Time Series Model for Bankruptcy Prediction via Adaptive Neuro-Fuzzy Inference System

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Abstract

Bankruptcy prediction has been addressed by many researchers in the field of finance since few decades. One of the best approaches to deal with this issue is considering it as a classification problem. In this paper a time series prediction model of bankruptcy via Adaptive neuro-fuzzy inference system (ANFIS) is formulated, which is capable of predicting the bankruptcy of a firm for any future time. The data used in this study has been extracted from the past financial records of ongoing and failed enterprises. The extracted financial ratios are preprocessed by calculating Altman's Z-score before feeding into Time series model. The Time series prediction is carried out using ANFIS to predict the bankruptcy at any given time which overcomes the limitation of Altman's basic model of bankruptcy prediction. Fuzzy Logic Tool box of MATLAB has been exploited for simulations and evaluation of the model. Numerical illustration is provided to demonstrate the efficiency of proposed model.

Keywords: *ANFIS, Bankruptcy prediction, Financial Ratios, Time series, Uncertainty, Z-Score*

1. Introduction

The financial position of a firm and its susceptibility for bankruptcy may critically affect the health of stakeholders like shareholders, creditors, employees, and business partners. Hence, the bankruptcy projection is of great interest to researchers and has become a common research topic in multiple disciplines. A large number of standardized financial ratios are utilized for the assessment of the financial state of a company. Bankruptcy prediction may help the investors to avoid huge economic losses. Financial ratios are also used by security analysts for the purpose of comparison between the strengths and weaknesses of different firms.

Several previous studies on business failure prediction have appeared in literature not only pertaining to neural network, but also to discriminant analysis, factorlogistic analysis and genetic algorithm. Numerous models have been developed to predict bank failures since the early 70s. These models are typically formulated as classification problems in a multidimensional space defined by a set of financial ratios. They differ in their assumptions in the form of discriminant function and sample distribution. Techniques used by these bankruptcy models include regression analysis [18, 29], multivariate discriminant analysis [25, 27], multivariate probit or logit analysis [11, 17], arctangent regression analysis [15] and factor analysis [33]. Although widely practiced, these models have been criticized for their problematic methodologies [10], and a satisfactory model is yet expected to be developed. Kolari, *et al.*, [14] used the logistic regression model based on some distinguishing variables in studies of classification, especially in bankruptcy prediction domain; whereas Tsai [32] found that the variables selected by T-statistic method are more stable and accurate in prediction of bankruptcy than other statistical feature selection methods. The limitations of discriminant analysis have motivated interests in developing alternative methods for predicting bankruptcy. [5, 7, 16] considered Type I and Type II errors as performance measures in bankruptcy prediction problem. Lin [16] determined the classification of a firm based on a cutoff value to balance Type I and Type II errors. He considered a firm with a predicted value greater than this cutoff value to be a bankrupt firm, otherwise a healthy firm. On one hand, [7] computed prediction accuracy as the percentage of the firms that are correctly classified to the healthy or bankrupt firms whereas on the other hand [5] considered Type I error to be more critical than Type II error in bankruptcy prediction problem.

Recent advances in artificial intelligence have introduced a machine learning approach to the bankruptcy prediction problem. Santomero and Vinso [24] estimated the probability of failure of commercial banks and the banking system. A study by Messier and Hansen [19] has demonstrated the usefulness of machine learning techniques for predicting corporate failures. Their method employs the ID3 algorithm [21, 22], which takes in examples of failed and non-failed corporations and generates a decision procedure in the form of a classification tree. Similar methods have been applied in other areas such as credit scoring [6] and loan evaluation [27]. Because of their symbolic nature, these techniques are recommended as knowledge acquisition tools for expert systems development [30]. Anandarajan, *et al.*, [3] put forward an application of NN generic algorithm using back propagation networks for prediction of bankruptcy. Atiya [4] developed a NN bankruptcy prediction model inspired by traditional credit risk models developed by Merton. A detailed review of structural credit risk models is presented by Crouhy, *et al.*, [9]. Santos, *et al.*, [25] performed analysis of the evolution of various financial indicators for a 3 years period and developed a framework encompassing around 16 models.

The most acceptable model of bankruptcy prediction, the Z-score model developed by Altman, came in the late 60’s [1]. The five variable Z-score model using Multiple Discrimination Analysis (MDA) showed very strong predictive power. Since mid 1980’s, neural networks have become the dominant research area in artificial intelligence and researchers have actively applied neural networks to classification problems including bankruptcy prediction. Tam and Kiang [31] use a set of financial ratios collected from a group of Texan banks. They show that Artificial Neural Network (ANN) with Multilayer Perceptron architecture is generally more accurate for predictions than are MDA, LR, k-Nearest Neighbor (k-NN), and the ID3 algorithm. Jo, Han and Lee [13] compared ANNA, MDA and Case Based Reasoning (CBR). They find correct classification in 83.79% of cases with ANNA, 82.22% with MDA, and 81.52% with CBR. Sharda and Patil [26] used 75 series from a systematic sample of 111 series and found that artificial neural network models performed as well as the automatic Box-Jenkins (Autobox) procedure. In the 36 deleted series, however, neither the artificial neural network nor Autobox models had enough data to estimate the models. The use of data mining techniques such as Artificial Neural Networks (ANN), decision trees and Support Vector Machine (SVM) for bankruptcy prediction started in the late 1980 [28].

