Hybrid Financial Analysis Model for Predicting Bankruptcy

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Abstract

The incidence of important bankruptcy cases has led to a growing interest in developing bankruptcy prediction models. Bankruptcy is a defective process and incurs costs on different stakeholders. By this time, several methods have been developed for predicting bankruptcy, including statistical and artificial intelligence techniques. Hybrid models have proven be a promising approach for classification system for predicting bankruptcy. This paper proposes a hybrid financial analysis model including static and trend analysis models to construct and train a back-propagation neural network (BPN) model. BPN model was applied to classify bankrupt and non-bankrupt Iranian firms listed in Tehran stock exchange (TSE) which provides a high predication rate. Sensitivity analysis determines that leverage financial ratio play important role in predicting bankruptcy.

Keywords: Financial distress, Hybrid financial analysis, artificial neural network

Introduction

Prediction and analysis of corporate financial performance is a crucial phenomenon in a developing country like Iran. The health and success of the firms are of widespread concern to policy makers, industry participants, investors, and managers. (O’Leary, 1998) The prediction of bankruptcy is one of the major activities to audit enterprise risks and/or uncertainties. Business failure can be defined as a situation that a firm cannot pay lenders, preferred stock shareholders, and suppliers, a bill is overdraw, or the law makes the firm go bankruptcy (Dimitras, Zanakis, & Zopounidis, 1996). Bankruptcy is a defective process which disturbs utilization of investment opportunity and waste resources. Bankruptcy incurs costs on beneficiary as investing bank, stakeholders, debtors, and business partner and company staff. Bankruptcy is not an impulsive outcome and it grows constantly in stages. Thus, the development of financial analysis models to predict business failures can be thought of as ‘early warning systems’, which proves to be very helpful for managers, and relevant authorities who can prevent the occurrence of failures. (Atiya, 2001) In addition, these models are able to assist the decision-makers of financial institutions to evaluate, assess and select the firms to collaborate with or invest in (Ahn,Cho, & Kim, 2000; Balcaen & Ooghe, 2006, Etemaid,et.al 2009)
Since the early 1990’s, neural networks, and multi-layer perceptron neural networks in particular, have been widely used to design bankruptcy prediction models. These neural networks make it possible to get around the statistical constraints of discriminant analysis, the main technique used to design such models since Altman. In addition, their ability to represent non-linear relationships makes them well-suited to modeling the frequently non-linear relationship between the likelihood of bankruptcy and commonly used variables (i.e. financial ratios)(du Jardin, 2010)

The detection of company operating and financial difficulties is a subject which has been particularly susceptible to financial ratio analysis. (Altman, 1968). Financial ratios hold for the long term period as well as for the short term period and traditionally, have been dominant in most research to date. Financial analysis includes fiscal indicators and statistical forecasting which allow people to measure the current fiscal condition of the operating units and consequently predict trends for their future fiscal condition. Fiscal indicators can be used to provide quantitative information to evaluate the fiscal conditions and compare current financial statements with that of previous years and also that of other similar units. Fiscal indicators focus on proportional distributions within the reports, which is usually called as ‘static analysis’ and on factors and trends over a relatively long period of time, which is referred as ‘dynamic analysis’ or ‘time serials analysis’. The process of developing fiscal indicators provides a framework for assembling and analyzing information about enterprises.

In general, there are two types of financial analysis models, which are static and trend analysis models (Damodaran,2002; Mulford & Comiskey, 2002). For the static financial analysis model, its main characteristic is aimed at some significant financial ratios and compares the relationship between these significant financial ratios and the outcomes they expected. On the other hand, the main characteristic of the trend financial analysis model is focused on tracking to the one or the few characteristic marks, maybe the value or the ratios or any others. Each of these two analysis models has its own distinctive capabilities and certainly some inherited limitations. It is believed that if the strengths and weaknesses of these two aforementioned models could be combined, more flawless analyses are likely to be acquired (Anandarajana & Anandarajanb,1999; Andr, Landajo, & Lorca, 2005; Calderon & Cheh,2002). (Huang, et al.,2008)

There are arguments which promote the consideration of the hybrid analysis model for bankruptcy prediction using some machine learning technique. The underlying problem to use of a large number of parameters as the inputs is that each parameter has its mutual influence. One specific parameter may not be significant in statistics, but it would present the significant result when several pieces of parameters ‘interact’ at the same time, which is called covariation (Gujarati, 2002).

