Financial Distress Prediction by a Radial Basis Function Network with Logit Analysis Learning

CHI-BIN CHENG*
Dept. of Industrial Engineering and Management, Chaoyang U. of Technology, Taiwan
168 Gifeng E. Rd., Wufeng, Taichung County, Taiwan
cbcheng@mail.cytut.edu.tw

CHING-LUNG CHEN
Dept. of Accounting, Chaoyang University of Technology, Taiwan
168 Gifeng E. Rd., Wufeng, Taichung County, Taiwan

CHUNG-JEN FU
Dept. of Accounting, National Yun-Lin University of Science and Technology, Taiwan
123 University Road, Sec. 3, Douliou, Yunlin 640, Taiwan

(Received June 2005; accepted July 2005)

Abstract—This paper presents a financial distress prediction model that combines the approaches of neural network learning and logit analysis. This combination can retain the advantages and avoid the disadvantages of the two kinds of approaches in solving such a problem. The radial basis function network (RBFN) is adopted to construct the prediction model. The architecture of RBFN allows the grouping of similar firms in the hidden layer of the network and then performs a logit analysis on these groups instead of directly on the firms. Such a manner can remedy the problem of nominal variables in the input space. The performance of the proposed RBFN is compared to the traditional logit analysis and a backpropagation neural network and demonstrates superior results to both the counterparts in predictive accuracy for unseen data. © 2006 Elsevier Ltd. All rights reserved.

Keywords—Financial distress prediction, Radial basis function network, Neural networks, Logit analysis.

1. INTRODUCTION

The ability to predict the possibility of financial distress of a company is important for many user groups such as investors, creditors, regulators, and auditors. In particular, auditors are facing a litigious environment where failing to identify a potential financial distressed firm can result in substantial costs [1]. The recent intentional manipulation of fraudulent financial reporting events, e.g., Procomp Informatics Ltd., Cradle Tech, Infodisk Taiwan, and Summit Computer Tech, of unexpected company failure have confirmed this observation.

The prediction of financial distress or bankruptcy has received considerable attention in the accounting, auditing, and financial literature over the past three decades. In an attempt to assist investors or auditors in their decision-making, researchers have relied on a number of statistical

*Author to whom all correspondence should be addressed.
0898-1221/06/$ - see front matter © 2006 Elsevier Ltd. All rights reserved.

Typeset by AATeX
methods to predict financial distress. These methods include multiple discriminant analysis (MDA) [2], probit models [3–6] and logit models [3,7]. Hamer [6] noted that the differences in predictive accuracy among these statistical methods were relatively insignificant.

With the advent of artificial neural networks (ANNs), researchers applied ANNs to a variety of problems with special emphasis on bankruptcy prediction. In the prior studies of ANNs in bankruptcy [8–11], Boritz et al. [8] pointed out that the backpropagation neural networks are the most adopted network structures. Meanwhile, considerable research has been conducted that compared the bankruptcy predictive accuracy of neural networks to other traditional techniques [1,5,11,12]. A review regarding the approaches that have been used for financial distress prediction is provided in Section 2 of this paper.

Using statistical methods in financial distress prediction have several benefits. For example, it can determine the importance of a variable toward the prediction. Moreover, the prediction results by statistical methods (e.g., logit and probit) can be expressed as a probability measure rather than a dichotomous classification (failing or healthy). In some decision-making settings, the probability expression is more useful especially the decision-maker needs to verify levels of response to risk of failure [7]. For example, when discussing commercial loan noncompliance, Chesser [13] observed that “noncompliance does not mean that a borrower will completely default on his loan, but rather that some work-out agreement will have to be arranged which will result in settlement of the loan under conditions less favorable to the lender than those specified in the original agreement”. Assessment of the likelihood of such an event makes possible such adjustment as risk-premiums [14].

