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Performance Analysis of Indian Stock Market Index using Neural Network Time Series Model

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Abstract— **Forecasting based on time series data for stock prices, currency exchange rate, price indices, etc., is one of the active research areas in many field viz., finance, mathematics, physics, machine learning, etc. Initially, the problem of financial time sequences analysis and prediction are solved by many statistical models. During the past few decades, a large number of neural network models have been proposed to solve the problem of financial data and to obtain accurate prediction result. The statistical model integrated with ANN (Hybrid model) has given better result than using single model. This work discusses some basic ideas of time series data, need of ANN, importance of stock indices, survey of the previous works and it investigates neural network models for time series in forecasting. The forecasting accuracy is analyzed and measured with reference to an Indian stock market index such as Bombay Stock Exchange (BSE) and NIFTY MIDCAP50 in this study and it is found that the right parameters number of epochs, learning rate and momentum is 2960, 0.28 and 0.5 respectively for forecasting network by conducting various experiment.**

Keywords- Neural Network; Time Series; Forecasting; Stock Index Performance

I. INTRODUCTION

A time series is a collection of observations made chronologically. The nature of time series data includes: large in data size, high dimensionality and necessary to update continuously. The increasing use of time series data has been initiated a great deal of research and development attempts in the field of time series data.

Time series forecasting is an active research area that has drawn considerable attention for applications in variety of areas. With the time series approach to forecasting, historical observations of the same variable is analyzed to develop a model in describing the underlied relationship. Over the past several decades, much effort has been devoted to the development and improvement of time series forecasting models [14, 22].

Improving forecasting especially time series forecasting accuracy is an important and a difficult task for facing decision makers in many areas. Despite the numerous time series models available, the research for improving the effectiveness of forecasting models has never been stopped.

Time series forecasting models conclude that combining forecasts from more than one model often lead to improved in performance especially when the models in the ensemble are quite different [6]. Artificial Neural Networks (ANNs) have shown [13, 18] to be an effective, general-purpose approach for pattern recognition [27], classification, clustering [29] and prediction with a higher degree of accuracy.

In Recent few years, artificial neural networks have been used successfully to model and forecast time series[30]. Artificial neural network models such as multilayer perceptrons (MLPs), radial basis function networks (RBF), general regression neural networks (GRNNs), etc. is used in time series forecasting. The rest of this paper is organized as follows. Section II gives the surveys related to neural network models for stock index prediction, and some basics of stock market and importance of stock index. Section III gives the method of finding performance evaluation. Section IV describes the results and discussion of performance evaluation and finally this comparative study is concluded in Section V.

II. LITERATURE SURVEY

A neural network is a processing device, either an algorithm or an actual hardware. The computing world has a lot to gain from neural networks, also known as artificial neural network or neural net. ANNs have three great advantages over traditional methods. At first, they have universal approximation capabilities second, they can recognize ‘‘on their own’’ implicit dependencies and relationships in data third, they can ‘‘learn’’ to adapt their behavior viz., prediction, to changed conditions quickly and without complication [10], [20].

W.K.Wong et al. pointed that, Time series forecasting is used to forecast the future based on historical observations [12]. Traditional methods, such as time-series regression, exponential smoothing and Auto Regressive Integrated Moving Average (ARIMA) are based on linear models [1]. All these methods assume linear relationships among the past values of the forecast variable and therefore non-linear patterns cannot be captured by these models. Recently, Artificial Neural Networks (ANN) has been proposed as a promising alternative to time-series forecasting. Tiffany Hui- Kuang Yu , Kun-Huang Huarng [19] noted that some successful applications of neural networks include credit ratings [9], Dow Jones Forecasting [8], customer satisfaction analysis [5], stock

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ranking [16], Foreign exchange rate forecasting [21] and tourism demand [15]. The reason is that the ANN is a universal function approximation which is capable of mapping any linear or non-linear functions.

