Forecasting the Daily Exchange Rate of Rupee against Major Currencies

Author:

Arushi Gupta

Officer Trainee, Indian Economic Service (2021)

arushigupta1795@gmail.com

Supervisor:

Dr. Vikram Dayal

Professor, Institute of Economic Growth (Delhi)

Abstract

This paper attempts to forecast the 10-day ahead daily nominal exchange rate of Indian Rupee against four major currencies, namely, the US Dollar, Euro, British Pound, and Japanese Yen. Literature points to a continuous debate on whether exchange rates follow a random walk or can be modelled; there is also a debate on whether one should use structural models or time series models to forecast exchange rates. This paper uses two core time series models, ARIMA and naïve, to forecast exchange rates. The Hyndman Khandakar Algorithm has been applied to build the ARIMA model. The results show that the ARIMA model provides a better forecast than the naïve model for the Dollar-Rupee exchange rate, while the naive model outperforms the ARIMA model for Euro, Pound and Yen.

Keywords: ARIMA, Forecasting, Hyndman Khandakar Algorithm, Naïve, Nominal Exchange Rate.

Acknowledgement

This paper, and the research behind it, would not have been possible without the exceptional support of my supervisor, Dr. Vikram Dayal. His knowledge, exacting attention to detail, and useful critiques of this research work have been an inspiration, and have kept my work on track.

I would also like to express gratitude for the constant guidance I have received from the faculty at the Institute of Economic Growth (IEG), Delhi. I am grateful to Mr. P.K. Jain, Librarian, IEG for his help in retrieving academic resources used in this research.

I am also grateful for the insightful comments offered by fellow Officer Trainees of the Indian Economic Service (2021). The generosity and expertise of one and all have improved this study in innumerable ways, and saved me from many errors; those that inevitably remain are entirely my own responsibility.

I. Introduction

Forecasting is an integral part of the decision-making process of managements and governments (Diebold, 2006). Forecasts of foreign exchange rates are particularly useful for central banks, the custodian of foreign exchange reserves of a country, and whose mandate is to ensure orderly conditions in the foreign exchange market (Reserve Bank of India). A country's exchange rate is one of the most closely monitored indicators, as fluctuations in exchange rates can have far reaching economic consequences (Ribeiro, 2016). Foreign exchange markets account for a significant and sizeable segment of financial markets in the world, with continuous trading throughout the day around the globe, and daily transactions amounting to trillions of dollars of different currencies (Khashei & Bijari, 2011). Since most foreign exchange transactions are settled in the future, exchange rate forecasts become important to predict the future cash flows. (Alessandro Nicita, UNCTAD). Forecasting exchange rate is crucial as it has significant impact on key macroeconomic fundamentals, such as oil price, interest rate, wage, unemployment, and the level of economic growth (Ramzan et al, 2012).

Exchange rate is the rate at which two national currencies exchange for each other (Lipsey & Crystal, 1995). The foreign exchange rate is the price of foreign currency in terms of domestic currency (Samuelson & Nordhaus, 1998; Usman & Adejare, 2013). Nominal exchange rate is expressed as the units of domestic currency needed to buy one unit of foreign currency (Dornbusch et al, 2005). "Forecasting whether the exchange rate will rise or fall tomorrow is about as predictable as forecasting whether a tossed coin will come down as a head or a tail. In both situations, you will be correct about 50% of the time, whatever you forecast. In situations like this, forecasters need to be aware of their own limitations, and not claim more than is possible" (Hyndman and Athanasopoulos, 2021).

The literature on forecasting often focuses on getting the best forecast at a point in time for a particular variable or variables, sometimes with certain benchmark methods, but also often with more complex, specialized and less transparent methods. Increasingly real-time data are available. This makes it possible to track and forecast such variables in real time, with regular updates. This implies that we should view both tracking and forecasting as continuous and dynamic. Foreign exchange rate is one topic that is of interest to governments, central banks and international agencies. How to forecast foreign exchange rate is one subject that all stake-holders face when making plans. The more accurate the forecast result is, the more effective the plan is. In this paper, by using ARIMA and naïve models, with daily nominal foreign exchange rate data from 2010 to 2022, we make the 10-day ahead forecast of the foreign exchange rate of the Indian Rupee against the US Dollar, Euro, British Pound and Japanese Yen. For continuous forecasting and updating, we use the Hyndman Khandakar algorithm-based ARIMA modelling, well suited to produce benchmark forecasts, and also facilitating real-time continuous forecasts. We seek to update our visualizations, note the divergence of forecasts with actual values, and produce new forecasts at regular intervals. Our exercise also helps us to explore the feasibility of such exercises being conducted in practical settings.

II. Literature Review

Time series forecasting models are based on analysis of historical data. They are based on the assumption that past data affects the forecasts of future data points. There are various models for forecasting exchange rates. A review of the literature on exchange rate forecasting suggests the use of naïve models, Neutral Networks (Verkooijen, 1996), ARIMA model (Tseng, 2001), (Znaczko, 2013), Least Squares model (Hongxing et al., 2007), Purchasing Power Parity model, and Balassa-Samuelson channel (David et al., 2010).

The efficient market hypothesis assumes that rational traders incorporate all available information relevant to the fundamental value of the exchange rate while valuating a currency. Given this, in the absence of any new and relevant information, exchange rates will reflect their fundamental values and there will be no opportunities for profitable trading (Nguyen, 2004). Economic and financial considerations suggest that exchange rates should be close to random walks, because if the change were predictable, one could make a lot of money with very little effort, and the very act of doing so would eliminate the opportunity (Diebold, 2006). Meese and Rogoff (1983) compared a number of time series and structural models on the basis of out of sample forecasting accuracy and found that in the short horizon (less than one year) random walk model outperforms a range of fundamentals-based models of exchange rate determination.

ARIMA models have been extensively used in time series forecasting of macro-financial indicators. Some applications from a survey of the literature include, inflation in Ireland (Meyler, 1998), stock prices (Mondal, 2014) , (Jarrett, 2011), and gold prices (Guha & Bandyopadhyay, 2016). With the forecast object as foreign exchange rate, ARIMA is also a good solution for prediction (Appiah & Adetunde, 2011), (Nwankwo, 2014), (Tlegenova, 2014). Nyoni (2018) has undertaken an extensive survey of empirical studies in Nigeria and other countries that use ARIMA-based time series approaches to forecast exchange rates. A majority of them find the simple ARIMA models to be an appropriate forecast methodology.

After examining the results of these studies above, we decide to use the ARIMA and Naïve models as the main methodology for forecasting the daily nominal exchange rate of the Indian Rupee against US Dollar, Euro, British Pound, and Japanese Yen.

III. Theories of Exchange Rate Determination

We discuss the five most popular theories of exchange rate determination, namely, the Purchasing Power Parity Hypothesis, Efficient Market Hypothesis, Balance of Payment Theory, Monetary Approach to Exchange Rate Determination, and Portfolio Balance Approach (Castillo, 2002).

1. *Purchasing Power Parity Theory:*

According to this theory, in the absence of transaction costs and trade barriers, the equilibrium exchange rate between the currencies of two countries should be equal (absolute version) or proportional (relative version) to the ratio of domestic to foreign price levels. Thus, a currency will lose value if there is inflation in the country as it erodes the purchasing power of the currency.

2. *Interest Rate Parity Hypothesis:*

Under the assumption of perfect capital mobility and perfect substitutability of assets, interest rate differentials between two countries should be unbiased predictors of changes in exchange rates.

3. *Balance of Payment Theory:*

According to this theory, equilibrium exchange rate is determined by the equilibrium in balance of payments, i.e. when there is neither a surplus nor a deficit in the current and capital accounts of the country.

4. *Monetary Approach to Exchange Rate Determination:*

According to this approach, exchange rate is determined by the equilibrium in the money markets of the two countries, i.e., balancing of the total demand and total supply of national currency in each country.

5. *Portfolio Balance Approach:*

The essence of this approach is that the exchange rate is determined in the process of equilibrating or balancing the demand for and supply of all financial assets (namely, nominal money, domestic and foreign bonds), of which money is only one form of asset. Thus, it extends the scope of the Monetary Approach and brings trade explicitly into the determination of exchange rates.

While these theories give us an idea about variables affecting exchange rates, since the adoption of floating exchange rate regimes in the 1970s and 1980s, observed deviations in short and medium-term exchange rates have been much too volatile to be explained by fundamentals-based exchange rate theory. This necessitates the need for empirical, time series models in forecasting exchange rates (Rauli Susmel, Bauer College of Business).

IV. Time Series Forecasting Models

This section explains the time series forecasting models used in this paper. Primary reference for this section is Diebold (2006).

1. Naïve models

Naïve models simply set the value of the forecast as the value of the last observation. Thus, the forecast plot resembles a straight horizontal line originating at the last observation. Given that ER_T is the nominal exchange rate at time 'T' (last observation of the dataset), the forecast of the exchange rate (ER) for all time periods 'T+h' (h >= 1) is given by:

$ER_{T+h|T} = ER_T$; for all h = 1, 2, 3, …

2. Autoregressive Process

These forecasts are based on a linear combination of past values of the variable to be forecasted. Given that ε_t is a purely random process with mean 0 and constant variance, and ER_t is the nominal exchange rate at time 't', the forecast of the exchange rate (ER), following an AR(p) process, at time 't+1' is given by:

$ER_t = c + \phi_1 ER_{t-1} + \phi_2 ER_{t-2} + \cdots + \phi_p ER_{t-p} + \varepsilon_t$, where ε_t is white noise.

