FORECASTING DSE BROAD INDEX: AN APPLICATION OF MULTI-LAYER FEED FORWARD NEURAL NETWORK

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Abstract: Predicting share prices of stock market is a common topic of research in all over the world because of interest of the mass investors. However, it is a challenging issue because price is affected by external factors and has higher volatility. In this study, Artificial Neural Network (ANN) is a latest tool which has used to predict the Dhaka Stock Exchange Broad Index (DSEX) for the duration from August, 2013 to December, 2018. DSEX represents around 97% of the total equity Market Capitalization. In this paper Three Layer Feed Forward Neural Network using Back propagation learning algorithm is used. The accuracy of the model is examined by calculating Root Mean Square Error (RMSE) values. The fitted ANN model showed better prediction pattern with smaller error values.

Keywords: *DSEX; ANN; Back Propagation Algorithm; RMSE*

1. INTRODUCTION

Predicting the future movement based on the previous and present data is the key point in inventory planning. Several techniques have been developed considering this problem to predict the future behavior of a series of events. Stock markets are complex dynamic systems because stock prices affected by external and internal factors such as political, economic issues. Therefore, stock price prediction for capitalists is very important to be able to return most of their investment will earn. Due to these reasons high volatility and a great amount of noise are raised in Stock market. That is why, forecasting the stock market data can be a challenging task.

Beside Multiple Regression Techniques [1] as statistical tool Time Series Analysis are also popular approaches to predict the future value of a series, however, when the series become non-linear or non-stationary in nature the forecasting ability of these tools have reduced [2]. A non- parametric approach, Neural Network [3], becomes a popular tool due to its capacity to be trained from the nature of the series and accuracy. Many researches have been done to compare Neural Networks with statistical methods [4, 5]. Yoon and Swales [6] found Neural Network technique as better tool for prediction of stock price when compared with Multivariate Discriminant Analysis approach. Neural network is a better model in compare with the Barone-Adesi and Whaley (BAW) American futures options pricing model in aspect of volatility forecasting of S&P 500 Index [7]. The accuracy of forecasting of ANN is higher than point estimation through regression [8] as well as through linear models [9].

The univariate neural network is used [10] to study the profitability of daily stock market index returns whereas Bayesian regularized artificial neural network as a novel method to forecast financial market behavior by [11]. For the Istanbul Exchange it was showed that the forecasting power of artificial neural network was higher than linear regression [12]. For the Indian Stock market ANN is used to model the Indian stock market in terms of Bombay stock exchange data [13]. With the help of Back propagation Algorithm an ANN model having three layers in the Network is used for forecasting Istanbul Stock Exchange National-100 Indices (ISE National - 100) with an accuracy of 74.51% [14]. A comparison of artificial neural network with the adaptive exponential smoothing method is made and found better performance of ANN for forecasting the market movement [15]. ANN has used in different stock exchanges such as Canadian stock returns [8], Chinese stock market [9], Brazilian stock market [15], Portuguese Stock market [16], Indian Stock Exchange [17, 18]. However, Roy and Ashrafuzzaman [19] failed to forecast stock price accurately in Bangladesh. Another research [20] tried to predict stock market efficiency in weak form of Dhaka Stock Exchange by using some non-parametric as well as some parametric methods. A robust method was suggested where Principal Component Analysis (PCA) is done to the data set to reduce high dimensionality for using back propagation neural network [21]. This method is used for the prediction of next day share price using DSE share prices. Hossain [22] has tried to forecast the General Index of Dhaka Stock Exchange (DSE) using ARIMA, ARCH, and GARCH models as well as made a comparison among their forecasting power.

This study will apply the method of artificial neural networks (ANN) as modern method of forecasting technique to forecast the stock market prices in terms of Dhaka Stock Exchange Broad Index (DSEX) and see how it could be used as an alternative method to traditional methods in case of Dhaka Stock Exchange (DSE) market. DSEX is the broad index of the exchange (Benchmark Index) which reflects around 97% of the total equity Market Capitalization. However, until recently, not too much work related to stock market indices forecasting based on ANN methods are found in Bangladesh. The goal of the research is to propose a suitable ANN model for DSE Broad Index (DSEX) and then discuss about the forecasting power in terms of forecasting errors.

