Back propagation Neural Networks in Financial Analysis of Stock Market Returns

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ABSTRACT

In this paper, we showed a method to forecast the stock price using neural networks. Predicting the stock market is very difficult since it depends on several known and unknown factors. In recent years, one of the techniques that have been used popularly in this area is artificial neural network. The power of neural network is its ability to model a nonlinear process without a priori knowledge about the nature of the process. We used back propagation neural network, to make the prediction. The objective of this study is to find out the effect of daily Exchange rate, FII Purchase, FII Sales on daily Closing Return of NIFTY by using back propagation Neural Network. The accuracy measure of prediction is defined in terms of the forecasting error, which is the difference between the actual and predicted value.

Keywords: Foreign Investors Inflow, Mean Square Error, Sum of Square Error, Mean Absolute Error, Root Mean Squared Error, Artificial Neural Networks, Multi Layer Preceptron and Back propagation Neural Network.

1. INTRODUCTION

Stock price forecasting is an important and hot topic in forecasting financial time series data. Since once the forecasting is successful, we could determine a suitable trading strategy and could get a very high profit. However, predicting the stock market is very difficult since it depends on several known and unknown factors, and frequently the data used for forecasting is noisy, uncertain, and incomplete Thawornwong S. and Enke D. [1].

According to the Efficient Market Hypothesis [2], [3], stock prices move very much like a random-walk process most of the time because stock markets are efficient to absorb any new information. Therefore, it is unlikely to predict the market movement based on past information to make a profit. However, there has been no consensus on the validity of the Efficient Market Hypothesis (EMH). Hsieh [4], Tsibouris and Zeidenberg [5] suggested that the stock market movement is not totally efficient based on their research works on American stock markets. Shmilovici et al. [6] reported that 10 of the 13 international stock indices tested and 60% to 84% of the TA25 stocks reject the EMH.

In recent years, one of the techniques that have been used popularly in this area is artificial neural network. Artificial Neural Networks are patterned after the parallel processing methods of the human brain. The biological brain is composed of billions of interconnected processing elements called neurons, which transmit information and strengthen when the brain learns. Neural Networks use interconnected processing elements that allow them to learn from mistakes, learn from example, recognize patterns in noisy data, and operate with

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incomplete information. By evaluating the processing capabilities of the human brain, neural networks attempt to overcome the limitations of traditional computers. An Artificial Neural Network (ANN) is a model composed of several highly interconnected computational units called neurons or nodes. Each node performs a simple operation on an input to generate an output that is forwarded to the next node in the sequence. This parallel processing allows for great advantages in data analysis.

Using back propagation algorithm, the network can be trained with available data to model an arbitrary system. The trained network is then used to predict the movements in the future. In order to increase the forecasting ability in terms of profit earning, Yao et al. [7] proposed a profit based adjusted weight factor for back propagation in which factors containing the profit, direction, and time information were added to the error function.

Artificial neural network models provide a powerful alternative to standard regression techniques for producing time-series and cross-sectional models. According to refenes et. al. [8] "Neural Networks are capable of making better prediction in capturing the structural relationship between a stock's performance and its determinant factors more accurately than Multiple Linear Regression models". Multiple regression analysis is the process of finding the least squares prediction equation, testing the adequacy of the model, and conducting tests about estimating the values of the model parameters. Mendenhall and Beaver [9] if stock market return fluctuations are affected by their recent historic behavior, neural networks which can model such temporal stock market changes can prove to be better predictors Tang et. al. [10] . The changes in a stock market can then be learned better using networks which employ a feedback mechanism to cause sequence learning. Neural networks are particularly useful for handling complex, non-linear univariate and multivariate relationships that would be difficult to fit using other techniques.

This paper investigates the systematic ways to use neural networks to predict stock market prices in the future. The objective of this study is to find out that how much the daily Closing Return of NIFTY are effected by daily Exchange rate, FII Purchase, FII Sales by using Artificial Neural Network.

2. Back Propagation Neural Networks

This paper investigates the systematic ways to use neural networks to predict stock market prices in the future. Neural networks can approximate any nonlinear function. As such flexible function approximators, they are powerful for pattern recognition, classification, and forecasting. The most commonly used neural networks in stock price prediction are back propagation neural networks. Back propagation neural networks are common because it is simple, easy to train and has a good performance.

