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Evaluation of the Performance of Autoregressive Integrated Moving Average (ARIMA) and Artificial Neural Networks (ANNs) Models: Application to Confirmed Cases of Covid-19 in Nigeria

Olafioye, Sunday Omotola [a], Oguntade, Emmanuel Segun [a] and Awogbemi, Clement Adeyeye [b*]

[a] *Department of Statistics, Faculty of Science, University of Abuja, Abuja, Nigeria.*
[b] *Department of Statistics, National Mathematical Centre, Abuja, Nigeria.*

Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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Abstract

In this study, the performance of Autoregressive Integrated Moving Average (ARIMA) and Artificial Neural Networks (ANNs) models was investigated and evaluated using daily confirmed cases of COVID-19 in Nigeria. The stationarity status of the data collected was established using Augmented Dickey Fuller unit root test. The residual normality test was also carried out with the residual plots indicating adequacy of the fitted ARIMA model. The results of neural networks were analyzed using back-propagation for multilayer feed-

**Corresponding author: Email: awogbemiadeyeye@yahoo.com;*

forward powered by sigmoid function. Utilizing backpropagation method based on three factors expressed in terms of the learning rate, the distance between the actual output and predicted output and the activation function, the network weights were generated The performance indices for ARIMA and ANNs models were evaluated using Mean Square Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE and the results revealed that the ARIMA model performed better than the ANN model considering the minimum prediction error and forecasting ability. The ARIMA (2, 1, 1) model appeared to be the best fitted model over the ANN model for the daily confirmed covid-19 cases considered.

Keywords: Coronavirus; performance evaluation; stationarity test; ARIMA models; artificial neural networks.

1 Introduction

Several research studies on COVID-19 predictions have been conducted with various proposed solution techniques The techniques fall into two broad areas, namely, statistical techniques such as exponential smoothing, autoregressive integrated moving average (ARIMA), Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model and soft computing technique akin to Artificial Neural Network [1].

The ARIMA models, also known as the Box-Jenkins models are mathematical models of persistence or autocorrelation in time series. They do not only uncover the hidden patterns in the given data but also generate forecasts and predict a variable's future values from its past values [2,3]. The use of ARIMA for forecasting time series is essential with uncertainty as it does not assume knowledge of any underlying model or relationships as in some other methods. ARIMA essentially relies on past values of the series as well as previous error terms for forecasting [4].

The parameters of ARIMA models are usually estimated by using Ordinary Least Squares (OLS) approach or maximum likelihood method. However, OLS approach imposes strict underlined assumptions on the model specification in the course of estimating the parameters for the purpose of achieving significant results. This is traceable to the fact that most data series or relations are usually non-linear in the parameter and can also be non-stationary.

An Alternative model that can be used to handle the problem of non-linearity and non-stationarity is Artificial Neural Network (ANN). ANN as a soft computing technique has been used extensively as a forecasting model in many areas of human endeavors [5]. An Artificial Neural Network consists of an interconnected group of artificial neurons that are physical cellular systems capable of obtaining, storing information and using experiential knowledge. It can also be regarded as a massively parallel combination of simple processing units which can acquire knowledge from an environment through a learning process and store the knowledge in its connections.

Nigeria recorded its first case of Covid-19 on the 27th February, 2020 with an index case of an Italian citizen who arrived Nigeria from Italy. The second case of Covid-19 was reported on the 9th March, 2020 in Nigeria as a contact of the index case. The disease spread through droplets which remain in the air for some period of time and also occurs through human interactions and contaminated fomites. The inhabitants from countries like United Kingdom, Germany, Italy Spain, USA, etc were considered as people with high risk factors [6,7].

For the treatment of COVID 19, there exists not any available therapeutic product which is effective for the cure of the disease. The virus could only be managed by a number of discovered medicines.

