Forecasting Short term USD/INR Exchange Rate -ARMA Approach

M.Sriram
Assistant Professor-Finance
SDMIMD, Mysuru
msriram@sdmimd.ac.in

Abstract

The present study has analysed the forecasting of exchange rate of USD/INR for the period 01/ 01/ 14 to 31/ 05/ 14. It is found that the time series data is stationary but not normally distributed. The auto regressive models were developed and it was found that ARMA (1,9) was the best fit model in predicting the exchange rate when compared to ARMA (1,0) and ARMA (1,1). Forecasting the exchange rate using the model was carried out for In-sample (Dynamic Forecasting) and Out-of-sample period (Static Forecasting). The study shows that the forecasted values were close to the actual values thus minimising the forecasting error.

Keywords : *ARMA, Stationary, Dynamic Forecasting, Static Forecasting, USD/INR*

Introduction

Exchange rate plays an important role in influencing the decision taken by the participants in the foreign exchange market namely investors, international traders (Importers and Exporters), banks, financial institutions, policy makers etc., across the globe. Forecasting exchange rate has become a key issue and it is more so with short term forecasting of the exchange rate. International traders and companies do a lot of planning in terms of raising short term funds from overseas markets, foreign exchange transactions in terms of receipts and payments and an accurate forecast of exchange rate may definitely put a company in a competitive position. Therefore, short term forecasting is vital for routine transactions and as well as for strategic decisions. For the multinational companies, an accurate forecasting of the foreign exchange rates is crucial since it improves their overall profitability (Huang et al., 2004). In the financial as well as managerial decision making process, forecasting is a crucial element (Majhi et al., 2009). Forecasting of the exchange rate is the foremost endeavor for the practitioners and researchers in the spree of international finance, particularly in case of the exchange rate which is floating (Hu et al., 1999). Since the breakdown of Bretton-Wood system, prediction of the exchange rate has become more important and has taken centre stage in International Finance. To develop models for forecasting the exchange rates is important in the practical and theoretical aspects. The importance of forecasting the exchange rates in practical aspect is that an accurate forecast can render valuable information to the investors, firms and central banks for in allocation of assets, in hedging risk and in formulating of policy. The theoretical significance of an accurate forecasting exchange rate is that it has vital implications for efficient market hypothesis as well as for developing theoretical model in the field of international finance (Preminger et al., 2005). Some corporate tasks that make forecasting the foreign exchange rate so important are, hedging decision, short-term financing decision, short-term investment decision, capital budgeting decision, earnings assessment and long-term financing decision (Madura, 2006)

Exchange rate can be forecast in two ways: one using multivariate approach wherein the exchange rate of a country is determined by various macro economic factors such as money supply, output, inflation, interest rate, balance of payment etc., A model will be created and efforts will be undertaken to explain the changes in the exchange rate by the explanatory variables (macro economic factors). Academics suggest different approaches to forecasting exchange rate like forward rate approach, interest rate parity approach. But the above referred methods suffer few limitations. One such limitation is that the data for these macroeconomic variables are available mostly on monthly basis, while in finance research one need to deal with very high frequency data such as daily, hourly or even minutes wise also. In order to overcome the limitations, univariate models are more appropriate. The model tries to predict the financial variables using information contained not only in their own past values but with the current and past values of an error term. This paper is an attempt to forecast the exchange rate of USD/INR using univariate time series models like ARMA (Auto Regressive Moving Average) approach. The paper comprises of five sections, viz., Objectives, Review of Literature, Data and Methodology, Analysis and Interpretation, Conclusion and directions for future research.

Objectives

The objectives of the study are the following-

a) To develop the best fit autoregressive model for determining the exchange rate of USD/INR.

b) To forecast the exchange rate for the sample of observations considered for the study.