3. Moving Average Process

These models are based on the idea that current and past shocks systematically feed into the current value of the time series. An MA model is a regression model with nothing but current and lagged disturbances on the right-hand side. Given that ε_t is a purely random process with mean 0 and a constant variance, and ER_t is the nominal exchange rate at time 't', the forecast of the exchange rate (ER), following an MA(q) process, at time 't+1' is given by:

$ER_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q}$

4. ARIMA Process

The ARIMA modelling approach proposed by Box & Jenkins (1976) is recognized as a benchmark technique in forecasting methods because of its structured modelling basis and acceptable forecasting performance (Goh & Teo, 2000). ARIMA models are a set of models that describe the process as a function of its own lags and white noise process (Box & Jenkins, 1974). A stochastic process (ER_t) is called an ARIMA (p, d, q) process if it is integrated of order ‘d’ and the d times differenced process (ER'_t) has an ARMA(p,q) representation, i.e.,

$ER'_t = c + \phi_1 ER'_{t-1} + \cdots + \phi_p ER'_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t$, where ER' is the d-times differenced time series.

V. Data Specification and Time Plots

The time series models in this paper use the following daily nominal exchange rates: Dollar-Rupee (USD/INR), Euro-Rupee (EUR/INR), Pound-Rupee (GP/INR), and Yen-Rupee (JPY/INR). Data for the paper spans the period from March 2010 to March 2022, out of which only recent data (post June 2021) has been used to fit the model. The data has been accessed from Bloomberg. The four countries chosen for the purpose of analysis in this paper are USA, Europe, UK, and Japan. This is because USA, Europe, UK and Japan are key trading partners of India. Further, Dollar, Euro, Pound and Yen are the most important floating currencies in the world, that is, currencies which move in response to the forces of demand and supply in the forex market, and are not actively managed by the respective central banks. The data used is available at daily frequency, with some missing observations. The missing observations correspond to weekends and public holidays. The time plots of USD/INR, Euro/INR, GBP/INR and JPY/INR shown below shed light on the evolving performance of these exchange rates.

1. Dollar-Rupee exchange rate

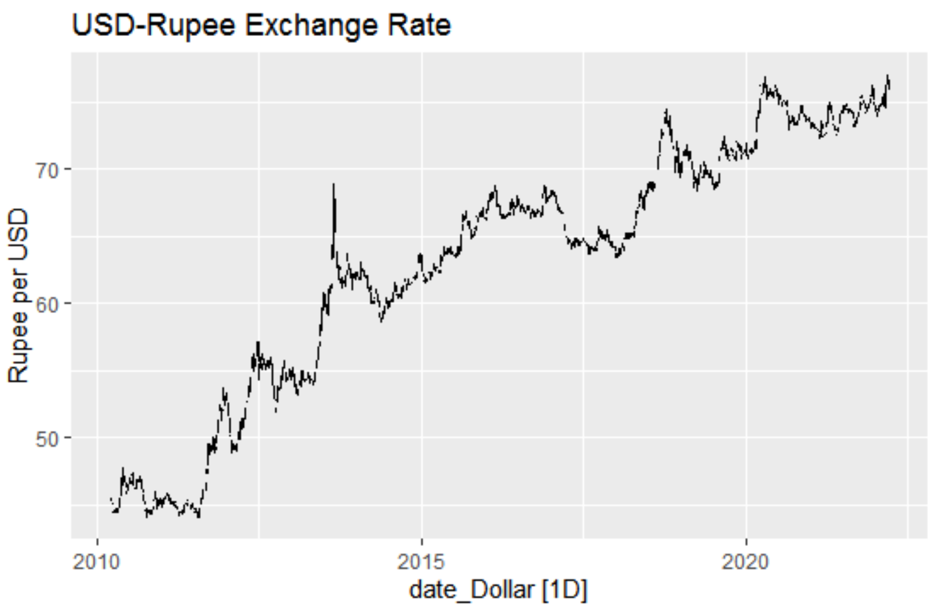


Figure 1: USD/INR exchange rate exhibits a long-run increasing trend, along with a cyclical (random) component.

The USD-Rupee exchange rate exhibits a long-run rise in the nominal exchange rate Rupee vis a vis Dollar. This observation is supported by the International Monetary Fund, which downgraded the 2026-27 projected estimate of India's nominal GDP (in dollar terms) from \$4.53 trillion (in the April 2021 World Economic Outlook report) to

$4.39 trillion in the (October 2021 World Economic Outlook report). A level shift and rapid depreciation is observed in the data after 2013, which coincides with the Fed's reversal of quantitative easing (taper tantrum). The fall in exchange rates (appreciation) during 2021 can be attributed to the high return on Indian equities and FPI inflows. Owing to the Russia-Ukraine crisis, escalated crude oil prices are expected to exert an upward pressure on the exchange rate.

2. *Euro-Rupee exchange rate*

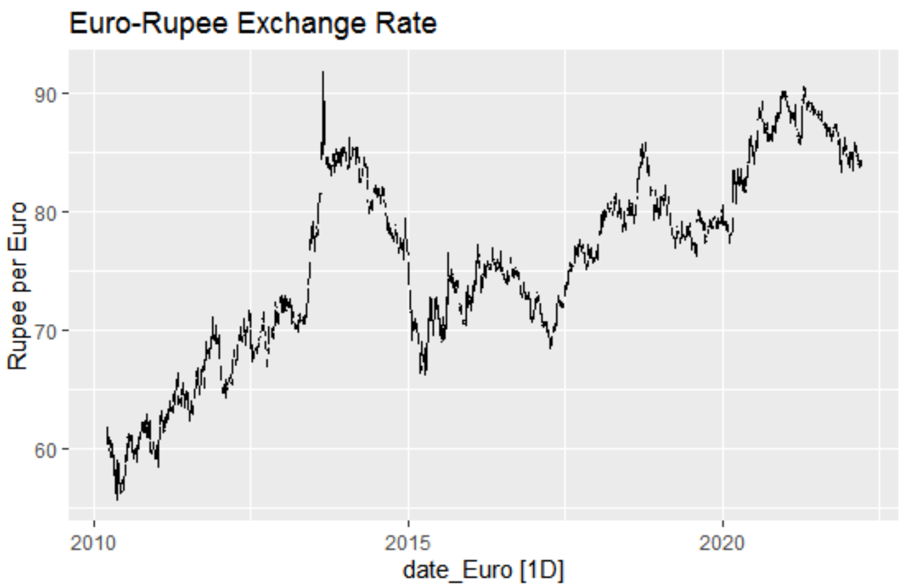


Figure 2: EUR/INR exchange rate exhibits an increasing trend, along with a cyclical (random) component.

There is a long run trend of increasing nominal exchange rates, with substantial cyclicity. Eurozone Debt Crisis contributed to the low value of Euro-Rupee exchange rate (weak Euro) from 2010 to 2012. However, Euro witnessed it sharpest rise during 2013, reaching a historical high in August. This was at the back of the post-crisis recovery programme undertaken by the European Union, including a Stability and Growth Pact and Outright Monetary Transactions. Euro witnessed its sharpest drop in 2015 due to the likelihood of an increase in US interest rates, the deepening crisis in Greece, and the effect of the ECB's quantitative easing programme. By end of 2021, the Euro endured a bruising year due to above target inflation and slow wage growth. This trend is expected to continue as the ECB has refused from increasing interest rates before the end of 2022. Further. The Russia-Ukraine crisis has significant economic repercussions on Europre, owing to its natural gas and commodity dependence on Russia and Ukraine.

3. *Pound-Rupee exchange rate*

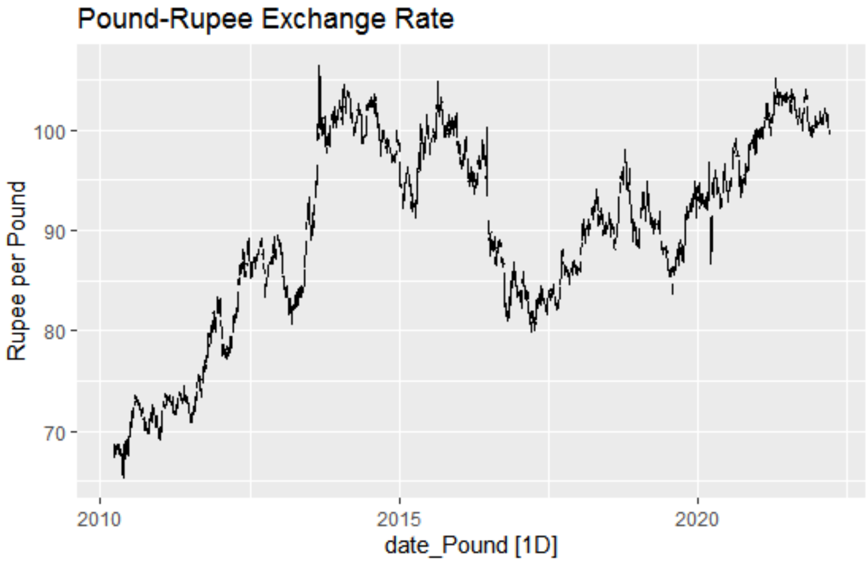


Figure 3: GBP/INR exchange rate exhibits a strong random/cyclical pattern, with a weakly (non-linear) increasing trend.

