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CORPORATE BANKRUPTCY PREDICTION USING BACKPROPOGATION NEURAL NETWORK

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ABSTRACT
Z-Score in practice has been commonly used to gauge the financial health of all companies. This paper describes the development of predictive model for corporate banks. Several methods have been proposed to predict financial bankruptcy from 1930 onwards, out of these several methods this research work focuses on the neural network for prediction of Altman's Z Score. The aim of our research is to establish that the neural networks can be used to predict the Z Score of the banking firms. The backpropagation neural networks been used to forecast the Z Score for the firms. The research work first estimates the internal parameters of the Z Score for a firm from 2001-2008 to the train the BPNN and uses the estimates of the year 2009 and 2010 values for the validation process. Finally it dwells to draw predictions for the period 2011-2015 and emphasizes the growing role of BPNN application based Z Score computation of financial Bankruptcy.

KEYWORDS: Z-Score, BPNN, Neural Networks.

INTRODUCTION

Forecasting the debtor's ability to repay his dues has long been a captivating issue for both the lenders and investors. Answering the question, how likely is it that the loan taken will be repaid on time, is central to the valuation and asset allocation of debt portfolios. Our evaluation of the Z-Score rather sheds light on the strengths and weaknesses of the firm to be used by lenders and investors for better understanding of the tools at their disposal when evaluating creditworthiness. Particularly in the light of recent turmoil in the credit markets, it is helpful to re-evaluate the performance of the widely-known firms to verify the capacity to pay back the accepted credit. The Z-Score, developed by Professor Edward Altman et al, is perhaps the most widely recognized and applied model for predicting financial distress (Bemmann 2005). Professor Altman developed this intuitively appealing scoring method at a time when traditional ratio analysis was losing favor with academics (Altman 1968). KMV was the first to commercialize the structural bankruptcy prediction model in the late 1980s.

A Review Of Bankruptcy Prediction Models Using Neural-Network (NN) Approaches

Research studies on using NNs for bankruptcy prediction have been continuing from 1990. It can be argued that there are saturation effects in the relationships between the financial ratios and the prediction of default. Currently, several of the major commercial loan default prediction products are based on NNs. Moody's Public Firm Risk Model [32] is based on NNs as the main technology. Many banks have also developed and are using proprietary NN default prediction models. Vellido *et al.* survey the use of NNs in business applications. Dimitras *et al.* provide a survey on the classical empirical approaches. Zhang *et al.* include in their paper a nice review of existing work on NN bankruptcy prediction. The majority of the NN approaches made a comparision between MDA and NN to forecast bankruptcy of firms. Odom and Sharda applied Altman's financial ratios as inputs to the NN and applied their method, as well as MDA as a comparison, to a number of bankrupt and solvent US firms. Tam and Kiang compared MDA, LR, K-nearest neighbor (KNN), ID3 (a decision tree classification algorithm), single-layer network, and multilayer network. For the case of one-year-ahead, the multilayer network was the best, while for the case of two-year-ahead, LR was the best. Salchenberger *et al.* compared NN with LR for the problem of predicting thrift failures. Kerling tested several cross-validation procedures and early-stopping procedures in a follow-through study. Leshno and Spector used novel NN architectures containing cross-terms and cosine terms. Lee *et al.* proposed hybrid models and specifically tested combinations of the models MDA, ID3, self-organizing maps and Neural networks. Kiviluoto used self-organizing maps on an extensive database of Finnish firms and compared them with MDA and learning vector quantization. Kaski *et al.* developed a novel self-organizing map procedure based on the Fisher metric and applied it also to a number of Finnish firms. Zhang *et al.* compared between NN and LR and employed a five-fold cross-validation procedure, on a sample of manufacturing firms. Yang *et al.* used probabilistic NNs (PNNs), which essentially implement the Bayes classification rule. Fan and Palaniswami propose the use of support vector machines (SVMs) for predicting bankruptcies among Australian firms. They also made a comparison with NN, MDA and learning vector quantization (LVQ).

MODEL DESIGN AND METHODOLOGY

In this paper, a two step methodology is taken into consideration.The part A provides the steps for the prediction of internal parameters of Z Score and the part B enlists the steps for the prediction of Z Score using artificial neural networks.

Part A: Formulation of Internal Parameters of Z Score
The basic inputs required 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. 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

BPNN Model application for Punjab National Bank
Punjab National Bank is a state-owned commercial bank located in New Delhi being incorporated in the year 1895 at Lahore .The bank has been the first Indian bank to have been started solely with Indian capital. Total business of the bank crossed Rs 5 lac cr as on December 2010 aided by rapid branch expansion.
The basic input sheets for all the internal parameters are formulated for Punjab National Bank. 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 input period has been from 2000-2006 which has been normalized from 1 to 8. Table 1 provides the details of the ratios and the values.