Though statistical methods have their benefits as discussed above, they are problematic when explanatory variables are nominal variables. Dummy variables are often used to represent different values of the nominal variables. Aldrich and Nelson [15] pointed out that the use of dummy variables in the probit analysis might result in a violation of the assumption that the error term has a cumulative normal distribution. Similarly, the same limitation exists for logit analysis.

Liang et al. [5] demonstrated by an accounting classification problem that ANN performed better than statistical methods when variables included both nominal and nonnominal variables. This finding motivates us to combine ANN and a statistical method in financial distress prediction. With this combination, we hope we can retain the advantages from both the statistical method and the ANN. Our approach comprises the radial basis function network (RBFN) and the logit analysis to construct the prediction model.

Our proposed RBFN is a three-layered (i.e., input, hidden, and output layers) feed-forward neural network. The input layer contains nodes that represent explanatory variables, which can be nominal or nonnominal. The input space is transformed to the hidden layer space that is always continuous. A logit analysis is conducted on this continuous space and output the prediction of the financial distress probability.

2. REVIEWS OF PRIOR METHODS

The application of financial statement analysis to bankruptcy prediction firstly started with univariate models that relied on the predictive value of a single financial variable [16], and soon led to multivariate models by using the multiple discriminant analysis (MDA) of Altman [2]. Discriminant analysis minimizes the expected misclassification cost under the assumptions of normality and equal dispersion. However, these assumptions are often violated in practice [17]. Shah et al. [18] also pointed out that the Gaussian distribution assumptions in MDA might not be tractable to real business problems.

Other statistical techniques such as probit and logit analysis were also popular approaches for financial distress prediction. The probit analysis uses statistical inference procedures to derive a linear model from a set of input data based on the assumption that the error term has a cumulative normal distribution. The model estimates the probability that each case falls in a
particular class. Logit analysis is very similar to the probit analysis, except that it assumes that the error term has a logistic distribution. Thus, the logit regression model of the financial distress prediction problem is defined as

\[ p = \frac{\exp(\beta_0 + \beta_1 x_1 + \ldots + \beta_m x_m)}{1 + \exp(\beta_0 + \beta_1 x_1 + \ldots + \beta x_m)}, \]  

where

- \( p \) : the probability of financial distress,
- \( x_i \) : explanatory variables of the prediction model, \( i = 1, \ldots, m \),
- \( \beta_0 \) : regression intercept,
- \( \beta_i \) : coefficients of the explanatory variables, \( i = 1, \ldots, m \).

It has been reported that the logit regression approach is often preferred over discriminant analysis [19].

In recent years, machine learning techniques including decision tree, case-based reasoning (CBR), artificial neural networks, and genetic algorithm (GA) became popular in the research area of financial distress prediction. These techniques were effective in financial distress prediction when nominal variables dominate. For example, Han et al. [20] showed that the accuracy of this type of learning techniques increased as the portion of nominal variables decreased in the classification model.

The principle of CBR is to remember a similar problem that has been solved in the past and adapt the old solution to solve the new problem [21]. Jo and Han [11] integrated CBR, ANN, and MDA to predict bankruptcy. They also compared the performances of the three respect techniques [12]. Decision tree learning is a method for approximating discrete-valued target function, in which the learned function is represented by a decision tree. Tam and Kiang [17] has compared the performance of the ID3 [22] decision tree with the neural network.

ANNs are another popular machine learning technique used in financial distress prediction [8,12,17,18,23]. An artificial neural network is a parallel system of highly interconnected processing units based on neurobiological models. ANNs are designed to mimic the human cognition function through parallel processing of signals. The processing units of the ANN are called neurons that are arranged in a number of hierarchical layers. One of the most widely implemented neural network architecture is the multilayered feed-forward structure with supervised-learning. This structure consists of input and output layers as well as one or more hidden layers. This kind of networks can be used to building nonlinear models for mapping the relation between the independent and the dependent variables.

