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Application of ARIMA and Artificial Neural Networks Models for Daily Cumulative Confirmed Covid-19 Prediction in Nigeria

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Abstract
Coronavirus 2019, commonly referred to as COVID-19, is a disease discovered in China towards the end of December 2019. This novel and highly infectious virus spreads rapidly across the globe. In Nigeria, as of June 2020, the cumulative number of COVID-19 cases reported was 25,694: out of this, 9746 cases were treated and 590 cases lost their lives. This research was aimed at comparing the prediction ability of ARIMA and ANN models. The aggregate COVID-19 cases reported in Nigeria was subjected to Box-Jenkins time series and Backpropagation gradient-based Artificial Neural Network Approaches for the prediction purpose. The data obtained from the Nigeria Centre for Disease Control (NCDC) was used. The data were identified to follow ARIMA (1, 2, 1) and were best trained by Bayesian Regularization Artificial Neural Network algorithm. The prediction performance of the two models were compared using RMSE, MAE and MAPE. The empirical results obtained show that the Artificial Neural Network model gives better predictions and forecasts over the ARIMA model.

Keywords: COVID-19, Box-Jenkins, ARIMA, ANN, Backpropagation

1. Introduction

Coronavirus disease 2019 (COVID-19) is a Ribonucleic acid (RNA) virus disease that presents fever, dry cough, and fatigue and occasional gastrointestinal disorder as symptoms [1]. The index case of COVID-19 was discovered at Wuhan city of China last year. During January 2020, a few weeks after the discovery of the virus, in-depth sequencing analysis of the selected samples revealed coronavirus as a contributing agent for the observed pneumonia [2]. When the cases of infected persons reached 118,000 with over 4000 deaths in 114 countries across the globe. The World Health Organization (WHO) affirmed a pandemic status on 11th March 2020 [2].

The WHO COVID-19 situation report of 30th June 2020 [4] indicated 10,375,897 cases with 507,373 mortalities worldwide. Two hundred and sixteen (216) countries in the world were affected so far with0 Nigeria having 25,694 confirmed cases and 590 deaths [3, 4].

In Nigeria, the first confirmed COVID-19 case was diagnosed on 27th February 2020. On the 9th March 2020, a Nigerian citizen from Ogun State, who had contact with the index case, was the second confirmed case for the virus. The confirmed cases of the outbreak within the first month were around 70, but significantly increased to nearly 1,350 persons within two months. Three cases were treated during the first month and the number of administered cases increased to 250 within the second month, but death toll rose to 40 from a single case within the same period [1].

Presently, there is no vaccine available for the virus. Therefore, there is the need to provide adequate health facilities so that the proportion at which the infection spreads is reduced. This calls for the cumulative confirmed cases prediction and forecasting of new cases for our health system's demand to be managed properly. Similarly, the modelling of COVID-19 infections can also aid public health officers to organize and make their resources to avoid more future occurrence of the disease. Box and Jenkins and other traditional methods have been found useful for predicting the disease outbreak [5-9]. Similarly, time series prediction of COVID- 19 pandemic has recently attracted the attention of many researchers who focused on traditional methods only [1, 10-14].

The application of Box and Jenkins method is basically uncertain because it considers no information of any fundamental model compared to other methods. It also basically counts on previous observations for the data and past error terms for forecasting [15-17]. But, in short-run forecasting, Box and Jenkins methods usually gives better results when compared to more complex structural models [17].

Artificial neural networks (ANNs) is a machine learning technique widely used for forecasting model in numerous disciplines which include economic, finance, business, engineering, science, health, foreign exchange among others [18-23]. Researchers and industrial practitioners have widely used ANNs to solve problems because they have numerous unique features. Ayodele *et al.* [15] reported that ANNs are self-adaptive and data-driven techniques requiring little assumptions but are capable of learning from the data and make a generalization about the observations from the results obtained. ANNs are universal approximator with the ability to powerfully estimate any continuous mapping to the preferred degree of precision. Lastly, ANNs give good results when solving nonlinear problems [24]. This technique is unlike Box and Jenkins methods for time series forecasting. For example, ARIMA assumes that the sequence of the data is obtained from linear processes which might be unsuitable for solving nonlinear problems [15, 25].

