Dynamic Recurrent FLANN Based Adaptive Model for Forecasting of Stock Indices

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Abstract. Prediction of future trends in financial time-series data are very important for decision making in the share market. Usually financial time-series data are non-linear, volatile and subject to many other factors like local or global issues, causes a difficult task to predict them consistently and efficiently. This paper present an improved Dynamic Recurrent FLANN (DRFLANN) based adaptive model for forecasting the stock Indices of Indian stock market. The proposed DRFLANN based model employs the least mean square (LMS) algorithm to train the weights of the networks. The Mean Absolute Percentage Error (MAPE), the Average Mean Absolute Percentage Error (AMAPE), the variance of forecast errors (VFE) is used for determining the accuracy of the model. To improve further the forecasting results, we have introduced three technical indicators named Relative Strength Indicator (RSI), Price Volume Change Indicator (PVCI), and Moving Average Volume Indicator (MAVI). The reason of choosing these three indicators is that they are focused on important attributes of price, volume, and combination of both price and volume of stock data. The results show the potential of the model as a tool for making stock price prediction.

1 Introduction

The price variation of stock market is a dynamic system and the disordered behavior of the stock price movement duplicates complication of the price prediction; however, the highly non-linear, dynamic complicated domain knowledge inherent in the stock market makes it very difficult for investors to make the right investment decisions promptly. It is necessary to develop an intelligent system to get real-time pricing information, reduce one obsession of investors and help them to maximize their profits. Financial Time series is considered to be a difficult problem in forecasting, due to the many complex features frequently present in such series are irregularities, volatility, trends and noise. Many researchers in the past have applied various soft computing techniques to predict the movements of the stock markets. Even though a lot of research going on the field of stock market prediction [1], [2], [3]; still it remains to be a big question whether stock market can be predicted accurately.

Tools based on artificial neural network (ANN) have gained popularity due to their inherent capability to approximate any non-linear function, less sensitive to error,

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tolerate noise, and chaotic components. Familiar ANN models like Multilayer Perceptron (MLP) [4], Radial Basis Function (RBF) [5], [6], Recurrent Neural Network (RNN) [7], Multi Branch Neural Networks (MBNN), Local Linear Wavelet Network (LLWN) [8], and hybrid models like Genetic-Neural Network [9], [10] are also demonstrated for stock price forecasting.

Further it is well known that the artificial neural network (ANN) suffers from slow convergence, local minimum, over fitting and generalization and number of neurons in the hidden layer are chosen by trial and error. Thus to overcome from this FLANN based simple network may be used for the prediction of time series data with a less computational overhead than the ANN network. Unlike the earlier FLANNs where each input is expanded to have several nonlinear functions of the input itself, only a few functional blocks comprising nonlinear functions of all the inputs is used in this paper thereby resulting in a high dimensional input space for the neural network.

The FLANN, originally proposed by Y.H.Pao and Y.Takefji [11] comprises a single layer neural network in which nonlinearity is introduced as a functional block, thus giving rise to a higher dimension input space. The normal practice of choosing the functional block with trigonometric functions such as cos(x), sin(x), cos(πx), sin(πx), [12] etc. or polynomials [13], [14], [15].

In this paper, we have suggested the Dynamic Recurrent Functional Link Artificial Neural Network (DRFLANN) architecture for prediction of prices of leading Indian stock indices. Our proposed DRFLANN structure is very simple with no hidden layer. The main advantage of the DRFLANN is the reduced computational cost in the training stage, while maintaining a good performance of approximation. The use of dynamic elements known to be adaptive parameters used in our proposed model along the connection strengths helps to improve the convergence speed of the network.

2 Dynamic Recurrent FLANN (DRFLANN) Model

This new proposed architecture of DRFLANN has much less computational complexity and causes high convergence speed. Fig.1 shows the single layer computationally efficient DRFLANN architecture.

