Management Dynamics

Volume 14 | Number 2 Article 6

December 2014

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Recommended Citation

Siddiqui, Taufeeque Ahmad and Abdullah, Yusuf (2014) "Non-Linear Relationship between Macroeconomic Variables and Stock Prices in India: An Artificial Neural Networks Approach," *Management Dynamics*: Vol. 14: No. 2, Article 6.
DOI: https://doi.org/10.57198/2583-4932.1102
Available at: https://managementdynamics.researchcommons.org/journal/vol14/iss2/6

NON-LINEAR RELATIONSHIP BETWEEN MACROECONOMIC VARIABLES AND STOCK PRICES IN INDIA: AN ARTIFICIAL NEURAL NETWORKS APPROACH

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ABSTRACT

Neural networks are powerful forecasting tools that draw on the most recent developments in artificial intelligence research. They are non-linear models that can be trained to map past and future values of time series data and thereby extract hidden structures and relationships that direct the data. Many studies have shown that artificial neural networks have the capacity to learn the underlying mechanics of stock markets. In fact, artificial neural networks have been widely used for forecasting financial markets. However, such applications to Indian stock markets are scarce. The paper investigates the application of artificial neural networks to the dynamic interrelations between macroeconomic variables i.e. Foreign Exchange rate, Foreign Exchange reserves and Wholesale price index. Multilayer perceptron network is used to build the monthly prices model for CNX Nifty and the network is trained using Error Back Propagation algorithm. It is found that the predictive power of the network model is influenced by the previous values . The study shows that satisfactory results can be achieved when applying neural networks to predict the Indian Stock prices.

Keywords: Stock market prediction, Neural networks, Financial forecasting, nonlinear time series Analysis.

JEL Classification: C22, C45, C53

INTRODUCTION

In the past, predictions as regards financial markets have been based on traditional statistical forecasting methods. Linear models have been the basis of such forecasting models. However, the presence of noise and non-linearity in the time series have made these models inaccurate. The successful application of non-linear methods in other areas of research has kindled the hopes of financial researchers. Nonlinear dynamics proposes a new way of viewing financial asset prices, and it suggests new techniques for empirically measuring their nature. The relation of past prices with future

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prices or one variable with the other variables is not linear, but nonlinear. This non-linearity implies that past price change can have wide ranging effects on future prices. Nonlinear dynamics tells when a prediction starts becoming unreliable. The best advice one can hope to get from such a prediction is that it is the best not to be in a particular market at all. Hence, an attempt is made in this study to understand the use of neural networks in the field of finance.

An artificial neural network has an ability to work parallel with input variables and consequently handle large sets of data quickly. The principal strength of the network is its ability to find patterns. ANNs provide a promising alternative tool for the forecasters. The inherently nonlinear structure of neural networks is particularly useful for capturing the complex underlying relationship in many real world problems.

The ability to accurately predict the future is fundamental to many decision processes in planning, scheduling, purchasing, strategy formulation and policy making. As such, forecasting is an area where a lot of efforts have been invested in the past. Yet, it is still an important and active field of human activity at the present time and will continue to be in the future.

One of the major application areas of ANNs is forecasting. Recent research activities in artificial neural networks (ANNs) have shown that ANNs have powerful pattern recognition capabilities (Widrow et al., 1994). Forecasting has a long history and the importance of this old subject is reflected by the diversity of its applications in different disciplines ranging from business to engineering.

LITERATURE REVIEW

Youngohc Yoon and George Swales (1991) demonstrated that the neural network approach is capable of learning a function that maps inputs to output and encoding it in magnitudes of the weights in the network connection. They compared Neural Network technique with Multivariate Discriminant Analysis approach and indicated that the Neural Network approach can significantly improve the predictability of stock price performance.

Trippi and DeSieno (1992) applied a neural network system to model the trading of Standard and Poor's 500 index futures. They found that the neural network system model outperforms passive investment in the index. Based on the empirical results, they favor the implementation of neural network systems into the mainstream of financial decision making.

Lawrence Kryzanowski ,Michael Galler ,David W, Wright (1993) determined the Artificial Neural Networks accuracy in predicting future return performance as either positive or negative or as negative neutral or positive. The Artificial neural Network correctly classifies 72% of positive or negative returns. Its accuracy in predicting the three-state out comes was high which could not have been achieved by chance alone.

