A Typical Framework for Forecasting and Trading Time Series Data Using Functional Link Artificial Neural Network

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***Abstract*— Prediction of time series data, whether the data related to the stock market or exchange rate is of enormous interest to traders or investors due to high profit in trading. Thus the prediction of time series data indices and its study are important to discover whether the next day's closing price would increase or decrease. For that reason, we construct a framework for predicting time series data by using a low complexity, adaptive functional link artificial neural network (FLANN) over a time frame varies from one day ahead to several weeks. The FLANN is basically a single layer structure in which non-linearity is introduced by enhancing the input pattern with nonlinear functional expansion. The architecture of FLANN will be trained with the working principle of heuristic stochastic algorithms to achieve the best forecasting and classification to increase in accuracy of prediction and decrease in training time. Heuristic and Stochastic refers to an experience-based technique for problem solving, learning, and discovery that find a solution which is not guaranteed to be optimal, but good enough for a given set of goals and helps in minimizing errors. The proposed project is based on all these parameters which will predict time series data using FLANN trained by heuristic stochastic algorithm. Extensive computer simulations will be carried out and it is compared with traditional artificial neural network to observe the accuracy of the FLANN model.**

Keyword-- FLANN, Prediction, Heuristic Stochastic Algorithm, functional expansion, stock market, Absolute Percentage Error (MAPE); Sum of Squared Error (SSE); Standard Deviation of Error (SDE

I. INTRODUCTION

In an optimistic scenario gain of investing in stocks reflects an enormous growth in economy in a short duration. Even though it poses an obstacle of high risk the investors never stops taking risks. Stock market is dynamically changing and unpredictable environment. The major part is to know when to buy and when to sell. So, it has long been identified as a challenging and important research area in finance. Traditionally, various statistical models have been introduced for forecasting the stock invests. But none of these models can really accurately predict the moment of particular share prices and beat the market because the stock markets are highly non-linear and non-stationary. A better learning technique conduces to take decisions regarding investments.As the technology has advanced rapidly, it offers leverage of using many tools in forecasting noisy environments to solve many problems in many fields, including stock market problems. Artificial Neural Network (ANN) [1] has also been successfully applied to solve the stock market prediction problems and also various real world problems regarding industry, business and science. Artificial Neural Networks (ANNs) especially the Multilayer Perceptron (MLP) [2] are capable of generating complex mapping between the input and the output space in performing arbitrarily complex nonlinear decision boundaries. The strongest advantage of ANN's is capable of learning complex nonlinear relationships; however, it is difficult to finely model the process of human reasoning. ANN's can produce good results even if the training data contains unobserved input patterns. ANN's with different neural networks algorithms can produce different results when trained and tested on the same dataset. But ANN's are not efficient for producing and effective result because of choosing the multiple layers between input and output layers. These hidden layers make the computations complex in terms of time and space. Hence an alternative approach named Functional Link Artificial Neural Network (FLANN) has been introduced to succor in avoiding these problems. This approach removes the hidden layer from the ANN architecture to help in reducing the neural architectural complexity and provides them with an enhancement representation of input nodes for the network to be able to perform a non-linear separable classification task. In spite of the numerous features of using artificial neural networks (ANNs) for financial stock time series data for forecasting compared to statistical models, the robustness of the models such as:

- ANNs with different neural networks algorithms can produce different results when trained and tested on the same data set.
- ANNs are susceptible to the network size and the size of the data set.

- ANNs suffer from over correct and as a result network architecture, learning parameters and training data have to be selected carefully.
- ANNs with single layer are ineffective producing good accuracy result since the financial time series stock data are highly nonlinear.
- ANNs are not efficient because of choosing the multiple layers between input and output layers for effective result.

The properties of expanding the input space into a higher dimensional space huge number of high-order neural network architecture without hidden units were introduced. The FLANN, originally proposed by Y. H. Pao [7] comprises a single layer neural network. The FLANN's are higher-order neural networks without hidden units are established by Y. H. Pao and Y.Takefji [8] in 1992. In spite of their linear nature, FLANNs can capture non-linear input-output patterns, provided that they are fed with a set of polynomial inputs, or a set of basis functions spanning of n-dimensional space, which are constructed from the original input patterns. This FLANN model can be used in numerous application domains like stock market forecasting [9], Dual Junction solar cells[10], wireless sensor networks[11], and etc. it has demonstrated its viability and robustness, and ease of computation in these fields.

In this paper, we have described the overview of ANN and FLANN along with conventional learning algorithm to forecast the time series data. We have used IBM stock time series data as input to the Multilayer Perceptron and FLANN techniques.

