FINANCIAL ASSESSMENT USING NEURAL NETWORKS

Ying Zhou[1] **and Taha Elhag**[2]

School of Mechanical, Aerospace and Civil Engineering, University of Manchester, P.O. Box 88, Sackville Street, Manchester, M60 1QD

Corporate bankruptcy always brings about huge economic losses to management, stockholders, employees, customers, and others, together with a substantial social and economical cost to the nation. Therefore, a model predicting corporate failure would serve to reduce such losses by providing a pre-warning for decision makers. An early warning signal of probable failure will enable both management and investors to take preventive actions and shorten the length of time whereby losses are incurred. Thus, an accurate prediction of bankruptcy has become an important issue in finance. The study aims to apply Artificial Neural Networks (ANNs) technique for financial assessment of organizations and to evaluate bankruptcy conditions. This paper reviews the literature on Artificial Neural Network (ANN) and other important methods used for bankruptcy prediction, such as conventional statistical methods and soft computation methods, followed by a discussion of a systematic development process of ANN models. In this research, NN models with Back propagation learning algorithm are trained and tested using data from 50 organizations, the simulation results are encouraging, and the training and testing accuracy is over 97%.

Keywords: artificial intelligence, bankruptcy prediction, modelling.

INTRODUCTION

Corporate bankruptcy always brings about huge economic loess to management, stockholder, employees, customers, and others, together with a substantial social and economical cost to the nation. Therefore, a model predicting corporate failure would serve to reduce such losses by providing a pre-warning to these stockholders. An early warning signal of probable failure will enable both management and investors to take preventive actions and shorten the length of time whereby losses are incurred. Thus, an accurate prediction of bankruptcy has become an important issue in finance. The incidence of important bankruptcy cases has led to an amazing growing interest in corporate bankruptcy prediction models since 1960s. Numerous researches have studied bankruptcy prediction over the past sixty years. As a result, various theories have evolved in an effort to explain or distinguish between firms that have failed.

There have been a fair number of previous studies in bankruptcy prediction. Kumar and Ravi (2006) surveyed studies and researches from 1968 to 2006, and reviewed the statistical and intelligent techniques in detailed for bankruptcy prediction. Adnan and Dar (2006) summarized from 89 published empirical investigations to categories the models used to forecast financial distress into three groups, statistical models, AIES models and theoretical models, and up-to-date the literature of bankruptcy prediction.

[1] ying.zhou@postgrad.manchester.ac.uk
[2] taha.elhag@manchester.ac.uk

Zhou, Y and Elhag, T (2007) Financial assessment using neural networks. *In:* Boyd, D (Ed) *Procs 23rd Annual ARCOM Conference,* 3-5 September 2007, Belfast, UK, Association of Researchers in Construction Management, 45-54.

Zhang, *et al.*, (2004) surveyed Artificial Neural Networks (ANNs) models in bankruptcy prediction. Other earlier notable published contributions are Yang *et al.* (1999), Zhang *et al.* (1998), Mckee (2000), Anandarajan (2001), and Atiya (2001), etc.

Interests in using ANNs for forecasting have led to a tremendous surge in research activities in the past decade (Zhang, *et al.*, 1998). Although ANNs is remarked as a promising forecasting tool because of its characteristics, such as data-driven and self-adaptive, universal functional-approximation, and also, nonlinear, they embody much certainty. Researchers to date are still not certain about the effect of key issues of ANNs' performances on real-world problem. This study will proceed with a brief review bankruptcy prediction literature and significant ANNs modelling issues, following with research design with Backpropagation ANNs employed, next, the simulation results are presented. In the financial section, the study is summarized and the implications of results are discussed.

