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PERFORMANCE AND COMPARATIVE ANALYSIS OF INDIAN STOCK MARKET DATA USING MULTI LAYER FEED FORWARD NEURAL NETWORK AND FUZZY TIME SERIES MULTI LAYER FEED FORWARD NEURAL NETWORK MODEL WITH TRACKING SIGNAL APPROACH

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ABSTRACT
This study, proposes a novel neural network and fuzzy-neural network approach for predicting the closing index of the stock market. It strives to adapt the number of hidden neurons of a Multi Layer Feed Forward Neural Network (MLFFNN) and Fuzzy Time Series Multi Layer Feed Forward Neural Network (FTS-MLFFNN) model. It uses the Tracking Signal (TS) and rejects all models which result in values outside the interval of [-4, +4]. The effectiveness of the proposed approach is verified with one step ahead of Bombay Stock Exchange (BSE100) closing stock index of Indian stock market. This novel approach reduces the over-fitting problem, reduces the neural network structure and improves prediction accuracy. In addition, the result of MLFFNN with TS approach is compared to FTS-MLFFNN with TS approach. The result indicates that the FTS-MLFFNN with TS approach outperforms the MLFFNN with TS approach.

KEYWORDS: Neural Network, Fuzzy Time Series, Tracking Signal, Performance Analysis, Stock Market

1. INTRODUCTION
Forecasting stock market return has gained more attention in recent days because of the fact that if the direction of the market is successfully predicted, the investors may be better guided. Though various prediction models are available, no model predicts consistently, which motivated the researcher to explore new model and ideas to forecast the stock market effectively. If any system be developed which can consistently predict the trends of the dynamic market, then it would make the owner of the system wealthy.

Time series forecasting is used to forecast the future based on historical observations. Traditional methods, such as time-series regression, exponential smoothing and ARIMA, are based on linear models. All these methods assume that linear relationships among the past values of the forecast vary, and therefore non-linear patterns cannot be captured by these models. In the last few years, a number of neural network models and hybrid models have been proposed for obtaining accurate prediction results. It is seen as an attempt to outperform the traditional linear and nonlinear approaches. Neural Networks are non-linear in nature and where most of the natural real world systems are non-linear in nature. NN are preferred over the traditional models. The reason is that the ANN is a universal function approximation which is capable of mapping any linear or non-linear functions.

Although NNs have the advantages of accurate forecasting, there are few issues [1-4] in NN modeling viz., (i) there is no systematic way to identify NN structure, the number of neurons in the hidden layer (ii) NN model suffers due to under-fitting or over-fitting problems.

To solve the problem of neuron numbers in the hidden layer issue, a geometric pyramid rule [5], for a three layer NN with m output and n input neurons, the hidden layer may have a square root (n∗m) neurons. A NN with 2N + 1 hidden neuron and one hidden layer is sufficient for N inputs, and observed that the optimum number of hidden layers and hidden neurons are highly problem dependent [6]. As the accuracy of NN model depends on the careful NN model design, a detailed Neural Network (NN) designing methodology and training

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process is reported in the literature [7-9]. The performance of various types of training algorithms [10-11] analyzed and the Levenberg-Marquardt training algorithm has better performance than all other training algorithms and also its error rate is very low when compared to all other training algorithms. Greg Heath [12] suggests that design of ten neural networks with different types of random initial weights to mitigate the occasional bad random start. Training a great number of ANN with different configurations and selecting the optimum model will improve forecasting accuracy [13].

In many applications [14-16] the data set is divided into two sets: training and testing set. This data partition leads to over-fitting or under-fitting in NN performance. To avoid over-fitting or under-fitting problem and increase the robustness of the NN performance, the original dataset is divided into three different part training set; validation set (a small portion of training set) and test set [17]. The published research articles [18-20] reported that the optimum NN model selection is based on minimum forecasting error in validation set of some performance measure (SMAPE, NMSE, RMSE, etc) and reports its corresponding results in test set to avoid over-fit problem.