2. MATERIALS AND METHODS

A. Data and Data Processing

The success of any data analysis eventually depends on the accessibility of the appropriate data. For this study, the data set which has been used is secondary in nature. The current DSE Broad Index (DSEX) which reflects around 97% of the total equity Market Capitalization has started to use from July 2013 that is why data from August, 2013 to December, 2018 is used on monthly basis. The data were obtained from the Monthly Economic Trends of Bangladesh Bank which are available in the website of Bangladesh Bank. About 80 % of the data (from August, 2013 to December, 2017) were used as training data and rest data (from January, 2018 to December, 2018) were used as testing data set. The analysis was performed using open source software R and the version was 3.2.3.

B. Artificial Neural Networks (ANN)

The human brain consists of neurons that send activation signals to each other and have the ability to learn from the past, according to a complex system of sending and receiving electrical pulses between neurons. This fact has encouraged many researchers and led to the establishment of the cognitive sciences, known as artificial intelligence and building the network, known as Artificial Neurons, and send activation signals to one another but is not a biological fact.

Multilayer Feed-Forward Neural Network

The main feature of ANN is to model the human thought process as an algorithm which can be efficiently run on a computer. There are several kinds of Neural Network model from which Back-Propagation Learning Algorithm for Multilayer Feed-Forward Neural Network using the conjugate gradient method to be used to model the DSEX data set. Multilayer feed forward network consists of more than one layer of artificial neurons, which allows only unidirectional forward connections of inputs and outputs. Typically, the network consists of a set of sensory units (source nodes) that constitute the input layer, one or more hidden layers of computation nodes, and an output layer of computation nodes. There are really two decisions that must be made regarding the hidden layers: how many hidden layers to actually have in the network and how many neurons will be in each of these layers. Almost all current problems solved by neural networks are well with just one hidden layer. Even though the hidden layers do not directly interact with the external environment, they have a remarkable influence on the final output.

On the other hand, though ANN model try to get accuracy in forecasting using minimum number of hidden layers and neurons, sometimes, to increase the accuracy of the model may need to increase hidden layers. Thus the number of hidden layers and the number of neurons within it should be carefully chosen. A multilayer feed-forward neural network has shown in Fig. 1 as example.

Activation Function in ANN

In ANN model, activation function is used to transform input signal to output signal of a node which is used as an input in the next layer. Activation function is the function of inputs (X) and applied it to get the output of that layer and feed it as an input to the next layer. There are several kinds of activation functions from which sigmoid activation function is most useful for training data that is also between 0 and 1.

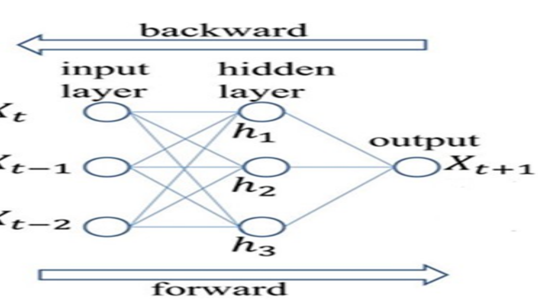


Fig. 1. Multilayer feed-forward neural network with one hidden layer.

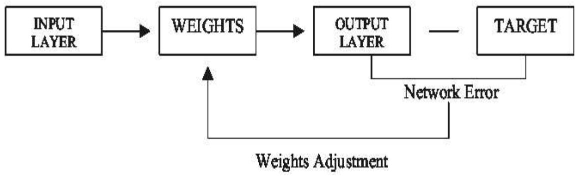


Fig. 2. Feed forward back propagation technique Back-Propagation Learning Algorithm.

The most popular learning method named Back propagation, an abbreviation for "backward propagation of errors", is a familiar method of training artificial neural networks. As the algorithm's name implies, the errors propagate backwards from the output nodes to the input nodes.

Fig. 2 showed that training network consists of following steps;

1. The input pattern is presented to the input layer of the network. These inputs are propagated through the network until they reach the output units where the network outputs depend on the input units, hidden units, weights of the network, and the activation function.
2. Based on the input units, hidden units and weights, the output pattern is constructed.
3. The accuracy of the model is obtained by minimizing error through back propagation.4. The connection weights are then adjusted and the neural network has just "learned" from an experience.
4. This process is repeated until the total network error becomes the smallest.