The Federal Government of Nigeria announced a lockdown in March 2020 across Lagos, Ogun states and the Federal Capital Territory (FCT) with effect from March 30 2020. In addition to the lockdown, social distancing rule was enforced by cancelling mass gatherings, closing businesses except for providers of essential goods and services.

This study therefore intends to contribute to a better understanding of the problem related to the covid-19 daily cases prediction. In order to achieve this, ARIMA is compared with (ANNs) to establish if the forecast power improves from one technique to other.

2 Literature Review on ARIMA and ANNs Models

2.1 On ARIMA models

The time series ARMA model was used by [8] to model projection of COVID 19 prevalence cases in East African countries such as Sudan, Ethiopia, Djibouti and Somalia. The research results indicated that progression in the frequency of cases in area of study ARIMA model and transfer function were used by [9] to model and forecast students' study achievement. The results indicated significant stability and accuracy by ARIMA model, but the transfer function showed better accuracy to predict students' academic performance.

The epidemiological trend of COVID 19 occurrence in European was modeled by [10] and it was observed that ARIMA had the lowest mean absolute percentage error values.

Applying ARIMA model in Turkey on the day 150 of COVID 19 disease, [11] predicted that the number of confirmed cases will not cut to zero level until 6 August 2021.

ARIMA model was fitted to predict the number of confirmed cases in India by [12] in both worst and optimistic scenarios. The worst cases scenario was predicted to have nearly about 700,000 cases by the end of April, 2020.

2.2 On artificial neural networks

The prediction ability of ARIMA and ANNs models was examined by [13] and the empirical results indicated that the ANN model gave better predictions values over the ARIMA model.

Artificial Neural Networks model was proposed by [14] to estimate and forecast the number of confirmed and recovered cases of COVID 19. The proposed model was based on the training data published in Saudi Arabia COVID- 19 demography using multilayer perception neural network. The results revealed that the number of recoveries could be between 2000 and 4000 per day.

Classification of COVID-19 patients from chest CT images was investigated by [15] using multi-objective differential evolution-based convolution neural networks. An extensive analysis showed that the model could classify the chest CT images at a good accuracy rate.

Stochastic time effective neural networks were used by [16] in predicting China global index and their study showed that the mentioned model outperformed the regression model.

Hybrid models with neutral networks and time series models were introduced by [17] to forecast the volatility of stock price index in two vision points: deviation and direction. The results showed that ANN time series models can increase the predictive power for the perspective of deviation and direction accuracy.

3 Methodology

3.1 Data source

The data used for this study were obtained from publications of the World Health Organization (WHO). The observations were series of Nigeria's daily confirmed cases of Covid-19 from February 28, 2020 to November 30, 2021.

3.2 Method of data analysis

3.2.1 Stationarity test

In this study, The Dickey-Fuller test is employed to carry out the stationarity status of the data collected.

The ARIMA and Artificial Neural Networks models are the two forecasting techniques deployed in this study to predict the daily confirmed cases of covid-19 data in Nigeria. The R software is also used for the data analysis.

3.2.2 ARIMA model

The ARIMA (p, d, q) is represented by the form

$$\theta_p(A)(1-A)^d z_t = \emptyset_q(A)b_t \tag{1}$$

where *p* is the Autoregressive (AR) lag order, *d* is the differencing order and *q* is the Moving Average (MA) lag order.

Thus,

$$\theta_p(A) = (1 - \theta_1 A - \theta_2 A^2 - \cdots - \theta_p A^p) \tag{2}$$

$$\emptyset_p(A) = (1 - \emptyset_1 A - \emptyset A^2 - \cdots - \emptyset A^p) \tag{3}$$

The seasonal pattern of the general form of ARIMA is given as

$$\theta_p(A)\theta_p(A^s)(1-A)^d(1-A^s)^d z_t = \emptyset_q(A)\theta\emptyset(A^s)_{b_t},(4) \tag{4}$$

where s is the seasonal period

3.2.3 ARIMA modeling procedure

The Box and Jenkins' modeling procedure consists of three iterative stages which are specification of the model, parameter estimation and diagnostic checking. The process is repeated many times up to when an acceptable model is obtained. The selected values can then be used to predict the future value of the data [18].

