"FORECASTING FOREIGN EXCHANGE RATES WITH TIME SERIES MODELS"

Shanya Singh [1], Dr. Amol Pande [2]

[1]Computer Engineering, Datta Meghe College of Engineering, Mumbai University, India

[2]Computer Engineering, Datta Meghe College of Engineering, Mumbai University, India

Abstract

This paper highlights the critical role of exchange rates in shaping the dynamics of the foreign exchange market, characterized by the unpredictable and volatile nature of currency rates. Predicting exchange rates is identified as a highly challenging aspect of financial time series forecasting. The examination of reversals in foreign exchange rate flows indicates a tendency for the true effective exchange rate to be on the higher side. Factors contributing to this complexity include the formation of expectations in financial markets, heterogeneity in expectations, market microstructure, and forecast performance. The use of various statistical measures reveals the presence of conditional heteroscedasticity. The research focuses on addressing this scenario through time series methods, emphasizing the significant utility of algorithms such as ARIMA, which utilizes autoregressive and moving averages, and SARIMA, incorporating past data and considering seasonal tendencies.

Keywords: Exchange rates, Foreign exchange market, Predicting exchange rates, Financial time series forecasting, True effective exchange rate, Conditional heteroscedasticity, Time series algorithms

1. INTRODUCTION

The forex market, with a daily trading volume surpassing $5.1 trillion, is the world's largest currency exchange platform. Despite its significance, accurately forecasting forex rates is challenging due to market volatility. Governments and businesses analyze currency rates meticulously for trading decisions. Precise predictions offer substantial profits and risk mitigation for investors and traders. Gathering time-series data enables a comprehensive examination of factors influencing rates, making accurate forecasting a formidable task. Exchange rate fluctuations can trigger crises, disrupting international dealings and straining government reserves.

Time series analysis is a vital method for anticipating future conditions. Exchange rates play a crucial role in shaping market dynamics, making forecasting financial time series challenging. Commonly used models include moving averages, ARIMA, and Seasonal-ARIMA. The research delves into tackling this situation using time series techniques, highlighting the invaluable efficacy of algorithms like ARIMA, which leverages autoregressive and moving averages, and SARIMA, which takes into account historical data and seasonal patterns.

2. BACKGROUND

Once a straightforward process, exchange rate calculation now plays a pivotal role in international business and banking decisions, necessitating accurate predictions. Exchange rate forecasting, driven by speculation, enables businesses and institutions to capitalize on fluctuating rates and global expansion. These forecasting techniques rely on models that establish relationships between variables, whether intrinsic or exogenous.

Past relationships persist into the future, underpinning various statistical models—exploratory, causal, extrinsic, and intrinsic—irrespective of their theoretical or statistical foundations. Achieving accuracy in forecasting demands stability while allowing room for potential profit from other forecasters' activities.

Developments in time series theory have popularized forecasting methods that leverage historical data to project future trends. Changes in the global monetary environment can significantly impact exchange rate forecasts, with a country's value subject to shifts in its balance of payments or insufficient alternative strategies.

Choosing a time-series forecasting method involves a delicate balance between accuracy and interpretability. While complex techniques offer greater precision, they may sacrifice ease of interpretation.

3. LITERATURE REVIEW

Numerous time-sensitive macroeconomic factors that have an immediate impact on the USD/BDT exchange rate have been included in the study. Biswas A, Uday IA, Rahat KM, Akter MS, Mahdy MRC show that these results will offer a new angle on how to determine and predict the USD/BDT exchange rate [1]. Ayitey Junior, M., Appiahene, P., Appiah, O. investigation's findings indicate that MAE, RMSE, MAPE, and MSE are the assessment metrics that are most frequently used, with EURUSD being the most actively traded currency pair internationally. The two methods for FX market forecasting that are most widely employed are LSTM and Artificial Neural Networks [2]. The proposed framework by T. Soni Madhulatha, Md. Atheeq Sultan Ghori uses five currency rates and various market variables to train and test it, evaluating its usefulness for predicting market volatility and future exchange rates [3]. The study by Surindar Gopalrao Wawale , Aadarsh Bisht, Sonali Vyas, Chutimon Narawish, Samrat Ray assessed currency importance and factors affecting stress levels due to increased currency exchange in the area's economy [4]. The adoption of GARCH and ARCH modelling is due to variance volatility. It is discovered that USD/PKR ARCH modelling performs better than GARCH modelling [5]. When compared to the ARIMA method and the Holt Winter Additive approach, the model created using the Double Exponential Smoothing method is the best model to forecast the volatility data with the lowest values of MAPE, MAE, and MAD [6]. In order to forecast the movement of the EUR/USD currency pair, two different LSTM models were used in this study. Profiting from trades can be achieved by accurately predicting the direction of a currency pair. This was the investigation's primary goal [7].

The study by Putri, K. S., & Halim, S. assessed currency importance and factors affecting stress levels due to increased currency exchange in the area's economy [8]. LSTM can handle larger data sets, while ARIMA struggles with learning, resulting in poorer prediction outcomes. Despite a large dataset, LSTM can produce consistent forecasts even with 100 data, demonstrating its superior learning capabilities [9]. All three currencies had the lowest MAPE values, making them the most effective. The study's computed MAPE values and previous research share commonalities [10]. Neural network-based forecasting outperforms GARCH in predicting US Dollar to Sri Lankan Rupee exchange rate [11]. The thesis by Daniya Tlegenova presents comparison results crucial for selecting a forecast model for forecasting and trading foreign exchange rates, determining the appropriateness of a precise model for accurate forecasting [12].

3.1. FINDINGS AFTER LITERATURE REVIEW

To promote economic growth, addressing challenges in the foreign currency exchange market is crucial. Analyzing machine learning parameters from past research can aid in optimizing forecasting methods. However, the data used in some studies is outdated and limited to a single currency. Neural networks, although used for rate forecasting, lack tailored architectures for time series modeling. Thorough investigation of real-world trading factors is essential for generating reliable forecasts.

3.2. PROBLEM STATEMENT

Forex is crucial for a nation's trajectory. Accurately predicting exchange rates is vital for decision-makers. The time series method aids in extrapolating future trends.

This paper reviews challenges in forecasting rates, including the forward premium conundrum and expectations formation.

Time series data shows recent trends relevant to future outcomes. The ARIMA model, inspired by sequential data, can predict financial markets but has limitations with seasonal data. SARIMA is used for seasonal data. Artificial neural networks (ANN) need adaptation for time series use.

We aim to assess projected outcomes for INR, EUR, JPY, and GBP exchange rates against the USD.

4. SCOPE OF RESEARCH

Exchange rates play a crucial role in shaping the dynamics of the foreign exchange market, yet forecasting these financial time series poses a significant challenge due to the inherent volatility and unpredictability of currency rates. This study aims to predict future trends in exchange rates by leveraging time-series data that encapsulates historical patterns, trends, and fluctuations.

To achieve this, the study employs the Auto Regressive Integrated Moving Average (ARIMA) and Seasonal-ARIMA model classes, which are widely used in this field. Specifically, the research compares projected outcomes for forecasting exchange rates of the INR, EUR, and GBP against the USD using these time series models.

The study focuses on data spanning from January 2020 to September 2023, organized on a weekly basis. It advocates for the adoption of time series models over neural networks due to their structured framework and relatively lower data requirements for training and prediction.