If we only consider the minority important financial ratios which lead people to place focus on these pieces of values, enterprises would be able to play tricks most frequently and cover up these conspicuous ratios. On the other hand, if we could put a lot of effort into the analysis with carefulness, enterprises which cover up the financial ratios would show their slip in some places (Mulford & Comiskey, 2002).

Literature review

The pioneers of the empirical approach are Beaver (1966), Altman(1968), and Ohlson(1980). Beaver was one of the first researchers to study the prediction of bankruptcy using financial ratio. So, the first approaches that were applied to bankruptcy forecasting were parametric statistical models. However, we must bear in mind that input data for bankruptcy prediction models are drawn from financial statement of firm. The specific features of such information suggested that the use of parametric models could lead to inefficient classification. So a series of nonparametric models were applied to bankruptcy forecasting. (De Andrs, 2010)
Aziz and A.Dar, 2006) developed their discussion based on three categories, in which the models are further grouped by their main investigative purpose which enlighten the developing process of various bankruptcy prediction models. These categories are as below:

**Statistical models:**
Focus on symptoms of failure/ Drawn mainly from company accounts/ Could be univariate or multivariate (more common) in nature/ Follow classical standard modelling procedures

**Artificially intelligent expert system models (AIES)**
Focus on symptoms of failure/ Drawn mainly from company accounts/ usually, multivariate in nature/ Result of technological advancement and informational development/ heavily depend on computer technology

**Theoretical models**
Focus on qualitative causes of failure/ Drawn mainly from information that could satisfy the theoretical argument of firm failure proposed by the theory /Multivariate in nature/ usually employ a statistical technique to provide a quantitative support to the theoretical argument

A careful analysis of various methods of corporate bankruptcy prediction leaves the impression that there is little to choose between them. The advance of information technology since the 1980s has motivated the development of technology-driven models as alternatives to classical statistical models. However, virtually all of the current models depend on a statistical heritage, one way or another. AIES models, for example, generally exploit both univariate and multivariate statistical techniques and may be considered as automated offspring of the statistical approach, albeit more sophisticated. Among these techniques, artificial neural networks have been used frequently. The main interest of a considerable amount of research was to explore the possibility of making more accurate prediction than the traditional statistical methods. (Boritz & Kennedy, 1995; Coates & Fant, 1992; Klersey & Dugan, 1995; Pompe & Feelders, 1997). Similarly, theoretical models are often developed by employing an appropriate available statistical technique rather than by building directly on theoretical principles. (Aziz and A.Dar 2006). The different types of three mentioned categories are shown in table 1.

**Table 1. Different types of three mentioned categories**

<table>
<thead>
<tr>
<th>Statistical models</th>
<th>AIES</th>
<th>Theoretical models</th>
</tr>
</thead>
<tbody>
<tr>
<td>Univariate (see Altman, 1993; Morris, 1998)</td>
<td>Recursively partitioned decision trees (an inductive learning model) (see Friedman, 1977; Pompe and Feelders, 1997)</td>
<td>Balance sheet decomposition measures (BSDM)/entropy theory (see Theil, 1969; Lev, 1973; Booth, 1983)</td>
</tr>
<tr>
<td>Multiple discriminant analysis (MDA) (see Klecka, 1981; Altman, 1993; Morris, 1998)</td>
<td>Case-based reasoning (CBR) models (see Kolodner, 1993)</td>
<td>Gambler’s ruin theory (see Scott, 1981; Morris, 1998)</td>
</tr>
<tr>
<td>Logit model (see Maddala, 1983; Theodossiou, 1991; Gujarati, 1998; Morris, 1998)</td>
<td>Genetic algorithms (GA) (see Shin and Lee, 2002; Varetto, 1998)</td>
<td>Credit risk theories (including JP Morgan’s CreditMetrics, Moody’s KMV model)</td>
</tr>
</tbody>
</table>

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Probit model
(see Maddala, 1983; Theodossiou, 1991; Gujarati, 1998; Morris, 1999)

Rough sets model
(see Pawlak, 1982; Ziarko, 1993; Dimitras et al. 1999)

Cumulative sums (CUSUM) procedures
(see Page, 1954; Healy, 1987; Kahya and Theodossiou, 1999)