(a) Specification of the model: This stage ensures that the time series variables are made stationary through the process of differencing. The graphs of autocorrelation function and that of partial autocorrelation functions are plotted to decide AR and MA components for further analysis.
(b) Parameter estimation: This is simply the process of estimating the parameters of the model using adopted computational algorithm.
(c) Diagnostic checking: This is the process of testing whether or not the estimated model adequately specifies a stationary univariate process.

3.2.4 Methods of model identification

Akaike Information Criterion (AIC): This is a single member score that can be used to determine which of the multiple models is most likely to be the best model.

$$AIC(p) = nln(\frac{\hat{\sigma}_t^2}{n}) + 2p \tag{5}$$

Bayesian Information Criterion (BIC): This measures the efficiency of parametized model in terms of predicting the data.

$$\mathrm{BIC(p)} = \mathrm{nln}\left(\frac{\hat{\sigma}_t^2}{\mathrm{n}}\right) + \mathrm{p} + \mathrm{pln(n)}\ , \tag{6}$$

where n is the number of observations sampled for model fitting, p is the total number of parameters used by the model is the sum of sample variance. The Smaller the values of AIC and BIC, the better the model

3.2.5 Evaluation of forecasting methods

The forecasting results of the models are evaluated using Mean Square Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). The model with the least error is chosen as the best [19]:

$$\mathrm{MSE} = \frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2 \quad (7)$$

$$\mathrm{RMSE} = \left(n^{-1}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2\right)^{\frac{1}{2}} \quad (8)$$

$$\mathrm{MAE} = n^{-1}\sum_{t=1}^{n}|y_t - \hat{y}_t| \quad (9)$$

3.2.6 Backpropagation for multilayer feedforward

Backpropagation method is based on three factors: the learning rate, the distance between the actual output and predicted output, and the activation function. The learning rate controls the size of change in weights in each step. If it is too small, the ideal point of convergence may be small. But in the case if the learning rate is too large, the algorithm might not converge at all. The learning rate should fall in the range $0 \le a \le 1$.

Let the error function be denoted by E_f and the rate of change in E_f with respect to the weight, β be written as

$$\Delta E_f(\beta) = \frac{\partial E_f}{\delta \beta_p}, \quad (10)$$

where β_p is the vector of all weights of the network at pth iteration.

The network weights are determined by

$$\beta_{p+1} = \beta_p + \Delta(\beta)_p, \quad (11)$$

where β_p are weights of the pth iteration, β_{p+1} are the parameters of $(p+1)^{th}$ iteration and $\Delta(\beta)_p$ is the learning process which can be expressed as

$$\Delta(\beta)_p = -a\nabla E_f(\beta), \quad (12)$$

where a referred to as learning rate is a positive constant.

Let $E_f = \frac{1}{2}\sum_{p=1}^{n}(T_p - Y_p)^2$ be a network objective function so that

$$Y_p = f\left(\sum_{j=1}^{m}\sum_{i=1}^{n} X_i v_{ji}\right) = f(X_p \beta_p) \quad (13)$$

From equation 15, the previous equation (12) can be rewritten as

$$\Delta E_f(\beta) = \frac{\partial E_f}{\partial \beta_p} = \frac{\partial E_f}{\partial v_{ji}} \quad (14)$$

Using sigmoid function as the activation function in ouput layer, we generate

$$f(u) = \frac{1}{1+e^{-u}}, \quad (15)$$

where

$$u = \sum_{j=1}^{m}\sum_{i=1}^{n} X_i v_{ji} \quad (16)$$

The gradient $\frac{\partial E_f}{\partial v_{ji}}$ can be expressed as

$$\frac{\partial \mathrm{E_f}}{\partial v_{ji}} = \frac{\partial \mathrm{E_f}}{\partial f(u)} \cdot \frac{\partial \mathrm{E_f}}{\partial (u)} \cdot \frac{\partial \mathrm{E_f}}{\partial v_{ji}} = f(u)(1 - f_p(u)(T_p - f_p) \quad (17)$$

