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Application of ARIMA Model in Forecasting Exchange Rate: Evidence from Bangladesh

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Abstract - **This paper attempts to apply the ARIMA time series model to forecast the exchange rate of seven currencies (United States Dollar, Euro, Pound sterling, Australian Dollar, Japanese Yen, Canadian Dollar and Swedish Krona) in terms of Bangladeshi Taka (BDT) and to investigate the accuracy of the model by comparing the forecasted rates with the actual exchange rates. It considered daily currency exchange rates (244 selling price) of seven currencies for twelve months from January 2018 to December 2018 to forecast the subsequent one month (25 selling rate) in January 2019 rate. The Durbin-Watson test result shows an autocorrelation in the daily foreign currency exchange rate with the previous rate. The Augmented Dickey-Fuller test result shows data have unit roots and non-stationary. But the 1st differencing becomes data stationary to apply d equal to 1 in ARIMA model. Also, autocorrelation function considers MA(0) and partial autocorrelation function considers AR(1) for the ARIMA model. So, ARIMA (1,1,0) models are selected based on Ljung-Box test, root mean square error, mean absolute percent error, mean absolute error and R-square values. By using the above ARIMA models, forecasted foreign currency exchange rates next one month calculated and compared with the respective actual rates, which validate with Chi-Square test, mean absolute percent error, mean square error, root mean square error values of Goodness fit test. The result shows that predicted foreign currency exchange rates follow ARIMA (1,1,0) model, which may be applied to forecast the foreign currency exchange rates in Bangladesh.**
Keywords: **ARIMA, Exchange Rate, Exchange Rate Forecasting, Time Series Model**

I. INTRODUCTION

Being one of the vital economic variables, exchange rate influences the financial decision taken by any economic entity whether public or private, financial or nonfinancial, manufacturing or service oriented and even by an individual. The government has to plan for its efficient economic performance which is influenced by its balance of payment. And it is the exchange rate that affects the balance of payment of a country. A private institution involved in international trade has to deal with different foreign currencies.

It has to understand the exchange rate even if it is not involved in international business, because it has to know how the financial performance of its competitors that deal with foreign currency would be affected by the change in exchange rate. A financial institution like a bank that buys and sells different foreign currencies regularly, is directly affected with the unfavorable movement of exchange rates. An individual, as a tourist or as a student going outside the country for study or as a patient moving overseas for taking medical treatment or as a receiver of remittance, is also affected by changes in exchange rate. As such, an attempt for accurate forecast of future exchange rate is of great importance for all.

Forecasting exchange rate is one of the leading issues for the academicians, practitioners and researchers in the area of economics and finance. An accurate and reliable forecast of exchange rate can provide valuable information to the economic agents for efficient allocation of resources, for hedging the price risk and for effective policy making. This is why researchers from different countries are still attempting to identify the appropriate model for forecasting the exchange rate over the last several decades.

Different time series models like ANN (Artificial Neural Network), ARIMA (Auto Regressive Integrative Moving Average), Exponential Smoothing, Fuzzy Neuron, LSS (Least Square Support) Vector etc. can be applied to forecast the exchange rate. Among all these stated techniques not each and every model is easily applicable for all. It requires having proper understanding on the models and very good skill on their application and interpretation of results found. Compared to the other forecasting techniques, application of ARIMA is easy and well understood. That's why this paper attempts to apply the ARIMA time series model to forecast the exchange rate of seven currencies in terms of Bangladeshi Taka (BDT) and investigate the accuracy of the model by comparing the forecasted rates to the actual exchange rates.

II. LITERATURE REVIEW

A good number of studies have been done by several researchers, in the context of different countries, to extend the work on application of different forecasting models (both parametric and non-parametric) in predicting the exchange rate of currencies.

Study by Meese and Rogof (1983) have found the models that works on the basis of random walk hypothesis as more efficient in forecasting exchange rates compared to those models that works based on macroeconomic indicators. On the contrary, Mark (1995) gets an opposite result by analyzing the movement of US Dollar (USD) against four major currencies for 18 years.

By combining different time series forecast models MacDonald and Marsh (1994) tried to analyze the exchange rate of USD/British Pound Sterling, and USD/Japanese Yen and Deutschemark/USD. They found that combined impact of the models results in more accurate forecast of exchange rates.

By applying both parametric and non-parametric models, Chinn and Meese (1995) examine the accuracy of forecasting exchange rate of U.S. Dollar against four currencies. In their study they used data for more than 17 years and reached to the conclusion that, in the short run, random walk models could better forecast the rates compared to the models based on fundamentals. But this superiority is lost when a larger periods of time i.e., more than 36 months is considered.