Many researchers [21-25] have addressed the above issues and tried to give a solution for the above problems by using different statistical and soft computing approaches. This study seeks to assert that even after selecting the optimal neural network model, there exists over-forecast or under-forecast in the training set, validation set and test set. The performance of NN model degrades if over-forecast or under-forecast occurs.

To solve the above mentioned problem, Ashok Kumar and Murugan proposed a novel MLFFNN with TS and MLFFNN without TS approach; and FTS-MLFFNN with TS approach and FTS-MLFFNN without TS approach. This study is the extension of the previous study.

A novel MLFFNN and FTS-MLFFNN with TS approach strives to adjust the number of hidden neurons of a MLFFNN and FTS-MLFFNN model. It uses the Tracking Signal and rejects all models which result in values outside the interval of [-4, 4]. TS is used to identify the presence of over-forecast or under-forecast in the NN model. The proposed MLFFNN and FTS-MLFFNN with TS approach systematically constructs different neural and fuzzy-neural network model from simple architecture to complex architecture; and the optimum neural and fuzzy-neural network model selection is based on the TS interval value [-4, 4] in the training set and validation set which contains minimum forecasting performance error in SMAPE of validation set for solving the problem of identifying the best NN model which reduces over-fitting or under-fitting problem.

Cecil Bozarth [26] reported that the TS is a statistical measure used to evaluate the presence of bias in the forecast model; and also it warns when there are unexpected outcomes from the forecast. Lean Yu et al., [27] proposed that adaptive, smoothing techniques are used to adjust the NN learning parameters automatically by tracking signals under dynamic varying environments. In their study, TS is used during the neural network training. In the present study, the TS is used to analyze and select the best neural network model after the neural network training to improve forecasting accuracy.

The contribution of this study is, first, different fuzzy-neural network architecture is created for forecasting the closing index of the BSE100 stock market. Second, the performance measure TS is introduced to select the optimum fuzzy-neural network model which reduces the network complexity; speeds up convergence; improves better forecast accuracy; and avoids over-forecast and under-forecast. Third, the in-sample and the out-of-sample forecasting performance analyzed using the different performance measure such as SMAPE, RMSE, POCID and TS using MLFFNN with TS approach and FTS-MLFFNN with TS approach. Fourth, the number of neurons in the hidden layer is identified for BSE100 stock market. Fifth, MLFFNN with TS approach is compared with FTS-MLFFNN with TS approach and FTS-MLFFNN with TS approach outperformed. Sixth, the experimental result shows that the in-sample model selection criteria are able to provide a reliable guide to out-of-sample performance and there exists an apparent connection between in-sample model fit and out-of-sample forecasting performance.

The rest of this study is organized as follows: Section 2 describes the essential part of MLFFNN model, fuzzy time series model, TS and performance measures which are used to assess the performance of the proposed approach; Section 3 describes the details of proposed MLFFNN with TS approach and FTS-MLFFNN with TS approach; Section 4 reports the experimental results attained by the MLFFNN with TS approach and FTS-MLFFNN with TS approach using real world financial time series such as BSE100. Finally, this study is concluded in section 5.

2. MATERIALS AND METHODS

2.1 Multi-Layer Feed Forward Neural Network Model

MLFFNN model comprises of an input layer, an output layer and one or more hidden layers. The hidden layer collects weight from input layer. Each subsequent layer collects weight from the previous layer. The neurons present in the hidden and output layers has biases, which are the connection from the units and its activation is always shown in Figure 1.