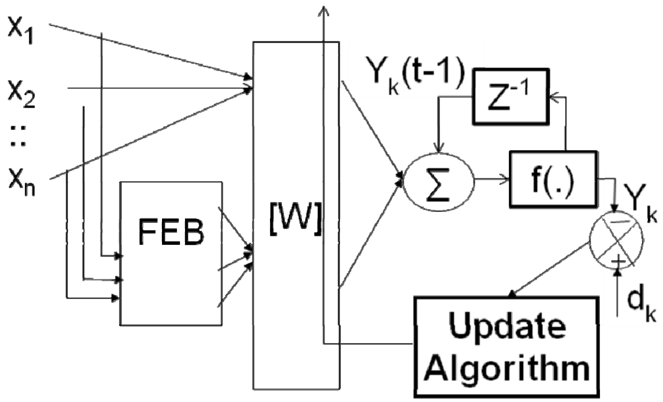

Fig. 1. The DRFLANN Architecture

Let the input vector pattern and target is given in eq. (1) from a selected data set of *n* number of elements.

$$X = \begin{bmatrix} x_1, x_2, \ldots\ldots, x_m \\ ::::::::::::::::::::::::::::: \\ x_{m+i}, x_{m+i+1}, \ldots\ldots, x_{n-1} \end{bmatrix} \quad \begin{bmatrix} x_{m+1} \\ :::::: \\ x_n \end{bmatrix} \tag{1}$$
$$\qquad\qquad \textit{Input Vector} \qquad\qquad \textit{Desired Vector}$$

There are $[x_1, x_2, \ldots\ldots, x_n]$ data set out of which the above matrix suggested the split of input pattern and desired vector for training and testing the model. We have used 70:30 ratios of the selected data for training and testing. Each input pattern is then applied to the Functional Expansion Blocks (FEBs) where the elements are functionally expanded through a set of tan hyperbolic trigonometric function as mentioned in eq. (2).

$$\begin{aligned} x_{m+1} &= \tanh(a_{01} + a_{11}x_1 + a_{21}x_2 + a_{31}x_3 + \ldots. + a_{m1}x_m) \\ x_{m+2} &= \tanh(a_{02} + a_{12}x_1 + a_{22}x_2 + \ldots\ldots\ldots\ldots\ldots + a_{m2}x_m) \\ &\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ x_M &= \tanh(a_{0M} + a_{1M}x_1 + a_{2M}x_2 \ldots\ldots\ldots\ldots\ldots + a_{mM}x_m) \end{aligned} \tag{2}$$

Where the adaptive parameters used to enhance the input pattern at the functional expansion block is represented in a matrix form in eq. (3)

$$A = \begin{bmatrix} a_{01} & a_{11} & a_{21} \ldots\ldots\ldots\ldots & a_{m1} \\ a_{02} & a_{12} & a_{22} \ldots\ldots\ldots\ldots\ldots & a_{m2} \\ \ldots\ldots & \ldots\ldots & \ldots\ldots\ldots\ldots & \\ a_{0M} & a_{1M} & a_{2M} \ldots\ldots\ldots\ldots & a_{mM} \end{bmatrix} \tag{3}$$

The final input at the input layer is now presented in eq. (4)

$$I = [x_1, x_2, \ldots\ldots, x_{m+1}, x_{m+2}, \ldots\ldots, x_M] \tag{4}$$

The estimated output of the model is calculated using eq. (5 & 6)

$$Y(t) = f(s) = \frac{1}{(1 + e^{(-0.5*S)})} \tag{5}$$

$$where \quad s = I(t)]^T * W \tag{6}$$

W is the vector used as connection strength of the network given in eq. (7)

Where $$W = [w_1, w_2, w_3, \ldots\ldots, w_m, w_{m+1}, \ldots\ldots, w_M] \tag{7}$$

The weight vector [W] and the adaptive parameters vector [A] are updated in the direction of the negative gradient of the performance function. Randomly the values are chosen to assign weight vector [W] and the adaptive parameter vector [A] to train the network. These random values are between 0 and 1.

Weight vector is updated using back propagation (BP) learning algorithm. The following eq. (8) is given as

$$w_{t+1} = w_t + e_t \frac{\partial o_t}{dw} \tag{8}$$

The weight adjustment is computed by eq. (9)

$$w_{t+1} = w_t + \alpha * e_t * (1 - o_t)^2 * I(t) \tag{9}$$

3 Analysis of Datasets and Selection of Inputs and Assessment Methods

The stock market or equity market time series is a financial measure in the world economy. For the purpose of analysis, we have used the data collected from Reliance Industries Limited (RIL), Bombay Stock Exchange (BSE), and International Business Machines Corp. (IBM) stocks for our studies. In this paper we have presented our IBM results collected from 20/05/2003 to 14/06/2012, a total number of 2300 trading days of data. Following 70:30 ratios, we have used 2000 days of trading data for training and remaining 300 days of trading day data for validating the model. The data used for simulating the model to forecast is on the closing price of index on each day The MATLAB implementation has done to simulate the forecasting model.