The Pound-Rupee exchange rate exhibits high cyclicity and a weakly increasing, non-linear trend. The drop post-2015 can be attributed to uncertainty in the Brexit trade negotiations, soaring cost of living, and a string of planned tax increases. The dramatic fall in 2016 can be attributed to speculations of a hard Brexit. The bounce in 2019 was because of a clear Conservative majority in the UK general elections, dispelling some Brexit-related uncertainty. The pound exhibited a mixed performance in 2021, rising and then falling: it was boosted by UK's swift vaccine roll-out programme, but then other countries caught up.

4. Yen-Rupee exchange rate

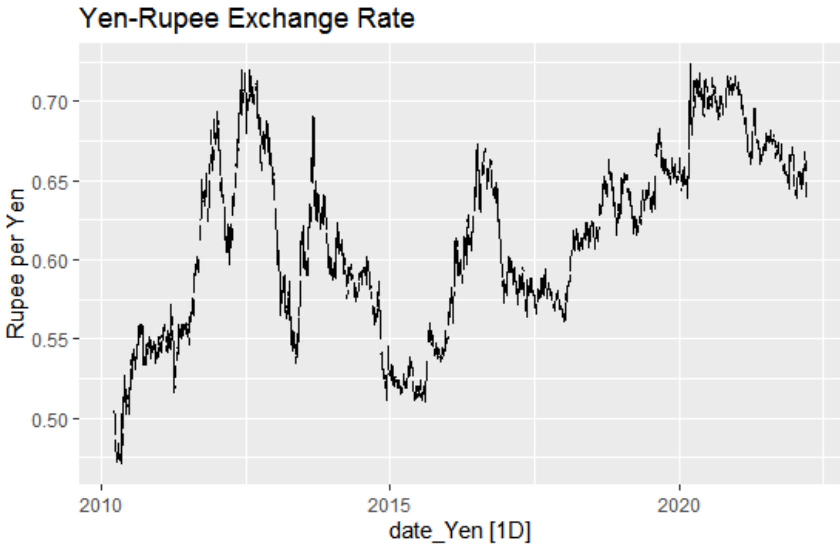


Figure 4: JPY/INR exchange rate exhibits a strong random/cyclic behaviour, with a weakly (non-linear) increasing long-run trend.

Movement of the Yen-Rupee exchange rate shows a highly volatile pattern. There was a steep fall in 2013 in the face of the aggressive monetary stimulus to revive Japan's falling economy. The unprecedented strengthening of Yen in 2016 can be attributed to aversion to global risks and increased capital inflows to Japanese safe-haven assets. Post-2020, Yen-Rupee exchange rate has been exhibiting a declining trend which is expected to continue. This is due to higher global interest rates, and a small (and declining) Japanese current account surplus.

VI. Methodology

Observing the time plots above, it appears that the Dollar-Rupee exchange rate exhibits a systematic upward trend, with a cyclical component. On the other hand, Euro-Rupee, Pound-Rupee and Yen-Rupee seem to follow a random walk, with long periods of apparent up and down trends, and sudden and unpredictable changes in direction (Diebold, 2006). The components of the workflow involved in estimating the models can be summarized by the following schematic:

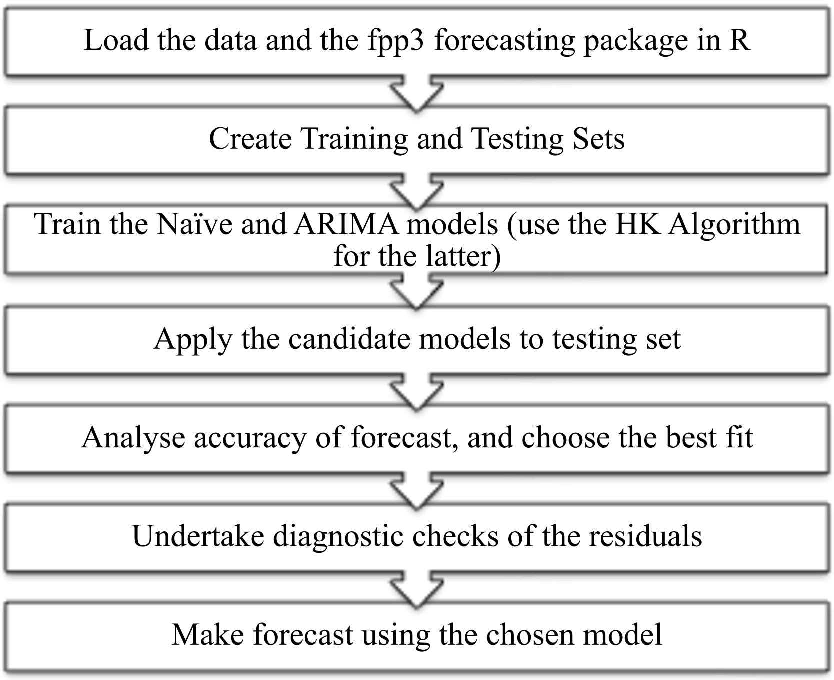


Figure 5: Components of the workflow (Schematic)

This paper follows the approach delineated in the book, Forecasting: Principles and Practices (3rd edition) by Rob J Hyndman and George Athanasopoulos. To implement the forecasts, fpp3 package in R has been used. To identify the appropriate ARIMA model, instead of a manual approach, we follow the Hyndman Khandakar Algorithm.

1. Training and testing sets

In order to judge the efficacy of forecasts, the model's performance needs to be assessed on new data which was not used to fit the model, but for which the actual observations are available. This new data forms the testing set, and the data that is used to fit the model forms the training set.

In this paper, training set spans the period from 1 June 2021 to 11 March 2022, while the testing set comprises of observations from 12 March 2022 to 21 March 2022. The forecasts are made for the period, 22 March 2022 to 31 March 2021. The significance of the testing set lies in the fact that a model that which fits the training data may not necessarily forecast well since a perfect fit can be artificially manufactured by over-fitting a model to training data with enough parameters. Including the entire history of observations from the beginning of the dataset (i.e. March 2010) is not advisable as it can deteriorate forecast accuracy because of the rapidly changing context and environment during the data period[1]. This is in accordance with the parsimony principle, "less is more", when it comes to time series forecasting.

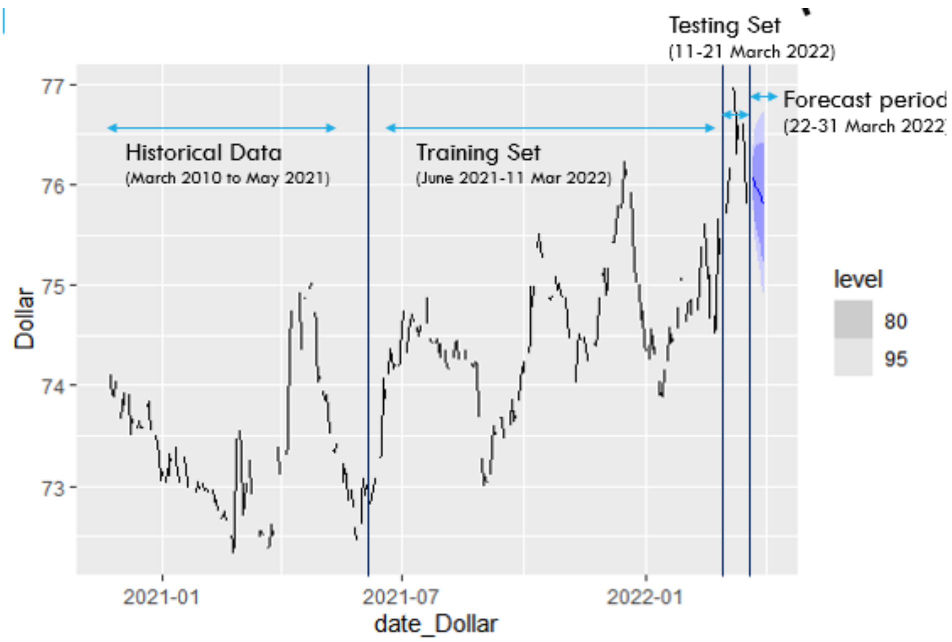


Figure 6: Subsetting of Data for Forecasting

2. *Hyndman Khandakar (HK) Algorithm*

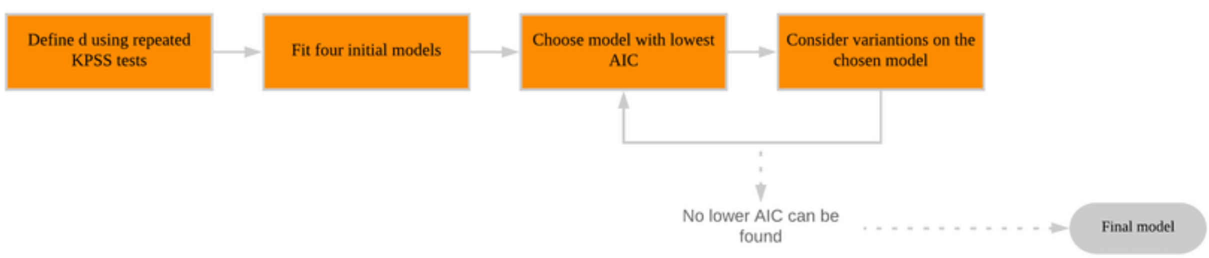


Figure 7: Hyndman Khandakar Algorithm (Schematic)

[1] When the entire data from March 2010 was used to train the model, the algorithm predicted an ARIMA(0,0,0) model, which is essentially white noise.

