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Predicting Bankruptcy of Public and Private Companies in Mauritius

Jayrani Cheeneebash*, Nicholas Khim On Cheong Foo, Ashvin Gopaul*****

Abstract

During the recent years, many incentives have been given to encourage people to become entrepreneurs and set up their own businesses or companies in Mauritius. This has contributed to an increase in the number of companies listed on the Stock Exchange of Mauritius. The aim of this paper is to provide prospective investors a means to determine the tendency of companies to go bankrupt. A comparison is made of the performance of the artificial neural networks method with the Altman Z-Score and the Taffler models on their ability to predict whether companies listed in Mauritius are prone to bankruptcy. The Z-Score and Taffler models use five and four financial ratios as variables, respectively, whereas the simulation of the ANN is carried out with only two different sets of inputs. After testing the three methods, their respective accuracy is recorded; it is found that ANN produced better results than both the Z-Score and Taffler Models.

Keywords: Bankruptcy, Altman Model, Taffler Model, Artificial Neural Networks, Prediction

Introduction

The volume of trading on the Stock Exchange of Mauritius has known an interesting upward trend since the last decade. This has certainly contributed to the expansion of the financial sector in Mauritius. While people seem more interested in investing, it is important to carry out an assessment of the financial health of companies periodically in order to avoid placing funds on firms prone to bankruptcy. A company is in a state of bankruptcy if it is not able to repay the debts owed to its creditors. The last 2008 financial crisis in the USA has shown that lending money to firms without performing rigorous risk assessment can be very damaging to the economy. Thus, it is very important for an investor to be aware of companies heading towards failure.

The bankruptcy phenomena tends to happen unexpectedly, though there may have been evident signs that a firm would be financially distressed at a certain time. For example, bad budgeting and accounting, poor decision-making and vision, high interest rates, and debt burdens are all factors accounting for business failure. More prominently, poor market conditions have had a contagious effect by firstly affecting the overall economy of the country, which then resulted in distressing local business operations, as well as consumer's spending power. Moreover, excessive market competitions have been a major issue in the financial market, as the consumer's demand factor changes constantly.

In this line, business failure has become a very popular topic and has gained attention for many years from stakeholders as well as researchers. The performance and success of a firm is a major concern, and the ability to forecast the likelihood of bankruptcy has been a key priority for most of the significant players. Hence, several studies have been carried out based on the use of financial ratios and various bankruptcy prediction models have been successfully developed during the last decade. Modelling methods have been based on statistical procedures such as multiple discriminant analysis (MDA), logistic regression, or hazard models. More recent work has extended the definition of bankruptcy to include wider measures of financial distress based on financial statements. Furthermore, some researchers have added some dynamics by including data reflecting changes in

* Associate Professor, Department of Mathematics, University of Mauritius, Mauritius. Email: jayrani@uom.ac.mu
** Student, University of Mauritius, Mauritius. Email: nicholascf.1106@gmail.com
*** Associate Professor, Department of Mathematics, University of Mauritius, Mauritius. Email: a.gopaul@uom.ac.mu

the macroeconomic environment, non-financial data, and other time variant factors.

As more firms have defaulted on their debts and filed for bankruptcy after the financial crisis, it has become important to learn how firms deal with financial distress. Though many studies have been conducted on different ways of managing financial distress and their effects on the company through either public or private restricting, the literature on bankruptcy prediction is still limited to certain sectors. Wruck (1990) defines financial distress as a situation where cash flow of a firm is not enough to cover its current financial obligations. In fact, a firm is classified as financially distressed if its earnings before interest, taxes, depreciation, and amortisation (EBITDA) are less than its reported financial expenses (interest expense on debt) for two consecutive years.

Beaver (1966) was the first to work in the field of bankruptcy. His work was based upon a univariate statistical approach in which a classification model was applied to identify business failure. He used a sample of a total of 79 bankrupt and 79 non-bankrupt companies and investigated which of the 30 financial ratios he identified had better predictive supremacy. His results led to the conclusion that the 'working capital to total debt' ratio was the best one, with a success rate of approximately 90% one year before failure.

Altman (1968) was the first to use the multiple discriminant analysis (MDA) to create a model for predicting failure. Out of the 22 financial ratios he analysed on a sample of 33 bankrupt and 33 non-failed companies, he concluded that five ratios were more significant for detecting distress in firms. He later used these five ratios as well as some weightage to create the famous Z-Score model, which gave an accuracy range between 80-90% in predicting failure one year before it happened. However, the Z-Score model faced much criticism, as researchers found that this model was only applicable to publicly traded companies. Later on, he successfully modified the model and presented the new Z' Model for companies in the private sector and the Z'' Model for non-manufacturer companies by mainly changing the variables in each model.

