Leveraging Machine Learning for Exchange Rate Prediction: A Business and Financial Management Perspective in Nigeria

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ABSTRACT

Purpose
The continuous availability of historical data for asset prices propelled more attention of researchers to use analytical algorithms to study the evolution of prices. This paper aims to use four machine learning algorithms to forecast the exchange rates in Nigeria.

Methodology
The paper employs Logistic Linear Regression, Support Vector Machine, Random Forest, and XGBoost algorithms to predict the univariate time series of Nigeria's exchange rate against the US dollar, using both hourly and daily data.

Findings
The findings indicate that the Random Forest (RF) model outperforms other approaches in predicting Nigeria's exchange rate against the US dollar, demonstrating the lowest prediction errors (MAE, MSE, RMSE, and MAPE). RF remains the most accurate model across both hourly and daily frequencies, with XGBoost emerging as the second-best performer.

Conclusions
This study applies machine learning models to enhance exchange rate prediction, demonstrating that the exchange rate series is not sensitive to data periodicity. The findings provide valuable insights for stakeholders in the foreign exchange market, aiding policymakers in selecting the most accurate forecasting techniques.

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1. Introduction

The exchange rate plays a crucial role in determining the value of foreign trade (Nag & Mitra, 2002). Along with other economic indicators such as money supply, consumer price index, interest rates, and inflation, the currency exchange rate is one of the most significant determinants of a country's overall economic health. Due to continuous demand pressures, exchange rates often fluctuate, leading to economic implications, including drastic effects on the prices of goods. Exchange rate volatility influences the growth of international trade markets, impacting economies worldwide. Additionally, exchange rates assist both private and government-owned businesses in evaluating risk and maximizing returns.

The literature identifies several factors that contribute to sudden fluctuations in exchange rates. Similar to stocks and other financial assets, exchange rates respond to macroeconomic factors and monetary policies (Hausman & Wongswan, 2011; Chatrath et al., 2014; Ben-Omrane & Savaser, 2016; Boudt et al., 2019; Indriawana et al., 2021). Given that exchange rate movements are unpredictable, accurately forecasting exchange rates is of great importance to various stakeholders (Ca' Zorzi et al., 2017). Predicting exchange rate returns is crucial for financial stability, reserve management, market regulation, and the overall monetary policy framework. Accurate predictions provide valuable insights for various stakeholders in the foreign exchange market, enabling them to make informed decisions. Such predictions facilitate comparisons between forecasting techniques, allowing stakeholders to identify the most accurate and effective method. The primary objective of this study is to evaluate and compare the accuracy and performance of different machine learning models in predicting exchange rates. This study employs clustering algorithms as an effective analytical tool to examine the evolution of exchange rates in Nigeria.

The continuous availability of historical asset price data in many economies has attracted the attention of market participants and researchers, leading to the use of various analytical algorithms to study price movements. Historical data is particularly relevant for stakeholders in analyzing and forecasting exchange rate trends. Implementing predictive models in exchange rate analysis aims to optimize gains while ensuring the protection of investors' funds. However, analyzing exchange rate time series presents challenges, including whether exchange rates behave similarly across different economic sectors and industries. This study employs four machine learning algorithms—logistic regression, support vector machines (SVM), random forest (RF), and XGBoost—to train and validate hourly exchange rate data. The models are implemented using Python's Scikit-learn (SKlearn) library. Model evaluation is conducted by computing statistical metrics that provide insights into the predictive performance of each model.

The analysis, based on hourly exchange rates, reveals that the random forest (RF) model outperforms other models, demonstrating the lowest prediction errors (MAE, MSE, RMSE, and MAPE). Furthermore, the results indicate that irrespective of the data frequency used, RF consistently exhibits superior predictive accuracy. It emerges as the optimal model for both daily and hourly exchange rate forecasting, with XGBoost ranking as the second-best option. This finding suggests that the trained predictive models are not highly sensitive to data periodicity.

The remainder of the paper is structured as follows: Section 2 presents a brief empirical review. Section 3 discusses the methodology, summarizing the forecasting models and measures of forecast accuracy. Section 4 presents the results, including summary statistics, stationarity tests, and forecast accuracy evaluations. Finally, Section 5 provides the conclusions.