Yao et al (1999) used moving average (MA), momentum (M), relative strength index (RSI), stochastic (%K), and moving average of stochastic (%D) to predict the Malaysian stock index using an ANN model for 303 trading days in 1990-1991. The significant aspect of the study was that the model after being used to predict the stock price was used successfully for commercial gains by stock trading. The yield obtained was more that the interest rate and other investment tools.

Phua et al (2001) use ANNs with genetic algorithms to do predictions on the Stock Exchange of Singapore. 360 samples (between August 1998 and January 31, 2000), with daily opening, daily high, daily low and closing prices with the trading volume of the index, have been examined. The result is promising as, a rate of 81% in predicting market direction has been achieved.

Egeli et al (2003) indicated that there has been no specific research on ISE stock market values and build an ANN model that uses previous day's index value, exchange rate and simple interest rate as input to forecast ISE price fluctuations. They constructed a model with the previous day's index value, the previous day's Turkish Lira/USD exchange rate, the previous day's overnight interest rate and 5 dummy variables each representing the working days of the week. They tried three different numbers of hidden layers (1, 2 and 4) and acquired the lowest error rate and the highest accuracy using a single hidden layer. They concluded that ANN models have been superior to the 5-day/10-day moving averages model.

Yumlu et al (2004) have studied 12 years of financial data (a set of ISE index closing values, USD values and two interest rates) using a modular ANN model.The authors concluded that the model outperformed the conventional autoregressive model used for comparison. They stated that the model introduces a powerful way to predict the volatility of financial time series data, contradicting EMH.

Qing Cao, Karyl B Leggio, Marc J.Schniederjans (2005) used Artificial Neural Networks to predict stock price movement (i.e. returns) for firms traded on the Shanghai Stock Exchange and compared the predictive power of univariate and multivariate neural network models. The results show that Neural Network outperformed the linear models compared. Those results were statistically significant across the sample firms. It was indicated that neural networks are useful tool for stock price Prediction in emerging markets like china.

E.L. de Faria and J.L. Gonzalez (2009) performed a study of the principal index of the Brazilian stock market through artificial neural networks and adaptive exponential smoothing method, respectively. The objective was to compare the forecasting performance of both methods with traditional forecasting methods, and in particular, to evaluate the accuracy of both methods to predict the signs of the market returns. Their results show that although both methods produce similar results regarding the prediction of the index returns in form of the sign of the market return, the neural networks outperform the adaptive exponential smoothing method in the forecasting of the market movement, with relative hit rates similar to the ones found in other developed markets.

OBJECTIVES OF THE STUDY

- To forecast future stock prices using artificial neural network.
- To train the network using backpropagation algorithm.
- To recommend the best model as per the obtained results.

METHODOLOGY

Data

The paper uses monthly data for the period January 2003 till August 2013. The variables which are considered in the study are closing prices of CNX Nifty 500 Index, The total Foreign Exchange reserves, Foreign Exchange rate (US$ vs. INR rate) and Wholesale price Index. The data are obtained from official web sites of NSE and RBI.

Multi-layer perceptron

In the present study Multilayer perceptron(MLP) has been employed to predict stock prices. A multilayer perceptron (MLP) is a feed forward artificial neural network model that maps sets of input data onto a set of appropriate outputs. A MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function (Rosenblatt, 1961). MLP utilizes a supervised learning technique called back-propagation for training the network (Rumelhart et al., 1986) MLP was first developed to mimic the functioning of the brain. It consists of interconnected nodes referred to as processing elements that receive, process, and transmit information. MLP consists of sensory units that make up the input layer, one or more hidden layers of processing units (perceptrons), and one output layer of processing units (perceptrons). The MLP performs a functional mapping from the input space to the output space. An MLP with a single hidden layer having H hidden units and a single output, y, implements mappings of the form.

(1)

$$y = F(W_\circ + \sum_{h=1}^{H} W_h Z_h$$

(2)

$$Z_h = F(\beta_{oh} + \sum_{j=1}^{n} \beta_{jh} X_j$$

where Z_h is the output of the hth hidden unit, Wh is the weight between the hth hidden and the output unit, and W0 is the output bias. There are *N* sensory inputs, *Xj*. The jth input is weighted by an amount *βj* in the hth hidden unit. The output of an MLP is compared to a target output and an error is calculated. This error is back-propagated to the neural networkand used to adjust the weights. This process aims at minimizing the mean square error between the network'sprediction output and the target output.

