Prediction of Financial Distress Companies on Bursa Malaysia Using Adaptive Neuro-Fuzzy Inference System

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***Abstract*— Financial distress prediction has been a topic of great interest over decades, not only to managers, but also to the external stakeholders of a company. The aim of this study is to examine the ability of the adaptive neuro-fuzzy inference system (ANFIS) in predicting the financial distress of public listed companies in Malaysia. The analysis is based on a sample of companies classified as PN17 by Bursa Malaysia over the period 2010-2015. The financial data of the distressed and financially healthy companies was collected for five years prior to classification as a PN17 company. Five financial ratios exist in the Altman model were used as the input variables. The results of this study indicate that the adaptive neuro-fuzzy inference system model has an accuracy rate of 86% prior to financial distress. This study will be useful to financial institutions, investors, creditors and auditors to identify companies that are likely to fall into financial distress.**

Keywords—ANFIS; Financial Distress; Prediction Model

I. Introduction

Financial distress prediction is one of the most popular issues which has been extensively studied in the finance literature over the past few decades. The corporate financial distress refers to a situation where a company's operating cash flows are not sufficient to satisfy the current financial obligations such as the trade credit and interest expenses.

Incidences of company failure affect many stakeholders and parties such as shareholders, suppliers, creditors, customers, employees and management itself. Laitinen and Kankaanpaa [1] asserted that due to its 'contagion-effects', the costs arising from the failure of a firm with a large network of related companies may cause a negative spiral to the general economic environment.

In Malaysia, companies that fall under the financial distress condition are classified as the PN17 companies (Practice Note 17). These companies are given temporary recovery period and required to restructure their financial affair. As at 1st June 2015, 21 companies falls under the PN17 classification which represent 2.32% of the total number of 907 listed companies on the Bursa Malaysia. The increasing number of these companies could undermine the public confidence and image of the Malaysian capital market. Therefore, the accurate and reliable financial distress prediction models are critically important to the listed companies so that they can take corrective actions in order to avoid financial distress and delisting.

This study develops a financial distress prediction model for the public listed companies in Malaysia using the Adaptive Neuro-Fuzzy Inference System (ANFIS). The analysis was based on a sample of companies which classified as PN17 by the Bursa Malaysia over the period of 2010-2015. The developed model achieved about 86% prediction accuracy when it was applied to forecast the financial distress on the sample under investigation.

The rest of the paper is organized as follows; Section 2 provides the evidence presented in the literature; Section 3 discusses the methodology; Section 4 presents the findings of the study; and Section 5 briefly summarizes the paper and provides some suggestions for future research.

II. Literature Review

Since the late 1960s, various techniques have been employed to accurately predict the financial distress of companies. Early approaches were based on the statistical methods pioneered by Beaver [2] who used univariate discriminant analysis to distinguish between failure and non-failure companies. A few years later, Altman [3] extended the Beaver's approach and developed a statistical model using the multiple discriminant analysis technique. The model which serves as a benchmark for the financial distress studies, was based on a score derived from a linear combination of five financial ratios which are the working capital, retained earnings, sales and earnings before interest and taxes to the total assets, and market value of equity to the book value of the total debt.

Although the Altman's multiple discriminant analysis model showed good accuracy, it has been criticized for several restrictive assumptions, such as linear separability, multivariate normality, and independence among input variables, which did not hold in the case of real applications. In order to overcome such limitations, some studies have proposed logit or logistic regression analysis to construct the predictive models. The first attempt was made by Ohlson [4] who developed a model with

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nine independent variables and found that the model could correctly predict over 92% of the failed companies two years earlier. The logit analysis has also been applied in the Malaysian context in several studies over the past two decades [5-6].

In the recent years, there has been a dramatic increase in the number of studies which supported the use of artificial neural networks (ANN) over the traditional statistical methods [7-9]. ANN is a nonlinear model that is easy to use and do not require any restrictive assumptions, such as linearity, normality as well as independence among input variables. The major drawback of ANN is its 'black box' data processing structure and the rules derived which are not easily understandable. To address these issues, several researchers [10-11] employed the ANFIS to develop the predictive model. Nevertheless, the literature shows that there is a lack of studies that use the ANFIS to predict the financial distress of listed companies in Malaysia.

III. Methodology

A. Sample Selection

The sample of this study consists of 64 public companies listed on the Bursa Malaysia, out of which 32 were classified as PN17 companies during the time period of 2010-2015 and 32 financially healthy companies. In order to reduce bias in selecting the sample for the financial prediction models, each financially distressed company was matched with a financially healthy company from the same industry and approximately the same asset size. The use of this type of sampling procedure is consistent with the studies by Beaver [2] and Altman [3]. The financial statements of the financially healthy companies were obtained for the same fiscal years as those of the financially distressed companies, that is, if the financially distress company has a financial year ending 31 Dec 2006, the financially healthy company would be chosen with financial statements ending in the same year.