2. Literature Review

Over the years, extensive studies have employed various approaches to significantly contribute to the literature on forecasting exchange rates. Researchers and academicians have explored diverse techniques to predict exchange rates between currencies of different countries. Kabari and Nwamae (2019) conducted research on predicting exchange rates of various currencies against the Nigerian Naira using multiple linear regression. Rodrigues et al. (2020) analyzed currency exchange rate behavior using singular spectrum analysis (SSA) and artificial neural networks (ANN), finding that a hybrid method combining SSA and ANN yielded the best performance. These studies collectively contribute to the understanding and prediction of exchange rate dynamics, offering valuable insights for financial decision-making.

Gbadebo et al. (2022) suggested utilizing model-based and univariate-based methods for forecasting volatile assets. Ledisi et al. (2020) focused their analyses on the exchange rates of the British Pound, US Dollar, and Euro against the Naira, sourcing their exchange rate data from the Central Bank of Nigeria. They evaluated the performance of their algorithms using metrics such as mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and the coefficient of determination (R-squared score), ultimately comparing the performances of these algorithms in forecasting exchange rates. Additionally, Olanloye et al. (2019) established in their related work that polynomial models predict exchange rates better than exponential models, with the polynomial model outperforming existing ones. They further predicted the exchange rate of the Naira from 1950 to 2050 on a yearly basis, concluding that by 2050, one American dollar would be equivalent to ₦800. The implementation of machine learning in this research was carried out using MATLAB.

Qu and Zhao (2019) demonstrated the efficacy of long short-term memory (LSTM) neural network models in deep learning for predicting foreign exchange prices. Through technical analysis, they compared two deep learning models: the LSTM neural network and the recurrent neural network (RNN). Their findings affirmed that the LSTM model outperformed the RNN model in terms of accuracy. Islam and Hossain (2020) presented a new hybrid model comprising the gated recurrent unit (GRU) and LSTM for forecasting exchange rates. Their results showed that the combination of these models predicted exchange rates more accurately compared to using GRU or LSTM models alone. These studies provide valuable insights into the effectiveness of deep learning models and hybrid approaches in forecasting exchange rates, contributing to the understanding and improvement of predictive models in the financial domain.

The literature on exchange rate movement remains extensive. A survey of available reviews shows that most evidence centers on factors that explain the dynamic behavior of exchange rates (Gbadebo et al., 2021) and on forecasting exchange rates. Due to the nature of the foreign exchange market in Nigeria, the exchange rate is identified as sensitive to macroeconomic factors (citation missing), financial assets (Oladapo et al., 2017; Bala-Sani & Hassan, 2018), reserve stocks (Nwachukwu et al., 2016; Kalu et al., 2019), and official intervention (Dayyabu et al., 2016). Announcement dates targeted at the behavior of exchange rates are also employed in research. Farhan and Fakhir (2019) aimed to identify the most accurate model for predicting the Iraqi Dinar's exchange rates against the US Dollar from 2008 to 2017. The following techniques were used for this purpose: time-series analysis with the Box-Jenkins method. The RMSE and MAE were used to compare the predictions made by the models. The ARIMA (1,1,1) model, a reliable technique for calculating exchange rates, generated the best forecasts.

Febriawan et al. (2023) emphasized the importance of forecasting the value of the Rupiah against the US Dollar, as the US Dollar serves as the global standard currency. Their study aimed to identify the optimal model, forecast the selling rate of the Rupiah against the US Dollar, and examine the characteristics of the daily selling rate. They used daily data from November 2020 to January 2023, with training data spanning November 2020 to November 2022 and testing data covering November 2022 to January 2023. The ARIMA (2,1,2) model was identified as the best, given its white-noise residuals, significant parameters, and lowest MSE and mean absolute percentage error (MAPE) values. The forecasted results for January 20–31, 2023, revealed that the highest selling price was Rp. 15,932.4 on January 30, while the lowest was Rp. 15,901.9 on January 20, with an average of Rp. 15,919.4. These findings assist exporters and importers in evaluating their business operations.

Mustapha et al. (2021) sourced monthly data on Nigeria from the Central Bank of Nigeria (CBN) Statistical Bulletin, covering the period from January 1981 to December 2018. They applied the seasonal autoregressive integrated moving average (SARIMA) model, an adaptation of the Box-Jenkins methodology. Based on AIC and BIC values, SARIMA (0,1,1) × (1,1,1)12 was selected from 456 data points as the optimal model. Using sample data for 2019, the estimated model was found sufficient for forecasting purposes. Given that the study predicted a decline in the value of the Naira following a seasonal pattern, the authors recommended that monetary policymakers consider the seasonal component when formulating economic stabilization strategies. Etuk (2013) employed a seven-day differencing method, which produced a new series that exhibited no obvious seasonality and an overall slightly negative trend. The results indicated that the model included a seasonal moving average component and a product of two moving average components, both of order one—one seasonal and one non-seasonal. The suggested SARIMA model was (0,1,1) × (0,1,1)7. Fitting it to the data demonstrated its suitability.