Operational Definition

Input layer - In this study lag 1 of monthly value of DSEX is used as the input variable. Since it is a univariate analysis, the input layer consists also the lag 1 of monthly value of DSEX.

Output - The predicted monthly value of the DSEX using input layer through the hidden layer is considered as output.

Hidden layer - Single hidden layer with 4 neurons is used for this study. The hidden layer is the combination of weighted lag 1 of monthly value of DSEX to produce predicted value of DSEX through Activation function.

C. Jarque-bera Test of Normality

Jarque–Bera test is a goodness-of-fit test to determine whether the data is distributed as normal or not. The test statistic JB is defined as,

$$JB = \frac{n}{6}\left(S^2 + \frac{1}{4}(k-3)^2\right) \quad (1)$$

Where n is the number of observations. S is the sample skewness, and K is the sample kurtosis. This statistic can be used to test the hypothesis that the data are from a normal distribution.

D. Augmented Dickey-Fuller (ADF) Test for Stationarity Test

Unit root test is applied to a time series data for checking non-stationary property. The Augmented Dickey–Fuller (ADF) testis a unit root test, the general equation for ADF is applied to the time series is a following model:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1}\Delta y_{t-p+1} - \varepsilon_t \quad (2)$$

Where α is a constant, β is the coefficient on a time trend and p is the lag order of the autoregressive process. This model can be implemented for the different values of p.

E. Performance (Error) Measuring Metrics

All the used forecasting techniques are assessed and compared on the basis of their out - sample forecasting error. A number of broadly used performance (error) measuring metrics, Root Mean Square Error (RMSE), Mean Absolute Error (MAE); Mean Absolute Percentage Error (MAPE); Theil's U, are utilized for evaluating performances of the models. Some short notes about them are given as follows:

Root Mean Square Error (RMSE)

The root-mean-square error (RMSE) is a frequently used measure of the differences between values predicted by a model (or an estimator) and the values actually observed. For a given data sample these individual differences are called residuals and are called prediction error when computed out-of-sample. The RMSE of predicted values $\hat{y}_t$ for times t of a dependent variable y is computed for n different predictions as the square root of the mean of the squares of the deviations:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{n}} \quad (3)$$

Mean Absolute Error (MAE)

The **mean absolute error (MAE)** is a common measure of forecast error in time series analysis (i.e. performance measuring metric) used to measure how close forecasts or predictions are to the eventual outcomes. The mean absolute error is given by

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|f_i - y_i| = \frac{1}{n}\sum_{i=1}^{n}|e_i| \quad (4)$$

The MAE is mean of the absolute errors $e_i = |f_i - y_i|$, where f_i is the forecasted and y_i the actual value.

Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) calculates the percentage of accuracy for fitted time series data; it can be expressed by the formula:

$$M = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \quad (5)$$

Where, A_t is the actual value and F_t is the forecast value. The difference between A_t and F_t is divided by the Actual value A_t again. It is a percentage error.

Theil's U statistic is a relative measure of accuracy which compares the results of forecasting with minimal historical data. The formula for calculating Theil's U statistic

$$U = \sqrt{\frac{\sum_{t=1}^{n-1}\left(\frac{\hat{Y}_{t-1} - Y_{t+1}}{Y_t}\right)^2}{\sum_{t=1}^{n-1}\left(\frac{Y_{t+1} - Y_t}{Y_t}\right)^2}} \quad (6)$$

Where, Y_t is the actual value of a point for a given time period t, n is the number of data points, and $\hat{Y}_t$ is the predicted value.

3. RESULT AND DISCUSSION

The mean DSE Broad Index is 8.48 with standard deviation 0.12 and the data is positively skewed with kurtosis -0.28. The minimum value in the logarithmic data is 8.28 and the maximum value is 8.75. From Jarque-Bera Normality Test, the original series does not follow normal distribution, however, its logarithm transformation is normal (Table II).

