International Journal of Research in Finance and Management

P-ISSN: 2617-5754
E-ISSN: 2617-5762
IJRFM 2024; 7(1): 56-63
www.allfinancejournal.com
Received: 08-01-2024
Accepted: 14-02-2024

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Predicting exchange rate between US Dollar (USD) and Indian rupee (INR): An empirical analysis using SARIMA Model

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DOI: https://doi.org/10.33545/26175754.2024.v7.i1a.283

Abstract
Prediction of exchange rates is an important task of traders and practitioners in the recent financial markets era. Many statistical and econometric models are used in the time series analysis and prediction of foreign exchange rates. This study investigates the behavior of weekly exchange rates of the Indian rupee (INR) against the US dollar (USD) using time series analysis. This study used the SARIMA model in forecasting the INR/USD by aggregating seasonal data patterns in the foreign exchange market. Weekly RBI reference exchange rates from June 2013 to June 2023 were considered for the analysis. Finally, a forecast for ninety days was calculated which showed a depreciation of the Indian rupee against the US Dollar. The study found that the SARIMA model can be a better forecasting ability in advance of the prediction of currency exchange rates and momentum in the currency market.

Keywords: Exchange rate, forecasting, SARIMA, INR/USD

1. Introduction

Forex trading is one of the most actively traded markets in the world, with an average daily trading volume of $5 trillion. There are various reasons for forex trading but, profit making is one of the major reasons (Sarangi et.al, 2022) [8]. Currency forecasting may assist traders, corporations and financial institutions in making better financial decisions. The accurate forecasting of time series data is challenging and for exchange rate is more difficult as well. Because it is difficult to predict as they continuously fluctuate (Najamuddin, Fatima, 2022) [11]. Exchange rate movements and their forecasting became an important financial problem in recent times and the increasing efforts of many researchers are focused in this direction. The behavior of exchange rates is expected to be highly non-linear and predictions in such a scenario are a very challenging problem to be solved (Tauser, Buryan, 2014) [5].

In recent times, many methods have been suggested and adopted to predict the prices of exchange rates. Time series and machine learning techniques are some of the most common approaches for predicting exchange rates (Politikasi, Dergisi, 2022) [4]. In the area of the international market, there have been various studies conducted for measuring volatility and forecasting future movements using linear and non-linear techniques such as Auto Regressive Integrated Moving Average (ARIMA), Support Vector Machine (SVM), Artificial Neural Network (ANN), fuzzy logic, etc. (Gupta, Kashyap, 2016) [7]

This study applied the SARIMA (Seasonal Autoregressive Integrated Moving Average) model which is considered the best time series forecasting technique for estimating time series data with seasonal patterns (Gounmeein, Ismail, 2020). SARIMA uses a variety of autoregression (AR) and moving average (MA) models, as well as differencing, to capture trends and seasonality in data which helps to get changes in currency values by anticipating exchange rates.

The remaining sections are organized as follows. Section 2 represents the literature review which explains the existing studies on exchange rate prediction. Section 3 describes the methods for the SARIMA framework used in this study. Section 4 presents the results of the analysis carried out; the conclusion of the study is given in Section 5.

2. Literature Review

currency market that allows people to buy and sell financial securities, commodities, derivatives, and currencies. Compared to all foreign currency markets is considered as largest and most liquid (Bank of International Settlements, 2022). Importers, exporters, speculators, investors, and the government are the participants who are involved in the currency market. The most widely used traded currency is the US dollar, and the next most popular currency pair is the EUR/USD by Bank of International Settlements. The fluctuations in the exchange rate largely depend on supply and demand (Rugman and Collinson 2006) [26].

When the government permitted banks to trade foreign currency with one another in 1978, the foreign exchange market in India officially began. The potential for India's exchange market has increased as a result of globalization and liberalization. During this time span (2009-2014), 77% of all trades were interbank forex transactions. As a result, the Indian forex market has become one of the key markets where international traders can profit from arbitrage (Babu *et al*. 2015) [1].

Forecasting models in finance became sophisticated in 1998 after presenting a study on daily stock market forecasting through the use of textual web data (Wuthrich et. al. 1998) [27]. Some of the researchers use quantitative data for forecasting the trends. Forecasting of intra-day exchange rate movements leads to better outcomes compared to random guessing only when weighted data is used for analysis. To further improve the accuracy of the prediction, Peramunetilleke and Wong (2002) [38] suggested that techniques must incorporate other numeric time series analyses.