Several other studies have applied ARIMA and GARCH models for exchange rate forecasting (Mohammed & Abdulmuhaymin, 2016; Onasanya et al., 2014; Awoyemi & Alagbe, 2011; David & Augustine, 2018). For instance, Mohammed and Abdulmuhaymin (2016) analyzed the Nigerian Naira–US Dollar exchange rate using data from 1972 to 2014 and identified ARIMA (0,2,1) as the best-fitting model. Awoyemi and Alagbe (2011) used the GARCH model to study the volatility of the Naira–US Dollar and Naira–British Pound Sterling exchange rates. Their study, which covered the period from 2006 to 2010, aimed to help the government manage short-term exposure to exchange rate volatility and provide investors with insights into future currency behavior. Similarly, David et al. (2016) applied GARCH and asymmetric variance models to analyze the Naira's exchange rate against four major currencies. Their findings indicated that volatility is highly persistent, and the asymmetric model performed better than the symmetric GARCH model. Saeed and Tularam (2016) compared various time-series models, including Holt-Winters (HW), ARIMA, and exponential smoothing (ES), to assess their performance in forecasting oil prices. Their results indicated that the ARIMA (2,1,2) model outperformed others, making it the preferred choice for forecasting in the oil market.

Overall, the literature demonstrates the effectiveness of ARIMA, SARIMA, GARCH, and deep learning-based models in exchange rate forecasting. The selection of an optimal model depends on factors such as stationarity, residual analysis, and forecast accuracy metrics. Future research should explore hybrid models and deep learning approaches for improved predictive accuracy.

3. Methodology

3.1. Pre-Tests

Preliminary requirements including basic statistics, (Seasonal Trend based on Loess) STL decomposition, and stationarity tests are completed before training and validating the log-transformed exchange rate series. The STL decomposition adopts a non-parametric algorithm that iterates loess smoother to refine y_t into 3 components. y_t consists of a trend (T_t), a seasonality (S_t), and an irregularity (l_t). The STL assumes S_t has the same cycle periodically. The cycle adopts a spectral analysis that shows the characteristics of oscillations of different wavelengths. The SLT split is given by Equation 1 (additive) and Equation 2 (multiplicative split).

$$y_t = T_t + S_t + l_t \quad (1)$$
$$y_t = T_t * S_t * l_t \quad (2)$$

The spectrum of a process y_t with an autocorrelation function (ω_τ) where, $\sum_\tau^n |\omega_\tau| < \infty$ is denoted $y(\omega_\tau)$, and $y(\omega_\tau) = \omega + 2\sum_{\tau=1}^{\infty} \omega_\tau \cos(2\pi\omega\tau)$.

The stationarity test, based on the unit root procedure, establishes the data-generating process and the order of integration. The paper administers both ADF (Augmented Dickey-Fuller) and KPSS (Kwiatkowski-Phillips-Schmidt-Shin) tests. For the exchange rate series denoted as z_t, ADF tests unit root by assuming z_t follows a stochastic process defined by equation (3):

$$z_t = a_0 + \varphi z_{t-1} + \sum_{i=1}^{p-1} \delta_i \Delta z_{t-i} + \Omega_t \quad (3)$$

Where p (Ω_t) is the lag length (Gaussian error). Equation (1), estimated using the least square, computes the ADF statistic $\tau_{ADF} = \hat{\varphi}_T - 1/se(\hat{\varphi}_T)$ and its standard error $\hat{\varphi}_T = se(\hat{\varphi}_T)$. ADF tests the null of non-stationarity of z_t (i.e., $H_0\colon \varphi = 1$) against the alternative of stationarity (i.e., $\varphi > 1$). The test is rejected if τ_{ADF} exceeds the critical value from a limiting distribution.

KPSS test assumes that z_t follows a $\text{ARlMA}(0,1,1)$ process defined by equation (4):

$$\Delta z_t = \theta_0 + a_t - \theta a_t - 1 \quad (4)$$

Equation (2), estimated using the least square, computes the KPSS test statistics, $\tau_{\text{KPSS}} = T^{-2}\sum_1^T \hat{S}_t^2 / \hat{\sigma}_\ell^2$. Note that $\hat{\sigma}_\ell^2$ is a consistent estimator of the long-run variance. KPSS tests the null of stationarity of z_t against the alternative of non-stationarity. The null is rejected if the statistics (τ_{KPSS}) exceeds the critical value reported.