Shin and Lee [28], applied a genetic algorithm for extracting meaningful rules for bankruptcy prediction. In their study, they also refer to numerous other artificial applications in bankruptcy. They use nine financial ratios to describe each of their 528 manufacturing cases, but the genetic algorithm based model for prediction finally uses only five of them. Recently, improvements have been proposed for the back-propagation algorithm and alternative artificial neural network models have been proposed. These improvements and alternatives will also need the same rigorous evaluation in managerial tasks such as forecasting and decision making.

In reality, the financial ratios fluctuate due to economic factors, which include interest rates, taxation changes, economic growth, inflation and exchange rates. Higher interest rates may deter investment because it costs more to borrow, a strong currency may make exporting more difficult because it may raise the price in terms of foreign currency, inflation may provoke higher wage demands from employees and raise costs, and higher national income growth may boost demand for a firm's products. The variation in financial data is also guided by the business cycle; especially recession. That is why it is difficult to quantify the values of these ratios with certainty. Fuzzy logic is utilized in dynamic surroundings to handle such variations and uncertainties. Fuzzy modeling, along with other techniques especially neural network, is recognized as a powerful tool that can facilitate the effective development of prediction models. The rule-based nature of fuzzy models allows better use of information expressed in the form of natural language statement and consequently, makes the models interpretation easier [8]. According to Purvinis, *et al.*, [20], conventional methods like fuzzy interpretability in terms of IF THEN rules instead of neural networks can be used for forecasting. Zanganeh, *et al.*, [34] used ANFIS and selected 25 initial variables extensively used in the bankruptcy prediction literature as stated by Ravi Kumar and Ravi [23]. Because fuzzy theory has intrinsic features of linguistic variables, it can minimize trouble on dealing with uncertain problems. The concept of fuzzy logic primarily focuses on people’s perception measurement instead of the precise and crisp measurement. Thus fuzzy logic combined with time series proves to be the best method which combines linguistic variables with the analyzing process of applying fuzzy logic into time series to solve the fuzziness of data.

The rest of this paper is organized as follows. Section 2 provides a brief overview of ANFIS architecture and it’s working. Section 3 discusses the formulation methodology for the proposed model consisting of preprocessing of financial data using the famous Altman’s Z-score calculation and time series prediction. Section 4 emphasizes on the prominence of the model with an experiment and its test results and finally, Section 5 presents summary and conclusion of this study.

2. ANFIS Overview

The Adaptive Network-based Fuzzy Inference System (ANFIS) proposed by Roger Jang [12] is one of the most commonly used fuzzy inference systems. ANFIS can serve as a basis for constructing a set of fuzzy ‘if-then’ rules with appropriate membership functions to generate the stipulated input-output pairs. Here, the membership functions are tuned to the input-output data and excellent results are possible. Fundamentally, ANFIS is about taking an initial Fuzzy Inference System (FIS) and tuning it with a back propagation algorithm based on the collection of input-output data. The basic structure of a fuzzy inference system consists of three conceptual components: A rule base, which contains a selection of fuzzy rules; a database, which defines the membership functions used in the fuzzy rules; and a reasoning mechanism, which performs the inference procedure upon the rules and the given facts to derive a reasonable output or conclusion. A basic fuzzy inference system consists of 5 layers as shown in Figure 1.

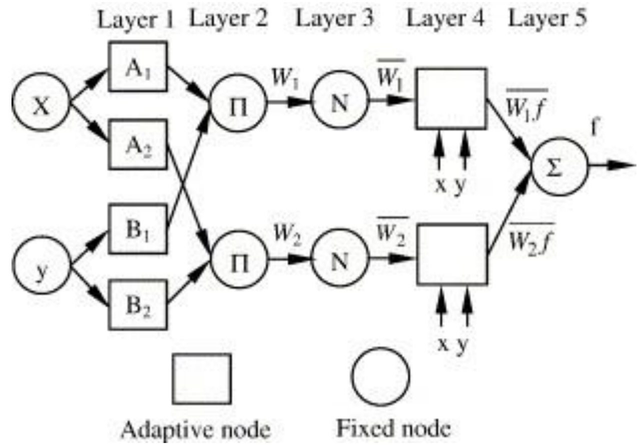


Figure 1. The Architecture of ANFIS Network

The node in the i^{th} position of the k^{th} layer is denoted as $O_{k,i}$, and the node functions in the same layer are of the same function family as described below:

Layer 1: This layer is the input layer, and every node i in this layer is a square node with a node function. $O_{1,i}$ is the membership function of A_i , and it specifies the degree to which the given x satisfies the quantifier A_i . Usually, we select the bell-shaped membership function as the input membership function, with maximum equal to 1 and minimum equal to 0.

$$O_{1,i} = \mu A_i(x) \qquad for\ i = 1,2... \tag{1}$$

where,

$$\mu A_i(x) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i}\right)^2\right]^{bi}}$$

where a_i , b_i and c_i are the parameters, b is a positive value and c denotes the center of the curve.

Layer 2: Every node in this layer is a square node labeled Π which multiplies the incoming signals and sends the product out by equation (2):

$$O_{2,i} = W_i = \mu A_i(x) \times \mu B_i(y) \qquad for\ i = 1,2,... \tag{2}$$

Layer 3: Every node in this layer is a square node labeled N. The i^{th} node calculates the ratio of the i^{th} rule's firing strength to the sum of all rules' firing strengths by the equation (3). Output of this layer can be called normalized firing strengths.

$$O_{3,i} = \bar{W}_i = \frac{W_i}{W_1 + W_2} \qquad for\ i = 1,2... \tag{3}$$

Layer 4: Every node i in this layer is a square node with a node function as seen from equation (4). Parameters in this layer will be referred to as consequent parameters.

$$O_{4,i} = \bar{W}_i f_i = \bar{W}_i \left(p_i + q_i + r_i \right) \tag{4}$$

where p_i, q_i and r_i are the parameters.

Layer 5: The single node in this layer is a circle node labeled Σ that computes the overall output as the summation of all incoming signals refers equation (5).

$$O_{5,i} = \sum \bar{W}_i f_i = \frac{\sum \bar{W}_i f}{\sum W_i} \tag{5}$$

ANFIS is tuned with a back propagation algorithm based on the collection of input–output data.

3. Model Formulation

Preprocessing is carried out on the financial ratios for calculating Z-score to prepare the training and test data set for ANFIS.

3.1. Z-Score Calculation on Financial Ratios

In Altman's study [1, 2], five ratios were determined as jointly being the best overall discriminators between business viability and failure. Altman's final discriminant function was

$$Z = 1.22\, x_1 + 1.4\, x_2 + 3.3 x_3 + 0.6 x_4 + 0.999 x_5 \tag{6}$$

where,

x_1 = Working Capital/Total Assets

x_2 = Retained Earnings/Total Assets

x_3 = EBIT/Total Assets

x_4 = Market Value of Equity/Book Value of Total Debt

x_5 = Sales/Total Assets

Z = Overall Index (Altman's Z score)

Given the values of the discriminant coefficients, it is possible to calculate a discriminant overall index called Altman's Z score for a firm. Based on critical value observations, Altman found that a Z score of 2.675 best discriminated between bankrupt and non-bankrupt firms; firms with Z scores above 2.675 generally were healthy, while firms with Z scores below 2.675 generally were financially distressed. The proposed model uses the results of the Altman Z score as an input to pattern classification of healthy and financially distressed firms. It is done so because Altman's findings have been the most widely and consistently referenced and used to date by both researchers and practitioners.

The proposed model which combines Altman's model with time series methodology is motivated by the following considerations:

(a) Altman's method can effectively predict for up to two years preceding failure, but not for later years.

(b) Altman's prediction technique has reference to business bankruptcy. The data used in this study also consists of financially distressed, but non-bankrupt firms. In two succeeding years, the firms may not necessarily become bankrupt but it may survive for few more years. This model combined with Altman's model can predict the possibility of failure of such firms in next p years.

(c) Altman used the actual year of failure as the most current year for his tests. The proposed model considers a set of historical data in the form of financial ratios, calculate their corresponding Z scores and then predict the same for future time period.