Since Meese and Rogoff (1983) [24] worked on forecasting exchange rates using the random walk model, there has been a significant amount of study to produce precise exchange rate forecasting. The fundamentals and trends of exchange rates have also been studied using time series models - ARIMA, GARCH, TAR, and SETAR models (Engel and Hamilton, 1990; Cheung and Wong, 1997; Kilian and Taylor, 2003; Gharleghi, Shaari, and Sarmidi, 2014) [28, 32, 33, 35]. Additionally, exchange rate predictions are made using machine learning models like ANN, SVM, genetic algorithms, etc. (see Albers *et al*., 1996; Kaastra and Boyd, 1996; Yao and Tan, 2000; Vojinovic and Kecman, 2001; Kamruzzaman and Sarker, 2003; Plakandaras, Papadimitriou, and Gogas, 2015; Sun, Wang) [37, 34, 30, 36, 31, 29].

Kamruzzaman investigated three neural-based forecasting models to predict six currencies, including the US dollar (USD), British pound (GBP), Singapore dollar (SGD), New Zealand dollar (NZD), Swiss franc (CHF), and Japanese yen (JPY), against the Australian dollar (AUD), using historical data and moving average technical indicators. The neural-based model was able to estimate the forex rates more accurately than the traditional ARIMA model, according to comparisons made between the two sets of data. The application of artificial intelligence and econometric model provides a depth overview of forecasting the REER dynamics (Quereshi et.al, 2023). Recent studies shown that wavelet transform with soft thresholds obtained great results for time series using ARIMA model (Zang, Khushi, 2020). The study conducted by Newaz, 2008 showed that ARIMA models provides a better forecasting of exchange rates than exponential smoothening and Naïve models do.

ARIMA and neural network models were used by Chattopadhyay to predict the sunspot. According to the results, the autoregressive neural network-based model performs much better than the autoregressive moving average and autoregressive integrated moving average-based models for the univariate forecast of the annual mean sunspot numbers (Chattopadhyay G *et al*., 2012) [23].

Alam Z (2012) [21] investigated the use of an autoregressive model for predicting and trading BDT/USD exchange rates from July 3, 2006 to April 30, 2010 as an in-sample period, and from May 1, 2010 to July 4, 2011 as an out-of-sample period. He came to the conclusion that when compared using statistical performance metrics, the ARMA and AR models together beat other models for predicting the BDT2/USD exchange rate.

Kashif *et al*. (2008) [22] used ARIMA, GARCH, and state space models to predict Pakistani exchange rates. Considered are the daily conversion rates between Pakistani rupees and US dollars. They discovered that state space models are more accurate in predicting the exchange rate model.

The literature on exchange rate prediction models in the Indian context is limited, and most studies focus on comparing the performance of the models with others rather than individual model evaluations. However, in global research, various models have been used to forecast exchange rates, including ARIMA, GARCH, TAR, SETAR, and machine learning models such as ANN, SVM, and genetic algorithms (Hendikawati *et al*. 2020) [9]. Overall, the literature suggests that different models have varying levels of accuracy in predicting exchange rates, and the choice of model depends on the specific context and data available.

Hence, this research using SARIMA model would contribute to the existing literature and help policymakers, investors, and market participants make more informed decisions regarding exchange rate forecasting.

3. Materials and Methods

Data

Weekly data of the Indian rupee and US dollar from June 2013 to June 2023 published on the website www.investing.com were used for this study consisting of 526 observations which were used to fit the forecasting model to test the accuracy of in sample forecast.