Marsh and Power (1996) used 22 forecasters for predicting the movements of three major currencies against the USD, including the random walk estimators. Goldberg and Frydman (1996) proved random walk models to be more efficient for application of all the structural exchange rate models. In their study they considered exchange rate of USD against the currency of Germany (German Mark).

However, in some of the analyzed series, Hwang (2001) found a long-term relationship between the exchange rate and the macroeconomic factors. In his study he found that two random walk models are more efficient in the short-run compared to other traditional models. Kilian and Taylor (2001) tried to get a combined effect of employing two models together, random walk models and the models that work based on macroeconomic indicators. Considering both types of models to be optimal in the long-run they find higher predictability of employing random walk models in the short-run. By applying neural networks Andreou *et al.,* (2002) attempts to predict the movement of four currencies against the Greek Drachma and come to the conclusion that information related to the time series data is more efficient compared to the information related to the macroeconomic factors in predicting the exchange rate.

Examining the forecasting efficiency of sixteen different models, Dunis *et al.,* (2006) found no single model that could forecast the exchange rate optimally. However, they revealed that "mixed model" outperformed all other individual models. Working on ARIMA-ANN and ARIMAMLP models, Matroushi (2011) recommended the latter one as the better model to be applied for forecasting the exchange rate compared to the other individual or combined models.

Wang *et al.,* (2016) combines ARIMA model to a three-layer ANN Model to predict the exchange rate and found that the combined models work better than the individual forecasting techniques. On the contrary, study conducted by Mucaj *et al.,* (2017) revealed combined hybrid model of ARIMA-ANN as the better forecaster than ARIMA and ANN models. By combining the typical exchange rate models along with the machine learning and Taylor Rule models Amat *et al.,* (2018) could estimate the exchange rate more accurately compared to the other individual models. Khashei *et al.,* (2020) combined the ARIMA and ANN models to forecast the exchange rate and concluded that the forecast ability of combined models is better than the other individual models.

Beside the aforementioned studies, a good number of studies have also been done to develop an appropriate model for forecasting the exchange rate most of which are out of the context of Bangladesh. A very few number of studies has been done to find out an appropriate model for forecasting the exchange rate in the context of Bangladesh. Alam (2012) applied autoregressive model to forecast the exchange rate of USD in terms of BDT for the period of July 03, 2006, to April 30, 2010, as in-sample and May 01, 2010, to July 04, 2011, as out of sample data set. The major finding of their study was that the ARMA model, in case of in-sample data set, and both the ARMA and AR models combinedly, in case of out-of-sample data set, outperform all other models.

On the contrary, Ahmed and Keya (2019) attempted to study the trend of exchange rate of USD in term of BDT by using time series data from the year 1971-72 to 2014-15. Through the application of all the possible ARIMA models and Box-Jenkins methodology they obtained ARIMA (2, 1, 1) as the best fitted model among all. Working on prices of 60 selected companies Chowdhury and Islam (2021) investigated that 83.33% of the sample companies follow ARIMA (1,1,0) model, 6.67% of them follows ARIMA (2,1,0) model and rest of the other companies follow ARIMA (3,1,0) model, ARIMA (4,1,0) model, ARIMA (1,0,0) model and ARIMA (2,0,0) model respectively. Finally, they concluded that ARIMA model is applicable to forecast the daily share prices of Chittagong Stock Exchange (CSE). No earlier studies, in the context of Bangladesh, focused beyond the exchange rate of USD in terms of BDT. As such, this study attempts to work on the exchange rate of seven currencies in terms of BDT and tries to find out a suitable ARIMA model for forecasting their exchange rates.

III. METHODOLOGY

To examine the applicability of time series method in forecasting foreign currency exchange rate to Taka a random sampling method has been used to collect the exchange rate (244 selling price) of seven randomly selected currency (United States Dollar, Euro, Pound sterling, Australian Dollar, Japanese Yen, Canadian Dollar and Swedish Krona) from the website of Bangladesh Bank (the central bank of Bangladesh) for the period January 2018 to December 2018. Then Durbin Watson test has been conducted for each foreign currency exchange rate data to observe the autocorrelation in each data set. The Augmented Dickey Fuller Test has been conducted to test the unit root for each company data.

Then the 1st difference has been calculated from the previous data values to make the data stationary for the ARIMA model of foreign currency exchange rate. After that, Auto Regressive Integrated Moving Average (ARIMA) has been developed based on the autocorrelation function (ACF) and partial autocorrelation function (PACF) with lag 16 from the collected data.