ANNs have recently been applied and found to be very efficient in modelling COVID- 19 pandemic [26, 27]. ARIMA model was compared with ANN to forecast the number of COVID- 19 infected persons by Leila *et al.* [28] with the basic backpropagation algorithm only. In Nigeria, time series models were used to predict COVID-19 cases [1, 29]. But this current research attempts to evaluate the performance of ANNs and ARIMA models in estimating COVID-19 daily cumulative confirmed cases, and specifically considered the training ANN with variants of Backpropagation algorithms unlike in the previous works.

2. Materials and Methods

Data for this research were obtained from the official COVID-19 site (https://covid19.ncdc.gov.ng/) of the Nigeria Centre for Diseases Control (NCDC). The data used for the daily confirmed cases covered the period from when the country recorded her index case (February 27, 2020) to June 30, 2020. Due to the nature of the series, the number of infections at a time, *t*, is determined by time *t-1* infections and hence to predict the number of new cases infected with COVID-19 in Nigeria, the Box-Jenkins ARIMA time series and Non-linear Auto-Regressive model (NAR) models were employed.

2.1 ARIMA Model

ARIMA model [30] is essentially employed in econometrics and statistics for time-series analysis. The model utilizes current values for the forecasting of the future values in the series. An ARIMA model is represented as ARIMA (p, d, q), where p is the Autoregressive (AR) lag order, d is the differencing order and q is the Moving Average (MA) lag order.

$$X_t = \mu + \emptyset_1 X_{t-1} + \cdots + \emptyset_p X_{t-p} + w_t + \theta_1 w_{t-1} + \cdots + \theta_p w_{t-q} \quad (1)$$

$$\Phi_p(B)X_t = 1 - \varphi_1 B - \cdots - \varphi_p B^p \quad (2)$$

$$\Theta_q(B)W_t = 1 + \theta_1 B + \cdots + \theta_q B^q \quad (3)$$

The process $\{X_t, t = 0, \pm1, \pm2, \ldots\}$ represents an ARMA (p, q) model when $\{X_t\}$ is stationary with each t satisfying the following:

$$\Phi_p(B)X_t = \Theta_q(B)W_t \quad (4)$$

where B is given by

$$B^i X_t = X_{t-i}, i = 0, \pm1, \pm2, \ldots \quad (5)$$

and $\{W_t\}$ is white noise such that $\sim N(0, \sigma^2)$. When the process involves a sequence of constant $\{\alpha_i\}$ which gives $\sum_{i=0}^{\infty} \alpha_i < \infty$ and

$$X_t = \sum_{i=0}^{\infty} \alpha_i W_{t-i}, t = 0, \pm1, \pm2, \ldots \quad (6)$$

it is said to be causal process.

The process $\{X_t, t = 0, \pm1, \pm2, \ldots\}$ represents an ARIMA (p, d, q) model when $Y_t = \nabla^d X_t = (1-B)^d X_t$ has a causal ARMA (p, q) model. This means

$$\Phi_p(B)(1-B)^d X_t = \Theta_q(B)W_t \quad (7)$$

where Φ_p and Θ_q are the polynomials for autoregressive and moving average processes respectively. B is the lag operator and $\{W_t\}$ represents a white noise process.

The maximum likelihood estimation procedure is often used for the estimation of the ARIMA model's parameters. The Box-Jenkins methodology is composed of three iterative stages of *model identification*, *parameter estimation* and *diagnostic checking* to select the most accurate model from ARIMA models. The process is repeated many times up to when an acceptable model is obtained (Figure 2.1). The selected model can then predict future values of the data.

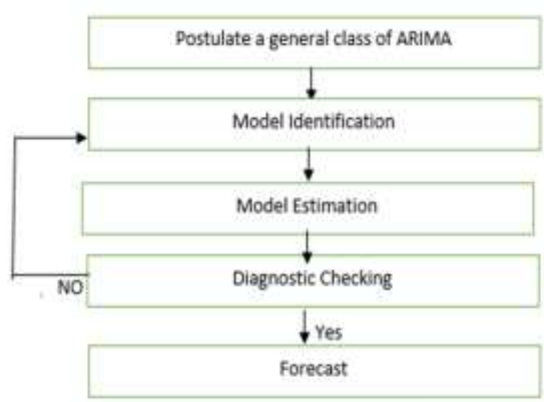

Figure 2.1: The Box-Jenkins Scheme for model selection

A central stage for proper model choice is to determine parameters of the model. One way is to consider the ACF and PACF of the data. Another way is by comparing the predicted values of the model with the actual values. Similarly, *Akaike Information Criterion (AIC)* and *Bayesian Information Criterion (BIC)* are extensively used methods for model identification and are given as:

$$AIC(p) = nln\left(\hat{\sigma}_t^2/_n\right) + 2p \qquad (8)$$

$$BIC(p) = nln\left(\hat{\sigma}_t^2/_n\right) + p + pln(n) \qquad (9)$$

where n represents number of observations sampled for the model fitting. p represents total parameters used by the model and $\hat{\sigma}_t^2$ is the sum of sample variance. Smaller values of AIC and BIC determine the best model.