SARIMA Model

The description of the ARIMA and SARIMA models was proposed by Box and Jenkins (1976) as follows:

A stationary time series (x_1) is called an autoregressive integrated moving average model of order p, d, q designated ARIMA (p, d, q), if

$$\Phi_p(B)\Delta^d x_t = \theta_q(B)\varepsilon_t \tag{1}$$

Whereas,

$$\Phi_p(B) = 1- \phi_1 B-\phi_2 B^2 \text{-----}\phi_p B^P \tag{2}$$

$$\theta_q(B) = 1+\theta_1 B + \theta_2 B^2 + \ldots+\theta_q B^q \tag{3}$$

$$\nabla^d = (1 - B)^d \quad (4)$$

where $\varphi_p(B)$ is a polynomial of autoregressive with order p is denoted by AR(p); $\theta q(B)$ is a polynomial of moving average with order q is denoted by MA(q). The number d is the non-seasonal differencing orders. B is the backward shift operator defined by $B^k Xt = X_{t-k}$.∇ is the non-seasonal differencing operator. Moreover, $\{\varepsilon t\}$ is a white noise process. In contrast, when the data have a phenomenon that repeated the pattern in time series data, the series is denoted by Seasonal ARIMA (p, d, q)(P, D, Q)$_s$. The generalized form of the SARIMA model can be written as:

$$\varphi_p(B)\Phi_p (B^s)\nabla^d\nabla_s^D x_t = \theta_q(B)\Theta_Q(B^S)\varepsilon t, \quad (5)$$

$$\text{whereas, } \Phi_p (B^S) = 1 - \Phi_1 B^S - \Phi_2 B^{2S} - \cdot \cdot \cdot - \Phi_p B^{p s} \quad (6)$$

Forecasting the Exchange Rate of..

$$\Theta_Q(B^S) = 1 - \Theta_1 B^S - \Theta_2 B^{2S} - \cdot \cdot \cdot - \Theta_Q B^{QS} \quad (7)$$

$$\nabla_S^D = (1 - B^S)^D \quad (8)$$

where Φ_P (B^S) is a polynomial of seasonal autoregressive with order P and seasonal period S is denoted by SAR(P); $\Theta_Q(B^S)$ is a polynomial of the seasonal moving average with order Q and seasonal period S is denoted by SMA(Q). ∇_S^D are the seasonal differencing operators.

4. Major results and discussions

This study first checked the dataset for missing values before proceeding with the analysis and eliminated them. To acquire a better understanding of data set, the factors support it and get essential insights of data characteristics, spot potential outliers, grasp data distribution elements, and to create framework for future exploratory data analysis and modelling efforts, descriptive statistics of the data were analysed as mentioned below in Table 1. Based on table 1 reports brief descriptive statistics of the dataset, which indicates that the average exchange rate closing price was 69.87 Indian rupee per dollar with the standard deviation of 6.32 INR.

Table 1: Showing Descriptive Statistics

	Open	High	Low	Close	Adj Close	Volume
count	527.000000	527.000000	527.000000	527.000000	527.000000	527.0
mean	69.326510	69.875849	68.897864	69.385042	69.385042	0.0
std	6.323881	6.342323	6.359296	6.322967	6.322967	0.0
min	56.500000	56.573002	54.700001	56.573002	56.573002	0.0
25%	64.248150	64.622749	63.954000	64.234803	64.234803	0.0
50%	68.443001	68.894997	67.959999	68.473999	68.473999	0.0
75%	73.985550	74.571449	73.540001	74.158001	74.158001	0.0
max	82.917999	83.386002	82.563004	82.932999	82.932999	0.0

Fig 1: Shows the Annual conversion rate

Figure 1 shows the line chart to represent the trend of the conversion rates between the INR/USD over the years by examining the historical trends through exchange rate dynamics and important patterns or events that affect these exchange rates.