II. FRAMEWORKS

A. *Artificial Neural Network*

Artificial Neural Networks (ANNs) are information processing model inspired by the way of human brain processes information. ANNs required knowledge through a learning process while the interneuron connection strength known as synaptic weights are used to store knowledge. Therefore with these abilities, Neural Networks provides a suitable solution for pattern recognition or data classification problems. One of the best known types of Neural Networks is the Multilayer Perceptron (MLP). It has one or more hidden layers in between the input and the output layer. Figure 1 illustrates the layout of MLP with single hidden layer. The function of hidden neurons is to provide the ANNs with the ability to handle non-linear input-output map-ping. By adding one more hidden layer, the network is able to extract higher order statistics, which is particularly valuable when the size of the input layer is large. The MLP networks are trained by adjusting the weight of connection between neurons in each layer. For training the network, MLP utilize a supervised learning technique called backpropagation [3-5], in which the network is provided with examples of the inputs and desired outputs to be computed, and then the error (difference between actual and expected results) will be calculated. Figure 1, depicted an example of MLP with Backpropagation [6]. With this architecture, the neurons are organized in layers and their signals are sent "forward" while the calculated errors are then propagated backwards. The idea of the back propagation algorithm is to reduced error, until the networks learned the training data. The training began with random weights, and the goal is to adjust them until the minimal error is achieved.

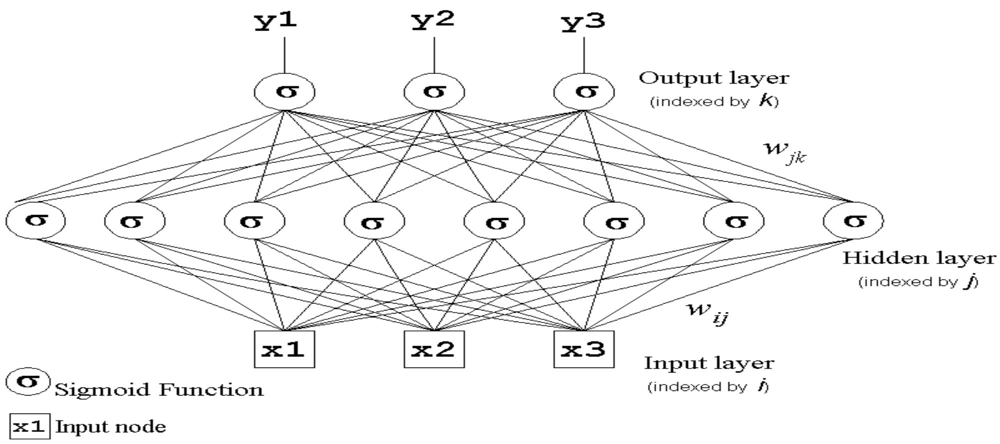

Fig. 1. The structure of single hidden layer MLP

B. *Functional Link Artificial Neural Network*

Functional Link Artificial Neural Network (FLANN) is a class of Higher Order Neural Networks (HONNs) that utilize higher combination of its inputs. It has been successfully used in many applications such as system identification, channel equalization, classification, pattern recognition and prediction. FLANN is much more modest than MLP since it has a single-layer network but still it is able to handle a non-linear separable classification task. The FLANN architecture is basically a flat network without any hidden layer which makes the learning algorithm used in the network less complicated. In FLANN, the input vector is extended with a suitably enhanced representation of the input nodes, thereby artificially increasing the dimension of the input space. The enhanced input features from the input layer are fed into the network and the weighted sums of inputs are calculated and pass it through activation function to produce network output. Figure 2 depicts the functional link artificial neural network structure up to second order with 2 inputs. The first order consist of the 2 inputs x1 and x2 while the second order of the net-work is the extended input based on the x1 and x2. It consists of functional expansion blocks to enhance the dimension of the input pattern space.