Back Propagation Algorithm

The back propagation training algorithm can be summarized in the following steps as:

Forward Propagation

Step 1: To initialize all w_{ij}'s to small random values with w_{ij} being the value of the connection weight unit j and unit i in the layer below.

Step 2: To present an input from the class m and specify the desired output. The desired output is 0(zero) for all the output nodes expect the mth node, which is 1.

Step 3 : To calculate actual output of all the nodes using the present value of w_{ij} The output node j, denoted by yj, is a nonlinear function of its total input given by:

$$y_j = 1/\left\{1+\exp\left(-\sum_i y_i w_{ij}\right)\right\}$$

Where, w_{ij} is the connection weight between unit j and unit i (unit i is one layer below unit j). After this is computed, its value becomes the activation level of unit j. This value is transmitted along the output connections. This particular nonlinear function is called a sigmoid function.

Backward Propagation

Step 4: To find an error term, δ_j, for all the nodes. If dj and yi stand for the desired and actual value of a node respectively, then for an output node,

$$\delta_j = (d_j - y_i) y_i (1 - y_i)$$

And for a hidden layer node,

$$\delta_j = y_i (1 - y_i) \sum_k \delta_k w_{jk}$$

Where, k is overall nodes in the layer above node j.

Step 5: To adjust weights by

$w_{ij}(n+1) = w_{ij}(n) + \propto \delta_j y_i + \eta\{w_{ij}(n) - w_{ij}(n-1)\}$ Where, (n+1), (n), and (n-1) index next, present and pervious, respectively. The parameter α is a learning rate similar to step size in gradient search algorithms, and η is constant between 0 and 1 which determines the effect of past weight changes on the current direction of movement in weight space. This provides a kind of momentum that effectively filters out high-frequency variations of the error surface. Small value of η gives instability of network. So η is chosen such that $0.25<\eta<0.75$.

Step 6: To present another input and to go back io stip 2. All the training inputs are presented cyclically until weights stabilize.

To summarize, the above algorithm is an iterative gradient descent procedure in the weight space which minimizes the total error between the desired and actual outputs of all the nodes in the system. It has been shown that MLP with two hidden layers can form any arbitrarily complex decision region in a feature space. However, no specific rule for selection of the number of nodes in the hidden layers has yet been developed.

3. Neural Networks Methodology

The networks tried to predict the Nifty daily stock index one day in the future. The National Stock Exchange (NSC)[13] is considered India's second exchange. The main index of the NSC is S&P CNX Nifty.

3.1 Background of the Financial Prediction

Since long time, the topic of market efficiency has been attracted a widespread interest and considerable research. This issues which have been hotly debated are the random walk and the efficient market hypothesis. The former theory assumes that prices are stochastic in nature, while the latter theory implies that profit opportunities do not exist in perfectly efficient markets, PAN [11]. That means both theories imply that in well functioning markets, prices are unpredictable. However, there are theoretical arguments and empirical research seriously questioning these two theories, and there is still no general agreement over the validity of both the random walk and the efficient market hypotheses. Many researchers provide evidence that stock market prices are predictable by publicly available information such as time-series data of financial and economic variables, Shadbolt and Taylor [12]. Forecasting is a process that produces a set of outputs by a given set of variables. The variables are normally past data. Basically, forecasting assumes that future values are based, at least in part, on past data. Past relationships can be found through study and observation. The ideas of forecasting using neural networks is to find an approximation of mapping between the input and output data through training. The trained neural networks are then used to predict the values for

the future. Prediction is made by exploiting implications hidden in past trading activities and by analyzing patterns and trends shown in price and volume charts (Smirlock and Starks, 1985; Brush 1986).

Using neural networks to predict financial markets has been an active research area, since the late 1980's [14],[11],[15]. In this article our Prediction is made by exploiting implications hidden in past trading activities and by analyzing patterns and trends shown in daily stock price and daily exchange rate return, FII Purchase and FII Sales.