2.2 The ANN-Based Technique for Forecasting

ANNs have been classified as either dynamic or static [31]. The static, otherwise known as feed forward networks, do not possess feedback features and do not have delays; the output of the network is directly obtained from the input via feed forward connections. Whereas the output of the dynamic networks does depend on the current or previous inputs, outputs, or states of the network in addition to the current input to the network. They are usually more efficient than static networks but has training difficulties [32]. Dynamic networks are capable of learning sequential or time-varying patterns since they have memory. Nonlinear Autoregressive (NAR) Neural Network is a dynamic network. The structure of NAR has l_x inputs, a hidden layer with H_0 neurons, and an output neuron (see Figure 2.2). The network can be trained by backpropagation algorithm.

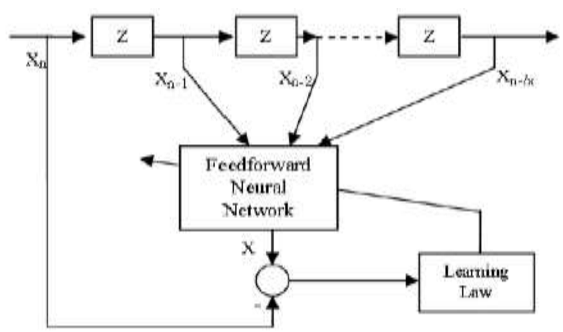

Figure 2.2: NAR Architecture

Similarly, the learning algorithm may be modified when the time series is smoother or rougher in order to get better results. The number of patterns and iterations of the network is modified by the learning rule for each time-step using Hurst's parameter, *H*, for the sequence $\{x_n\}$. To forecast one-step ahead for the sequence $\{x_e\}$, x_n is considered as input. Therefore, the output is thus given as:

$$x_e(n+1) = F_p\left(Z^{-1}I(\{x_n\})\right) \qquad (10)$$

where F_p represents nonlinear predictor function, x_e is the predicted value at $n+1$. The neural network is composed of neurons, hidden layers and transfer function. A time series neural network which is known as nonlinear autoregressive (NAR) NN is used to minimize the mean squared error (MSE) and therefore any architecture of such network that gives the least MSE is chosen as the best NAR architecture describing a time series.

2.3 Evaluation Techniques

The forecasting results of the models were evaluated using root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). The model with the least RMSE, MAE and MAPE was chosen as the best one:

$$RMSE = (n^{-1}\textstyle\sum_{t=1}^{n}(y_t - \hat{y}_t)^2)^{\frac{1}{2}} \qquad (11)$$

$$MAE = n^{-1}\textstyle\sum_{t=1}^{n}|y_t - \hat{y}_t| \qquad (12)$$

$$]MAPE = n^{-1}\textstyle\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{\hat{y}_t}\right| * 100 \qquad (13)$$

3. Results and Discussion

The time plot of the series (Figure 3.1) is significantly trending upward**,** which suggests non-stationarity of the series. But, ARIMA modelling requires that the series be stationary and free of any form of trend. The Augmented Dickey-Fuller (ADF) **t**est was employed to check the stationarity of the series in Table 3.1. The results showed that the series attained stationarity after second difference (ADF test: t=-11.13063 and P<0.001) and Figure 3.2 show**ed** that the time plot of the second**-**order difference series is stationary. The series was however not stationary at level and first difference. The series is therefore ready for modelling via the Box-Jenkins ARIMA modelling approach having attained stationarity after second difference. Since the ACF of the differenced series displayed a sharp cutoff and has negative autocorrelation at lag one (Figure 3.3), indicates that precisely MA (1) terms should be used in the forecasting equation.

