies. To achieve the main goal of the study, research hypothesis based on the selected model is as follows:
H1: Financial distress of the companies listed in Tehran Stock Exchange can be properly predicted using artificial neural network.

4. Study variables
In this study, the dependent variable is a qualitative and discrete variable subject to a nominal scale. This variable called bankrupt or non-bankrupt company. In this study, the dependent variable is the probability of bankruptcy which assigns zero and one values to bankrupt and non-bankrupt companies, respectively. Moreover, the independent variable included 16 financial ratios selected based on the study of more than
forty articles by which and the final ratios are obtained. Table 1 shows a summary of the independent variables.

5. Data analysis and findings

A network consists of a number of units called neurons. These neurons are processing elements. Each artificial neuron receives and processes the inputs, and delivers an output signal. The input can be raw data or output to other processing elements. The output could be the final product or as input to other neurons. Main features of neural networks can be classified based on their structure and dynamic or operational characteristics. The network neural data processing is not based on a hierarchical model, rather it is based on the parallel analysis of complex data in to its main elements. Network structure can be classified as single-layer, multi-layer, irreversible or feedback.

Matlab software was used to design the neural network. Numbers and figures in the form of one or more variables form the inputs of neural networks. These inputs would change to one or more output variables after specific analyses and processing. Inputs play the role of independent variables and outputs are dependent variables. In the present study, 16 financial ratios were considered as the network inputs. The network output consists zero and one values for bankrupt and non-bankrupt companies, respectively. Generally, the sample data were used in three different forms in the neural networks: Training set, testing set and validation set data.

1. Training data: Most of the data sample is related to this kind of data. They play an important role in the training of the network. In this study, 70% of training data were considered.

2. Testing data: This kind of data is selected randomly and can be used to evaluate the network performance. 15% of data used in this study was among the testing data.

3. Validation set data: the minimum amount of data is considered in this category which is used to validate the model for the final controlling. 15% of data used in this study was among validation set data.

Perceptron feed forward networks was used for network training. In this network, the response is always processed in the forward path and does not return to the former layer neurons. Backpropagation was used for general approach of the learning the Perceptron network which in return, it had different algorithms. Neurons are the most important component of an artificial neural system classified in three main input, output and hidden layers in which neurons in the input layer receive input data. Hidden and output layers are responsible for information processing. In these units, algebraic operations are performed on input data and then obtained result is transferred to next layers. Selection of the number of hidden layers and its neurons does not follow any particular rule.

Output functions are responsible for the overall computation of the output. The common function used in the neural networks is hyperbolic tangent function defined as follows:

\[ F(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \]

In this study, the mean squared errors (MSE) and R value have been considered as network power evaluation criteria. Related network for data a year before the bankruptcy is as Figure 1 follows:

As it can be observed, the input layer includes one hidden layer with 15 neurons and 16 agents and a hidden layer with 15 neurons while the output layer consists of one output. W and b are weight and constant bias value, respectively.

Hypothesis of this study about investigation of the proper capability of artificial neural network model for bankruptcy prediction of companies listed in Tehran Stock Exchange was proposed and tested. Levels of accuracy and predictive power of the model in 5, 4, 3, 2 and 1 year prior to bankruptcy was 93.2%, 94.2%, 95.2%, 97.3% and 98.8%, respectively. These results confirmed the study hypothesis. The results reconfirmed the performance of artificial neural network model and financial ratios based on accounting reports for bankruptcy prediction. The results of the study are consistent with results of Liang Yang (2008), Wu (2008), Brockett (2006) studies. Table 2 clearly shows prediction and error value of the neural network for a period of 5 years.
Discussion and conclusion

Bankruptcy prediction is one of the interesting and important studies in the financial field. It is possible to save companies from danger of bankruptcy by bankruptcy prediction and then finding its root causes. In this study, the neural network model was used. Initially, only the fiscal year data in one year was used to design a neural network model. Then data was used based on the information in the financial statements (\( t \) - \( t-5 \ )) in terms of accuracy in bankruptcy prediction. The study statistical population consisted of all companies listed in the Tehran Stock Exchange by considering the imposed limitations. Sample companies in this study were selected in the form of two financially bankrupt (47) and non-bankrupt (120) companies. In this study, the criteria for selection of bankrupt companies was Article 141 of the Commercial Code. In the present study, 16 financial ratios were considered for the five years before bankruptcy to implement the models of companies financial health prediction as the network inputs. The network output consists zero and one values for bankrupt and non-bankrupt companies, respectively. Generally, the sample data were used in three different forms in the neural networks: Training set, testing set and validation set data. Moreover, MATLAB software was used for analysis of neural network. According to the obtained results, the neural network in the all years had the most accuracy in prediction of companies' financial distress. The neural network classified all companies with financial distress in an appropriate group based on data related to one year before bankruptcy. Investigations indicated that estimates based on data related to one year before bankruptcy had the most accurate value of prediction. In general, the neural network approach has been successful with greater accuracy and lower error value in bankruptcy prediction. The obtained results indicate the superiority of Artificial Neural Network in bankruptcy prediction.