From equation (18), we derive

$$\frac{\partial \mathrm{u}}{\partial v_{ji}} = X_i \quad (18)$$

In order to analyze the residual, the value of $\frac{\partial \mathrm{E_f}}{\partial f(u)} \frac{\partial \mathrm{f(u)}}{\partial (u)}$ needs to be determined as follows:

$$\frac{\partial \mathrm{E_f}}{\partial f(u)} = \frac{\frac{\partial}{2}(T_p - f_p(u))^2}{\partial f(u)} = \left(T_p - f_p(u)\right) \frac{\frac{\partial}{2}(T_p - f_p(u))}{\partial f(u)} = -(T_p - f_p(u)) \quad (19)$$

Therefore,

$$\frac{\partial f(u)}{\partial u} = -f_p(u)\left(1_p - f_p(u)\right) \quad (20)$$

Substituting equations (20), (21) and (22) into equation (19), we have

$$\frac{\partial \mathrm{E_f}}{\partial v_{ji}} = \frac{\partial \mathrm{E_f}}{\partial f(u)} = \frac{\partial \mathrm{f(u)}}{\partial (u)} \cdot \frac{\partial (\mathrm{u})}{\partial v_{ji}} = -f_p\left(1 - f_p(u)\right)(T_p - f_p(u))X_i \quad (21)$$

Equation (19) is rewritten as:

$$\Delta E_f(\beta) = \frac{\partial E_f}{\partial \beta_p} = \frac{\partial \mathrm{E_f}}{\partial v_{ji}} = -X_i \mathrm{f_p}(u)(1 - f_p(u)(T_p - f_p(u)) \quad (22)$$

Substituting (24) into (16) and subsequently into (15), we generate the frequency of the iterations and $\Delta(\beta)_p$of the learning process as

$$\begin{aligned} \beta_{p+1} &= \beta_p + aX_i \mathrm{f_p(u)}\left(1 - f_p(u)\right)\left(T_p - f_p(u)\right) \\ &= \beta_p + aX_i \mathrm{f_p(u)}\left(\mathrm{X_p}, \beta_p\right)\left(1 - f_p\left(\mathrm{X_p}, \beta_p\right)\right)\left(T_p - f_p\left(\mathrm{X_p}, \beta_p\right)\right), \end{aligned} \quad (23)$$

where a is the learning rate, $\left(T_p - f_p\left(\mathrm{X_p}, \beta_p\right)\right)$ is the distance between the actual output and the predicted output and $\mathrm{f_p(u)}\left(\mathrm{X_p}, \beta_p\right)$ is the activation function.

4 Empirical Results

Table 1. Descriptive statistics

		Statistic	**Std. Error**
Mean		333.67	15.00
95% Confidence Interval for Mean	Lower Bound	304.22	
	Upper Bound	363.12	
5% Trimmed Mean		284.71	
Median		188.50	
Variance		144370.72	
Std. Deviation		379.96	
Minimum		.00	
Maximum		2464.00	
Range		2464.00	
Interquartile Range		411.00	
Skewness		2.003	.096
Kurtosis		4.67	.193

Table 2. Outlier test

			Case Number	Value
New_cases	Maximum	1	331	2464.00
		2	329	1964.00
		3	338	1883.00
		4	323	1867.00
		5	335	1861.00
	Minimum	1	638	.00
		2	636	.00
		3	634	.00
		4	628	.00
		5	595	.00[a]