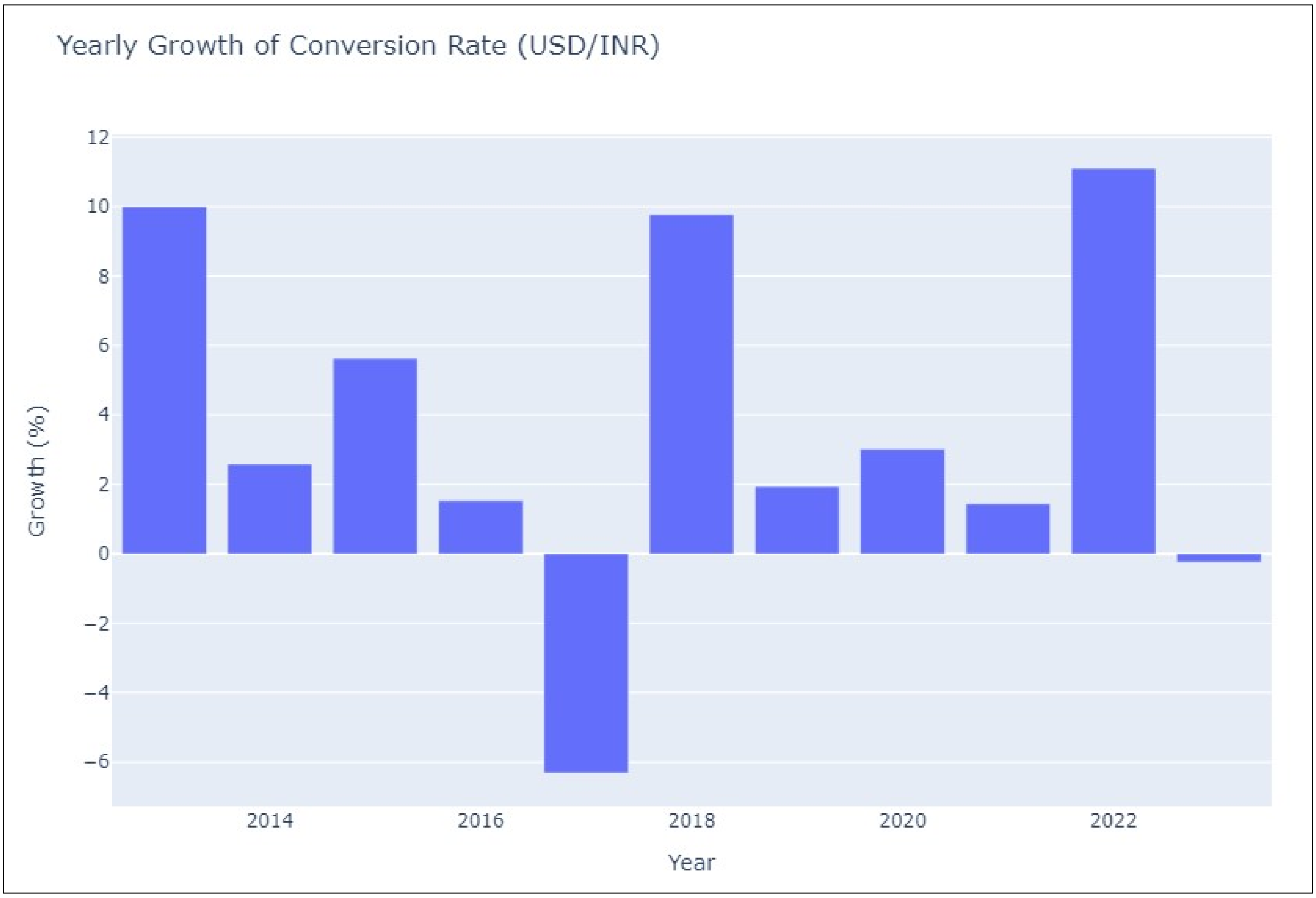

Fig 2: Conversion Rate Annual Growth

The below figure shows the compounded yearly increase of the INR/USD exchange rate to discover times of economic strength or weakness, important actions impacting currency rates, or long-term patterns in INR/USD conversion rates.