The paper estimates the ML models used for the forecasts. The performances of the models are compared using forecast accuracy metrics such as mean absolute error (MAE); mean squared error (MSE); root mean squared error (RMSE); R-squared (R^2) score; mean absolute percentage error (MAPE). The measures are employed to make appropriate judgment on the best forecast model. Table 3.1 describes the predictive accuracy measures.

Lastly, the paper confirms whether the forecast is sensitive to the choice of the exchange rate frequency used. Hence, an alternative data frequency – the daily series of the exchange rate was observed, trained and validated accordingly.

Table 3.1.Predictive accuracy measures

Accuracy Measure	Accuracy Scale
MAE	$\frac{1}{m}\sum_{t=1}^{m}\lvert e_t\rvert$
MSE	$\frac{1}{n}\sum_{t}^{n}(y_t - \widehat{y_t})^2$
RMSE	$\left(\frac{1}{m}\sum_{t=1}^{m}(e_t)^2\right)^{1/2}$
R^2(score)	$1 - \frac{\sum_t^n(\widehat{y_t} - y_t)^2}{\sum_t^n(y_t - \overline{y_t})^2}$
MAPE	$\frac{100}{m}\sum_{t=1}^{m}\lvert\frac{e_t}{y_t}\rvert$

Note: mean absolute error (MAE); mean squared error (MSE); root mean squared error (RMSE); R-squared (R^2) score; mean absolute percentage error (MAPE).

Source: Author's own elaboration

3.2. Forecasting Models

3.2.1 Logistics Linear Regression

The logistic linear regression (LLR) offers clear coefficients that illuminate how each independent variable influences the dependent variable, providing insight into the underlying dynamics driving exchange rate fluctuations. LLR is simple to implement and serves as a foundation for more complex algorithms. The dependent variable y_i takes the values of 1 and 0 with p_i and $1 - p_i$ probabilities and has a Bernoulli probability density. Considering the situation where the dependent variable is equal to (5):

$$P(y_i = 1) = p_i = \frac{1}{1+\mathrm{e}^{-x\beta}} \quad (5)$$

is obtained. Here β is (k +1)×1 dimensional parameter vector and **x**, k + 1 dimensional explanatory variable matrix. For y = 1, the odds ratio can be shown with:

$$\frac{P(y=1)}{1-P(y=1)} = \frac{p_i}{1-p_i} \quad (6)$$

By using the logarithm of the odds ratio value

$$\log it(y_i = 1) = \ln\frac{p_i}{1-p_i} = \mathbf{x}\boldsymbol{\beta} \quad (7)$$

y_i, (i= $1, 2, \ldots, n$) are labels to data (supervised learning) and **x** are input training vector.

3.2.2. Support Vector Regression

Support Vector Regression (SVR) offers a promising avenue for predicting the exchange rate between the Nigerian Naira and the US Dollar. SVR draws upon principles derived from linear regression, thereby extending its utility and adaptability to various modeling scenarios within the realm of finance. The nonlinear nature of the exchange rates makes the SVR suitable for this task. SVR achieves this flexibility through the use of kernel functions, which map the input data into higher-dimensional spaces where linear relationships is more apparent. The problem is written as finding the hyperplane that minimises training errors through slack variables

$$\min_{\omega,b,\xi} 0.5\omega^T\omega + C\sum_{i=1}^{m} \xi_i$$
$$\text{const: } y_i(\langle\omega, x_i\rangle + b) \geq 1 - \xi_i; \xi_i > 0\ (i = 1, \ldots, m) \quad (8)$$

Where, ω are the coefficients of the hyperplane, b is the bias term, ξ_i are slack variables, ε is margin of tolerance and $y_i(\langle\omega, x_i\rangle)$ is the mapping of input (x_i) into a higher-dimensional space.

3.2.3. Random Forest

When it comes to predicting exchange rates, the Random Forest (RFs) algorithm emerges as a robust and versatile tool in the realm of machine learning. Leveraging a powerful tree learning technique, RFs construct a multitude of Decision Trees during the training phase, each based on a random subset of the dataset and features. During prediction, the algorithm aggregates the outputs of all trees, employing either a voting mechanism for classification tasks or averaging for regression tasks. With their proven ability to deliver reliable forecasts across diverse environments, RFs stand as a cornerstone in the quest to predict exchange rates accurately. The random forest (regression) predictor is defined as:

$$\hat{f}_{\mathrm{rf}}^{B}(x) = \frac{1}{B}\sum_{b=1}^{B} T(x; \Theta_b) \quad (9)$$

B is the number of trees $\{T(x; \Theta_b)\}_1^B$ grown, Θ_b characterizes the b the random forest tree in terms of split variables, cutpoints at each node, and terminal-node values. Intuitively, reducing m will reduce the correlation between any pair of trees.