TABLE I. DESCRIPTIVE STATISTICS OF THE ORIGINAL AND LOGARITHMIC

Statistics	Original Index (DSEX)	Logarithmic Index (LogDSEX)
Observations	53	53
Minimum	3937.68	8.28
Maximum	6306.86	8.75
Mean	4842.21	8.48
First Quartile	4507.58	8.41
Median	4629.64	8.44
Third Quartile	5074.31	8.53
Std. Deviation	606.31	0.12
Skewness	0.92	0.72
Kurtosis	-0.05	-0.28

TABLE II. THE NORMALITY TEST AND STATIONARITY TEST OF THE ORIGINAL, LOGARITHMIC SERIES

Statistics	Original Index (DSEX)	Logarithmic Index (LogDSEX)	Decisions
Jarque-Bera Normality Test	7.53 ($p<0.05$)	4.73 ($p>0.05$)	Original series is not normal. However the log series is normal.
ADF Test for Unit Root	-1.19 ($p>0.10$)	-1.48 ($p>0.1$)	Both the original and logarithmic data are non-stationary.

Augmented Dickey Fuller (ADF) test indicates that the series DSEX and LogDSEX are non-stationarity, therefore several models can be used to examine the volatility over time. DSEX monthly data indicates that, it is a non-stationary time series (Fig. 3). This series varies randomly over time and there is no global trend or seasonal note. The original data were transformed using the natural logarithm to reduce the impact of outliers. One of the advantages of using this transformation is the fixation of variation of the time series that allows no loss of important information from the data. Therefore, the time series that will be used in the analysis is the natural logarithm of the DSE Broad Index (i.e. LogDSEX).

A. *Fitting the Artificial Neural Network (ANN) Model*

A three-layer feed forward neural network with single hidden layer was chosen for forecasting DSEX which is also used in [23]. Five lags of the input layer with eight neurons in the hidden layer are examined to find the model. In addition, three values (0.01, 0.05 and 0.10) of learning rate are used for fitting the model. The best network is chosen on the basis of lowest RMSE value [7, 24]. The back propagation algorithm is utilized to estimate the neural network models.

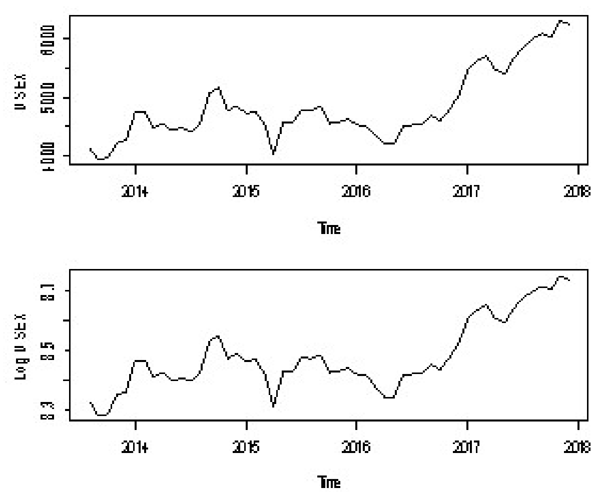


Fig. 3. Time series plots of monthly DSEX, log DSEX.

The RMSE estimates in Table III showed that the network that takes 1 lag as input and contains 4 neurons in the hidden layer with learning rate 0.01 provides the smallest RMSE value (0.0292) and therefore is chosen to apply to the data under study. Before applying the ANN technique to the logarithmic DSE Broad Index (DSEX) time series data, Brock, Dechert, and Scheinkman (BDS) test of non-linearity in data is performed.

For BDS test under the null hypothesis of data are independently and identically distributed (I.I.D.), we reject the null hypothesis (since, $p<0.05$) and conclude that the time series is non- linearly dependent, which is one of the indications of chaotic behavior. This finding from BDS test justifies the fitting of ANN to the series under study.

Fig. 4 showed the pattern of the suggested back propagation neural network model with one input neurons, five hidden neurons and one output neuron in the respective layers. The estimated coefficients are also shown in the given figure.