Literature Review

Slini, et. al (2001) used stochastic autoregressive integrated moving average ARIMA model for maximum ozone concentration forecasts in Athens, Greece. For this purpose, the Box-Jenkins approach is applied for the analysis of a 9-year air quality observation record. The model developed is checked against real data for 1 year. The results show a good index of agreement, accompanied by a weakness in forecasting alarms. Saab, et. al(2001) investigate different univariate-modeling methodologies and try, at least, a one-step ahead forecast for monthly electric energy consumption in Lebanon. Three univariate models are used, namely, the autoregressive, the autoregressive integrated moving average (ARIMA) and a novel configuration combining an AR (1) with a high pass filter. The AR (1)/high pass filter model yields the best forecast for this peculiar energy data. McAleer (2002) used various Box–Jenkins Autoregressive Integrated Moving Average (ARIMA) models over the period 1975(1)–1989(4) for tourist arrivals to Australia from Hong Kong, Malaysia and Singapore. The fitted ARIMA model is found to be valid when tourists arrival were forecasted for Singapore for the period

1990(1)–1996(4). Kamruzzaman et al., (2003) mention that the performance of all ANN related models are better than the ARIMA model. Furthermore, they reveal that all the ANN based models are capable to predict the foreign exchange market closely. Preminger et al., (2005)state that foreign exchange rate forecasting robust models have a tendency for improving Autoregressive and Neural Network model's forecasting accuracy at each time sphere, as well as even of random walk for predictions done at a one-month time - sphere. They also mention that robust models have considerable market timing capability at each forecast horizons. Bissoondeeal et al. (2008) conduct a research for forecasting foreign exchange rates with nonlinear models and linear models and reveal that usually, NN models outperform compared to the time series models which are traditionally applied in forecasting the foreign exchange rates. Pradhan et al., (2010) conducted a study on Forecasting Exchange Rate in India: An Application of Artificial Neural Network (ANN) Model and reveal that ANN model is a successful tool for forecasting the exchange rate. Moreover, they reveal that it is possible to extract information concealed in the exchange rate and to predict it into the upcoming. Dua et al., (2011) did a study on modelling and forecasting the Indian RE/USD exchange, governed by the managed floating foreign exchange rates regime, with vector autoregressive (VAR) and Bayesian vector autoregressive (BVAR) models find that extension of monetary model for incorporating forward premium, capital inflows' volatility as well as order flow is an effective way to improve forecasting accuracy of the selected model. Md. Zahangir Alam (2012) in his study examined the application of autoregressive model for forecasting and trading the BDT/USD exchange rates from July 03, 2006 to April 30, 2010 found that ARMA model was better in forecasting the exchange rate.

Data and Methodology

The exchange rate of USD/INR has been taken between 01-01-14 and 31-05-14. For modelling and forecasting purposes, the period is divided into two categories, namely- In sample period (t=1......T) and out of sample period (t= T+1,......, T+H). The in sample period is from 01-01-14 to 19-04-14 and out of sample period is from 20-04-14 to 31-05-14. There are 100 observations in the In sample period and 41 observations in the out of sample period.

$t=1 \longrightarrow t=T$ | $t=T+1 \longrightarrow t=T+H$

Distribution of Data- To analyse the pattern of distribution of data skeweness and kurtosis have been calculated. Zero skewness implies symmetry in the distribution whereas kurtosis indicates the extent to which probability is concentrated in the centre and especially at the tail of the distribution. Kurtosis measures the peakedness of a distribution relative to the normal distribution. A distribution with equal kurtosis as normal distribution is called 'mesokurtic'; a distribution with small tails is called 'platykurtic' and a distribution with a large tail is called 'leptokurtic'. Eviews 7 has been used to calculate skewness and kurtosis.

Unit Root Test (Stationarity Test): Empirical work based on time series data assumes that the underlying time series is stationary. Broadly speaking a data series is said to be stationary if its mean and variance are constant (non-changing) over time and the value of covariance between two time periods depends only on the distance or lag between the two time periods and not on the actual time at which the covariance is computed (Gujarati, 2003). A unit root test has been applied to check whether a series is stationary or not. Stationarity condition has been tested using Augmented Dickey Fuller (ADF).