Here the Auto regression with p lag AR(p) may be defied as follows.

$$y_t = \mu + \sum_{i=1}^{p} \gamma_i y_{t-i} + \epsilon_t$$

Where, y_t is the foreign currency exchange rate at time t, μ is constant, γ_i is the coefficient of lag variable, y_{t-i} is the share price at time (t – i) and ϵ_t is the error term.

The Moving average with q lag MA(q) may be defined as follows.

$$y_t = \mu + \sum_{i=1}^{q} \theta_i y_{t-i} + \epsilon_t$$

Where, y_t is the share price at time t, μ is constant, θ_i is the coefficient of lag variable, y_{t-i} is the share price at time (t – i) and ϵ_t is the error term. Now autoregressive moving average ARMA (p,q) model combines both p autoregressive terms with q moving average terms as follows.

$$y_t = \mu + \sum_{i=1}^{p} \gamma_i y_{t-i} + \sum_{i=1}^{q} \theta_i y_{t-i} + \epsilon_t$$

Then, to make the ARMA (p,q) model, it is required make the data is stationary. To convert the data into stationary differencing I(d) is made. Where, d is the differencing made to make the data stationary. Now the model is ARIMA (p,d,q) with autoregressive p lag, differencing d to make stationary and moving average q lag. Then the selection of ARIMA (p,d,q) is done from 244 foreign currency exchange rate (January 2018 to December 2018) data to forecast each foreign currency exchange rate values.

The selected model is tested with Ljung-Box test, root mean square error (RMSE), mean absolute percent error (MAPE), mean absolute error (MAE) and R-square values. After that with the help of selected ARIMA model, next 25 trading days in the month of January 2019 forecast values are calculated. Then these calculated forecasted foreign currency exchange rate using ARIMA model are compared with the actual foreign currency exchange rate by goodness-of-fit test, root mean square error (RMSE), mean absolute percent error (MAPE), mean square error (MSE) in IBM SPSS Statistics 26 and STATA 15 statistical packages.

A. Objective of the Study

The major objective of the study is to investigate the nature of daily exchange rate of seven currencies (United States Dollar, Euro, Pound Sterling, Australian Dollar, Japanese Yen, Canadian Dollar and Swedish Krona) in terms of BDT and select a suitable ARIMA model to forecast their daily exchange rates.

B. Hypothesis

The study tests the following three hypotheses.

1. Hypothesis 1

Null Hypothesis (H_0): There are no autocorrelation in the daily foreign currency exchange rate.

Alternative Hypothesis (H_1): There are autocorrelation in the daily foreign currency exchange rate.

2. Hypothesis 2

Null Hypothesis (H_0): There is no unit root in the daily foreign currency exchange rate.

Alternative Hypothesis (H_1): There is a unit root in the daily foreign currency exchange rate.

3. Hypothesis 3

Null Hypothesis (H0): There is no significant difference between the actual daily foreign currency exchange rate and the model forecasted daily foreign currency exchange rate.

Alternative Hypothesis (H1): There is a significant difference between the actual daily foreign currency exchange rate and the model forecasted daily foreign currency exchange rate.

IV. RESULTS AND DISCUSSION

The daily foreign currency exchange rate is shown with line diagram in Fig. 1.

It is observed from the above figure that the daily foreign currency exchange rate has a trend value with constant intercept in y-axis. Now to test the autocorrelation, the Durbin-Watson test result of daily foreign currency exchange rate is shown in Table I.