3.2.4. XGBoost

XGBoost, also referred to as extreme gradient boosting, is engineered for efficient and scalable training of data. The machine learning model harnesses the power of optimized distributed gradient boosting. This ensemble learning method amalgamates the predictions of multiple weak models culminating in a robust and accurate prediction for exchange rate fluctuations. XGBoost has garnered widespread acclaim in machine learning, owing to its prowess in handling large datasets and delivering state-of-the-art performance across various tasks. It emerges as a cornerstone in the quest to forecast exchange rates accurately, offering not only scalability and efficiency but also robust handling of missing data, culminating in reliable predictions essential for financial decision-making. XGBoost has some features, including a novel distributed weighted quantile sketch algorithm for weighted data, sparsity-aware for missing values, and a cache-aware algorithm for large datasets. The objective function of XGBoost is defined as:

$$L(\varphi) = \sum_i l(\hat{y}_i, y_i) + \sum_k \Omega(f_k) \quad (10)$$

Whereas, l is a differentiable convex loss function that measures the difference between y_i and $\hat{y}_i$ which are actual and predicted values. The regularisation term Ω in the second component of equation (11) can be defined as:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \parallel w \parallel^2 \quad (11)$$

Where γ is the complexity parameter controlling the number of leaf nodes, T is the number of leaf nodes, w is the weight of leaf nodes, and λ is the parameter that is used for avoiding overfitting.

3.3. Data

The hourly exchange rate of Naira/Dollar was used. The series spans from 01/06/2023 to 05/01/2024. The periods mark the epoch where the exchange rate was completely liberalized. The series is log-transformed to control likely outliers and ensures relative smoothness to remove striations. The standard process of time-series forecasting was followed. We divide the time series into training samples and validation. The models were fitted (trained) with 70% of the data sample, while validation (testing) was conducted on the remaining 30% of the samples.

4. Results and Implications

4.1. Results

The estimations follow the procedure described in the earlier section. Table 4.1 (Figure 4.1) shows the computed statistics (plot) of the log-exchange rate series. The series are asymmetrically distributed with a higher (negative) degree of skewness and the Jarque-Bera test, is significant and, rejects the normality null for the full, training set and validation sets. The plot identifies that the series fluctuates with noted jumps and striations.

Table 4.1.Simple statistics

Statistics	Full	Training	Validation
Mean	6.652	6.648	6.652
Median	6.652	6.648	6.652
Maximum	6.817	6.817	6.817
Minimum	6.135	6.135	6.135
Skewness	-3.761	-3.859	-3.790
Kurtosis	19.023	21.967	28.819
JB(Stat)	1286.6	7138.2	1979.3
JB(p value)	0.000	0.000	0.000
# of Obs	735.0	316.0	1051.0

Source: Author's own elaboration

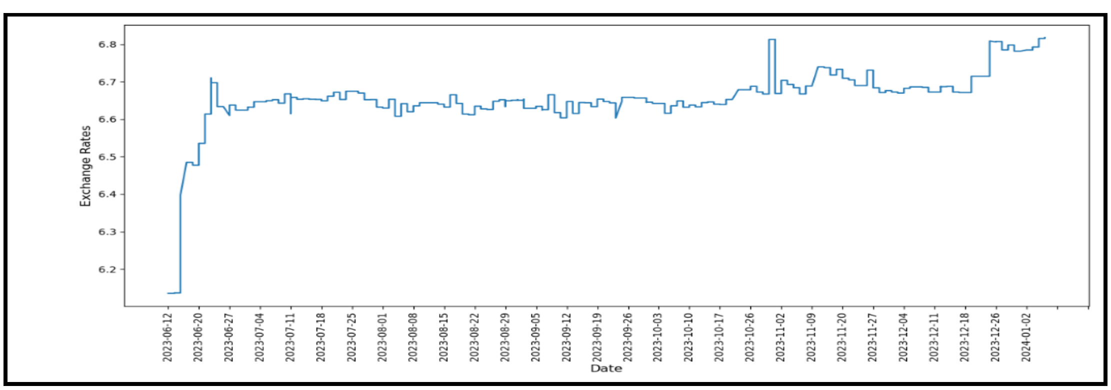

Figure.1. Time series plot
Source: Author's own elaboration

The study applies the STL decomposition function to decompose the observed exchange rate series into characterized time series components of trend, seasonal and residuals, using the stl() decomposition algorithms. Figure 4.2 (Table 4.2) reports the decomposition plot (statistics) for the STL decomposition of the observed exchange rates. As would be expected, while the trend component depicts upward movement, the remainder (residual) converges toward the mean and the seasonality part exhibits oscillates repetitively over time.