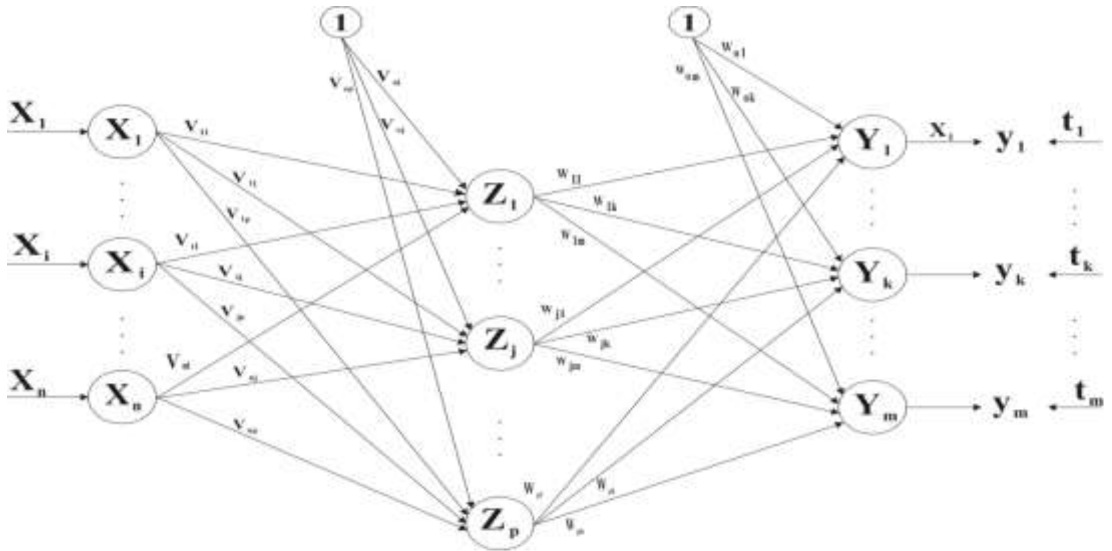

Figure 1. Multi Layer Feed Forward Neural Network

The bias term also acts as weights and it shows the architecture of Back Propagation Neural Network, illustrating only the direction of information flow for the feed forward phase. During the back propagation phase of learning, signals are sent in the reverse direction. The inputs are sent to the back propagation network and the output obtained from the net could be either binary 0, 1 or bipolar -1, +1 activation function. The error back propagation training algorithm is purely based on the gradient descent method [28].

2.2 Fuzzy Time Series Model

Fuzzy time series models, a complement of traditional time series models, have become more increasingly popular in recent years. Some successful application of fuzzy time series models such as high-order models, first-order models, bivariate models, multivariate models seasonal models and hybrid models [15].

Fuzzy time series data are structured by fuzzy sets. Let U be the universe of discourse, such that $U = \{u_1, u_2, \dots . u_n\}$. Let us defined a fuzzy set A of U by $A = \frac{f_A(u_1)}{u_1} + \frac{f_A(u_2)}{u_2} + \ . \ . \ . \ \frac{f_A(u_n)}{u_n}$ where f_A is the membership function of A, and $f_A\!: U \rightarrow [0\,,1]. f_A(u_i)$ is the membership value of u_i in A, where $f_A(u_i) \epsilon [0\,,1]$ and $1 \le i \le n$. Tiffany Hui-Kuang Yu and Kun-Huang Huarng [15] proposed a sequence of steps to design a Neural Network based Fuzzy Time Series (NNFTS) model.

2.3 Tracking Signal

The calculation of the TS [26] is represented in the equation (4). If the forecast value is lower than the actual value then the model is in under forecasting and TS will be positive. If the forecast value is higher than the actual value then the model is in over forecasting and TS will be negative. If the TS limit is between the interval [-4, +4] then the forecast model is working correctly. The threshold of 4 is really a threshold of 3.75 (3SD). This 3.75 number comes from the statistical control limit theory which establishes the relationship between Mean

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Absolute Error or Deviation and Standard Deviation. The relationship between the Standard deviation and MAD in a normally distributed population is built as 1.25 MAD = 1 SD (standard deviation of the distribution).

2.4 Forecasting Performance Measure

The forecasting performance is evaluated using the statistical measures, namely, symmetric mean absolute percentage error [19] (SMAPE), the percentage of change in direction [18] (POCID), Root Mean Square Error [15] (RMSE) and Tracking Signal [26] (TS).