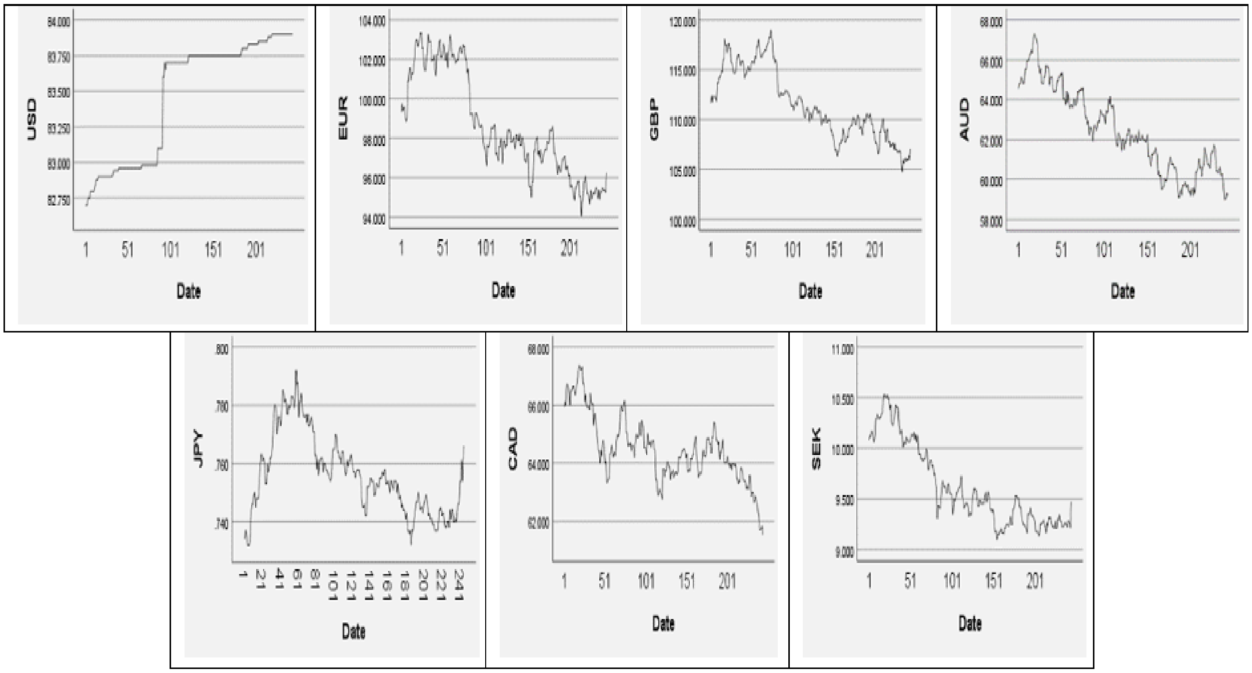

Fig. 1 Line diagram of daily foreign currency exchange data

TABLE I DURBIN WATSON TEST, AUGMENTED DICKEY-FULLER TEST RESULT

Name of the Currency	Variable Name	Durbin Watson test Statistic	Daily Exchange Rate Dickey-Fuller Z(t) Statistic (p-value)	1st Difference Daily Exchange Rate Z(t) Statistic (p-value)
United States Dollar	USD	0.040	1.530 (0.5187)	16.107 (0.0000)
Euro	EUR	0.144	1.232 (0.6596)	16.508 (0.0000)
Pound sterling	GBP	0.100	0.906 (0.7858)	15.506 (0.0000)
Australian Dollar	AUD	0.189	1.027 (0.7433)	16.825 (0.0000)
Japanese Yen	JPY	0.083	2.128 (0.2334)	16.697 (0.0000)
Canadian Dollar	CAD	0.140	1.299 (0.6297)	16.560 (0.0000)
Swedish Krona	SEK	0.122	1.463 (0.5519)	14.889 (0.0000)

The Durbin-Watson test statistics of daily foreign currency exchange rate varies from 0.040 to 0.189 (Table I). It is observed that all the test statistics values of Durbin-Watson test are nearly zero, which rejects the null hypothesis 1 and provides an evidence of having autocorrelation in the daily foreign currency exchange rate. The Augmented Dickey Fuller Test result of daily foreign currency exchange rate of each currency values are tested for unit root, which is shown in Table I.

The test statistics Z(t) for Augmented Dickey-Fuller Test varies from 0.906 to 2.128 (with p-value 0.2334 to 0.7858). The p-values of Augmented Dickey-Fuller Test of daily foreign currency exchange rate are greater than 0.05, which implies that there is not enough evidence to reject the null hypothesis 2. So, the daily foreign currency exchange rate of the selected currency data is non-stationary.

Now, the non-stationary daily foreign currency exchange rate are deducted from the previous values (1st differencing) of daily foreign currency exchange rate to make them stationary for applying the ARIMA model. The 1st difference daily foreign currency exchange rate is shown with line diagram in Fig 2.

Then the Augmented Dickey-Fuller Test has been conducted again for each daily foreign currency exchange rate to test the stationary of the data value and the result is shown in Table I. The test statistics for Augmented Dickey-Fuller Test for 1st difference varies from 14.889 to 16.560 (with each p-value 0.0000).

In these cases, the null hypothesis 2 is rejected (as the p-values are less than 0.05) and the daily foreign currency exchange rate (with 1st differencing) of the selected currency data is stationary to apply ARIMA model. Now all the 1st difference values are stationary and considered d equal to 1 for the daily foreign currency exchange rate in ARIMA(p,d,q) model.