First of all the network has to be trained to produce the correct output with minimum error. To achieve the minimum error the network first has to be trained until it produces a tolerable error. This is how the training is done. Input is fed to the input nodes, from here the middle layer nodes take the input value and start to process it. These values are processed based on the randomly allocated initial weight of the links. The input travels from one layer to another and every layer process the value based on the weights of its links. When the value finally reaches the output node, the actual output is compared with the expected output. The difference is calculated and it is propagated backwards, this is when the links adjust their weights. After the error has propagated all the way back to first layer of middle level nodes, the input is again fed to the input nodes. The cycle repeats and the weights are adjusted over and over again until the error is minimized. The key here is the weight of different links. The weights of the links will decide the output value.

MLP-based forecasting

The present study uses Neural network package of IBM-SPSS. This software applies artificial intelligence techniques to automatically find the efficient MLP architecture. Typically, the application of MLP requires a training data set and a testing data set . The training data set is used to train the MLP and must have enough examples of data to be representative for the overall problem. The testing data set should be independent of the training set and is used to assess the classification/prediction accuracy of the MLP after training. An error back-propagation algorithm with weight updates occurring after each epoch was used for MLP training.

It has to be noted that the lagged variables have been also used to program the network in order to accomodate any seasonal trends. Since the data is monthly, lag orders of 1,3,6,12 have been taken which refers to previous month trend,quarterly trend, semi-annual trend and annual trend respectively.

The MLP structure is determined automatically by the SPSS software which works on the principle of Keep the best model(KTB). In order to assess the accuracy of forecast, Mean Squared Error (MSE) has been used as measure of fit, as suggested by Zhang et al. (2004).

EMPERICAL RESULTS

The following tables provide the MLP network information for the best structure as obtained by SPSS. The values are obtained for testing data.

Table 1: Results for all three independent variables (Total Foreign Exchange reserves, Foreign Exchange rate (US$ vs. INR rate) and the Wholesale price Index)

Lag order	MLP Structure	SSE	MSE	RMSE	Relative error
0	3-5-1	1.089	0.0085	0.0923	5.2%
1	3-3-1	0.630	0.0049	0.0704	5.6%
3	3-1-1	3.543	0.0283	0.1687	14.3%
6	3-2-1	1.122	0.0093	0.0963	6.7%
12	3-2-1	1.545	0.0131	0.1144	10.3%

Table 1 depicts results as regards all the three independent variables (Total Foreign Exchange reserves, Foreign Exchange rate (US$ vs. INR rate) and the Wholesale price Index) to forcast stock prices. The table illustrates various lag orders (0, 1, 3, 6 and 12) and different MLP structures (3-5-1, 3-3-1, 3-1-1, and 3-2-1). The table also contains SSE, MSE, RMSE and relative errors for all the mentioned lags orders and MLP structures. It can be infered from the Table that MLP structure of 3-3-1 with lag order of 1 has the least MSE of 0.0049, followed by MLP structure of 3-5-1 with lag 0 which has MSE of 0.0085. Lag order 3 has the highest MSE of 0.0283.

Table 2: Results for two independent variables (Foreign Exchange rate (US$ vs. INR rate) and the Wholesale price Index)

Lag order	MLP Structure	SSE	MSE	RMSE	Relative error
0	2-3-1	1.796	0.0140	0.118	11.4%
1	2-2-1	0.998	0.0079	0.0886	5.1%
3	2-9-1	1.308	0.0105	0.1023	5.2%
6	2-1-1	3.350	0.0277	0.1664	23.6%
12	2-2-1	2.218	0.0191	0.1383	13.8%

Table 2 shows that when Foreign Exchange rate (US$ vs. INR rate) and the Wholesale price Index are taken as independent variables the best MLP structure is again for lag order 1 with network infrastructure of 2-2-1. The given structure yields MSE of 0.0079.