LITERATURE REVIEW

The high individual and social costs encountered in corporate bankruptcies make this decision problem very important to parties such as auditors, management, government policy makers, and also banks and investors. Bankruptcy is a worldwide problem and the number of bankruptcies can be considered as index of the robustness of individual country economies. The costs associated with this problem have led to special disclosure responsibilities for both management and auditors (Mckee, T. E. 2000). Insolvency is usually considered to apply to a company if it cannot pay its debts as they fall due, and it is the threat or occurrence of insolvency which is normally be precursor of formal restructuring arrangements (Rees, 1995). Insolvency could arise from any number of causes and there are numerous classifications of these. Table 1 presents one such listing.

Table 1: Possible causes of insolvency (Rees, 1995)

Low and declining real profitability
Inappropriate diversification – into unfamiliar industries or not away from declining ones
Import penetration into the firm's home markets
Deteriorating financial structures.
Difficulties controlling new or geographically dispersed operations.
Over-trading in relation to the capital base.
Inadequate financial control over contracts.
Inadequate control over working capital.
Failure to eliminate actual or potential loss-making activities.
Adverse changes in contractual arrangements.

There has been significant prior research on financial distress prediction using a wide variety of techniques:

- Univariate ratio models (Beaver, 1966)
- Multiple discriminant analysis (Altman, 1968)
- Linear probability models (Meyer and Pifer, 1970)
- Multivariate conditional probability models such as Probit and Logit (Ohlson, 1980)
- Recursive partitioning models (Marais *et al.*, 1984; Frydman *et al.*, 1985; Mckee, 1995a, b)
- Survival analysis (proportional hazard model) (Lane *et al.*, 1986)
- Expert systems (Messier and Hansen, 1988)

- Mathematical programming (Grupa *et al.*, 1990)
- Neural Networks (Bell, *et al.*, 1990; Tam and Kiang, 1992; Zhang *et al.*, 1999)
- Rough sets approach (Slowinski and Zopoundis, 1995)
- Genetic Algorithm (Koze, 1992; Banzhaf *et al.*, 1998; Lensberg *et al.*, 2006)
- Hybrid model with Neural network and Fuzzy rules ({Vlachos and Tolias, 2003)

Compared with these employed methods, ANNs provide an attractive alternative tool for both forecasting researchers and practitioners. Several distinguishing features of ANNs make them valuable and attractive for a forecasting task.

First, as opposed to the traditional model-based methods, ANNs are data-driven self-adaptive methods in that there are few a prior assumptions about the models for problems under study. They learn from examples and capture subtle functional relationships among the data even if the underlying relationships are unknown or hard to describe. Thus ANNs are well suited for problems whose solutions require knowledge that is difficult to specify but for which there are enough data or observations.

In addition to that, ANNs can generalize. After learning the data presented to sample, ANNs can often correctly infer the unseen part of a population even if the sample data contain noisy information. As forecasting is performed via prediction of future behaviour, it is an ideal application area for neural network.

Third, ANNs are universal functional approximator. It has been shown that a network can approximate any continuous function to any desired accuracy (Irie and Miyake, 1988). Compared with traditional statistical methods, ANNs have more general and flexible function forms can effectively deal with. Any forecasting model assumes that there exists an underlying relationship between inputs and outputs. Frequently, traditional statistical models have limitations in estimating this underlying function due to the complexity of the real system.

Last but not at least, ANNs are nonlinear. Forecasting has long been the domain of linear statistics. The traditional approaches to time series forecasting, assumes that the time series under study are generated from linear processes. Linear models have advantages in that they can be understood and analyzed in great detail, and they are easy to explain and implement. In fact, real world systems are often nonlinear. Although the formulation of a nonlinear model to a particular data set is a very difficult task since there are too many possible nonlinear patterns and a prespecified nonlinear model may not be general enough to capture all important features, ANNs, which are well-known nonlinear data-driven approach as opposed to the above model-based nonlinear methods, are capable of performing nonlinear modelling without a priori knowledge about the relationships between inputs and outputs. Thus, ANNs are more preferable in nonlinear forecasting than others.

Much of the proposed neural network development methodology is adapted from conventional software and expert systems development. Neural network development places a stronger emphasis on experimentation and multiple simulation development methods. This systematic approach is shown in Figure 1.