The HK algorithm combines the unit root test for stationarity, minimisation of the Akaike Information Criterion, and Maximum Likelihood Estimation to obtain the appropriate ARIMA model. The algorithm applies the KPSS (Kwiatkowski–Phillips–Schmidt–Shin) test to determine the order of integration, where the number of differences vary between 0 and 2 ($0 \leq d \leq 2$). The values of p and q are chosen by fitting four models in a stepwise manner (ARIMA(0,d,0), ARIMA(2,d,2), ARIMA(1,d,0), ARIMA(0,d,1): with constant if d = 0 or 1, and without constant if d = 2). The order magnitudes which give the lowest AIC value are chosen as the current model. Further variations of +/- 1 in p and/or q, and inclusion/exclusion of constant are considered. Finally, the model with the lowest AIC value is chosen as the final model.

3. *Choosing between the Naïve and ARIMA models*

Along with the ARIMA estimation, a naïve model is fitted on the training set. The accuracy results of the ARIMA and naïve model are compared in the testing set. Appropriate model with lower discrepancy between forecasted and actual observations (point forecasts observed graphically), and lower values of mean squared error, mean absolute error, etc. is chosen.

4. *Testing the Model*

For the chosen model to be coherent, one-step-ahead forecast errors should be white noise. If this is not the case, i.e. the errors are serially correlated, then it means that the errors contain additional information, and are forecastable. Thus, the forecast does not use all the available information, and can be improved upon (Diebold, 2006).

5. *Undertaking the forecast*

Once the residuals from the chosen model are found to be white noise, the appropriate model is fit to make the 10-day ahead forecast of the nominal exchange rates.

VII. Results

The results of the ARIMA(1,0,0) forecast for Dollar suggest an increase in the nominal exchange rates between 22 March 2022 to 31 March 2022. The naïve forecasts for Euro, Pound and Yen (owing to significant cyclicity in the exchange rate evolution over time) suggest a constant forecast at the value of exchange rate on the last available day (i.e. 21 March 2022).

The coefficient of the AR(1) component in the ARIMA(1,0,0) model for Dollar-Rupee exchange rate is significant and less than 1, meaning that the series returns to its mean slowly. The naïve forecasts for Euro, Pound and Yen follow from the fact that these exchange rates follow random walk, and so the last period exchange rate is the best possible forecast with the given information. This is in accordance with the efficient market hypothesis discussed above.

Application of the methodology on the training and testing sets yields the following results.

1. ARIMA models chosen by HK algorithm

The HK algorithm is applied to all four exchange rates. The algorithm fits an ARIMA(1,0,0) model for the Dollar-Rupee, Pound-Rupee and Yen-Rupee exchange rates, and ARIMA(0,0,0) for the Euro-Rupee exchange rate.

2. Accuracy test results and interval forecast in the testing set[2]

The ARIMA model forecasts are then compared with the naïve model forecasts. Accuracy tests and graphical analysis suggest the choice of ARIMA(1,0,0) for the Dollar-Rupee exchange rate (see below), and the naïve model for exchange rate of Rupee with Euro, Pound, and Yen (see Appendix A).

[2] To prevent cluttering, only the results for Dollar-Rupee exchange rates are presented here. The results for the other exchange rates are given in Appendix A.

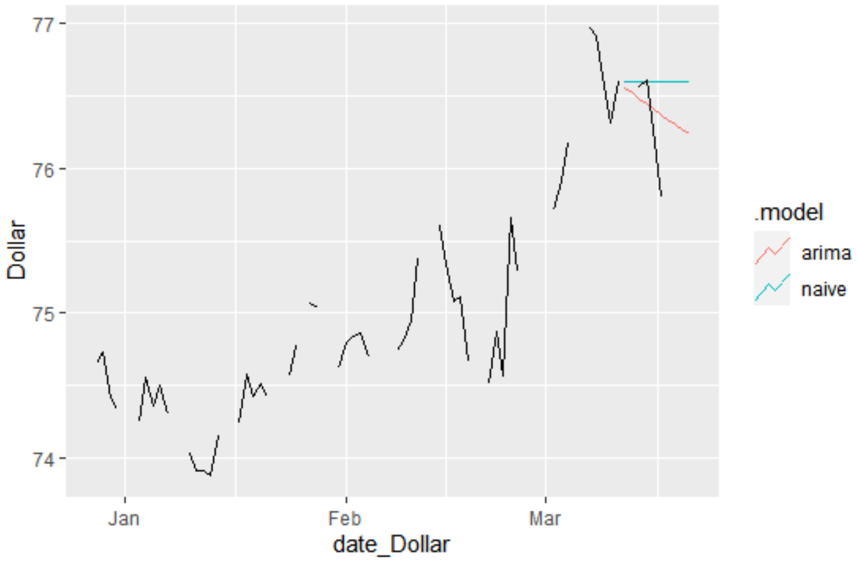


Figure 8: Point forecasts of the USD/INR exchange rate in the testing set

Table 1: Accuracy test results for USD/INR forecasts

.model	.type	ME	RMSE	MAE	MPE	MAPE	ACF1
arima	Test	-0.11651	0.28063	0.218825	-0.15403	0.28761	0.238509
naive	Test	-0.32304	0.440257	0.33004	-0.42509	0.434227	0.283231

ARIMA(1,0,0) seems to be a better fit as compared to the naïve model for forecasting the daily Dollar-Rupee exchange rates. This is reinforced both by the point forecasts in the testing set being closer to the observed values for ARIMA (Figure 8), and by its lower error values in the accuracy tests (Table 1).

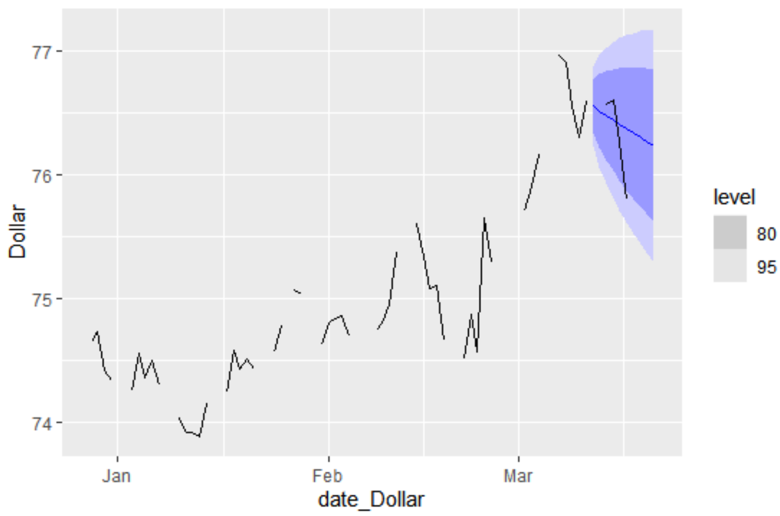


Figure 9: Interval forecasts of the USD/INR exchange rate based on ARIMA(1,0,0) model in the testing set.

Interval forecasts based on the ARIMA model further validate its choice over the naïve model. All realisations lie within the confidence intervals (Figure 9).

3. Error Diagnostics[3]

The results of the diagnostic test on the residuals from the chosen models (ARIMA(1,0,0) for USD/INR and naïve for EUR/INR, GBP/INR and JPY/INR) confirm that they satisfy the properties of white noise. Thus, there is no forecastability in the forecast errors. This confirms that our chosen models are adequate and can be used for forecasting.