3.2 Inputs Selection

This study uses a Back propagation Neural Network for prediction of daily NIFTY stock from 1 April, 2005 to 30 March, 2007 (total 500 observations). The data is obtained from the NSE site (www.nseindia.com), RBI site (www.rbi.org.in), SEBI site (www.sebi.gov.in). The data considered in this study are daily stock returns of NIFTY, daily Exchange Rate Rupee/US Dollar, daily FII Purchase, and daily FII Sales. Closing NIFTY is taken as dependent variable and exchange rate, FII purchase, FII sales are taken as independent variable. For this study the output is the forecasted daily stock return.

The stock market can display varying characteristics for various exchange rate (Rupee/US Dollar), FII purchase, and FII sales. So it is necessary to develop model for predicting daily stock return of NIFTY.

First of all in the analysis of the data is to determine if the series is stationary. A time series is said to be stationary if there is no systematic change in mean (no trend), in variance, and, if so, periodic variations have to be removed.

To detect nonstationarity, the study uses a stationary test, called the unit root test (Augmented Dickey Fuller and Philip Perron). The null hypothesis tested here is "the series is non-stationary". If the absolute value of the statistic is greater than the critical Value, then the null hypothesis is rejected and hence the series is stationary.

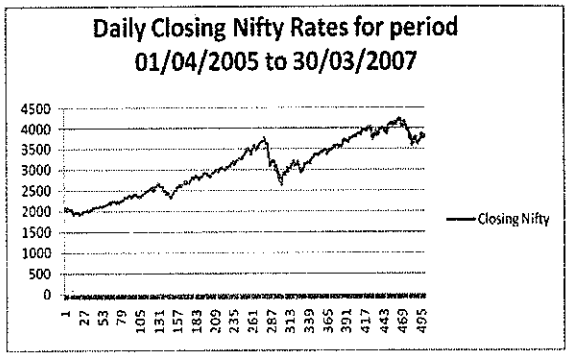


Figure 1.1

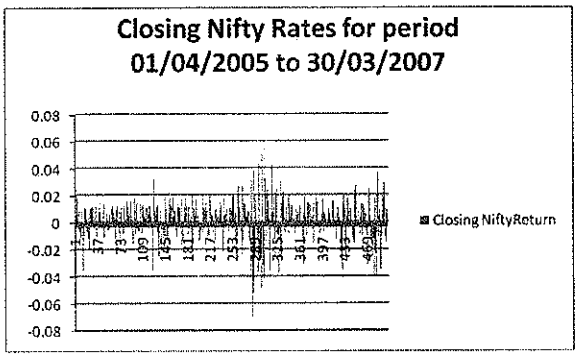


Figure 1.2

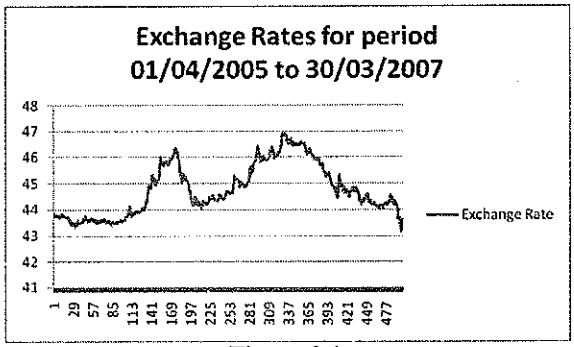


Figure 2.1

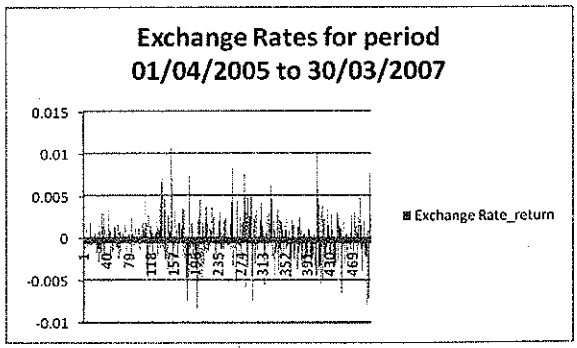


Figure 2.2

3.3 Networks Selection

To design a Neural Network Model for a particular forecasting problem is a difficult task. Modeling should be considered carefully because it affects the performance of an ANN. First important factor is to determine the appropriate architecture, that is, the number of layers, number of nodes in each layer. Other network design decisions include the selection of activation functions of the hidden and output nodes, the training algorithm, and performance measures.

