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Forecasting Exchange Rates using Neural Neworks

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Abstract

The foreign exchange (FOREX) market is larger, in terms of trading volume than any other market, financial or otherwise. Developments in the foreign exchange market determine the levels and chages in exchange rates, which have significant implications for business and exonomics. In this paper an attempt has been made forecasting the daily exchange rates of Indian Rupee (INR) to U.S. Dollar (USD) using Box-Jenkins methodology for building ARIMA model and artificial neural networks (ANN) for building Multilayer Perceptron (MLP) and Recurrent Neural Network (RNN) models. The sample data is used from April 2011 to March 2015. RMSE, MAE and MAPE are used for the comparison of the models.
Result of this study shows that RNN is performing better than ARIMA and MLP in forecasting the daily exchange rates INR to USD.

Keywords: Exchange Rate forecasting, ARIMA, MLP and RNN.

INTRODUCTION

The financial market is divided into four components: capital markets, commodities, foreign exchange and derivatives[2]. Building a forecasting model for exchange rates has always been a challenging area of research to applied econometricians and statisticians. The exchange rates play an important role in controlling dynamics of the exchange market. As a result, the appropriate prediction of the exchange rate is crucial factor for the success of many businesses and fund managers [2][3]. Forecasting exchange rate is quite important not only for the firms having their business spread over different countries or firms planning to raise long or short terms funds from international markets but alos for the firms confined their entire business in the domestic market only, because a change in foreign exchange rate can change the business and competition scenario for the firms. Every transaction arising from international trade or investment must pass through the foreign exchange market, since these transactions involve the exchange of currencies [4]. Furthermore, developments in the foreign exchange market determine the levels of and changes in exchange rates, which have significant implications for businesses and economies. Exchange rates are inherently noisy, nonstationary and deterministically chaotic. One general assumption is mage in such cases is that the historical data incorporate all those behaviour and as result, the hisdtorical data is the major input in the prediction process.

In time series forecasting, the past data of the prediction variable is analyzed and modeled to capture the patterns of the historic changes in the variable [5]. These models are then used to forecast the future prices. One of the most common and popular linear method is the Autoregressive integrated moving average (ARIMA) model [1][5]. However, ARIMA is a general univariate model and it is developd based on the assumption that the time series being forecasted are linear and stationary.

Artificial neural network (ANN) or simply neural network (NN) has been used as research tools in several fields. In particular, NN exercises a parameterized nonlinear function that can approximate nonlinear systems for prediction purpose. As far as the economic applications are concerned, NN has been widely applied to financial and macro-econometric areas [7]. The Multilayer perceptron network (MLP) model has been the most popular form of NN model used for forecasting. It is a feedforward neural network with a learning process in both hidden layer and output layer units. The MLP model is statistic having a learning process in both hidden and output layers in a forward direction. The recurrent neural network (RNN) allows the solution process to be dynamic. As far as the economic applications are concerned, the RNN is one of the most interesting types of NN model, as it is able to capture the dynamic behavior of the series, but RNN models have not been developed and applied as much as others in economics[6][7].
This study will try to reveal the fact whether artificial neural networks methodology produces superior results than Box-Jenkins methodology.

REVIEW OF ARIMA MODEL

Forecasting is one of the main objective of the time series analysis. The method of forecasting should include factors such as how the forecast is to be used, properties of the time series, how many observations are available the forecasting horizon etc; Time-series models predict on the assumption that the future is a function of the past [5]. Since time is often an important factor in decision-making, time-series forecasts were developed to utilize time in the foundation of the forecast. Therefore, time-series forecasts are based on a sequence of historical data points that are measured over any length of time, including daily, monthly or yearly. In many empirical timeseries it is observed that the means are not fixed but they exhibit a sort of homogeneity in the sense that two different parts of a time series behaviour alike i.e one part of the series behave much like in other part . This type of Time series is known as homogeneous non stationary time series

The important class of models for which dth difference is stationary mixed auto regressive moving average models are called Auto Regressive Integrated Moving Average Models (ARIMA) [1]. If the data is non- stationaray, we convert it into stationary by stabilizing variance using logarithmic transformation and stabilizing mean using successive differencing. The special feature of Non Stationary time series are variance is not constant and mean of the timeseries is also not constant over time. The ARIMA model for the timeseries [1] is denoted by ARIMA (p ,d ,q) and is defined as

$$\phi(B)\nabla^d Z_t = \theta(B)a_t$$

Where $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - ...... - \phi_p B^p$

is a polynomial in B of order ‘p’ and is known as AR operator.

$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 .... - \theta_q B^q$ is a polynomial in B of order ‘q’ and is known as MA operator.