Although ANNs have the advantages of accurate forecasting, their performance in some specific situation is inconsistent. Based on the study of [1] , [20], Lean Yu et al. [11] noted that ANNs are a kind of unstable learning methods, i.e., small changes in the training set and/or parameter selection can produce large changes in the prediction. Undoubtedly being much more powerful than traditional time series processing techniques, neural networks have several disadvantages [2] [3] [4].

According to Dimitri Pissarenko [4], the most neural network business application studies utilize multilayered feed forward neural networks with the back propagation learning rule (MLP/EBP2). Apart from MLP/EBP, Hopfield networks and self-organizing maps [28] are of practical importance in the financial domain.

The domain of financial time series prediction is a highly complicated task due to following reasons; First, Financial time series often behave nearly like a random-walk process. Second, Financial time series are subject to regime shifting, i.e., statistical properties of the time series are different at different points in time i.e., the process is time-varying. Third, Financial time series are usually very noisy, i.e. there is a large amount of random unpredictable day-to-day variations and finally, In the long run, a new prediction technique becomes a part of the process to be predicted, i.e. it influences the process to be predicted.

The design of a neural network successfully predicting a financial time series is a complex task. Iebeling Kaastra a, Milton Boyd [7] presents an introductory guide in the design of neural network for forecasting economic time series data. While designing an ANN the following sequence of steps to be followed Data collection, Create the network, Configure the network, Initialize the weights and biases, train the network, Test/Validate the network and finally use the network.

A stock market or exchange is the center of a network of transactions where securities buyers meet sellers at a certain price. It is essentially dynamic, non-linear, complicated, nonparametric, and chaotic in nature. The time series are multi-stationary, noisy, random, and has frequent structural breaks. In addition, stock market's movements are affected by many macro-economical factors such as general economic conditions, commodity price index, political events, firms' policies, bank rate, exchange rate, investors' expectations, institutional investors' choices, movements of other stock market, psychology of investors, etc.

A stock market index should capture the behavior of the overall equity market. stock markets in virtually every developed and most developing economies, with the world's largest markets being in the United States, United Kingdom, Japan, India, China, Canada, Germany, France, South korea and Netherlands. In this study, the BSE and NIFTY MIDCAP50 are considered for stock market index evaluation and prediction. Historically, from 1979 until 2012, Indian Stock Market (SENSEX) averaged 5462 Index points reaching an all time high of 21005 Index points in November of 2010 and a record low of 113 Index points in December of 1979 [23] , [24].

III. Prepare Your Paper Before Styling

In this study, the one-step-ahead forecasting strategies are considered. Let y1,y2,y3…yt be a time series. At time t for t>=1, the next value yt+1 is predicted based on the observed realizations of yt,yt-1,yt-2,….y1.

Back propagation neural network architecture is multi layer, feed forward neural network consisting of an input layer, a hidden layer and an output layer. The neurons present in the hidden and output layers have biases, which are the connection from the units and its activation is always one as shown in Fig. 1. The bias term also acts as weights and it shows the architecture of BPN, depicting only the direction of information flow for the feed forward phase. During the back propagation phase of learning, signals are sent in reverse direction. The inputs are sent to the BPN and the output obtained from the net could be either binary 0, 1 or bipolar -1, +1 activation function.

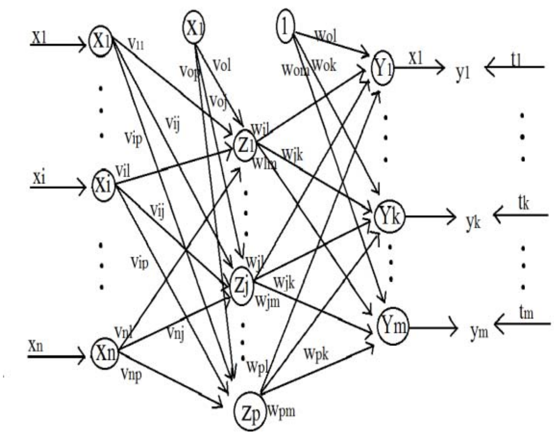

Figure 1. Feed forward with back propagation Architecture

The error back propagation learning algorithm is purely based on the gradient descent method [17].