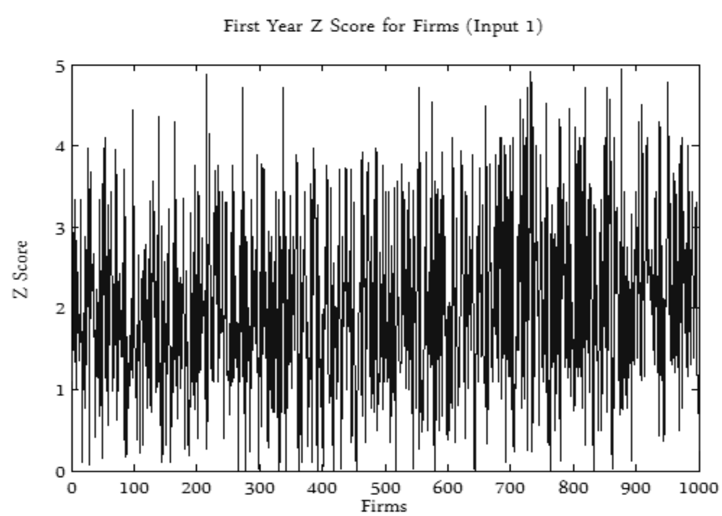
3.2. Time Series Prediction via ANFIS

The training data for ANFIS consists of the Z-score calculated in the previous section. From the whole set of collected data, around 2012 sets are used for training ANFIS and 480 sets are used testing the performance results of the model. With a proper training scheme and fine filtered data-sets, ANFIS is capable of predicting the financial status of firms quite accurately since it learns from the training data. Since the training is required only once, this model makes itself immediately available for operation as and when required.

In time series prediction, the past values of Altman's Z-score up to time 't' are used as input and the objective is to predict the Z value at some future time '$t+p$'. From the predicted Z value the firm can be classified easily into Bankrupt or non-Bankrupt in coming years. The standard method for this type of prediction is to create a mapping from D points of the time series spaced 'Δ' apart; that is $\left[x\left(t-\left(D-1\right)\Delta\right)\right]...x\left(t-\Delta\right),x\left(t\right)$ to predict a future value $x\left(t\ +\ p\right)$.

4. Experiment and Results

The ANFIS model that can predict $x(t$ + p) from the past values of Z score, the training data format is [x(t -6), x(t-4), x(t- 2), x(t); x(t + 2)]. For instance, if the data of current year relates to year 2010 and prediction is to be done for 2013, then the input data format will become [x(2010-9), x(2010-6), x(2010- 3), x(2010); x(2010 + 3)], *i.e.*, Z scores of 4 years from 2001 to 2010. The plots of training data for four years used in the form of input vector are shown in Figure 2.