Augmented Dickey–Fuller (ADF) Test: Augmented Dickey-Fuller (ADF) test has been carried out which is the modified version of Dickey-Fuller (DF) test. ADF makes a parametric correction in the original DF test for higher-order correlation by assuming that the series follows an AR (p) process. The ADF approach controls for higher-order correlation by adding lagged difference terms of the dependent variable to the right-hand side of the regression. The Augmented Dickey-Fuller test specification used here is as follows:

$$Yt = b0 + \beta\Delta\, Yt\text{-}1 + \mu 1\, \Delta Yt\text{-}1 + \mu 2\, \Delta Yt\text{-}2 + \ldots + \mu p\, \Delta Yt\text{-}p + et \ldots\ (1)$$

Yt represents time series to be tested, b0 is the intercept term, β is the coefficient of interest in the unit root test, $\mu 1$ is the parameter of the augmented lagged first difference of Yt to represent the pth-order autoregressive process, and et is the white noise error term.

Autoregressive Model

According to autoregressive model, a forecast is a function of previous values of the time series (Hanke and Wichern, 2009). This model takes the following equation:

$$yt = \mu + \varphi 1 y_{t-1} + \varphi 2 y_{t-2} + \cdots + \varphi p y_{t-p} + u_t \text{ .... } (2)$$

Where,

Yt = the actual rate of return at period t

M = constant

Φ = co-efficient

ut = a white noise disturbance term

Autoregressive Moving Average Model

This model represents the present value of a time series depends upon it past values which is the autoregressive component and on the preceding residual values which is the moving average component (Sermpinis, Dunis and Laws, 2010). The ARMA (p,q)model has the following general form:

$$Yt = \varphi_0 + \varphi 1 Y_{t-1} + \varphi 2 Y_{t-2} + \cdots + \varphi p Y_{t-p} + \varepsilon t - w1_{\varepsilon t-1} - w2_{\varepsilon t-2} - \cdots - wq_{\varepsilon t-q} \ (3)$$

Where,

Yt = the dependent variable at time t

Yt-1, Yt-2, and Yt-p = the lagged dependent variables

ϕ0, ϕ1, ϕ2, and ϕp = regression coefficients

εt = the residual term

εt- 1, εt- 2, and εt- p = previous values of the residual

w1, w2, and wq= weights

The AR(p) is determined using PACF and MA(q) is determined using ACF. The no. of lagged terms to be included in the model is identified based on the minimum value of AIC and SBC criteria.

Forecasting

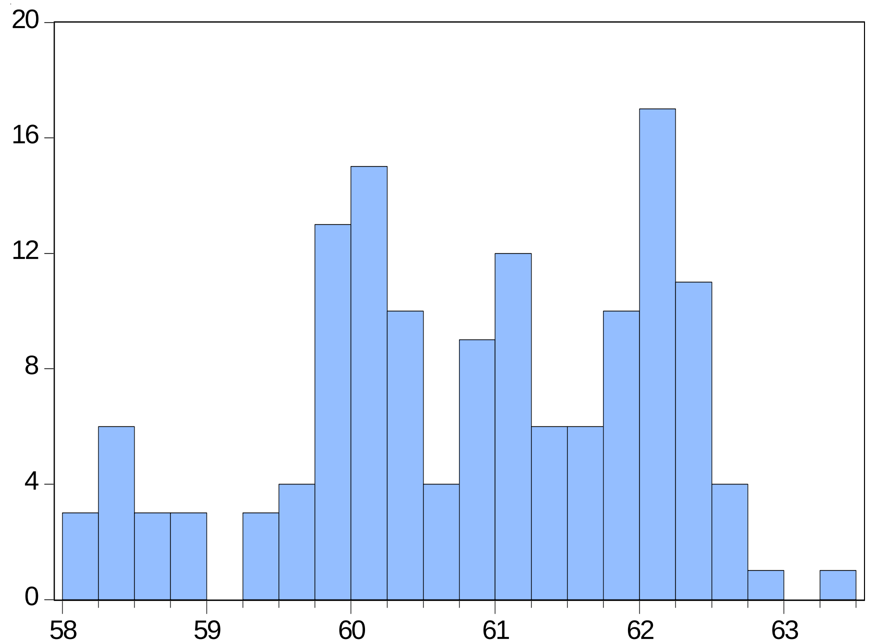
There are two types of forecasting in ARMA model building- Dynamic and Static Forecast. Dynamic forecasts are those generated for the same set of data which was used to estimate model's parameters which is otherwise called In-sample forecasts. The observations of out of sample period will be forecast using estimated parameters of In - sample observations and it is referred to as Static forecasting. Forecasting is done using EViews 7.

