Efficient Financial Time Series Forecasting Model using DWT Decomposition

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***Abstract*—This paper proposes an efficient time series forecasting model for exchange rates. Previous literature reveals that Functional Link Artificial Neural Network (FLANN) is very effective in financial time series forecasting involving less computational load and fast forecasting capability. Autoregressive Integrated Moving Average (ARIMA) models are well known for their remarkable forecasting accuracy. In this literature, we have used Discrete Wavelet Transform (DWT) to decompose the in-sample training data into linear (detailed) and nonlinear (approximate) components, then applied ARIMA and FLANN model to forecast the respective components. The proposed method amalgamate the unique strengths of ARIMA, FLANN and DWT to improve the forecasting accuracy of a financial time series data. Simulation results show superiority of the proposed method.**

I. Introduction

Time series forecasting is a very dynamic research topic in various domains of science and engineering [1]. Time series forecasting has numerous applications in diverse field including financial forecasting, weather forecasting, stock market prediction etc. The main aim of analyzing the time series is to formulate a mathematical model that can be used to forecast desired number of future observations. Several inherent issues of a time series make future forecasting difficult. The accuracy of the future forecasts solely depends on the fitted model. Forecasting a financial data is a challenging and complex problem due to its high volatile nature [2].

In the literature, many statistical and soft computing tools have been applied on financial time series. Many soft computing techniques such as Artificial Neural Network (ANN), Genetic algorithm [3], Fuzzy logic [4] etc. have been applied on financial time series. These Models have more time complexity. Autoregressive Integrated Moving Average (ARIMA) model developed by Box and Jenkins [5], which is an effective model in time series forecasting. However, it relies upon the correlation analysis which makes it unsuitable for nonlinear patterns [6]. Functional Link Artificial Neural Network (FLANN) has been used in the literature for forecasting exchange rates and stock markets [2], [7]. In [8], FLANN has been applied for seasonal time series forecasting. FLANN involves less computational complexity and easily implementable because of the absence of hidden layers. It does not involve setting up the parameters like number of hidden layers and hidden nodes. The major issue with financial time series is how to improve the forecasting accuracy by using a model which involves less computation.

Wavelet transform has been applied in different problems of engineering, signal processing and statistics [9]. From the previous literature, it is evident that wavelet transform improves the forecasting accuracies [10], [11]. S & P index is decomposed using wavelet to forecast the future observations [10]. Haar wavelet decomposition is used in stock price time series for removing noise in order to achieve more precise forecasts [12]. Input data is partitioned into different regions using haar wavelet together with clustering algorithm [13]. In Choi et al. [14], sales time series is forecasted using hybrid SARIMA and wavelet transform. Wavelet transform is used in Conejo et al. [15] to decompose electricity time series in order to increase accuracy after applying ARIMA on decomposed part. Wavelets have also been used for improving ANN forecasting accuracy [16], [17].

In this study, we investigate a method to forecast financial time series effectively with low computational cost. The method adequately model the linear and nonlinear correlation structures of a time series through ARIMA and FLANN respectively, after a prior decomposition of original time series through Discrete Wavelet Transform (DWT). This hybrid method compiles the modeling strengths of ARIMA, FLANN and DWT. The investigated method is compared with FLANN in terms of five popular error measures. The rest of the paper is organized as follows. Section II describes the traditional time series models. Section III presents the hybrid approach. The discussion on various simulation results has been made in Section IV. Finally, Section V concludes the paper.

II. Time Series Models

A. ARIMA Model

ARIMA models are the most popular statistical models for time series forecasting [5]. In this model, the future values of a time series are generated from a linear function of the past observations and white noise terms. An ARIMA (p,d,q) model can be mathematically expressed as follows:

$$\begin{aligned}\mathbf{y}_t = \alpha_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \ldots + \beta_p y_{t-p} + \\ \varepsilon_t - \alpha_1 \varepsilon_{t-1} - \alpha_2 \varepsilon_{t-2} - \ldots - \alpha_q \varepsilon_{t-q}\end{aligned} \quad (1)$$