Suggestions

Considering the fact that bankruptcy costs a lot for companies, it is suggested that managers of companies use a neural network model designed for bankruptcy prediction. Using this model, manager can predict the company bankruptcy and prevent the risk of bankruptcy with the help of experts to examine the related reasons and causes of this bankruptcy. It is suggested that investors, banks, government, auditors and other users of accounting information use the models of this study for evaluation of the stock exchange Companies, decision-making regarding purchase of shares of the company, performance evaluation and announcement of the continuing activities of the company. It is suggested that potential investors use the model presented in this study to determine the future status of the companies when making investment decisions. It is also suggested that potential investors try to sell their shares in case of observing the signs of future bankruptcy. According to this facts that auditors should report on their audit about continuity of related operations, it is suggested that they use financial ratios and proposed model in this study.
References

Table 1. The study independent variables

<table>
<thead>
<tr>
<th>Row</th>
<th>Name of independent variable</th>
<th>Formula</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>X 1</td>
<td>Debt ratio</td>
<td>(\frac{\text{Total Debt}}{\text{Total Assets}})</td>
<td>Financial Leverage</td>
</tr>
<tr>
<td>X 2</td>
<td>Current Ratio</td>
<td>(\frac{\text{Current assets}}{\text{Current debts}})</td>
<td>Liquidity</td>
</tr>
<tr>
<td>X 3</td>
<td>Total asset turnover ratio</td>
<td>(\frac{\text{Net sales}}{\text{total assets}})</td>
<td>Operation</td>
</tr>
<tr>
<td>X 4</td>
<td>Current debt to total assets</td>
<td>(\frac{\text{current debts}}{\text{total assets}})</td>
<td>Financial Leverage</td>
</tr>
<tr>
<td>X 5</td>
<td>Total debt ratio</td>
<td>(\frac{\text{Total shareholders' equity}}{\text{current debts} - \text{current assets}})</td>
<td>Financial Leverage</td>
</tr>
<tr>
<td>X 6</td>
<td>Working capital to total assets ratio</td>
<td>(\frac{\text{current debts}}{\text{total assets}})</td>
<td>Liquidity</td>
</tr>
<tr>
<td>X 7</td>
<td>Accumulated profits and losses to total assets ratio</td>
<td>(\frac{\text{Accumulated profits and losses}}{\text{total assets}})</td>
<td>Liquidity</td>
</tr>
<tr>
<td>X 8</td>
<td>to equity ratio</td>
<td>(\frac{\text{shareholders' equity}}{\text{Net incom}})</td>
<td>Operation</td>
</tr>
<tr>
<td>X 9</td>
<td>Operating cash flow to total debt ratio</td>
<td>(\frac{\text{Operating cash flows}}{\text{total debts}})</td>
<td>Liquidity</td>
</tr>
<tr>
<td>X 10</td>
<td>Operating cash flow to interest payments ratio</td>
<td>(\frac{\text{Operating cash flow}}{\text{interest payments}})</td>
<td>Liquidity</td>
</tr>
<tr>
<td>X 11</td>
<td>Earnings before interest and taxes deductions to financial expenses ratio</td>
<td>(\frac{\text{Earnings before interest and taxes deductions}}{\text{financial expenses}})</td>
<td>Profitability</td>
</tr>
<tr>
<td>X 12</td>
<td>Operating cash flow to total assets ratio</td>
<td>(\frac{\text{Operating cash flow}}{\text{total assets}})</td>
<td>Liquidity</td>
</tr>
<tr>
<td>X 13</td>
<td>Inventory turnover ratio</td>
<td>(\frac{\text{Cost of sold goods}}{\text{average inventory}})</td>
<td>Operation</td>
</tr>
<tr>
<td>X 14</td>
<td>Frequency of the liquidation of debtors</td>
<td>(\frac{\text{Selling}}{\text{average of receivable accounts}})</td>
<td>Operation</td>
</tr>
<tr>
<td>X 15</td>
<td>Frequency of creditors deposit</td>
<td>(\frac{\text{Buying}}{\text{average of payable accounts}})</td>
<td>Operation</td>
</tr>
<tr>
<td>X 16</td>
<td>Earnings Before Interest Tax Azksr compared to net sales</td>
<td>(\frac{\text{Earnings before interest and taxes deductions}}{\text{net sales}})</td>
<td>Profitability</td>
</tr>
</tbody>
</table>

Figure 1. The neural network for data one year before bankruptcy
<table>
<thead>
<tr>
<th>Description</th>
<th>First year</th>
<th>Second year</th>
<th>Third year</th>
<th>Fourth year</th>
<th>Fifth year</th>
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<tbody>
<tr>
<td>Number of correct predictions of the bankrupt companies</td>
<td>45</td>
<td>44</td>
<td>42</td>
<td>39</td>
<td>36</td>
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<tr>
<td>Number of correct predictions of the non-bankrupt companies</td>
<td>120</td>
<td>119</td>
<td>117</td>
<td>118</td>
<td>118</td>
</tr>
<tr>
<td>Number of the model errors in predictions of the bankrupt companies</td>
<td>2</td>
<td>3</td>
<td>5</td>
<td>8</td>
<td>11</td>
</tr>
<tr>
<td>Number of the model errors in predictions of the non-bankrupt companies</td>
<td>0</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Percentage of correct pre- Company Forecasts Bankrupt</td>
<td>95.7</td>
<td>93.5</td>
<td>88.7</td>
<td>83</td>
<td>77</td>
</tr>
<tr>
<td>Percentage of correct predictions of the bankrupt companies</td>
<td>100</td>
<td>98/8</td>
<td>97/8</td>
<td>98/5</td>
<td>98/7</td>
</tr>
<tr>
<td>Percentage of correct predictions of the non-bankrupt companies</td>
<td>98/8</td>
<td>97/3</td>
<td>95/2</td>
<td>94/2</td>
<td>93/2</td>
</tr>
<tr>
<td>General error of the model</td>
<td>1/2</td>
<td>2/7</td>
<td>4/8</td>
<td>5/8</td>
<td>7/7</td>
</tr>
</tbody>
</table>