Taffler (1984) used MDA to create a model, which could predict failure among businesses based in the UK. Out of about 80 financial ratios analysed, four were selected as the predictor variables in his model. Later, several versions of this model were developed by varying the last variable on its scoring function.

Springate (1978) followed Altman's work by using MDA to develop his own model. Out of the 19 financial ratios studied, four of them were found to be more significant in predicting insolvency. Upon testing on a sample of 40 companies, this model produced an accuracy rate of about 92.5%. Conan and Holder (1979) elaborated a business failure model for companies situated in France using MDA as well. They studied how 31 financial ratios would perform on a sample of about 190 small and medium companies for the period 1970-1975, and concluded that only five ratios were sufficient for predicting failure. A company would be classified as failed if the Z-Score is less than 0.16. Ohlson (1980) was the first to use logistic regression approach in the field of bankruptcy. The use of MDA model was criticised since most models tend to follow a normal distribution and its output does not necessarily predict the probability of default of companies. Ohlson proposed that using logit analysis would solve this problem and provide better predictive results. This model was made up of nine independent variables and was tested on a sample of 105 bankrupt public companies. It was found that the model was about 90% accurate. Zmijewski (1984) used the probit technique to predict failure. His independent variables or ratios were chosen based mostly on how well they performed in previous bankruptcy studies. The model was found to be approximately 95% accurate. Fulmer (1984) also used MDA to test about 40 financial ratios on a sample of 30 bankrupt and 30 non-bankrupt companies. The model was approximately 97% accurate one year before failure.

Coats and Fant (1993) proposed a back-propagation ANN model in the field of bankruptcy. They used five independent variables as input and tested the network. They found that the network completely outperformed the MDA models used to predict failure with a success rate of 91% in classifying failed firms, compared to a success rate of 72% under MDA analysis.

Fletcher and Goss (1993) used ANN to predict insolvency. They used three independent variables on a sample of 18 failed and 18 non-failed companies. The results obtained were much more accurate than the results obtained from models under the logistic regression method.

Shumway (2001) created a hazard model to predict business failure. He compared the results obtained from his model with results from static models and concluded that the hazard model provided a much better success rate. He also claimed that, while previous studies showed that only financial ratios could be used as predictor variables, market variables such as stock return and market size could also be considered.

Vassalou and Xing (2004) used option pricing model to determine whether default risk of firms could be assessed in equity returns. Agarwal and Taffler (2007) decided to compare the predictability of models that use accounting ratios as variables with those models that use market variables. They concluded that between them, there was minimum difference in terms of their predictive accuracy.

The aim of this study is to predict bankruptcy in both private and public companies in Mauritius using three different methods, namely the Z-Score model (Altman, 1968), Taffler Model (Taffler, 1984), and the Artificial Neural Network (ANN) (Mc Culloch & Pitts, 1943), and to assess which model provides a better accuracy rate. An appropriate ANN is designed for the data set and a comparative study is then performed.

The paper is structured as follows: the next section deals with the materials and methods used in our study. We describe the population sample, data analysis, and the different methods used in this paper. Next, we present the different simulation results and the comparative study. The novelty of this paper is to find whether an appropriate ANN model for the listed companies is as efficient as the traditional methods in the context of the Mauritian economy. Such a study has not been performed on Mauritian companies and we wanted to see which if these methods fit well and can be applied as a tool in decision making.

Materials and Methods

This section provides the research methodology that will be used to predict bankruptcy in both private and public Mauritian companies. In this study, the Altman Z-Score, Taffler model, and the Artificial Neural Network (ANN) were chosen for the simulation. These models were selected based on how successful they have been in previous research done in the field of bankruptcy. Both the Z-Score and the Taffler model use five and four accounting ratios as variables, respectively, and the score obtained will define the status of the companies following the 'zone of discrimination' of the two models, while the ANN uses these variables as input to give a single output, which will classify companies as sound or failed. A failed firm is assigned the number '1', whereas non-failed firms are assigned the number '0'.

The samples used in this study are given in Table 1.