Partial adjustment processes
(see Laitinen and Laitinen, 1998; Gujarati, 1998)

(see Black and Scholes, 1973; Merton, 1973), CSFB's CreditRisk þ (see Credit Suisse, 1997), and
KcKinsey's CreditPortfolio View (see Wilson, 1997a, b, 1998)

Artificial neural networks

ANNs were developed as a computational technique to model the inner-workings of the human brain, as a type of Artificial Intelligence. Neural networks learn by experience, generalize from previous experiences to new ones, and can make decisions. The first major steps towards developing a computer information processing system based on the human brain was made by McCulloch and Pitts in 1943. The major advantage of ANNs is that they do not have the restrictive assumptions, such as normality and linearity, of the (previously discussed) conventional statistical methods. In addition, due to their flexibility, ANNs can deal with outliers, missing data and multicollinearity better than other techniques. (Benjamin, 2005)

Essentially, an ANN is a soft computing technique modelled on the workings of the human brain. The topology of an ANN (in Bankruptcy prediction) involves connected layers of neurons:

- One layer of input neurons (usually financial ratios),
- One or more hidden layers of interconnected neurons, and
- One output layer of neurons (usually just one boolean fail or success neuron).

A simple example of an ANN for Bankruptcy prediction with one hidden layer is shown in below figure 2.3. Each connection between neurons has an associated weight that relates to the likelihood that the connection will be fired and used in the decision. Prior to its use, the ANN is ‘trained’ like a human brain. The common transfer function is shown below.

\[ Y_j = f\left( \sum W_{ij}X_i - \theta_j \right) = f(\text{net}_j) \]

where \( Y_j \) means the output signal of the neuron, \( f \) for the transfer function of the neuron, i.e. transferring the input value of the neuron into the output value of the neuron, \( W_{ij} \) for the interconnected weight of the neuron to express the incentive intensity that input signals toward neurons, \( X_i \) for the input signal of the neuron, and \( \theta_j \) for the outlier value of the neuron.

A multilayer network is typically trained by a back propagation learning algorithm. It performs weights tuning to define whatever or not hidden unit representation is most effective at minimizing the error of misclassification. That is, for each training example its inputs are fed into the input layer of the network and the predicted outputs are calculated. The differences between each predicted output and the corresponding target output are calculated. This error is then propagated back though the network and the weights between two layers are adjusted so that if the training example is presented to the network again, then the error would be less. As a result, the algorithm captures properties of the input instances which are most relevant to learning the target function (Haykin, 1999).
Research methodology
The data set used for this research consists of 120 Iranian companies. All of them were or still are listed on the Tehran Stock Exchange (TSE). 60 companies went bankrupt under paragraph 141 of Iran Trade Law from 2001 through 2009. The other 60 companies are “matched” companies, from the same period of listing on the TSE. Because of small population, we could not match two groups in each of industries.

We apply a three stages predictive variable selection process. At the first stage, bankruptcy prediction literature was reviewed and some variables were selected as predictive variables. These financial ratios were chosen based on popularity in literature. In the second stage, variables were selected based on availability of the necessary data.

In the third stage, using Delphi technique and a panel of experts was used to select final variables. In the first round, questionnaires about the appropriate financial ratio were sent to experts and they were requested to select the right one which best can participate in predicting bankruptcy prediction. After first round, an anonymous summary of the experts’ forecasts as well as the reasons they provided for their judgments, was provided. Then, experts are encouraged to revise their earlier answers in light of the replies of other members of their panel. During this process the range of the answers decrease and the group converge towards the “appropriate financial ratio”. Finally, 10 ratios were selected.

The hybrid financial analysis model

10 ratio items with influence power and the practice to set each ratio its own weight are used. These 10 ratios can be classified into four categories, which are Liquidity, Operating, Profitability and Leveraging as shown in Table 2.

Next, the difference between the base previous period and base period are analyzed and the variable-rate of each of the aforementioned 4 categories is calculated.

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1 Under paragraph 141 of Iran Trade Law, a firm is bankrupt when its total value of retained earnings is equal or greater than 50% of its listed capital.
Variable rate = \text{Date at previous period – Data base period} / \text{Data at base period}

After calculating each ratio’s variable rate, and then we can refer to Table 1 for more detail. Each category’s variable rate is converted based on the weights; these variable rates can be represented as the variation of the categories. Table 3 shows one sample example of the categories variable rates.

