

# Application of Neural Network in Prediction of Financial Viability

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**Abstract-** Bankruptcy prediction is very important for all the organization since it affects the economy and causes a rise in many social problems with incremental high costs. There are large number of techniques that have been developed to predict the bankruptcy of firms, which helps the decision makers such as investors and financial analysts to plan in accordance to the financial position of the firm regarding the terms of credit as well as the recovery of the lent amount. The Altman Model for prediction of financial bankruptcy has been considered in this work. 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.

**Index Terms-** Bankruptcy prediction, financial ratio models, BPNN

## I. INTRODUCTION

Interest in bankruptcy prediction has long been confined to academics, with most of the published material restricted to business and accounting journals specializing in esoteric and complicated subjects. A possible reason why insolvency prediction models have not gained greater use in the business community is because it has been difficult to calculate the results. With the wide spread use of personal computers and the internet, the utilization of an insolvency prediction model is now practical and available to all.

## II. PRIOR RESEARCH

There have been many methods that have been adopted to predict the bankruptcy .Some of these techniques is as follows:

### • Fuzzy Rule Based Model

The earliest applications of fuzzy set theory are knowledge based systems whose core is a set of fuzzy 'if-then' rules. Most of these systems derive these fuzzy 'if-then' rules from human experts. The generation of fuzzy if-then rules from numerical data involves (i) the fuzzy partition of a pattern space into fuzzy subspaces and (ii) the determination of fuzzy if-then rules for each fuzzy partition. The performance of such a

classification system depends on the choice of a fuzzy partition.

### • Neural Network

Back-Propagation Neural Network model is the most popular methodology in the neural networking. This model considers corporate factors and different sample matches but also uses financial ratios within different periods to construct Back-Propagation Neural Network models. There are three layers in neural network, the first layer—input layer, the second—hidden layer and the third layer—output layer. The hidden layer can be one or more layers, but we adopted the typical three-layer architecture in this study. The transfer function was sigmoid function. The neurons of input layer were predictors. The outputs of neurons in output layer were the output of BPNN. There are links to connect the neurons of each layer. Every link has a relative weight to represent the importance of input information. The algorithm of BPNN is to input data from input layer into hidden layer where data were transferred by the log sigmoid function, and then output into output layer. BPNN uses sample data for its prediction taken from open market of listed companies in Taiwan electronic industries for the effect of prediction correctness for one-year prior of crisis.

### • Hybrid Model using Neuro-Fuzzy Model

The process of making credit-risk evaluation decision is complex and unstructured. Neural networks are known to perform reasonably well compared to alternate methods for this problem.

However, a drawback of using neural networks for credit-risk evaluation decision is that once a decision is made, it is extremely difficult to explain the rationale behind that decision. Researchers have developed methods using neural network to extract rules, which are then used to explain the reasoning behind a given neural network output. These rules do not capture the learned knowledge well enough. Neuro-fuzzy systems have been recently developed utilizing the desirable properties of both fuzzy systems as well as neural networks. These Neuro-fuzzy systems can be used to develop fuzzy rules naturally. In this model, we analyze the beneficial aspects of using both Neuro-fuzzy systems as well as neural networks for credit-risk evaluation decisions.

### • Hybrid Model using Genetic, Fuzzy and Neural networks Model

Neural network is good for non-linear data with learning capacity. Its disadvantage is black box approach (after training difficult to trace how they work). Fuzzy Neural Network adds rules to Neural Network that overcome black box but learning capacity is reduced. Genetic Fuzzy Neural Network is proposed to avoid black box

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approach and to improve learning efficiency.

- **Genetic Algorithm**

Genetic Algorithms are general-purpose search and optimization procedures. They are inspired by the biological evolution principle of survival of the fittest. The genetic algorithm (GA) is a search heuristic that mimics the process of natural evolution. This heuristic is routinely used to generate useful solutions to optimization and search problems. Genetic algorithms belong to the larger class of evolutionary algorithms (EA), which generate solutions to optimization problems using techniques inspired by natural evolution, such as inheritance, mutation, selection and crossover.

- **Fuzzy c-means Clustering**

The Fuzzy c-means algorithm is a method of clustering which allows one piece of data to belong to two or more clusters. This method was developed by Dunn (1973) and improved by Bezdek (1981). It is frequently used in pattern recognition. Under the Fuzzy c-means approach, each given datum does not belong exclusively to a well defined cluster, but it can be placed in a middle way. This belonging to more than one cluster is represented by probability coefficients. This method is based on minimization of the following objective function

- **Multivariate Adaptive Regression Splines (MARS) model**

As stated earlier Multivariate Adaptive Regression Splines (MARS) is a multivariate nonparametric regression technique developed by Friedman (1991). Its main purpose is to predict the values of a continuous dependent variable. MARS can be considered as a generalisation of classification and regression trees (CART) (Hastie, Tibshirani, & Friedman, 2003) [19], and is able to overcome some limitations of CART. MARS does not require any priori assumptions about the underlying functional relationship between dependent and independent variables. Instead, this relation is covered from a set of coefficients and piecewise polynomials of degree q (basis functions) that are entirely driven from the regression data.