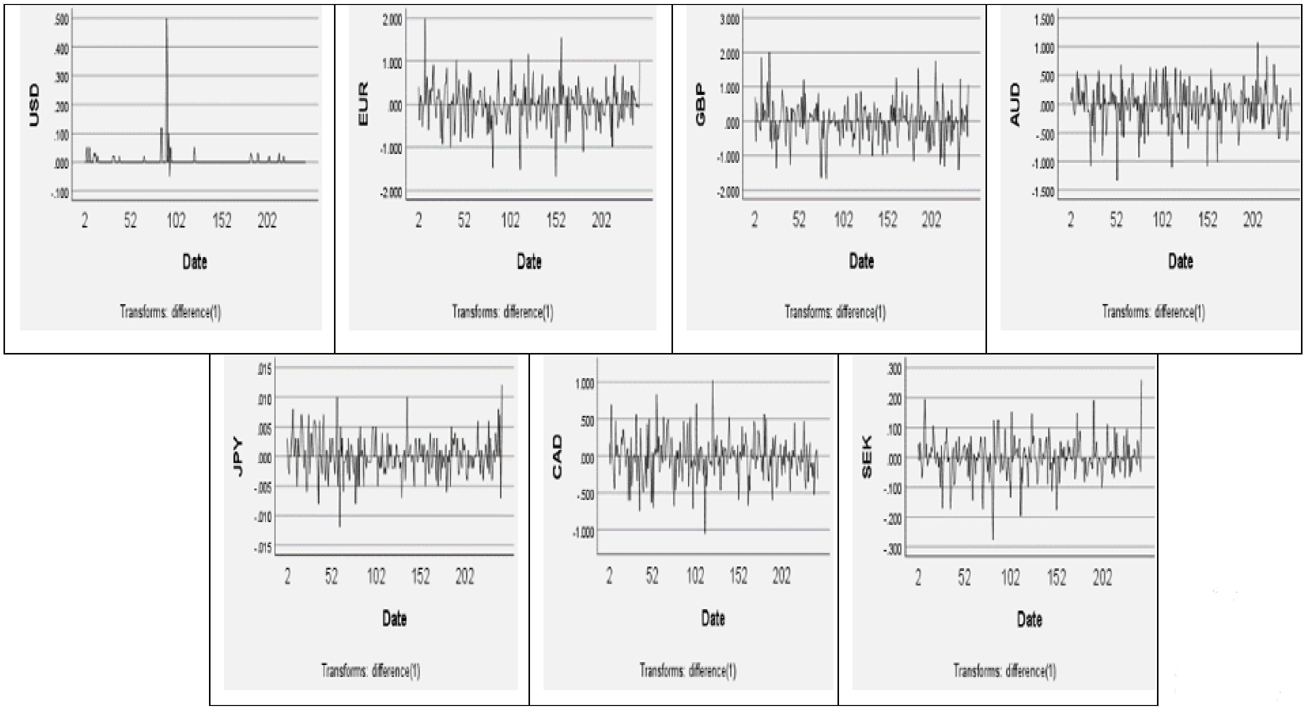

Fig. 2 Line diagram of daily foreign currency exchange (1st difference) data

To select MA lag value in ARIMA model the autocorrelation function (ACF) (with lag 16) diagram for each daily foreign currency exchange rate is created and result is shown in Fig. 3.