In general, ANNs have higher predictive accuracy than traditional statistical techniques such as MDA, logit, and probit models for both financial and nonfinancial institution [1]. Boritz et al. [8] examined predictive accuracy of two different ANN learning algorithms to a number of statistical techniques. They concluded that ANNs appeared to have a higher predictive accuracy but they were sensitive to the proportion of bankrupt firms in the training samples. The commonly used learning algorithm in the ANN based studies was the backpropagation algorithm. There are typically two difficulties with the use of the backpropagation algorithm:

1. the algorithm usually requires much computational time to obtain a good enough approximation of the target function, and
2. the gradient based searching method of the backpropagation algorithm is easy to trap in a local minimum.

Genetic algorithm (GA) first proposed by Holland [24] is a stochastic optimization approach based on the concepts of biological evolutionary processes. GA encodes each point in a solution space into a binary string called a chromosome. Operations of chromosomes including selection, crossover, and mutation, are used to generate new chromosomes so as to explore the solution space. Each chromosome is evaluated by a fitness function. Such a fitness function corresponds
to the objective function of the original problem. The advantage of using GA in financial distress prediction is that it is capable of extracting rules from the sample data so that the resultant model is easy to understand for users [25]. Kim and Han [26] encoded each prediction rules as a chromosome that contain segments corresponding to attributes in the condition part of the rule and the class (i.e., bankrupt or nonbankrupt) in the conclusion part of the rule. The learning performance of the GA model is evaluated by a composite measure of accuracy and coverage. The accuracy measure is defined as the proportion of the number of accurately classified cases to the cases to which the rules can be applicable, while the coverage measure indicates how well the condition parts of the rules are universally applicable to all cases. Though Kim and Han [26] reported that the GA approach outperformed the ANN approaches, their approach is limited by the validation of the training examples. The training examples were obtained through experts' subjective ratings for companies. Such ratings may not be consistent from expert to expert, and hence affects the validation of the learning result.

3. RADIAL BASIS FUNCTION NETWORK (RBFN)

The RBFN contains three layers, namely, the input layer, the hidden layer, and the output layer, as shown in Figure 1. The input layer receives the explanatory variable vector. The output layer containing a single node produces the outcome of the prediction model. The hidden layer in the RBFN works as a clustering mechanism, in which each hidden node represents a cluster center.

The hidden layer contains q hidden nodes. The active functions \( h_j, j = 1, \ldots, q \), of these hidden nodes are Gaussian functions, i.e.,

\[
h_j(x) = \exp \left[ -\left( \frac{x - u_j}{\sigma_j} \right)^2 \right],
\]

where \( u_j = [u_{j1}, \ldots, u_{jm}]^T \) and \( \sigma_j \) are the center and deviation of the Gaussian function, respectively. The arrangement of \( u_j \) and \( \sigma_j \) are such that appropriate clusters are formed from the input vectors in order that the hidden nodes cover the portions of input space within which the training data actually occur [27]. Meanwhile, the connection weights \( w_j, j = 1, \ldots, q \), between the hidden layer and the output node can be interpreted as the desired output for an input vector located exactly at the center of its corresponding hidden node.

The output of the original RBFN is defined as a weighted average of the incoming signals from the hidden layer. In order to obtain a probabilistic prediction of the financial distress, the present study uses the logistic function to be the active function of the output node. Moreover, a bias node, which always produce a signal of 1, with the connect weight \( b \) is added in the hidden layer. Consequently, the output of the network is calculated as

\[
\hat{p} = \frac{\exp \left( b + \sum_{j=1}^{q} h_j(x) w_j \right)}{1 + \exp \left( b + \sum_{j=1}^{q} h_j(x) w_j \right)}.
\]

Figure 1. Architecture of RBFN.
3.1. Learning Algorithm

A hybrid-learning algorithm is formulated for the RBFN in which the learning of the parameters in the hidden nodes is self-organized while that of the connection weights is supervised. The goal of hidden node parameter learning is to arrange these hidden nodes such that they can effectively represent the clusters of input vectors. The c-mean clustering algorithm is used to achieve this goal. The resultant updating rule for $u_j$ is expressed as

$$u_j^{\text{new}} = u_j^{\text{old}} + \eta (x - u_j^{\text{old}}),$$

where $\eta$ is the learning rate.