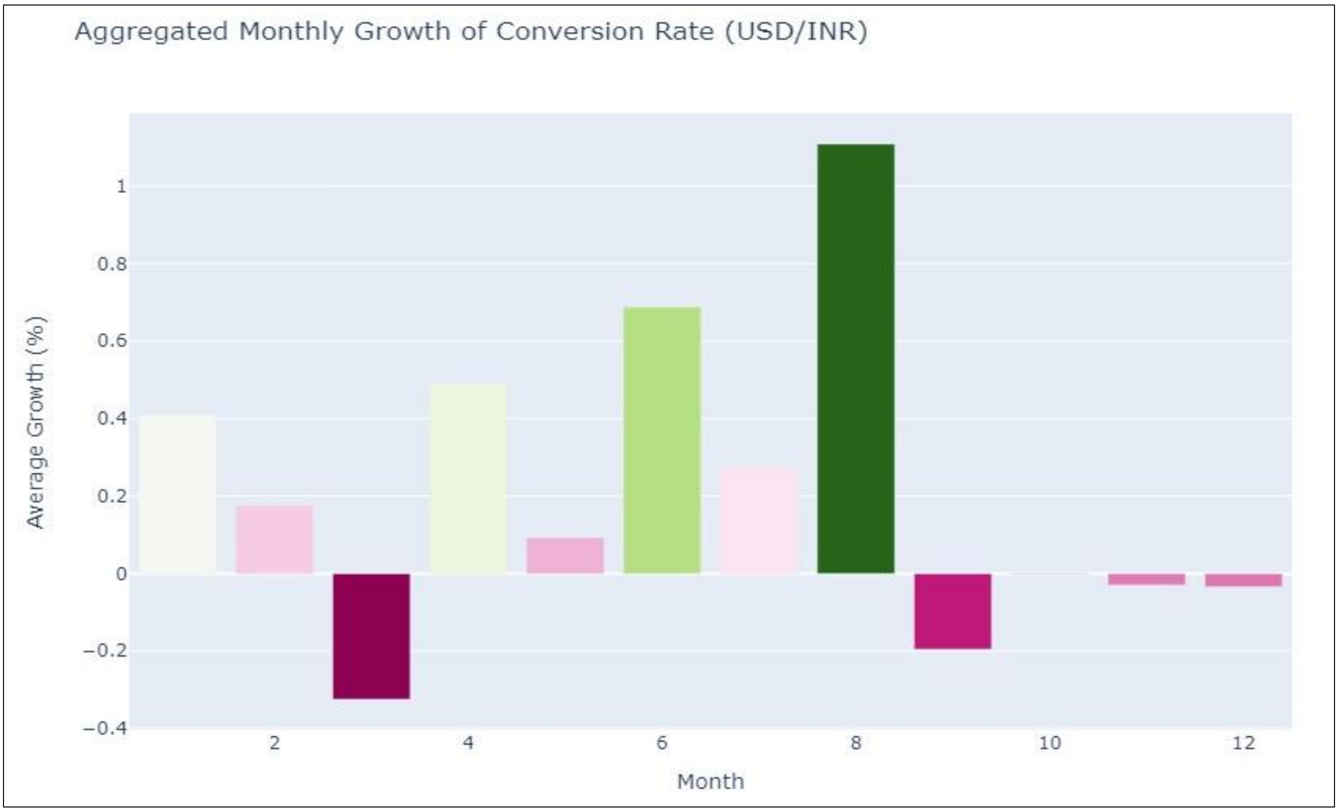

Fig 3: Monthly Growth of the Conversion Rate

The above figure 3 indicates that the USD value has consistently decreased in Month 3 i.e., January and March. This implies that the INR tends to strengthen against the USD during these months, dropping the conversion rate. Meanwhile, in the second quarter, the USD improved against the INR every year. The USD value against INR jumped peak in August but decreased in September, increased annually in the fourth quarter, and fell again in December.