Table 1: Sample Size used for Prediction

Types of Companies	*No. of Bankrupt Companies*	*No. of Non-Bankrupt Companies*	*Total*
Private	34	34	68
Public	20	20	40

We note that the size of the companies was not homogenous. Consequently, the companies selected vary mostly in size (from small to large enterprises), based on their turnover.

Data Collection

All financial data used in this study were extracted from income statements, as well as from balance sheets obtained from the Corporate and Business Registration Department of Mauritius. The data collected is as follows.

Table 2: Data Collected from Mauritian Companies

Abbreviation	*Definition*	*Abbreviation*	*Definition*
WC	Working Capital	S	Sales
TA	Total Assets	BVE	Book Value of Equity
RE	Retained Earnings	EBT	Earnings Before Taxes
EBIT	Earnings Before Interest and Taxes	CL	Current Liabilities
MVE	Market Value of Equity	CA	Current Assets
TL	Total Liabilities		

The data extracted for all bankrupt companies (declared as 'defunct' in the Corporate and Business Registration Department) was prior to a year before failure, while data collected for all 'live' or non-failed companies was from the latest financial statement obtained.

Data Analysis

We first apply both the Altman Z-Score model and the Taffler model to evaluate their predictive ability in the public and private sector Mauritian companies. Based on the data obtained from each company in each sector, the financial ratios or variables of the models were then computed and the respective *Z*-Score and *T*-Score were calculated. Furthermore, these variables were then used as input for, and then tested on, the different population sample mentioned above for the ANN process.

The Altman Model

MDA is a statistical technique mostly used for classifying patterns and predicting a qualitative (dependent) variable from various independent variables, whereby the dependent variable normally consists of two groups – in this case, bankrupt and non-bankrupt. This technique was also used to derive a linear combination equation of the independent variables, where a specific coefficient or weight is assigned to each of these variables. The discriminant function (standard Z-Score Model) is given as follows.

$$Z = 1.2x_1 + 1.4x_2 + 3.3x_3 + 0.6x_4 + 0.999x_5 \quad (1)$$

where,

$$x_1 = WC/TA,\ x_2 = RE/TA,$$

$$x_3 = EBIT/TA,\ x_4 = MVE/TL, \text{ and } x_5 = S/TA.$$

However, Eq. (1) can be applied only to public companies due to the 'market value of equity to total liabilities' ratio. The score obtained is the basis of the classification of companies as given in Table 3.

Table 3: Zone of Discrimination of the Z-Score Model for Public Companies

Z-Score	*Interpretation of Z-Score*
If Z > 3	Firm is considered safe
If 1.8 < Z < 3	Firm is in the 'grey zone', that is, it is on the verge of going bankrupt
If Z < 1.8	Firm is considered bankrupt

Note: In this study, if a firm's score lands in the grey zone, the firm would be considered a failure.

Altman later modified his model and presented the Zeta or *Z'* model, which could predict failure for companies mainly in the private sector. Coefficients were revised and the 'market value of equity to total liabilities' ratio was replaced with the 'book value of equity to total assets' ratio. The *Z'* model was presented as follows.

$$Z = 0.717v_1 + 0.847v_2 + 3.107v_3 + 0.42v_4 + 0.999v_5 \quad (2)$$

where,

$$v_1 = WC/TA,\ v_2 = RE/TA,$$

$$v_3 = EBIT/TA,\ v_4 = BVE/TL, \text{ and } v_5 = S/TA.$$

The procedure of computing the variables and the *Z'* score of each private company was carried out. The classification of firm was done as per the new zone of discrimination of the *Z'* score model, as shown in Table 4.

Table 4: Zone of Discrimination of the Z'-Score Model for Private Companies

Z'-Score	*Interpretation of Z'-Score*
If *Z* > 2.9	Firm is considered safe
If 1.23 < *Z* < 2.9	Firm is in the 'grey zone', that is, it is highly likely to go bankrupt
If *Z* < 1.23	Firm is considered bankrupt

Hence, in this study, the standard Z-Score model and the revised Z' model was used to predict failure for Mauritian public and private companies, respectively.

The Taffler Model

Taffler model uses the same principle as the Altman's model, in using MDA to build on a bankruptcy prediction model. His work resulted in identifying a set of four key financial ratios chosen from an overall sample of 80 ratios. Each variable was assigned a unique coefficient and the final function was obtained as shown below.

$$T = 0.53x_1 + 0.13x_2 + 0.18x_3 + 0.16x_4 \quad (3)$$

where, $x_1 = EBT/CL,\ x_2 = CA/TL,\ x_3 = CL/TA,$

and $x_4 = S/TA.$

In this study, the model was tested in both samples of public and private companies. Classification was done as per the zone of discrimination given in Table 5.