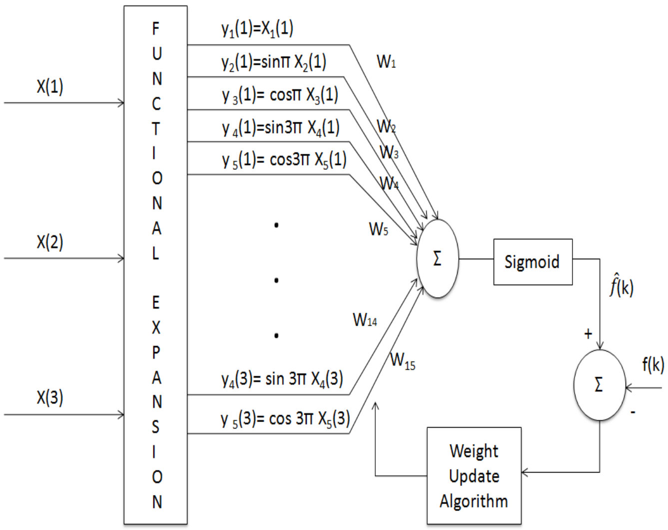

Fig. 1. FLANN Model

where y_t and ε_t are the actual value and white noise at time t respectively. p and q are the model order, whereas α_i and β_j are the model parameters. d represents degree of ordinary differencing required to make the series stationary. Box-Jenkins model building methodology [6] is used to estimate the values of p, d and q. ARIMA models are not very effective for modeling a general real-world time series due to the linearity restriction.

B. FLANN Model

FLANN is a model proposed by Pao [18] in 1989 . Single layer neural network can be used in place of Multi-layer neural network to overcome the computational complexities [19]. Due to the linear nature of single layer network, it may fail to represent the nonlinear problems. Therefore, in this model the input vector is functionally expanded to overcome the issue of linearity [20].

Feature Extraction:

Financial time series data are not used directly as a input. Features are extracted from the data and used as a input in the FLANN Model in order to achieve better forecasting accuracies [2]. First, the data is normalized using the maximum value present in the data to ensure that the data lie between 0 to 1. In this paper, we have taken number of inputs as three.

a) First input is taken as the 12^{th} month value. In order to extract the features of previous data we have started the input value from 12^{th} month.

b) Second input is taken as the mean of the values from 1^{st} to 12^{th} month.

c) Third input is taken as the variance of the values from 1^{st} to 12^{th} month.

These features are calculated separately for the time series of rupee, yen and pound.

Fig. 1 shows the FLANN model [2], [8]. As shown in Fig. 1, data from the dataset are given as input. In this study, we have taken number of inputs as three and number of expansions equal to five. Let, M be the number of months for which total data is available. M_1 be the number of months for training and M_2 be the number of months for testing. Suppose, X_m be the normalized data where $m = 1, 2, 3, ..., M$. Here, inputs are $X = [X(1), X(2), X(3)]$. Then, each input is functionally expanded. We have used trigonometric expansion which can be represented as:

$$\mathbf{y} = [y_1(k), y_2(k), ..., y_I(k)] \tag{2}$$

Here, $k = 1, 2, 3$ and $I = 5$. The expansion of each input can be written as:

$$y_i(k) = [X_i(k), sin(2n-1)\pi X_i(k), cos(2n-1)\pi X_i(k)]^T \tag{3}$$

where $n = 1, 2$ and $i = 1, 2, 3, 4, 5$. Random weights are initialized from 0 to 1. Then, the expanded 15 values are multiplied to weights and summed up to produce the output of the linear part of the model. This output is then passed through a nonlinear function (a sigmoid function) to produce the estimated output. This estimated output is compared with the corresponding desired output and the resultant error for the available pattern is used to evaluate the change in m^{th} weight in each experiment is given by [2]:

$$\triangle \mathbf{w}_m(j) = \frac{1}{N} \sum_{n=1}^{N} 2\mu \mathbf{y}(j)\mathbf{e}(j) \tag{4}$$

Here, N are the patterns to be applied and j is the iteration number. Then, the weight update equation is given by:

$$\triangle \mathbf{w}_m(j+1) = \mathbf{w}_m(j) + \triangle \mathbf{w}_m(j) \tag{5}$$