Table 3. Tests of normality of series

	Statistic	df	Sig.	Statistic	df	Sig.
New_cases	.190	642	.000	.782	642	.000

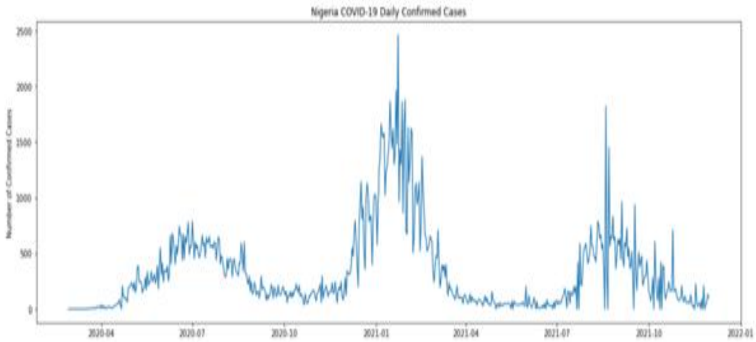

Fig. 1. Series plot on daily basis

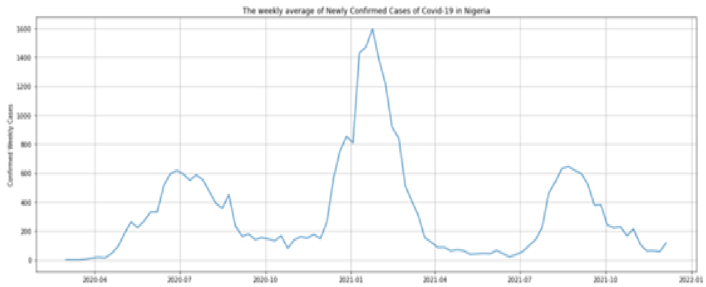

Fig. 2. Series plot of weekly basis

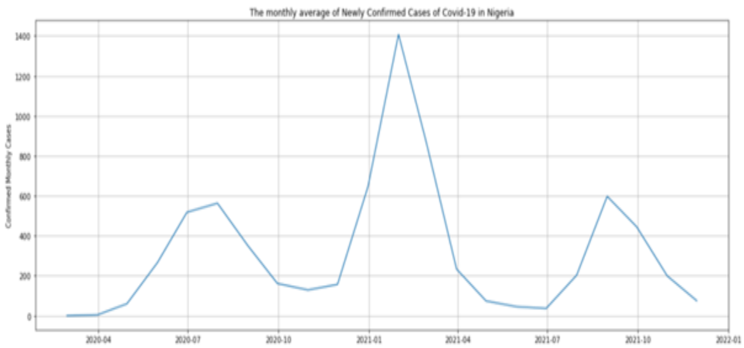

Fig. 3. Series plot on monthly basis

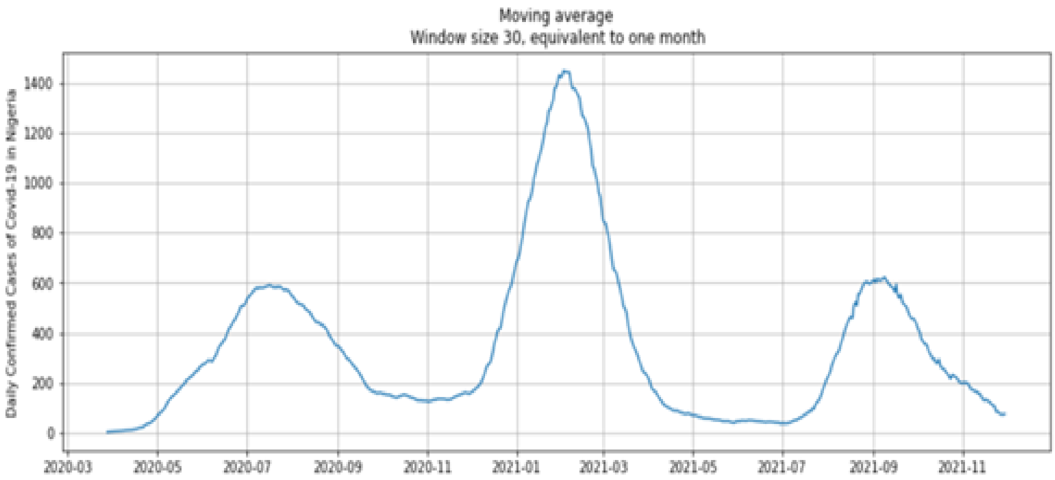

Fig. 4. Series plot of monthly moving average

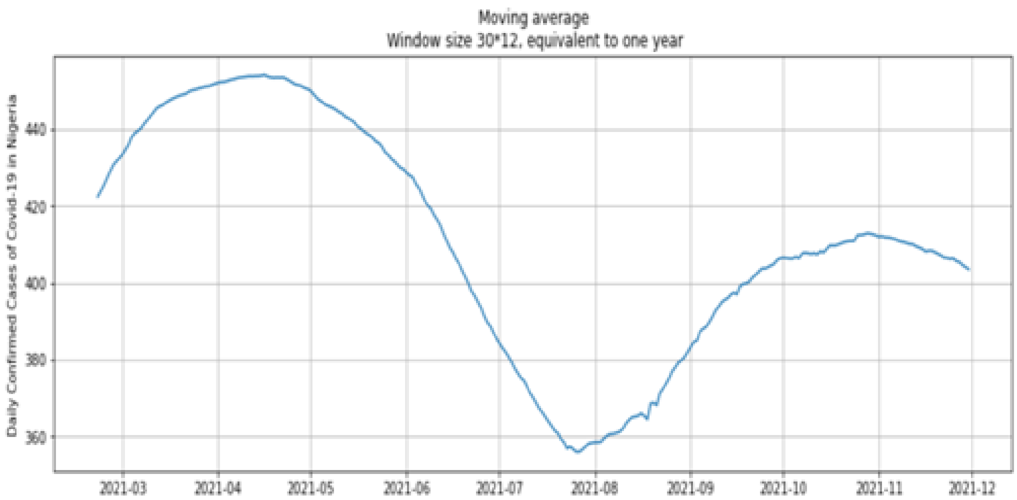

Fig. 5. Series plot of yearly moving average

Table 4. Dickey-fuller test at ∝ level

```
Results of Dickey-Fuller Test:
Test Statistic                  -2.955419
p-value                          0.039273
#Lags Used                      18.000000
Number of Observations Used    623.000000
Critical Value (1%)             -3.440890
Critical Value (5%)             -2.866190
Critical Value (10%)            -2.569247
dtype: float64

 Data is non-stationary
```

```
Results of Dickey-Fuller Test:
Test Statistic                  -4.816889
p-value                          0.000050
#Lags Used                      15.000000
Number of Observations Used    626.000000
Critical Value (1%)             -3.440839
Critical Value (5%)             -2.866168
Critical Value (10%)            -2.569235
dtype: float64

Data is stationary
```