The entire input data patterns including technical indicators are normalized to values between 0.0 through 1.0. The normalization formula in eq. (10) is used to express the data in terms of the minimum and maximum value of the dataset.

$$u = (x_i - x_{\min})/(x_{\max} - x_{\min}) \tag{10}$$

Where, 'u 'and 'x ' represents normalized and actual value respectively.

3.1 Forecasting Analysis with Technical Indicators

We carry out forecasts by using each of the technical indicators listed below combining with inputs to the network. Technical indicators are any class of metrics whose value is derived from generic activity in a stock or asset. The Technical indicators look to predict the future price value by looking at past patterns. A brief explanation of each indicator is mentioned here.

To reduce the over learning of the proposed model and to reduce the complexity of the architecture, we have tried with three important technical indicators namely RSI (5), PVC (5), and MAVI (5, 20). The reason of choosing these three variables is that they are focused on two prime aspects stock data i.e. price, and volume. The selected three indicators mention below in eq. (11).

$$RSI(5) = \sum_{i=1}^{n} Max(\Delta x_i, 0) \Big/ \sum_{i=1}^{n} |\Delta x_i| \qquad PVC(5) = \sum_{i=1}^{n} (\Delta x_i \times \Delta v_i) \Big/ \sum_{i=1}^{n} (|\Delta x_i \times \Delta v_i|) \qquad MAVI(5,20) = MV_5 / MV_{20} \tag{11}$$

Where x_i is the closing price on the i$^{\text{th}}$ day, $\Delta x_i = x_i - x_{i-1}$, $\Delta v_i = v_i - v_{i-1}$, MV5 is 5 day moving average of trading volume, and MV20 is 20 day moving average of trading volume.

3.2 Assessment of Forecasting Results

The proposed DRFLANN architecture is authenticated with testing results based on the various issues discussed before to study the accuracy of forecasting results. The Mean Absolute Percentage Error (MAPE) in eq. (12) represents the absolute average prediction error between actual and forecast value. This gives the repulsive effect of very small prices; the Average Mean Absolute Percentage Error (AMAPE) in eq. (13) is adopted and compared. The impact of the model uncertainty needs to be measured on forecast results, the variance of forecast errors (σ^2_{Err}) in eq. (14) is used. The smaller the variance, the more accurate is the forecast results and more confidence is the model.

$$MAPE = \left(\frac{1}{N} \sum_{j=1}^{N} \frac{abs(e_j)}{y_t} \right) \times 100\% \tag{12}$$

$$AMAPE = \left(\frac{1}{N} \sum_{j=1}^{N} \left[\frac{abs(e_j)}{\bar{y}} \right] \right) \times 100\% \quad where \quad \bar{y} = \frac{1}{N} \sum_{j=1}^{N} [\, y_t \,] \tag{13}$$

$$\sigma^2_{Err} = \left(\frac{1}{N} \sum_{j=1}^{N} \left[\frac{abs(e_j)}{\bar{y}} \right] - AMAPE \right)^2 \tag{14}$$

Where $e = y_t - y$, y_t & y represents the actual and forecast values; $\bar{y}$ is the average value of actual price; σ^2_{Err} variance of forecast error and N is the forecasting period.

4 Simulation Results

Simulation study is carried out using the data set IBM stock. The below listed case studies are reported in the paper to show the limited impacts on price forecast errors. We have shown a set of figures based on testing results and comparison tables to show the impact of case studies on to our model.

Computer simulations for training and testing results were plotted using different case studies to validate the model. Finally the performance evaluation in stock price prediction is given in table1. For a fair comparison, same data set is used for the forecasting the prices.

Case Study 1

In this section, the DFLARNN model is trained with the data set mentioned above and the simulation testing result portrayed in Fig. 2 without using technical indicators.

Case Study 2 - A

In this section, the DFLARNN model is trained with the data set mentioned above using technical indicator Relative Strength Indicator (RSI)

Case Study 2 - B

In this section, the DFLARNN model is trained with the data set mentioned above using technical indicator Relative Strength Indicator (RSI) and Price Volume Change Indicator (PVC).