Table 4.3 reports the outcome for the stationary test in verifying the stationarity of the series. The ADF test fails to reject the null of non-stationarity. The KPSS test rejects the null of stationarity at a significance. The results confirm non-stationarity for the full, training, validation series. This is non-surprising due to the volatile nature of the hourly exchange rates. The ADF and KPSS tests are highly significant at 1% after differencing. This shows that the exchange rate series is integrated (differenced stationary).

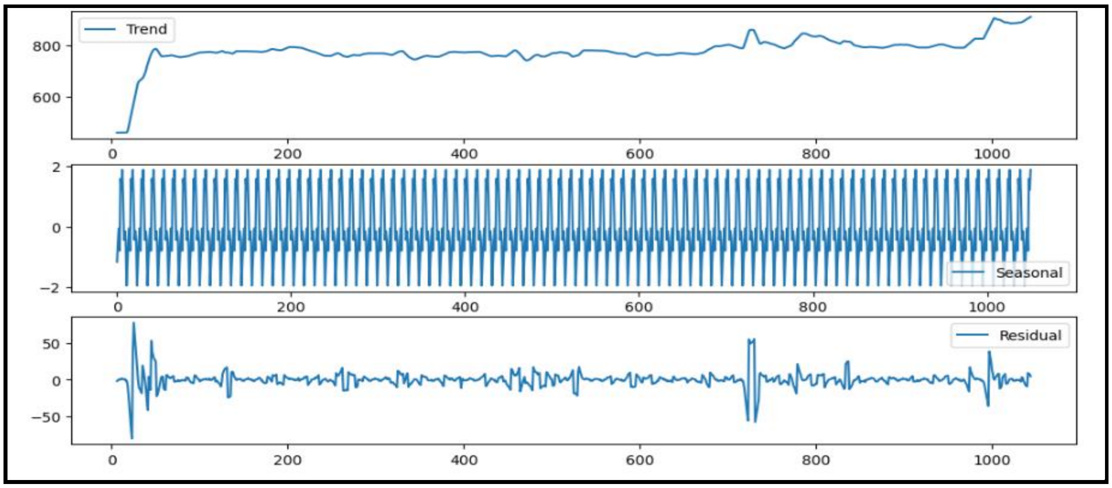

Figure.4.2. **STL Decomposition of The Hourly Exchange Rate Series**

Source: Author's own elaboration

Table 4.2.STL Decomposition

Statistics	**Trend**	**Seasonal**	**Residual**
Minimum	461.89	-1.96	-79.79
Maximum	908.07	1.89	77.39
Mean	777.69	0	0.15
Median	773.25	-0.15	0.15
1st Quartile	762.49	-0.67	-2.58
2nd Quartile	773.25	-0.15	0.15
3rd Quartile	794.6	1.22	2.95
IQR	5.54	5.54	5.54
IQR%	187.57	187.57	187.57

Note: *IQR: Interquarltie range; IQR%: Percentage IQR.*

Source: Author's own elaboration

Table 4.3.Stationary Test

	Level			Diff		
Method	**Full**	**Trained**	**Test**	**Full**	**Trained**	**Test**
ADF						
τ_{ADF}	-2.423	-1.321	-1.826	-6.259	-11.73	-4.77
@1%	-3.475	-3.486	-3.66	-3.475	-3.486	-3.66
@5%	-2.882	-2.88	-2.96	-2.882	-2.88	-2.96
@10%	-2.577	-2.57	-2.62	-2.577	-2.57	-2.62
KPSS						
τ_{KPSS}	2.463	0.829	1.362	0.264	0.343	0.185
@1%	0.739	0.739	0.739	0.739	0.739	0.739
@5%	0.463	0.463	0.463	0.463	0.463	0.463
@10%	0.347	0.347	0.347	0.347	0.347	0.347

Note: *Regardless of the ADF test equation, which includes the Intercept with or without the Time Trend, the series remains non-stationary at levels but are differenced stationary.*