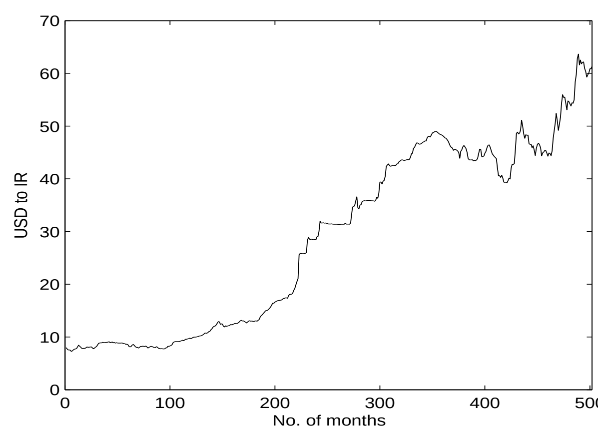

Fig. 2. USD to IR data

III. DWT BASED ARIMA-FLANN HYBRID METHOD

Wavelet transform is used to decompose the historical price data into mutual orthogonal set of wavelets or basis functions. These functions are small waves located in different times, the wavelet transform can provide information about both the time and frequency domains. In this study, DWT is used to obtain a prior decomposition of a time series into low and high frequency components [14]. During decomposition, a given signal is decomposed into several other signals with different levels of resolution. It is possible to recover the original time domain signal without losing any information. Wavelets transform has reverse process which is called the inverse wavelet transform or signal reconstruction [11], [14].

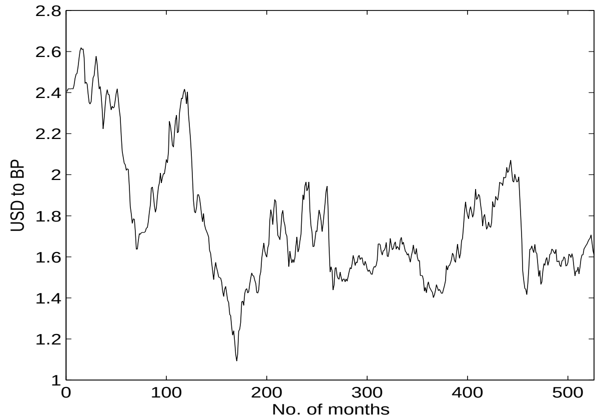

Fig. 3. USD to BP data

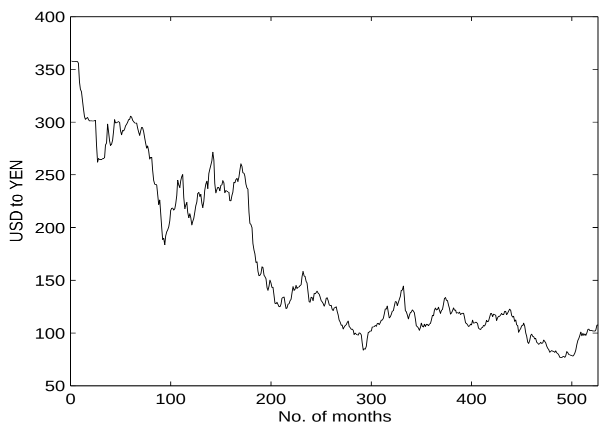

Fig. 4. USD to YEN data

In the decomposition phase, the series is decomposed into high (detailed) pass filter which picks up the higher frequency component of the series and low (approximate) pass filter which picks up the lower frequency component of the series. The reconstruction is just a reversed process of decomposition. ARIMA is fitted to the reconstructed detailed part and then forecasts are generated for the linear component. Then, the FLANN is fitted to the corresponding residuals together with the approximate part which results in generating the forecasts for nonlinear component. Finally, the combined final forecasts are obtained through adding the two linear and nonlinear component-wise forecasts [21]. Flow chart for the method is shown in Fig. 5

IV. Experimental Setup

A. Data Collection

The hybrid method is tested on 3 datasets. All these datasets are taken from www.forecasts.org. All the datasets are shown in Figs. 2-4. In addition, description of the three datasets is given in Table I.