Case Study 2 - C

In this section, the DFLARNN model is trained with the data set mentioned above and the simulation testing result portrayed in Fig. 3 using technical indicator Relative Strength Indicator (RSI), Price Volume Change Indicator (PVC).and Moving Average Volume Indicator (MAVI)

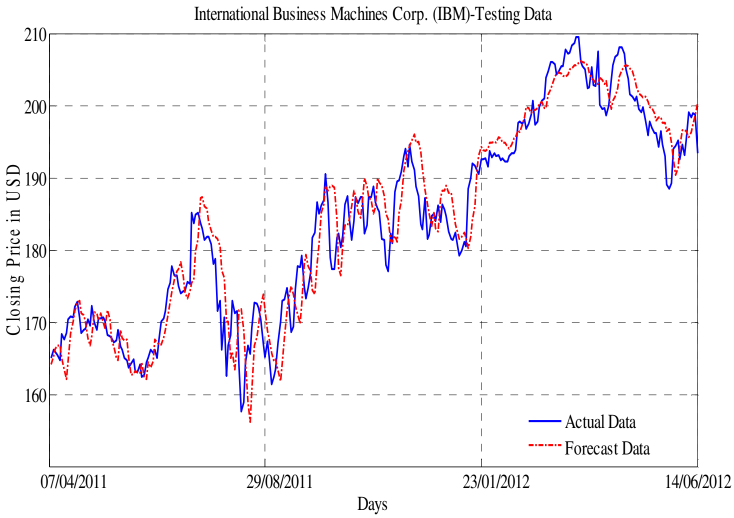

Fig. 2. International Business Machines Corp. (IBM) Stock Testing results

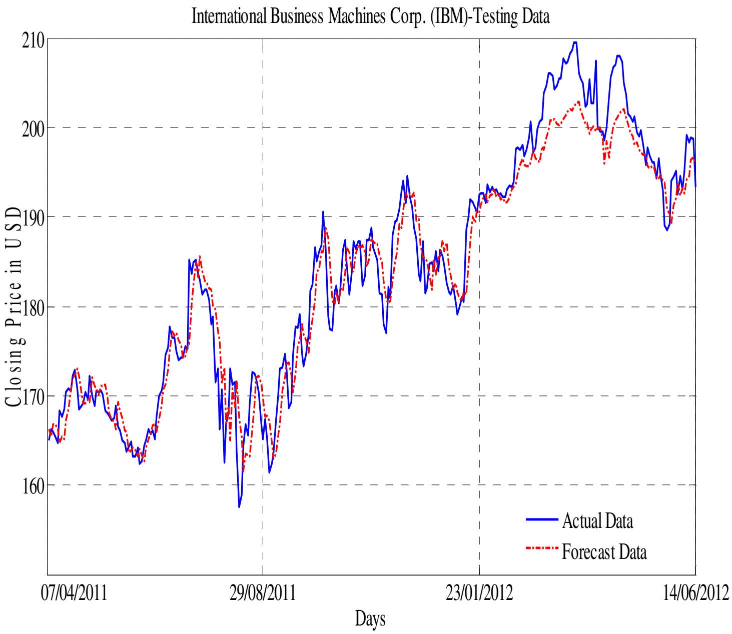

Fig. 3. International Business Machines Corp. (IBM) Stock Testing results

Table 1. Performance Comparison on daily closed price of various case studies

Method	Duration (300 Days)	Performance Assessments		
		MAPE	AMAPE	Variance (σ^2_{Err})
Case-1	07/04/2011 to 14/06/2012	1.810284	1.814413	0.032266
Case-2 (A)	07/04/2011 to 14/06/2012	1.579375	1.581133	0.024502
Case-2 (B)	07/04/2011 to 14/06/2012	1.523785	1.528979	0.022913
Case-2 (C)	07/04/2011 to 14/06/2012	1.434505	1.463944	0.021005

5 Conclusions

Predicting the stock market index is of great interest because successful prediction of stock prices may be guaranteed benefits. The task is very complicated and very difficult for the trader's to make decisions on buying or selling an instrument. In this study, Dynamic Recurrent FLANN Based Adaptive Model is adopted to predict the stock market return on the various stock indices like BSE, IBM etc. The study on IBM stock data shows that the performance of stock price prediction can be significantly enhanced. This model based on stock market prediction model employing the RMS based weight update mechanism is introduced to make our model computationally much more efficient. Further this proposed DRFLANN model, composed of data pattern and technical indicators, improves the performance of forecast results. Further to achieve better robust result using this model we will try different learning methods along with optimization procedure.

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