TABLE III. THE ROOT MEAN SQUARE ERROR (RMSE) VALUES FOR DIFFERENT NEURAL NETWORK MODELS WITH COMBINATIONS OF LAG INPUTS, UNITS IN THE HIDDEN LAYER AND THE LEARNING RATES

Lag	Units in Hidden Layer	RMSE values			Lag Input	Units in Hidden Layer	RMSE values		
		(0.01)	**(0.05)**	**(0.10)**			**(0.01)**	**(0.05)**	**(0.10)**
1	1	0.1520	0.1520	0.1520		5	0.0458	0.0458	0.0458
	2	0.0300	0.0300	0.0300		6	0.0456	0.0456	0.0456
	3	0.0298	0.0298	0.0298		7	0.0459	0.0459	0.0459
	4	**0.0292**	0.0292	0.0292		8	0.0459	0.0459	0.0459
	5	0.0297	0.0297	0.0297	4	1	0.1420	0.1420	0.1420
	6	0.0298	0.0298	0.0298		2	0.0398	0.0398	0.0398
	7	0.0298	0.0298	0.0298		3	0.1420	0.1420	0.1420
	8	0.0297	0.0297	0.0297		4	0.0399	0.0399	0.0399
2	1	0.1357	0.1357	0.1357		5	0.0416	0.0416	0.0416
	2	0.0336	0.0336	0.0336		6	0.0416	0.0416	0.0416
	3	0.0327	0.0327	0.0327		7	0.0416	0.0416	0.0416
	4	0.0280	0.0280	0.0280		8	0.0415	0.0415	0.0415
	5	0.0318	0.0318	0.0318	5	1	0.1265	0.1265	0.1265
	6	0.0331	0.0331	0.0331		2	0.0397	0.0397	0.0397
	7	0.0332	0.0332	0.0332		3	0.1266	0.1266	0.1266
	8	0.0335	0.0335	0.0335		4	0.0371	0.0371	0.0371
3	1	0.1557	0.1557	0.1557		5	0.0452	0.0452	0.0452
	2	0.0463	0.0463	0.0463		6	0.0455	0.0455	0.0455
	3	0.1557	0.1557	0.1557		7	0.0457	0.0457	0.0457
	4	0.0467	0.0467	0.0467		8	0.0456	0.0456	0.0456