B. Data Collection

The financial data of the selected distressed and non-distressed companies were collected for five years prior to being listed under the PN17 categories by the Bursa Malaysia. For example, for a company which was announced as distressed in 2015, the variables were computed for the year 2014 (year 1), 2013 (year 2), 2012 (year 3), 2010 (year 4) and 2009 (year 5). The name of companies listed under PN17 was obtained from the Media Releases and Companies Announcements from the Bursa Malaysia website, while the financial data were collected from the Thomson Reuters Datastream.

C. Financial Indicators

This study used the same five financial ratios as in the Altman's study as the input variables for the development of financial distress prediction models. These financial ratios could be classified into three broad categories that reflected the company's profitability, liquidity and efficiency. The list of the selected financial ratios is presented in Table I.

D. Adaptive Neuro-Fuzzy Inference System(ANFIS)

The Adaptive Neuro-Fuzzy Inference System proposed by Jang [12] is a fuzzy system that employs the ANN theory to determine its properties. It utilizes the mathematical properties of the ANN to tune the rule-based fuzzy system such as the fuzzy membership function parameters extracted from the features of the data set that describes the system behavior.

TABLE I. List of Selected Financial Ratios

Ratio	Initials	Category
Earnings before interest and taxes / total assets	EBITTA	Profitability
Retained earnings/ total assets	RETA	Profitability
Working capital/ total assets	WCTA	Liquidity
Market value equities/ book value of total debt	METD	Liquidity
Sales/total assets	STA	Efficiency

In order to simplify the explanation, the fuzzy inference system under consideration is assumed to have two inputs *x* and *y*, and one output variable *z*. The first order of the Sugeno fuzzy model with two fuzzy if–then rules can be represented as follows:

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1 x + q_1 y + r_1$

Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2 x + q_2 y + r_2$

where *p*, *r*, and *q* are the linear output parameters. Fig. 1 demonstrates the architecture of the equivalent ANFIS system. This architecture is formed by using five layers and the functions of each layer is explained below.

Layer 1: This layer consists of square nodes that fuzzifying inputs with chosen membership function. Every node in this layer is an adaptive note with a node function

$$O_{1,i} = \mu_{A_i}(x), \quad \text{for } i = 1, 2 \text{ or } O_{1,i} = \mu_{B_{i-2}}(y), \quad \text{for } i = 3, 4$$

where $O_{1,i}$ is the membership function of A_i and B_i. The parameters in this layer are called the premise parameters.

Layer 2: This is a layer of rules. Every node in this layer multiplies the incoming signal from layer 1 and the output is the firing strength of the rule.

$$O_{2,i} = w_i = \mu_{A_i}(x) \cdot \mu_{B_i}(y) \text{ for } i = 1, 2.$$

Layer 3: This is a layer of normalization. Every node in this layer calculates the ratio of the i[th] rule firing strength to the sum of all the firing strength of the rules'.

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2} \text{ for } i = 1, 2.$$

Layer 4: This is the clarification layer. Every node in this layer multiplies the normalized firing strength with the parameter set function. The parameters in this layer are called the consequent parameters.

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_1 + q_1 + r_1)$$

where p_1, q_1 and r_1 are the parameters.

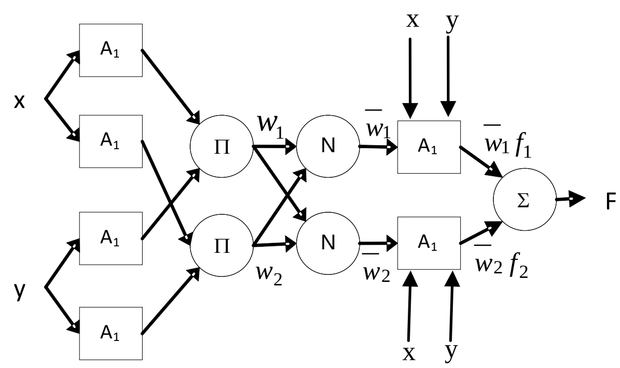

Fig. 1. ANFIS Architecture

Layer 5: The single node in this layer calculates the overall output as the summation of all incoming signals.

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i\left(p_1 + q_1 + r_1\right)$$

IV. Results and Discussion

A. Descriptive Statistics

To identify any difference between the financially and non-financially distressed companies, the descriptive statistics are calculated based on the selected financial ratios. Table II presents a summary of the input variables to estimate the model in this study. As expected, the non-PN17 or financially healthy companies have a higher mean value for all the variables compared to the mean of PN17 companies. In addition, the mean values of RETA, WCTA and EBITTA for the distress companies are negative which indicates that the companies have a weaker ability to survive during a credit crunch. The non-financially distressed companies also have a lower standard deviation for all the variables except for STA.