Table 3: Results for two independent variables (Total Foreign Exchange reserves and the Wholesale price Index)

Lag order	MLP Structure	SSE	MSE	RMSE	Relative error
0	2-2-1	2.864	0.0224	0.1496	13%
1	2-1-1	3.755	0.0296	0.1720	16.%
3	2-2-1	3.302	0.0264	0.1625	18.7%
6	2-4-1	1.555	0.0129	0.1133	7.7%
12	2-1-1	2.938	0.0253	0.1591	19.1%

From Table 3 it can be infered that when Total Foreign Exchange reserves and the Wholesale price Index are taken as independent variables the best fitted model comes out to be of lag order 6 with MSE of 0.0129. MLP structure of this model is 2-4-1.

Table 4: Results for two independent variables (Total Foreign Exchange reserves and Foreign Exchange rate (US$ vs. INR rate))

Lag order	MLP Structure	SSE	MSE	RMSE	Relative error
0	2-4-1	1.597	0.0125	0.1117	8.1%
1	2-3-1	1.127	0.0089	0.0942	10.1%
3	2-2-1	2.701	0.0217	0.1470	19.9%
6	2-7-1	2.401	0.0198	0.1409	17.0%
12	2-5-1	0.975	0.0084	0.0917	7.1%

Table 4 shows that using Total Foreign Exchange reserves and Foreign Exchange rate (US$ vs. INR rate) as independent variables yield lag order 0 with MLP structure of 2-4-1 as the best model. MSE for this model is 0.0125.

Table 5: Independent variable importance analysis through MLP

Variable	Importance	Normalized Importance
Foreign Exchange Rate	0.311	47.3%
Foreign Exchange Reserves	0.032	4.8%
Wholesale Price Index	0.658	100.0%

Table 5 exemplifies independent variable importance analysis. The table shows that Wholesale price index is the most important variable with 0.658 relative importance followed by foreign exchange rate (0.311) and foreign exchange reserve (0.032).

Appendix depicts actual and predicted data of CNX Nifty 500, from March 2011 to August 2013 (forecasted period). The data is based on the best model among the combinations of the variables which is with lag order of 1 with all the three independent variables. The model with MLP structure of 3-3-1 yielded the lowest MSE of 0.0049.

CONCLUSION

The study has proposed ANN models on the basis of MSE to forecast the stockprices. The paper uses monthly data for the period January 2003 till August 2013. The variables which are considered in the study are closing prices of CNX Nifty 500 Index, The total Foreign Exchange reserves, Foreign Exchange rate (US$ vs. INR rate) and Wholesale price Index. The forecast on the basis of proposed models have been computed and compared. It is found that the best forecast for the stock prices has been with lag order of 1 with all the three independent variables. This model with MLP structure of 3-3-1 yielded the lowest MSE of 0.0049 among all the combinations of the variables.

Furthermore, according to Independent variable importance analysis which has been computed through MLP it is found that among the three variables WPI has the highest importance of 0.658 followed by Foreign Exchange Rate (0.311) and Foreign Exchange Reserves (0.032). It can be concluded that WPI has high impact on stock returns which is evident from the fact that during high inflationary era in a given country, the stock markets tend to plummet.

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Appendix: MLP predicted CNX 500 values compared with actual values

Period	Actual	Predicted	Period	Actual	Predicted
Aug-2013	4175.85	4290.4	May-2012	3913.05	4360.8
Jul-2013	4379.65	4315.2	Apr-2012	4178.35	4345.8
Jun-2013	4510.9	4344.6	Mar-2012	4221.8	4347.4
May-2013	4681.45	4380.6	Feb-2012	4275.55	4320.4
Apr-2013	4641.75	4366.5	Jan-2012	4082.85	4342.8
Mar-2013	4438.35	4361.9	Dec-2011	3597.75	4422.1
Feb-2013	4477.5	4387.5	Nov-2011	3811.25	4470.4
Jan-2013	4795.3	4384.5	Oct-2011	4215.9	4440.1
Dec-2012	4743.45	4377.7	Sep-2011	3978.35	4496.2
Nov-2012	4675.25	4381.3	Aug-2011	4038.35	4478.4
Oct-2012	4448.85	4379.5	Jul-2011	4424.05	4454.6
Sep-2012	4504.35	4346.6	Jun-2011	4522.95	4424.2
Aug-2012	4129.9	4328.3	May-2011	4492.9	4436.2
Jul-2012	4126.45	4330.0	Apr-2011	4615.3	4357.7
Jun-2012	4170.65	4297.6	Mar-2011	4626.45	4320.7