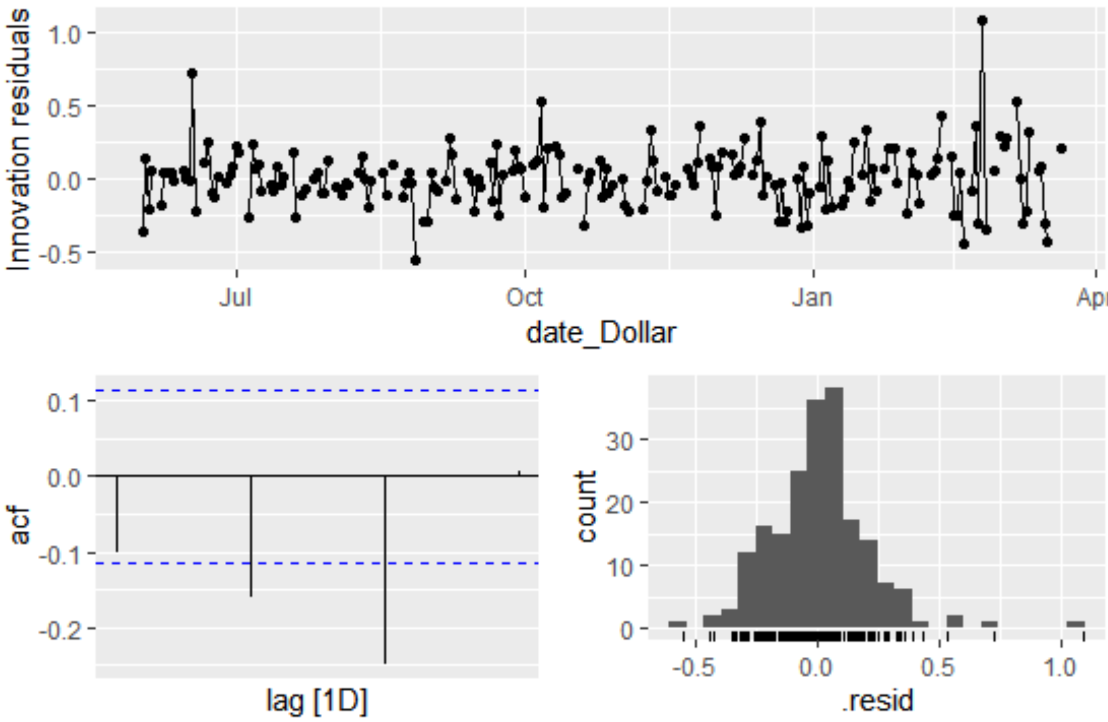


Figure 10: Residual diagnostics on USD/INR forecast errors

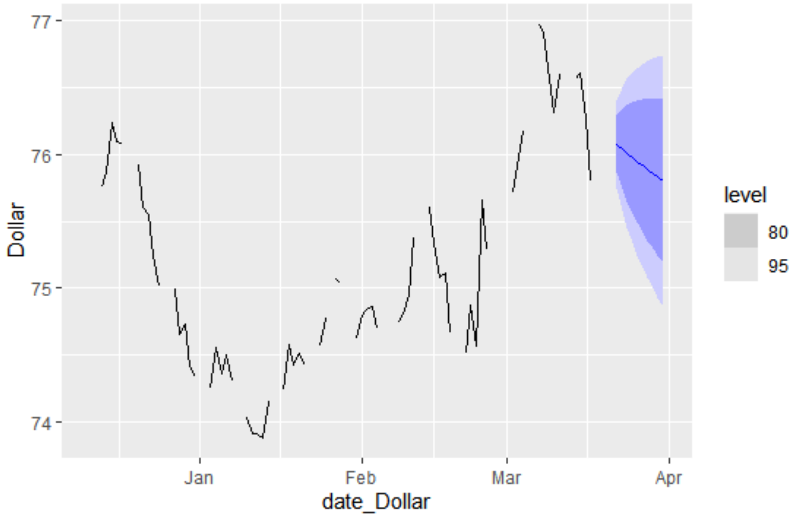
The graphs in Figure 10 show that the ARIMA method produces forecasts that appear to account for all available information. The mean of the residuals is close to zero and there is no significant correlation in the residuals series (as seen from ACF plot). The time plot of the residuals shows that the variation of the residuals stays almost same across the historical data, apart from the one outlier, therefore the residual variance can be treated as constant. This can also be seen on the histogram of the residuals. The histogram suggests that the residuals may not be normal — the right tail seems a little too long. Consequently, forecasts from this method will probably be quite good, but prediction intervals that are computed assuming a normal distribution may be inaccurate.

[3] To prevent cluttering, only the results for Dollar-Rupee exchange rates are presented here. The results for the other exchange rates are given in Appendix B.

4. ***Forecast equations and 10-day ahead forecasts***

i. Dollar-Rupee exchange rate: ARIMA(1,0,0) w/ mean

$USD_{t+1} = 1.44 + 0.98*USD_t + \varepsilon_t$
(AIC= -16.14, BIC= -5.2)

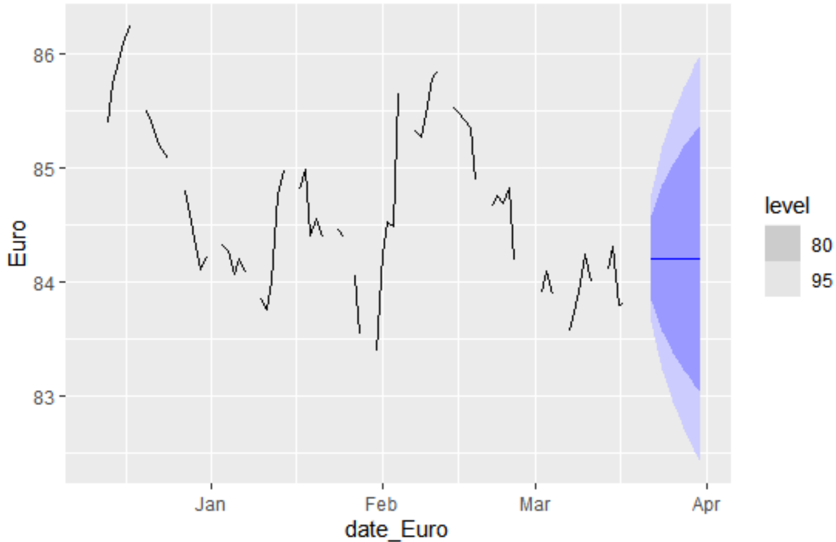


date_Dollar	22-03-2022	23-03-2022	24-03-2022	25-03-2022	26-03-2022	27-03-2022	28-03-2022	29-03-2022	30-03-2022	31-03-2022
Forecast_Dollar	76.073	76.040	76.008	75.976	75.946	75.915	75.886	75.857	75.829	75.802

ii. Euro-Rupee exchange rate: Naïve model

$EUR_{t+1} = 84.207 + \varepsilon_t$

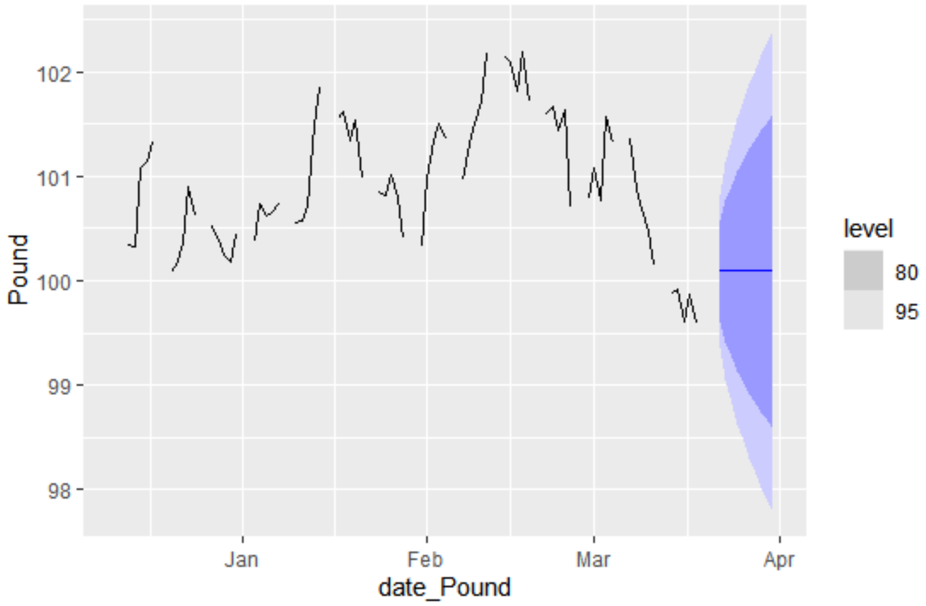
(sigma^2: 0.0822)



date_Euro	22-03-2022	23-03-2022	24-03-2022	25-03-2022	26-03-2022	27-03-2022	28-03-2022	29-03-2022	30-03-2022	31-03-2022
Forecast_Euro	84.207	84.207	84.207	84.207	84.207	84.207	84.207	84.207	84.207	84.207

iii. Pound-Rupee exchange rate: Naïve model

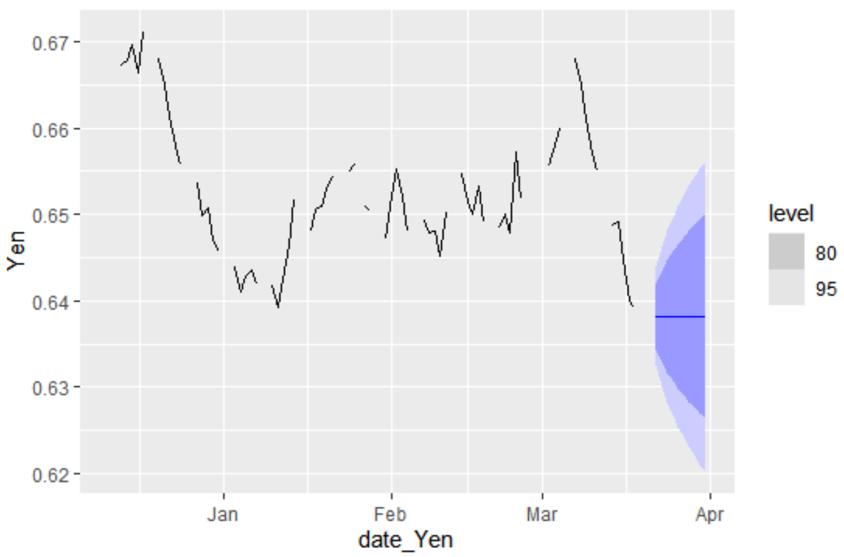
$GBP_{t+h} = 100.093 + \varepsilon_t$
(sigma^2: 0.1412)



date_Pound	22-03-2022	23-03-2022	24-03-2022	25-03-2022	26-03-2022	27-03-2022	28-03-2022	29-03-2022	30-03-2022	31-03-2022
Forecast_Pound	100.093	100.093	100.093	100.093	100.093	100.093	100.093	100.093	100.093	100.093

iv. Yen-Rupee exchange rate: Naïve model

$JPY_{t+1} = 0.638 + \varepsilon_t$
(sigma^2: 0.0022)



date_Yen	22-03-2022	23-03-2022	24-03-2022	25-03-2022	26-03-2022	27-03-2022	28-03-2022	29-03-2022	30-03-2022	31-03-2022
Forecast_Yen	0.638	0.638	0.638	0.638	0.638	0.638	0.638	0.638	0.638	0.638