5. PROPOSED ARCHITECTURE

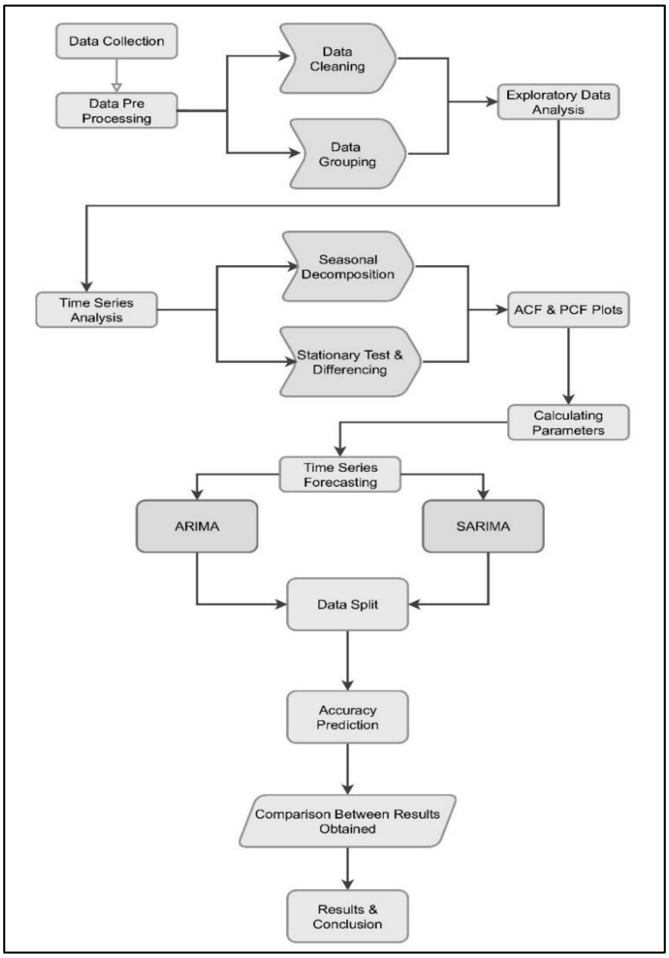

Fig. 1. Proposed Architecture

6. METHODOLOGY

The methodology involves several steps aimed at effectively analyzing time series data and forecasting exchange rates.

Pre-processing: Null values are removed from the dataset to streamline prediction complexity. The data is then grouped on weekly basis.

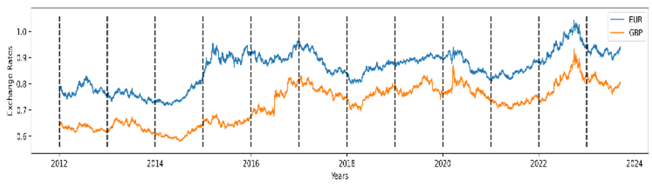

Fig. 2. Visualizing EUR and GBP Trends

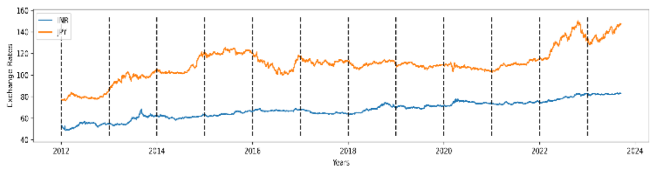

Fig. 3. Visualizing INR and JPY Trends

Time Series Analysis:

Decomposition, Stationarity Tests & Differencing: The dataset spanning a 1-year timeframe is subjected to decomposition to identify trends and seasonal variations.

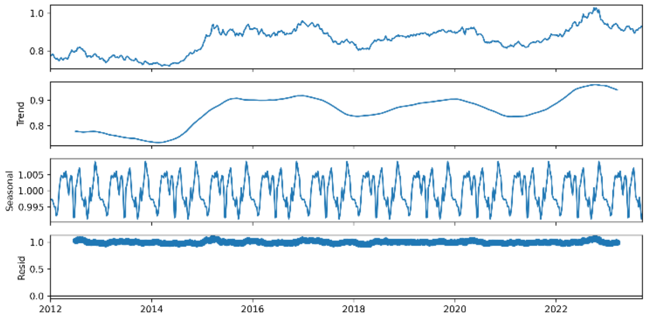

Fig. 4. (a) Seasonal Decomposition USD – EUR rates

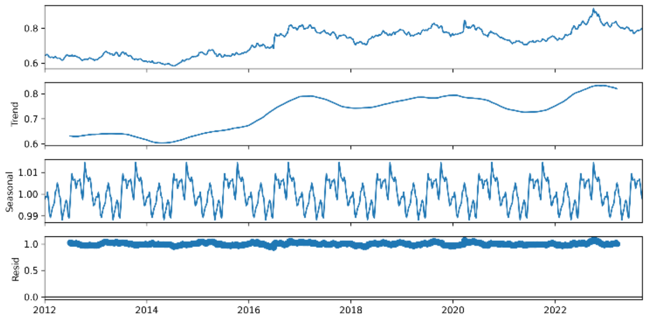

Fig. 4. (b) Seasonal Decomposition USD – GBP rates

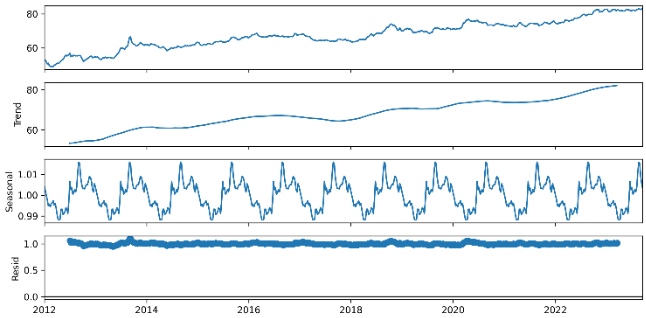

Fig. 4. (c) Seasonal Decomposition USD – INR rates

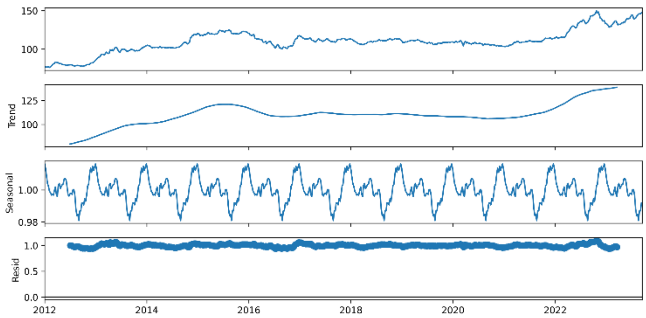

Fig. 4. (d) Seasonal Decomposition USD – JPY rates

In each of the four instances, we've observed the following trends:

Trend: The trend feature depicts a downward curve, seemingly stabilizing before experiencing a slight increase towards the end.

Seasonality: Annually, the seasonal aspect follows a cyclic pattern, culminating towards its peak towards the year's conclusion.

Residuals: Typically, the residual factor maintains a value of one, which aligns logically with our utilization of the multiplicative model.

Stationarity tests, - the Dickey-Fuller test and Rolling Statistics are conducted to ensure the statistical properties of the data remain constant over time.

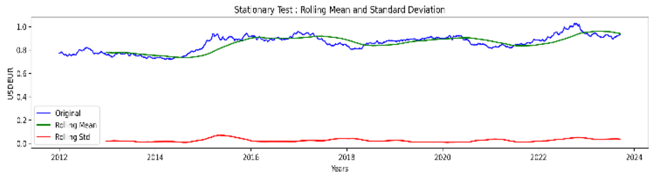

Fig. 5. (a) Rolling Mean & Standard Deviation USD - EUR

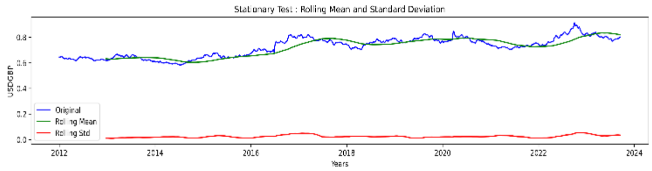

Fig. 5. (b) Rolling Mean & Standard Deviation USD - GBP

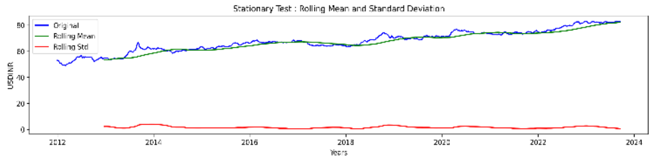

Fig. 5. (c) Rolling Mean & Standard Deviation USD - INR

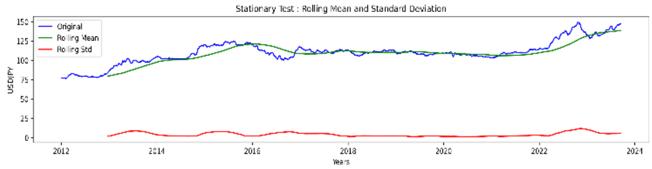

Fig. 5. (d) Rolling Mean & Standard Deviation USD – JPY

Results of Dickey-Fuller Test	
Test Statistic	-1.827307
p-value	0.366991
#Lags Used	5.000000
Number of Observations Used	606.000000
Critical Value (1%)	-3.441187
Critical Value (5%)	-2.866321
Critical Value (10%)	-2.569316