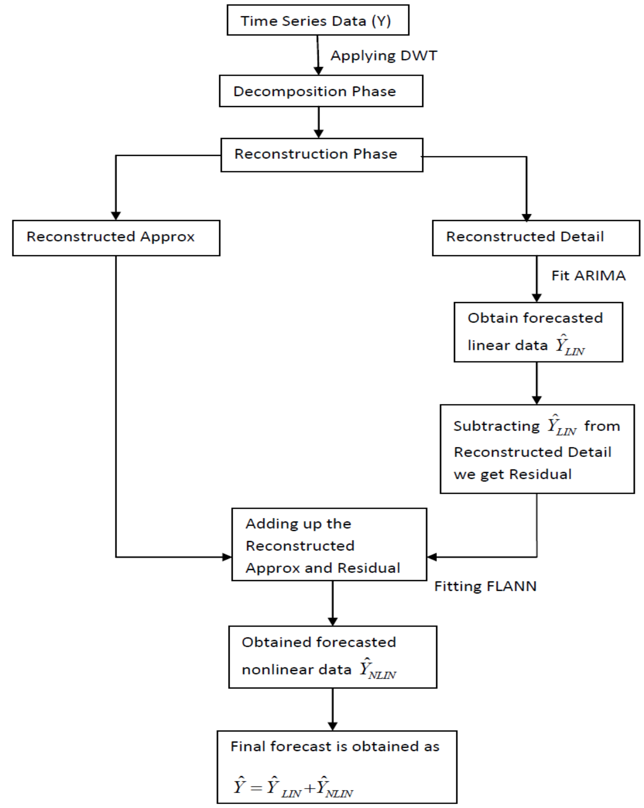

Fig. 5. Flow chart of DWT based ARIMA-FLANN method

TABLE I. Description of the three financial time series datasets

Time series	Description
1US Dollar to Indian Rupee	01-Jan-1973 to 01-Oct-2014 Total size- 502 , Train size- 468 , Test size- 34
1US Dollar to British Pound	01-Jan-1971 to 01-Oct-2014 Total size- 526 , Train size- 492 , Test size- 34
1US Dollar to Japanese Yen	01-Jan-1971 to 01-Oct-2014 Total size- 526 , Train size- 492 , Test size- 34

B. Training and Testing Process

In this literature, Mean Square Error (MSE) is considered as the cost function for training process. During training, the weights having the minimum MSE value for their forecast are stored for testing the network. In this study, we have tested our performance using other four functions i.e., Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE) and Sum of Squared Error (SSE). Actual output and estimated output are compared to evaluate the optimal values for different performance measures. The main objective is to minimize the MSE value for the testing pattern.
MSE is calculated as:

$$MSE = \frac{1}{N} \sum_{t=1}^{N} \mathbf{e}_t^2 \tag{6}$$

MAE is calculated as:

$$MAE = \frac{1}{N} \sum_{t=1}^{N} \mid \mathbf{e}_t \mid \tag{7}$$

MAPE is calculated as:

$$MAPE = \frac{1}{N}\sum_{t=1}^{N} \mid \frac{\mathbf{e}_t}{\mathbf{y}_t} \mid \times 100 \tag{8}$$

RMSE is calculated as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N} \mathbf{e}_t^2} \tag{9}$$

SSE is calculated as:

$$SSE = \sum_{t=1}^{N} \mathbf{e}_t^2 \tag{10}$$

V. RESULTS AND DISCUSSIONS

In this study, FLANN model is compared with the DWT based hybrid ARIMA-FLANN method using the forecasting accuracy measures, i.e., MSE, MAE, MAPE, RMSE and SSE. Table II gives the forecasting results of USD to IR conversion. For hybrid method, ARIMA (6,0,0) is taken along with FLANN. Results of USD to BP conversion is shown in Table III, ARIMA of order (4,0,0) along with FLANN has been used. Table IV gives the predicted results for USD to YEN conversion, hybrid method consists of ARIMA (0,1,0) and FLANN.

In all the three financial time series data it can be clearly seen from the results that our proposed DWT hybrid ARIMA-FLANN model outperforms the FLANN model. All the results of actual and forecasted data are shown in Figs. 6-8.