The initial values of $u_j$ are roughly determined by observing the dispersion of the sample data. The learning of $\sigma_j$ is determined using the $k$-nearest neighbor heuristics. This heuristic scheme varies the value of $\sigma_j$ in order to achieve a certain overlap between hidden nodes such that they form a smooth and continuous interpolation over those regions of the input space. $\sigma_j$ is updated by taking the average of the Euclidean distances between the $j$th node center and all of its $k$-nearest neighboring node centers.

Equation (3) indicates that the output of the RBFN is derived from a logistic function of the hidden nodes' outputs. This implies that the learning of the connection weights can be formulated as a logit analysis problem. From equation (3), it can be seen that when all the $h_j(x)$ are fixed, $\hat{p}$ is a logistic function incorporating $w_j$ as unknown coefficients. By defining the performance measure of the network as a mean square error (MSE) in equation (5), the identification of $w_j$ is achieved by using logit analysis to minimize MSE.

$$\text{MSE} = \frac{1}{N} \sum_{k=1}^{N} (p_k - \hat{p}_k)^2,$$

where $N$ is the sample size.

3.2. Generalization of the RBFN

Sometimes, a neural network may adapt itself so well to the training data that it loses its prediction capability for new input data supplied after the training process has been completed. Consequently, it is important to prevent the occurrence of over fitting, or equivalently, to guarantee the generalization of the network. Generalization refers to constructing a model which performs a satisfactory mapping of the training data while still retaining the ability to approximate the outputs of any future new input data.

The accuracy of approximating the training data and the generalization of the network are usually conflict. A great number of hidden nodes generally yield high accuracy of the approximation, but it inevitably leads to poor generalization of the network. Therefore, it is important to find the appropriate number of hidden nodes of the FRBFN that balances the two goals: a high accuracy of approximation and a good generalization to the future unseen data. Specifying the optimal number of hidden nodes is achieved by means of the cross-validation technique. The principal of cross-validation is to divide the sample data into a construction subsample, which forms the training data set, and a validation subsample, which forms the test data set. The construction subsample is used to train the network, and the validation subsample is used to test the generality of the network once it has been trained by the construction subsample.

The steps of the cross-validation technique can be summarized as follows,

1. determine the number of hidden units (starting with a small number),
2. train the network with the training set data,
3. recall the network trained in the previous step with the test set data, and record the performance measure produced by this network,
4. increase the number of hidden units and return to the first step, and
5. adopt the network which produces the maximum performance measure as the optimum configuration.
4. RESEARCH DESIGN

Most of the previous studies on financial distress prediction have emphasized on the use of accounting numbers. However, accounting information represented by nominal terms may contribute to the prediction accuracy of the model. Therefore, the present study uses both quantitative and nominal variables in the prediction model.

4.1. Explanatory Variable Selection

Seven explanatory variables are adopted in our model. Three of them are quantitative variables and the rest are qualitative (nominal) variables.

4.1.1. Quantitative variables

**Financial Distress Index Measured by Zmijewski’s Model (FDI).** Rather than directly treating individual financial ratios as explanatory variables, the ratios are aggregated into an overall score by the use of the probit model of Zmijewski [4] as done in [1]. These financial ratios are measured to proxy the profitability, leverage, and liquidity of the firms. The Zmijewski model calculates a surrogate for the probability of bankruptcy, \( z^* \), as

\[
\begin{align*}
z^* &= -4.803 - 3.6(\text{ROA}) + 5.4(\text{FNL}) - 0.1(\text{LIQ}),
\end{align*}
\]

where

- ROA = Net income/Total assets
- FNL = Total debt/Assets
- LIQ = Current assets/Current liabilities

A higher value of \( z^* \) indicates greater probability of bankruptcy.