Dickey-Fuller Test Statistics USD – EUR

Results of Dickey-Fuller Test	
Test Statistic	-1.358038
p-value	0.602220
#Lags Used	2.000000
Number of Observations Used	609.000000
Critical Value (1%)	-3.441133
Critical Value (5%)	-2.866298
Critical Value (10%)	-2.569304

Dickey-Fuller Test Statistics USD – GBP

Results of Dickey-Fuller Test	
Test Statistic	-0.977170
p-value	0.761500
#Lags Used	1.000000
Number of Observations Used	610.000000
Critical Value (1%)	-3.441116
Critical Value (5%)	-2.866290
Critical Value (10%)	-2.569300

Dickey-Fuller Test Statistics USD – INR

Results of Dickey-Fuller Test	
Test Statistic	-1.024771
p-value	0.744123
#Lags Used	1.000000
Number of Observations Used	610.000000
Critical Value (1%)	-3.441116
Critical Value (5%)	-2.866290
Critical Value (10%)	-2.569300

Dickey-Fuller Test Statistics USD – JPY

In all four currencies, our observations indicate that -
The time series does not appear to be stationary upon visual inspection.
Rolling statistics: The mean shows a declining trend, while the standard deviation demonstrates relatively minor fluctuations.
The test statistic for the Dickey-Fuller hypothesis surpasses the critical threshold (1%), further confirming the non-stationarity of the time series.

Differencing:
Differencing is used in ARIMA and SARIMA models to transform non-stationary time series data into stationary data.

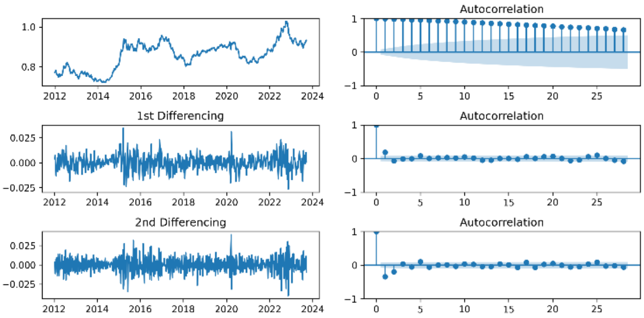

Fig. 6. (a) Differencing USD – EUR rates

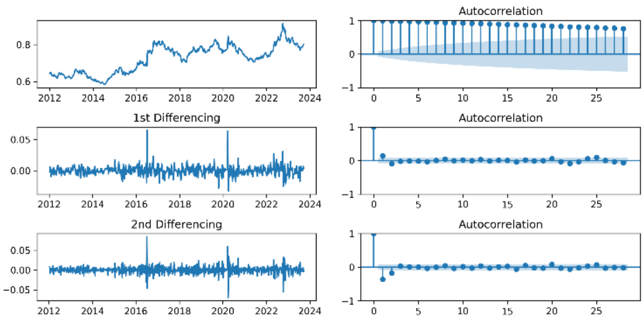

Fig. 6. (b) Differencing USD – GBP rates

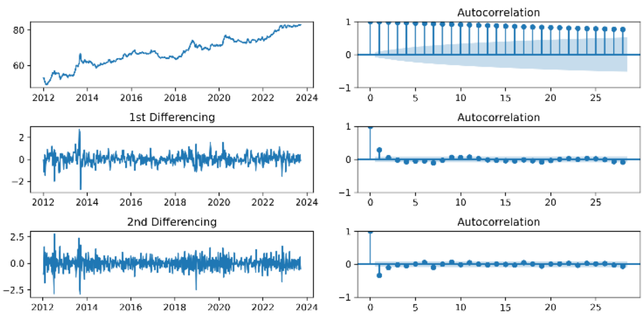

Fig. 6. (c) Differencing USD – INR rates

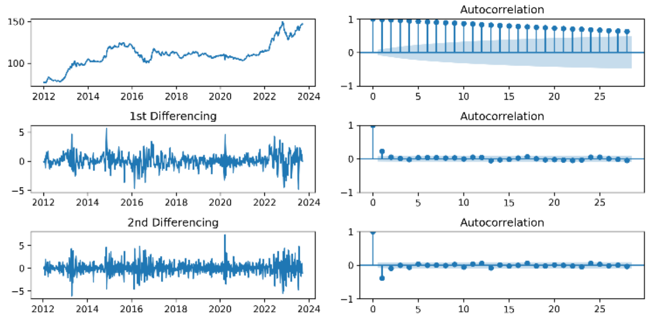

Fig. 6. (d) Differencing USD – JPY rates

By taking differences between consecutive observations, we can eliminate trends or seasonal effects, leaving behind the underlying stationary component of the time series.
After conducting the Dickey-Fuller test again, we analyze the plot and test statistics to verify the stationarity of our data.

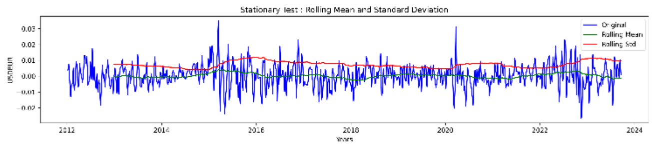

Fig. 7. (a) Rolling Mean & Standard Deviation USD – EUR

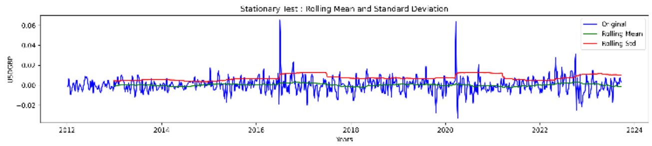

Fig. 7. (b) Rolling Mean & Standard Deviation USD – GBP

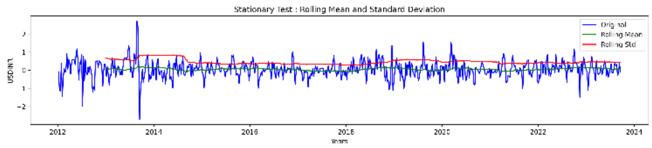

Fig. 7. (c) Rolling Mean & Standard Deviation USD – INR

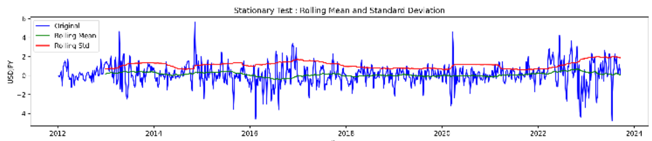

Fig. 7. (d) Rolling Mean & Standard Deviation USD – JPY

The rolling mean and standard deviation values now meet the criteria for stationarity.
With the test statistic falling below the critical value (1%) and the p-value being less than 0.05, we conclude that the time series has achieved stationarity.

ACF and PACF Analysis:
Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots are generated to analyze the correlation between observations at different time points. These plots provide insights into the randomness of the data, its connections, and aid in determining the appropriate parameters for autoregressive (AR) and moving average (MA) models.