In the following measure f_t represents forecasted value and y_t represents actual value, $e_t = y_t - f_t$ represents the forecast error and n represents t size of the test set.

The global performance of a forecasting model is evaluated by the SMAPE [19] which is used in NN3 (monthly time series), NN5 (daily time series) and NNGC1 (Neural Network Grand Competition) forecasting competition. A smaller SMAPE value suggests the better forecasting accuracy. It can be expressed as

$$SMAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|e_t|}{(y_t + f_t)/2} X100 \qquad (1)$$

The RMSE[10] is the square root of calculated MSE. All the properties of MSE hold for RMSE as well. RMSE can be expressed as

$$RMSE = \frac{\sqrt{\sum_{t=1}^{n} {e_t}^2}}{n} \qquad (2)$$

POCID (Percentage of Change in Direction) [18] maps the accuracy in the forecasting of the future direction of the time series. A larger POCID value indicates better forecasting accuracy. It leads to 100 % means, the model is considered as a perfect model. It can be represented as

$$POCID = 100\frac{\sum_{t=1}^{n} D_t}{n} \qquad (3)$$

$$where\ D_t = \begin{cases} 1\ if\ (y_t - y_{t-1})(f_t - f_{t-1}) \geq 0 \\ 0\ otherwise \end{cases}$$

Cecil bozrath [26] reported that the Tracking Signal (TS) is used to pinpoint forecasting models that need adjustment. As long as the TS are between -4 and +4, assume the model is working correctly. It can be represented as,

$$TS = \frac{\sum_{t=1}^{n} e_t}{MAD} \qquad (4)$$

The Mean Absolute Deviation (MAD) measures the average absolute deviation of forecasted values from original ones.

$$MAD = \frac{\sum_{t=1}^{n} |e_t|}{n} \qquad (5)$$

2.5 Proposed Methodology

2.5.1 MLFFNN with TS Approach

Over-fitting is one of the main issues in neural network modeling. In order to reduce the over fitting problem, this study proposed an iterative approach of MLFFNN which is used to forecast the closing index of the stock market. MLFFNN trains different networks by using a different random initial weight with different neurons

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and different data division ratio. Training parameter and the weight play an important role in NN modeling to increase the forecasting accuracy. The proposed approach tries to find optimal parameter, particularly neuron counts in the hidden layer, and optimal weight for the forecasting problem in time series.

Forecasting strategies have taken a step ahead of prediction in this study. Let y_1, y_2, y_3 ….. y_t be a time series. As time t for t>=1, the next value y_{t+1} is predicted based on the observed realizations of y_t, y_{t-1}, y_{t-2} ….. y_1. The resulting network can be used for multi-step prediction by feeding the prediction back to the input of network recursively. The MLFFNN with TS approach is represented in [29].

2.5.2 FTS-MLFFNN with TS Approach

This study proposes a novel approach Fuzzy Time Series Multi-Layer Feed Forward Neural Network with Tracking Signal (FTS-MLFFNN with TS) which is used to forecast the closing index of the stock market [30]. Multi-Layer Feed Forward Neural Network (MLFFNN) receives fuzzified data and trains different network by using different random initial weight and different neurons. The Tracking Signal measure is used to reject all FTS-MLFFNN model which results in values outside the interval of [-4, +4] in training set and validation set of different neural networks.

3. RESULTS AND DISCUSSION

3.1 BSE100 Index – MLFFNN with and without TS Approach

The effectiveness of the proposed MLFFNN with TS approach and is tested on BSE100 index. The dataset consists of BSE100 closing stock index for the period from January 1, 2010 to December 31, 2012 from the BSE Website [21]. For each neural network created with different random initial weight for neuron 1 to neuron 10. The choice of random initial weight (trial) size and maximum neuron size is selected by the user. In this study, random initial weight size is 15 and maximum neuron size is 10. This configuration applies to the data division ratio 50/25/25.