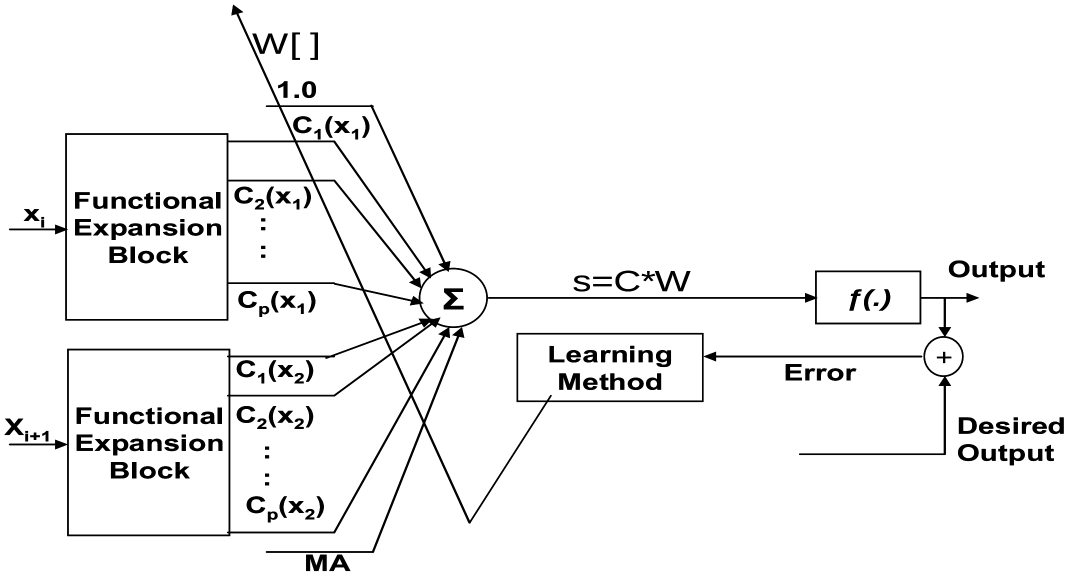

Fig. 2. The FLANN structure

$$X_k = [x_1(k), x_2(k), ..., x_i(k), ..., x_n(k)]^T \tag{1}$$

Let each element of the input pattern before expansion be represented in X_k. Where each element $x_i(k)$ is functionally expanded using functional expansion block between $1 \le i \le p$, where $p = 6$ i.e. number of expanded points for each input element. There are many different polynomial basis functions like Chebysheb, Laguerre, Legendre, and Power Series used in functional expansion block to enhance the input pattern. In Fig.2 each input pattern $[x_i, x_{i+1}]^T$ can be enhanced through these basis functions. The expanded output pattern for each $[x_i, x_{i+1}]^T$ is a combination of lower and higher order polynomials. In this study the basic architecture is applied with input pattern $[x_i, x_{i+1}]^T$ where $1 \le i \le n$. The total number of output patterns mapped with input pattern is fourteen ($l = 14$), where in there are twelve from the functional expansion block, one is bias and one is the technical indicator MA in eq. (2). The vector [C] in eq. (3) consists of values of the enhanced input pattern along with bias and MA. The weighted input pattern is then applied to the summer. The weight vector [W] in eq. (4) used for the input pattern is randomly initialized between -1.0 to +1.0.

$$MA = (1.0 + c_1(x_1) + c_2(x_1) + ... + c_p(x_1) + c_1(x_2) + c_2(x_2) + ... + c_p(x_2))/13 \tag{2}$$

$$C = [1.0, c_1(x_i), c_2(x_i), ..., c_p(x_i), c_1(x_{i+1}), c_2(x_{i+1}), ..., c_p(x_{i+1}), MA]^T \tag{3}$$

$$W = [w_0, w_1, w_2, w_3, w_4, w_5, w_6, w_7, w_8, w_9, w_{10}, w_{11}, w_{12}, w_{13}] \tag{4}$$

The learning process involves updating of the weights [W] of the FLANN. The back propagation (BP) algorithm is used to update the weights. The output of the model is given by

$$o = \tanh(s) \tag{5}$$

Where, the linear activation‘s’ is given by

$$s = C * W \tag{6}$$

The updated rule for the weight wk is given by the recursive formula

$$w_{k+1} = w_k + e_k \frac{\partial o_k}{dw} \tag{7}$$

Since the $o = \tanh(s)$ function is used at the output node, the updated rule becomes

$$w_{k+1} = w_k + \alpha * e_k * (1 - o_k)^2 * C_k(x) \tag{8}$$

A. Chebysheb Basis Polynomial Function

This basis function named Chebysheb Polynomial used in our FLANN architecture to enhance the input pattern.

The lower order and the higher order Chebysheb Polynomials are given in eq. (9) & (10)

$$\begin{aligned} c_1(x_i) &= x, & c_2(x_i) &= 2x^2 - 1 \\ c_3(x_i) &= 4x^3 - 3x, & c_4(x_i) &= 8x^4 - 8x^2 + 1 \end{aligned} \tag{9}$$

The higher order Chebysheb Polynomials can be generated using the below mentioned generalized recursive formula.

$$c_{r+1} = 2 * x * c_r(x) - c_{r-1}(x_i) \tag{10}$$

III. FINANCIAL TIME SERIES PREDICTION

B. Stock Exchange Time Series Data

The stock market or equity market time series is a financial measure in the world economy. Market participants include individual retail investors, institutional investors such as mutual funds, banks, insurance companies and hedge funds, and also publicly traded corporations make decisions on investment and trading. For the purpose of analysis, we have used the data collected from IBM stock for our studies. The total number of historical data is collected are 3000 trading days. The model is simulated to forecast on the closing price of index on each day. The MATLAB implementation has done to simulate the forecasting model Table.