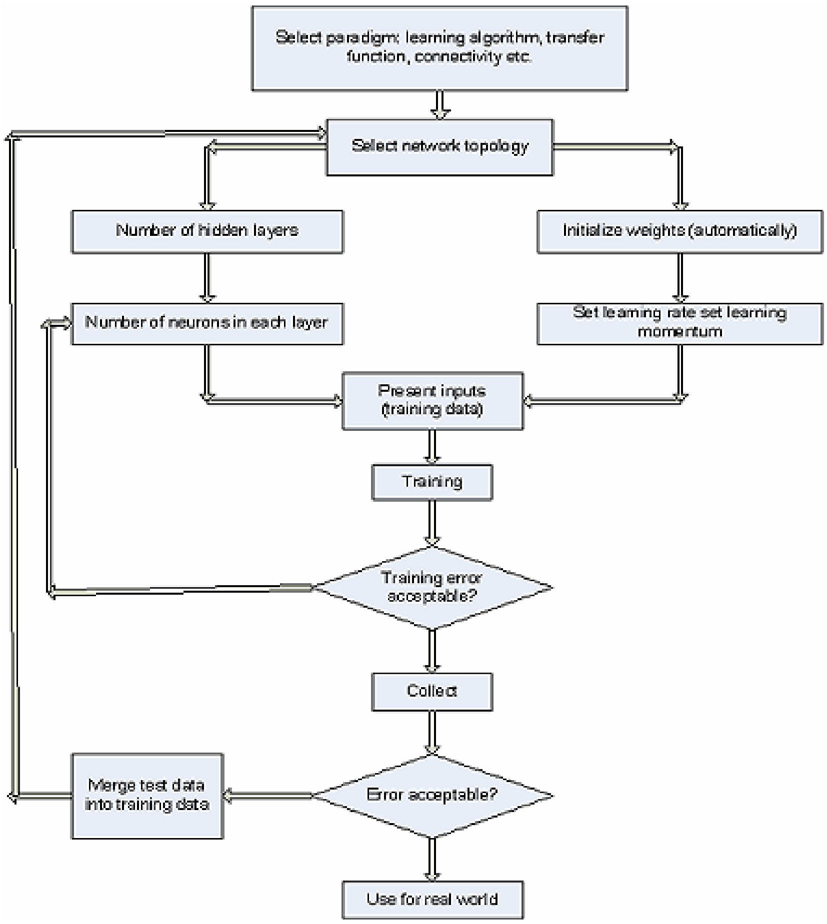

Figure 1 A systematic neural network development process (Elhag and Boussabaine, 2002)

Table 2 Common parameters in designing a neural network (Kaastra, I. and Boyd, M. 1996)

Data pre-processing
Frequency of data – daily, weekly, ,monthly, quarterly
Type data – technical, fundamental
Method of data sampling
Method of data scaling- maximum/minimum, mean/standard deviation
Training
Learning rate per layer
Momentum term
Training tolerance
Epoch size
Maximum number of runs
Number of times to randomize weights
Size of training, testing and validation sets
Topology
Number of input neurons
Number of hidden layers
Number of hidden neurons in each layer
Number of output neurons
Transfer function for each neuron
Error function

As Zhang *et al.* (2004) pointed out that, the major decisions a neural network forecaster must make include data preparation, input variable selection, choice of network type and architecture, transfer function, and training algorithm, as well as model validation, evaluation and selection.

Table 2 lists the most common parameters that a researcher must choose when designing a neural network forecasting model. As Kaastra and Boyd (1996) pointed that, the cost of such flexibility in modelling time series data is that the researcher must select the right combination of parameters. As a result of the large number of parameters and the relatively recent introduction of neural networks to finance, deciding on the appropriate network paradigm still involves much trial and error.