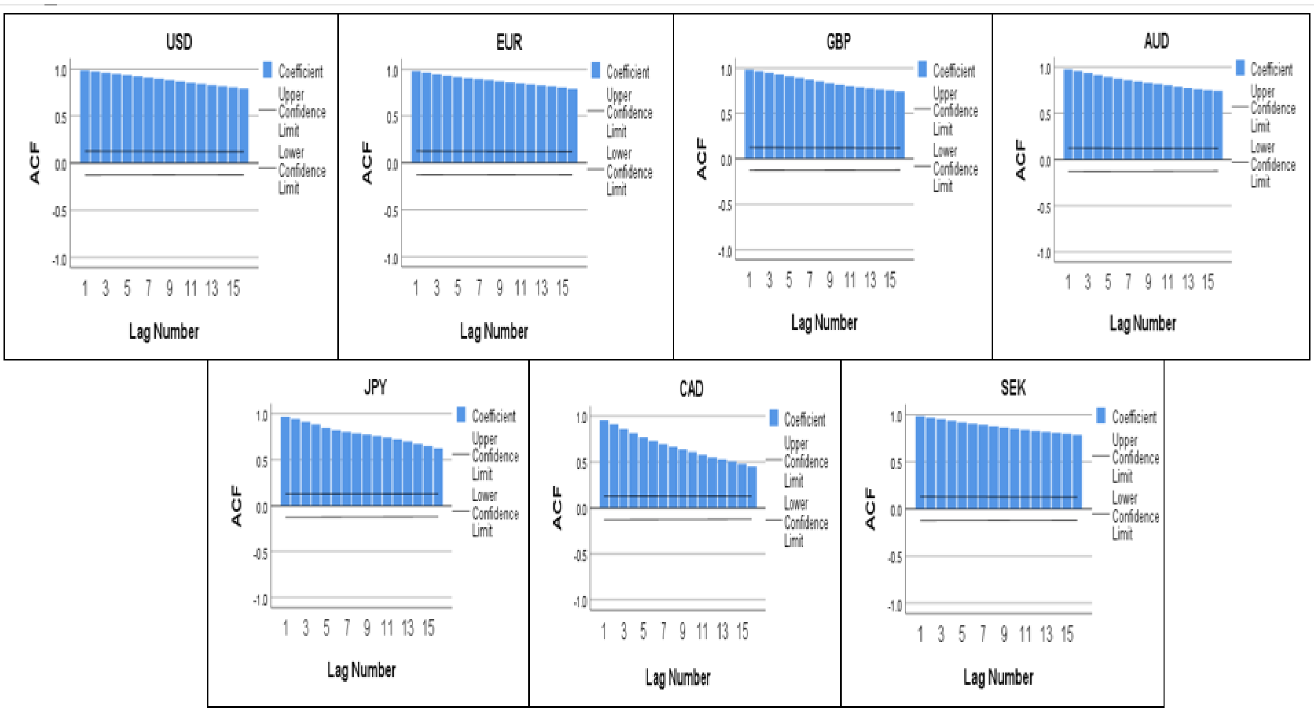

Fig. 3 ACF diagram of daily foreign currency exchange rate

The above fig. 3 shows that the autocorrelation factors decrease gradually, and all the values are higher than the confidence interval for all cases. So, no moving average slag value is convenient for the ARIMA model development. It is convenient to consider MA(0) for the ARIMA model of each foreign currency exchange rate. Now to select AR lag value in ARIMA model, the partial autocorrelation function (PACF) diagram (with lag 16) for each foreign currency exchange rate is created and result is shown in Fig. 4.