Table 5: Zone of Discrimination of the Taffler Model

Taffler Score	*Interpretation of the Taffler Score*
If $T > 0.3$	Firm is considered sound
If $0.2 < T < 0.3$	Firm is likely to go bankrupt
If $T < 0.2$	Firm is considered bankrupt

ANN in Predicting Failure

As an alternative to any MDA or other models, the ANN has become the new way to predict corporate failure. A neural network is normally made up of several layers of computing elements called nodes. Each node is connected to one other and receives an input signal from the other nodes. The input signals are then processed through a transfer function such that the nodes could output the transformed signal. ANN are usually categorised by their network style – the number of layers, number of nodes in each layer, and how the nodes are linked to each other. The most popular figure of the ANN is the multi-layer perceptron, where the nodes are arranged in a 'feed-forward' system. The very first layer at the bottom is known as the input layer, where data and information are normally received. The middle layer, commonly known as the hidden layer, transforms the signals obtained from the inputs; lastly, the upper layer (output layer) gives the final result. This is illustrated in Fig. 1.

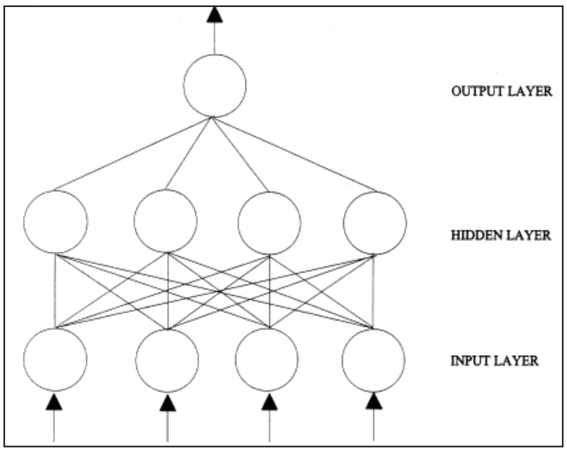

Fig. 1: A Normal Feed-Forward ANN (Zhang et al., 1999)

The ANN did not quite convince people until the late 1980s, when it became quite popular and successful due to the creation of new technologies and major improvement in its algorithm – more notably the back-propagation algorithm. Since then, many studies have been carried out using the ANN approach, mostly in the field of medicine and finance, such as in bond rating, stock market predictions, financial analysis and forecasting, and lastly, in predicting failure. The most recent research done in financial distress have suggested that ANN are powerful tools for pattern recognition and classification due to its non-linear parametric assumptions, and therefore, great predictive results were obtained as stated earlier.

Hence, in this study, the ANN was also applied to predict distress in Mauritian companies. The network uses the ratios of the above models as input, and together with a set of neurons, the training process of the network was done. The output obtained would suggest whether a firm is classified as distressed or not.

The ANN method was implemented in the following steps. All bankrupt companies were attributed the number '1' and all non-bankrupt firms were given the number '0' for classification pattern. The five and four respective variables of the *Z*-Score and Taffler model were used separately as input and a set of neurons were applied with each model. The training, validation, and testing set were then calibrated to predict bankruptcy in only public companies. The five and four variables of the *Z*-Score or *Z*'-Score and Taffler models were also used separately as input. A set of neurons were assigned and calibration of the training, validation, and testing set were done to predict bankruptcy for private companies. Confusion matrices, as well as the receiver operating characteristic (ROC) plot, were mainly used to evaluate the performance of the network.

Results and Discussions

This section discusses the different simulation techniques used to predict failure in Mauritian companies, as well as their respective results. Variables and the individual scores of each model are tabulated and examined, and the results obtained are provided and discussed. Finally, a comparative analysis of the predictive accuracy of each model for the public and private companies is carried out and discussed.

We first find the *Z*-Score for the sample of 20 already failed firms and later used on the 20 non-bankrupt companies.

Case of Public Companies

As shown in Table 6, the different variables and scores were calculated and analysed. We find that out of the 20 public sample firms chosen, the *Z*-Score was able to correctly predict failure of only ten companies, while the remaining ones were wrongly categorised as their scores were greater than three. Hence, as per the following results, the model was found to be 50% accurate in predicting failure for the failed public Mauritian companies.

