Bankruptcy Prediction and Neural Networks clubbed for Z Score Analysis of Oriental Bank of Commerce

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Abstract— Of the methods used to build bankruptcy prediction models in the last twenty years, neural networks are among the most challenging. Despite the characteristics of neural networks, most of the research done until now has not taken them into consideration for building financial failure models, nor for selecting the variables to be included in the models. The aim of our research is to establish that to improve the prediction accuracy of the models, variable selection techniques developed specifically for neural networks may well offer a useful alternative to conventional methods

Index Terms— Ohlson's models, neural networks, discriminant analysis.

1 INTRODUCTION

The history of bankruptcy prediction models can be divided into two main periods. The first starts with Altman's and Ohlson's models. During this period i.e. from the late 1960's to the late 1980's, research relied largely on discriminant analysis and logistic regression that were the most accurate models. But by research it was seen that these methods suffer from major drawbacks and the real input-output variables dependency. But then it has gradually become clear that other methods should be studied and used to create bankruptcy models. The second period begins in the late 1980's, when many authors, in attempts to overcome the limitations described above, undertook research to assess the ability of non-parametric methods to accurately predict the risk of bankruptcy or the risk of financial failure. It was also during this period that non-linear techniques such as neural networks emerged in this field of research and demonstrated their frequent ability to outperform most existing techniques, whether parametric or not.

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2 LITERATURE REVIEW

A reading of the major articles published over the past 50 years shows that, when developing business failure models, researchers usually considered a large set of variables identified on the basis of general considerations out of which only a few are finally chosen based on statistical issue. The general inputs are often identified without using any automatic process but is arbitrarily chosen based on the popularity of variables in literature or on their predictive ability as assessed in previous studies. This historical set was built up on the strength of the seminal work done by researchers who, in the 1930's, first assessed the usefulness of financial ratios as a means of predicting corporate failure and by those who contributed to an understanding of the role played by multivariate statistical methods in the field of bankruptcy prediction.

Among these researchers prime in the list are Altman, Odom and Sharda, Zmijewski and Zavgren. All of this work may be viewed as the initial step towards the elaboration of a comprehensive set of essential bankruptcy predictors, which has been complemented over the years by other variables, whether they are accounting-based measures of the financial health of a firm or not .The second group, on the other hand, is most often selected through a computer based procedure designed to mine the former group for the best set of variables, depending on an evaluation criterion to define the inputs.. Indeed, many authors use such criteria to build neural network models. But Leray and Gallinari have stated that since many parametric variable selection methods rely on the hypothesis that input-output variable dependence is linear or that input variable redundancy is well measured by the linear correlation of these variables. Moreover, many of those who have developed neural models have identified their final sets of variables simply on account of their popularity in the financial literature. If one analyzes the linking these studies, it is clear that the criteria used to assess the legitimacy of most of these variables make sense only in a linear context. Very little research has used either a genetic algorithm or a method suitable for non-linear techniques to take into account the characteristics of neural networks, and in each case, with only few variables, small samples and without attempting comparisons of several methods or criteria; the significance of these experiments is thus reducedormatted.

3 MODELDESIGN AND METHODOLOGY

In this paper, a two step methodology has been adopted. The part A provides the steps formulated for the prediction of internal parameters of Z Score, followed by part B which enlists the steps followed for the prediction of Z Score using artificial neural networks.

Part A: Formulation of Internal Parameters of Z Score

The basic ratios are formulated from details mentioned in published statements like balance sheet, cash flow statements, yearly details of banks, profit and loss statements obtained from CMIE database, Reserve Bank of India. Data is also taken from the official websites of the banks and financial institutions and the internet. Prior researchers have identified financial ratio for bankruptcy prediction and the usefulness of these financial ratios for bankruptcy prediction can be known from the literature survey. Consequently this research work uses financial data i.e. published time series data for the last 11 years from 2000 to 2009.