Table 2-Financial ratios and weights

<table>
<thead>
<tr>
<th>Categories</th>
<th>Financial ratios</th>
<th>Weights</th>
</tr>
</thead>
<tbody>
<tr>
<td>Liquidity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Current ratio</td>
<td></td>
<td>0.5</td>
</tr>
<tr>
<td>Quick ratio</td>
<td></td>
<td>0.5</td>
</tr>
<tr>
<td>Operating</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inventory turnover ratio</td>
<td></td>
<td>0.5</td>
</tr>
<tr>
<td>Total asset turnover ratio</td>
<td></td>
<td>0.5</td>
</tr>
<tr>
<td>Profitability</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Return on shareholder’s equity</td>
<td></td>
<td>0.25</td>
</tr>
<tr>
<td>Profit margin = net income/sale</td>
<td></td>
<td>0.25</td>
</tr>
<tr>
<td>Return on total assets = net income/average total asset</td>
<td></td>
<td>0.25</td>
</tr>
<tr>
<td>Gross margin</td>
<td></td>
<td>0.25</td>
</tr>
<tr>
<td>Leveraging</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Debt to equity ratio</td>
<td></td>
<td>0.5</td>
</tr>
<tr>
<td>Debt to asset</td>
<td></td>
<td>0.5</td>
</tr>
</tbody>
</table>

Table 3 - Category variable –rates (an example)

<table>
<thead>
<tr>
<th>Categories</th>
<th>Financial ratios</th>
<th>Base period</th>
<th>Previous period</th>
<th>Weights</th>
<th>Variable rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Liquidity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Current ratio</td>
<td></td>
<td>1.34</td>
<td>1.27</td>
<td>0.5</td>
<td>1.28</td>
</tr>
<tr>
<td>Quick ratio</td>
<td></td>
<td>0.77</td>
<td>0.22</td>
<td>0.5</td>
<td></td>
</tr>
<tr>
<td>Operating</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.79</td>
</tr>
<tr>
<td>Inventory turnover ratio</td>
<td></td>
<td>2.36</td>
<td>1.4</td>
<td>0.5</td>
<td></td>
</tr>
<tr>
<td>Total asset turnover ratio</td>
<td></td>
<td>0.8</td>
<td>0.61</td>
<td>0.5</td>
<td></td>
</tr>
</tbody>
</table>

Back-propagation neural network

The MATLAB software, neural network toolbox is used to construct and train the back-propagation neural network (BPN). There are 12 variables as the input, in which 4 category ratios between the base period and previous period, 4 category ratios between the previous period and the period before the previous period, and the last 4 are dummy variables used to analyze each category’s trend between different periods. The output number ‘1’ represents a ‘fine enterprise’ and ‘-1’ for a ‘risk enterprise’. Note that there are two hidden layers of the neural network model. Table 4 provides some examples of the input and output information.
Table 4 - Examples of the input information

<table>
<thead>
<tr>
<th>ComNo</th>
<th>Date</th>
<th>Ratio_1a</th>
<th>Ratio_1b</th>
<th>Ratio_1c</th>
<th>Ratio_2a</th>
<th>Ratio_2b</th>
<th>Ratio_3a</th>
<th>Ratio_3b</th>
<th>Ratio_4a</th>
<th>Ratio_4b</th>
<th>Ratio_4c</th>
<th>state</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>C</td>
<td>C</td>
<td>R</td>
<td>R</td>
<td>R</td>
<td>R</td>
<td>R</td>
<td>R</td>
<td>R</td>
<td>R</td>
<td>R</td>
<td>U</td>
</tr>
<tr>
<td>U</td>
<td>I</td>
<td>I</td>
<td>I</td>
<td>I</td>
<td>I</td>
<td>I</td>
<td>I</td>
<td>I</td>
<td>I</td>
<td>I</td>
<td>O</td>
<td>I</td>
</tr>
<tr>
<td></td>
<td>3.86</td>
<td>-0.35</td>
<td>1.00</td>
<td>-0.69</td>
<td>-0.19</td>
<td>-1.00</td>
<td>-0.16</td>
<td>-0.35</td>
<td>1.00</td>
<td>-0.35</td>
<td>0.04</td>
<td>-1</td>
</tr>
</tbody>
</table>

Row 1: Field name.
Row 2: Data type, C is category, R is real.
Row 3: Practice parameter, U is uselessness, I is input, O is output.
Row 4–end: Data value.
Ratio_1x–Ratio_4x: The numbers of the categories.
ComNo: Company number.
Ratio_na: Variable-rate between Base Period and Previous Period.
Ratio_nb: Variable-rate between Previous Period and the Period before Previous Period.
Ratio nc: Trends between Ratio_na and Ratio_nb, if Ratio_na > Ratio_nb then 1, if Ratio_na < Ratio_nb then _1.
State: Risk state of the enterprise, risk is _1, fine is 1.