Measures of the Statistical Performance of the Model

The statistical performance measures are, namely mean absolute error (MAE); mean absolute percentage error (MAPE); root mean squared error (RMSE); and Theil-u, are used to select the best model for the data used for the present study. For all four of the error statistics retained, the lower the output the better is the forecasting accuracy of the model concerned.

Analysis and Interpretation

Table I Descriptive Statistics



Series: USD_INR	
Sample 1 141	
Observations 141	
Mean	60.82558
Median	60.98730
Maximum	63.45000
Minimum	58.20300
Std. Dev.	1.232869
Skewness	-0.344611
Kurtosis	2.296664
Jarque-Bera	5.697046
Probability	0.057930

Table I shows the descriptive statistics of the daily exchange rate of USD/INR for the period selected for the study. The mean exchange rate is Rs60.82 and there is fluctuation in the exchange rate when the minimum and maximum values are compared. The minimum exchange rate is Rs58.203 and the maximum rate is Rs63.45 respectively. Skewness is negative (-0.344)indicating a relatively long left tail compared to the right one. Kurtosis with a value of 2.29 indicates short tail and the distribution is platykurtic. According to Jarque Bera Statistics, the series is not normally distributed. Figure I shows the graphical representation of the daily exchange rate.

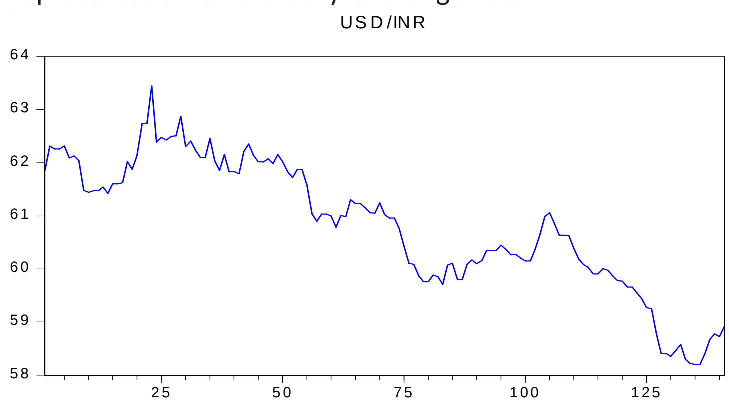


Figure 1- Exchange Rate of USD/INR

Table II ADF Unit Root Test

Particulars	t value	Probability
At level	-0.6718	0.8492
At first difference	-12.6829	0.00

Table II shows Unit Root Test for the data under study. It can be seen from the table that data is non stationary at level and becomes stationery at first difference thereby rejecting the null hypothesis that data has unit root.