1. (Current Assets-Current Liabilities)/Total Assets
2. Retained Earnings/ Total Assets.
3. EBIT/ Total Assets
4. Equity/Total Liabilities

Part B: Prediction of Z Score Internal Parameters using BPNN

1. Catering to Neural Network inputs
2. Tolerance level Minimization
3. Data convergence using Neural Networks
4. Formulation of Absolute error
5. Prediction of ratios in each Ratios pillar
6. Data Validation

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4 BPNN Model Application for Oriental Bank of Commerce

Oriental Bank of Commerce (OBC) was established in 1943 in the city of Lahore, which is currently in Pakistan. After the Indo-Pak partition, the registered office was shifted to Amritsar. During the 1970s, the bank suffered a serious financial crisis, which forced the owners of the bank to close down business. However, the employees came forward to make it a co-operative institution and continued business operations. Since then, the bank has expanded its horizons in terms of its customer base as well as product range. In 1980, the bank was nationalized by the Government of India. Oriental Bank of Commerce has made its mark in priority sector banking services. It has specialized products and services for small and medium enterprises (SME) and the rural population. Low-interest rate loans and debt restructuring facilities are available for enterprise customers.

The basic input sheets for all the internal parameters are formulated for OBC. The process of input ratio formulation uses the book formulae for computation of the ratios, which will further be used as input parameters for Artificial Neural Network. The Altman Z-Score prediction uses the Neural Network (1, 5, 4).The number if input rows are 1. The hidden layers are 5 and the outcomes are 4 internal parameters. The input point is time and output has been the required ratios. The period for input has been from 2000-2006 which has been normalized from 1 to 8.The details of the ratios and the values are enlisted in the table 1.

Backpropogation Neural Network has been used to transfer data sets. Trained network is used for prediction of ratios for the forthcoming two years being 2008, 2009 and 2010. The initial weights of the neural paths were in the range of -0.02 to 0.05. Convergence study of neural network was carried out for difference tolerance error of 1,0.75,0.5,0.4,0.3,0.2,0.1,0.01,0.001. The predicted values obtained from the neural network were compared with the actual field data or the arithmetic computation done from the published statements. The convergence study is detailed in Table 2.

[1] Table 1: *Training Pattern for ICICI bank Internal Parameters of Z-Score*

Time	Parameters			
	(CA-CL)/Total Assets	Retained Earnings/ Total Assets	EBIT/ Total Assets	Equity/Total Liabilities
2001	0.943326	0.04565	0.11216	0.007112
2002	0.924254	0.042033	0.109782	0.005968
2003	0.936343	0.041991	0.113615	0.005665
2004	0.93354	0.046744	0.098214	0.004695
2005	0.913661	0.045946	0.070938	0.003561
2006	0.909643	0.053183	0.074808	0.003267
2007	0.921352	0.066547	0.074801	0.003389

Table2: Z-Score Convergence Study for OBC

Toler-ance	Ratios	2008			2009			2010		
		Actual	Pre-dicted	% Error	Actual	Predicted	% Error	Actual	Predicted	% Error
0.001	(CA-CL)/TOTAL ASSETS	0.9248	0.9284	-0.3926	0.9283	0.9305	-0.2342	0.9548	0.9305	2.5420
	Retained Earnings/Total Assets	0.0590	0.0665	-12.8097	0.0491	0.0665	-35.5867	0.0451	0.0665	-47.4605
	EBIT/Total Assets	0.0769	0.0673	12.5202	0.0882	0.0689	21.8416	0.0834	0.0733	12.1179
	Equity/Total Liability	0.0028	0.0036	-30.1897	0.0022	0.0036	-63.7073	0.0018	0.0036	-99.2469
	Z Value	6.7790	6.8847	-1.5605	6.8445	6.9164	-1.0498	6.9728	6.9237	0.7033

A BPNN of size 1-5-4 is used for prediction. The error of tolerance to stop the execution was 0.5. It took the network 1994455 epochs to converge.

5 BPNN Modeling analysis, results and out Comes.

After the computation of the basic ratio pillars, as suggested by Table 1, this section uses the ratios as inputs to train the network. The network after training computes the values of the ratios from 2008 upto the year 2015 at different tolerance level. The validation is done by the values obtained for the year 2008 to 2010.The tolerance level that provides the closest values is considered for prediction. A 1-6-5 size backpropagation neural network is used for prediction of the Z-Score internal parameters. The internal parameters are than used in the formula to find the Z-Score value for the banks upto the year 2015. Table 3 provides details of the percentage error at the adopted level of tolerance.