**Ratio of Business Groups’ Cross-Holding Investments (RCI).** The research report published by Taiwan Economic Research Center in 1999 indicates that the cross-holding phenomenon is widespread in business groups in Taiwan among listed firms inducing monitoring inefficiency of the board, which in turn, helps trigger financial distress. For this reason, we use the ratio of conglomerate companies’ cross-holding investments to reflect the unique institutional situation in Taiwan.

**Firm Size (SIZE).** Becker et al. [28] suggested that firm size was a surrogate variable for numerous omitted variables in financial distress prediction and its inclusion increased the goodness of fit of the model. Thus, we include the firm size in our prediction model. The firm size is calculated as the natural logarithm of equity by market value.

4.1.2. Qualitative variables (Nominal variables)

**Auditor Changes (AC).** Lennox [29] reported that companies switching auditor decrease the chance of receiving a modified audit report. Firms with successful opinion shopping may replace an auditor in hopes to receive a qualified opinion from the successive auditor, when the incumbent auditor is unwilling to make a compromise on the signs of financial distress. Therefore, we expect that auditor changes will be more likely to occur among companies in financial trouble than companies in financial healthiness. Kluger and Shields [30] also reported that the financial information published by auditor-changed firms prior to auditor changes decision is likely to be of higher quality than similar information from firms that does not change auditors. Schwartz and Menon [31] also examined the auditor change in the filing financially troubled companies and pointed out that the failed firms had a significantly greater ratio of auditor change than the non-failed firms. Therefore, the present study incorporates the auditor-change as an auditor-client interactive explanatory variable into the prediction model. The value of this variable is binary, i.e., 1 for yes and 0 for no.
AUDITOR OPINION (AO). Hopwood et al. [32] and Choi and Jeter [33] observed that an auditor may decide to issue the modified qualified instead of going-concern qualified audit report to evade unwilling replacement of the auditor when the audited firm was in fact encountering financial trouble. To capture such strategic behaviors of auditors, this study uses the modified qualified audit report as one of the nominal explanatory variables. The value of this variable is binary, i.e., 1 denotes such a report and 0 otherwise.

NEGATIVE OPERATING CASH FLOW (NCF). Financial distress will take place if a firm has no sufficient cash to repay debts as they become due. The situation of current cash flows should be a good indicator of the probability of financial distress, if current cash flows do reflect future financial status. In the earlier cash flow prediction models, Gentry et al. [34,35] and Aziz et al. [36] concluded that the cash flow model was superior to Altman’s [2] model and gave better early warning to bankruptcy. Inspired by their studies, this study incorporates the cash flows to capture its association to the client’s subsequent financial distress. The present study defines the status of cash flow as a nominal variable, negative operating cash flow in the prior year, i.e., 1 for negative cash flow and 0 else.

BETA COEFFICIENT (BETA). According to the capital asset pricing model (CAPM), the required return on equity capital for a firm is an increasing function of its systematic risk. Conventional wisdom also suggested that the systematic risk of financial distressed firms should increase, presumably because of increases in leverage associated with financial distress [37]. Thus, it is reasonable to anticipate that the positive effect of leverage on systematic risk would seem to apply to financial distressed firms and the systematic risk of such firms is initially greater than average. The present study incorporates such concept in the prediction model by dividing firms into aggressive stock for which the $\beta$ coefficient greater than 1 and neural/defensive stock for the $\beta$ coefficient less than or equal to 1. The variable BETA denotes this classification, i.e., 1 for aggressive stock and 0 else.