Cross validation

Cross-validation is a way to predict the fit of a model to a hypothetical validation set when an explicit validation set is not available. The goal of cross-validation is to estimate the expected level of fit of a model to a data set that is independent of the data that were used to train the model. There is different approach for validation as holdouts method, K-fold cross validation, leave-one-out cross validation.
The holdout method is the simplest kind of cross validation. The data set is separated into two sets, called the training set and the testing set. The function approximator fits a function using the training set only. Then the function approximator is asked to predict the output values for the data in the testing set.
K-fold cross validation is one way to improve over the holdout method. The data set is divided into k subsets, and the holdout method is repeated k times. Each time, one of the k subsets is used as the test set and the other k-1 subsets are put together to form a training set.
Leave-one-out cross validation is K-fold cross validation taken to its logical extreme, with K equal to N, the number of data points in the set. That means that N separate times, the function approximator is trained on all the data except for one point and a prediction is made for that point.
In this research, we use holdout method for cross validation.

Sensitivity analysis

A technique used to determine how different values of an independent variable will impact a particular dependent variable under a given set of assumptions. This technique is used within specific boundaries that will depend on one or more input variables. Sensitivity analysis is very useful when attempting to determine the impact the actual outcome of a particular variable will have if it differs from what was previously assumed. In this research, we omitted each category and measured the error of model, which it means that error related to the function of this category in model and by this process; we can understand the importance of each category in predicting model.
Experiment

Evaluation methods

The system evaluation is based on a confusion matrix shown in Table 5. In addition, five measures are used for further analyses described below.

- **Total prediction accuracy (Total_Compare):**
  This measures the rate of prediction accuracy of the model for fine and risk enterprises.

- **Risk identification 1 (RealF(SysF)):**
  This result is used to examine the model in terms of the degree of identifying risk enterprises as real risk enterprises.

- **Risk identification 2 (RealR(SysR)):**
  This result means that the model can identify risk enterprises in the dataset of real risk enterprises.

- **Prediction error 1 (SysF(RealF)):**
  This shows the prediction error rate of the model to incorrectly classify fine enterprises into risk enterprises.

- **Prediction error 2 (SysR(RealR)):**
  Opposed to Prediction error 1, this presents the prediction error rate of the model to incorrectly classify risk enterprises into fine enterprises.

### Table 5- The confusion matrix

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Fine enterprise</td>
<td>Risk enterprise</td>
</tr>
<tr>
<td>Fine enterprise</td>
<td>S₁₁</td>
<td>S₁₂</td>
</tr>
<tr>
<td>Risk enterprise</td>
<td>S₂₁</td>
<td>S₂₂</td>
</tr>
<tr>
<td>Total</td>
<td>Nₓ₁</td>
<td>Nₓ₂</td>
</tr>
</tbody>
</table>

Results

To train the neural network model (BPN), the input parameters are 12 and the hidden layers are 2. As different numbers of neurons in the hidden layer can result in different prediction rates, the authors test the model by using different numbers of neurons in the two hidden layers. Different testing results were achieved by considering different training epochs and learning rate and convergence.

As a result, authors choose the “best” model for the following case studies, which is 12-12-24-1 neural network model with learning rate 0.1 and convergence 0,01 and epochs 10,000.

Data set 1 - The first dataset contains 50 fine and 30 risk enterprises. Table 7 shows the prediction result.

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Fine enterprise</td>
<td>Risk enterprise</td>
</tr>
<tr>
<td>Fine enterprise</td>
<td>47</td>
<td>3</td>
</tr>
<tr>
<td>Risk enterprise</td>
<td>6</td>
<td>24</td>
</tr>
<tr>
<td>Total</td>
<td>53</td>
<td>27</td>
</tr>
</tbody>
</table>

Total_Compare: 
(47 + 24)/80 = 89%

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RealF(SysF): 24/27 = 89%
RealR(SysR): 24/30 = 80%
SysF(RealF): 3/50 = 0.6%
SysR(RealR): 6/30 = 20%

Data set 2 - The first dataset contains 15 fine and 10 risk enterprises. Table 7 shows the prediction result.