The standard *Z*-Score was then used on the 20 sample non-bankrupt firms. The procedure of computing and tabulating their variables and scores was again carried out. Upon analysing the scores of each company in Table 7, the model was found to be fairly accurate in predicting non-bankrupt firms. Out of the 20 selected companies, the model was able to correctly forecast 14 companies and misclassified six. Furthermore, the accuracy rate of the model for predicting non-failure of firms was calculated and found to be 70%. Overall, for both failed and healthy firms, the Altman model was 60% accurate in prediction.

Table 6: Variables of the Z-Score Model and the Respective Scores for Failed Public Firms

Failed Public Companies	*WC/TA*	*RE/TA*	*EBIT/TA*	*MVE/TL*	*S/TA*	
	X1	*X2*	*X3*	*X4*	*X5*	*Z*
C1	−2.01367	−5.88071	−0.89608	1.411871	0	−12.7593
C2	−0.00464	0.073876	0.081038	2.959701	0.081038	2.222059
C3	0.027395	0.145493	0.020804	24.85852	0.026824	15.24713
C4	−0.02508	−0.0469	−0.04284	26.66523	0	15.76201
C5	−3.89825	−0.48688	−0.07986	15.11859	0.617818	4.065292
C6	0.590388	0.199873	0.04148	14.35422	0.174279	9.91181
C7	−1.55553	−2.04668	−0.00503	0.958607	0	−4.17344
C8	0.177941	0.00356	0.003428	0.515918	0.311268	0.850332
C9	0.190812	0.126532	−0.02696	40.864	0.001711	24.83726
C10	0.057322	0.055516	0.019575	0.022151	0.086218	0.310527
C11	−7.4798	−12.5408	−2.1108	3.093455	0	−31.6424
C12	0.015387	0.015121	-0.086	13.21115	0.023751	7.70625
C13	−0.01188	−0.38523	−0.43645	1.296173	0.054958	−1.16124
C14	0.285476	−0.66725	−0.45439	72.65105	0	41.49957
C15	0.205654	−0.23002	−0.04929	0.110609	0.103407	−0.06822
C16	0.272633	−1.25077	0.164995	0.353854	0.185701	−0.48161
C17	0.069513	0.006673	0.003319	127.3033	0.010791	76.49648
C18	0.628147	−0.15431	0.050408	10.57281	0.133406	7.181043
C19	0.098655	−0.03387	0.042204	1.401303	0.103576	1.154501
C20	0.928101	−0.9281	0.048708	34.18289	0.040496	20.52531

Table 7: Variables of the Z-Score Model and the Respective Scores for Non-Failed Public Firms

Safe Public Companies	*WC/TA*	*RE/TA*	*EBIT/TA*	*MVE/TL*	*S/TA*	
	X1	*X2*	*X3*	*X4*	*X5*	*Z*
C1	0.1071	0.2979	0.0522	5.6197	0.5394	4.6285
C2	0.0495	0.3007	0.0330	0.2532	0.0487	0.7898
C3	0.1742	0.3666	0.0566	9.4280	0.3897	6.9553
C4	(0.1116)	0.1942	(0.1349)	3.1453	0.0564	1.6362
C5	0.8184	0.2383	0.0260	38.6615	0.0538	24.6523
C6	0.2086	0.6055	(0.5943)	39.7050	0.9064	23.8655

Safe Public Companies	*WC/TA*	*RE/TA*	*EBIT/TA*	*MVE/TL*	*S/TA*	
	X1	*X2*	*X3*	*X4*	*X5*	*Z*
C7	0.3390	0.3927	0.1362	294.4615	0.1069	178.1896
C8	0.6404	0.6335	0.4534	1.4168	0.9299	4.9306
C9	0.2030	0.4295	0.1067	675.1688	2.2779	408.5740
C10	(0.0309)	0.2325	0.0256	87.6386	0.7183	53.6736
C11	(0.1654)	0.0565	0.0310	31.6195	0.0345	18.9891
C12	0.1219	0.3065	0.0660	269.9544	0.8881	163.6532
C13	0.2637	0.2566	0.0420	1.6910	0.3753	2.2039
C14	0.0662	0.4053	0.0839	0.9719	0.9608	2.4667
C15	0.0031	0.0166	0.0242	101.0509	0.2547	60.9918
C16	0.7197	0.0115	0.2114	4.9071	0.6600	5.1811
C17	(0.1127)	0.1775	0.1422	1.6535	4.1675	5.7381
C18	(0.0209)	0.1287	0.0189	6.3845	0.0203	4.0685
C19	(0.0219)	0.1694	0.0272	0.2037	0.4018	0.8242
C20	0.1463	0.4456	0.1271	1.3575	0.5945	2.6271