Table III Correlogram Analysis of Exchange Rate USD/INR

Date: 06/24/14 Time: 10:05

Sample: 1 141

Included observations: 141

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|*******	.|*******	1	0.972	0.972	136.19	0.000
.|*******	.|. |	2	0.943	-0.053	265.11	0.000
.|*******	.|. |	3	0.912	-0.035	386.60	0.000
.|******|	.|. |	4	0.880	-0.037	500.53	0.000
.|******|	*|. |	5	0.845	-0.075	606.28	0.000
.|******|	.|. |	6	0.808	-0.032	703.87	0.000
.|******|	*|. |	7	0.769	-0.074	792.84	0.000
.|***** |	.|. |	8	0.733	0.041	874.22	0.000
.|***** |	.|. |	9	0.699	0.021	948.76	0.000
.|***** |	.|* |	10	0.671	0.109	1018.1	0.000
.|***** |	.|. |	11	0.644	-0.014	1082.5	0.000
.|**** |	.|. |	12	0.616	-0.054	1141.9	0.000
.|**** |	.|. |	13	0.590	0.010	1196.7	0.000
.|**** |	.|. |	14	0.566	0.011	1247.5	0.000
.|**** |	.|* |	15	0.549	0.097	1295.7	0.000
.|**** |	.|. |	16	0.531	-0.045	1341.1	0.000
.|**** |	.|. |	17	0.513	0.007	1383.9	0.000
.|**** |	.|. |	18	0.495	-0.021	1424.1	0.000
.|*** |	.|. |	19	0.480	0.040	1462.2	0.000
.|*** |	.|. |	20	0.464	-0.040	1498.1	0.000
.|*** |	*|. |	21	0.440	-0.181	1530.6	0.000
.|*** |	.|. |	22	0.414	-0.038	1559.6	0.000
.|*** |	.|. |	23	0.384	-0.060	1584.9	0.000
.|*** |	.|* |	24	0.363	0.183	1607.6	0.000
.|** |	.|. |	25	0.340	-0.052	1627.6	0.000
.|** |	.|. |	26	0.319	0.051	1645.5	0.000
.|** |	.|. |	27	0.299	-0.008	1661.3	0.000
.|** |	.|. |	28	0.277	-0.060	1675.0	0.000
.|** |	.|. |	29	0.256	0.016	1686.7	0.000
.|** |	.|. |	30	0.241	0.016	1697.3	0.000
.|** |	.|. |	31	0.228	0.021	1706.8	0.000
.|** |	.|. |	32	0.215	-0.010	1715.3	0.000
.|* |	.|* |	33	0.204	0.103	1723.1	0.000
.|* |	.|. |	34	0.197	0.003	1730.4	0.000
.|* |	.|. |	35	0.191	-0.017	1737.4	0.000
.|* |	.|. |	36	0.188	0.003	1744.1	0.000

Table III show the correlogram analysis of the exchange rate USD/INR. The table shows presence of autocorrelation and that there are around nine spikes on the AC (Autocorrelation) and one spike for PAC(Partial Autocorrelation) thereby concluding that ARMA model can be constructed and the possible models are ARMA(1 0) , ARMA (1,1) and ARMA (1,9).

Table IV ARMA Models

Particulars	**ARMA(1,0)**	**ARMA (1,1)**	**ARMA(1,9)**
AR(1)	0.97150(35.784)*	0.984267(42.13)*	0.98367(41.43)*
MA(1)	----------	-0.169467(-1.934)**	----------------
MA(9)	------------	--------------	-0.20245(-2.19)*
R^2	0.921	0.925	0.931
Adj R^2	0.920	0.923	0.930
AIC	.028	0.021	0.018
SBC	0.08	0.100	0.07

*Significant @ 5 % ** Significant @ 10%

The values in the parenthesis are t values. Table IV shows the results for ARMA (1,0) , ARMA (1,1) and ARMA (1,9) and it can be seen that ARMA(1,9) has a slightly higher R^2 and adjusted R^2 when compared to ARMA (1,0) and ARMA (1,1). In terms of AIC criterion, ARMA (1,9) has the least value when compared to models ARMA (1,0) and ARMA (1,1). Therefore, ARMA (1,9) is the best fit model to forecast the exchange rate of USD/INR.