Table 5. ARIMA candidate models

```
Performing stepwise search to minimize aic
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=8439.895, Time=0.95 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=8761.770, Time=0.03 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=8610.302, Time=0.06 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=8448.350, Time=0.26 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=8759.772, Time=0.01 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=8451.611, Time=0.38 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept   : AIC=8438.181, Time=0.48 sec
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=8448.454, Time=0.26 sec
 ARIMA(2,1,0)(0,0,0)[0] intercept   : AIC=8496.888, Time=0.08 sec
 ARIMA(3,1,1)(0,0,0)[0] intercept   : AIC=8440.007, Time=0.64 sec
 ARIMA(3,1,0)(0,0,0)[0] intercept   : AIC=8473.101, Time=0.10 sec
 ARIMA(3,1,2)(0,0,0)[0] intercept   : AIC=8441.895, Time=0.94 sec
 ARIMA(2,1,1)(0,0,0)[0]             : AIC=8436.187, Time=0.21 sec
 ARIMA(1,1,1)(0,0,0)[0]             : AIC=8446.460, Time=0.12 sec
 ARIMA(2,1,0)(0,0,0)[0]             : AIC=8494.890, Time=0.04 sec
 ARIMA(3,1,1)(0,0,0)[0]             : AIC=8438.012, Time=0.27 sec
 ARIMA(2,1,2)(0,0,0)[0]             : AIC=8437.963, Time=0.30 sec
 ARIMA(1,1,0)(0,0,0)[0]             : AIC=8608.303, Time=0.03 sec
 ARIMA(1,1,2)(0,0,0)[0]             : AIC=8449.614, Time=0.24 sec
 ARIMA(3,1,0)(0,0,0)[0]             : AIC=8471.103, Time=0.05 sec
 ARIMA(3,1,2)(0,0,0)[0]             : AIC=8439.900, Time=0.39 sec

Best model:  ARIMA(2,1,1)(0,0,0)[0]
Total fit time: 5.876 seconds
```

Table 6. Summary of ARIMA model results

```
                             ARIMA Model Results
==============================================================================
Dep. Variable:                    D.y   No. Observations:                  611
Model:                 ARIMA(2, 1, 1)   Log Likelihood                 742.058
Method:                       css-mle   S.D. of innovations              0.072
Date:                Wed, 01 Dec 2021   AIC                          -1474.117
Time:                        22:50:17   BIC                          -1452.041
Sample:                             1   HQIC                         -1465.530

==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const       9.337e-05      0.001      0.125      0.900      -0.001       0.002
ar.L1.D.y     -0.1387      0.053     -2.598      0.009      -0.243      -0.034
ar.L2.D.y     -0.1660      0.047     -3.499      0.000      -0.259      -0.073
ma.L1.D.y     -0.6660      0.040    -16.842      0.000      -0.744      -0.588
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1           -0.4178           -2.4183j            2.4541           -0.2772
AR.2           -0.4178           +2.4183j            2.4541            0.2772
MA.1            1.5015           +0.0000j            1.5015            0.0000
-----------------------------------------------------------------------------
```