Table 8: Scores Obtained from Taffler Model for Failed Public Firms

Safe Public Companies	*EBT/CL*	*CA/TL*	*CL/TA*	*S/TA*	
	X1	*X2*	*X3*	*X4*	*T*
C1	−0.38409	0.213898	2.561591	0	0.285324
C2	1.410582	0.914563	0.05435	0.081038	0.889251
C3	1.215206	0.441823	0.012211	0.026824	0.707986
C4	−1.629	0.04653	0.0263	0	−0.85259
C5	0.018189	0.103146	4.390731	0.617818	0.912231
C6	0.225586	3.768223	0.17777	0.174279	0.669313
C7	−0.00324	0	1.555535	0	0.278282
C8	0.058595	0.272421	0.058495	0.311268	0.126802
C9	−12.1412	33.21943	0.00212	0.001711	−2.11567
C10	0.516091	0.789347	0.028365	0.086218	0.395044
C11	−0.27146	0.054603	7.911804	0	1.287349
C12	−137.13	25.1827	0.000636	0.023751	−69.4013
C13	−1.24337	0.415961	0.406273	0.054958	−0.52299
C14	70.8111	45.4881	0.006417	0	43.44449
C15	−0.21965	1.304513	0.332833	0.103407	0.129628
C16	0.225147	1.374822	0.727367	0.185701	0.458693
C17	0.068333	0.813134	0.036395	0.010791	0.150201
C18	0.304566	4.455929	0.157063	0.133406	0.790307
C19	1.591242	0.127804	0.024821	0.103576	0.881013
C20	2.993163	58.03297	0.016273	0.040496	9.140071

From Table 8, we find that out of the 20 sample failed firms, the model was able to classify only nine firms correctly, while 11 firms were found to be misclassified. Hence, the accuracy of the model was calculated to be only 45%. The model was then applied to the sample of 20 non-bankrupt firms and each variable and *T*-Scores were again computed.

Table 9: Scores Obtained from Taffler Model for Non-Failed Public Firms

Safe Public Companies	EBT/CL X1	CA/TL X2	CL/TA X3	S/TA X4	T
C1	0.339864	0.709743	0.130394	0.539357	0.382163
C2	0.821281	0.124591	0.037042	0.048714	0.465937
C3	0.123192	1.359418	0.459513	0.389735	0.387086
C4	−0.16775	0.861196	0.804262	0.056375	0.176835
C5	0.265032	1.50645	0.098177	0.053839	0.362591
C6	−5.44348	0.620391	0.147931	0.906394	−2.63274
C7	1.691143	0.78959	0.080525	0.106937	1.030557
C8	1.260773	2.780885	0.359598	0.929935	1.243242
C9	0.138927	1.183871	0.643391	2.277879	0.707806
C10	0.061569	0.261496	0.137446	0.718291	0.206293
C11	0.036576	0.797788	0.846817	0.034508	0.281046
C12	0.138614	1.094084	0.380374	0.888124	0.426263
C13	0.576229	0.573411	0.062658	0.375328	0.451276
C14	0.728729	0.539191	0.111784	0.960784	0.630168
C15	0.939592	1.122272	0.025737	0.25472	0.689267
C16	2.626103	1.526284	0.08051	0.659993	1.710342
C17	0.205798	0.776461	0.678643	4.167543	0.998976
C18	0.755331	0.129349	0.023954	0.020284	0.424698
C19	0.011013	0.423735	0.323982	0.401805	0.183528
C20	1.249778	1.217673	0.099036	0.594467	0.933621

Following the results obtained from Table 9, the model was able to correctly predict the non-failure of 15 companies, while five of them were predicted to go bankrupt. Hence, the model was proven to be 75% accurate for the sample of non-failed public firms. An overview of the performance of the Taffler model gives it a 60% rate of correct prediction.

The ANN was applied using the five variables of the *Z*-Score, and the four variables of the Taffler model as input, separately, in Matlab software 2016. Furthermore, all 20 failed public firms were assigned the number ‘1’, while the 20 safe firms were assigned the number ‘0’ for classification process, and later, these were used as target for the network.