VIII. Conclusion and Scope for Further Research

There is a rich literature on forecasting exchange rates for developed and developing countries using a variety of approaches. Most studies find the simple ARIMA models to be appropriate for forecasting exchange rates. The efficient market hypothesis, however, suggests that financial variables cannot and should not be perfectly forecastable. If this is so, there might be arbitrage opportunities that would automatically destroy the existence of such predictable patterns. Going by this hypothesis, thus, the naïve forecast seems to be the best forecast possible. Our study is accordance with both these viewpoints. The ARIMA(1,0,0) model is the chosen model for the short-term (10 day ahead), daily Dollar-Rupee exchange rate forecast. On the other hand, to forecast the short-term (10 day ahead), daily Euro-Rupee, Pound-Rupee and Yen-Rupee exchange rates, the naïve model seems to be the preferred model.

The fundamentality of exchange rates as one of the key macroeconomic indicators necessitate the need for their forecasts. However, their inherently noisy and chaotic behaviour make reliable forecasting challenging. Advanced forecasting techniques that use neural networks and ensemble forecasts can be employed. There is some evidence supporting the superiority of artificial neural network forecasting models because of their ability to extract non-linear and interactive effects (Kamruzzaman and Sarker, 2003). Another forecasting approach based on a non-linear regression model is Facebook's Prophet Model (Taylor and Letham, 2018). This was originally used for forecasting daily data with complex seasonality and holiday effects. This makes them highly relevant to forecast exchange rates. Ease of their application in the fpp3 package make them a natural extension to the research undertaken here. Further, we flagged the issue of missing observations (corresponding to weekends and public holidays) in our data. As an extension to this paper, we intend to look at possible interpolation techniques, and subsequently, undertake the forecasts. Dua and Suri (2019) study the interlinkages between the four exchange rates considered in this paper, and finds significant bi-directional causality between them. Modelling these exchange rates in a Vector Autoregressive Integrated Moving Average (VARIMA) framework can provide better forecasts that takes feedback relationships between exchange rates into account, thus improving the accuracy of forecasts. Thus, using the benchmark models of forecasting, we generate basic forecasts, whose scope can be further expanded by building on these core models.

IX. References

Babu, A.S. & Reddy, S.K. (2015). Exchange Rate Forecasting using ARIMA, Neural Network and Fuzzy Neuron. Finance and Accounting, Institute of Management Technology (IMT), Hyderabad, Telangana, India.

del Castillo, G. (2002). Determinants of Nominal Exchange Rates: A Survey of the Literature. In Macroeconomic Management. USA: International Monetary Fund. Retrieved Mar 27, 2022, from https://www.elibrary.imf.org/view/books/071/04393-9781589060944-en/ch10.xml

Diebold, Francis X. (2006). Elements of Forecasting. University of Pennsylvania.

Dornbusch, R., Fischer, S & Startz, R (2005). Macroeconomics, McGraw-Hill, Tata.

Dua, Pami & Suri, Ritu. (2019). Interlinkages Between USD–INR, EUR–INR, GBP–INR and JPY–INR Exchange Rate Markets and the Impact of RBI Intervention. Journal of Emerging Market Finance. 18. S102-S136. 10.1177/0972652719831562.

https://www.rbi.org.in/scripts/FS_Overview.aspx?fn=5#:~:text=The%20Reserve%20Bank's%20exchange%20rate,buying%20or%20selling%20foreign%20currencies.

Hyndman, Rob J & Athanasopoulos, George (2021). Forecasting: Principles and Practice (3rd ed). Monash University, Australia.

J.H. Wang & J.Y. Leu (1996). Stock Market Trend Prediction Using ARIMA-based Neural Networks. Proc. of IEEE Inl. ConJ on Neural Networks, vol. 4, pp. 2160-2165.

J. Kamruzzaman & R.A. Sarker (2003). Forecasting of Currency Exchange Rates using ANN: A Case Study. International Conference on Neural Networks and Signal Processing, pp. 793-797 Vol.1, doi: 10.1109/ICNNSP.2003.1279395.

J. Nguyen (2004). The Efficient Market Hypothesis: Is It Applicable to the Foreign Exchange Market? Faculty of Business-Economics Working Papers, University of Wollongong.

Khashei, M. & Bijari, M. (2011). Exchange rate forecasting better with hybrid artificial neural networks models math, Computer Science, 1 (1): 103 – 125.

http://scik.org/index.php/jmcs/article/viewFile/17/12

Lipsey, R.G. & Crystal, K.A. (1995). Economics, Oxford University Press, London.

M.K. Newaz (2008). Comparing the Performance of Time Series Models for Forecasting Exchange Rate. BRAC University Journal, vol. V, no. 2, pp. 55-65.

Nyoni, Thabani (2018). Modeling and Forecasting Naira / USD Exchange Rate In Nigeria: a Box - Jenkins ARIMA approach. University of Zimbabwe. https://mpra.ub.uni-muenchen.de/88622/1/MPRA_paper_88622.pdf

Patnaik, Ila & Sengupta, Rajeshwari (2021). Understanding the Dynamics of the Rupee-Dollar Exchange Rate. Ideas for India. https://www.ideasforindia.in/topics/macroeconomics/understanding-the-dynamics-of-the-rupee-dollar-exchange-rate.html

Ramzan, S., Ramzan, S & Zahid, F. M (2012). Modeling and Forecasting Exchange Rate Dynamics in Pakistan using ARCH Family Models. Electronic Journal of Applied Statistical Analysis, 5 (1): 15 – 19. http://dx.doi.org/10.1285/i20705948v5n1p15

Ribeiro, P.J. (2016). Forecasting Exchange Rates in the Presence of Instabilities, PhD Thesis, University of Glasgow. http://theses.gla.ac.uk/7519/

Samuelson, P. A & Nordhaus, W. D (1998). Economics, McGraw-Hill, New Delhi. http://mhhe.com/economics/samuelson17/

Shmueli G & Lichtendahl Jr. K (2016). Practical Time Series Forecasting with R. Axelrod Schnall Publishers.

Susmel, Rauli. International Finance FINA 7360 Lecture Notes, Bauer College of Business).

Usman, O.A. & Adejare, A.T. (2013). Effect of Exchange Rate Volatility on Nigerian Economy (1991 – 2000). International Journal of Academic Research in Economics and Management Sciences, 2 (6): 172 – 184. http://dx.doi.org/10.6007/IJAREMS/v2-i6/801

Appendix A: Accuracy test results and interval forecast in the testing set for Euro, Pound and Yen

1. Euro-Rupee exchange rate

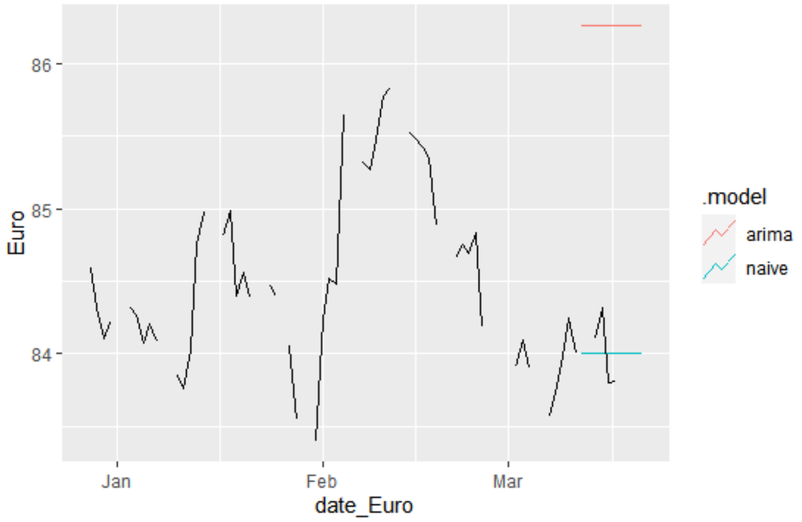


Figure A1: Point forecasts of the EUR/INR exchange rate in the testing set

Table A1: Accuracy test results for EUR/INR forecasts

.model	.type	ME	RMSE	MAE	MPE	MAPE	ACF1
arima	Test	-2.21598	2.225659	2.215984	-2.63722	2.637225	0.04516
naive	Test	0.04074	0.211262	0.20042	0.047865	0.238398	0.04516

Naïve model seems to be a better fit as compared to the ARIMA model for forecasting the daily Euro-Rupee exchange rates. This is reinforced both by the point forecasts in the testing set being closer to the observed values for the naïve model (Figure A1), and by its lower error values in the accuracy tests (Table A1).