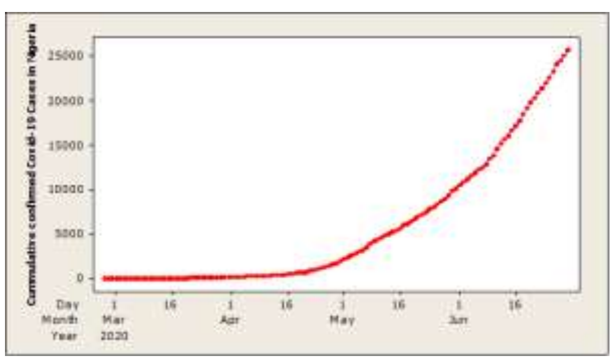

Figure 3.1: Time plot of the Cumulative confirmed covid-19 cases at level

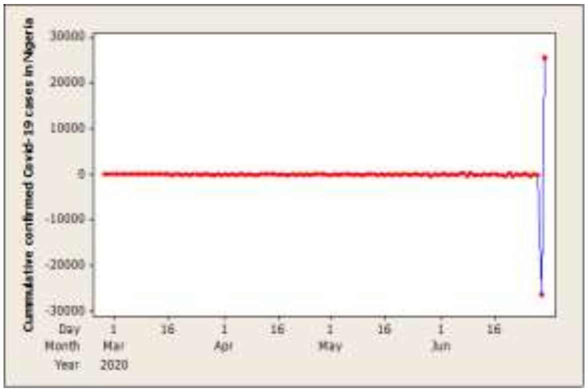

Figure 3.2: Time plot of the Cumulative confirmed covid-19 at second order differencing

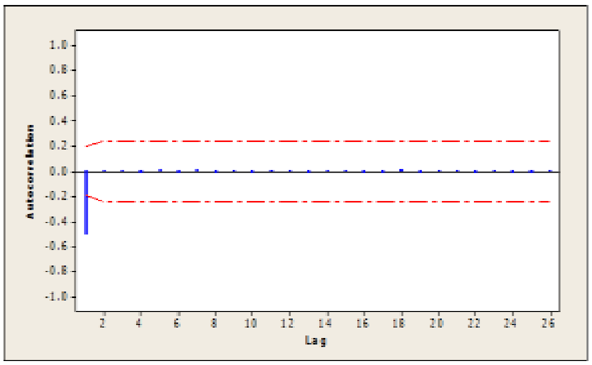

Figure 3.3: ACF of Daily Cumulative confirmed Covid-19 cases after second differencing

Table 3.1: ADF unit Root tests of the series at level and after second differencing

Series	Test value	p-value	Remarks
At level	3.962357	1.0000	Not stationary
First difference	-0.580453	0.8690	Not stationary
Second difference	-11.13063	0.0000	Stationary

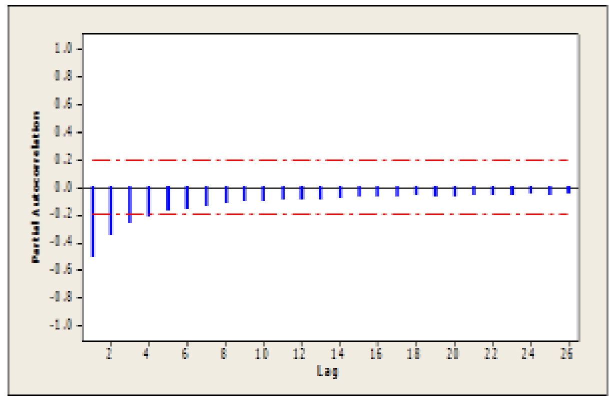

Figure 3.4: PACF of Daily Cumulative confirmed Covid-19 cases after second differencing

Table 3.2: ARIMA Model Selections

Model	AIC	HQC	SIC
ARIMA (1,2,1)	**11.75003**	**11.79172**	**11.85297**
ARIMA (1,2,2)	11.77485	11.81653	11.87779
ARIMA (1,2,3)	11.78952	11.83121	11.89246
ARIMA (1,2,4)	11.78743	11.82912	11.89037

Table 3.3: Estimation results of the ARIMA model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.378178	1.883791	3.385821	0.0010
AR (1)	-0.211591	0.104114	-2.032300	0.0448
MA (1)	-0.769021	0.064711	-11.88394	0.0000
SIGMASQ	6780.140	945.6407	7.169890	0.0000
R^2	0.434380	Mean dep. Variable		4.784314
Adjusted R^2	0.417065	Standard deviation dep. variable		110.0262
Stan. Error of reg.	84.00524	AIC		11.75003
Sum squared residuals	691574.3	SC		11.85297
Log likelihood	-595.2516	HQC		11.79172
Fisher-statistic	25.08705	Durbin-Watson statistic		2.187056
Pro (Fisher-statistic)	0.000000			
Inverted AR Roots	-0.6			
Inverted MA Roots	79			