The network has 3 layers, one input layer, one output layer and one hidden layer. The number of hidden units is chosen through the experimental performance. As the results, the hidden layer with five hidden nodes performed best for back propagation network. An iteration of 50000 passes is carried over the training. The maximum input value is 10000.0 and the maximum output value is 1.0. These maximum input value and maximum output value specify the upper bounds on the values of the inputs and outputs of the network. The minimum R-squared level is .99999.

3.4 Training Strategy

The major problem in training a neural network is deciding when to stop training. If we stop the training unsuitably, the network may be over-fitting. Over-fitting occurs when the system memorizes patterns and thus looses the ability to generalize (or predict) input data that it has never seen. Over-fitting can occur by having too many hidden nodes or training for too much time. The network was trained by back propagation algorithm with early stopping, a technique to avoid over-fitting [1]. Every 1000 training cycles, mean squared error (MSE) of the validating data was examined. The error told us whether the network was over-fitting or not. If it decreased, the training was continued. Otherwise the training was stopped.

To experiment with neural networks, we used WinRATS (v. 5.00), (http://www.estima.com)which provides the tools to implement and test various configurations of back propagation neural networks and learning algorithms.

4. General Descriptions of The Experiments

Stationarity Test: The Augmented Dickey Fuller test statistics and Philip Perron Test statistics as given in following table. The input and output series have been tested for Stationarity.

Forecasting performance results

Unit Root Test of Two Series

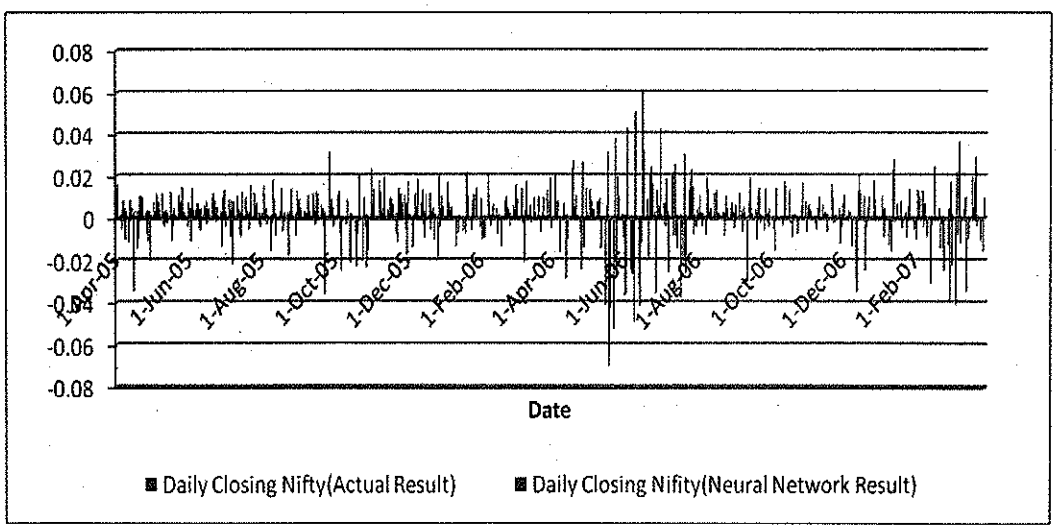
Series	Augmented Dickey FullerTest		Philip Perron Test	
	Statistic	Critical Value (5% Critical Value)	Statistic	Critical Value (5% Critical Value)
Daily Closing Nifty	- 9.563573	- 2.8677	- 20.91897	- 2.8676
Exchange Rate	- 9.106490	- 2.8677	- 21.35800	- 2.8676
fiip	- 4.298148	- 2.8677	- 11.24999	- 2.8676
fiis	- 4.414005	- 2.8677	- 9.641936	- 2.8676

An important parameter in the multilayer perception problem is the estimation of the prediction error. This section is focused on forecasting ability of the back propagation neural network. The sample period is form 01/04/2005 to 30/03/2007 and the total observations are 500 data. The forecasting has been made from back propagation Neural Network model and we have find out the following results.