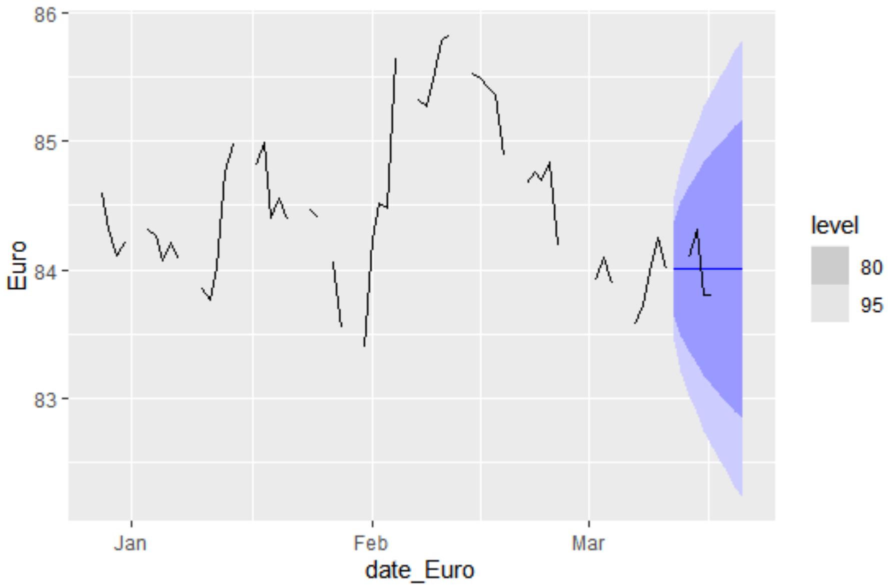


Figure A2: Interval forecasts of the EUR/INR exchange rate based on naïve model in the testing set.

Interval forecasts based on the naïve model further validate its choice over the ARIMA model. All realisations stay within the confidence intervals (Figure A2).

2. *Pound-Rupee exchange rate*

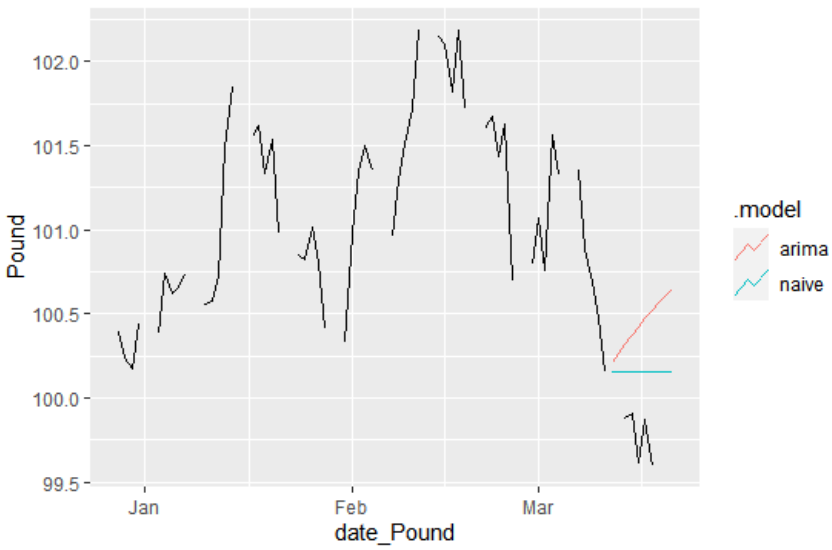


Figure A3: Point forecasts of the GBP/INR exchange rate in the testing set

Table A2: Accuracy test results for GBP/INR forecasts

.model	.type	ME	RMSE	MAE	MPE	MAPE	ACF1
arima	Test	-0.63168	0.655829	0.631679	-0.63301	0.63301	-0.07467
naive	Test	-0.3265	0.369413	0.3265	-0.32736	0.327358	-0.21369

Naïve model seems to be a better fit as compared to the ARIMA model for forecasting the daily Pound-Rupee exchange rates. This is reinforced both by the point forecasts in the testing set being closer to the observed values for the naïve model (Figure A3), and by its lower error values in the accuracy tests (Table A2).

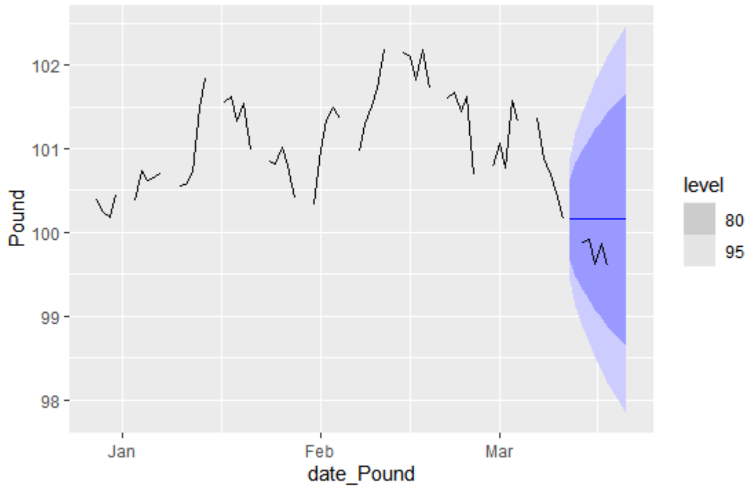


Figure A4: Interval forecasts of the GBP/INR exchange rate based on naïve model in the testing set.

Interval forecasts based on the naïve model further validate its choice over the ARIMA model. All realisations stay within the confidence intervals (Figure A4).

3. Yen-Rupee exchange rate

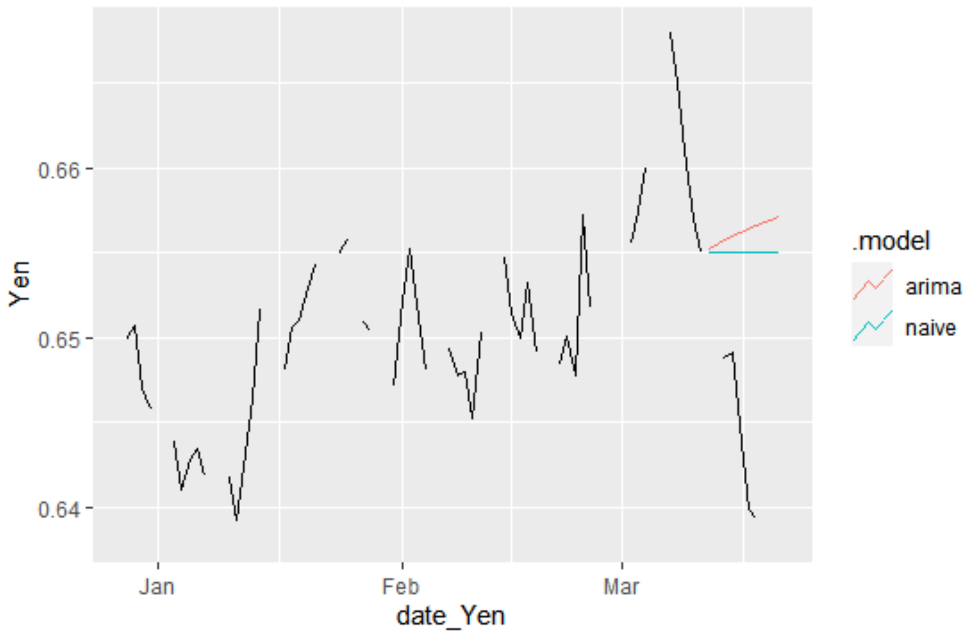


Figure A5: Point forecasts of the JPY/INR exchange rate in the testing set

Table A3: Accuracy test results for JPY/INR forecasts

.model	.type	ME	RMSE	MAE	MPE	MAPE	ACF1
arima	Test	-0.01298	0.013865	0.012976	-2.02232	2.02232	0.472251
naive	Test	-0.01165	0.012477	0.01165	-1.81573	1.815734	0.48769

Naïve model seems to be a better fit as compared to the ARIMA model for forecasting the daily Yen-Rupee exchange rates. This is reinforced both by the point forecasts in the testing set being closer to the observed values for the naïve model (Figure A5), and by its lower error values in the accuracy tests (Table A3).

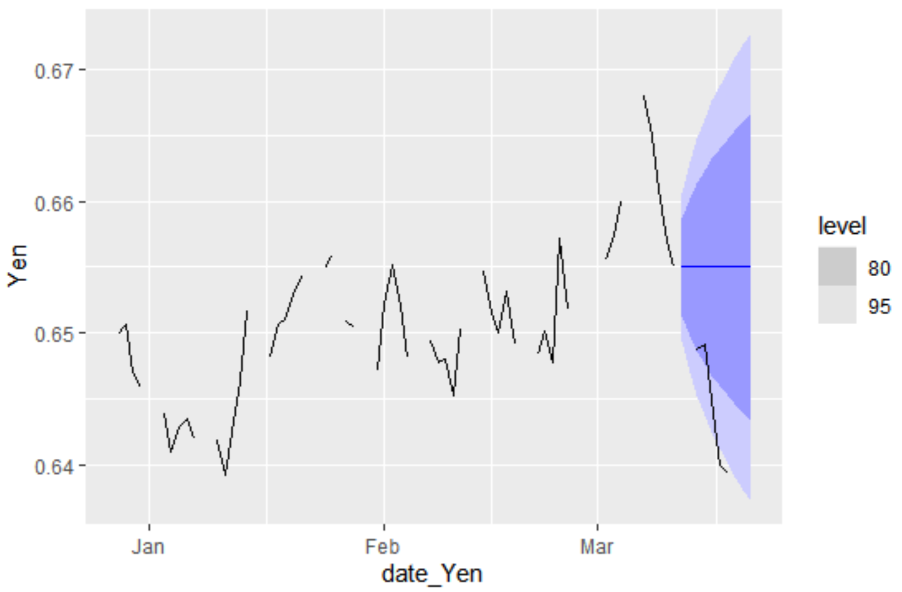


Figure A6: Interval forecasts of the JPY/INR exchange rate based on naïve model in the testing set.