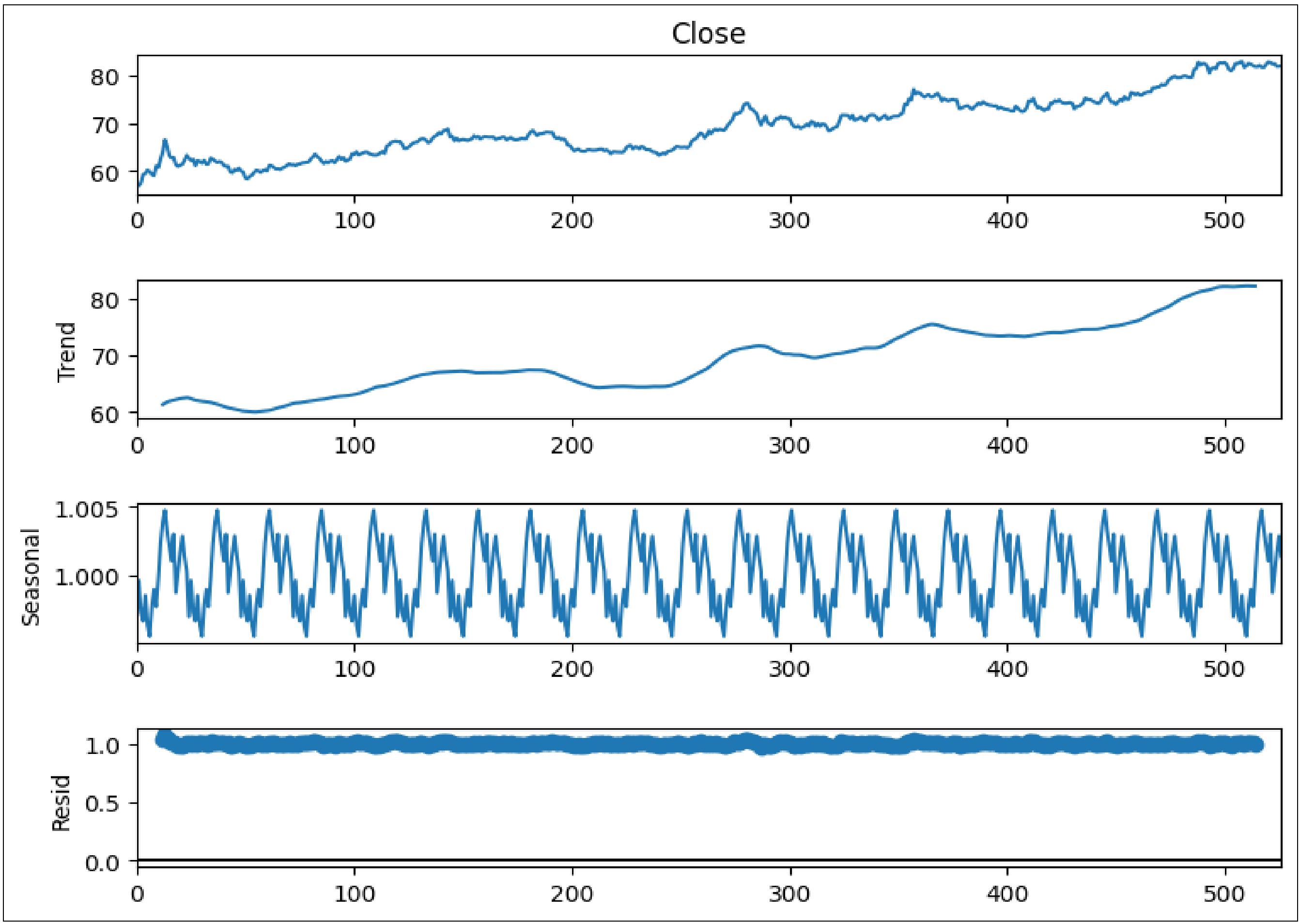

Fig 4: Shows the seasonal decomposition

Seasonal decomposition of the USD/INR separates the different data components: trends, seasonality, and residual or random fluctuations. There is a seasonal pattern in this data to use SARIMA as the most appropriate algorithm for this data.

Table 2: Shows the SARIMA model summary

Sarimax Results						
Dep. Variable				**Close No. Observations**		
Model:	SARIMAX(2, 1, 0)x(2, 1, 0, 52)			Log Likelihood		-473.
`Date:	Sat, 29 Jul 2023			AIC		957.
Time:	16:11:13			BIC		978.
Sample:	0			HQIC		965.
	- 527					
Covariance Type:	opg					
	coef	std err		P*1	[0.025	0.975]
ar.L1	0.0136	0.043	0.320	0.749	-0.070	0.097
ar.L2	0.0622	0.039	1.581	0.114	-0.015	0.139
ar.S.L52	-0.6332	0.045	-14.050	0.000	-0.722	-0.545
ar.S.L104	-0.2865	0.045	-6.370	0.000	-0.375	-0.198
sigma2	0.4111	0.023	17.860	0.000	0.366	0.456
Ljung-Box (L1) (Q):			0.00	Jarque-Bera (JB):		17.91
Prob(Q):			0.96	Prob (JB):		0.00
Heteroskedasticity (H):			0.97	Skew:		0.03
Prob(H) (two-sided):			0.85	Kurtosis:		3.95

The parameter estimate of the best-fitted Sarima (2,1,0) is given in Table 2. Using SARIMA, need to find the p, d, and q values to show the parameter seasonal = True determines that the time series shows a seasonal pattern. The parameter m= 52 shows the seasonal periodicity of weekly data and 2,1,0 is the p, d,q value.