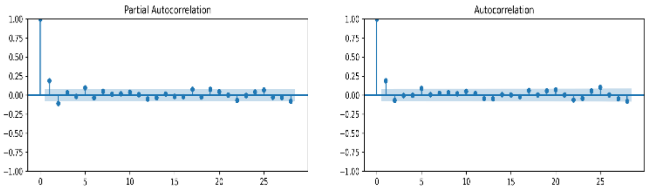

Fig. 8. (a) PACF and ACF plots for USD – EUR rates

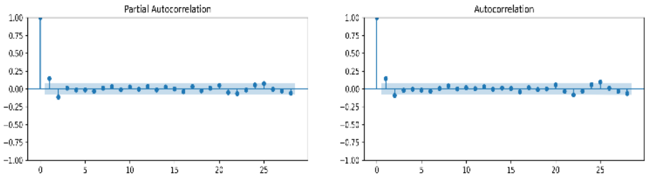

Fig. 8. (b) PACF and ACF plots for USD – GBP rates

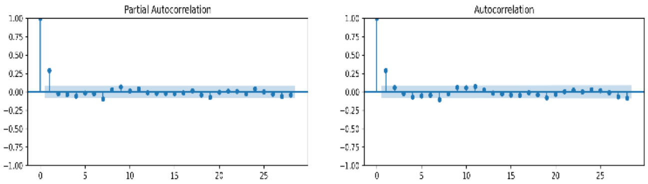

Fig. 8. (c) PACF and ACF plots for USD – INR rates

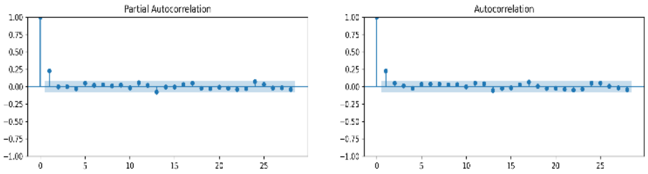

Fig. 8. (d) PACF and ACF plots for USD – JPY rates

For USD to EUR rates, the identified parameters are p = 2, d = 1, and q = 2.
For USD to GBP rates, the determined parameters are p = 2, d = 1, and q = 2.
Concerning USD to INR rates, the determined parameters are p = 2, d = 1, and q = 2.
Regarding USD to JPY rates, the established parameters are p = 1, d = 1, and q = 1.

In each of the four cases, when employing these p, d, and q values in the ARIMA model, the resulting p-value exceeded 0.05. Consequently, we determined the optimal p, d, and q parameters by conducting a grid search, aligning with the p, d, and q values derived from the plotted data.
We'll employ a grid search to pinpoint the combination of parameters that yields the most suitable model for our time series data, prioritizing the attainment of the lowest AIC score. AIC (Akaike Information Criterion) - A lower AIC score indicates a better fit.
Following the grid search conducted for all four currencies, the obtained parameters are as follows:
USD to EUR: p = 2, d = 0, q = 1
USD to GBP: p = 1, d = 0, q = 2
USD to INR: p = 1, d = 0, q = 0
USD to JPY: p = 4, d = 0, q = 2

ARIMA Model Fitting & Evaluation:
Mathematical Equation:

$Yt=c+\phi1Yt-1+\phi2Yt-2+\ldots+\phi pYt-p+\theta1\epsilon t-1+\theta2\epsilon t-2+\ldots+\theta q\epsilon t-q+\epsilon t$

Yt is the value of the time series at time.

c is a constant

$\phi1$, $\phi2$, ϕp are the parameters of the autoregressive (AR) part of the model.

$Yt-1$, $Yt-2$, $Yt-p$ are the lagged values of the time series.

$\theta1$, $\theta2$, θq are the parameters of the moving average (MA) part of the model.

$\epsilon t-1$, $\epsilon t-2$, $\epsilon t-q+\epsilon t$ are the residuals (errors) of the model.

p is the order of the autoregressive part.

q is the order of the moving average part.

d parameter represents the degree of differencing needed to make the time series.

Model Fitting:
The ARIMA model is fitted to the data, and its performance is evaluated using the Akaike Information Criterion (AIC). The lower the AIC score indicates better model fit, and a grid search is conducted to determine the optimal parameters for the ARIMA model.

Now, let's examine the results for each currency obtained by applying the p, d, and q values derived from the grid search method.

Dep. Variable:	USDEUR	No. Observations:	612
Model:	ARIMA(2, 0, 1)	Log Likelihood	2125.046
Date:	Mon, 16 Oct 2023	AIC	-4240.092
Time:	07:46:43	BIC	-4218.008
Sample:	01-01-2012 - 09-17-2023	HQIC	-4231.503
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
const	0.8577	0.034	25.136	0.000	0.791	0.925
ar.L1	0.6704	0.127	5.290	0.000	0.422	0.919
ar.L2	0.3187	0.127	2.519	0.012	0.071	0.567
ma.L1	0.5352	0.115	4.656	0.000	0.310	0.760
sigma2	5.598e-05	2.52e-06	22.220	0.000	5.1e-05	6.09e-05

Ljung-Box (L1) (Q):	0.03	Jarque-Bera (JB):	41.59
Prob(Q):	0.86	Prob(JB):	0.00
Heteroskedasticity (H):	1.05	Skew:	0.15
Prob(H) (two-sided):	0.75	Kurtosis:	4.24

ARIMA Model Fitting Results (USDEUR)

Dep. Variable:	USDGBP	No. Observations:	612
Model:	ARIMA(1, 0, 2)	Log Likelihood	2093.611
Date:	Mon, 16 Oct 2023	AIC	-4177.221
Time:	18:08:51	BIC	-4155.138
Sample:	01-01-2012 - 09-17-2023	HQIC	-4168.632
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
const	0.7232	0.046	15.765	0.000	0.633	0.813
ar.L1	0.9931	0.005	192.493	0.000	0.983	1.003
ma.L1	0.1665	0.031	5.429	0.000	0.106	0.227
ma.L2	-0.0841	0.033	-2.541	0.011	-0.149	-0.019
sigma2	6.204e-05	1.35e-06	45.832	0.000	5.94e-05	6.47e-05

Ljung-Box (L1) (Q):	0.00	Jarque-Bera (JB):	7281.28
Prob(Q):	0.99	Prob(JB):	0.00
Heteroskedasticity (H):	3.24	Skew:	1.94
Prob(H) (two-sided):	0.00	Kurtosis:	19.45

ARIMA Model Fitting Results (USDGBP)

Dep. Variable:	USDINR	No. Observations:	612
Model:	ARIMA(1, 0, 0)	Log Likelihood	-433.546
Date:	Mon, 30 Oct 2023	AIC	873.092
Time:	20:07:03	BIC	886.342
Sample:	01-01-2012 - 09-17-2023	HQIC	878.246
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
const	68.0290	12.440	5.469	0.000	43.647	92.410
ar.L1	0.9993	0.002	417.297	0.000	0.995	1.004
sigma2	0.2389	0.008	30.818	0.000	0.224	0.254

Ljung-Box (L1) (Q):	51.10	Jarque-Bera (JB):	469.84
Prob(Q):	0.00	Prob(JB):	0.00
Heteroskedasticity (H):	0.51	Skew:	0.01
Prob(H) (two-sided):	0.00	Kurtosis:	7.29

ARIMA Model Fitting Results (USDINR)

Dep. Variable:	USDJPY	No. Observations:	612
Model:	ARIMA(4, 0, 2)	Log Likelihood	-953.850
Date:	Mon, 06 Nov 2023	AIC	1923.701
Time:	09:20:46	BIC	1959.035
Sample:	01-01-2012	HQIC	1937.443
	- 09-17-2023		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
const	110.1583	22.635	4.867	0.000	65.794	154.523
ar.L1	-0.4470	0.038	-11.736	0.000	-0.522	-0.372
ar.L2	0.8926	0.027	33.015	0.000	0.840	0.946
ar.L3	0.8005	0.032	24.691	0.000	0.737	0.864
ar.L4	-0.2500	0.032	-7.898	0.000	-0.312	-0.188
ma.L1	1.6867	0.022	75.703	0.000	1.643	1.730
ma.L2	0.9775	0.023	42.055	0.000	0.932	1.023
sigma2	1.3149	0.052	25.279	0.000	1.213	1.417

Ljung-Box (L1) (Q):	0.01	Jarque-Bera (JB):	223.01
Prob(Q):	0.90	Prob(JB):	0.00
Heteroskedasticity (H):	1.63	Skew:	-0.08
Prob(H) (two-sided):	0.00	Kurtosis:	5.95

ARIMA Model Fitting Results (USDJPY)

The residuals depict the variance between the observed values and those predicted by the model. Plotting these residuals allows us to gauge the model's adequacy in fitting the data.