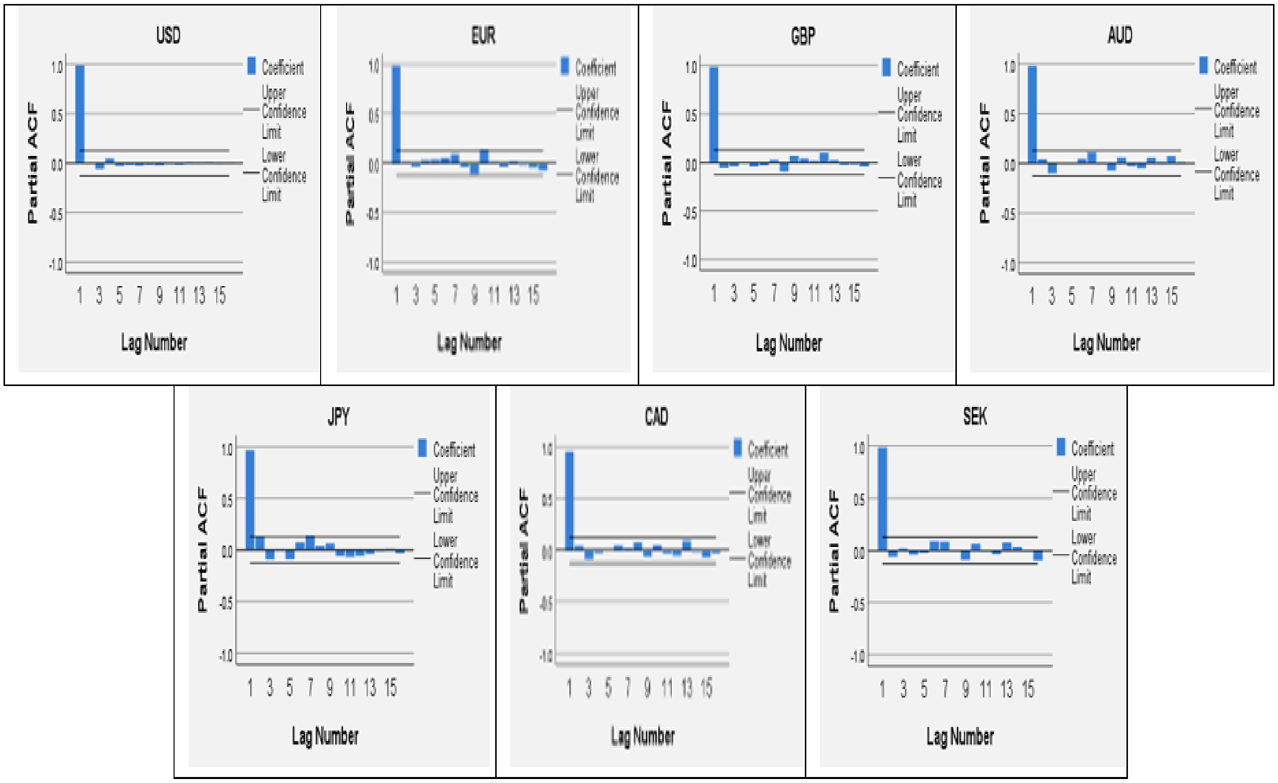

Fig. 4 PACF diagram of daily foreign currency exchange rate

From the Fig. 4, one partial autocorrelation values are higher than the confidence interval in each cases that can be selected for AR(p) model. So, it is convenient to consider AR(1) for the ARIMA model of each foreign currency exchange rate. Now, the coefficient of each selected ARIMA model is calculated and shown in Table II.

TABLE II ARIMA MODEL WITH MODEL FIT VALUES RESULT

Variable Name	Model Selection	ARIMA Model	Ljung-Box Test Q (p-value)	RMSE	MAPE	MAE	R-Square value
USD	ARIMA (1,1,0)	$Y_t = 0.005 + 0.029\ Y_{(t-1)}$ Difference 1	20.936 (0.229)	0.035	0.011	0.010	0.993
EUR	ARIMA (1,1,0)	$Y_t = -0.013 + 0.067\ Y_{(t-1)}$ Difference 1	19.057 (0.325)	0.462	0.321	0.317	0.969
GBP	ARIMA (1,1,0)	$Y_t = -0.019 + 0.005\ Y_{(t-1)}$ Difference 1	22.650 (0.161)	0.559	0.350	0.390	0.975
AUD	ARIMA (1,1,0)	$Y_t = -0.022 + 0.069\ Y_{(t-1)}$ Difference 1	12.521 (0.768)	0.352	0.399	0.249	0.972
JPY	ARIMA (1,1,0)	$Y_t = 0.000 - 0.094\ Y_{(t-1)}$ Difference 1	17.295 (0.437)	0.003	0.304	0.002	0.944
CAD	ARIMA (1,1,0)	$Y_t = -0.018 + 0.057\ Y_{(t-1)}$ Difference 1	14.815 (0.609)	0.286	0.311	0.201	0.938
SEK	ARIMA (1,1,0)	$Y_t = -0.002 - 0.003\ Y_{(t-1)}$ Difference 1	17.902 (0.395)	0.063	0.432	0.042	0.975

The Ljung-Box Test Q-statistics value varies from 12.521 to 22.650 (p-value 0.161 to 0.768). For every ARIMA model Ljung-Box Test p-values are greater than 0.05. The root mean square error (RMSE) values of the ARIMA model varies from 0.003 to 0.559 (all of which are near to zero). Moreover, the mean absolute percentage error (MAPE) of each model varies from 0.011 to 0.432 (all of which are less than 5%). The mean absolute error (MAE) values of the model also varies from 0.002 to 0.390 (all of which are near to zero). So, the ARIMA (1,1,0) model is an excellent fit model for the foreign currency exchange rate. The R-Square value values vary from 0.938 to 0.993. So, 93.8% to 99.3% of the foreign currency exchange rate data are represented by the selected ARIMA (1,1,0) model. By using the above respected ARIMA (1,1,0) models, the respected forecasted foreign currency exchange rate values with 95% confidence interval for January 2019 (25 trading days) are calculated and result is shown in the following Fig. 5.