RESEARCH DESIGN

The sample data, which selected from FAME database, are from UK manufacturing industry. Although data are selected from manufacturing industry, these models are also applicable for construction firms, since industry-characters of those two industries are relatively similar. In order to detect maximal difference between bankrupt and nonbankrupt firms; this research employs matched samples based on some common characteristics in the data collection process. Characteristics used for this purpose include asset or capital size and sales, industry category or economic sector, geographic location, number of branches, age, and charter status, *et al.* this sample selection procedure implies that sample mixture ratio of bankrupt to nonbankrupt firms is 50% to 50%.

Financial ratios chosen to be significant tool for bankruptcy prediction study since 1960s, the classical financial ratios introduced by Altman (1968) are still popular in recent researchers in business forecasting. According to the studies of Tamari (1978), the ratios of the failed firms were consistently lower than those of the continuing firms. Furthermore, in most cases, the ratios declined several years prior to bankruptcy or failure. The ratios used can be conveniently classified into three groups according to the financial weaknesses they explore, which are liquidity ratio, gearing ratio and profitability ratio. Therefore according to those empirical researches and studies, three financial ratios (X1, X2, and X3) were selected to be predictors.

As reviewed by Aziz and Dar (2006), more than 60% of the studies used financial ratios to predict failure in firms; others employed a mix of financial ratios and other variables, from macroeconomic, industry-specific locations, to other firm-specific variables, like firm size, firm age, corporate governances structure and management practices. And also, as Adnan and Dar (2006) recommended that non-financial information is more important than financial ratios in some specific circumstance, which selected by genetic algorithm, which include firm size and firm age. Hence, firm size (X6) and firm age (X5) are selected as presents of non-financial information.

Thus, input variables involved in this experiment are a combination of financial ratios and non financial information.

Table 3 List of selected predictors

X1 (WC/TA)	**Working Capital / Total Assets**
X2 (TO/TA)	Turnover / Total Assets
X3 (CR)	Current Assets / Current Liabilities
X4 (FS)	Firm size $\log_{10}$ (Total Assets)$_t$
X5 (FA)	Firm age $\log_{10}$ (1900 +1+t-Year Founded)
	** t: the year to be predicted

Back-propagation neural network is employed to build up the prediction model, since the feedforward back-propagation architecture is the most popular, most effective and easy-to-earn model for complex, multi-layered networks, which contributes more than other types of neuron networks. This architecture has spawned a large class of network types with many different topologies and training methods. Its greatest strength is in nonlinear solutions to ill-defined problems.

There are 4 built-up models in this study, they distinct from each other by different number of nodes in hidden layer. All sample data are spited into two data sets, 80%:20% and 70%:20%. The number of iterations for training is 50,000 for each model, and one-pass for testing. Prediction accuracy will be measured in terms of ABS error (absolute error).

NN MODEL DEVELOPMENT AND RESULTS ANALYSIS

Table 4 shows prediction errors of all models with first data set. Model D with 4 hidden neurons shows better accuracy than other models, the training accuracy and testing accuracy are over 97%, which shows a remarkable performance of ANN in application of bankruptcy prediction area.

Table 4 ABS error for models with first data splitting set

Model Number	**Hidden Number**	**80 % : 20%**	
		Training	Testing
A	1	7.97%	9.63%
B	2	8.46%	9.46%
C	3	5.39%	10.81%
D	4	2.81%	2.47%

Table 5 shows prediction errors of all models with second data set. Still Model D with 4 hidden neurons shows better accuracy than other models in terms of both training and testing results.

Table 5 ABS error for models with second data splitting set

Model Number	**Hidden Number**	**70 % : 30%**	
		Training	Testing
A	1	8.54%	9.60%
B	2	8.90%	8.23%
C	3	6.74%	10.71%
D	4	2.51%	5.09%

As illustrating information in Figure 2(1), the average performances of models with first data set are much better than the other ones, which imply that the ANN models are sensitive to the data splitting set.