The difference operator is taken as $\nabla = 1 - B$, **B** is the Backward shift operator $B^k Z_t = Z_{t-k}$ and d is the number of differences required to achieve stationarity

Once stationarity and seasonality have been addressed, the next step is to identify the order (i.e., the p and q) of the autoregressive and moving average terms. The primary tools for doing this are the autocorrelation plot and the partial autocorrelation plot. Sample autocorrelation plot and the sample partial autocorrelation plot are compared with theoretical plots. But in real life one will hardly get the patterns similar to the theoretical one, so to use iterative methods and select the best model on the basis of following criteria; relatively small AIC (Akaike’s information criteria) or SBC (Schwarz’s Bayesian criteria), relatively small of Standard Error (SE), and white noise residuals of the model. (which shows that there is no significant pattern left in the ACFs and PACFs of the residuals) [1][5].

REVIEW OF ARTIFICIAL NEURAL NETWORKS

Artificial Neural Network (ANN) is a field of research aimed at building a computationally feasible machine-based cognitive system that tries to capture key aspects of the human cognition process. Although in terms of speed of processing, the human brain is much inferior to modern microprocessors, its superiority lies in its organization of the processing of a high-dimensional array of input variables [6]. Parallelism or connectionism, adaptability and self-organization are the main attributes of the brain’s signal-processing mechanism. Recently neural networks have been used for modeling nonlinear economic relationship because of its ability to extract complex nonlinear and interactive effects. Neural networks are a class of nonlinear model that can approximate any nonlinear function to an arbitrary degree of accuracy and have the potential to be used as forecasting tools in many different areas. There are many different neural net learning algorithms found in the literature. No study has been reported to analytically determine the generalization performance of each algorithm [8].

The neural networks approach is one of the most important fields of Artificial Intelligence (AI), which is a modern science used in a lot of modern and complex applications, such as robotics industry systems, decision support systems, automated control systems, and identification and prediction systems. ANN approach is an efficient forecasting tool. This method consists of algorithms that mimic the features of brain of human being. These features are generating and exploring
new knowledge by learning . ANN consists of some elements that should be determined carefully because they effect the methods forecasting performance. The essential elements that determine the ANN are Architecture structure and learning algorithm. The architecture is determined by deciding the number of layers and number of neurons nodes in each layer and there is no general rule for determining the best architecture. The links that connect the neurons of a layer to the neurons of an other layer are called weights. These weights are determined by a learning algorithm that updates their values [6][7][8].
Multi Layer perceptron (MLP) / Backpropogation Network (BPN) is a feedforward neural network with one or more layers between input and output layer. Feedforward means that data flows in one direction from input to output layer (forward). This type of network is trained with the backpropagation learning algorithm.

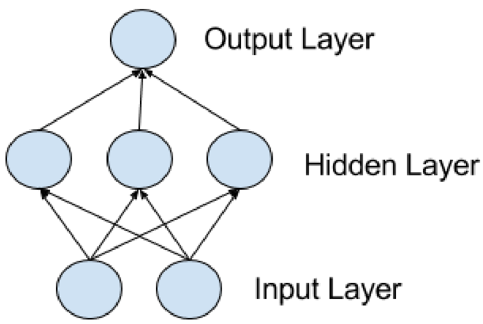

Figure 1 : MLP/BPN Architecture

Feedforward back propagation network is one of the most neural networks architectures that is used widely for forecasting due to its simple usage and success. The multilayer feed forward ANN consists of three parts: input, hidden and output layers as shown in Figure 1. Each layer consists of neurons and stating the neurons number in each layer determines the architecture structure. Back Propagation algorithm is one of the most used learning algorithms which updates the weights based on the difference between the output value of the ANN and the desired real value [7]. In the forecasting, the inputs are the past observations and the output is the predicted value.

Multilayer perceptron (MLP)/Backpropogation Network (BPN) allow only feedforward connections between each neurons and the neurons in the following layer [7][8]. Recurrent neural networks in contrast allow arbitrary connections between neurons, both forward and recurrent (feedback). A nonlinear mapping obtained by a recurrent neural network is not only dependent on the current input, but also is dependent on the previous inputs through the feed back connections to the input. RNNs can use their internal memory to process arbitrary sequences of inputs. RNN is a dynamic network and is able to capture the dynamic behavior of complex data [8], especially nonlinear time series. The learning algorithm in the RNN model is exactly same as that in the BPN model, using gradient descent rule, which adjusts the weights based on the derivatives of the error with respect to weights. Due to the presence of the feedback, the derivatives become more complicated and so the computations take much loner. As a result, the learning time in RNN model is usually much longer than that in BPN models [7][8].
The feedforward multilayer perceptron (MLP) network is used frequently in time series prediction. MLP network, however, has a major limitation that it can only learn an input-output mapping which is static. Thus, it can be used to perform a nonlinear prediction of a stationary time series. A time series is said to be stationary, when its statistics does not change with time [1][2][5]. In many real world problems, however, the time when certain feature in the data appears contains important information. More speci cally, the interpretation of a feature in data may depend strongly on the earlier features and its ap-
pearance time.
The Elman network, which is known as partial recurrent network or simple recurrent network (SRN) is shown in Figure 2.