Using the already computed five variables of the *Z*-Score model as input and defining the target data (1 for bankrupt and 0 for non-bankrupt) for output purposes, the next step was to choose any training, validation, and testing sample for the network. Thus, the training, validation, and testing sample were chosen to be 50%, 25%, and 25%, respectively, and a set of ten neurons was selected to work and process data in the hidden layer. Hence, a two-layer feed-forward network was created and is shown in Fig. 2.

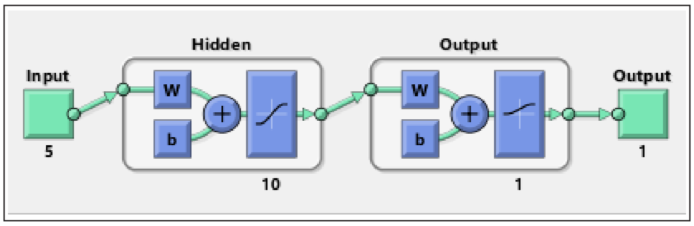

Fig. 2: Structure of the Network Used to Predict Failure with Five Inputs

The network was then trained, and the confusion matrix as well as the ROC plot were used to evaluate the performance of the ANN.

Fig. 3 shows the various confusion matrices of the training, validation, and testing, and the overall combination of the three samples. The training confusion matrix shows that 18 out of 20 random sample firms for training process were properly classified, while two were incorrect, thus making the model 90% accurate for the training sample. The All Confusion matrix was then obtained. It represents the overall performance of the ANN; it was found that 34 out of the 40 sample public firms were correcly categorised, while six were wrongly classed. Thus, the overall accuracy rate of the network was observed to be 85%. For the several ROC graphs obtained for the ANN process, if the simulated graph approaches closely to the true positive rate, the model is said to be more accurate. Hence, the ROC plot in Fig. 3 indicates that the application of using five inputs for the ANN in predicting failure of public Mauritian companies had good predictive ability.

The ANN was then applied using the four variables of the Taffler Model as input data and ten neurons were chosen to act in the hidden layer. However, the training, validating, and testing set were changed accordingly, where 40% of the public sample firms were used for training process and 30% of the sample were used for both the validation and testing process. The network was trained and evaluated through the confusion matrices and ROC plot as given in Fig. 4.

