**JMSS**

# Modeling US Dollar and Nigerian Naira Exchange Rates During COVID-19 Pandemic Period: Identification of a High-performance Model for New Applications

**Ugochinyere Ihuoma Nwosu[1]** 👤 🆔 , **Chukwudi Paul Obite[2]** 👤 🆔 ✉ **and Desmond Chekwube Bartholomew[3]** 👤 🆔

[123]*Department of Statistics, Federal University of Technology Owerri, Nigeria*

✉ **Corresponding Author**: Chukwudi Paul Obite, **E-mail**: Chukwudi.obite@futo.edu.ng

| ARTICLE INFORMATION | ABSTRACT |
|---|---|
| | This study modeled the US Dollar and Nigerian Naira exchange rates during COVID-19 pandemic period using a classical statistical method – Autoregressive Integrated Moving Average (ARIMA) – and two machine learning methods – Artificial Neural Network (ANN) and Random Forest (RF). The data were divided into two sets namely: the training set and the test set. The training set was used to obtain the parameters of the model, and the performance of the estimated model was validated on the test set that served as new data. Though the ARIMA and random forest performed slightly better than the neural network in the training set, their performance in the test set was poor. The neural network with 5 nodes in the input layer, 5 nodes in the hidden layer and 1 node in the output layer (ANN (5,5,1)) performed better on the new data set (test set) and is chosen as the best model to forecast for future USD to NGN exchange rate. The information from the high-performance model (ANN (5, 5, 1)) for modeling the USD to NGN exchange rate will assist econometric trading of the currencies and offer both speculative and precautionary assistance to individuals, households, firms and nations who use the currencies locally and for international trade. |
| | |

## 1. Introduction

The COVID-19 is a respiratory pandemic disease, novel, scary and calamitous in a mode of action (Appiah, 2011). The disease has caused global economic crises and disrupted the global calendar. Novelty and severity of the disease have compelled scientific investigations and technological innovations at both international and local levels in order to combat the disease. With increased research, funding and disease understanding and management, the mortality rate has reduced in some parts of the world without economic recovery (Nwosu and Obite, 2021; Okon and Ikpang, 2020). However, this is unfortunate because the global economy must recover from having a better livelihood.

The exchange of currency is crucial for international trade (Nwankwo, 2014; Nyoni, 2018). In most countries, international trade represents a notable gross domestic product (GDP) (Nyoni, 2018). International trade and associated financial transactions are critical because such transactions and economic policies are eminently connected to living standards. The exchange rate depreciates if the amount of domestic currency required to purchase a foreign currency increases, while the exchange rate appreciates if the amount of domestic currency required to obtain a foreign currency reduces (Okon and Ikpang; 2020).

The outbreak of COVID-19 has affected the USD to NGN exchange rate. The outbreak has resulted in border closure, drop in oil prices, depletion in Nigeria excess crude account, etc. and all these will impact the USD to NGN exchange rate. The combination of bad health caused by the novel virus and impoverished livelihood of Nigerians resulting from exorbitant USD to NGN exchange rates during the pandemic period is a disaster. The need to guide economic policies and measurement and evaluation through modelling to save Nigeria's economy while sustaining her financial relationship with the United States motivated the present study. Three models, namely Autoregressive Integrated Moving Average (ARIMA), Artificial Neural Network (ANN) and Random Forest (RF) were chosen for the test. As for tactics in the present study, the three models were assayed in a pretest

before application and the results obtained justified their use in modeling of USD to NGN exchange rates. The ARIMA model is a classical statistical method, whereas ANN and RF are machine learning models (Rundo et al., 2019). Machine learning is a part of artificial intelligence that enables information technology systems to recognize patterns based on existing algorithms and data sets and use the same to develop sustainable solution concepts. Recent studies (Nyoni, 2018; Okon and Ikpang 2020; Bakawu et al., 2020) modeled USD to NGN exchange exchanges with debatable results. Apart from the need for more studies in order to provide clarifications, our study considered a list of models and included both classical and machine learning models and used updated data during the COVID-19 pandemic period. The specific objectives were to identify high performance and adaptable model(s) for forecasting USD and NGN exchange rates and determine the adequacy of the models based on the model diagnostic tools.

## 2. Methods

The USD to NGN exchange rate data used in this study is secondary, from exchange-rates.org. The data are 5-day weekly data collected from August 2020 to January 2021. The data were divided into two sets: the training set and the test set. The training set is 70% of the data, while the remaining 30% is for the test set. The training set was used to obtain the model's parameters, and the performance of the estimated model was validated on the test set that served as new data. Data were divided to avoid overfitting, where a model will fit the data used to model it well but performs poorly on a new set.

We modelled the USD to NGN exchange rate using a classical statistical method – Autoregressive Integrated Moving Average (ARIMA) – and two machine learning methods – Artificial Neural Network (ANN) and Random Forest (RF) – so as to select the best model to forecast for future USD to NGN exchange rate. Two different sets of explanatory variables were considered for both the ANN and RF models. The first set had time, Lag1 and a 2-day Moving Averages (MA2) as the explanatory variables, while the second set added two more variables, Lag5 and a 5-day Moving Averages (MA5), to the first set to make it five explanatory variables. The two variables – Lag5 and MA5 – were added to check whether they will improve the performance of the ANN and RF models.

The Lag1 and MA2 variables were chosen as they were the closest lag and moving averages to the current USD to NGN exchange rate, while the Lag5 and MA5 variables were chosen because the USD to NGN exchange rate data is a 5-day weekly data. The data were collected from Monday to Friday of each week. The ARIMA model developed by Box and Jenkins (1976) and explained by Nwosu and Obite (2021) was used to model the USD to NGN exchange rate data.

The suggested model was compared to models with parameters close to it in order to identify a better model using the Akaike Information Criterion (AIC), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). The final model can be used to forecast only if the residuals of the ARIMA model are white noise. The ACF plot of residuals, time series plot of residuals, etc., is used for such a test. Furthermore, a mathematical representation of the ANN model is given as:

$$\widehat{y}_k(x_i, w) = \Phi_0(\alpha_k + \sum_{h=1}^{H} w_{hk}\Phi_h(\alpha_h + \sum_{j=1}^{J} w_{jh}x_{ij})) \qquad 4$$

where

$\widehat{y}_k(x_i, w)$ is the estimated response variable,

$w_{jh}$ is the weight,

$x_{ij}$ is the input node,

$\alpha_h$ is the bias that can be interpreted as the intercept in a linear regression,

$\Phi_0$ and $\Phi_k$ are activation functions.

A final transformation $\Phi_0$ is applied to the output (Obite et al., 2020), and the quadratic error function given in equation (5) was used in this study to determine the weights.

$$E_Q = \sum_{k=1}^{K} \sum_{i=1}^{n} (\hat{y}(x_i, w) - y_{ik})^2 \qquad 5$$

where

$\widehat{y}_k(x_i, w)$ is the estimated response variable, and

$y_{ik}$ is the response variable.

The importance of each input node was estimated using the Olden method (2004).

Two ANN models – ANN-1 and ANN-2 –were used in this study. The ANN-1 had three nodes in the input layer, while the ANN-2 had five nodes in the input layer, as already explained. The explanatory variables (input nodes) were normalized using the min-max normalization method to help the neural network to converge quickly (Nwokike et al., 2020). The Random Forest machine learning method was applied, as already explained by Ho (1998). Figure 1 is a plot of a random forest.
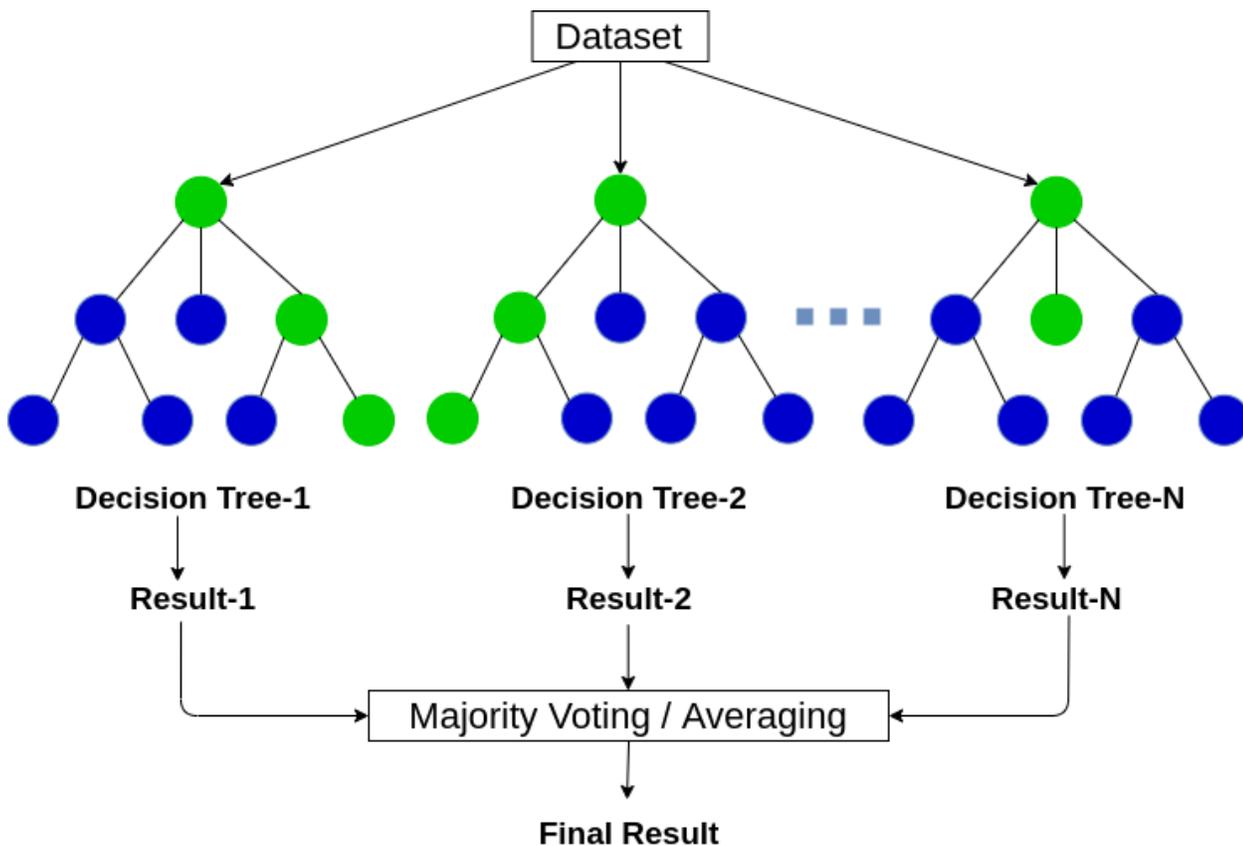


Source: Analyticsvidhya.com

Figure 1: A random forest plot

The increase in mean square error (%IncMSE) and the increase in node impurity (%IncNodePurity) were used to estimate the variable importance. They show the increase in mean square error or impurity when a variable is randomly permuted. A less critical variable will not change the %IncMSE and %IncNodePurity much when randomly permuted.

The RMSE, MAPE and Nash-Sutcliffe Efficiency (NSE) were used as performance measures to select the best model for the USD to NGN exchange rate data. The model with the least RMSE and MAPE values and highest NSE value is the best model.

## 3. Results
### 3.1 The ARIMA model
The steps stated in Nwosu and Obite (2021) were used to determine the parameters (p, d, q) of the ARIMA model. The plot of the USD to NGN exchange rate data in Figure 2 and the Augmented Dickey-Fuller test (P-value (0.092) > 0.05) show that the data are not stationary and there is need for differencing. The data became stationary (P-value (0.01) < 0.05) after the first

differencing. The first order of differencing suggests a "1" value for the "d" parameter. The PACF and ACF plots in Figure 3 and 4 respectively suggest an order "2" and "1" for both the "p" and "q" parameters, respectively. There was a sharp cut to the significant limit after the second and first lags in the PACF and ACF plots respectively. The suggested ARIMA model of order (2, 1, 1) is compared models with parameters closed to it as stated in Nwosu and Obite (2021) using the AIC, RMSE and MAPE get the best ARIMA model, as shown in Table 1.
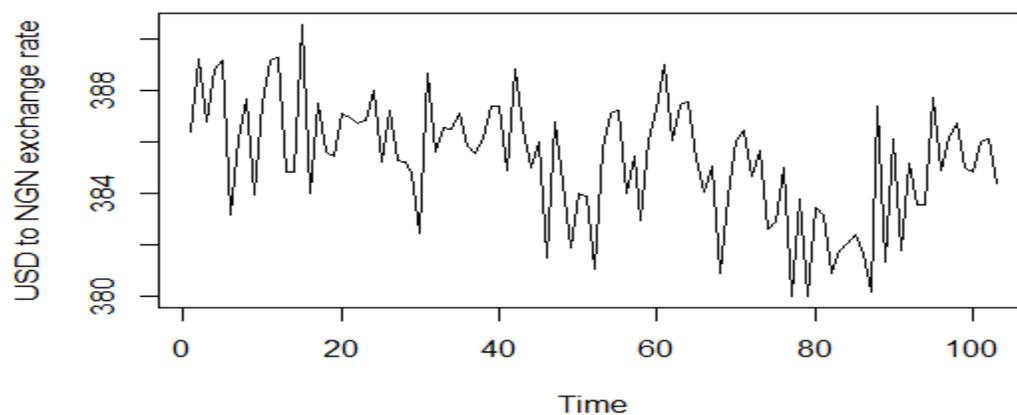
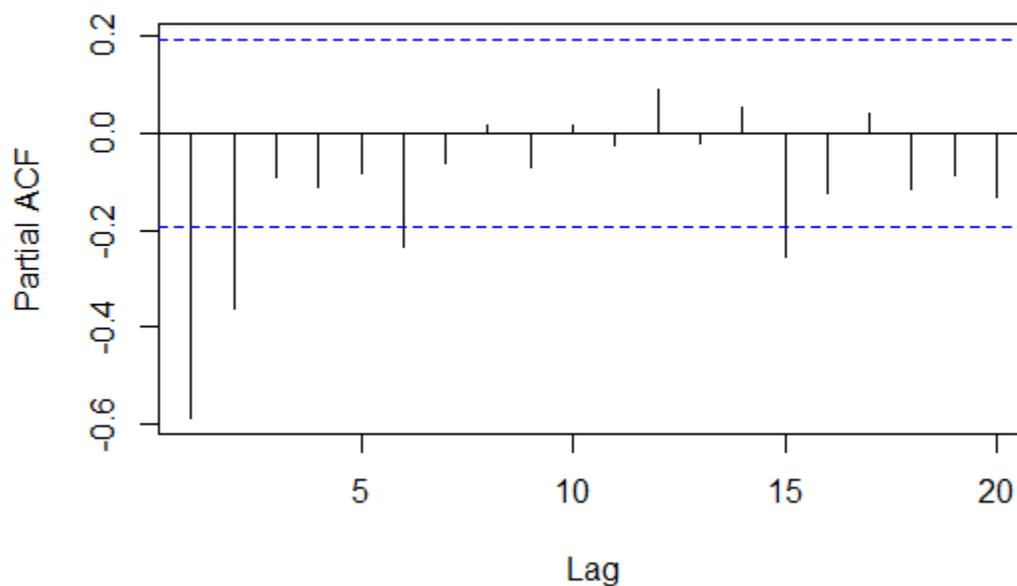Figure 2: The plot of the USD to NGN exchange rate.

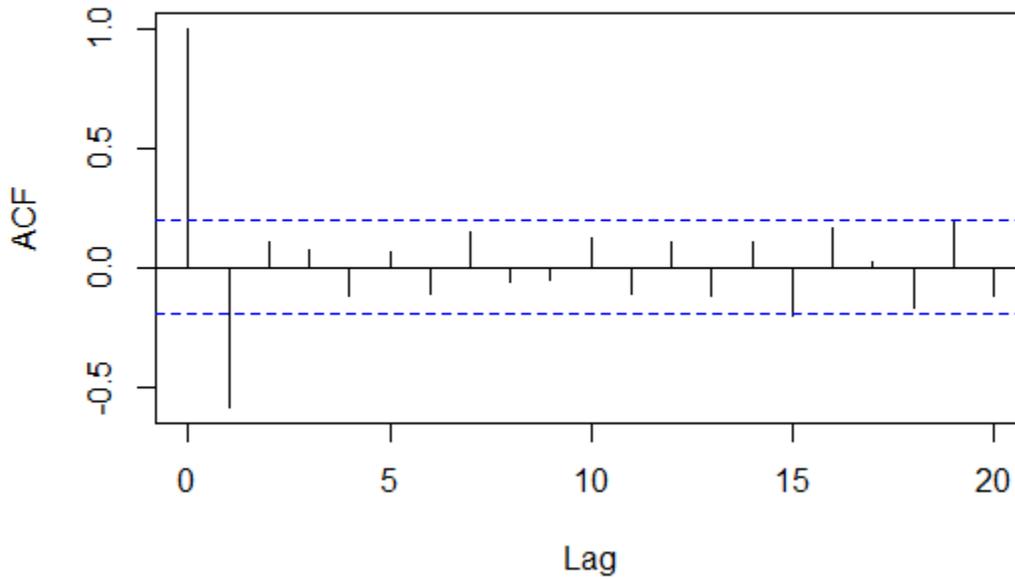Figure 3: The PACF plot of the USD to NGN exchange rate.

Figure 4: The ACF plot of the USD to NGN exchange rate.

Table 1: The different ARIMA models.

|  | RMSE | MAPE | AIC |
|---|---|---|---|
| **ARIMA (2,1,1)** | 2.050 | 0.016 | 447.43 |
| **ARIMA (3,1,2)** | 1.969 | 0.004 | 441.92 |
| **ARIMA (5,1,2)** | 1.966 | 0.004 | 445.69 |
| **ARIMA (3,1,1)** | 1.969 | 0.004 | 439.97 |

The ARIMA (3,1,1) model is selected as the best as it has almost the same RMSE and MAPE values and the least AIC value when compared to the other orders of the ARIMA model. The coefficients of the ARIMA (3,1,1) model are shown in Table 2.

Table 2: The coefficients of the ARIMA (3,1,1) model.

|  | ar1 | ar2 | ar3 | ma1 |
|---|---|---|---|---|
| **Coefficient** | 0.033 | 0.2546 | 0.2088 | -0.9387 |
| **s.e.** | 0.114 | 0.1128 | 0.107 | 0.057 |

The ARMIA (3,1,1) residual was used to plot three different graphs, as shown in Figure 5. The residual does not have any trend, all the lags of the residuals are within the significance limit of the ACF plot and they follow a normal distribution. This means that the residuals from the ARIMA (3,1,1) model are white noise and the model is suitable to be used for the forecast.
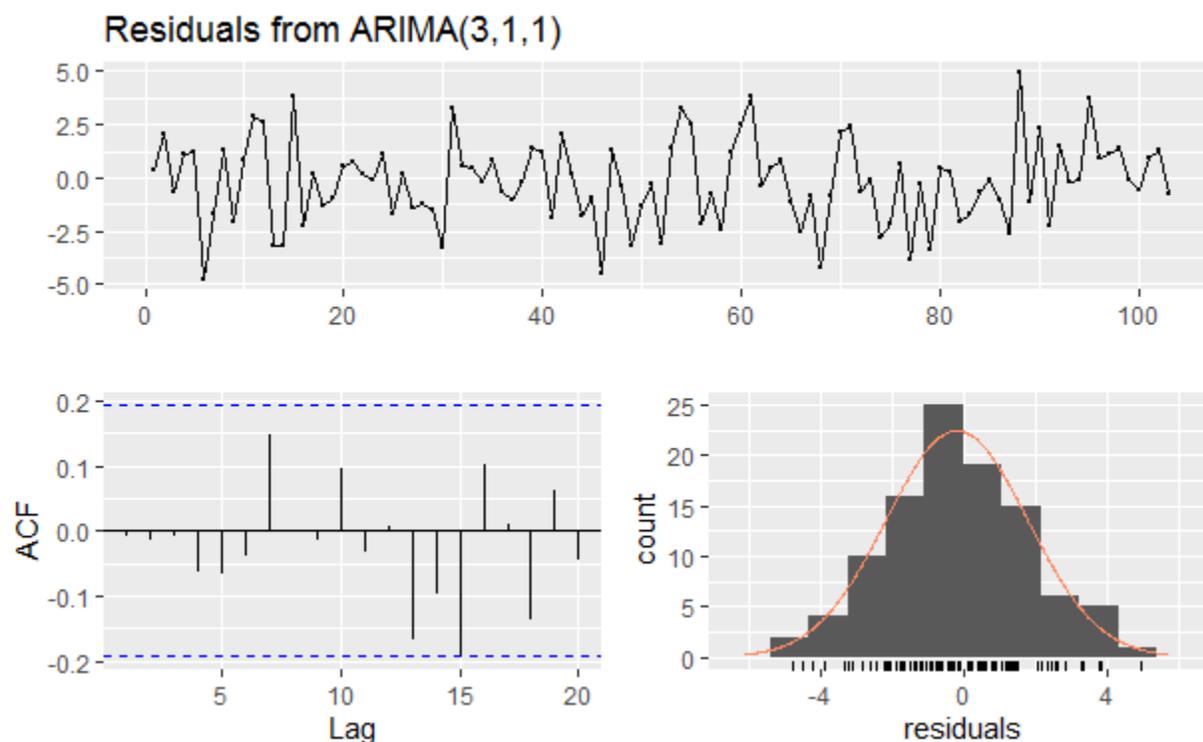
Figure 5: The plot of the residuals of ARIMA (3,1,1) model.

### 3.2 Artificial Neural Network
**The ANN-1 model**
The input layer of the ANN-1 model has three nodes – time, lag 1 and MA 2. The lag 1 and the MA 2 variables were chosen as part of the explanatory variables as they are the closest lag and moving averages to the recent USD to NGN exchange rate. A different number of nodes ranging from 1 to 7 were used in the model's hidden layer. The performance of the models for the different number of nodes in the hidden layer for both the training and test sets are shown in Table 3. The ANN-1 model with seven nodes was selected as the best as it does not overfit the training set and performs well in the test set. The neural network of the ANN-1 (ANN (3,7,1)) is shown in Figure6 and the weights of the network in Appendix A.

Table 3: The ANN-1 models with different node size in the hidden layer.

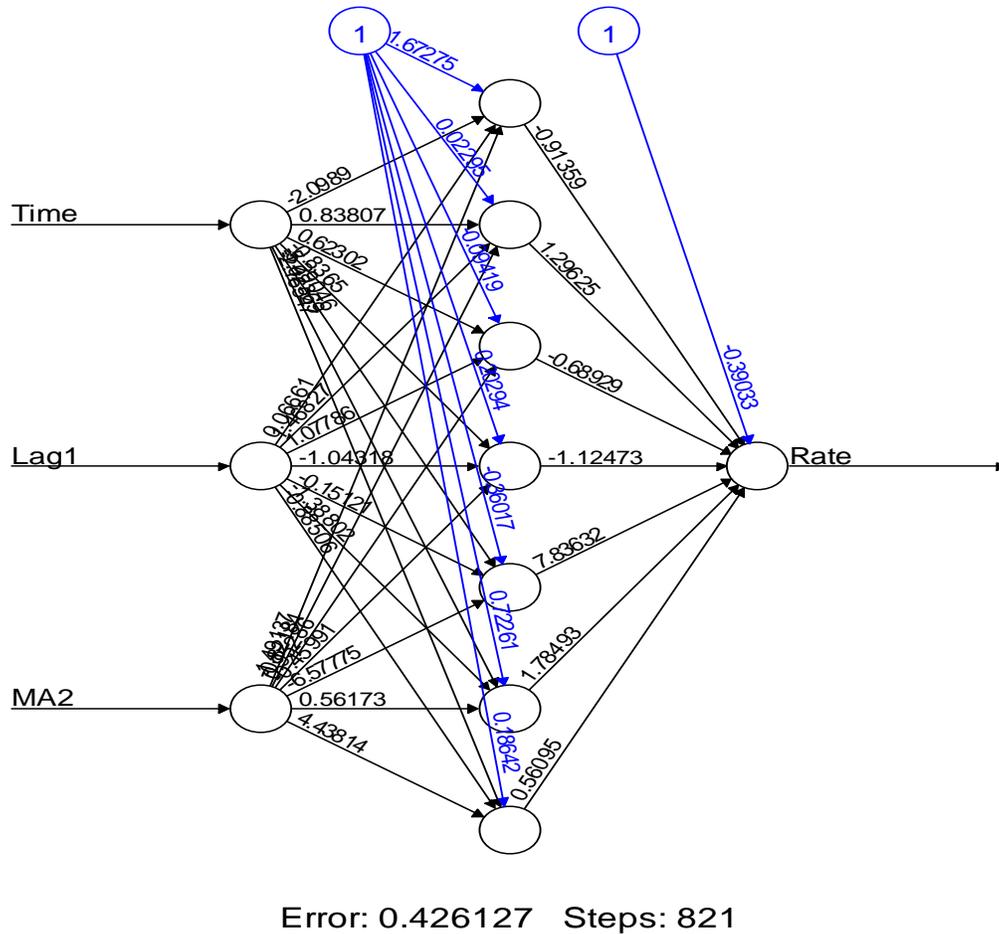| Training set | | | | Test set | | | |
|---|---|---|---|---|---|---|---|
| Node size | RMSE | MAPE | NSE | Node size | RMSE | MAPE | NSE |
| 1 | 7.154 | 0.01622 | -0.220 | 1 | 1.936 | 0.00397 | 0.282 |
| 2 | 7.233 | 0.01633 | -0.247 | 2 | 1.951 | 0.00403 | 0.271 |
| 3 | 6.990 | 0.01582 | -0.164 | 3 | 1.952 | 0.00402 | 0.270 |
| 4 | 6.984 | 0.01583 | -0.162 | 4 | 1.953 | 0.00405 | 0.270 |
| 5 | 6.682 | 0.01517 | -0.064 | 5 | 1.941 | 0.00400 | 0.278 |
| 6 | 5.954 | 0.01361 | 0.155 | 6 | 1.931 | 0.00397 | 0.286 |
| 7 | 5.054 | 0.01134 | 0.391 | 7 | 1.827 | 0.00383 | 0.361 |

Error: 0.426127   Steps: 821

Figure 6: The neural network of the ANN (3,7,1) model.

**The ANN-2 model**

The input layer of the ANN-2 model has five nodes – time, lag 1, MA 2, lag 5 and MA5. The lag 5 and the MA 5 variables were added to the explanatory variables of the ANN-1 model as the USD to NGN exchange rate data is a 5-day weekly data to see if it will improve the predictive ability of the neural network. The data are collected from Monday to Friday of each week. Different nodes ranging from 1 to 7 were also used in the hidden layer of the model. The performance of the models for the different number of nodes in the hidden layer for both the training and test sets are shown in Table 4. The ANN-2 model with five nodes was selected as the best as it does not overfit the training set and performs well in the test set. The neural network of the ANN-2 (ANN (5,5,1) is shown in Figure 7 and the weights of the network in Appendix B.

Table 4: The ANN-2 models with different node size in the hidden layer.

| Training set | | | | Test set | | | |
|---|---|---|---|---|---|---|---|
| Node size | RMSE | MAPE | NSE | Node size | RMSE | MAPE | NSE |
| 1 | 6.061 | 0.01407 | 0.125 | 1 | 1.958 | 0.00409 | 0.266 |
| 2 | 7.283 | 0.01645 | -0.264 | 2 | 1.866 | 0.00381 | 0.333 |
| 3 | 6.004 | 0.01402 | 0.141 | 3 | 1.907 | 0.00395 | 0.304 |
| 4 | 7.377 | 0.01682 | -0.297 | 4 | 1.893 | 0.00390 | 0.314 |
| 5 | 4.164 | 0.00792 | 0.587 | 5 | 1.851 | 0.00388 | 0.344 |
| 6 | 6.620 | 0.01539 | -0.044 | 6 | 1.830 | 0.00375 | 0.358 |
| 7 | 7.456 | 0.01690 | -0.325 | 7 | 1.898 | 0.00391 | 0.310 |
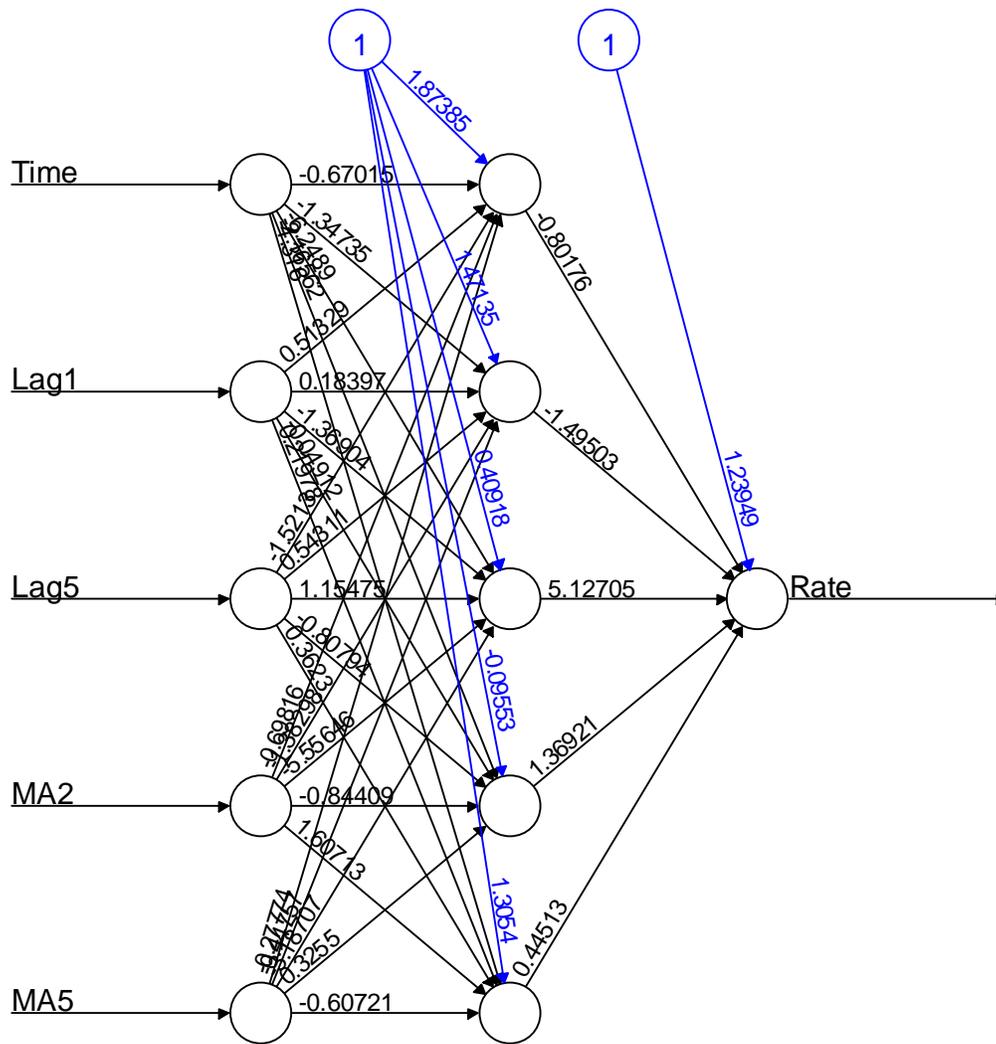
Error: 0.437324   Steps: 603

Figure 7: The neural network of the ANN (5,5,1) model.

The selected ANN (3,7,1) and ANN(5,5,1) models are compared to know if the addition of the lag 5 and MA 5 variables to the explanatory variables improve the predictive ability of the neural network. The performance of both models is tested in both the training and test sets. The ANN (5,5,1) model performed almost similar to the ANN (3,7,1) in the test set but performed better than the ANN (3,7,1) model in the training set, as shown in Table 5. The addition of the lag 5 and MA 5 variables to the explanatory variables slightly improved the predictive ability of the neural network. The importance of each of the five explanatory variables in the input layer is shown in Figure 8. The time, MA2 and MA5 variables affect predicting the USD to NGN exchange rate.

Table 5**:** Comparison of the ANN (3,7,1) and ANN (5,5,1) models.

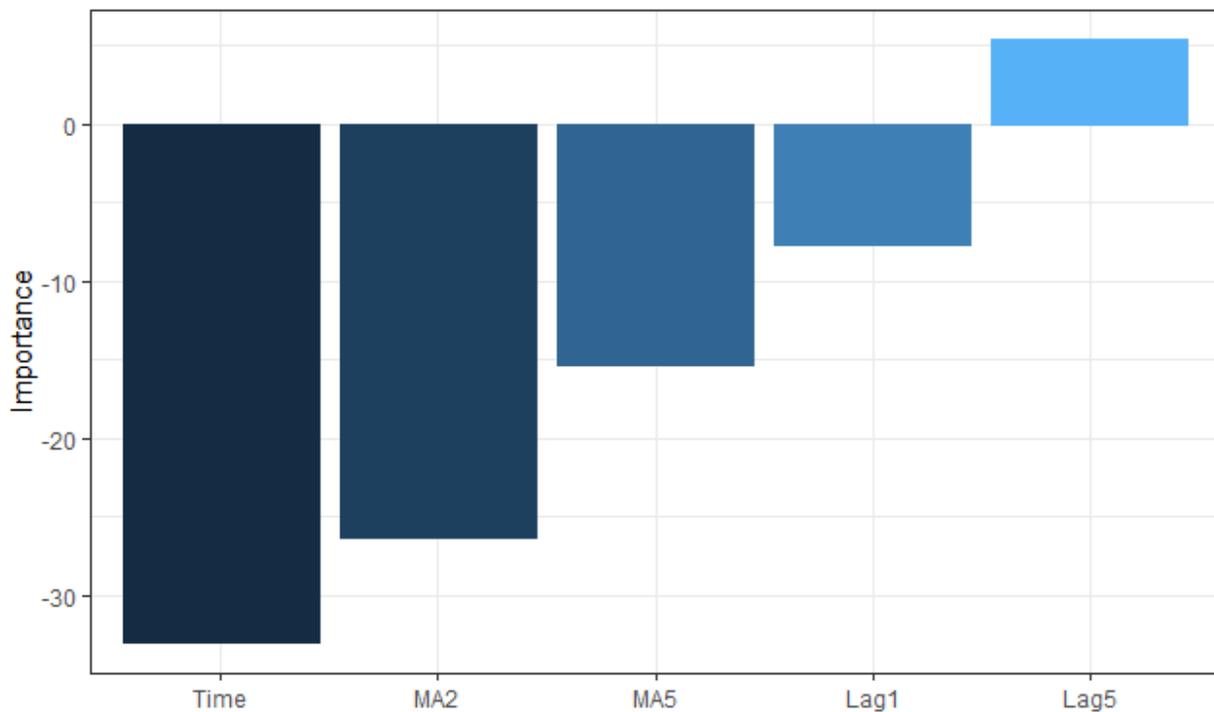| | Training | |
|---|---|---|
| | **ANN(3,7,1)** | **ANN(5,5,1)** |
| **RMSE** | 5.0543 | 4.1637 |
| **MAPE** | 0.0113 | 0.0079 |
| **NSE** | 0.3912 | 0.5869 |
| | Test | |
| | **ANN(3,7,1)** | **ANN(5,5,1)** |
| **RMSE** | 1.8267 | 1.8505 |
| **MAPE** | 0.0038 | 0.0039 |
| **NSE** | 0.3611 | 0.3443 |



Figure 8: Variable importance of the ANN (5,5,1) model.

### 3.3 Random Forest

Two random forest models – RF-1 and RF-2 – are used to model the USD to NGN exchange rate data. The RF-1 model has three explanatory variables like the ANN-1 model, while the RF-2 model has five explanatory variables like the ANN-2 model. Two explanatory variables – lag 5 and MA 5 – were added to the RF-1 model to see if it will improve the predictive ability of the random forest model like the ANN model. The number of trees for the models is 500. Three variables were sampled for splitting at each node in the RF-1 model while five variables were sampled for splitting at each node in the RF-2 model. The choice of the number of variables to be sampled for splitting at each node was selected by using the different performance measures. The performance of the RF-1 and RF-2 models in the training and test sets is shown in Table 6. The addition of the Lag 5 and MA 5 variables did not improve the predictive ability of the random forest model. The RF-1 model slightly outperformed the RF-2 model in both the training and test set. The RF-1 model is selected as the best random forest model. The effect and variable importance of each of the explanatory variables are shown in Figure 9. The time variable has more effect in predicting the USD to NGN exchange rate while the Lag 1 variable has the least effect, as shown in the increase in mean square error (%IncMSE) and the increase node impurity (%IncNodePurity) in Figure 8.

Table 6: Comparison of the RF-1 and RF-2 models.

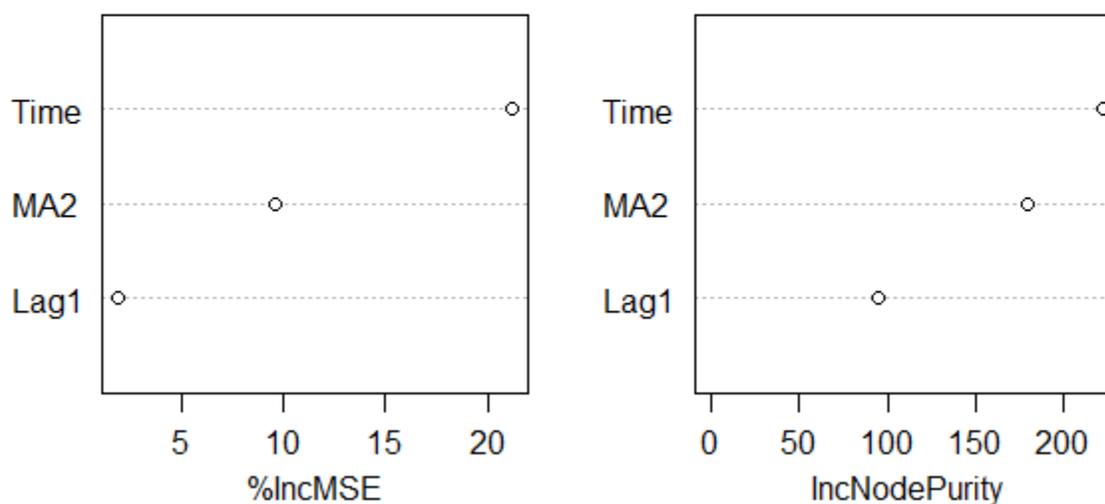| | Training | |
|---|---|---|
| | **RF - 1** | **RF – 2** |
| **RMSE** | 0.9130 | 0.9171 |
| **MAPE** | 0.0019 | 0.0019 |
| **NSE** | 0.8404 | 0.8390 |
| | **Test** | |
| | **RF - 1** | **RF – 2** |
| **RMSE** | 7.7609 | 7.8874 |
| **MAPE** | 0.0180 | 0.0179 |
| **NSE** | -0.4354 | -0.4825 |



Figure 9: Variable importance of the RF-1 model.

### 3.4 Comparison of the ARIMA, ANN and RF Models

The performance of the ARIMA (3,1,1), ANN (5,5,1) and RF-1 models in both the training and test sets were compared as shown in Table 7 to know the best model for the USD to NGN exchange rate data. The ARIMA (3,1,1) and RF-1 performed slightly better than the ANN (5,5,1) in the training set but their performance in the test set was poor. The ANN (5,5,1) model did not overfit the training set and performed very well in the new data (test set) that were not used to train it. The ANN (5,5,1) is chosen as the best model to use to forecast for future USD to NGN exchange rate.

Table 7: Comparison of the ARIMA (3,1,1), ANN (5,5,1) and RF-1 models.

| | **Train** | | |
|---|---|---|---|
| | **ANN(5,5,1)** | **RF - 1** | **ARIMA(3,1,1)** |
| **RMSE** | 4.1637 | 0.9130 | 1.9691 |
| **MAPE** | 0.0079 | 0.0019 | 0.0041 |
| **NSE** | 0.5869 | 0.8404 | 0.2575 |
| | **Test** | | |
| | **ANN(5,5,1)** | **RF - 1** | **ARIMA(3,1,1)** |
| **RMSE** | 1.8505 | 7.7609 | 8.0039 |
| **MAPE** | 0.0039 | 0.0180 | 0.0182 |
| **NSE** | 0.3443 | -0.4354 | -0.5266 |

## 4. Discussion

The results revealed that the ARIMA model mostly used by researchers (Okon and Ikpang, 2020; Nwankwo, 2014; Onasanya et al., 2013; Appiah and Adetunde et al., 2011) to model the USD to NGN exchange rate was outperformed by the two machine learning models – ANN and RF. Though the ARIMA and random forest performed slightly better than the neural network in the training set, their performance in the test set was poor. The neural network with 5 nodes in the input layer, 5 nodes in the hidden layer and 1 node in the output layer (ANN (5,5,1)) performed better on the new data set (test set) and is chosen as the best model for forecasting the USD to NGN exchange rate for the coming months and years. Comparative assessment revealed that Onasanya and Adeniji (2013) used time-domain model for forecasting Nigerian Naira and US Dollar. The authors applied the time domain model that uses the Box Jenkins approach to the naira/dollar exchange rate from January 1994 to December 2011. The ARIMA (1, 2, 1) was selected after confirming that the residuals of the model are white noise. Appiah and Adetunde (2011) also used the ARIMA model to fit the US Dollar and Ghana Cedi exchange rate. They chose the ARIMA (1, 1, 1) as the most appropriate model and used it to forecast for a period of two years. Nwankwo (2014) analyzed the Nigerian Naira to US Dollar exchange rate using the ARIMA model. He used the data for 1982 to 2011 to fit the model. The AR (1) was the preferred model. It had a better prediction than other ARIMA models. Okon and Ikpang (2020) extended the work of modelling Nigerian Naira to US Dollar exchange rate to assess the effect of the COVID-19 on the rate of exchange. They used the ARIMA model to fit the data. Therefore, our decision to test ARIMA model as well as machine learning models during COVID-19 pandemic period is greatly justified and our findings revealed that the two machine learning models – ANN and RF beat the ARIMA model.

## 5. Conclusion

In this study, we identified a high performance and adaptable model(s) for forecasting USD and NGN exchange rates and determined the adequacy of the models based on the model diagnostic tools. The machine learning models performed better than the classical ARIMA model in fitting the USD and NGN exchange rates and are suitable for forecasting.

The information from the high-performance model (ANN (5, 5, 1)) for modeling the USD to NGN exchange rate will assist econometric trading of the currencies and offer both speculative and precautionary assistance to individuals, households, firms and nations who use the currencies locally and for international trade.

We recommend that a hybrid ARIMA-ANN model be fitted on the USD to NGN exchange rate data and the result be compared with the ANN model to ascertain if the hybrid ARIMA-ANN model will outperform the ANN model.

**Appendices**
**APPENDIX A:** The weights of the ANN-1 model

|  | Weight |  | Weight |
|---|---|---|---|
| Error | 0.43 | Time to HL5 | -5.29 |
| reached threshold | 0.01 | Lag1 to HL5 | -0.15 |
| Steps | 821 | MA2 to HL5 | -6.58 |
| Intercept to HL1 | 1.67 | Intercept to HL6 | 0.72 |
| Time to HL1 | -2.10 | Time to HL6 | -1.02 |
| Lag1 to HL1 | 0.07 | Lag1 to HL6 | -1.39 |
| MA2 to HL1 | -1.49 | MA2 to HL6 | 0.56 |
| Intercept to HL2 | 0.02 | Intercept to HL7 | 0.19 |
| Time to HL2 | 0.84 | Time to HL7 | -2.17 |
| Lag1 to HL2 | 1.47 | Lag1 to HL7 | -0.89 |
| MA2 to HL2 | -0.82 | MA2 to HL7 | 4.44 |
| Intercept to HL3 | -0.09 | Intercept to Rate | -0.39 |
| Time to HL3 | 0.62 | HL1 to Rate | -0.91 |
| Lag1 to HL3 | 1.08 | HL2 to Rate | 1.30 |
| MA2 to HL3 | 0.95 | HL3 to Rate | -0.69 |
| Intercept to HL4 | 0.20 | HL4 to Rate | -1.12 |
| Time to HL4 | -0.84 | HL5 to Rate | 7.84 |
| Lag1 to HL4 | -1.04 | HL6 to Rate | 1.78 |
| MA2 to HL4 | -0.46 | HL7 to Rate | 0.56 |
| Intercept to HL5 | -0.36 |  |  |

**APPENDIX B:** The weights of the ANN-2 model

|  | Weight |  | Weight |
|---|---|---|---|
| Error | 0.44 | MA5 to HL3 | -3.19 |
| reached threshold | 0.01 | Intercept to HL4 | -0.10 |
| Steps | 603 | Time to HL4 | -2.17 |
| Intercept to HL1 | 1.87 | Lag1 to HL4 | -0.05 |
| Time to HL1 | -0.67 | Lag5 to HL4 | -0.81 |
| Lag1 to HL1 | 0.51 | MA2 to HL4 | -0.84 |
| Lag5 to HL1 | -1.52 | MA5 to HL4 | 0.33 |
| MA2 to HL1 | -0.70 | Intercept to HL5 | 1.31 |
| MA5 to HL1 | -0.28 | Time to HL5 | -1.32 |
| Intercept to HL2 | 1.47 | Lag1 to HL5 | 0.22 |
| Time to HL2 | -1.35 | Lag5 to HL5 | 0.36 |
| Lag1 to HL2 | 0.18 | MA2 to HL5 | 1.61 |
| Lag5 to HL2 | 0.54 | MA5 to HL5 | -0.61 |
| MA2 to HL2 | -1.38 | Intercept to Rate | 1.24 |
| MA5 to HL2 | -0.45 | HL1 to Rate | -0.80 |
| Intercept to HL3 | 0.41 | HL2 to Rate | -1.50 |
| Time to HL3 | -6.25 | HL3 to Rate | 5.13 |
| Lag1 to HL3 | -1.37 | HL4 to Rate | 1.37 |
| Lag5 to HL3 | 1.15 | HL5 to Rate | 0.45 |
| MA2 to HL3 | -5.56 |  |  |

## References

[1] Appiah S.T, Adetunde I.A. (2011). Forecasting exchange rate between the Ghana Cedi and the US Dollar using time series analysis. *Current Research Journal of Economic Theory*, *3*(2), 76-83.

[2] Bakawu M.A., Abdulkadir A., Maitoro S.U. and Malik A. (2020). Evaluation of models for forecasting daily foreign exchange rates between Nigerian Naira and US Dollar amidst volatility. *International Journal of Science and Business, 4*(1), 95-105.

[3] Box GEP, Jenkins GM (1976). *Time Series Analysis: Forecasting and control. Rev. ed.* San Francisco: Holden-Day. doi:10.1109/34.709601

[4] Ho T.K. (1998). The Random Subspace Method for Constructing Decision Forests. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *20*(8), 832-844. doi:10.1109/34.709601.

[5] Nwankwo S.C. (2014). Autoregressive integrated moving average (ARIMA) model for exchange rate (Naira to Dollar). *Academic Journal of Interdisciplinary Studies*, *3*(4), 429-434.

[6] Nwokike C.C., Offorha B.C., Obubu M., Ugoala C.B. and Ukomah H.I. (2020). Comparing SANN and SARIMA for forecasting frequency of monthly rainfall in Umuahia. *Scientific African*, *10*. https://doi.org/10.1016/j.sciaf.2020.e0062

[7] Nwosu U.I. and Obite C.P. (2021). Modeling Ivory Coast COVID-19 cases: identification of a high-performance model for utilization. *Results in Physics* 20. https://doi.org/10.1016/j.rinp.2020.103763.

[8] Nyoni T. (2018). Modeling and forecasting Naira/USD exchange rate in Nigeria: a Box-Jenkins ARIMA approach. Munich Personal RePEc Archive. https://mpra.ub.uni.muenchen.de/88622/

[9] Obite C.P., Olewuezi N.P., Ugwuanyim G.U. and Bartholomew D.C. (2020). Multicollinearity Effect in Regression Analysis: A Feed Forward Artificial Neural Network Approach. *Asian Journal of Probability and Statistics, 6*(1), 22-33. https://doi.org/10.9734/AJPAS/2020/v6i130151

[10] Okon E.J. and Ikpang I.N. (2020). Modeling and forecasting exchange rate values between Naira and US Dollar to assess the effect of covid-19 pandemic period on the rate. *Asian Journal of Probability and Statistics, 8*(1), 55-65.

[11] Olden J.D., Michael K.J., and Russell G.D. (2004). An accurate comparison of methods for quantifying variable importance in artificial neural networks using simulated data. *Ecological Modelling,178*, 389-397.

[12] Onasanya O.K, Adeniji O.E. (2013). Forecasting of exchange rate between Naira and US Dollar using time domain model. *International Journal of Development and Economic Sustainability*, *1*(1), 45-55.

[13] Rundo F, Trenta T, Luigi di Stallo A. and Battiato S. (2019). Machine learning for quantitative finance applications: a survey. *Applied Sciences* 9. doi 10.3390/app9245574.