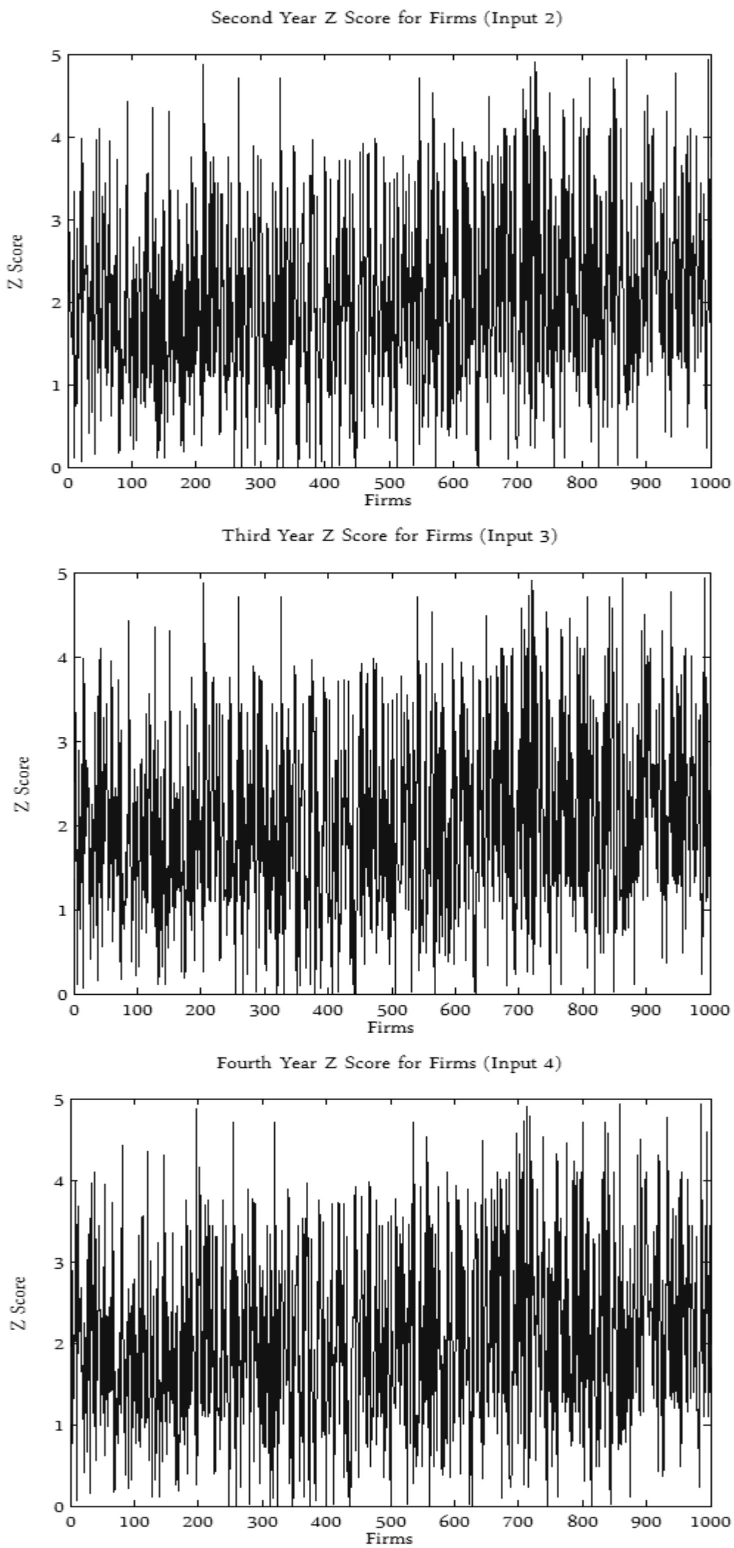


Figure 2. Training Input Data used for ANFIS Prediction

The Fuzzy Logic Toolbox of MATLAB is used to develop the ANFIS model with 4 inputs and single output as given in Figure 3.

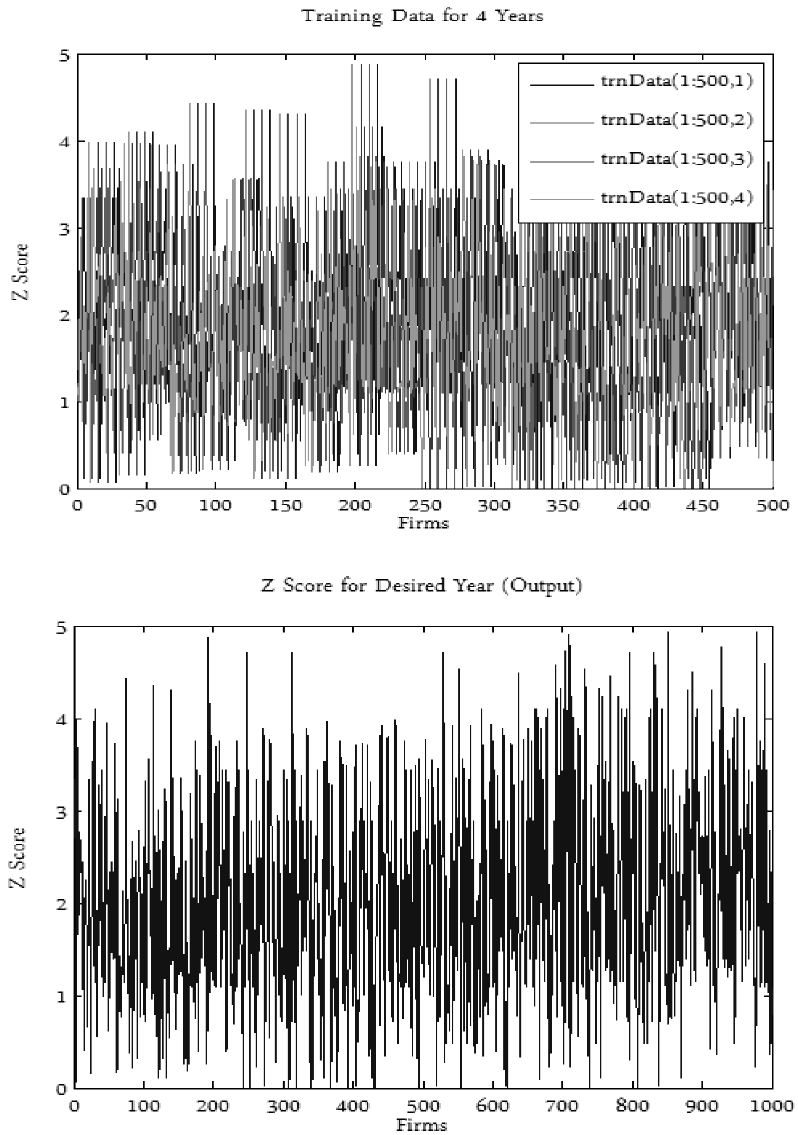


Figure 3. Training Input-Output Data used for ANFIS Prediction

Figure 4 depict the comparison between the expected actual output and the output produced by ANFIS. The result of ANFIS prediction and its corresponding errors are presented in Figure 5.