	No. of Observation	MSE	RMSE	MAE	SSE
Back propagation Neural Network	500	0.0002119649	0.0145590127	0.010517453168303800	0.1057704608

The network was trained with all the data (500 observations) to produce daily stock market prediction model. It can be observed that, the movement of daily stock return is predictable. The performance of back propogation model was made on the basis of MSE (Mean Square Error). The MSE of 500 test record are ovbiously smaller. It means back propogation neural network is better predicter. Thus the expiremet shows that back propogatin neural network model with three input nodes, five hidden nodes and one output node can be used for better prediction. The correlation r between daily actual closing nifty result and daily closing nifty Neural Network result is 0.061327684.

Following figure depicts the BPNN, Actual closing nifty daily prices.



5. Conclusion

This paper showed a systematic method to forecast the times series stock price using neural networks with back propagation. We proposed a new method to develop a neural network model for daily stock return prediction of NIFTY and also show the effect of Exchange Rate, FII Purchase, and FII Sales on daily return of Nifty stock Stock return. The reliability of this model depends on data collected from the stock market.

In the future, we plan to integrate neural network with some other techniques such as genetic algorithm or fuzzy logic. Genetic algorithm can be used to identify optimal network architecture and training parameters. Fuzzy logic provides the ability to account for some uncertainty produced by the neural network predictions (Thawornwong and Enke). Their uses in conjunction with neural network could provide an improvement for stock market prediction.

References

[1] Thawornwong . S and Enke . D, *"The adaptive selection of financial and economic variables for use with artificial neural networks"*, Neurocomputing, Vol. 56, PP. 205-232, 2004.

[2] Fama . E . F, *"Efficient capital markets: A review of theory and empirical"*, Journal of Finance, Vol. 25, PP. 383-417,1970.

[3] Malkiel . B. G, *"A Random Walk Down Wall Street"*, 7th ed. W. W. London, UK and New York, NY: Norton & Company, 1999.

[4] Hsieh . A. D, *"Chaos and non-linear dynamics: Application to financial markets"*, Journal of Finance, Vol. 46, PP.1833-1877, 1991.

[5] Tsibouris. G and Zeidenberg. M, *"Testing the efficient market hypothesis with gradient descent algorithms"*, in Neural Networks in the Capital Markets, A. Refenes, Ed. New York, NY: John Wiley & Sons, PP. 127-136, 1996.

[6] Shmilovici .A, Alon-brimer .Y and Hauser.S, *"Using a stochastic complexity measure to check the efficient market hypothesis"*, Computational Economics, Vol. 22, No. 2-3, PP.273-284, 2003.

[7] Yao J.T, Tan C.L, *"Time dependent directional profit model for financial time series forecasting"*, In proceeding of the IJCNN, Como, Italy, Vol. 5, PP.291 - 296, 2000.

[8] Refenes, Zapranis and Francis, Journal of Neural networks, *"Stock Performance Modeling Using Neural Networks: A Comparative Study With Regression Models"*, Vol. 7, No. 2, PP.375-388, 1994.

[9] Mendenhall and Beaver, *"Introduction to Probability And Statistics"*, Ninth Edition, International Thomson Publishing, 1994.

[10] Tang, Almeida and Fishwick, *"Simulation, Time series forecasting using neural networks vs. Box-Jenkins methodology"* , PP. 303-310, November 1991.

[11] PAN. H.P, *"A joint review of technical and quantitative analysis of the financial markets towards a unified science of intelligent finance"*, Proc.2003 Hawaii International Conference on Statistics and Related Fields, June 5-9, Hawaii, USA, 2003.

[12] Shadbolt J. and Taylor J.G, *"Neural Network and the Financial Markets. Predicting, Combining and Portfolio Optimisation"*, Springer, 2002.

[13] National Stock Exchange (NSE), www.nse-india.com.

[14] Azoff. E. M, *"Neural network time series forecasting of financial market"*, JohnWiley & Sons Ltd, 1994.

[15] Swales. G.S and Yoon. Y, *"Applying artificial neural networks to investment analysis"*, Financial Analysts Journal, 48 (5), 1992.

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