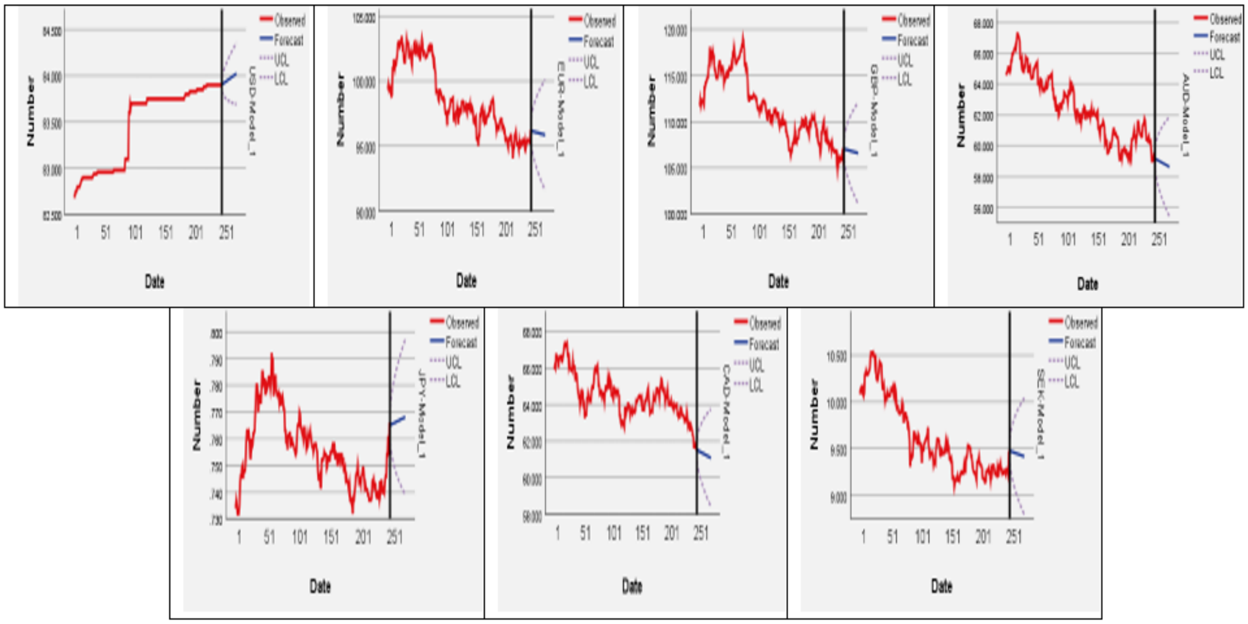

Fig. 5 Forecasted value of ARIMA (1,1,0) model

After calculating the predicted foreign currency exchange rate values for January 2019 (25 trading days), the actual foreign currency exchange rate values of January 2020 (22 trading days) are compared with goodness fit test and result is shown in Table III.

TABLE III ARIMA MODEL VALIDATE OF FOREIGN CURRENCY EXCHANGE RATE

Variable Name	Goodness of fit test statistic Chi-Square value (p-value)	MAPE	MSE	RMSE
USD	0.021 (1.000)	0.123	0.072	0.269
EUR	0.106 (1.000)	0.483	0.408	0.639
GBP	1.309 (1.000)	1.718	5.588	2.364
AUD	0.721 (1.000)	1.978	1.697	1.303
JPY	0.001 (1.000)	0.548	0.000	0.005
CAD	1.886 (1.000)	3.140	4.622	2.150
SEK	0.090 (1.000)	1.500	0.034	0.184

The Chi-Square values of goodness of fit test varies from 0.001 (p value is 1.000) to 1.886 (p value is 1.000) (all of which are greater than 0.05). The mean absolute percentage error (MAPE) of the goodness of fit test varies from 0.123 to 3.140 (all of which are less than 5%). The mean square error (MSE) values of the goodness of fit test also vary from 0.000 to 5.588 (all of which are very low).

The root mean square error (RMSE) values of the goodness of fit test vary from 0.005 to 2.364 (all of which are very low). As a result, there is not enough evidence to reject the null hypothesis 3. This implies that, there is no significant difference between the actual foreign currency exchange rate and forecasted foreign currency exchange rate. Therefore, it may be concluded that ARIMA (1,1,0) model is the most suitable model that can be applied to predict the forecast of foreign currency exchange rate.

V. CONCLUSION

It is observed from the Durbin-Watson test result that there is autocorrelation in the daily foreign currency exchange rate with their previous foreign currency exchange rate. The Augmented Dickey-Fuller Test result shows, the daily foreign currency exchange rate data have unit roots and non-stationary. But the 1st differencing of the foreign currency exchange rate data is stationary to apply d equal to 1 in ARIMA model. The autocorrelation function (ACF) of each foreign currency exchange rate data shows that it is convenient to consider MA(0) for the respective ARIMA model. The partial autocorrelation function (PACF) of each foreign currency exchange rate shows that autocorrelation AR(1) has been considered for the ARIMA model of foreign currency exchange rate. Now, from the January 2018 to December 2018 foreign currency exchange rate data (244 selling price) ARIMA (1,1,0) model are selected based on Ljung-Box Test Q, root mean square error (RMSE), mean absolute percent error (MAPE), mean absolute error (MAE) and R-square values. By using the above ARIMA models January 2019 (25 selling rate) forecasted share values with confidence interval are calculated. These predicted foreign currency exchange rate are compared with the actual foreign currency exchange rate of January 2019 (25foreign currency selling rate) of the respective foreign currency and validate with Chi-Square test, mean absolute percent error (MAPE), mean square error (MSE), root mean square error (RMSE) values of Goodness of fit test. The result shows that predicted foreign currency exchange rate follow ARIMA(1,1,0) model. Finally, it may be concluded that the above ARIMA model may be applied to forecast the foreign currency exchange rate in Bangladesh.

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