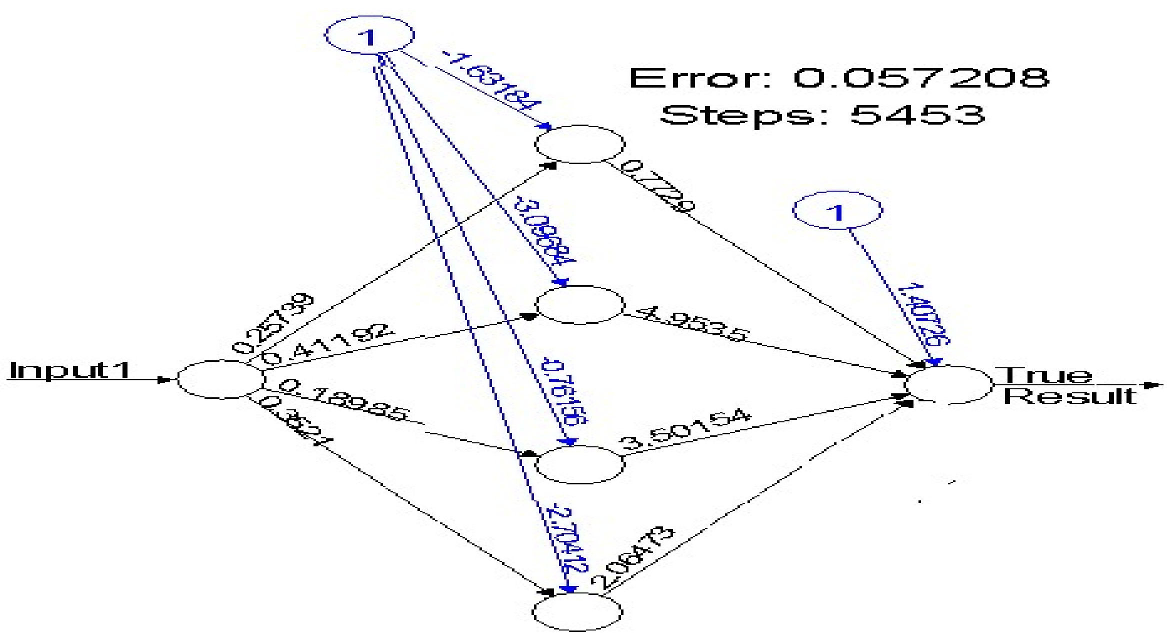
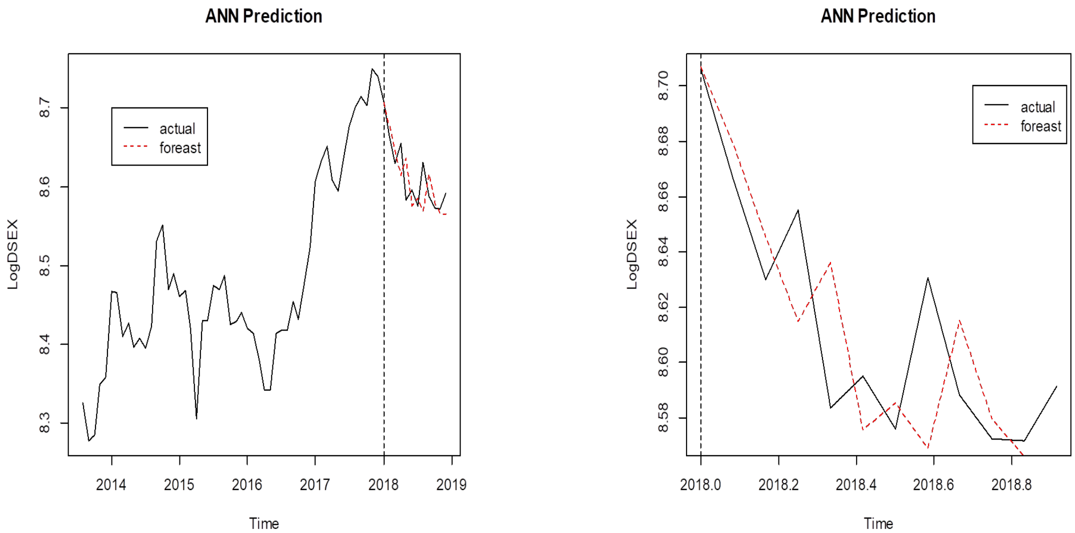


Fig. 4. Proposed Neural Network model with 1 hidden layer.



(a) (b)

Fig. 5. Forecasted pattern of ANN model using (a) the whole data set; (b) the out-sample data set

TABLE IV. THE ACCURACY INDICES FOR SELECTED ANN MODEL

Accuracy Measure	Under Multilayer FFNN model
RMSE	0.02919
MAE	0.02321
MAPE	0.26916
Theil's U	0.00337

B. Accuracy and Forecasting Pattern of the Fitted Model

The idea of the performance of the fitted model in forecasting can be obtained by using several accuracy measures. Table IV presents the estimated value of Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Percent Absolute Error (MAPE) and Theil's U index to evaluate the performance of the model. On the basis of the out-sample forecast errors using data from January, 2018 to December, 2018, the accuracy indices are computed which showed that the errors are relatively smaller and exhibits better forecasting accuracy.

In Figure 5(a) the prediction pattern of Three Layer Feed Forward Neural Network model is exposed and in figure 5(b) the pattern is showed using only the out-sample range which is more specific to understand the pattern very clearly and it indicates that the fitted model has comparatively better prediction ability.

4. CONCLUSION

Artificial Neural Networks (ANN) are constructed in such a way that they are capable of making relation among input layer values with output layer values to generated network which would be capable for predicting the future values with optimum accuracy. In this paper, Three Layer Feed Forward Neural Network using Back propagation learning algorithm is used to forecast DSEX with minimum error values. The accuracy of the model is examined by calculating RMSE values. However, Back Propagation has some problems regarding Local Minima. Therefore, in selecting the best model special care should be given. The fitted ANN model showed better prediction pattern with smaller error values. This model can be used for forecasting movement of DSEX and applied for investment policy to optimize gain.

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