4.2. Data Selection

The present study focuses on the financial distress prediction of the firms in Taiwan. Financial distress firms are defined on the ground of the detailed rules and regulations of Taiwan Stock Exchange (TAIEX), which include changes in transaction modes of listed stocks, or, self-filing for temporary suspension in trading as signs of financial troubles are revealed. Our financial distress sample is composed of the listed firms on the Taiwan Stock Exchange which have incurred financial distress during the period from January 1, 1996 through December 31, 2004. The reasons for only considering TAIEX-listed firms are two folds. First, the listed companies in Taiwan are subject to regulation and scrutiny by the Taiwanese Securities and Exchange Commission and Taiwan Stock Exchange Corporation, and they are required to disclose financial data and release important operational information to the investors. In addition to the benefit of constructing a more or less homogeneous group of financial distress firms, such a practice also help collecting the necessary data. Second, important pieces of information of the listed corporations are rather widely reported and/or commented by mass media so that the financial distress announcement can be double-checked by relevant newspaper reporting. The year 1996 is chosen as the starting year of the data population due to data availability and manageability.

Sixty-four companies are identified to incur financial distress during the sampling period, which is approximately 1.33% (i.e. 64/4802) of the population. Due to the scarcity of financial distress firms, a matched-pair design is used to compose the sample data. Each financial distress firm is matched with two healthy firms randomly selected from a group of firms which are in the same industry and with comparable firm size. This matching process results in a sample of 192 firms, in which the data of financial distress firms are their conditions of the explanatory variables one year prior to the occurrence of financial distress. A summary of the sample data is given in Table 1.
Table 1 indicates that approximately 9.38% of the 192 sample firms changes auditor firm. There are approximately 27% and 40%, respective, of the 192 sample firms grouped as aggressive stock and incurred negative operating cash flow in the prior accounting year. The ratio receiving unqualified audit report prior one year of 192 sampled firms is about 54.64%. Besides, the financial distress index from Zmijewski’s [4] model ranges from -4.3207 to 3.7092. The ratio of business group’s cross-holding investments is approximately 21%.

To assess the predictive accuracy of the proposed model, the sample is split into two subsamples, namely a training sample (size of 154) and a holdout sample (size of 38). This 80 : 20 combination follows the suggestion by Anandarajan et al. [1]. To maintain the generalization of the proposed RBFN, the training sample is further divided to a training dataset (with N = 124) and a cross-validation dataset (with N = 30).

### Table 1. Descriptive statistics of the variables (N = 192).

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Min</th>
<th>First Quartile</th>
<th>Median</th>
<th>Third Quartile</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>FDI</td>
<td>-1.6048</td>
<td>1.3808</td>
<td>-4.3207</td>
<td>-2.5166</td>
<td>-1.7865</td>
<td>-0.8333</td>
<td>3.7092</td>
</tr>
<tr>
<td>RCI</td>
<td>0.2150</td>
<td>0.1580</td>
<td>0</td>
<td>0.0981</td>
<td>0.1913</td>
<td>0.2951</td>
<td>0.8552</td>
</tr>
<tr>
<td>SIZE</td>
<td>6.8228</td>
<td>0.4267</td>
<td>5.8240</td>
<td>6.5164</td>
<td>6.8083</td>
<td>7.0617</td>
<td>8.5982</td>
</tr>
<tr>
<td>AC</td>
<td>0.0938</td>
<td>0.2922</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>AO</td>
<td>0.4536</td>
<td>0.4987</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>NCF</td>
<td>0.4010</td>
<td>0.4914</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>BETA</td>
<td>0.2708</td>
<td>0.4456</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Legends:
FDI: Financial distress index calculated by the Zmijewski’s model [4]
RCI: Ratio of business groups’ cross-holding investments
SIZE: Firm size, as measured in the natural logarithm of total assets
AC: Auditor firm changes, taking the numerical value of 1 if auditor firm is replaced
AO: Audit opinion, taking the numerical value of 1 if a qualified opinion other than a going-concern qualified opinion is issued
NCF: Negative operating cash flow, taking the numerical value of 1 if firm’s operating cash flow is negative in the prior accounting period
BETA: Beta coefficient, taking the numerical value of 1 if firm’s beta coefficient is larger than 1, otherwise 0

5. COMPUTATIONAL RESULTS AND DATA ANALYSIS

Through the generalization process discussed in Section 3.2, a RBFN with six hidden nodes was constructed. To evaluate the performance of the proposed RBFN in financial distress prediction, the prediction results of the RBFN were compared with traditional Logit analysis and a backpropagation neural network (BPN). The construction of the BPN was also through the generalization process, which resulted in a BPN with one hidden layer consisting of nine nodes.