1. Initialize weights and learning rate.
2. Perform steps 3-10 when stopping condition is false.
3. Perform steps 4-9 for each training pair.
4. Each input unit receives input signal xi and sends it to the hidden unit, $i = 1$ to n
5. Each hidden unit $z_j, j = 1$ to p, sums its weighted input v_{ij}signals to calculate net input:
   $z_{inj} = v_{0j} + \sum_{i=1}^{n} x_i v_{ij}$
   Calculate output of the hidden unit by applying its activation functions binary or bipolar sigmoidal over z_{inj}
   $z_j = f(z_{inj})$ and send the output signal from the hidden unit to the input of output layer units.
6. For each output unit $y_k, k = 1$ to m, calculate the net input:

$y_{ink} = w_{0k} + \sum_{j=1}^{p} z_j w_{jk}$ and apply the activation function to compute output signal $y_k = f(y_{ink})$

7. Each output unit $y_k = 1$ to m, receives a target pattern corresponding to the input training pattern and computes the error correction term $\delta_k = (t_k - y_k) f'(y_{ink})$, on the basis of error correction term, update the change in weights and bias $\Delta w_{jk} = \alpha \delta_k z_j$ and $\Delta w_{0k} = \alpha \delta_k$ also send δ_k to the hidden layer backwards .
8. Each hidden unit $z_j, j = 1$ to p, sums its delta inputs from the output units $\delta_{inj} = w_{0k} + \sum_{k=1}^{m} \delta_k w_{jk}$, the term δ_{inj} gets multiplied with the derivative of $f(z_{inj})$ to calculate the error term: $\delta_j = \delta_{inj} f'(z_{inj})$ on the basis of the calculated δ_j, update the change in weight and bias:
$$\Delta v_{ij} = \alpha \delta_j x_i \text{ and } \Delta v_{0j} = \alpha \delta_j$$
9. Each output unit $y_k, k = 1$ to m, update the bias and weights:
$w_{jk}(new) = w_{jk}(old) + \Delta w_{jk}$ and $w_{0k}(new) = w_{0k}(old) + \Delta w_{0k}$
Each hidden unit zj, j=1 to p, updates its bias and weights:
$v_{ij}(new) = v_{ij}(old) + \Delta v_{ij}$ and $v_{0j}(new) = v_{0j}(old) + \Delta v_{0j}$
10. Check for the stopping condition. The stopping condition may be certain number of epochs reached or when the actual output equals the target output.

The feed forward back propagation neural network is designed to predict stock index for single step ahead, next day i.e., short term prediction. Convergence of the BPN is based on learning algorithm and some important learning factors, such as the initial weights, the learning rate, updating rule, the size and nature of training set, and the architecture such as number of layers and number of neurons per layer.

For the forecasting problem, the natural measure of performance is the prediction error. The use of only one error for evaluating the model performance does not show the prediction clearly. For this reason more performance criteria should be considered to make a robust evaluation of the results and final desirable goals. This study analyses the following performance measurement Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Percentage Mean Absolute Deviation (PMAD), Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) are evaluated by using the following equation (1-5) [25].

The forecast error is the difference between the actual value and the forecast value for the corresponding period.

$$E_t = Y_t - F_t$$

Where E is the forecast error at period t, Y is the actual value at period t, and F is the forecast value at period t.

Measures of aggregate error:

$$\text{Mean Absolute Error (MAE)} = \frac{\sum_{t=1}^{N} |E_t|}{N} \quad (1)$$

$$\text{Mean Absolute Percentage Error(MAPE)} = \frac{\sum_{t=1}^{N} |\frac{E_t}{Y_t}|}{N} \quad (2)$$

$$\text{Percent Mean Absolute Deviation (PMAD)} = \frac{\sum_{t=1}^{N} |E_t|}{\sum_{t=1}^{N} |Y_t|} \quad (3)$$

$$\text{Mean Square Error (MSE)} = \frac{\sum_{t=1}^{N} Et^2}{N} \quad (4)$$

$$\text{Root Mean Square Error (RMSE)} = \sqrt{\frac{\sum_{t=1}^{N} Et^2}{N}} \quad (5)$$