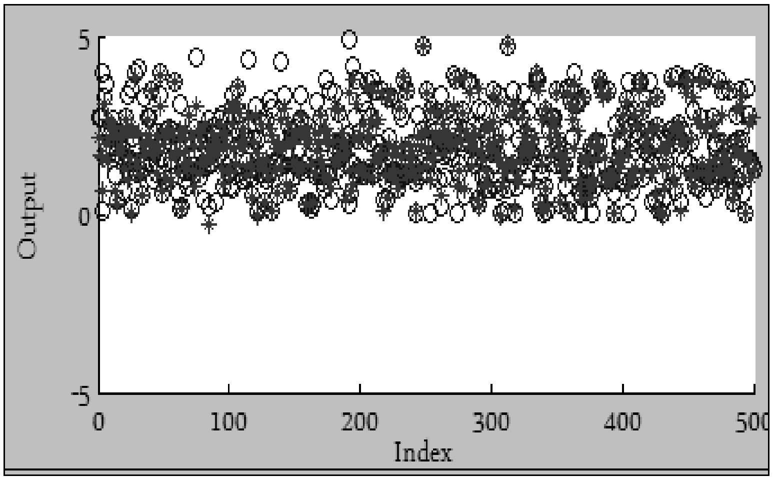


Figure 4. Actual Output (in o) vs. FIS Output (in *)

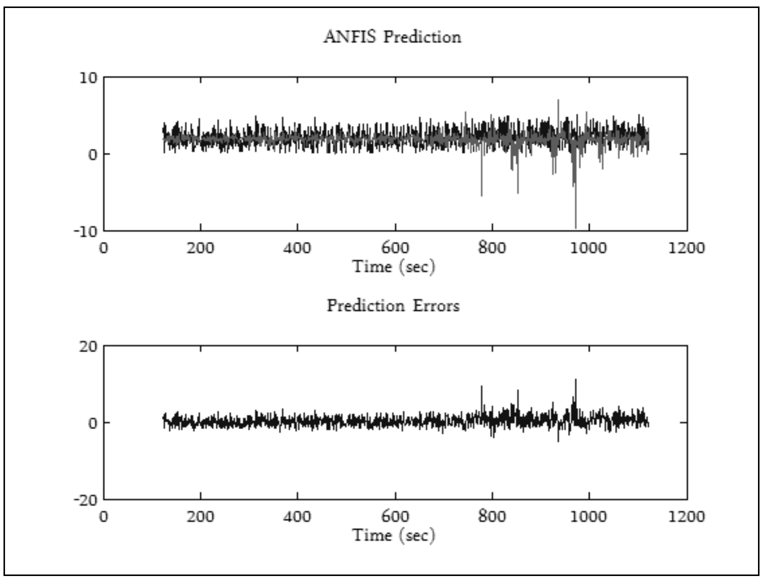


Figure 5. ANFIS Prediction and Corresponding Errors

Table 1 shows the performance of prediction done by ANFIS model for next 4 years obtained using 1000 sample training data sets and 3 gbell membership functions.

Table 1 Statistics for Comparison of Prediction Model Performance

Prediction	Training Data	Training RMSE	Checking RMSE	Prediction Error
t + 1	1000	0.5994	0.0847	0.8506
t + 2	1000	0.6441	1.0451	0.6511
t + 3	1000	0.3659	0.2954	0.3872
t + 4	1000	0.4397	0.3026	0.6182
t + 4	2000	0.4725	0.3911	0.3204

From the 5 runs performed for next 4 years, it is obvious to note that the training error is higher than the checking error. It is observed that the prediction error decreases for first three years and then starts increasing from the 4^{th} year onwards. For the two runs performed for 4^{th} year, it can be concluded that for better prediction of farther years, ANFIS requires longer training with more number of training data.

Figure 6 shows the non-linear surface of the Sugeno Fuzzy model for the problem of time series prediction. As per the above discussion, ANFIS with four inputs and three membership functions per input is used. The ANFIS structure consisting of 12 input membership functions and 81 rules is shown in Figure 7.