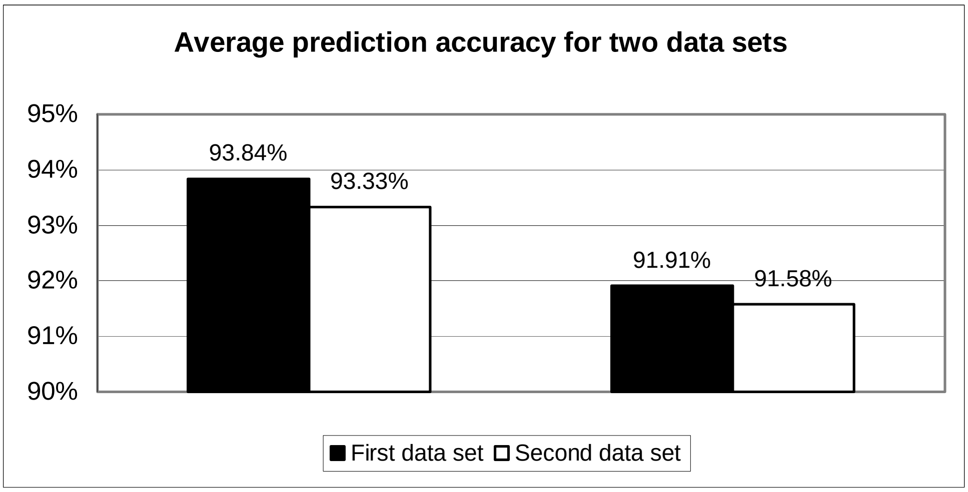

Figure 2(1) Average prediction accuracy for all models with different parameters

Figure 2(2) shows accuracy of models with different hidden node. The average performance of model with 4 hidden nodes is relatively outperformed among models, which indicates that building appropriate network architecture is the key of success.

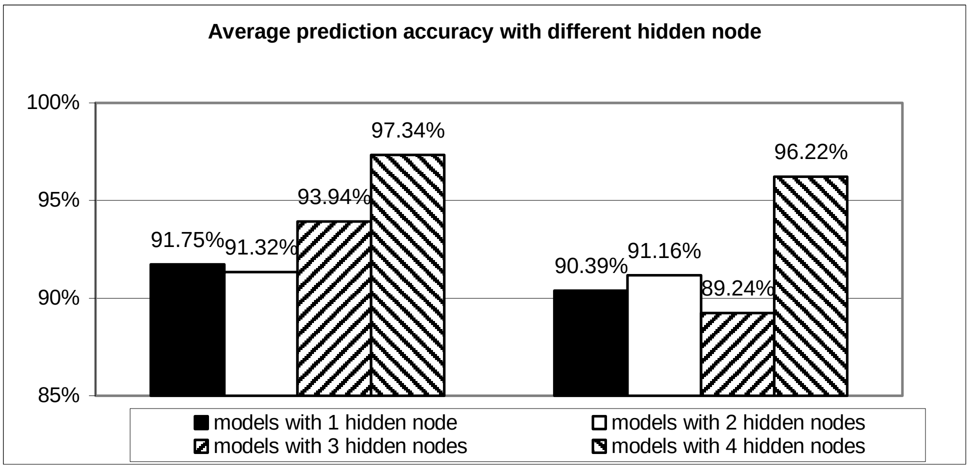

Figure 2(2) Average prediction accuracy for all models with different parameters

Compared with previous empirical researches and studies in bankruptcy prediction, the developed neural network model D with four hidden nodes in this study outperformed others, both the training and hold-out sample accuracy are up to 97%, while the accuracy of neural network models developed by Bell *et al.* (1990), Tam and Kiang (1992) and Zhang *et al.* (1999) etc, are around 90%.