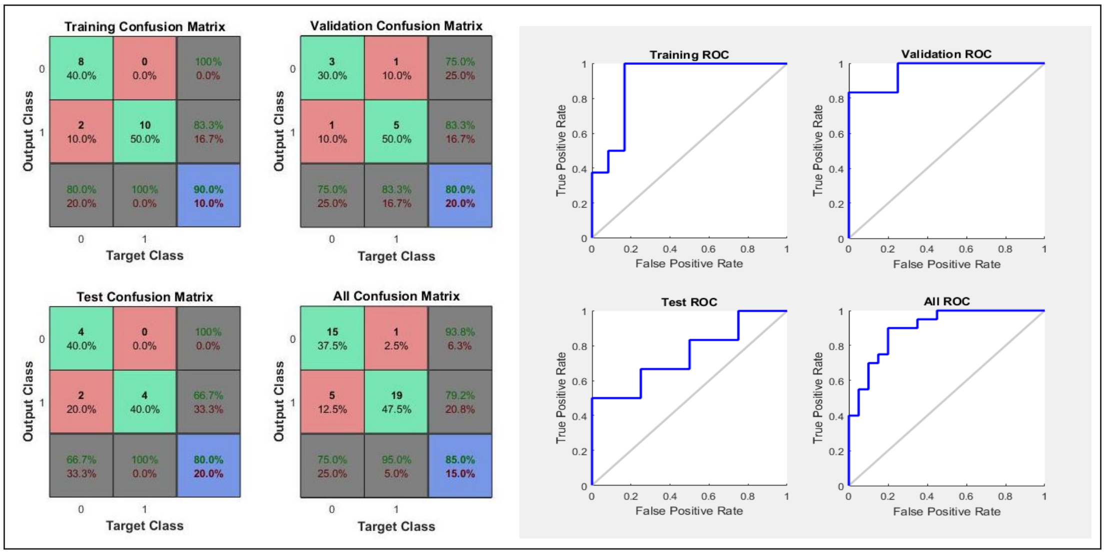

Fig. 3: Confusion Matrices and ROC Plot of the Trained ANN with Five Inputs

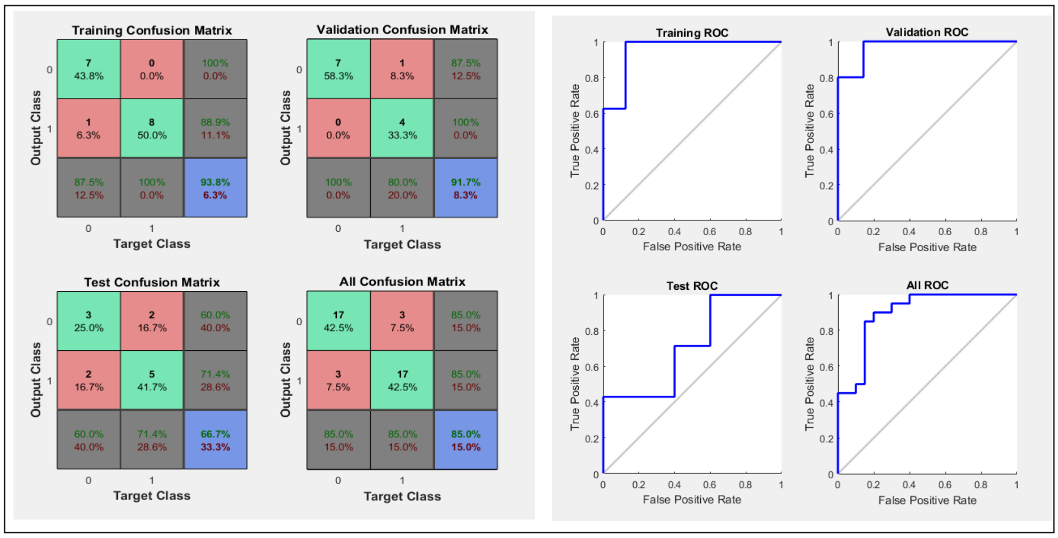

Fig. 4: Confusion Matrices and ROC Plot of the Trained ANN with Four Inputs

Fig. 4 shows that the training process of the ANN proved to be extremely accurate by classifying 15 out of 16 firms correctly, thus providing an accuracy rate of 93.8% for the training set. The All Confusion matrix was then taken into consideration and it was found that the model performed quite well with an overall accuracy rate of 85%. Moreover, the ROC plot shows that the model was quite efficient in classifying the sample of public firms, as the plot is approaching the true positive rate axis.

Our results show that both the *Z*-Score and Taffler model obtained an accuracy rate of 60%, while the ANN resulted in an accuracy rate of 85%. Hence it can be assumed that, in this case, the ANN offers better predictive ability compared to the two other MDA models.

Case of Private Companies

We have carried out a similar analysis for the case of private companies, with the exception that the Altman *Z'*-Score model is considered this time. For the ANN model, the five variables of the *Z'* model were used as input and the target data was the number '1' for bankrupt and '0' for non-bankrupt private companies. Around 25 neurons were chosen to process data in the hidden layer, and the training, validation, and testing sample were set at 40%, 30%, and 30%, respectively. Hence a two-feed-forward layer was obtained and trained. In addition, a second attempt for ANN was done by considering the four variables of the Taffler model as input and 20 hidden neurons were chosen for the process. The training, validation, and testing sample were the same as before.

Table 10 illustrates the different overall accuracy rate obtained from the three specified bankruptcy models mentioned before.

Table 10: Accuracy Rate of the Models for the Private Companies

	Z'-Score	*ANN (Five Variables)*	*T-Score*	*ANN (Four Variables)*
Accuracy (%)	60.3	75	50	77.3

The success rate of the *Z'*-Score and *T*-Score obtained are 60.3% and 50%, respectively, while the ANN obtained a higher success rate of 75% and 77.3%, depending on the number of inputs used. As a result, it can be concluded that the ANN was the better model to predict distress in the sample of private firms.

Conclusion

In this paper, we have used the Altman *Z*-Score model, Taffler model, and the ANN model to predict failure and non-failure of the public Mauritian companies. In addition, we have compared the last two models together with the Altman *Z'*-Score model for private companies. Our results show that both MDA models provided a relatively acceptable accuracy rate, while the ANN completely outperformed them with a much better level of accuracy. The comparison of these three methods will enable financial managers to analyse the performance of companies and eventually detect, in advance, if a company is prone to bankruptcy. This work clearly shows that ANN definitely provides predictive supremacy over the two MDA models and it should be useful to the decision makers.

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