***Table 3:* Prediction of Internal Parameters of Z-Score using BPNN.**

S.No	Tolerance	Years	Output			
			(Current Assets – Current Liability) / Total Assets	Retained earnings/ Total Assets	Earnings Before Interest and Tax / Total Assets	Equity/Total Liability
1	0.001	2009	0.93163	0.06655	0.06822	0.00370
2		2010	0.93180	0.06655	0.07204	0.00376
3		2011	0.93166	0.06655	0.07500	0.00382
4		2012	0.93154	0.06655	0.07697	0.00387
5		2013	0.93145	0.06655	0.07829	0.00391
6		2014	0.93139	0.06655	0.07923	0.00395
7		2015	0.93135	0.06655	0.07992	0.00397

6. OBSERVATIONS:

The validation was carried out for all the internal parameters of Z-Score value. The Z-Score internal parameter estimates were considered from 2001 to 2007 were applied to train the backpropagation neural network and subsequently estimates of the year 2008 to 2010 the data values were used for validation. Based on these values predictions were drawn using BPNN from 2011 to 2015.these values have then been substitutes in the Z-Score formula for market credits to compute the Z-Score values from 2008 to 2015. The market has witnessed several ups and downs during the period 2005 and 2010 and the modeled BPNN has been able to closely predict the Z-Score values from 2005 to 2010. The trained BPNN has been able to forecast the Z-Score values in approximation to the actual values suggesting that the BPNN has the ability to forecast the Z-Score parameters financial ratios.

Year	2009	2010	2011	2012	2013	2014	2015
Z Score	6.879118	6.950205	6.995233	6.924572	6.421925	6.925549	6.925768

The Z Score values reveal that it is safe to lend to OBC as the values lie in the safe zone. The bank can get credit at relaxed norms. Even the period of repayment can be long.

For OBC bank the movement of Z-Score has been from 0.1% to 4.6%. The trend exhibited by the predicted value is from 0.6% to 7.8%. (Figure No: 1)

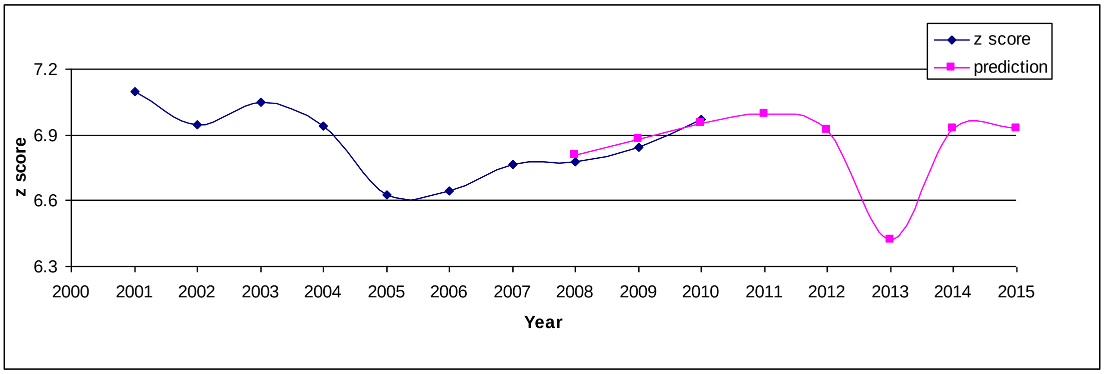

Figure No: 1 -Z Score for OBC

7 CONCLUSION

The tailored BPNN is found to be of immense utility at the time of predicting the viability of lending to any firm. The obtained Z score validation suggests that the neural network can predict closely. The tailored back-propagation neural network endeavors to predict the internal parameters of a firm to regulate the bankruptcy and assess the credit viability when a bank requires credit and can also be utilized to plan the periods of recovery of the lent amount.

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