The results of performance measure of 10 models from 1-1-1 to 1-10-1 were generated. Here 1-1-1, first part represents neuron counts in the input layer, second part represents neuron counts in the hidden layer and third part represents the neuron counts in the output layer.Every neural network model contains fifteen different random initial weight generations. From the ten architectures of different trial, some models are extracted by the MLFFNN with TS approach which contains the interval [-4, +4] in the tracking signal of training set and validation set. Rejection of the model is represented in Table 1 which does not contain the interval [-4, +4] in the training set and validation set of tracking signal. Rejection of the model and selection of model using MLFFNN with TS approach is represented in Table 1.

Table 1: NN Model rejection and selection using in different data division ratio 50/25/25

Ratio	Model Rejection	Model Selection
50/25/25	1-2-1, 1-5-1, 1 -7-1, 1-10-1	1-1-1, 1-3-1, 1 -4-1, 1-6-1, 1 -8-1, 1-9-1

The performance measure of SMAPE, POCID and TS of training set, validation set and test set using MLFFNN with TS approach and MLFFNN without TS approach for the BSE100 index in the year 2010 to 2012 as shown in the Table (2). The results of optimum models are reported in table 2.

Table 2: Performance Evaluation by SMAPE, POCID, TS and POA using MLFFNN without and with TS Approach

50/25/25 Ratio	MLFFNN without TS			MLFFNN with TS		
Measure	Train	Val	Test	Train	Val	Test
SMAPE	0.85	0.73	0.92	0.87	0.76	0.84

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POCID	77.10	75.90	74.90	77.60	73.30	76.50
TS	2.22	5.89	34.20	0.00	0.17	0.04
POA	99.15	99.27	99.08	99.13	99.24	99.16

From Table 2, it is observed that the MLFFNN with TS approach outperformed MLFFNN without TS approach with respect to the performance measure SMAPE, POCID, TS and POA. The best forecasting model is identified by a smaller value in SMAPE and a larger value in POCID.

3.2 BSE100 Index – FTS-MLFFNN with and without TS Approach

The effectiveness of the proposed FTS-MLFFNN with TS approach is tested on BSE100 index. The dataset consists of BSE100 closing stock index for the period from January 1, 2010 to December 31, 2012 from the BSE Website[28]. For each NN created with different random initial weight for neuron 1 to neuron 18. The choice of random initial weight (trial) size and maximum neuron size is selected by the user. In this study, random initial weight size is 15 and maximum neuron size is 18 for BSE100 stock market index. The data division ratio is 50/25/25.

The results of performance measure of 18 different models from 9-1-9 to 9-18-9 were generated. Every FTSNN model contains fifteen different random initial weight generations. From the eighteen architectures of different trial, some models are selected by the FTSNN with TS approach which contain the interval [-4, +4] in the tracking signal of training dataset and validation dataset; and some models are rejected by the FTSNN with TS approach which does not contain the interval [-4, +4] in the training dataset and validation dataset of tracking signal. Rejection of the model and selection of model using FTSNN with TS approach is represented in Table 3.

Table 3. Model rejection and selection in FTS-MLFFNN with TS approach

Ratio	Model Rejection	Model Selection
50/25/25	9 -1-9, 9-3-9, 9-4-9, 9-5-9, 9-6-9, 9-8-9, 9-9-9, 9-10-9, 9 -11-9, 9-12-9, 9-13-9, 9-14-9, 9 -16-9, 9-17-9	9-2-9, 9-7-9, 9-15-9, 9-18-9

The performance measure of SMAPE, RMSE, POCID and TS of training set, validation set and test set using FTSNN with TS approach and FTSNN without TS approach for the BSE100 index in the year 2010 to 2012 with 50/25/25 data division ratio and the result of optimum model is reported in Table 4 and the best forecasting results are highlighted by bold face.