IV. PERFORMANCE ANALYSIS AND RESULT COMPARISONS

After the text edit has been completed, the paper is ready for the template. Duplicate the template file by using the Save As command, and use the naming convention prescribed by your conference for the name of your paper. In this newly created file, highlight all of the contents and import your prepared text file. You are now ready to style your paper; use the scroll down window on the left of the MS Word Formatting toolbar. This section describes the dataset used, the training and test procedure for neural networks and the statistical test for experiment. There are two types of indices, NIFTY and SENSEX. Nifty consists of a group of 50 shares. SENSEX consists of a group of 30 shares. Mainly there are two exchanges in India. NSE, National stock exchange - Nifty is listed with NSE. BSE (Bombay stock exchange) - Sensex is listed with BSE [26]. The data set consists of BSE100 closing stock index for the period from 2007 to 2011, from the BSE Website [23]. The dataset consists of NIFTY MIDCAP50 closing stock index for the period of 2007-2011 from the NSE Website [24]. The total number of time period may vary from year to year. The table I consists of number of year taken for prediction, total number of observation, number of observation used for training and number of observation used for testing for two stock market.

Each time period consists of opening stock, lowest price, highest price, closing stock, shares traded, turnover and dividend yielded, etc. From the historical data, closing price of stock is only extracted for prediction.

TABLE I. DATASET FOR BSE100 AND NIFTY MIDCAP50

Year	No. of Year	Total Number of time period	Training Data used for BSE100 and NIFTY MIDCAP50	Testing data used for BSE100 and NIFTY MIDCAP50
2011	1	232	162	70
2010 to 2011	2	499	349	150
2009 to 2011	3	742	519	223
2008 to 2011	4	988	692	296
2007 to 2011	5	1237	866	371

To illustrate the accuracy of the model, two complex time series BSE100 and NIFTY MIDCAP50 are considered. The standard statistical performance measurement is used for evaluating an Indian stock market index. MATLAB is used to performance evaluation and graph representation.

For this study, feed forward with back propagation neural network architecture is used. This network contains one input layer, one hidden layer and one output layer. Sigmoid function used as activation function for hidden and output layer. Gradient descent algorithm used as learning function. After the training analysis, the learning factor such as epoch, learning rate and momentum is set to 2960, 0.28 and 0.5 respectively.

The experimental procedure is training and testing process. For each complete training and test cycle have a pair of training set and testing set as shown in Table I. The training set has closing index for the particular year (input) from day n and prediction (output) from day n+1. The testing set has closing index for the particular year (input) from day n (last dada of trainingdata+1), and prediction (output) from day n+1 (last data of training data+1). 70% of the data is used for training and 30% of the data is used for testing. During the training process, the learning parameters such as learning rate (between 0 and 1), momentum rate (between 0 and 1) and number of epochs can be adjusted if the expected or nearly expected output does not produced by this model. If the expected output is reached then stop the training process. This model is used to predicting the closing price of one day in advance.

A. *Bombay Stock Exchange (BSE 100)*

There are five experiments conducted on BSE100 stock market data. Experiment1 uses one year 2011 of data only. Second experiment uses two years of data 2010 and 2011. Next experiment uses three years of data from 2009 to 2011. Fourth experiment uses four years of data from2008 to 2011. Experiment5 uses five years of data from 2007 to 2011. Every experiment the forecasting accuracy measured such as MAE, MAPE, PMAD, MSE and RMSE.

Table II shows the statistical results of the experiments. All five experiments have 0.28, 0.5 and 2960 as the learning rate, momentum rate, and training epochs respectively. From the table II, for one year data set of year 2011, the value of RMSE is 73.8. For two year data set of year 2010 to 2011, the value of RMSE is 70.5. The error rate is slightly decreased in two year data set than one year data set. For three year data set of year 2009 to 2011, the value of RMSE is 71.8.