Source: Author's own elaboration

The paper completes the model evaluation by providing computed statistics that offer insights into the performance of various models for predicting the hourly exchange rates. Table 4.4 shows the outcome of the forecast accuracy (absolute and percentage) measures in the validation periods for the hourly exchange rates log-differenced series. For the main analysis based on the hourly exchange rates, the evidence supposes that relative to LLR, SVR and XGB, the random forest (RF) emerges the top performer having the lower prediction errors (MAE, MSE, RMSE and MAPE). The evidence records exceptional performance with an MAE of 0.007, MSE of 0.000, and RMSE of 0.014. The RF has the highest R^2-score of 0.973, suggesting a high degree of explained variance. MAPE is significantly lower at 0.111, further highlighting its precision. Following closely is the XGBoost, which showcases remarkable accuracy by exhibiting a strong predictive power, having an MAE of 0.033, MSE of 0.005, RMSE of 0.072 as well as an impressive R^2-score of 0.516. Although its MAPA of 0.621 is high but still relatively remains lower compared to that from LLR and SVR, underscoring its reliability.

Table 4.4.Forecast accuracy

Method	**LLR**	**SVR**	**RF**	**XGB**
MAE	0.041	0.054	0.007	0.033
MSE	0.006	0.003	0.000	0.005
RMSE	0.076	0.063	0.014	0.072
R^2-score	0.346	0.466	0.973	0.516
MAPE	0.626	0.819	0.111	0.621

Source: Author's own elaboration

The paper demonstrates a sensitivity analysis of the exchange rate based on a daily time series. The STL decomposition plots and statistics for the daily series are presented in Figure 4.3 and Table 4.5. The daily data exhibit negative skewness (i.e., asymmetrical distribution) and leptokurtic properties (highly peaked distributions) in both the training and validation sets. The trend component of the STL plots is relatively smooth but reveals non-stationary patterns. The residual components converge toward the mean, while the seasonal component oscillates. Since the outcome is similar to that of the hourly series, this suggests that the exchange rate series may not be sensitive to data periodicity.

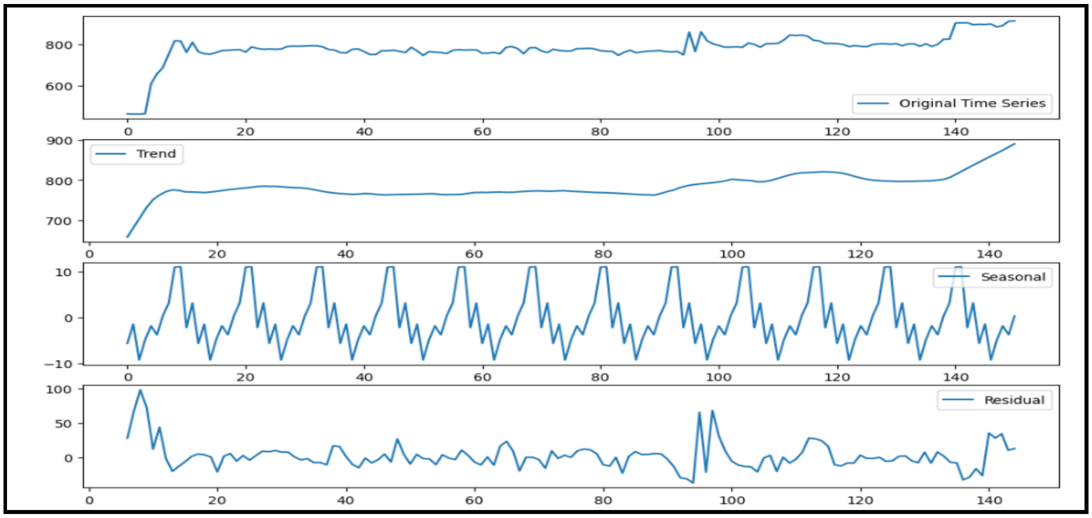

Figure.4.3. STL Decomposition of The Daily Exchange Rate series
Source: Author's own elaboration

Table 4.5.STL Decomposition Statistics (Daily Series)

Statistics	Trend	Seasonal	Residual
Minimum	658.77	-9.23	-37.48
Maximum	890.05	11.05	98.09
Mean	784.3	-0.17	-0.09
Median	774.79	-1.79	-0.09
1st Quartile	768.09	-4.85	-8.35
2nd Quartile	774.79	-1.79	-0.01
3rd Quartile	798.48	3.19	7.53
IQR	30.39	8.03	15.88
IQR%	3.81	252.01	210.79

Note: IQR: Interquartile range; IQR%: Percentage IQR.