Table 4. Performance measures of train, validation and test set for the year 2010 – 2012 of BSE 100 Index

Measure	FTS-MLFFNN With TS			FTS-MLFFNN Without TS		
	Train	Val	Test	Train	Val	Test
SMAPE	0.60	0.96	**0.46**	0.61	0.82	0.47
RMSE	46.10	62.40	**36.90**	50.70	58.90	37.40
TS	3.81	-2.04	**15.10**	-18.50	-10.40	18.90
POCID	92.20	95.20	**92.00**	85.00	82.40	81.80

From Table 4, it is observed that the FTS-MLFFNN with TS approach outperformed FTS-MLFFNN without TS approach with respect to the performance measure SMAPE, POCID, TS and POA. The best forecasting model is identified by a smaller value in SMAPE and a larger value in POCID.

3.3 Comparative Analysis of MLFFNN with TS approach and FTS-MLFFNN with TS Approach

The results of performance measure in train, validation and test set is reported in four aspects (i) whether the forecasting error is high or low (ii) over fitting problem, i.e., whether the in-sample model selection criteria is able to provide a reliable guide to out-of-sample performance or not? (iii) correctness of the predicted direction in the test set (iv) effectiveness of the tracking signal.

First, the performance measure SMAPE of test set in FTS-MLFFNN with TS approach is low when compared to MLFFNN with TS approach. Second, the difference between training set and test set in FTS-MLFFNN with TS approach is very close to each other when compared to MLFFNN with TS approach. This is the main purpose of TS being used in this study.

Third, the performance measure POCID of test set in FTS-MLFFNN with TS approach is high when compared to MLFFNN with TS approach. It indicates the correctness of the forecasting direction is high in the FTS-MLFFNN approach. For example, in FTS-MLFFNN with TS approach, the performance measure POCID of test set in FTS-MLFFNN with TS approach is 76.50; the performance measure POCID of test set in MLFFNN with TS approach is 74.90. It indicates that the correctness of the forecasting direction is very high in FTS-MLFFNN with TS approach when compared to MLFFNN with TS approach. The higher POCID value indicates better forecasting model.

Fourth, the TS value is within the interval [-4, +4] in all data division ratios. It indicates that the level of over-forecasting and the level of under-forecasting is controlled by TS measure. The value of TS in the test set is very low when compared to MLFFNN without TS approach in all types of data division ratio. For example, in the data division ratio 50/25/25 ratio, the performance measure TS of train and test set is 0.00 and 0.04 in MLFFNN with TS approach; the performance measure TS of train and test set is 2.22 and 34.20 in MLFFNN without TS approach. It indicates that the level of over-forecasting and the level of under-forecasting are identified by TS measure.

From Table 2 and Table 4, it is observed that the FTS-MLFFNN with TS approach outperformed MLFFNN with TS approach with respect to the performance measure SMAPE, POCID, TS and POA.

4. CONCLUSION

This study proposed a novel Multi Layer Feed Forward Neural Network (MLFFNN) and Fuzzy Time Series Multi Layer Feed Forward Neural Network (FTS-MLFFNN) model with Tracking Signal (TS) approach. It is proposed to forecast one-step-ahead closing index of stock market and it is applied to BSE100. It has analyzed the neuron number in the hidden layer and performance measure of SMAPE, RMSE, POCID and TS in the training dataset, validation dataset and test dataset. This study observed that the FTS-MLFFNN with TS approach outperformed MLFFNN with TS approach with respect to the performance measure SMAPE, POCID, TS and POA. This study recommends to increase the prediction accuracy, the best forecasting model is selected by the presence of tracking signal interval [-4, +4] in the training set and validation set; and minimum error value in SMAPE of validation set.

The proposed FTS-MLFFNN with TS approach can be used as an alternative forecasting tool for time series forecasting. In this study, only single variable is taken for prediction; In future, multi variables will be taken for prediction to improve the accuracy of stock market; It will be applied to identify hidden neurons in the multiple hidden layer; and also it will be applied to different types of NN model for forecasting closing stock index/price of stock market data.

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