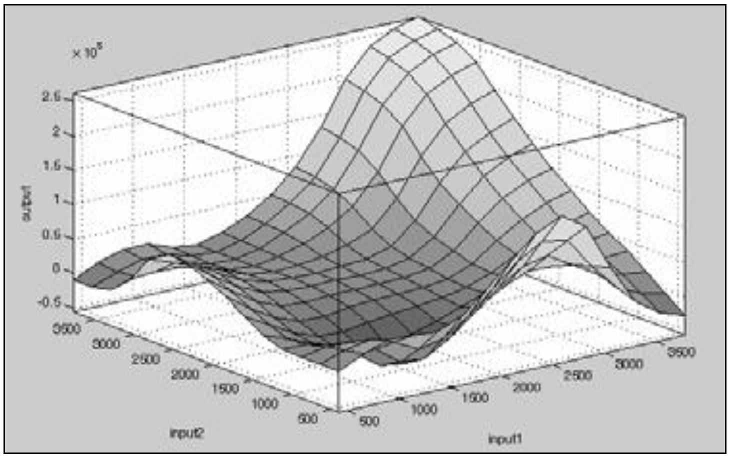


Figure 6. Input/Output Surface View of ANFIS

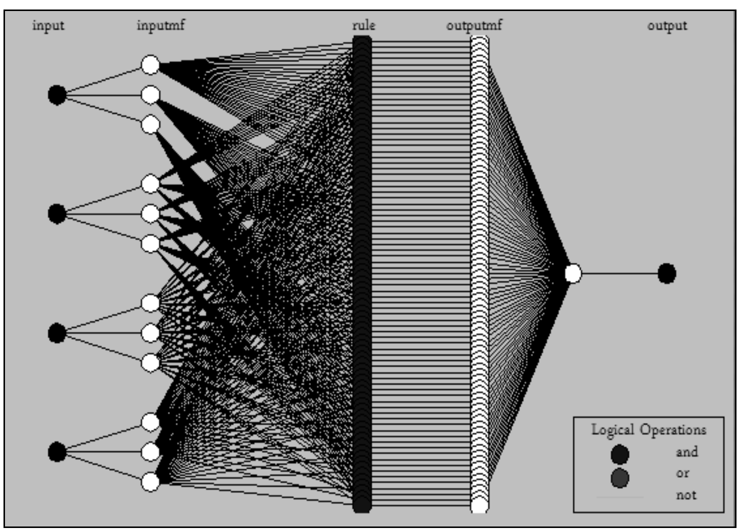


Figure 7. ANFIS Structure

The functions used in the simulation and evaluation are as follows:

GENFIS1 – This function generates a Sugeno type Fuzzy Inference System for Adaptive Neural Network training using a grid partition method. As multiple input/single output FIS was required, a file consisting of input data is passed as an argument to this function. The input data contains total $N+1$ columns, where the first N columns represent the input data, and the last column stands for the output data.

EVALFIS – This function performs fuzzy inference calculations to simulate the Fuzzy Inference System for the input data 'U' and returns the output data 'Y'. For a system with N input variables and output variables, 'U' is $M \times N$ matrix, each row being a particular input vector and Y is $M \times L$ matrix, each row being a particular output vector.

5. Summary and Conclusion

The number of failed banks has reached a matchless height since the great Depression. Research in developing predictive models for bank failures is therefore warranted and desirable in this turbulent period. ANFIS shows very good learning and prediction capabilities, which makes it an efficient tool to deal with uncertainties encountered in this venture. The significance of the proposed model is the ability to predict the financial strength of firms at any future time. The implementation of ANFIS model is less complicated than that of sophisticated identification and optimization procedures. Compared to fuzzy logic systems, ANFIS has automated identification algorithm and easier design and compared to neural networks it has less number of parameters and faster adaptation. Neural networks take time to learn but once trained, they can offer an equitable performance because they are model-independent and flexible enough to adapt any functional forms. Moreover, this model adopts a neural network design that minimize over-fitting. Over-fitting is minimized because the neural network's training is halted when performance starts to decline. From the results of experiment conducted, a major conclusion can be drawn that the prediction capability of the model depends on the size of data used for training. Combined with Altman's *Z*-score, ANFIS based time series prediction model is unique and novel as it is simple, reliable and the chances of mis-predictions are least.

References

[1] E. I. Altman, "Financial Ratios, Discrimination Analysis and the Prediction of Corporate Bankruptcy", Journal of Finance, **(1968)**, pp. 589-609.
[2] E. I. Altman, "Corporate Financial Distress and Bankruptcy", New York, NY: John Wiley and Sons, **(1993)**.
[3] M. Anandarajan, P. Lee and A. Anandarajan, "Bankruptcy predication using neural networks", Article in Business Intelligence Techniques: A Perspective from Accounting and Finance, M. Anandarajan, A. Anandarajan and C. Srinivasan (eds.) Germany: Springer-Verlag, **(2004)**.
[4] A. F. Atiya, "Bankruptcy Prediction for Credit Risk Using Neural Networks: A Survey and New Results", IEEE Transactions on Neural Networks, vol. 12, no. 4, **(2001)**.
[5] A. Aziz and A. Humayon, " Corporate bankruptcy: where we stand?", Corporate Governance, vol. 6, **(2006)**, pp. 18-33.
[6] C. Carter and J. Catlett, "Assessing Credit Card Applications Using Machine Learning", IEEE Expert, vol. 2, no. 3, **(1987)**, pp. 71-79.
[7] C. B. Cheng, C. L. Chen and C. J. Fu, "Financial distress prediction by a radial basis function network with logit analysis learning", Computers & Mathematics with Applications, **(2006)**, pp. 579–588.
[8] S. Chokri, "Fuzzy neural model for bankruptcy prediction", The Business Review, **(2007)**.
[9] M. Crouhy, D. Galai and R. Mark, "A comparative analysis of current credit risk models", Journal of Banking & Finance, vol. 24, **(2000)**, pp. 59–117.
[10] R. A. Eisenbeis, "Pitfalls in the application of discriminant analysis in business, finance and economics", The Journal of Finance, vol. 32, no. 3, **(1977)**, pp. 875-900.
[11] G. A. Hanweck, "Predicting bank failures, Research Papers in Banking and Financial Economics", Financial Studies Section, Board of Governors of the Federal Reserve System, Washington, DC, **(1977)**.