TABLE II. PERFORMANCE ANALYSIS FOR BSE100

Year	No. of Year	MAE	MAPE	PMAD	MSE	RMSE
2011	1	60.8	0.0123	0.0122	5.45 x 103	73.8
2010-2011	2	57.0	0.0111	0.0110	4.96 x 103	70.5
2009-2011	3	57.2	0.0109	0.0107	5.16 x 103	71.8
2008-2011	4	61.2	0.0113	0.0111	5.87 x 103	76.6
2007-2011	5	56.6	0.0103	0.0102	4.99 x 103	70.6

The error rate is slightly decreased in three year data set than one year data set. For four year data set of year 2008 to 2011, the value of RMSE is 76.6. The error rate is slightly increased in four year data set compare than one year, two year and three year data set. For Five year data set of year 2007 to 2011, the value of RMSE is 70.6. Similarly other values of MAE, MAPE, PMAD and MSE is also verified and found the error rate is slightly decreased in five year data set than one year, three year and four year data set. Finally, it concludes that this model gives best forecast result for two year data set and five year dataset, and it gives better forecast result for one year, three year and four year data set.

Fig.2 shows the sample training output for four year dataset, BSE-2008-2011, the learning characteristics of the NN model obtained through simulation for one day in advance. The result of the training diagram, Fig.2, is reasonable because the final mean square error is small.

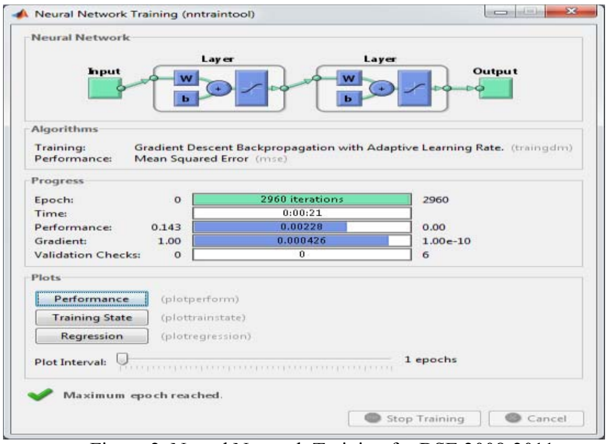

Figure 2. Neural Network Training for BSE 2008-2011

Fig. 3 shows prediction graph for 4year data set, 2008 to 2011 solid line represent forecasted data and dotted line represents actual data. X –axis represents time period, t and Y – axis represents closing stock index. It shows the performance accuracy of the actual data versus forecasted data.

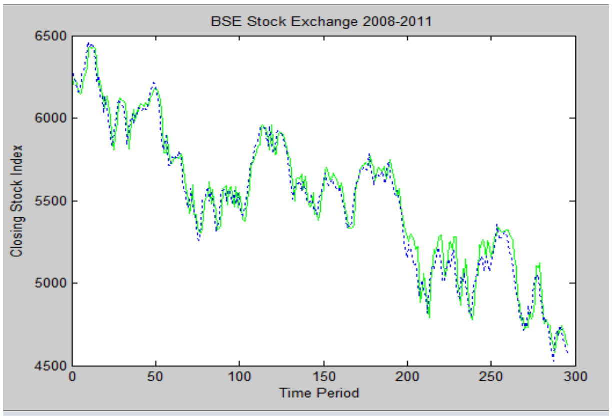

Figure 2.Plot Diagram for BSE100 2008 to 2011

Fig. 4 to Fig. 8 shows the regression plots to display the network outputs with respect to targets for training and test sets for BSE100 market. For a perfect fit, the data should fall along a 45 degree line, where the network outputs are equal to the targets. For this prediction problem, the fit is reasonably good for all datasets, with R values in each case of 0.97 or above except for one year data set.