Source: Author's own elaboration

Table 4.6 shows the outcome of the forecast accuracy for the daily exchange rate series. The RF reports low prediction errors with MAE of 0.023, MSE of 0.002, and RMSE of 0.045, but a high R^2(score) of 0.435, indicating strong predictive ability. The MAPE is relatively low at 0.355, affirming its accuracy. The XGBoost exhibits strong predictive power for daily exchange rate prediction. With an MAE of 0.015, MSE of 0.000, RMSE of 0.020, and an outstanding R^2(score) of 0.820, thus the XGB outperforms the SVR and LLR. Its MAPE is the lowest among all models at 0.224, underscoring its reliability. It falls short compared to RF in terms of error metrics and R^2(score).

Both LLR and SVR show weaker performance, with relatively higher errors and negative R^2(score). The outcome, based on the provided evaluation metrics, is like the estimation when the hourly series was used. The results (Table 4 and Table 5) suggest that irrespective of the data frequency used (hourly or daily), the RF is superior and more accurately predicts the exchange rate series than others. It emerges as the optimal model for both daily and hourly exchange rate prediction tasks, with XGBoost following closely as the second-best option. Thus, the outcome of the exchange rate series, as trained on the predictive models, is not sensitive to the data periodicity.

Table 4.6.Forecast Accuracy (Daily Series)

Method	LLR	SVR	RF	XGB
MAE	0.043	0.062	0.023	0.015
MSE	0.003	0.005	0.002	0.000
RMSE	0.056	0.067	0.045	0.020
R^2(score)	-0.397	-0.201	0.435	0.820
MAPE	0.644	0.928	0.355	0.224

Note: Methods implemented to establish the accuracy of different forecast models SVR, LIN, RF and XGB

Source: Author's own elaboration

4.2. Managerial Implication

The findings have significant implications for exchange rates, the Nigerian foreign exchange market, and financial markets. They are also relevant to researchers and academics interested in empirical finance. The results suggest that the proposed model provides the most accurate price forecasts for exchange rates. Hence, these findings serve as a guide for various stakeholders in the exchange rate market—particularly traders, policymakers, and investors—enabling them to make informed decisions in light of the market's excessive volatility. Accurate predictions help minimize potential losses and risks for investors, traders, and other market participants. Moreover, the forecast models have implications for asset allocation strategies. Our optimal model provides early warning signals to financial market investors, helping them mitigate massive losses caused by sporadic volatility. Asset managers may seek to minimize risk by adopting the least-error forecast models to predict exchange rate movements. Traders may also consider holding foreign exchange as a safe haven and a potential substitute for traditional assets and commodities (Kliber et al., 2019).

5. Conclusion

The prediction of exchange rates is a crucial application of modern time series forecasting. Because exchange rates are noisy, non-stationary, and deterministically chaotic, research has extensively contributed to forecasting the series using available historical (Ajao et al., 2017; Chandrasekara & Tilakaratne, 2009; Yaser & Atiya, 1996; Deboeck, 1994; Box & Jenkins, 1994). Exchange rate forecasting is a challenging task in finance, and using inadequate tools and models for forecasting can lead to erroneous adjustments with adverse effects on decision-making processes (Fat & Dezsi, 2011; Yu et al., 2007). Some scholars emphasize the need to examine how exchange rates are influenced by economic, inflationary, interest rate, political, and psychological factors (Erdogan & Goksu, 2014), while others advocate for a univariate approach. The difficulty in accurately predicting exchange rate movements underscores the need for further research in this area (Simwaka, 2007).

Despite its contributions, this study has certain limitations. First, it considers only a limited time period to ensure that the exchange rate series is not influenced by monetary policy interventions. Second, the study defines the exchange rate as the simple average of daily bid-ask price quotes. While this approach aligns with previous studies (Bauwens & Giot, 2000), other research suggests that using closing prices may help mitigate heteroskedasticity. Third, the study does not account for microstructure effects and high-frequency data, such as second- or minute-level exchange rate trading. As a result, the forecast models are not converted into a trading strategy, which could otherwise be compared to a Monte Carlo simulation of trading strategies where buy/sell decisions are random. Lastly, the forecasts are based on the log-transformed exchange rate series rather than their returns. Given that observed series are often noisy and prone to over prediction, future research may consider using log-returns to improve accuracy. Future studies may seek to address these limitations. For instance, while this paper focuses on predicting exchange rates using actual series data, future research could explore alternative generalized functions of exchange rate data to enhance forecasting accuracy.

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