[12] J. -S. R. Jang, "ANFIS: Adaptive-network-based fuzzy inference system", IEEE Transactions on Systems, Man and Cybernetics, vol. 23, no. 3, **(1993)**, pp. 665–685.
[13] H. Jo, I. Han and H. Lee, "Bankruptcy prediction using case based reasoning, neural networks, and discriminant analysis", Expert System Application, vol. 13, no. 2, **(1997)**, pp. 97-108.
[14] J. Kolari, D. Glennon, H. Shin and M. Caputo, "Predicting large US commercial bank failures", Journal of Economics and Business, vol. 54, no. 321, **(2002)**, pp. 361–387.
[15] L. Korobow and D. Stuhr, "Performance measurement of early warning models", Journal of Banking & Finance, vol. 2, no. 9, **(1985)**, pp. 267-273.
[16] T. H. Lin, "A cross model study of corporate financial distress prediction in Taiwan: Multiple discriminant analysis, logit, probit and neural networks models", Neurocomputing, **(2009)**, pp. 3507-3516.
[17] D. Martin, "Early warning of bank failure, a logit regression approach", Journal of Banking & Finance, vol. 1, no. 3, **(1977)**, pp. 249-276.
[18] P. A. Meyer and H. Pifcr, "Prediction of bank failures", Journal of Finance, vol. 25, **(1970)**, pp. 853-868.
[19] W. F. Messier and J. Hansen, "Inducing rules for expert system development: An example using default and bankruptcy data", Management Science, vol. 12, **(1988)**, pp. 1403-1415.
[20] O. Purvinis, R. Virbickait˙e and P. Sukys, "Interpretable Nonlinear Model for Enterprise Bankruptcy Prediction", Nonlinear Analysis: Modeling and Control, vol. 13, no. 1, **(2008)**, pp. 61–70.
[21] J. R. Quinlan, "Discovering rules by induction from large collection of examples", In Expert Systems in Micro Electronic Age, Edinburgh University Press, **(1979)**.
[22] J. R. Quinlan, "Induction of decision trees", Machine Learning, vol. 1, no. 1, **(1986)**, pp. 81-106.
[23] P. R. Kumar and V. Ravi, "Bankruptcy prediction in banks and firms via statistical and intelligent techniques – A review", European Journal of Operational Research, vol. 180, no. 1, **(2007)**, pp. 1–28.
[24] A. M. Santomero and J. Vinso, "Estimating the probability of failure for commercial banks and the banking system", Journal of Banking & Finance, vol. 1, no. 2, **(1977)**, pp. 185-205.
[25] M. F. Santos, P. Cortez, J. Pereira and H. Quintela, "Corporate bankruptcy prediction using data mining techniques", WIT Transactions on Information and Communication Technologies, vol. 37, **(2006)**.
[26] R. Sharda and R. Patil, "Neural Networks as Forecasting Experts: An Empirical Test", Proceedings of the 1990 International Joint Conference on Neural Networks Meeting, vol. 2, **(1990)**, pp. 491-494.
[27] M. J. Shaw and J. Gentry, "Using an expert system with inductive learning to evaluate business loans", Financial Management, vol. 17, no. 3, **(1988)**, pp. 45-56.
[28] K. S. Shin, T. S. Lee and H. J. Kim, "An application of support vector machines in bankruptcy prediction model", Expert Systems with Applications, vol. 28, **(2005)**, pp. 127-135.
[29] J. F. Sinkey, "A multivariate statistical analysis of the characteristics of problem banks", Journal of Finance, vol. 30, no. 1, **(1975)**, pp. 21-36.
[30] K. Y. Tam, "Automated construction of knowledge bases from examples", Information Systems Research, vol. 1, no. 2, **(1990)**, pp. 144-167.
[31] K. Y. Tam and M. Y. Kiang, "Managerial applications of neural networks: The case of bank bankruptcy", OMEGA, vol. 19, no. 5, **(1992)**, pp. 429-445.
[32] C. F. Tsai, "Feature selection bankruptcy prediction", Knowledge-Based Systems, vol. 22, no. 2, **(2009)**, pp. 120-127.
[33] R. G. West, "A factor-analytic approach to bank condition", Journal of Banking & Finance, vol. 9, no. 2, **(1985)**, pp. 253-266.
[34] T. Zanganeh, M. Rabiee and M. Zarei, "Applying Adaptive Neuro-Fuzzy Model for Bankruptcy Prediction", International Journal of Computer Applications, vol. 20, no. 3, **(2011)**.

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