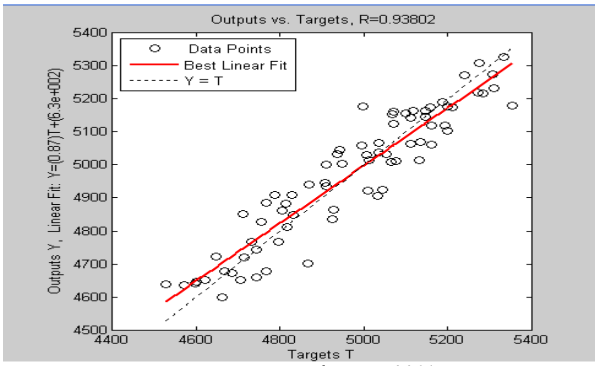

Fig. 4 Regression for Year 2011

The value of R in every test case is represented in table III for BSE100. In the case of the value of R is one, and then this model is perfect fit. From the figure 4 to 8, the data fall along near to 45 degree for all test cases. So, it may be considered as perfect fit. The value of R in year 2011 shows 0.93 and rest of the year shows 0.98 and 0.99. From the table III concludes the performance may degrade if the data set contains small amount of data and achieves the better performance if the data set containing large amount of data set.

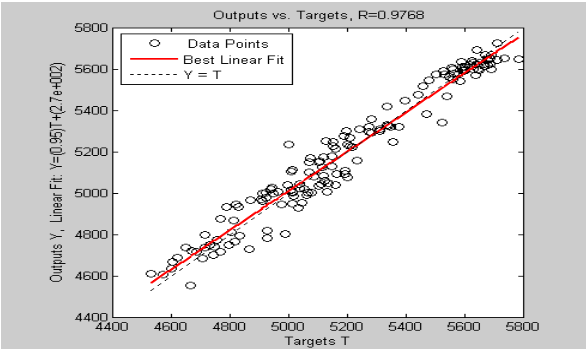

Fig. 5 Regression for Year 2010 to 2011

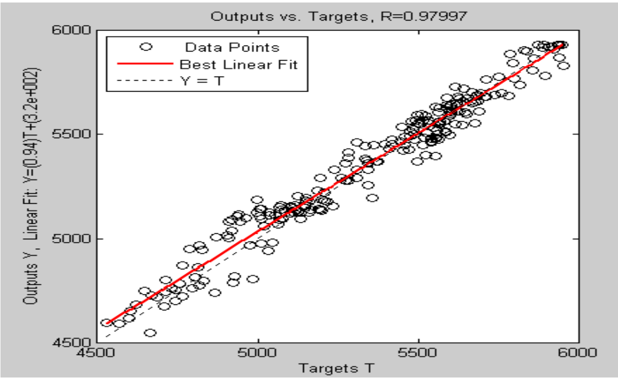

Fig. 6 Regression for Year 2009 to 2011

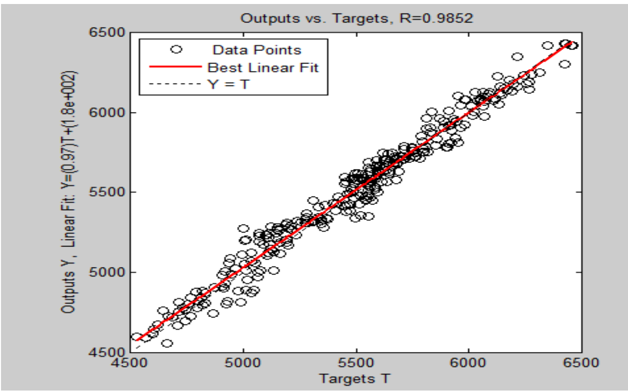

Fig. 7 Regression for Year 2008 to 2011

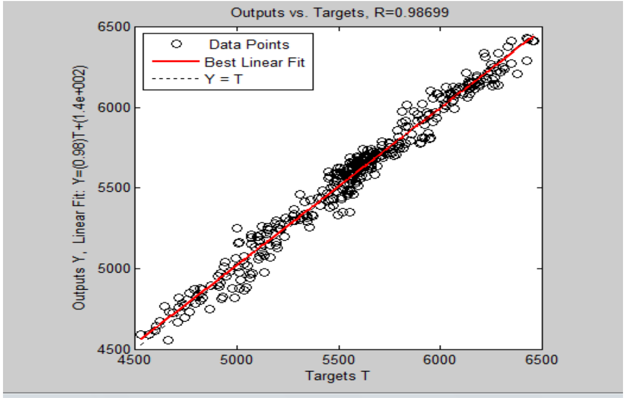

Fig. 8 Regression for Year 2007 to 2011

TABLE III. REGRESSION ANALYSIS – R VALUE

Year Vs Stock market	2011	2010 to 2011	2009 to 2011	2008 to 2011	2007 to 2011
BSE	0.93	0.98	0.98	0.99	0.99