C. Data Normalization

Before the architecture to be trained and tested on real data, the stock time series data are pre-processed. The linear transformation formula is applied for normalizing the data between 0 and 1. The normalization rule is given in eq. (16).

$$u = (x - x_{\min})/(x_{\max} - x_{\min}) \tag{16}$$

Where 'u' and 'x' represent the normalized and original data; $x_{\max}$ and $x_{\min}$ represents the maximum and minimum values among the original data.

D. Performance Measures

To evaluate the performance measures of the proposed forecasting models in forecasting stock time series finance data, different criterions are used. This accuracy evaluation is computed in function of the true financial data that collected. The main absolute percentage error (MAPE) method, the sum squared error (SSE) method, and the standard deviation of error.

(SDE) method is defined in eq. (17), eq. (18), & eq. (19) respectively.

$$MAPE = \frac{1}{N}\sum_{j=1}^{N}[abs(e)/\bar{y}\ ]\times 100 \qquad where \quad \bar{y} = \frac{1}{N}\sum_{j=1}^{N}[\,y\,] \tag{17}$$

$$SSE = \sum_{j=1}^{N}[abs(e)]^2 \tag{18}$$

$$SDE = \sqrt{\frac{1}{N}\sum_{j=1}^{N}[abs(e) - \bar{e}]^2} \qquad where \quad \bar{e} = \frac{1}{N}\sum_{j=1}^{N} abs(e) \tag{19}$$

Where $e = y_t - y$, y_t & y represents the forecast and actual values; $\bar{y}$ is the average value of forecasting period; and N is the number of forecasted period.

E. Experimental results & Performance Evaluation

The experimental results using our forecasting models are shown in figures below.

Results below showing are taken from ANN model.

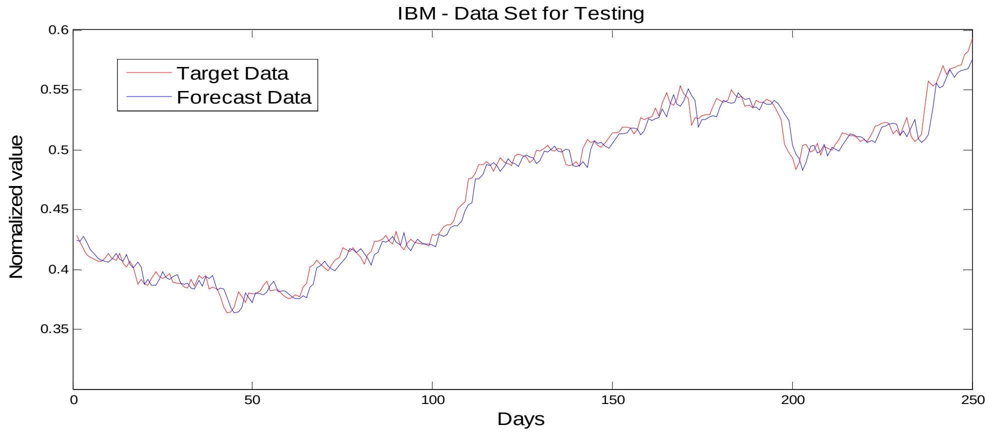

Fig. 3. Target and Predicted IBM data (one day ahead for 250days)

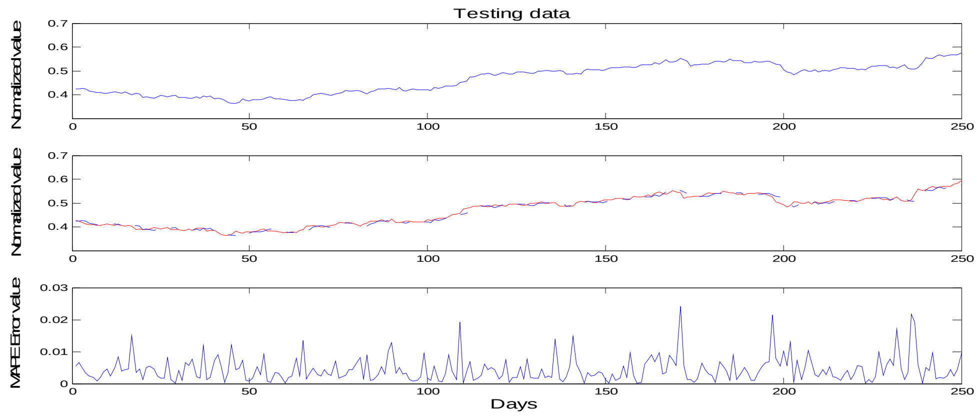

Fig. 4. MAPE error plot for Target and Predicted IBM data (one day ahead for 250days)

Results below showing are taken from FLANN model.