CONCLUSION

In this study, 4 models were built with different parameters, such as the number of hidden neurons, data splitting set for training and testing. From these results, it can be concluded that:

First of all, Artificial Neural Network, a machine learning and self data driven technique, does play an important role in Bankruptcy Prediction; it can be a promising tool in business forecasting. Compared with the traditional statistical techniques and other popular methods used for business forecasting, the ANN is more remarkable, with its achievements in terms of training accuracy 97.19%, and testing accuracy 97.53%, while, the best classification accuracy of statistical approaches is around 96%, and the general testing accuracy of other methods is lower than 95% so far.

In the second place, it is significant to point out that building a successful neural network is a combination of art and science and software alone is not sufficient to solve all problems in the process. It is a pitfall to blindly throw data into a software package and then hope it will automatically give a statistical solution (Zhang, 2004). According to the performances of each pilot model, the highly interconnected neural network is extremely sensitive to its structure, modelling issues that affect the performance of an ANN must be considered carefully, that is the appropriate architecture, such as the size of each layer, the number of nodes in the model, the data splitting set, etc.

Last but not at least, due to the weakness of overfitting and the difficulty of choosing parameters for Artificial Neural network, the nonlinear promising tool can't applied to all circumstances probably. So far, there is no thumb guideline of how to systematically build a preferable neural network model to all application. Although the past researchers have attempted to derive some guidelines from the literature, it is still generalizing across broad problem categories. Replication of the studies using different algorithms, architectures and data preparation techniques is needed to refine these guidelines with specific application area.

There are also some limitations of this study. First , the selection of inputs variables are from up-to-data literature review, for future work, a method of how the input variables be optimally selected for ANN is needed to develop systematically, since selection inputs is one of the most important processes in bankruptcy prediction modelling. Second, due to one of the major aim of bankruptcy prediction is to provide an early warning signal for investors and banks, a multi-status output is more preferred than binary ones for future studies.

REFERENCES

Adnan, M Z and Dar, H A (2006), 'Predicting corporate bankruptcy; where we stand/', Corporate Governance, 6 (1), 18-33.

Altman, E I (1968), 'Financial ratios, discriminant analysis and the prediction of corporate bankruptcy', Journal of Finance, 23 (4), 589-609.

Anandarajan, M, Lee P, and Anandarajan, A (2001), 'Bankruptcy prediction of financially stressed firms: An examination of the predictive accuracy of artificial neural network.' International Journal of Intelligent Systems in Accounting, Finance and Management, 10 (1), 69-81.

Armstrong, J S and Fildes, R (1995), 'Correspondence: On the selection of error measures for comparisons among forecasting methods', Journal of Forecasting, 14 (1), 67-71.

Atiya, A F (2001), 'Bankruptcy prediction for credit risk using neural networks: A survey and new results.' IEEE Transactions on Neural Networks, 12 (4), 929-35.

Banzhaf, W, Nordin, P, Keller, R E and Francone, F D (1998), Genetic Algorithm-an introduction (San Francisco, CA: Morgan Kaufmann).

Beaver, W H (1966), 'Financial ratios as predictors of failure', Journal of Accounting Literature, 4, 71-111.

Bell, T B, Ribar G S and Verchio, J (1990), 'Neural nets versus logistic regression: a comparison of each model's ability of predict commercial bank failures', Proceedings of the 1990 Symposium on Auditing problems (University of Kansas), 29-54.

Elhag, T M S, Boussabaine, A H (2002), 'Tender Price Estimation Using Artificial Neural Networks II: Modelling', Journal of Financial Management of Property and Construction, 7 (1), 49-64.

Fishwick, P A (1989), 'Neural network models in simulation: A comparison with traditional modelling approaches', Proceedings of Winter Simulation Conference (Washington, D.C.), 702-10.

Frydman H, Altman, E I and Kao D (1985), 'Introducing recursive partitioning for financial classification: the case of financial distress.' Journal of Finance, 40 (1), 269-91.

Gupta Y P, Rao R P and Baggi, P K (1990), 'Linear goal programming as an alternative to multivariate discriminant analysis: a note.' Journal of Business, Finance and Accounting, 17 (4), 593-98.