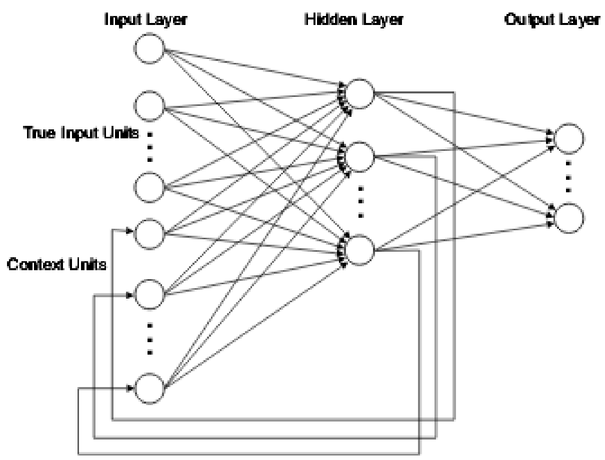

Figure 2: Elman Recurrent Neural Network Architecture

In an SRN, the outputs of the hidden layer are allowed to feedback onto itself through a buffer layer [7][8]. These are the only feedback connections in the network and the weights from the hidden layer to the context layer are constant values. All other connections are feedforward with adjustable weights. Although, simple in structure, this network is capable of learning to perform powerful tasks [6].

METHODOLOGY

The aim of this section is to provide experimental results of the proposed method. The results of forecasting using Box-Jenkins statistical model and ANN models are presented. The reported results are then analyzed and compared. Typically, the commonly used forecast error measurements are applied for estimating the quality of forecasting methods. These error measurements are: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE).

In this study, exchange rates of INR/USD data has been downloaded from the International Monetary Fund: www.imf.org/external/np/fin/data/. This data is stored in .csv file which can be opened in MS-Excel. In this study the data from April 2011 to March 2015 is taken. The main aim of the study in this paper is to model and forecast the data of the exchange rates of INR/USD using time series with SPSS. The time series model is identified using Box-Jenkins methodology. ACF plot is given in the Figure 3 and PACF plot is given in the Figure 4.