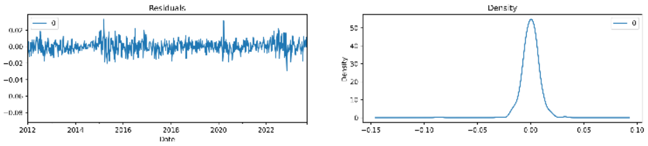

Fig. 9. (a) Residuals for USD – EUR rates.

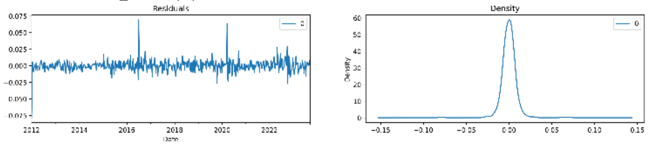

Fig. 9. (a) Residuals for USD – GBP rates.

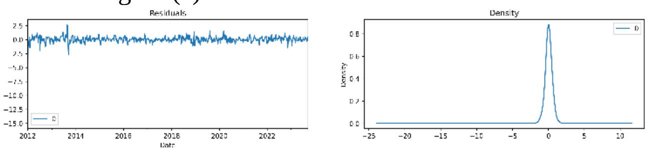

Fig. 9. (a) Residuals for USD – INR rates.

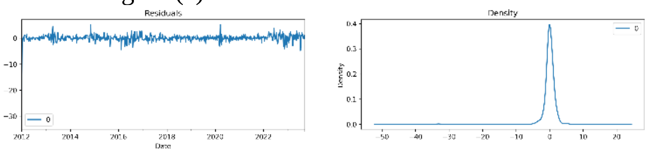

Fig. 9. (a) Residuals for USD – JPY rates.

We've also visualized the predicted values of a model along with confidence intervals to assess how effectively the model captures the underlying patterns in the data and to gain insights into the potential range of future outcomes.
The confidence interval illustrates the probable range within which the true value is expected to lie.

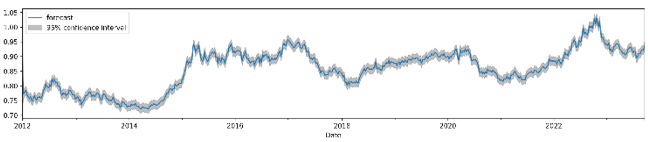
Fig. 10. (a) Confidence Interval for USD – EUR rates.

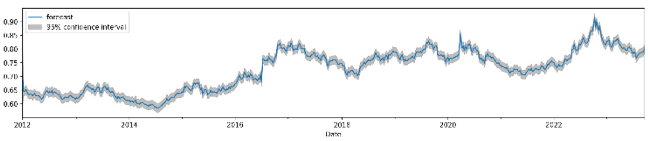
Fig. 10. (b) Confidence Interval for USD – GBP rates.

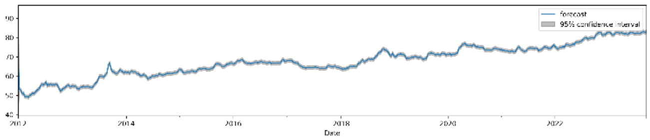
Fig. 10. (c) Confidence Interval for USD – INR rates.

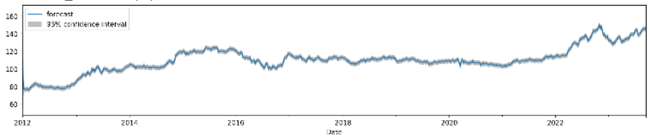
Fig. 10. (d) Confidence Interval for USD – JPY rates.

Model Evaluation:

Train-Test Split: 80% of the data is used as the training set, while 20% data is reserved for testing the models.

Visual Inspection: Graphing the observed values alongside the predicted values.

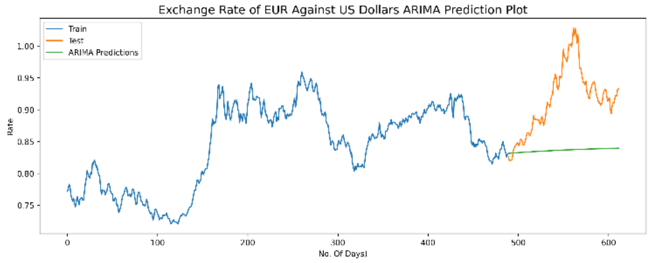

Fig. 11. (a) Prediction Plot for USD – EUR rates.

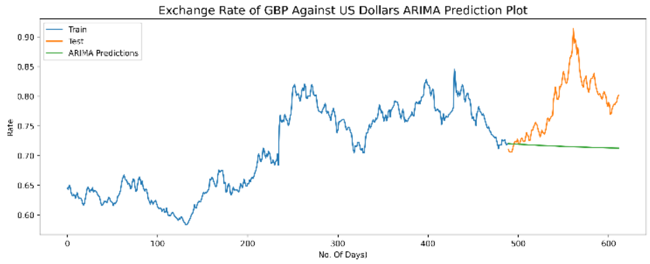

Fig. 11. (b) Prediction Plot for USD – GBP rates

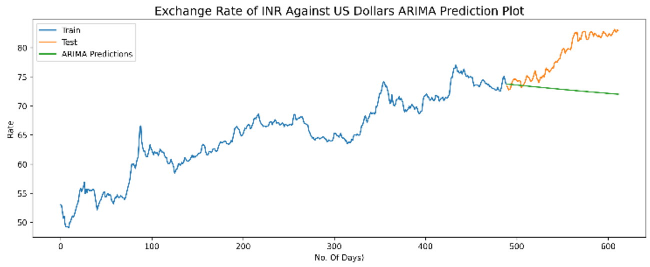

Fig. 11. (c) Prediction Plot for USD – INR rates

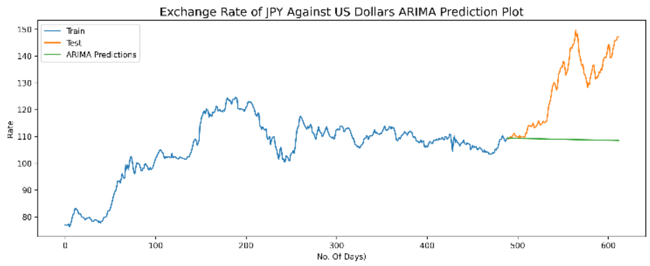

Fig. 11. (d) Prediction Plot for USD – JPY rates.

Assessing forecast accuracy using performance metrics:

Metrics	USDEUR	USDGBP	USDINR	USDJPY
MAPE	9.56%	9.99%	7.90%	17.32%
ME	0.079	0.070	5.67	18.82
MAE	0.080	0.071	5.73	18.83
MPE	9.47%	9.83%	7.81%	17.31%
RMSE	0.093	0.087	6.96	22.90
ACF1	0.973	0.975	0.979	0.975
Corr.	0.679	-0.719	-0.955	-0.887
Min-Max	8.48%	8.73%	7.08%	13.84%

These were the metrics into the overall accuracy and performance of the model in forecasting. Lower values of MAPE, MAE, RMSE, and Min-Max Error indicate better accuracy, while higher values of ACF1 and correlation suggest stronger predictive capability.

SARIMA Model Fitting & Evaluation:
Mathematical Equation:

$Yt=c+\phi 1Yt-1+\phi 2Yt-2+\ldots+\phi pYt-p+\theta 1\epsilon t-1+\theta 2\epsilon t-2+\ldots+\theta q$
$\epsilon t-q+\epsilon t+\phi PYt-m+\theta Q\epsilon t-m$

m is the seasonal period.
ϕP is the seasonal autoregressive parameter.
θQ is the seasonal moving average parameter.

Model Fitting:

Performing a grid search for SARIMA (Seasonal Autoregressive Integrated Moving Average) model parameters based on the obtained non-seasonal parameters (p, d, q) from ARIMA involves searching for the seasonal components of the model. SARIMA extends ARIMA by incorporating seasonal terms.