### Various Feature Models:

For the bankruptcy prediction, there are 5 models used popularly for all the techniques. They are as follows

- **Altman Model**

A predictive model created by Edward Altman in the 1960s. This model combines five different financial ratios to determine the likelihood of bankruptcy amongst companies. The Altman [1968] study is used as the standard for comparison for subsequent bankruptcy classification studies using discriminant analysis. The ratios are:

$$Z = 0.012X1 + 0.014X2 + 0.033X3 + 0.006X4 + 0.999X5.$$

Where

$X1 = \text{Net working capital/total assets}$

$X2 = \text{Retained earnings/total assets}$

$X3 = \text{Earnings before interest and taxes/total assets.}$

$X4 = \text{Market value of equity/book value of total liabilities.}$

$X5 = \text{Sales/total assets.}$

- **Ohlson Model**

Ohlson employed logistic regression to predict company failure, to overcome the limitations of Altman. This model consists of the following ratios:

$$Z = 1 / [1 \exp - (a [b.sub.1] TLTA [b.sub.2] WCTA [b.sub.3] CLCA [b.sub.4] OENEG [b.sub.5]$$

$$NITA [b.sub.6] FUTL [b.sub.7] INTWO [b.sub.8] CHIN)]$$

Where,

$Z = \text{the probability of bankruptcy for a firm}$

$TLTA = \text{Total liabilities divided by total assets.}$

$WCTA = \text{Working capital divided by total assets.}$

$CLCA = \text{Current liabilities divided by current assets.}$

$OENEG = 1 \text{ If total liabilities exceed total assets, } 0 \text{ otherwise.}$

$NITA = \text{Net income divided by total assets.}$

$FUTL = \text{Funds provided by operations (income from operation after depreciation) divided by total liabilities.}$

$INTWO = 1 \text{ If net income was negative for the last 2 years, } 0 \text{ otherwise.}$

$CHIN = (NIt - NIt_{-1}) / (|NIt| + |NIt_{-1}|)$ , where  $NIt$  is net income for the most recent period.

The denominator acts as a level indicator. The variable is thus intended to measure the relative change in net income.

- **Zmijewski Model**

This model is used to predict bankruptcy using probit model. It consists of 3 ratios as:

$NITL = \text{Net income divided / total liabilities.}$

$TLTA = \text{Total liabilities divided / total assets.}$

$CACL = \text{Current assets divided / current liabilities.}$

- **Shumway Model**

Shumway improved on the basic bankruptcy models by combining market ratios along with the traditional financial ratios [13]. This model is defined as follows:

$$Z = 1 / [1 \exp - (a [b.sub.1] NITA [b.sub.2] TLTA [b.sub.3] ERR [b.sub.4] SDR)]$$

Where

$Z = \text{the probability of bankruptcy for a firm}$

$NITA = \text{Net income/total assets}$

$TLTA = \text{Total liabilities/total assets}$

$ERR = \text{Excess rate of return (i.e., a firm's rate of return minus the market's rate of return)}$

$SDR = \text{Standard deviation of residual returns (Residual return = a firm's realized rate of return - its expected rate of return)}$

### III. MODEL DESIGN AND METHODOLOGY

In this paper, a two step methodology has been adopted. The part A provides the steps formulated for the prediction of financial ratio pillars, followed by part B which enlists the steps followed for the prediction of financial ratios using artificial neural networks.

#### 1) Part A: Formulation of Ratio Pillars

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 researches 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. This research tries to present a holistic view by incorporating all various ratios and then relating them to examine the explanatory capabilities of the financial ratios to suggest the position of the bank. Construction of the basic ratios into ratio pillars is a vital ingredient of the basic work done prior to deployment of neural network.

**Part A: Ratios have been constructed for the needful being**

1.  $(\text{Current Assets} - \text{Current Liabilities}) / \text{Total Assets}$
2.  $\text{Retained Earnings} / \text{Total Assets}$ .
3.  $\text{EBIT} / \text{Total Assets}$
4.  $\text{Equity} / \text{Total Liabilities}$

**Part B: Prediction of Financial Ratios using ANN Model**

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

**IV. BPNN MODEL APPLICATION FOR AXIS BANK**

Axis Bank, formerly UTI Bank, is India's third largest private-sector bank after the significantly larger

ICICI Bank and HDFC Bank. It is engaged in Large & Mid Corporate Banking, Retail Banking, SME banking, Agri-business banking, International Banking, treasury etc. It has the largest EDC (Electronic Data Capturing) network, the third largest ATM network and the fourth largest base of debit cards in India. As of 31st December, 2010 it had a very wide network of more than 1281 branches including 169 Service Branches and over 5303 ATMs. It has the largest EDC network, the third largest ATM network and the fourth largest base of debit cards in India.