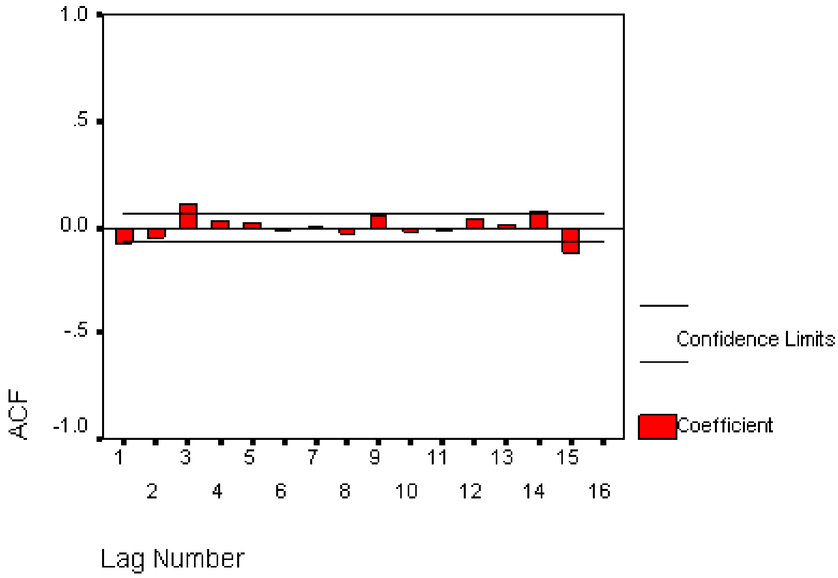

Figure 3 : ACF Plot

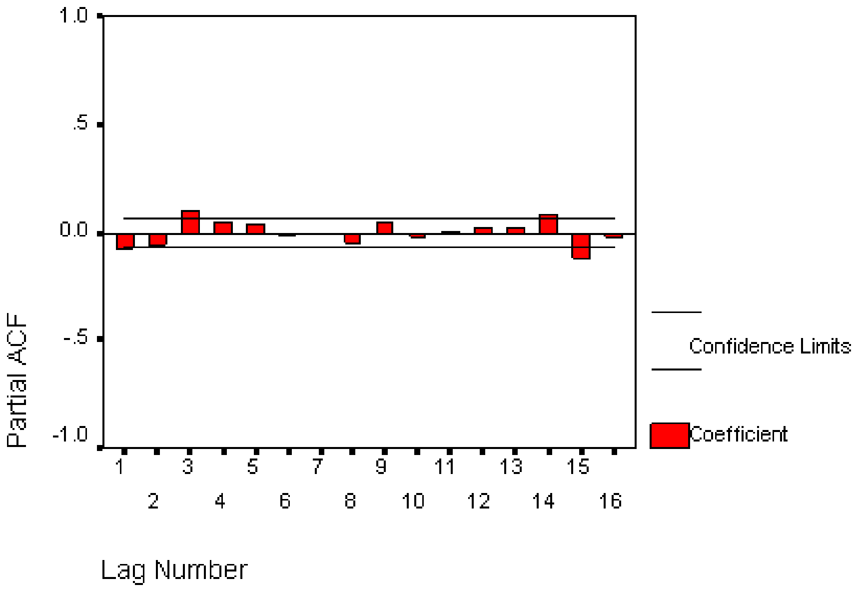

Figure 4 : PACF Plot

In model identification, extensive use of Correlogram and partial Correlogram is made. So, for the identification of the model one must verify ACF's and PACF's. The ACF plot in Figure 3 showed one spike at lag 3 and PACF plot in Figure 4 also showed one spike at lag 3. Therefore the number of initial significant ACF and PACF spike is 1 i.e. q=1 and p=1 respectively. Based on this the tentative models will be assumed. Minimum AIC and SBC values will decide which model will be the best among the tentatively assumed models as shown in the Table 1.

Table 1: AIC and SBC values of ARIMA models

Box –Jenkins models	AIC	SBC
ARIMA(1,1,0)	187.04192	196.7358
ARIMA(0,1,1)	**186.50348**	**196.19737**
ARIMA(1,1,1)	188.33094	202.87177

From the above Table 1, it is clear that ARIMA (0,1,1) would be the best model because it has minimum AIC and SBC values.
Therefore ARIMA (0,1,1) is the model used for forecasting future values.

$\mathbf{Z_t = (1- 0.08610363B)a_t + 0.00164515}$ is the ARIMA (0,1,1) model.

The exchange rates of INR/USD is forecasted using MLP /BPN. The Backpropogation algorithm is used to train the BPN model. The Neurosolutions 5.1 is used to train BPN and to generate the out-of-sample forecasts. The data is normalized as (0,1). The following assumptions are used to train the BPN model:

Data	:	Daily data from April 2011 to March 2015 Network architecture: BPN
Training Algorithm	:	BP algorithm (gradient-descent rule)
Learning rate	:	0.4
Momentum rate	:	0.25
Number of epochs	:	1600
Number of observations	:	942
Activation/ transfer function	:	sigmoid

Under the dynamic model of RNN, the exchange rates of INR/USD is forecasted. The BP algorithm is used to train the RNN model which is similar to training the BPN model. The data is normalized as (0,1). The Neurosolutions 5.1 is used to train RNN and to generate out-of-sample forecasts with the following assumptions:

Data	:	Daily data from April 2011 to March 2015
Network architecture	:	RNN
Training Algorithm	:	BP algorithm (gradient-descent rule)
Learning rate	:	0.5
Momentum rate	:	0.3
Number of epochs	:	850
Number of observations	:	942
Activation/ transfer function	:	sigmoid

CONCLUSIONS

In this paper, two forecasting methods are presented:one is based on statistical models and the other is using ANN. The first method employed Box-Jenkins model which is usually used to predict time series. In the second method, artificial neural network models (BPN and RNN). The two methods are applied to predict the exchange rates of INR/USD of the period from April 2011 to March 2015. For each method, the experimental results are given and analyzed based on statistical standards such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage and Error (MAPE).

Table 2 : Comparative performance ARIMA and ANN Methods

MODEL	Observations	RMSE	MAE	MAPE
ARIMA(0,1,1)	942	1.43029	0.232082	0.10437
MLP (with one hidden layer)	942	1.12167	0.194182	0.09053
RNN (with one hidden layer)	942	0.71943	0.07672	0.03816

From the above Table 2, gives the comparison between the statistical model and the ANN models which shows that theRNN model gives lower errors and higher accuracy for the prediction of exchange rates of INR/USD during training and testing. Therefore, the prediction done by ANN will be more consistent and gives a good predicted observations.

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