Now, let's examine the results for each currency obtained by applying the values derived from the grid search method.

SARIMAX Results

Dep. Variable:	USDEUR	No. Observations:	612
Model:	SARIMAX(1, 0, 1)	Log Likelihood	2116.653
Date:	Mon, 16 Oct 2023	AIC	-4227.307
Time:	07:49:01	BIC	-4214.066
Sample:	01-01-2012	HQIC	-4222.156
	- 09-17-2023		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	1.0002	0.000	2369.538	0.000	0.999	1.001
ma.L1	0.2311	0.032	7.269	0.000	0.169	0.293
sigma2	5.662e-05	2.54e-06	22.332	0.000	5.17e-05	6.16e-05

Ljung-Box (L1) (Q):	0.19	Jarque-Bera (JB):	40.77
Prob(Q):	0.67	Prob(JB):	0.00
Heteroskedasticity (H):	1.08	Skew:	0.04
Prob(H) (two-sided):	0.57	Kurtosis:	4.26

SARIMA Model Fitting Results (USDEUR)

SARIMAX Results

Dep. Variable:	USDGBP	No. Observations:	612
Model:	SARIMAX(1, 0, 1)	Log Likelihood	2085.385
Date:	Mon, 16 Oct 2023	AIC	-4164.770
Time:	12:44:28	BIC	-4151.530
Sample:	01-01-2012	HQIC	-4159.620
	- 09-17-2023		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	1.0003	0.001	1883.037	0.000	0.999	1.001
ma.L1	0.1618	0.025	6.449	0.000	0.113	0.211
sigma2	6.276e-05	1.39e-06	45.121	0.000	6e-05	6.55e-05

Ljung-Box (L1) (Q):	0.00	Jarque-Bera (JB):	6449.30
Prob(Q):	0.96	Prob(JB):	0.00
Heteroskedasticity (H):	3.31	Skew:	1.71
Prob(H) (two-sided):	0.00	Kurtosis:	18.56

SARIMA Model Fitting Results (USDGBP)

SARIMAX Results

Dep. Variable:	USDINR	No. Observations:	612
Model:	SARIMAX(0, 1, 1)x(1, 0, 1, 12)	Log Likelihood	-383.581
Date:	Mon, 30 Oct 2023	AIC	775.162
Time:	20:11:09	BIC	792.729
Sample:	01-01-2012	HQIC	782.002
	- 09-17-2023		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ma.L1	0.3039	0.030	10.239	0.000	0.246	0.362
ar.S.L12	-0.5579	0.067	-8.284	0.000	-0.690	-0.426
ma.S.L12	0.6025	0.066	9.076	0.000	0.472	0.733
sigma2	0.2098	0.007	30.133	0.000	0.196	0.223

Ljung-Box (L1) (Q):	0.06	Jarque-Bera (JB):	490.25
Prob(Q):	0.80	Prob(JB):	0.00
Heteroskedasticity (H):	0.58	Skew:	-0.11
Prob(H) (two-sided):	0.00	Kurtosis:	7.43

SARIMA Model Fitting Results (USDINR)

SARIMAX Results

Dep. Variable:	USDJPY	No. Observations:	612
Model:	SARIMAX(4, 0, 2)	Log Likelihood	-2197.141
Date:	Mon, 06 Nov 2023	AIC	4408.282
Time:	09:30:33	BIC	4439.153
Sample:	01-01-2012	HQIC	4420.292
	- 09-17-2023		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-1.5181	0.167	-9.079	0.000	-1.846	-1.190
ar.L2	5.7797	0.309	18.712	0.000	5.174	6.385
ar.L3	-0.8972	0.466	-1.926	0.054	-1.810	0.016
ar.L4	-2.4207	0.296	-8.183	0.000	-3.001	-1.841
ma.L1	-268.1641	4.213	-63.652	0.000	-276.421	-259.907
ma.L2	-62.8421	18.427	-3.410	0.001	-98.959	-26.725
sigma2	0.0003	3.3e-05	10.419	0.000	0.000	0.000

Ljung-Box (L1) (Q):	5.92	Jarque-Bera (JB):	158.20
Prob(Q):	0.01	Prob(JB):	0.00
Heteroskedasticity (H):	1.58	Skew:	0.28
Prob(H) (two-sided):	0.00	Kurtosis:	5.44

SARIMA Model Fitting Results (USDJPY)

SARIMA diagnostics refers to the process of evaluating the performance and adequacy of a (SARIMA) model.

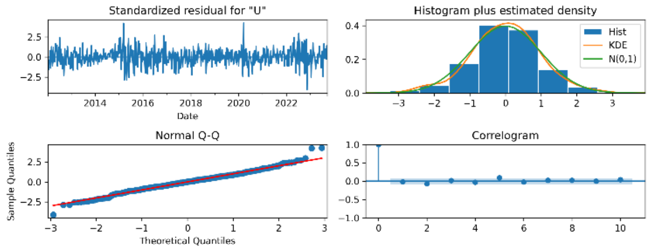

Fig. 12. (a) SARIMA Diagnostics for USD - EUR

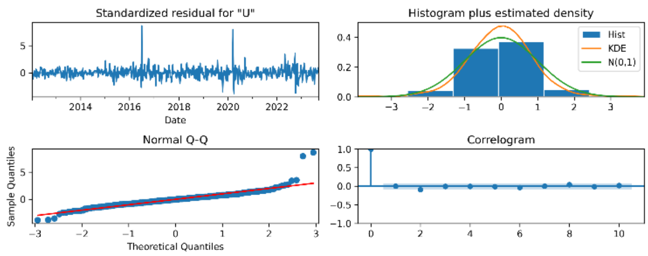

Fig. 12. (b) SARIMA Diagnostics for USD - GBP

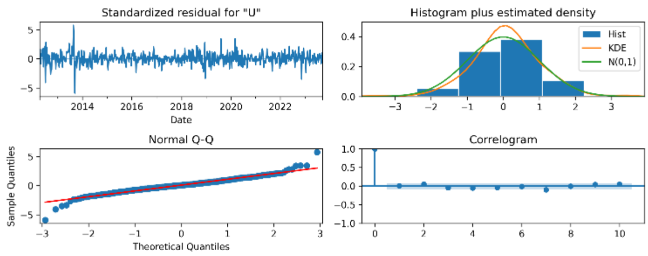

Fig. 12. (c) SARIMA Diagnostics for USD - INR

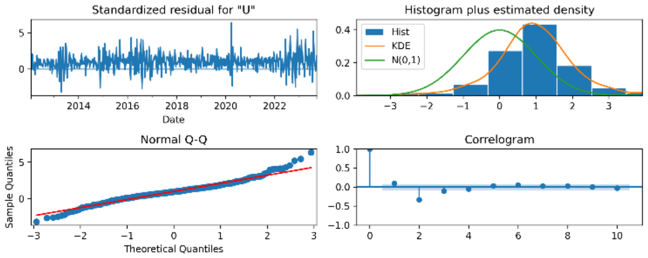

Fig. 12. (d) SARIMA Diagnostics for USD – JPY

Top Left: The residual errors appear to fluctuate around a mean of zero and exhibit uniform variance.
Top Right: The density plot indicates a normal distribution centered around zero.
Bottom Left: Ideally, all data points should align precisely with the red line. Deviations from this alignment may suggest skewness in the distribution.
Bottom Right: The Correlogram (ACF plot) demonstrates that the residual errors are not autocorrelated. Autocorrelation in the residuals would imply the presence of unexplained patterns in the model.

Model Evaluation:
Train-Test Split: 80% of the data is used as the training set, while 20% data is reserved for testing the models.

Visual Inspection: Graphing the observed values alongside the predicted values.