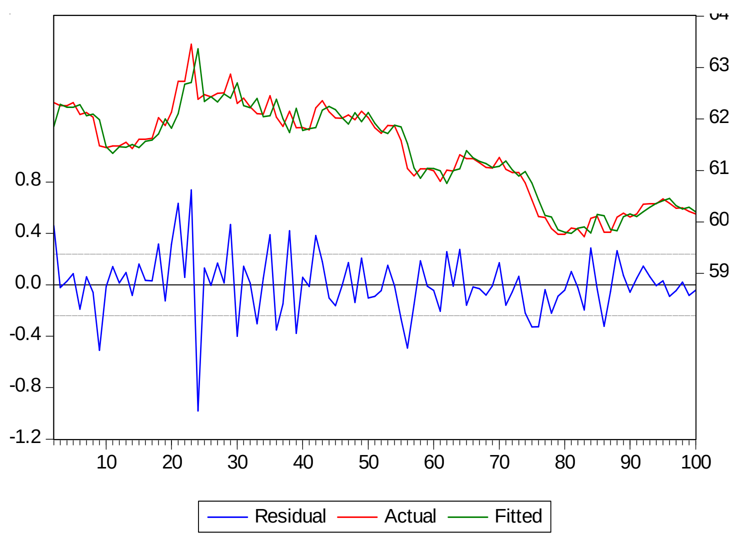


Figure 2 Dynamic Forecasting- Actual Vs Fitted

Table V

Statistical Performance of ARMA Models- In Sample Data

Particulars	**ARMA (1,0)**	**ARMA (1,1)**	**ARMA (1,9)**
Men Absolute Error	0.656	0.622	0.61
Mean Absolute percentage Error	1.066	1.01	1.002
Root Mean Squared Error	0.7837	0.7566	0.71
Theil-U	0.007	0.006	0.006

Table V shows the statistical performance of all the ARMA models developed. The errors are related to forecasting the exchange rate for the in sample data, which otherwise is called as dynamic forecasting. Among the errors, root mean squared error is considered the most appropriate tool to evaluate the best model. The lower the root mean squared error, the better the model is in predicting the exchange rate. Among the three models developed, ARMA (1, 9) has the least root mean squared error of 0.71 when compared to ARMA (1, 0) with 0.7837 and ARMA (1,1) with 0.7566 respectively. Therefore, ARMA (1, 9) is considered the best model for forecasting the exchange rate of USD/INR. Figure 2 shows the actual exchange rates and the forecasted exchange rates for ARMA (1, 9). It can be seen from the figure that the actual values of the dollar moves closely with the forecasted value and hence the inference is that the model developed has the forecasting ability to predict the exchange rate.

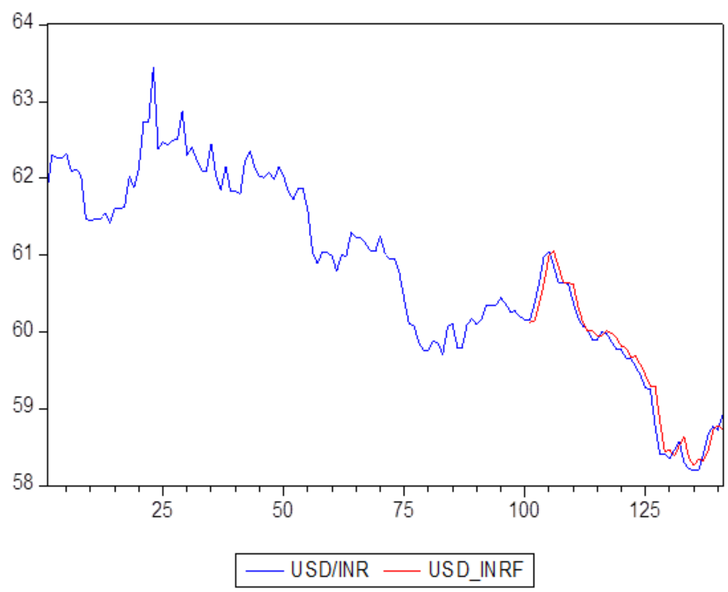


Figure 3- Static Forecasting- Actual Vs Fitted

Table VI

Statistical Performance of ARMA Models- Out- of - Sample Data

Particulars	ARMA (1,0)	ARMA (1,1)	ARMA (1,9)
Men Absolute Error	0.140	0.151	0.134
Mean Absolute percentage Error	0.236	0.254	0.22
Root Mean Squared Error	0.179	0.190	0.176
Theil-U	0.0015	0.0016	0.001