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fine enterprise</td>
<td>14</td>
<td>1</td>
</tr>
<tr>
<td>Risk enterprise</td>
<td>3</td>
<td>7</td>
</tr>
<tr>
<td>Total</td>
<td>17</td>
<td>8</td>
</tr>
</tbody>
</table>

Total_Compare: (14 + 7)/25 = 84%.
RealF(SysF): 7/8 = 88%
RealR(SysR): 7/10 = 70%
SysF(RealF): 1/15 = 0.7%
SysR(RealR): 3/10 = 30%

Data set 3 - The first dataset contains 16 fine and 9 risk enterprises. Table 7 shows the prediction result.

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fine enterprise</td>
<td>17</td>
<td>2</td>
</tr>
<tr>
<td>Risk enterprise</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Total</td>
<td>18</td>
<td>7</td>
</tr>
</tbody>
</table>

Total_Compare: (17 + 5)/25 = 88%.
RealF(SysF): 5/7 = 71%
RealR(SysR): 5/6 = 83%
SysF(RealF): 2/19 = 11%
SysR(RealR): 1/6 = 17%

Data set 4 - The first dataset contains 13 fine and 12 risk enterprises. Table 7 shows the prediction result.

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fine enterprise</td>
<td>12</td>
<td>1</td>
</tr>
<tr>
<td>Risk enterprise</td>
<td>3</td>
<td>9</td>
</tr>
<tr>
<td>Total</td>
<td>15</td>
<td>10</td>
</tr>
</tbody>
</table>

Total_Compare: (9 + 12)/25 = 84%.
RealF(SysF): 9/10 = 90%
RealR(SysR): 9/12 = 75%
SysF(RealF): $1/13 = 8\%$
SysR(RealR): $3/12 = 25\%$

Figure 2. Summary of three datasets

Sensitivity analysis
This study aims to identify the effective predictive financial ratios. The result of sensitivity analysis has shown in figure 3. As you can see, the number at above of each column represents the error of the model by omitting financial ratios as input. It is clear that the most error related to leveraging (n) and operating trend.

Figure 3. Sensitivity analysis
Discussion
Regarding to the experimental results, the proposed hybrid financial analysis model combining with BPN is capable of providing a very high prediction accuracy rate. Fig. 2 summarizes the performance of using the first three datasets for prediction. The result shows that our system can produce a high rate of risk identification (i.e. Total_compare, RealF(SysF), and RealR(SysR)) and a low rate of prediction error (i.e. SysF(RealF) and SysR(RealR)) by using three different datasets.

Moreover, an important contribution of this paper is identification of the effective predictive financial ratios. Thus, Sensitivity analysis is ranking the financial ratio by measuring the error of model by omitting each category and leveraging (n) and operating trend are identified as highly predictive factors.

Conclusion
Bankruptcy is a highly significant worldwide problem that affects the economic well being of all countries. The high social costs incurred by various stakeholders associated with bankrupt firms have spurred searches for better theoretical understanding and prediction capability. Business failure prediction can be approached differently by using machine learning techniques, whose prediction accuracy has shown more superior to other traditional statistical methods. In this paper, the authors use a hybrid financial analysis model composed of static and trend analysis models (i.e. operating, profitability, leveraging and liquidity). The experimental results report that the proposed model using a back-propagation neural network produces good performance of prediction accuracy.

This paper also seeks to assess the analytical quality of ratio analysis. It suggested that relatively sophisticated analysis is developed but the role of some financial ratio in predicting bankruptcy are dominant over others ratio.

However, there are some limitations in this study. First of all, the size of population may be small. Another restriction of this model is that it requires much time for training and constructing the prediction model, which is the limitation of neural networks technique.

Finally, the model provides insight into the complex interaction of bankruptcy related factors and suggests avenues for future research. For example, the weight of every ratio, the choice of the ratios, instance selection by using genetic algorithms for example (Kim, 2006), the periods of the hybrid model, and the relations for each other, and the design of dummy variables are all possible areas deserving further investigation and/or exploration.

References:


