FUDMA Journal of Sciences (FJS)
ISSN online: 2616-1370
ISSN print: 2645 - 2944
Vol. 10 No. 18, September, 2026, pp 162 – 170
DOI: https://doi.org/10.33003/fjs-2026-1018-5841

A Persistence-Driven Naïve-LSTM Residual Hybrid Model for Forecasting the United States Dollar-Nigerian Naira Exchange Rate

[1]Yusuf Musa Malgwi, [1]Saad Aliyu Abba and *[2]Noro Gyemang Pam

[1]Department of Computer Science, Faculty of Computing, Modibbo Adama University, Yola, Adamawa State, Nigeria.
[2]Department of Computer Science, School of Science Technology, Federal Polytechnic Kaltungo, Gombe State, Nigeria.

*Corresponding authors' email: gyemangn@gmail.com

ABSTRACT

Accurate exchange-rate forecasting is important for financial planning, investment decision-making, and economic risk management, particularly in emerging economies such as Nigeria. This study evaluates a residual-based Hybrid Naïve-LSTM model for forecasting the Nigerian Naira against the United States Dollar using daily Central Bank of Nigeria (CBN) exchange-rate data from October 2009 to August 2026. Brent crude oil prices were incorporated as an exogenous variable, while feature engineering produced 49 predictors comprising exchange-rate lags, returns, moving averages, volatility measures, calendar variables, and crude-oil features. Exploratory analysis indicated strong persistence, non-stationarity, and substantial volatility in the exchange-rate series. The proposed Hybrid Naïve-LSTM model was evaluated against a standalone Naïve persistence model and an ARIMA-LSTM state-of-the-art benchmark under comparable experimental conditions. The results show that the Naïve model achieved the best overall performance, recording an MAE of 15.3367, RMSE of 34.9274, MAPE of 1.3733%, and R^2 of 0.9947. The proposed Hybrid Naïve-LSTM model achieved an MAE of 18.7539, RMSE of 36.2391, MAPE of 1.8465%, and R^2 of 0.9943. These findings demonstrate that, despite the ability of LSTM-based hybrid models to capture nonlinear residual patterns, the strong persistence of the Nigerian Naira–US Dollar exchange-rate series enabled the simple Naïve model to outperform the more complex alternatives. The study therefore highlights the importance of benchmarking complex deep-learning models against strong persistence-based baselines when forecasting highly persistent financial time series. Future research should investigate alternative deep-learning architectures with explicit regime-switching mechanisms, multi-horizon forecasting, and a broader set of macroeconomic variables.

Received: 29 Aug. 2026
Accepted: 08 Sep. 2026
Published: 24 Sep. 2026

Keywords: Exchange Rate Forecasting; Naïve-LSTM; Residual Hybrid Model; United States Dollar–Nigerian Naira; Deep Learning

INTRODUCTION

The foreign exchange (FOREX) market plays a vital role in the global economy, influencing international trade, investment, monetary policy, and financial decision-making. Exchange rates are sensitive to changing economic and financial conditions, with their movements having particularly important implications for developing economies such as Nigeria, including trade, inflation, external financing, and economic stability (Ibekwe & Ajijola, 2022). The United States Dollar (USD) is especially significant to Nigeria because of its role in international trade, external debt servicing, foreign reserves, and cross-border transactions.

The volatility and dynamic nature of exchange rates make accurate forecasting important for financial planning, risk management, budgeting, and decision-making by policymakers, financial institutions, businesses, and individuals. However, exchange rate forecasting is challenging because currency movements are influenced by factors such as monetary policy, oil prices, market expectations, and broader macroeconomic conditions, resulting in nonlinear, dynamic, and potentially non-stationary patterns (Cheung et al., 2019. Traditional approaches such as Autoregressive Integrated Moving Average (ARIMA), exponential smoothing, and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) can capture specific temporal and volatility patterns but may have limitations in modelling complex nonlinear relationships (Ibraeva et al., 2023). Consequently, machine learning and deep learning methods, including Support Vector Machines, Artificial Neural Networks, and Long Short-Term Memory networks, have increasingly been explored for financial time-series forecasting (Adekoya et al., 2021).

Hybrid forecasting models have also gained attention because they combine the complementary strengths of different modelling techniques. In particular, statistical models can capture identifiable temporal structures, while neural networks can learn nonlinear patterns that may be difficult for conventional models to represent (Khashei et al., 2021). In the Nigerian context, Odion et al. (2025) reported promising results using an ARIMA-LSTM hybrid model for USD/NGN forecasting. However, ARIMA-based hybrid approaches generally involve stationarity testing, differencing, parameter identification, and model specification, which can increase modelling complexity.

This study therefore proposes a Naïve-LSTM residual hybrid model for forecasting USD/NGN and SAR/NGN exchange rates. The approach uses the most recent observed exchange rate as a naïve baseline and employs an LSTM network to learn the temporal and nonlinear patterns contained in the residuals between the observed values and baseline forecasts. The final prediction is obtained by combining the baseline forecast with the predicted residual. Unlike ARIMA-based hybrid models, the proposed approach avoids explicit

ARIMA parameter identification and stationarity modelling, providing a comparatively simple and flexible forecasting framework. The study evaluates this approach on historical USD/NGN and SAR/NGN exchange rate data to assess its applicability across two currencies of economic and practical relevance to Nigeria and to contribute further evidence on hybrid deep learning methods for financial time-series forecasting.

Related Works

Several studies have examined statistical, machine learning, and deep learning techniques for foreign exchange rate forecasting. In Nigeria, Ukabuiro and Stella (2023) found that GRU outperformed ANN and LSTM in USD/NGN prediction, while Ibekwe and Ajijola (2022) reported that Random Forest performed better than OLS and Decision Tree models. Similarly, Abimbola et al. (2022) found SVM superior to Linear Regression for DOL/NGN forecasting. Evidence from other economies also highlights the effectiveness of advanced learning models, with Bi-LSTM, Random Forest, and CNN-BiLSTM demonstrating strong performance in forecasting exchange rates against the Bangladeshi Taka (Mahmud et al., 2024), while LSTM outperformed SVR and BPNN in forecasting the Ghanaian Cedi when Google Trends and macroeconomic variables were incorporated (Adekoya et al., 2021).

Traditional statistical and hybrid approaches have likewise shown promising results. Magaji and Garba (2022) identified ARIMA(0,1,1)-GARCH(1,1) as an effective model for capturing Nigerian exchange-rate dynamics and volatility, whereas Ugoh et al. (2023) reported ARIMA(0,2,2) as the most suitable model for forecasting the Naira/US Dollar and Gambian Dalasi/US Dollar. Hybrid deep learning models have also demonstrated advantages, as Islam and Hosan (2021) found that GRU-LSTM generally outperformed standalone models in short-term FOREX forecasting. For USD/NGN, Lawal et al. (2025) reported complementary strengths between ARIMA and LSTM, while Odion et al. (2025) demonstrated strong performance using an ARIMA-LSTM hybrid model. Related financial forecasting studies further show that LSTM can perform effectively in short-term Bitcoin prediction, although the relative performance of ARIMA and Prophet varies across forecasting horizons (Mudassir et al., 2020; Angelo et al., 2023).

Collectively, these findings indicate that forecasting performance depends on the characteristics of the financial time series, the modelling technique, and the forecasting horizon. Traditional models remain useful for capturing linear temporal patterns, whereas machine learning and deep learning methods can learn complex nonlinear relationships. Hybrid architectures offer a means of combining these complementary capabilities. However, research on Nigerian exchange rates has largely focused on standalone models and conventional hybrid structures, leaving scope for investigating alternative architectures, such as the proposed Naïve-LSTM residual hybrid model, for forecasting USD/NGN and SAR/NGN exchange rates under changing market conditions.

MATERIALS AND METHODS

Figure 1 gives diagrammatic description of the proposed system, and the steps involved are discussed in subsequent subsections.

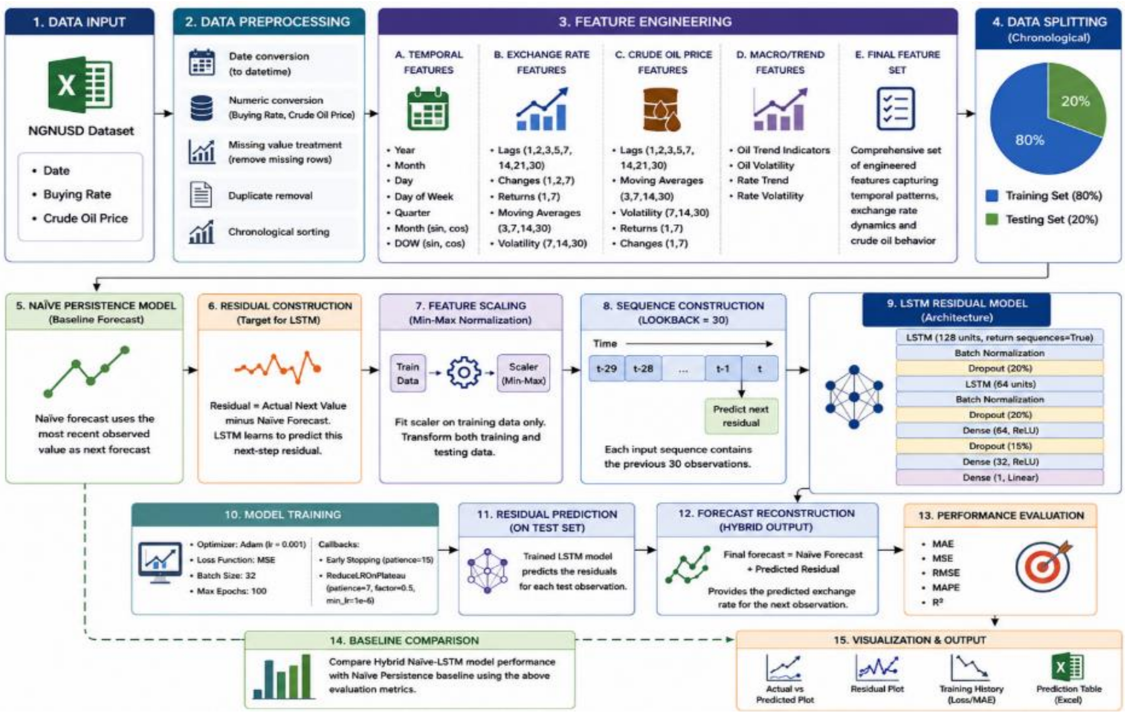

Figure 1: Proposed Framework

Data Collection

The study used historical daily USD/NGN exchange-rate data obtained from the Central Bank of Nigeria (CBN), covering 23 October 2009 to 5 August 2026. After integration with the selected macroeconomic variable, the final dataset comprised 4,110 observations. The data represent business-day records, excluding weekends and public holidays, while valid repeated exchange-rate values were retained. Table 1 summarizes the features and nature of the resulting dataset.

Table 1: Sample of the Features of the Data and State the Nature Dataset

Currency	Date	Buying Rate	Central Rate	Selling Rate	Crude Oil Price
US DOLLAR	2009-10-23	147.6100	148.1100	148.6100	39.6293
US DOLLAR	2009-10-26	148.1400	148.6400	149.1400	39.7707
US DOLLAR	2009-10-27	148.1400	148.6400	149.1400	39.7707
…	…	…	…	…	…
US DOLLAR	2025-12-30	1444.6828	1445.1828	1445.6828	363.5136
US DOLLAR	2025-12-31	1434.7571	1435.2571	1435.7571	363.7076

Macroeconomics Variable

Crude oil price was selected as the macroeconomic variable due to Nigeria's dependence on petroleum exports and the established relationship between oil prices and exchange rates (Wang, 2026). Daily CBN oil-price data were integrated with the exchange-rate dataset, with lags, moving averages, volatility measures, returns, and changes generated to capture short- and medium-term effects. Other macroeconomic variables were excluded because of limited, mainly monthly, or incomplete data that would require frequency conversion or imputation.

Data Processing and Feature Engineering

The USD/NGN dataset was preprocessed to ensure consistency and preserve chronological integrity. The Date, Buying Rate, and Crude Oil Price variables were standardized, with no missing values requiring imputation, and the observations were chronologically ordered to prevent look-ahead bias. Feature engineering generated 49 features covering temporal characteristics, historical exchange-rate behavior, movements, trends, volatility, and crude-oil dynamics. These included time-based variables, exchange-rate and crude-oil lags, moving averages, returns, changes, and rolling volatility measures across different time horizons. All features were derived exclusively from current or past observations to preserve the temporal structure and avoid information leakage.

Training and Testing Strategy

The data were chronologically divided into 80% training (3,113 observations) and 20% testing (779 observations), with random shuffling avoided to preserve temporal order and prevent data leakage. Scaling parameters were estimated from the training set and applied to the test set. A 30-observation lookback window was used for LSTM sequence construction. The model was trained using Adam (learning rate = 0.001), batch size of 32, a maximum of 100 epochs, and MSE loss. Early stopping with best-weight restoration and ReduceLROnPlateau were applied to improve generalization and reduce overfitting.

Proposed Naïve-LSTM Residual Hybrid Model

Two forecasting approaches were evaluated: a Naïve Persistence model and the proposed Naïve-LSTM residual hybrid model. The Naïve model was adopted as the benchmark because exchange-rate series commonly exhibit strong short-term persistence, making the most recent observation a strong baseline for the subsequent value. Preliminary experiments with direct ANN-LSTM forecasting indicated difficulty in accurately learning the complete exchange-rate level. Therefore, the proposed approach decomposes the forecasting task into a persistence component and a residual-learning component.

The Naïve forecast is defined as

$$\hat{y}_t^N = y_{t-1} \qquad (1)$$

Where y_{t-1} represents the most recently observed exchange rate and $\hat{y}_t^N$ represents the naïve forecast. The corresponding residual is calculated as

$$e_t = Y_t - \hat{Y}_t^N \qquad (2)$$

An LSTM network was subsequently trained to learn the temporal and nonlinear patterns contained in the residuals using sequences of the engineered features. Rather than predicting the absolute exchange-rate level directly, the LSTM estimates the residual adjustment to the Naïve forecast. The final hybrid prediction is therefore expressed as

$$y_t^H = \hat{y}_t^N + \hat{e}_t \qquad (3)$$

Where $\hat{e}_t$ denotes the residual predicted by the LSTM.

LSTM Architecture

The residual-learning network comprised two stacked LSTM layers with 128 and 64 units, followed by batch normalization, dropout, and dense layers with 64 and 32 neurons using ReLU activation. A single linear output neuron was used to predict both positive and negative residuals. The architecture is presented in Table 2.

Table 2: LSTM Architecture

Layer	Configuration
LSTM	128 units, return sequences = True
Batch Normalization	Applied
Dropout	20%
LSTM	64 units
Batch Normalization	Applied
Dropout	20%
Dense	64 neurons, ReLU
Dropout	15%
Dense	32 neurons, ReLU
Output	1 neuron, Linear

The proposed architecture combines the persistence property of the Naïve model with the nonlinear sequence-learning capability of LSTM. While the Naïve component provides the baseline exchange-rate level, the LSTM learns deviations from this baseline using historical exchange-rate, temporal, and crude-oil features. This residual-based formulation reduces the need for the network to model the entire exchange-rate level and focuses learning on movements not captured by the persistence component.

Evaluation Metrics

The forecasting models were evaluated using five widely adopted performance metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R2).

RESULTS AND DISCUSSION

This section presents the implementation and evaluation of the proposed Naïve-LSTM residual hybrid model for forecasting the NGN/USD exchange rate. Using daily exchange-rate data and engineered temporal, historical, and crude-oil features, the analysis covers feature engineering, exploratory analysis, model evaluation, prediction and residual analysis, and comparison with the Naïve persistence baseline.

Feature Engineering Results

Feature engineering generated 49 predictors to capture temporal dependence, historical exchange-rate behavior, market movements, volatility, and crude-oil dynamics. The features comprised calendar and cyclical variables, exchange-rate lags, changes, returns, moving averages, and rolling volatility measures, together with corresponding crude-oil prices, lags, trends, returns, changes, and volatility measures. These features enabled the model to capture both exchange-rate persistence and the potential short- and medium-term effects of crude-oil price movements.

Table 3: Engineered Features Used for NGN/USD Forecasting

Feature Category	Variables/Features	Role
Date	Date	Temporal/index variable
Calendar Features	Year, Month, Day, DayOfWeek, Quarter	Predictor
Cyclical Calendar Features	Month_Sin, Month_Cos, DayOfWeek_Sin, DayOfWeek_Cos	Predictor
Buying Rate Lags	Lag1, Lag2, Lag3, Lag5, Lag7, Lag14, Lag21, Lag30	Predictor
Buying Rate Changes	Change_1D, Change_2D, Change_7D	Predictor
Buying Rate Returns	Return_1D, Return_7D	Predictor
Buying Rate Moving Averages	MA3, MA7, MA14, MA30	Predictor
Buying Rate Volatility	STD7, STD14, STD30	Predictor
Current Crude Oil Price	Oil_Current	Predictor
Crude Oil Lags	Oil_Lag1, Oil_Lag2, Oil_Lag3, Oil_Lag5, Oil_Lag7, Oil_Lag14, Oil_Lag21, Oil_Lag30	Predictor
Crude Oil Moving Averages	Oil_MA3, Oil_MA7, Oil_MA14, Oil_MA30	Predictor
Crude Oil Volatility	Oil_STD7, Oil_STD14, Oil_STD30	Predictor
Crude Oil Returns	Oil_Return_1D, Oil_Return_7D	Predictor
Crude Oil Changes	Oil_Change_1D, Oil_Change_7D	Predictor
Buying Rate	Current Buying Rate	Target variable

Dataset Presentation

The experimental dataset consists of 4,110 daily NGN/USD Buying Rate observations from the Central Bank of Nigeria, covering 23 October 2009 to 5 August 2026. The Buying Rate is the target variable, while crude-oil prices and engineered temporal and historical features serve as predictors.

Historical NGN/USD Exchange-Rate Trend

Figure 2 shows a persistent upward trend in the daily NGN/USD Buying Rate, with periods of relative stability and several structural shifts. The rate was around ₦150/USD before 2015, ₦305/USD during 2016-2020, and ₦410/USD during 2021-2022.

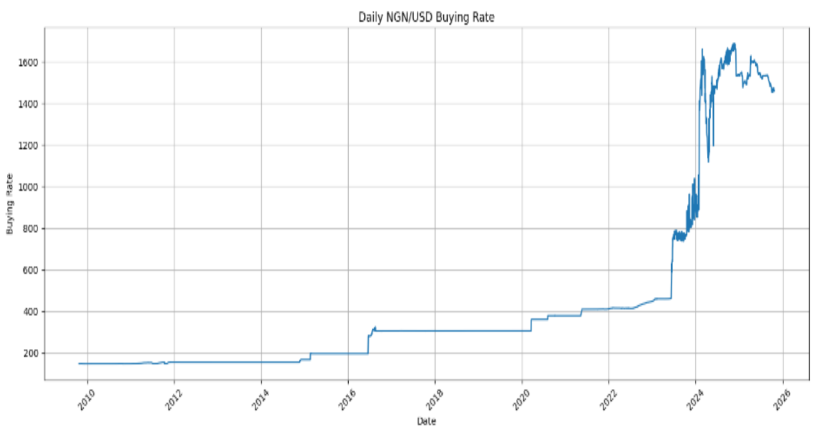

Figure 2: Historical NGN/USD Exchange-Rate Trend

More pronounced upward movements occurred in 2016, 2023, and 2024, with the rate exceeding ₦750/USD in mid-2023 and reaching values above ₦1,600/USD during 2024. The series subsequently showed some degree of consolidation during 2025–2026. These changes indicate substantial regime shifts and increasing exchange-rate variability in the latter part of the study period.

Daily Exchange-Rate Changes and Returns

To examine short-term movements in the NGN/USD exchange rate, daily changes and percentage returns were calculated.

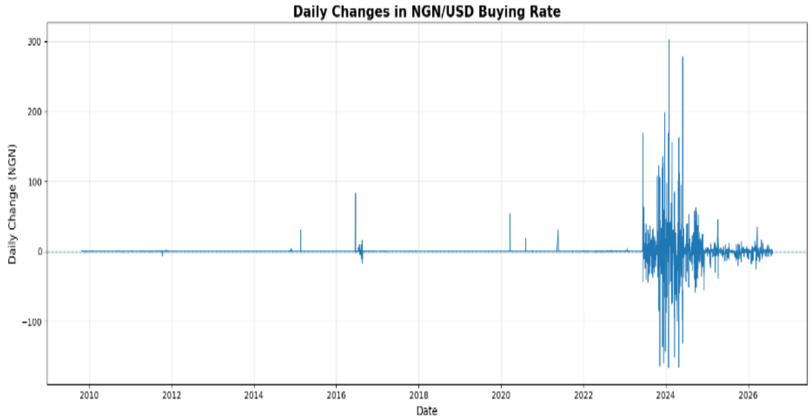

Figure 3: Daily Changes and Returns of the NGN/USD Buying Rate

Figure 3 shows that daily changes and percentage returns were generally small during stable periods but increased substantially during exchange-rate adjustments. The largest positive change was ₦303.02 (34.09%) on 30 January 2024, followed by ₦278.08 (23.25%) on 30 May 2024, while the largest decline was ₦165.82 (15.70%) on 26 January 2024. These sharp movements indicate nonlinear and highly variable short-term dynamics.

Table 4: Top 10 Largest Absolute Daily Changes in NGN/USD Buying Rate

Date	Buying Rate (NGN)	Daily Change (NGN)	Daily Return (%)	Direction
2024-01-30	1,191.94	+303.02	+34.09%	Depreciation
2024-05-30	1,474.19	+278.08	+23.25%	Depreciation
2023-12-22	1,038.63	+198.22	+23.59%	Depreciation
2024-01-25	1,055.88	+169.49	+19.12%	Depreciation
2023-06-14	631.77	+169.39	+36.63%	Depreciation
2024-01-26	890.06	-165.82	-15.70%	Appreciation
2024-04-25	1,164.34	-165.10	-12.42%	Appreciation
2024-01-31	1,356.38	+164.44	+13.80%	Depreciation
2023-11-10	800.50	-163.76	-16.98%	Appreciation
2024-04-26	1,326.85	+162.51	+13.96%	Depreciation

Rolling Volatility of the NGN/USD Exchange Rate

Rolling volatility was examined to determine whether the variability of the exchange-rate series remained constant throughout the study period.

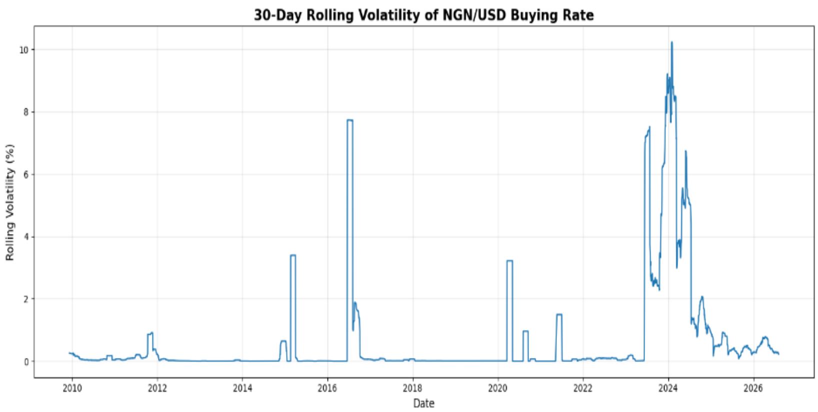

Figure 4: 30-Day Rolling Volatility of the NGN/USD Buying Rate

Rolling volatility was analyzed to determine whether exchange-rate variability remained constant over time. Figure 4 shows substantial time-varying volatility and clustering. Earlier periods exhibited relatively moderate volatility, including episodes around 2015, 2016, and 2020. However, volatility increased considerably after 2023, reaching particularly high levels in early 2024 before subsequently moderating. The observed variation indicates that the exchange-rate series contains distinct low- and high-volatility regimes, demonstrating the difficulty of maintaining consistent forecasting accuracy during periods of rapid market adjustment.

Distribution of the NGN/USD Buying Rate

The distribution of the Buying Rate was examined to understand the concentration and spread of exchange-rate observations.

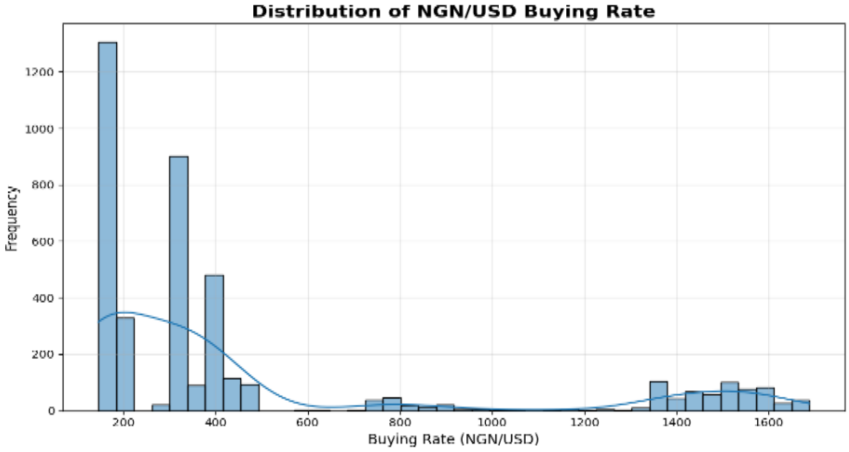

Figure 5: Distribution of the NGN/USD Buying Rate

Figure 5 shows a highly non-normal, multimodal distribution, with major concentrations around ₦150-₦200, ₦300-₦350, and ₦400-₦450, and a long right tail extending beyond ₦1,600. These patterns reflect distinct historical exchange-rate regimes and substantial later-period depreciation, indicating strong structural changes and non-constant exchange-rate levels.

Autocorrelation and Exchange-Rate Persistence

Autocorrelation analysis was performed to examine the relationship between the current NGN/USD Buying Rate and its previous observations.

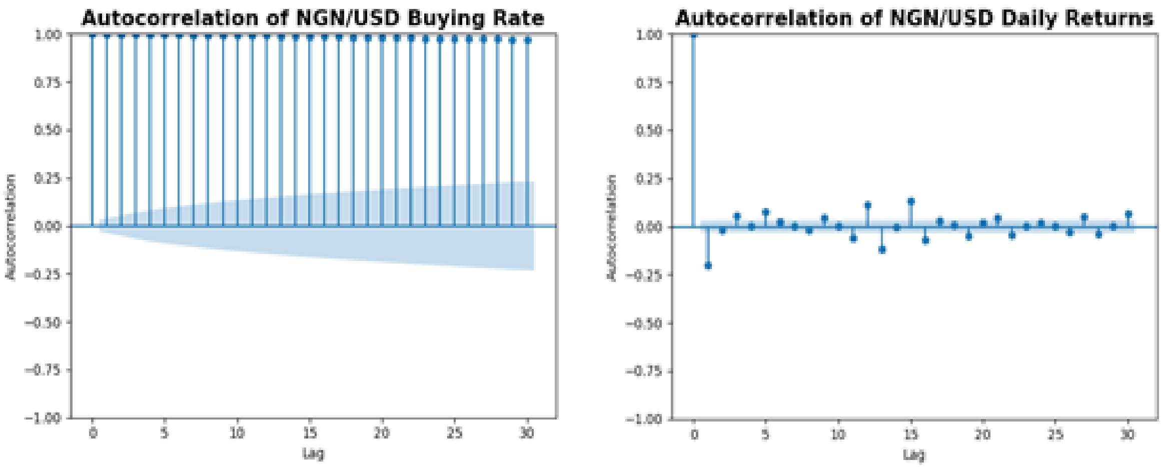

Figure 6: Autocorrelation Function of the NGN/USD Buying Rate and Daily Returns

Figure 6 shows strong autocorrelation in NGN/USD exchange-rate levels, indicating substantial persistence, while daily returns exhibit rapid decay and remain largely within the confidence bounds after the initial lags. This supports the Naïve persistence model as a benchmark and motivates residual learning to capture additional nonlinear patterns.

Summary of NGN/USD exploratory findings

The exploratory analysis covered 4,110 daily NGN/USD observations from 23 October 2009 to 5 August 2026. The exchange rate ranged from ₦146.60 to ₦1,687.78, with a mean of ₦464.72, median of ₦304.95, and standard deviation of ₦455.31, indicating substantial variability. Although the mean daily change was small, extreme movements exceeding ₦300 were observed, reflecting significant short-term shocks. The strong autocorrelation of exchange-rate levels further indicates substantial persistence and supports the use of the Naïve model as the baseline.

Table 5: Descriptive Summary of the NGN/USD Buying Rate

Measure	**Result**
Study Period	23 October 2009 – 5 August 2026
Number of Observations	4,110
Mean Buying Rate	464.72
Standard Deviation	455.31
Minimum Buying Rate	146.60
Median Buying Rate	304.95
Maximum Buying Rate	1,687.78
Mean Daily Change	0.2958
Maximum Positive Daily Change	303.0190
Maximum Negative Daily Change	-165.8170
Maximum Absolute Daily Movement	303.0190

Performance Evaluation

The out-of-sample results show that the Naïve persistence model outperformed the Hybrid Naïve-LSTM across all five evaluation metrics. It achieved lower MAE, MSE, RMSE, and MAPE, with 15.3367, 1,219.9227, 34.9274, and 1.3733%, respectively, while also recording a slightly higher R^2 of 0.9947 compared with 0.9943 for the hybrid model.

Table 6: Performance Metrics

Metric	**Naïve**	**Hybrid Naïve-LSTM**	**Better Model**
MAE	15.3367	18.7539	Naïve
MSE	1,219.9227	1,313.2721	Naïve
RMSE	34.9274	36.2391	Naïve
MAPE	1.3733%	1.8465%	Naïve
R^2	0.9947	0.9943	Naïve

These results indicate that the most recent exchange-rate observation provided strong information for one-step-ahead forecasting, while residual learning did not yield additional predictive value during the test period. The findings further suggest that greater model complexity does not necessarily improve forecasting accuracy when the series exhibits strong short-term persistence.

NGN/USD Actual versus Predicted Values

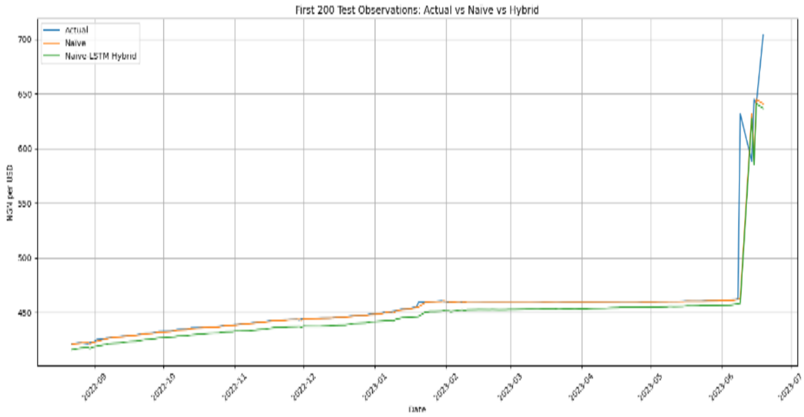

Figure 7: Actual NGN/USD vs. Naïve Baseline and Hybrid Naïve-LSTM Predictions (First 20 Test Observations)

Figure 7 shows that the Naïve model closely followed the actual NGN/USD values during stable periods, while the Hybrid Naïve-LSTM generally underestimated the exchange rate due to negative residual predictions. Both models experienced larger errors during the sharp exchange-rate movements of 2023–2024. The residual analysis further indicates that the hybrid model introduced a downward bias during stable periods, resulting in additional error rather than improving the persistence forecasts.

The residual results for the initial test observations further illustrate this behavior. The Naïve model maintains very small errors during the stable period, whereas the hybrid model produces a systematic downward bias because of the negative residual estimates. This indicates that the LSTM residual component introduced additional error rather than correcting the small deviations generated by the persistence forecast.

Residual Analysis

An analysis of prediction errors was conducted to evaluate model bias, calibration, and error variance across both architectures during the out-of-sample test period.

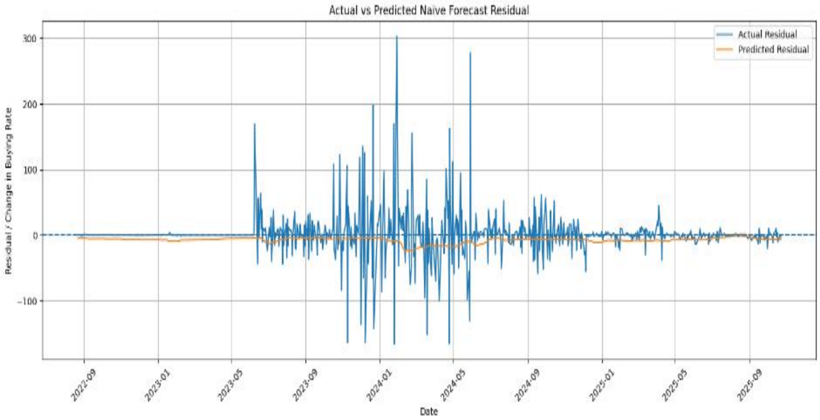

Figure 8: Actual vs. Predicted Naïve Forecast Residuals

Figure 8 shows substantial volatility in the actual residuals during the 2023-2024 exchange-rate adjustments, ranging from approximately -₦166 to +₦303. In contrast, the LSTM-predicted residuals remained relatively close to zero and showed limited variation, with some negative bias. This indicates that the LSTM did not adequately capture large residual shocks and therefore provided insufficient corrective information to improve the Naïve forecast.

Discussion

The exploratory analysis indicates that the NGN/USD exchange-rate series exhibits strong persistence, substantial dispersion, structural changes, and periods of elevated volatility. The Buying Rate ranged from ₦146.60 to ₦1,687.78, with a mean of ₦464.72 and standard deviation of ₦455.31. The difference between the mean and median (₦304.95) and the multimodal distribution indicate substantial changes in exchange-rate regimes over the study period. The large daily movements observed during 2023 and 2024 further demonstrate the presence of short-term shocks that are difficult to anticipate using historical observations alone.

The autocorrelation analysis provides further evidence of strong persistence in the exchange-rate level, while daily returns exhibit considerably weaker dependence. This characteristic explains the strong performance of the Naïve persistence model, which uses the most recent exchange-rate observation as the forecast for the subsequent observation. The result demonstrates that, for one-step-ahead NGN/USD forecasting, the latest observed exchange rate contains substantial predictive information.

The out-of-sample evaluation confirms this observation. The Naïve model achieved lower MAE, MSE, RMSE, and MAPE than the Hybrid Naïve-LSTM model. The Naïve model also achieved a slightly higher R^2 (0.9947) than the hybrid model (0.9943). The consistent advantage across all evaluation metrics indicates that the LSTM residual component did not provide sufficient incremental predictive information to improve the persistence forecast.

The residual analysis provides an explanation for the inferior performance of the hybrid approach. During relatively stable periods, the LSTM generated persistent negative residual estimates despite the actual exchange-rate movements being small and predominantly positive. This introduced a systematic downward bias into the hybrid forecasts. During the major exchange-rate disruptions of 2023 and 2024, the LSTM also substantially underestimated the magnitude of the observed residual movements. Thus, the residual learner neither adequately captured extreme exchange-rate shocks nor consistently improved predictions during stable periods.

In a nutshell, the findings demonstrate that increased model complexity does not necessarily translate into improved forecasting accuracy. Although the proposed Hybrid Naïve-LSTM model incorporated nonlinear sequence learning and engineered temporal, exchange-rate, and crude-oil features, the simple Naïve persistence model remained more accurate and robust for the evaluated NGN/USD series. The findings therefore emphasize the importance of strong baseline models in exchange-rate forecasting and suggest that future improvements should focus on approaches capable of explicitly addressing structural breaks, regime changes, and extreme market movements.

CONCLUSION

This study investigated the effectiveness of a residual-based Hybrid Naïve-LSTM model for forecasting the Nigerian Naira–United States Dollar (NGN/USD) exchange rate using daily historical observations and engineered temporal, exchange-rate, and crude-oil features. The findings revealed strong persistence, structural changes, volatility clustering, and occasional extreme movements in the exchange-rate series. Despite the use of LSTM-based residual learning to capture nonlinear deviations from the persistence forecast, the proposed Hybrid Naïve-LSTM model did not outperform the Naïve baseline, which achieved lower MAE, MSE, RMSE, and MAPE and a slightly higher R^2 on the out-of-sample test set. The results demonstrate that, for the evaluated NGN/USD series and forecasting horizon, the most recent exchange-rate observation provides a strong basis for one-step-ahead prediction, while the additional LSTM component introduced prediction bias without sufficient incremental accuracy. Future work will investigate regime-aware, attention-based, and advanced hybrid forecasting approaches capable of better capturing structural breaks, extreme movements, and nonlinear dynamics in the NGN/USD exchange-rate series.

REFERENCES

Abimbola, K. A., Abiola, O. A., & Akinola, S. O. (2022). Predicting the trend of Dollar/Naira exchange rate using regression. *Journal of Science and Logics in ICT Research, 8*(2), 51–59.

Adekoya, A. F., Nti, I. K., & Weyori, B. A. (2021). Long short-term memory network for predicting exchange rate of the Ghanaian cedi. *FinTech, 1*(1), 25–43.

Angelo, M. D., Fadhiilrahman, I., & Purnama, Y. (2023). Comparative analysis of ARIMA and Prophet Algorithms in Bitcoin price forecasting. *Procedia Computer Science, 227*, 490–499. https://doi.org/10.1016/j.procs.2023.10.550

Cheung, Y. W., Chinn, M. D., Pascual, A. G., & Zhang, Y. (2019). Exchange rate prediction redux: New models, new data, new currencies. *Journal of International Money and Finance, 95*, 332–362.

Ibekwe, U., & Ajijola, L. (2022). Modelling the Naira/US Dollar currency exchange rates using Decision Tree, Ordinary Least Squares and Random Forest machine learning algorithms. *UNILAG Journal of Business, 8*(2), 53–74.

Ibraeva, Z. E., Bektemyssova, G., & Ahmad, A. R. (2023). Fuzzy model for time series forecasting. *Scientific Journal of Astana IT University, 2023*, 93–102. https://doi.org/10.37943/13eotu7482

Islam, M. S., & Hossain, E. (2021). Foreign exchange currency rate prediction using a GRU-LSTM hybrid network. *Soft Computing Letters, 3*, 100009. https://doi.org/10.1016/j.socl.2020.100009

Khashei, M., Bijari, M., & Hejazi, S. R. (2021). Combining seasonal ARIMA models with computational intelligence techniques for time series forecasting. *Soft Computing, 16*(6), 1091–1105. https://doi.org/10.1007/s00500-012-0805-9

Lawal, M. M., Abdulrauf, A., Delmut, R. D., & Tohomdet, L. K. Evaluating the Effectiveness of ARIMA and LSTM Models in Predicting USD/NGN Trends. *Machine learning, 13*, 14.

Magaji, B., & Garba, J. (2022). Forecasting the exchange rate of Nigerian Naira to United State Dollar using ARIMA-GARCH model. *Dutse Journal of Pure and Applied Sciences, 8*(3b), 87–96.

Mahmud, T., Akter, T., Anwar, S., Aziz, M. T., Hossain, M. S., & Andersson, K. (2024). Predictive modeling in Forex trading: A time series analysis approach. In *2024 IEEE Second International Conference on Inventive Computing and Informatics (ICICI)* (pp. 390–397). IEEE. https://doi.org/10.1109/ICICI62254.2024.00070

Mudassir, M., Bennbaia, S., Unal, D., & Hammoudeh, M. (2020). Time-series forecasting of Bitcoin prices using high-dimensional features: A machine learning approach. *Neural Computing and Applications, 32*, 1–15. https://doi.org/10.1007/s00521-020-05129-6

Odion, P. O., Lawal, M. M., & Abdulrauf, A. (2025). A comparative analysis of an enhanced hybrid model for predicting Dollar against Naira exchange rate using deep learning and statistical methods. *Journal of Computing Theories and Applications, 2*(4), 511–522. https://doi.org/10.62411/jcta.12513

Ukabuiro, I., & Stella, A. (2023). Prediction models for Forex data exchange system. *International Journal of Innovative Science and Research Technology, 8*(12), 1725–1728.

Ugoh, C. I., Jammeh, L. B., Ugo, M. N., Guobadia, E. K., & Ngene, C. S. (2023). Modeling and forecasting Nigerian Naira/US Dollar and the Gambian Dalasi/US Dollar exchange rates: A comparative study. *African Journal of Mathematics and Statistics Studies, 6*(1), 12–26. https://doi.org/10.52589/AJMSS-XHLDL3XG

Wang, Y. (2026). Crude oil prices, exchange rates, and monetary policy in Canada. *Applied Economics*, 1-18.