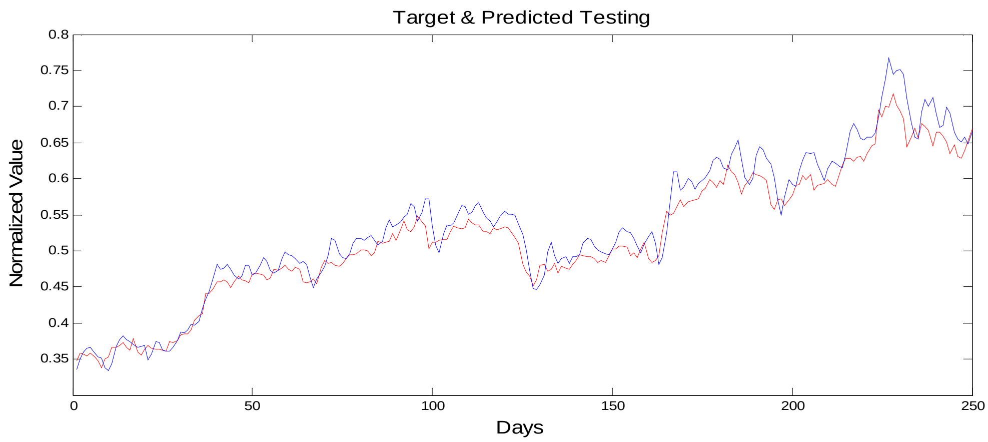

Fig. 5. Target and Predicted IBM data (one day ahead for 250days)

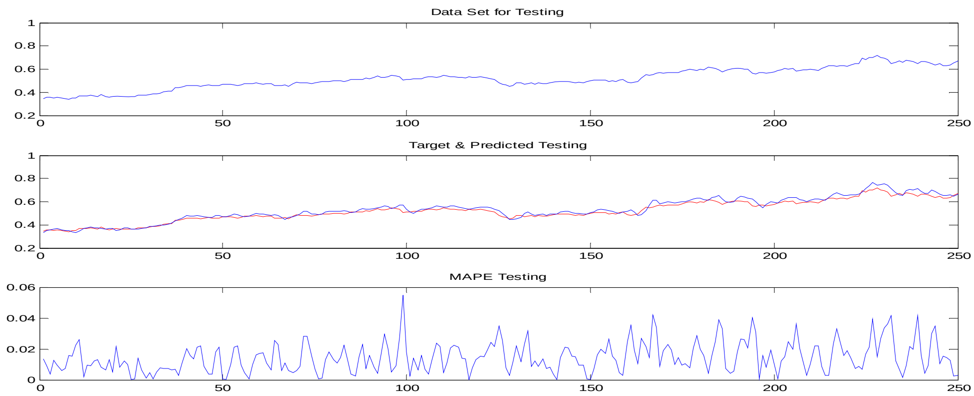

Fig. 6. MAPE error plot for Target and Predicted IBM data (one day ahead for 250days)

TABLE I. One day ahead forecasted Price of IBM stock

Date	True Data	Forecasted Data FLANN	Forecasted Data ANN
1-Jul-10	122.57	125.79	120.92
2-Jul-10	121.86	124.35	121.24
5-Jul-10	121.86	123.98	120.45
6-Jul-10	123.46	126.15	124.61
7-Jul-10	127.00	127.65	125.42
8-Jul-10	127.97	129.3	122.42
9-Jul-10	127.96	130.11	123.51
12-Jul-10	128.67	128.19	124.67
13-Jul-10	130.48	127.12	130.4
14-Jul-10	130.72	128.98	125.5

TABLE III. Performance comparison on daily closed price of various networks

Methods	SSE	SDE	MAPE
FLANN	53.47	27.2	2.023
ANN	62.15	34.11	2.571

IV. CONCLUSION

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. The studies we found that by using FLANN based model using Chebysheb polynomial basis function is better approach to forecast comparing to conventional method is better. Suggested architectures are employed to predict the IBM stock data. The structure of FLANN model is simple and has less complexity over artificial neural network. By using suitable combinations of technical and fundamental parameters it gives the better results too. Different performance parameters are used for 10 days of forecasted data to compare our results.

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