B. NIFTY MIDCAP50

There are five experiments conducted on NIFTY MIDCAP50 stock market data. Experiment1 uses one year 2011 of data only. Second experiment uses two years of data 2010 and 2011. Next experiment uses three years of data from 2009 to 2011. Fourth experiment uses four years of data from2008 to 2011. Experiment5 uses five years of data from 2007 to 2011. Every experiment the forecasting accuracy measured such as MAE, MAPE, PMAD, MSE, and RMSE.

TABLE IV. PERFORMANCE ANALYSIS FOR NIFTY MIDCAP50

Year	No. of Year	MAE	MAPE	PMAD	MSE	RMSE
2011	1	26.1	0.0129	0.0130	1.01 x 103	31.7
2010 to 2011	2	26.3	0.0124	0.0121	1.06 x 103	32.5
2009 to 2011	3	30.2	0.0136	0.0133	1.47 x 103	38.4
2008 to 2011	4	36.5	0.0149	0.0150	2.24 x 103	47.3
2007 to 2011	5	32.8	0.0132	0.0129	1.71 x 103	41.3

Table IV shows the statistical results of the experiments. All five experiments have 0.28, 0.5 and 2960 as the learning rate, momentum rate, and training epochs respectively. From the table IV, for one year data set year 2011, the value of RMSE is 31.7. For two year data set year 2010 to 2011, the value of RMSE is 32.5. The error rate is slightly increased in two year data set than one year data set except the measurement of MAPE and MAD. For three year data set year 2009 to 2011, the value of RMSE is 38.4. The error rate is slightly increased in three year data set than one year and two year data set. For four year data set, year 2008 to 2011, the value of RMSE is

47.3. The error rate is slightly increased in four year data set compare than one year, two year and three year data set. For Five year data set, year 2007 to 2011, the value of RMSE is 41.3. . Similarly other values of MAE, MAPE, PMAD and MSE is also verified and found the error rate is decreased in five year data set than four year data set. Finally, it concludes better forecast result for all sets of data, one year, two year, three year, four year and five year data set.

Fig.9 to Fig.13 shows the regression plots to display the network outputs with respect to targets for training and test sets for NIFTY MIDCAP50. For this prediction problem, the fit is reasonably good for all datasets with R values in each case of 0.98 or above.