B. Performance of ANFIS

To develop the ANFIS prediction model, the sample was further randomly split into the training and testing samples. The training set comprised 22 financially distressed and 10 financially healthy companies to be used for the development of the predictive model. The remaining 22 distressed companies and 10 non-distressed companies were assigned to the testing sample. This sample will be used to track errors during the training in order to prevent overtrainings to evaluate the predictability of the model.

The ANFIS model was trained using the MATLAB R2014a environment. A generalized bell-shaped membership function (gbellmf) was selected as an input membership function and a linear membership function as an output membership function. The number of membership functions was set to three and the number of epochs was fixed to be 100. The genfis2 function of MATLAB was used to generate a Sugeno-type fuzzy inference system.

TABLE II. Descriptive Analysis

Variables	Mean		Standard Deviation	
	PN17	***Non-PN17***	***PN17***	***Non-PN17***
WCTA	-0.2028	0.3309	0.9445	0.1935
RETA	-0.4408	0.2350	1.3722	0.2525
EBITTA	-0.0012	0.0739	0.9437	0.0546
METD	0.9410	2.2309	2.0115	2.3360
STA	0.6196	0.8770	0.5107	0.4885

The ANFIS model was trained using the MATLAB R2014a environment. The number of epochs was fixed to be 100. The trained ANFIS model has 31 rule nodes, each nodes was represented as a locally-defined linear functions. The subtractive clustering with a radius of 0.2 was used to generate a Sugeno-type fuzzy inference system.

By comparing the observed values with the predicted values from the ANFIS model, the result shows that the root mean squared error (RMSE) values were 0.0099. The plot of the training error per epoch is shown in Figure 2.

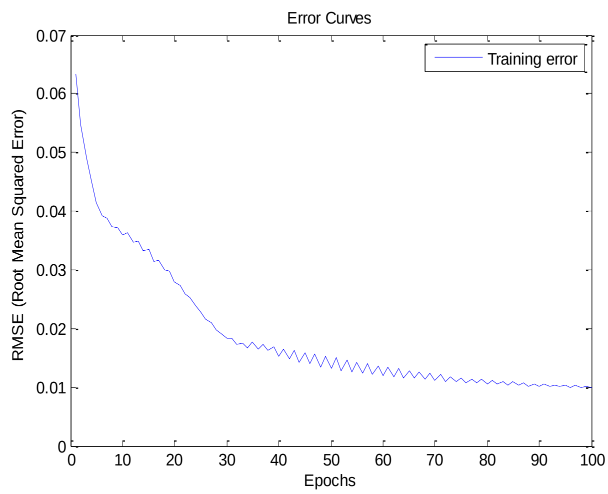

Fig. 2. The plot of RMSE per training epoch

The results obtained by using the ANFIS on the testing sample are presented in Table III. The results indicate that the overall accuracy of the ANFIS model was 86%. The highest accuracy rate was 90% for year 1. Out of 10 financially healthy companies, 9 (90% percent) were correctly classified as healthy companies and 9 out of 10 financially distressed companies (90%) were correctly classified as distressed companies. On top of that, the results also showed that the accuracy of the model fell off consistently except for the fourth year. According to Altman [3], the reason for this occurrence is, after the second year, the discriminating power of any model will lose its predictive ability.

TABLE III. CLASSIFICATION RESULTS

			Predicted		
			Non-PN17	PN17	% correct
Year 1	Observed	Non-PN17	9	1	90%
		PN17	1	9	90%
	Overall				90%
Year 2	Observed	Non-PN17	9	1	90%
		PN17	2	8	80%
	Overall				85%
Year 3	Observed	Non-PN17	8	2	80%
		PN17	1	9	90%
	Overall				85%
Year 4	Observed	Non-PN17	10	0	100%
		PN17	2	8	80%
	Overall				90%
Year 5	Observed	Non-PN17	8	2	80%
		PN17	2	8	80%
	Overall				80%

V. CONCLUSIONS

This study developed a financial distress prediction model for the public listed companies in Malaysia using the ANFIS. The results of 86% correct classification of the distressed and financially healthy companies were in agreement with Vlachos and A Tolias's [11] findings which showed that the ANFIS is a promising approach in the prediction of firm stability. The limitation of this study is that the number of sample for the financially distressed companies is relatively small. Therefore, in the future, the use of more extensive data is recommended in order to improve the accuracy rate of the predictive model.

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