TABLE II. RESULTS FOR USD TO IR

Forecasting Model	FLANN	Proposed
MSE	0.019755	0.009742
MAE	0.135577	0.093802
MAPE	14.94333	10.30467
RMSE	0.140553	0.098702
SSE	0.671673	0.331234

TABLE III. RESULTS FOR USD TO BP

Forecasting Model	FLANN	Proposed
MSE	0.048984	0.013717
MAE	0.217202	0.115962
MAPE	35.65701	19.03467
RMSE	0.221324	0.117121
SSE	1.66546	0.466387

TABLE IV. RESULTS FOR USD TO YEN

Forecasting Model	FLANN	Proposed
MSE	0.092436	0.004229
MAE	0.303506	0.053384
MAPE	118.8734	20.02986
RMSE	0.304032	0.065032
SSE	3.142808	0.143793

VI. CONCLUSION

In this paper, a DWT based hybrid ARIMA-FLANN based model is introduced for financial time series forecasting. The most challenging task is to determine the exact nature of a real-world time series. ARIMA assumes linear data generation function, whereas FLANN is suitable for nonlinear financial

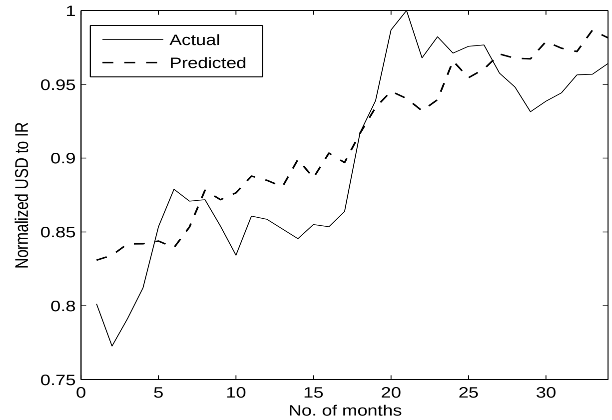

Fig. 6. Testing USD to IR data and its forecast

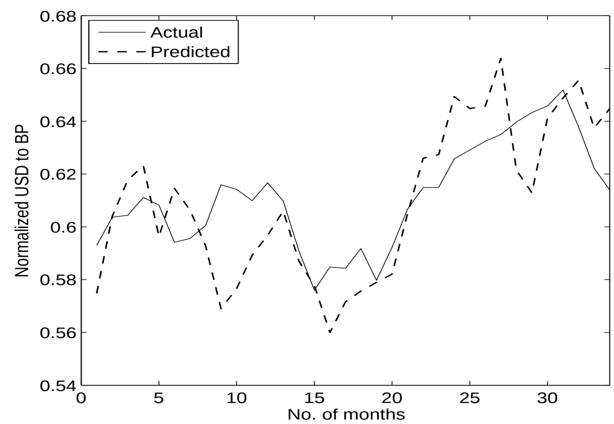

Fig. 7. Testing USD to BP data and its forecast

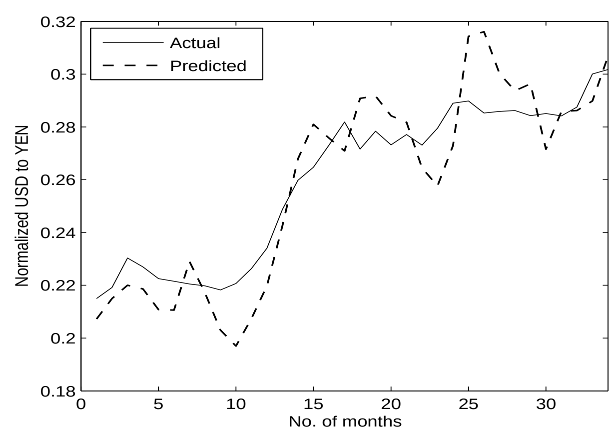

Fig. 8. Testing USD to YEN data and its forecast

time series. The DWT based hybrid method provides prior decomposition of time series data into low and high frequency components. So, that ARIMA is fitted on the high frequency linear part and FLANN is fitted on the low frequency nonlinear part. The final combined forecasts obtained for proposed hybrid method outperforms FLANN model.

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