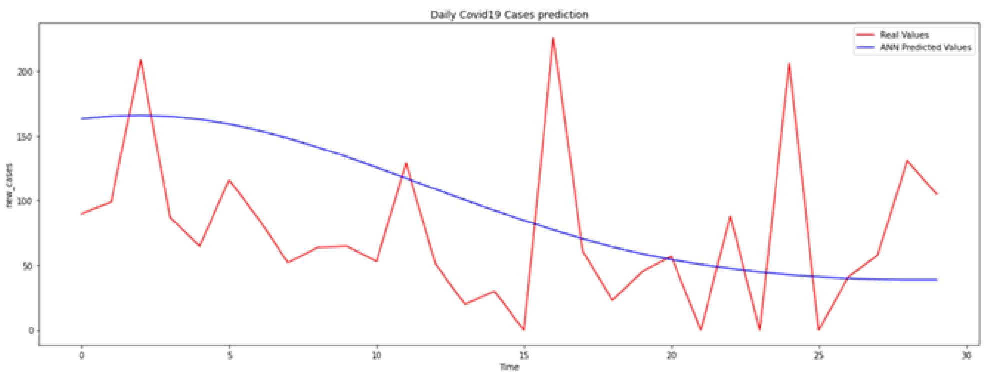

Fig. 6. ANN prediction plot

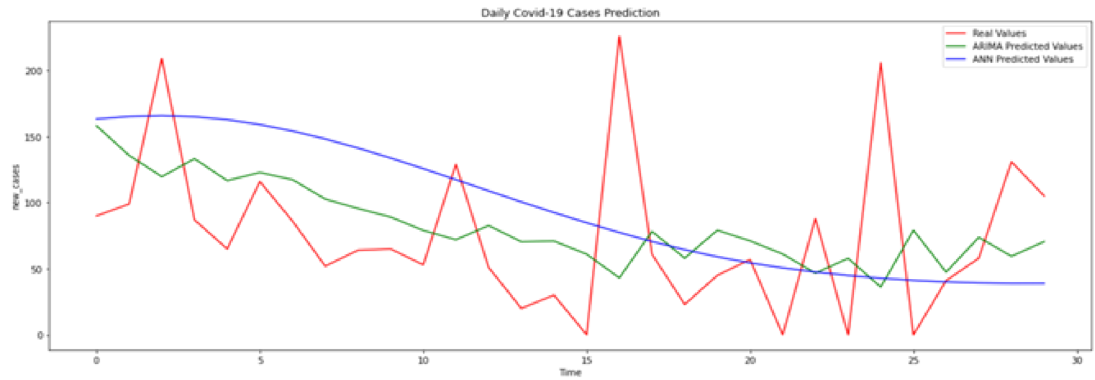

Fig. 7. Models prediction plots for ARIMA, ANN and real values

Table 7. Prediction table for ARIMA and ANN model

Date	Confirmed Cases	ARIMA Prediction	ANN Prediction
1/11/2021	90	158	163
2/11/2021	99	136	165
3/11/2021	209	120	166
4/11/2021	87	133	165
5/11/2021	65	117	163
6/11/2021	116	123	159
7/11/2021	86	117	154
8/11/2021	52	103	148
9/11/2021	64	96	141
10/11/2021	65	89	134
11/11/2021	53	79	126
12/11/2021	129	72	117
13/11/2021	51	83	109
14/11/2021	20	70	101
15/11/2021	30	71	93
16/11/2021	0	61	85
17/11/2021	226	43	77
18/11/2021	61	78	71
19/11/2021	23	58	64
20/11/2021	45	79	59
21/11/2021	57	71	54
22/11/2021	0	61	51
23/11/2021	88	47	48
24/11/2021	0	58	45
25/11/2021	206	36	43
26/11/2021	0	79	41
27/11/2021	41	47	40
28/11/2021	58	74	39
29/11/2021	131	59	39
30/11/2021	105	71	39

Table 8. ARIMA and ANN Models Evaluation Techniques

Finite Model Properties	MSE	RMSE	MAE
ARIMA	4123.910982	64.21768434	50.83978733
ANN	5066.314303	71.1780465	60.56677167

5 Discussion of Results

From Table 1, the mean, median and the standard error of the time series are 333.6729, 188.5000 and 379.96147 respectively. However, the standard error is observed to be higher than the mean, suggesting a very high volatility in the series.

From Table 2, the series have at least 5 highest and lowest values which implies that presence of outliers in series. This is however not good for the application of the modeling techniques and thus may lead to non-robust modeling performance From Table 3, the normality tests are significant since their respective p-values are less than the level of significance..This shows that the series is not normally distributed at 5% level of significant. The series are also not stationary and therefore, the logarithm of the series will have to be transformed.

From Table 8, the RMSE value of ARIMA model, 64.217 is less than the RMSE value of ANN model, 71.178. This pattern of differences is consistent with the MSE and MAE, where the ARIMA model is observed to have returned the least values in all cases. Therefore, the smaller the finite model property, the better is the model.

6 Conclusion

In this study, evaluation of performance of ARIMA and ANNs has been conducted with application to the daily confirmed cases of COVID 19 in Nigeria. The evaluation criteria for ARIMA and ANNs were compared and the results revealed that the ARIMA model outperformed ANNs considering their minimum prediction errors and forecasting abilites. The ANNs model used forward propagation algorithm with three units in the hidden layer, and two lags. The ARIMA (2,1,1) is found to be the best fitted model for the daily confirmed COVID-19 cases in Nigeria among other Box Jenkins models.

Competing Interests

Authors have declared that no competing interests exist.

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