Interval forecasts based on the naïve model further validate its choice over the ARIMA model. All realisations stay within the confidence intervals (Figure A6).

Appendix B: Residual diagnostics for Euro, Pound and Yen

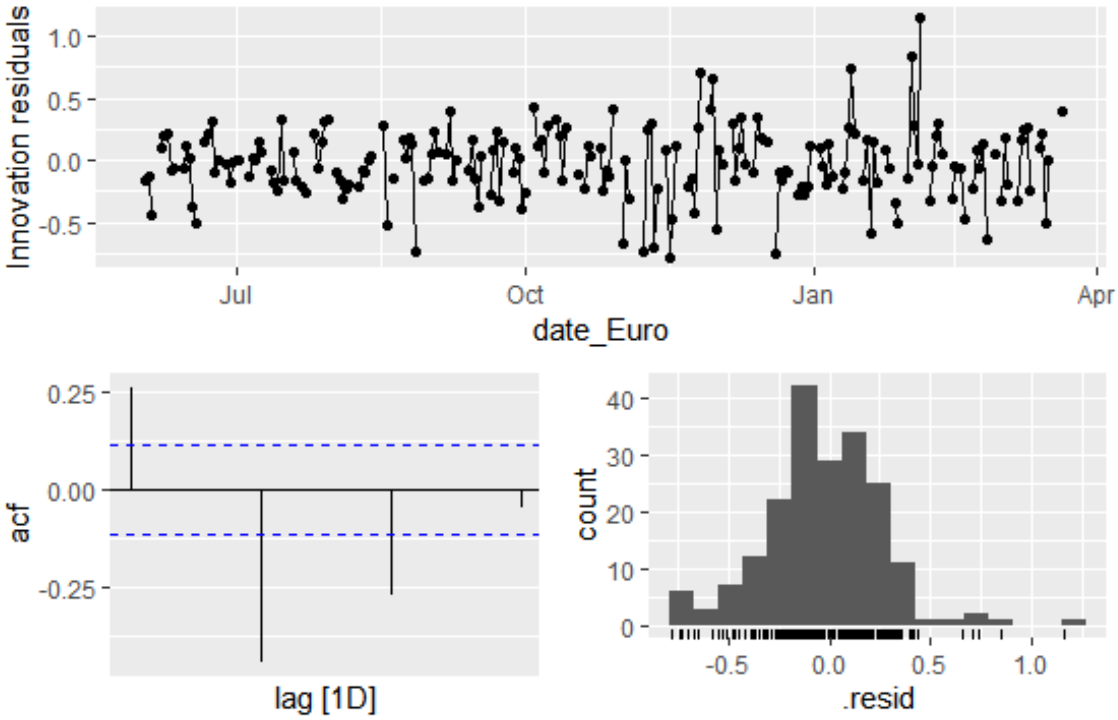


Figure B1: Residual diagnostics on EUR/INR forecast errors

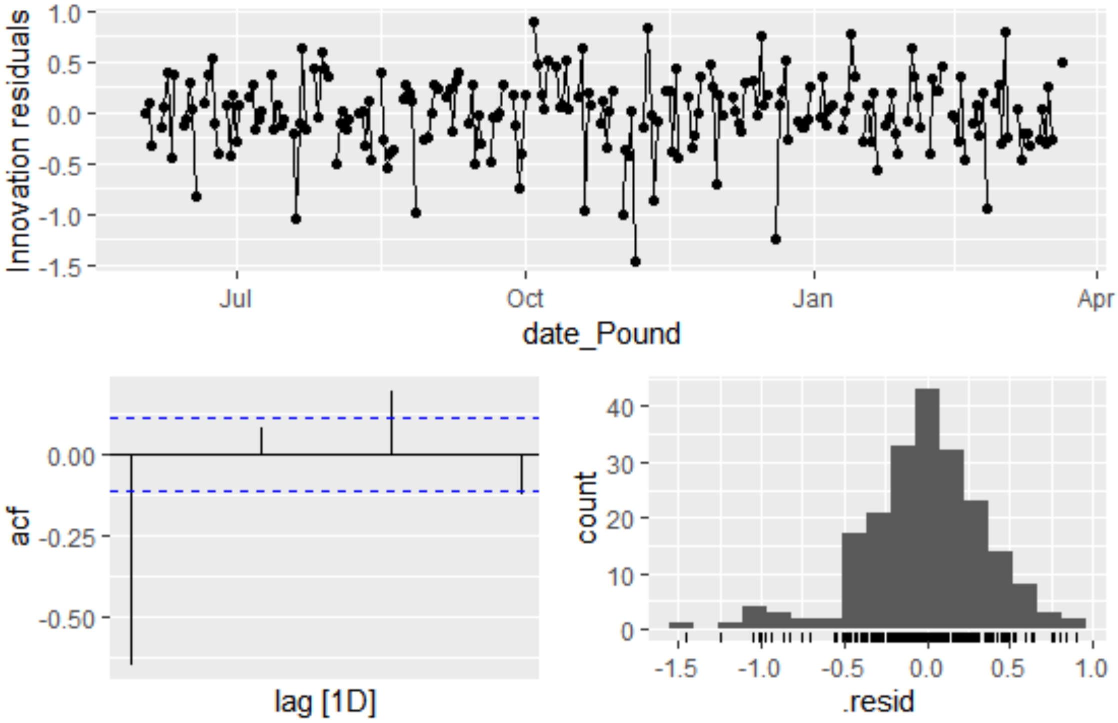


Figure B2: Residual diagnostics on GBP/INR forecast errors

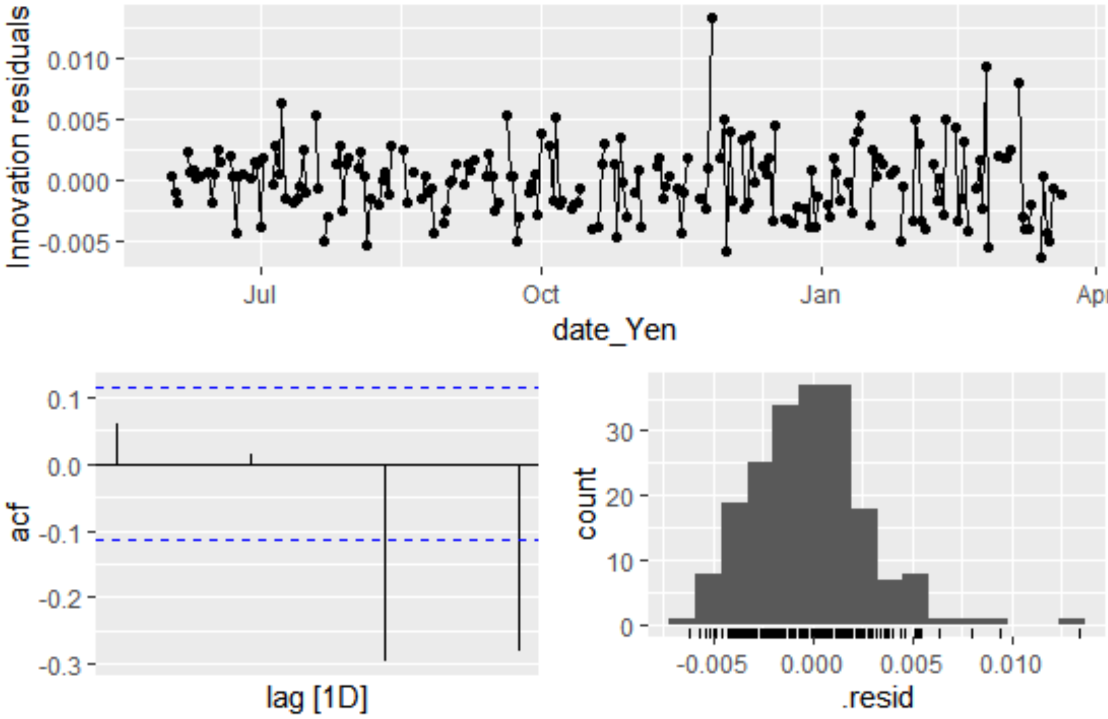


Figure B3: Residual diagnostics on JPY/INR forecast errors

The graphs in Figures B1-B3 show that the naïve model produces forecasts that appear to account for all available information. The mean of the residuals is close to zero and there is no significant correlation in the residuals series (as seen from ACF plot). The time plot of the residuals shows that the variation of the residuals stays almost same across the historical data, apart from the one outlier, therefore the residual variance can be treated as constant. This can also be seen on the histogram of the residuals. The histogram suggests that the residuals may not be normal — the right tail seems a little too long. Consequently, forecasts from this method will probably be quite good, but prediction intervals that are computed assuming a normal distribution may be inaccurate.