Table VI shows the statistical performance of all the ARMA models developed for the study and more so for the Out of sample data. The out of sample data is for 41 days. The errors are related to forecasting the exchange rate for the in sample data, which otherwise is called as static forecasting. Among the errors, root mean squared error is considered the most appropriate tool to evaluate the best model. The lower the root mean squared error, the better the model is in predicting the exchange rate. Among the three models developed, ARMA (1, 9) has the least root mean squared error of 0.176 when compared to ARMA (1,0) with 0.179 and ARMA (1,1) with 0.190 respectively. Therefore, ARMA (1,9) is considered the best model for forecasting the exchange rate of USD/INR. Figure 3 shows the actual exchange rates and the forecasted exchange rates for ARMA (1,9). The actual rates are USD_INR and the forecasted values are USD_INRF. It can be seen from the figure that the actual values of the dollar for 41 days moves closely with the forecasted value and hence the inference is that the model developed has the forecasting ability to predict the exchange rate.

Conclusion and Directions for Further Research

The study finds that exchange rate of USD/INR can be determined using auto regressive approach for short term period. The study also concludes that ARMA (1,9) is the best fit model to predict the exchange rate of USD/INR when compared to ARMA (1,0) and ARMA (1,1) respectively. Using the developed autoregressive model, forecasting was carried out. The results have shown that the forecasting values were very close to the actual values thereby minimising the forecast errors. Therefore, the autoregressive model identified was a better model in predicting the movement in the exchange rate. The paper concludes that the exchange rate of USD/INR depends upon the previous day's rate and the error term of ninth day preceding the current date. The argument of Chu (1978) that ARMA models are good for short term forecasting is similar to the findings of the present study. Using ARMA models for long term forecasting has certain limitations such as presence of serial correlation among the residuals, residuals not normally distributed etc. These issues were present in the study of Md. Zahangir Alam (2012), in which the author found ARMA (1, 1) and AR (1) models to forecast BDT/USD exchange rate for a longer duration.

Future research can take longer data period to forecast the exchange rate. Issues such as randomness, volatility and structural breaks in the data will crop up when long duration data are handled. The researchers can explore developing appropriate models addressing all the above issues.

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Annexure

Table Showing the Actual and Fitted Values of Static Forecasting

Date	Actual	Fitted
21/4/14	60.154	60.127
22/4/14	60.373	60.1434
23/4/14	60.653	60.374
24/4/14	60.988	60.642
25/4/14	61.056	60.995
26/4/14	60.853	61.053
27/4/14	60.636	60.84
28/4/14	60.636	60.647
29/4/14	60.631	60.639
30/4/14	60.389	60.620
01/5/14	60.185	60.341
02/5/14	60.080	60.130
03/5/14	60.029	60.013
04/5/14	59.904	60.022
05/5/14	59.904	59.951
06/5/14	60.004	59.952
07/5/14	59.976	60.011
08/5/14	59.874	59.983
09/5/14	59.778	59.925
10/5/14	59.773	59.818
11/5/14	59.656	59.790

12/5/14	59.656	59.663
13/5/14	59.546	59.690
14/5/14	59.439	59.568
15/5/14	59.276	59.442
16/5/14	59.255	59.297
17/5/14	58.785	59.292
18/5/14	58.408	58.838
19/5/14	58.408	58.448
20/5/14	58.354	58.466
21/5/14	58.466	58.387
22/5/14	58.578	58.526
23/5/14	58.292	58.633
24/5/14	58.228	58.365
25/5/14	58.203	58.264
26/5/14	58.203	58.340
27/5/14	58.414	58.324