Table 1: Training Pattern for PNB Internal Parameters of Z-Score

Input	**Output**			
Time	(CA-CL)/Total Assets	Retained Earnings/ Total Assets	EBIT/ Total Assets	Equity/Total Liabilities
2000	0.865784	0.038987	0.081279	0.003921
2001	0.862777	0.041978	0.080515	0.003342
2002	0.870653	0.047153	0.076046	0.003639
2003	0.881733	0.051326	0.068712	0.003077
2004	0.872751	0.073619	0.062138	0.003081
2005	0.863976	0.06938	0.055071	0.002498
2006	0.894067	0.067643	0.056393	0.00217

A 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 are compared with the actual values for the years specified for validation as suggested by Table 2.

Table 2: Z-Score Convergence Study for PNB

Tolerance	**Ratios**	**2008**			**2009**			**2010**		
		Actual	Predicted	% Error	Actual	Predicted	% Error	Actual	Predicted	% Error
0.1	(CA-CL)/Total Assets	0.89899	0.87594	2.56394	0.88504	0.87550	1.07780	0.89033	0.87512	1.70739
	Retained Earnings/Total Assets	0.06445	0.06394	0.78576	0.06444	0.06526	-1.26928	0.06446	0.06631	-2.87319
	EBIT/Total Assets	0.07405	0.06374	13.92099	0.08573	0.06185	27.85153	0.07572	0.06008	20.65577
	Equity/Total Liability	0.00194	0.00253	-30.52694	0.00158	0.00240	-51.78324	0.00128	0.00228	-78.92966
	Z Value	6.60706	6.35228	3.85628	6.59373	6.34772	3.73095	6.56082	6.34370	3.30935

A BPNN of size 1-5-4 is used for prediction. The error of tolerance to stop the execution was 0.1. It took the network 1864455epochs to converge.

BPNN Modeling analysis, results and outcomes
After the computation of the basic ratios 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**.**

Tolerance	Years	Output			
		(Current Assets – Current Liability) / Total Assets	**Retained earnings/ Total Assets**	**Earnings Before Interest and Tax / Total Assets**	**Equity/Total Liability**
0.1	2009	0.87560	0.06541	0.06167	0.00239
	2010	0.87520	0.06652	0.05975	0.00226
	2011	0.87483	0.06742	0.05792	0.00214
	2012	0.87451	0.06814	0.05622	0.00203
	2013	0.87423	0.06872	0.05466	0.00193
	2014	0.87398	0.06919	0.05324	0.00184
	2015	0.87378	0.06957	0.05196	0.00177

Observations& Findings

The process of validation was conducted 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. Despite the fact that the market has witnessed several ups and downs during the period 2005 and 2010 it has been found that 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.

Table 4 : Z Score values

Year	2009	2010	2011	2012	2013	2014	2015
Z Score	6.541449	6.526344	6.3402014	6.3367889	6.5333807	6.3312390	6.3290514

The Z Score values reveal that it is safe to lend to PNB 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 PNB the movement of Z-Score has been from 0.2% to 3.1%. The trend exhibited by the predicted value is from 0.2% to 3%. (Figure No: 1)

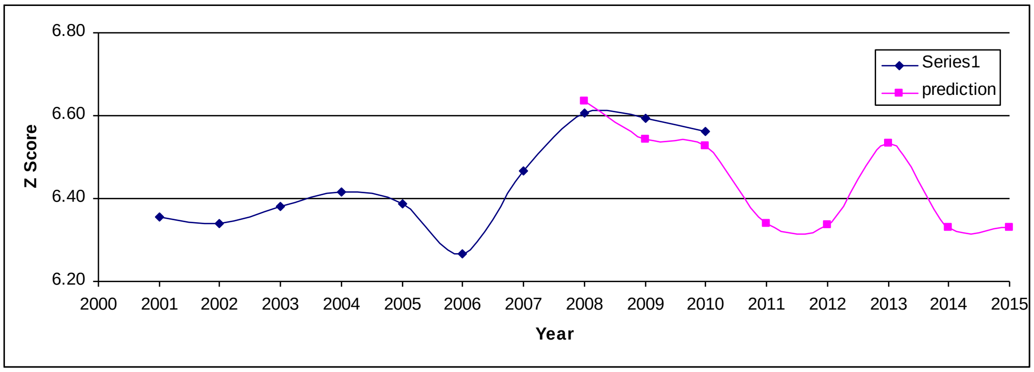

Figure 1: Z-Score PNB

CONCLUSION

The tailored BPNN is found to be of immense utility to predict the Z value to suggest the bankruptcy position of the firm. The obtained Z score validation suggests that the neural network can predict closely. The tailored back-propagation neural network can aptly predict the required internal parameters of the Z Score. The value of Z can also be obtained accurately by using BPNN. The Z values obtained can be utilize to decide the repayment schedule and tenure of loan recovery for the mentioned firm.

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