A widely used measure of the predictive accuracy is the percentage of correct classification of the examples to financial distress or healthy firms. Two kinds of misclassification are type 1 error (i.e., a financial distress firm incorrectly classified as a healthy firm) and type 2 errors (i.e., a healthy firm being classified as a financial distress firm). The classification of a firm is determined by a cutoff probability which is set to balance type 1 and type 2 errors. A firm with a predicted probability greater than this cutoff value is considered as a financial distress firm, otherwise a healthy firm.

The selection of the cutoff probability should reflect the relative costs of type 1 and type 2 errors for each decision of classification. Generally, the cost of classifying a problematic firm as a healthy firm is significantly greater than that of misclassifying a healthy firm as a problematic firm [1]. For example, the investor could lose the total investment in making a type 1 error, whereas the investor would lose the opportunity to earn dividends and capital gains [14]. However, practically it is difficult to know the true relative costs of type 1 and type 2 errors. A commonly used alternative is assuming the two types of errors having equal costs, which equals to determining the cutoff probability by minimizing the classification error rate (e.g., [1,14]). The error rate is
Table 2. Training results by the three respective models.

<table>
<thead>
<tr>
<th></th>
<th>Logit</th>
<th>RBFN</th>
<th>BPN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Error rate (training)</td>
<td>15.32%</td>
<td>14.51%</td>
<td>5.27%</td>
</tr>
<tr>
<td>Error rate (holdout)</td>
<td>18.42%</td>
<td>13.15%</td>
<td>18.43%</td>
</tr>
</tbody>
</table>

defined as the ratio of the number of errors to the number of examples examined. The present study adopted the error rate to determine the cutoff probability and evaluate the predictive accuracy of a model.

Table 2 illustrates the training results by the three models, in which, the cutoff probability for the logit model is 0.475 and the model’s error rate is 15.32%; the cutoff probability for the proposed RBFN model is 0.475 and the model’s error rate is 14.5%; while the cutoff value for the BPN model is 0.47 and the model’s error rate is 5.27%. The prediction accuracy of the three models regarding the holdout sample is also presented in Table 2. Although BPN produces a least error rate for the training sample, its prediction accuracy for the holdout sample is the worst among the three models. This result implies that BPN tends to over-fit the training sample. The results in Table 1 show that the proposed RBFN outperforms both the Logit model and the BPN model with respect to the prediction accuracy for the holdout sample.

6. CONCLUSIONS AND FUTURE RESEARCH

This paper has presented the use of the RBFN neural network in the construction of the financial distress prediction model. The RBFN enables the combination of the neural network learning and the logit analysis, and hence provides two advantages in predicting financial distress. First, neural networks usually outperform the statistical methods when the explanatory variables are a mix of nominal and non-nominal variables. Second, the embedded logit analysis in the RBFN can produce prediction that is expressed as the probability of financial distress and hence, make the prediction results more interpretable. Computational results demonstrated that the proposed RBFN outperformed both the logit model and the backpropagation neural network in predictive accuracy for unseen data.

Due to infrequent occurrence of company failure, the present study selected sample firms separately from the distressed firm population and the nondistressed firm population. Such a choice-based sampling technique may result in nonrandom sample and hence produce biased estimates [4]. To correct the choice-based sample bias, Zmijewski [4] used weighted exogenous sample maximum likelihood (WESML) [38] with probit model to predict bankruptcy. In our future research, the WESML method will be integrated with the logit learning in the RBFN to solve the problem of choice-based sample bias.

REFERENCES