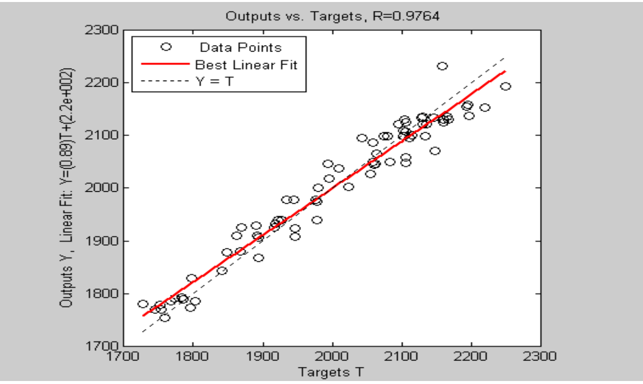

Fig. 9 Regression for Year 2011

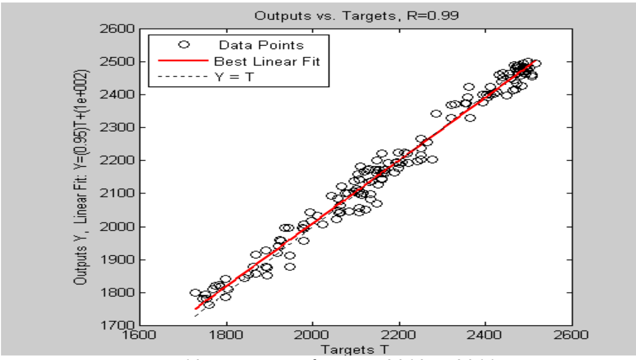

Fig. 10 Regression for Year 2010 to 2011

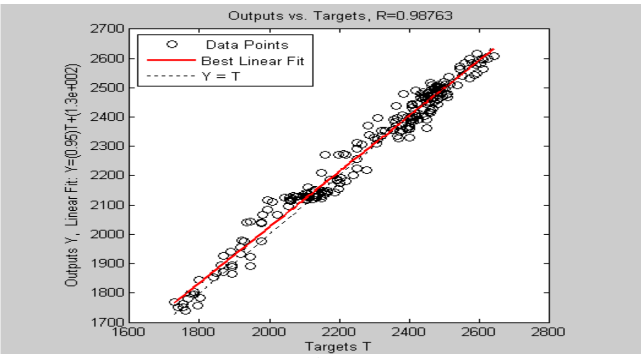

Fig. 11 Regression for Year 2009 to 2011

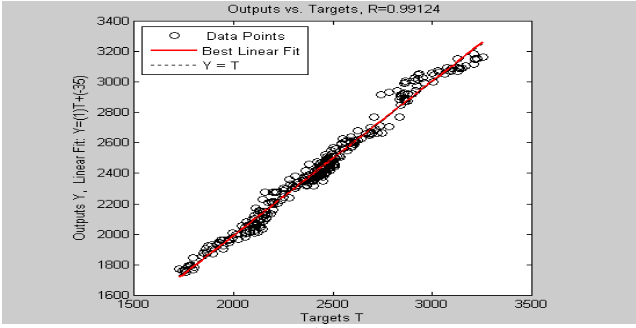

Fig. 12 Regression for Year 2008 to 2011

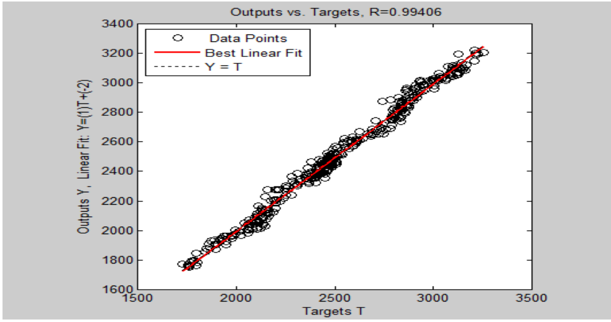

Fig. 13 Regression for Year 2007 to 2011

The value of R, in every test case is represented in Table V for NIFTY MIDCAP50. In the case of value of R is one, and then this model is perfect fit. From the figure 9 to 13, the data fall along near to 45 degree for all test cases, it may be considered as perfect fit.

TABLE V. REGRESSION ANALYSIS – R VALUE

Year Vs Stock market	**2011**	**2010 to 2011**	**2009 to 2011**	**2008 to 2011**	**2007 to 2011**
NSE	0.98	0.99	0.99	0.99	0.99

From the Table II and IV, concludes that this feed forward back propagation neural network model achieves better forecasting result if the dataset contains one to five years of data. In every year the performance measurement in Table IV is lower than Table III. So, this neural network model is found to be suitable for NIFTY MIDCAP50 closing stock index.

V. CONCLUSION

In this study, for performance of between BSE100 stock market index and NIFTY MIDCAP50 stock market index is studied by neural network model and measured aggregation where observed viz., MAE, MAPE, PMAD, MSE and RMSE. The results and further detailed with regression and forecasting accuracy explained by various tables of data and figures. The result shows that the performance is comparatively best. From the result it is observed that an optimal feedback weighting factor learning rate is 0.28, momentum is 0.5 and epoch is 2960. This model achieved the lower prediction error and it may be fit into any stock market data. This model can predict this time series perfectly, if the source data with less noise term, and the prediction get worse when the noise variation is increased.

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