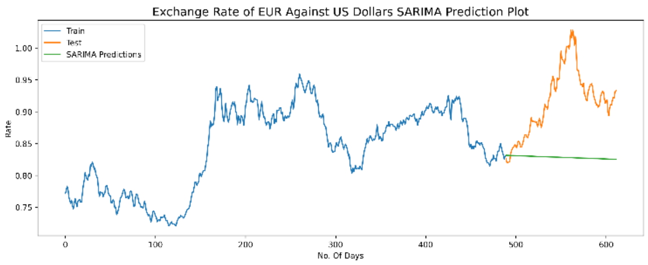

Fig. 13. (a) SARIMA Prediction Plot for USD – EUR rates.

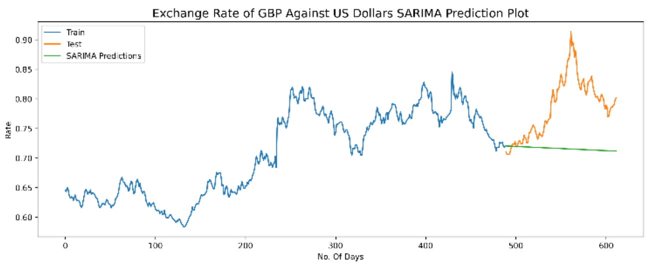

Fig. 13. (b) SARIMA Prediction Plot for USD – GBP rates.

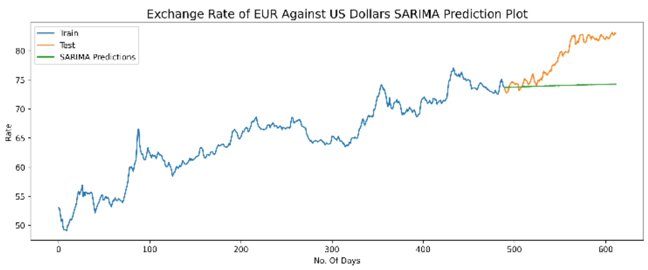

Fig. 13. (c) SARIMA Prediction Plot for USD – INR rates.

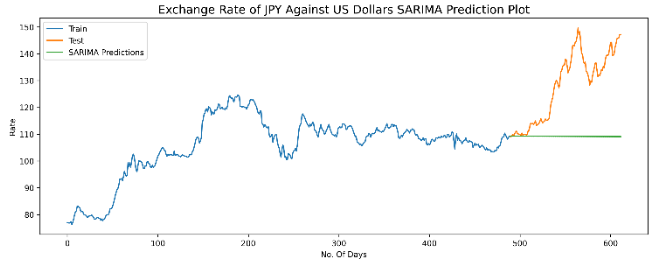

Fig. 13. (d) SARIMA Prediction Plot for USD – JPY rates.

Assessing forecast accuracy using performance metrics:

Metrics	USDEUR	USDGBP	USDINR	USDJPY
MAPE	10.62%	9.96%	6.20%	17.00%
ME	0.087	0.070	4.52	18.55
MAE	0.088	0.071	4.59	18.56
MPE	10.52%	9.80%	6.10%	17.00%
RMSE	0.102	0.087	5.65	22.57
ACF1	0.973	0.975	0.979	0.975
Corr.	-0.596	-0.666	0.953	-0.831
Min-Max	9.32%	8.70%	5.67%	13.64%

These were the same metrics into the overall accuracy and performance of your model in forecasting SARIMA as well.

Performance Comparison:
A comparison plot is generated to visually assess and contrast the performance of both models in forecasting exchange rates, utilizing their respective metrics.

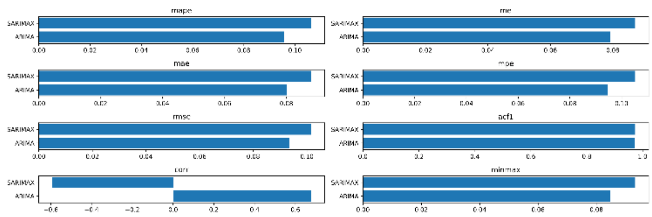

Fig. 14. (a) ARIMA vs SARIMA Performance Comparison (USDEUR)

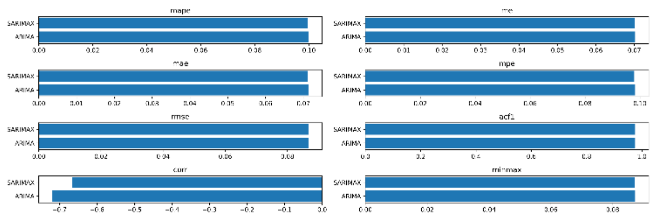

Fig. 14. (b) ARIMA vs SARIMA Performance Comparison (USDGBP)

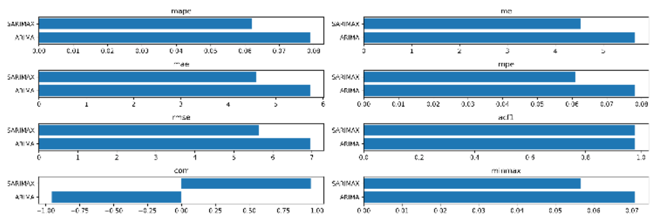

Fig. 14. (c) ARIMA vs SARIMA Performance Comparison (USDINR)

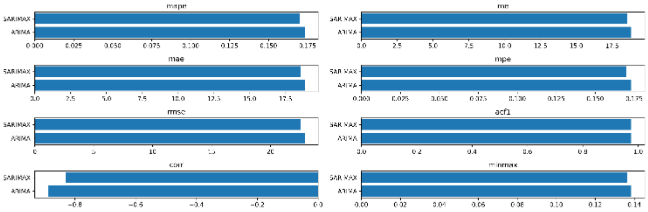

Fig. 14. (d) ARIMA vs SARIMA Performance Comparison (USDJPY)

Performance Testing: To fortify the reliability of our models, we'll subject them to rigorous testing with varying data sizes and historical events. This will help assess their performance under different conditions. By testing across different data scales, we'll gauge their scalability and adaptability. Introducing historical events into the analysis will evaluate their ability to respond to real-world fluctuations. Cross-validation techniques will ensure consistent performance, while sensitivity analysis will pinpoint areas for improvement. Finally, out-of-sample testing will validate their predictive capabilities in practical scenarios. Through these measures, we aim to bolster the models' effectiveness in forecasting exchange rates.

Defined Test Case Scenarios:
Case 1 - This scenario revolves around implementing the model on one year of data, coinciding with the occurrence of the COVID-19 event (1 Year: 2020)
Cases 2 to 5 will primarily explore the model's performance as we incrementally expand the dataset.
Case 2 - 2 Years: 2012, 2013
Case 3 - 4 Years: 2012, 2013, 2014, 2015
Case 4 - 6 Years: 2012, 2013, 2014, 2015, 2016, 2017
Case 5 - 8 Years: 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019