The basic input sheets for all the eight pillars are formulated for AXIS Bank. The process of ratio pillar formulation uses the book formulae for computation of the ratios in each pillar, 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 of 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

Backpropagation 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. A BPNN of size 1-5-4 is used for prediction. The error of tolerance to stop the execution was 0.01. It took 1445578 epochs to converge.

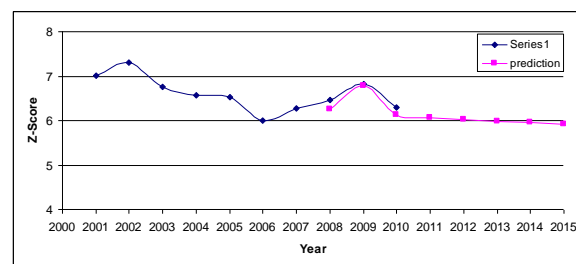
**V. BPNN MODELING ANALYSIS, RESULTS AND OUTCOMES**

After the computation of the basic ratio pillars, as suggested by Table 1, this section uses the ratios in each pillar as inputs to train the network. The network after training computes the values of the ratios from 2009 upto the year 2015 at different tolerance level. The validation is done by the values obtained for the year 2009 and 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 then used in the formula to find the Z-Score value for the banks upto the year 2015. The tolerance level is 0.2. It took the network 1445578 epochs to converge. Table 3 provides details of the percentage error at the adopted level of tolerance.

**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 2008 were applied to train the backpropagation neural network and subsequently estimates of the year 2009 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 2009 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.

For axis bank the movement of Z-Score has been from 0.9% to 8%. The trend exhibited by the predicted value is from 0.4% to 10%. (Graph No: 1)



**Graph No: 1: Z Score for Axis Bank.**

**VI. CONCLUSION**



In times of economic distress the BPNN model would provide assistance to finding the financial viability of the firm using Z score incorporating BPNN. 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. In this article we reviewed the problem of bankruptcy prediction using NNs. We have proposed novel inputs being internal parameters of Z score. As can be seen from the results, the new indicators (included ratios) influence the credit lending and act as the central factors for prediction of credit. This can be explained by the tendency of the financial to be highly volatile, not only of the health of a firm, but also of the health of the economy, which in turn affects the creditworthiness of the firm. The analysis also suggests that the model can forecast the financial position of the firm in case of loan value enhancement as well as the extension of the repayment period implying to be effective in the designing of policy measures related to credit viability thus proves to be a vital tool to regulate the occurrence of credit defaults.

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**Table 1: Training Pattern for Axis bank Internal Parameters of Z-Score**

S.N	Input Parameters			
	(CA-CL)/Total Assets	Retained Earnings/ Total Assets	EBIT/ Total Assets	Equity/Total Liabilities
1	0.950572	0.015749	0.083173	0.148266
2	0.957791	0.029424	0.08302	0.358879
3	0.912015	0.035076	0.073607	0.157147
4	0.899522	0.037467	0.060077	0.14487
5	0.89667	0.05655	0.044953	0.142296
6	0.803163	0.064118	0.062841	0.096473
7	0.871017	0.042475	0.05446	0.061756

**Table 2: Z-Score Convergence Study for Axis Bank**

S. No	Tolerance	Ratios	2008			2009			2010		
			Actual	Predicted	% Error	Actual	Predicted	% Error	Actual	Predicted	% Error
1	0.01	(CA-CL)/TOTAL ASSETS	0.88	0.86	2.26	0.93	0.86	8.57	0.01	0.85	0.88
2		Retained Earnings/Total Assets	0.08	0.06	18.92	0.07	0.07	1.94	0.09	0.07	0.08
3		EBIT/Total Assets	0.06	0.05	17.22	0.07	0.04	46.14	0.06	0.04	0.06
4		Equity/Total Liability	0.05	0.04	26.73	0.03	0.06	-46.81	0.03	0.05	0.05
5		Z Value	6.47	6.25	3.48	6.83	6.77	10.01	0.79	6.12	6.47

**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	0.01	2009	0.87560	0.06541	0.06167	0.00239
2		2010	0.87520	0.06652	0.05975	0.00226
3		2011	0.87483	0.06742	0.05792	0.00214
4		2012	0.87451	0.06814	0.05622	0.00203
5		2013	0.87423	0.06872	0.05466	0.00193
6		2014	0.87398	0.06919	0.05324	0.00184
7		2015	0.87378	0.06957	0.05196	0.00177