Irie, B and Miyake, S (1988), 'Capabilities of three-layered perceptions.' Proceedings of the IEEE International Conference on Neural Networks (I), 641-48.

Kaastra, I. and Boyd, M. (1996), 'Designing a neural network for forecasting financial and economic time series', Neurocomputing, 10 (2), 215-36.

Koze, J R (1992), 'Genetic Programming: on the programming of computers by means of natural selection.' (Massachusetts Institute of Technology).

Kumar, P R and Ravi, V (2006), 'Bankruptcy prediction in banks and firms via statistical and intelligent techniques-a review', European Journal of Operational Research, August, Article in press.

Lane, W R, Looney, S W and Wansley W (1986), 'An application of the Cox proportional hazards model to bank failure', Journal of Bank and Finance, 10, 511-31.

Lensberg, T, Eilifsen, A and Mckee, T E (2006), 'Bankruptcy theory development and classification via genetic programming', European Journal of Operational Research, 169, 677-97.

Marais, M, Patell, J and Wolfson, M (1984), 'The experimental design of classification models: recursive partitioning and bootstrapping to commercial bank loan classifications. ‘Journal of Accounting Literature, 22, 87-114.

Mckee, T E (1976), 'Discriminant prediction of going concern status: a model for auditors.' Sixtieth American Accounting Association Annual Meeting, 294-321.

Mckee, T E (1995a), 'Predicting bankruptcy via induction ', Journal of Information Technology, 10, 26-36.

Mckee, T E (1995b), 'Predicting bankruptcy via induction: an extension', in Bonson Sierra G.J., E. (ed.), Artificial intelligence in Accounting, Finance, and Tax (Huelva, Spain: J. Carrasco).

Mckee, T E (2000), 'Developing a Bankruptcy Prediction Model via Rough Set Theory', International Journal of Intelligent Systems in Accounting, Finance and Management, 9 (3), 159-73.

Messier, W F and Hansen J V (1988), 'Inducing rules for expert system development: an example using default and bankruptcy data', Management Science, 34 (12), 1403-15.

Meyer, P A and Pifer, H W (1970), 'Prediction of bank failures', Journal of Finance, 25, 853-68.

Ohlson, J (1980), 'Financial ratios and the probabilistic prediction of bankruptcy', international Journal of Intelligent Systems in Accounting, Finance and Management, 7 (1), 187-97.

Pawlak, Z (1982), 'Rough Sets', International Journal of Information and Computer Sciences, 11 (3), 341-56.

Rees, B (1995), Financial analysis (second edition: Prentice Hall).

Slowinski, R and Zopounidis, C (1995), 'Application of the rough set approach to evaluation of bankruptcy risk', International Journal of Intelligent Systems in Accounting, Finance and Management, 4 (1), 27-41.

Tam, K Y and Kiang, M. Y. (1992), 'Managerial application of neural networks: The case of bank failure predictions', Management Science, 38 (7), 926-47.

Vlachos, D and Tolias, Y A (2003), 'Neuro-Fuzzy Modelling in Bankruptcy Prediction', Journal of Operational Research, 13 (2), 165-74.

Yang, Z R, Platt, M B and Platt, H D (1999), 'Probabilistic neural networks in bankruptcy prediction', Journal of Business Research, 44 (1), 67-74.

Zhang, G P, Patuwo, P, and Hu, M Y (1998), 'Forecasting with artificial neural networks: The state of art. ‘International Journal of Forecasting, 14 (1), 35-62.

Zhang, G P, Hu, Y M, Patuwo, B E and Indro, D C (1999), 'Artificial neural networks in bankruptcy predictions: General framework and cross-validation analysis.' European Journal of Operational Research, 116 (1), 16-32.

Zhang, G P (2004), 'Business Forecasting with Artificial Neural Networks: An Overview', Business Forecasting with Artificial Neural Networks (Georgia State University, USA), 1-22.