7. RESULT ANALYSIS

In case of ARIMA,

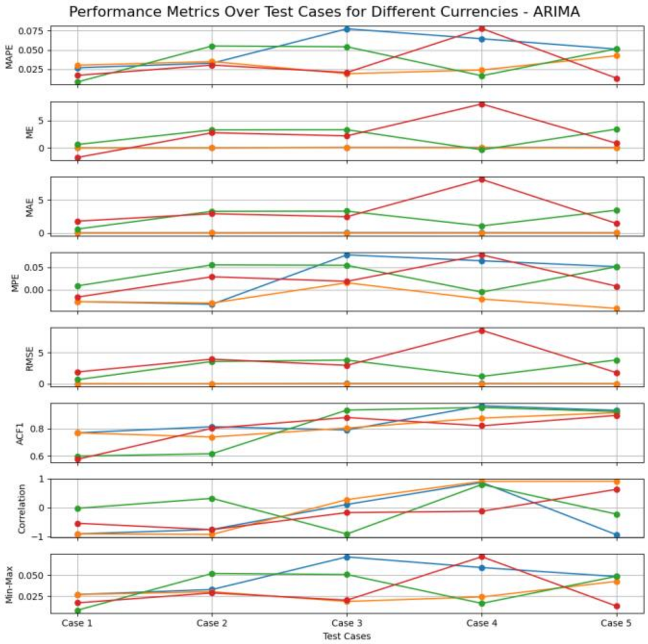

Fig. 15. (a) ARIMA Testing Results

In case of SARIMA,

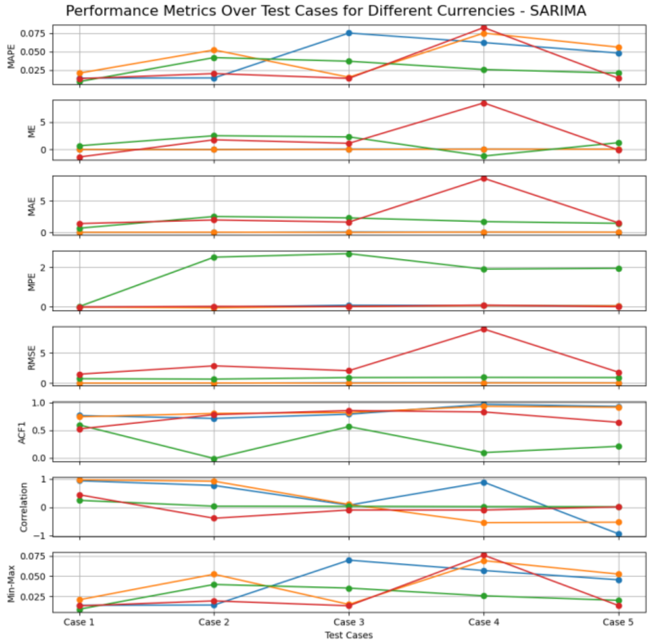

Fig. 15. (b) SARIMA Testing Results

Small Datasets:
ARIMA and SARIMA models excelled with very small datasets, making highly accurate predictions by leveraging limited but relevant historical data. Their strong performance in such scenarios highlights their ability to forecast immediate trends effectively.
Large Datasets:
With larger datasets, the models continued to perform well, effectively utilizing extensive historical data to produce comprehensive and reliable predictions. This demonstrates the robustness and scalability of ARIMA and SARIMA, proving their capability in handling complex forecasting tasks.
Medium-Sized Datasets:
The models showed satisfactory performance with medium-sized datasets but faced challenges in capturing the data nuances. These datasets, being transitional, were neither small enough to emphasize immediate trends nor large enough for a complete historical context, leading to less precise predictions. However, the models still provided valuable insights, indicating potential areas for improvement.

The study reveals the flexibility and robustness of ARIMA and SARIMA models, making them suitable for various forecasting applications. Despite challenges with medium-sized datasets, the overall results are promising. These models can support strategic decision-making in finance and other sectors. Continuous refinement and hybrid approaches can further enhance their predictive accuracy and reliability, paving the way for better economic forecasting.

8. CONCLUSION

Utilizing the Time Series Model Algorithm, we used both SARIMA and ARIMA.
First, we ensured that all the pertinent parameters needed for computation—p, d, and q for ARIMA and P, D, Q, m in addition to p, d, and q for SARIMA—had been determined.
Following training and testing of both models, we discovered that ARIMA outperformed SARIMA. However, the two

models functioned pretty much in the same way. The comparison chart is visible.

We obtained between 75 and 80 percent accuracy for both models after training and testing data throughout the whole data set, that is, 80% training and 20% testing.

After that, we chose a few test scenarios and put both models to the test. The results showed that, for smaller data sets, accuracy was above 90%, but that accuracy also gradually dropped as the data set grew.

It is evident from the fact that both models perform well on smaller data sets that the ARIMA and SARIMA models will be most effective on relatively recent historical data. This makes a lot of sense in our situation when forecasting foreign currency rates because recent events or history do cause rate movements.

However, in the case of a large dataset with no significant factors affecting the rates over the years, the model provided satisfactory and commendable results.

DATA AVAILABILITY STATEMENT

The data supporting the findings of this study are openly available in Yahoo Finance at https://finance.yahoo.com/currencies/ without restrictions. Users can freely access and download the datasets for further analysis or replication of the results presented in this paper.

ACKNOWLEDGEMENT

The secret to success is inspiration and direction. I want to express my gratitude to all of my sources of inspiration. My project advisor, Dr. A. Pande, deserves my sincere gratitude and admiration for his inspiration, priceless assistance, prompt assistance, clear recommendations, and great supervision that enabled us to comprehend and meet the project's objectives. His specific instructions and insightful criticism have been really helpful to us in completing this assignment successfully. We would like to express our heartfelt gratitude to all of the professors for their insightful advice and guidance during the project's design process. We find it challenging to recognize each of them individually because of the value of their efforts in so many different ways.

DECLARATION

This manuscript represents original work and is not being submitted elsewhere for consideration. All authors contributed significantly to the study and preparation of the manuscript. The authors declare no conflicts of interest related to this study. The study was conducted in accordance with ethical guidelines, and all participants provided informed consent. This work received no external funding. The data that support the findings of this study are available from the trusted source upon reasonable request (https://finance.yahoo.com/currencies/)

REFERENCES

[1] Biswas A, Uday IA, Rahat KM, Akter MS, Mahdy MRC (2023) – “Forecasting the United State Dollar(USD)/Bangladeshi Taka (BDT) exchange rate with deep learning models: Inclusion of macroeconomic factors influencing the currency exchange rates”. PLoS ONE 18(2): e0279602. https://doi.org/10.1371/journal.pone.0279602

[2] Ayitey Junior, M., Appiahene, P., Appiah, O. et al. “Forex market forecasting using machine learning : Systematic Literature Review and meta-analysis”. J Big Data 10, 9 (2023). https://doi.org/10.1186/s40537-022-00676-2

[3] T. Soni Madhulatha, Md. Atheeq Sultan Ghori, - “Foreign Exchange Rates Prediction for Time-series Data using Advanced Q-sensing Model” (2022) - https://ceur-ws.org/Vol-3335/DLQ_short1.pdf

[4] Surindar Gopalrao Wawale , Aadarsh Bisht, Sonali Vyas, Chutimon Narawish, Samrat Ray – “An overview: Modeling and forecasting of time series data using different techniques in reference to human stress” - Neuroscience Informatics, Volume 2, Issue 3 (2021) https://doi.org/10.1016/j.neuri.2022.100052

[5] Sohail Akhtar, Maham Ramzan, Sajid Shah, Iftikhar Ahmad, Muhammad Imran Khan, Sadique Ahmad, Mohammed A. El-Affendi, Humera Qureshi, "Forecasting Exchange Rate of Pakistan Using Time Series Analysis", Mathematical Problems in Engineering, vol. 2022, Article ID 9108580, 11 pages, 2022. https://doi.org/10.1155/2022/9108580

[6] Ting Heng Sheng, Mohd Saifullah Rusiman, Norziha Che Him, Suliadi Firdaus Sufahani, Efendi Nasibov, “Analysis of time series for Malaysian currency exchange rate to the United States currency”, AIP Conference Proceedings 2355, 060012 (2021) https://doi.org/10.1063/5.0053700

[7] Yıldırım, D.C., Toroslu, I.H. & Fiore, U. “Forecasting directional movement of Forex data using LSTM with technical and macroeconomic indicators”. Financ Innov 7, 1 (2021). https://doi.org/10.1186/s40854-020-00220-2

[8] Putri, K. S., & Halim, S. (2020). Currency movement forecasting using time series analysis and long short-term memory. International Journal of Industrial Optimization, 1(2), 71–80. https://doi.org/10.12928/ijio.v1i2.2490

[9] Lemonjava, Givi. (2019). “TIME SERIES MODELS FOR FORECASTING EXCHANGE RATES”. Globalization and Business. 4. 149-160. 10.35945/gb.2019.08.020.

[10] Tlegenova, Daniya. (2015). Forecasting Exchange Rates Using Time Series Analysis: The sample of the currency of Kazakhstan.

[11] Nanayakkara, Sajeeka & Chandrasekara, Vasana & Jayasundara, Mangalika. (2014). Forecasting Exchange Rates using Time Series and Neural Network Approaches. European International Journal of Science and Technology. 3. 2.

[12] Daniya Tlegenova (2013) - “Forecasting Exchange Rates Using Time Series Analysis : The sample of the currency of Kazakhstan”