The three-month (July - September) predicted values obtained from the SARIMA (2,1,0) model were reported and plotted in Table 3 and Figure 5, respectively. Figure 5 exhibits the forecast for three months ahead of exchange rates. Three-month point prediction values were plotted in the red line.

Table 3: Prediction of future exchange rates from the fitted ARIMA model.

527	82.276836
528	82.469744
529	82.302249
530	82.188740
531	82.219358
...	
613	86.556983
614	86.612887
615	86.698329
616	86.748962
617	86.553490
Name: predicted mean, Length: 91, dtype: float 64	

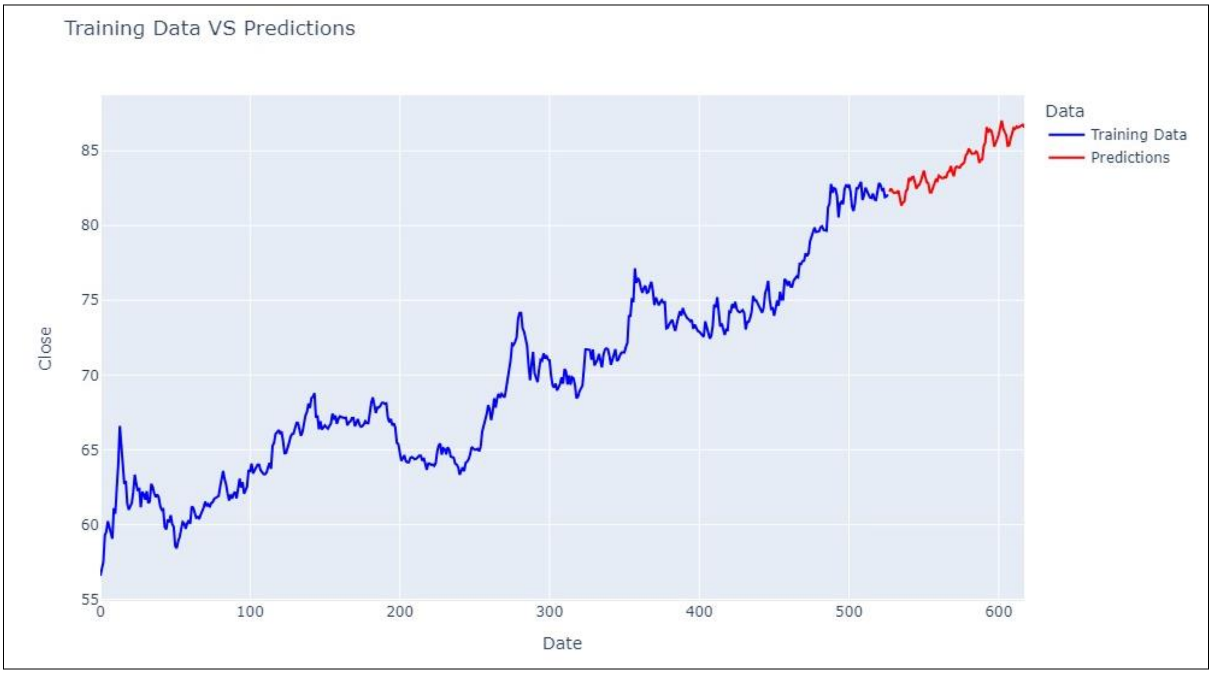

Fig 5: Time series plot of forecast exchange rates from the SARIMA (2,1,0) model.

5. Conclusion

The SARIMA model captures seasonal trends in the past values of the data to predict future value. Hence, it can predict currency exchange rates for various currencies. This model helps in informed decisions related to currency trading and international business operations. The momentum prediction has been tested with INR/USD weekly exchange rate data. As evidenced by the obtained results, the best fitting model was found to be the SARIMA (2,1,0) model and appropriate to forecast future exchange rates. The SARIMA model can be a better forecasting ability in advance of prediction of currency exchange rate and momentum in the currency market. But the accuracy of the model depends on several factors including data quality and the currency market's stability. This study can be expanded in the future to explore more neural network software, testing more parameters to increase the accuracy of the prediction.

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