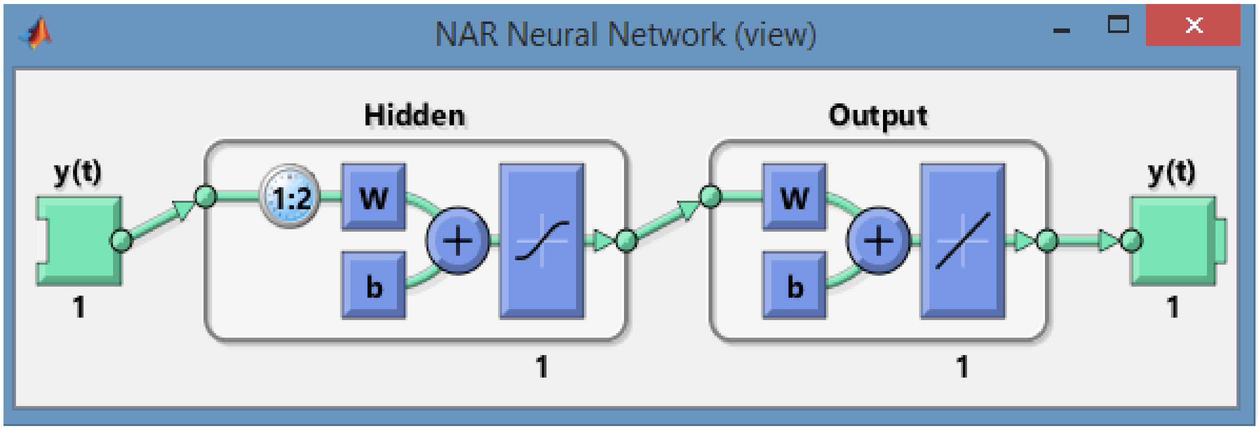

Figure 3.5: A series parallel NAR.

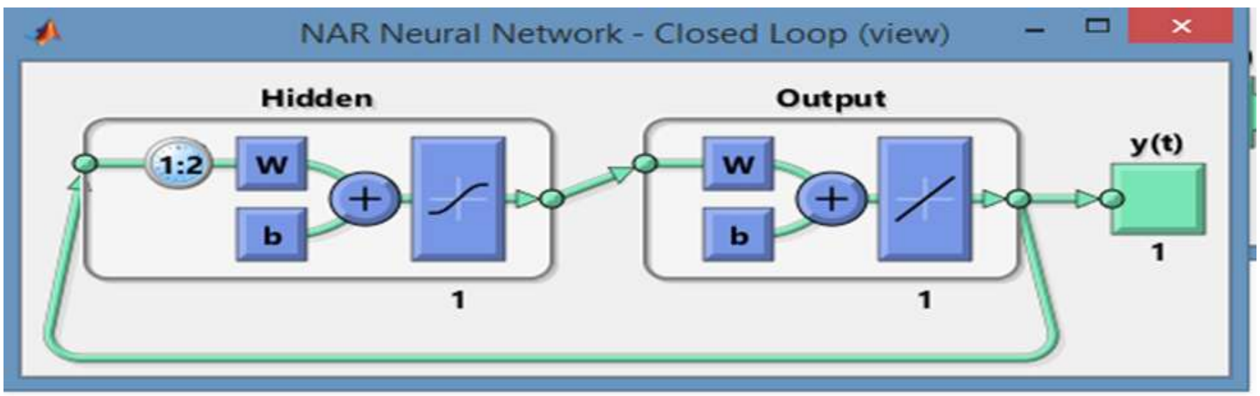

Figure 3.6: A parallelized NAR.

Table 3.4: Comparison of ANN Selected Models based on MSE

Variants of Backpropagation	Mean Square Error
Gradient descent (GD)	0.0043678
Scaled conjugate gradient (SCG)	0.00020407
Levenberg-Marquardt (LM)	$3.359e^{-9}$
Bayesian Regularization (BR)	$1.1391e^{-12}$

Table 3.5: Evaluation of the selected models' performance

Measures	ARIMA (1,2,1)	Bayesian Regularization (BR)
RMSE	0.007891	0.001995
MAE	0.006709	0.001411
MAPE	0.003166	0.000666

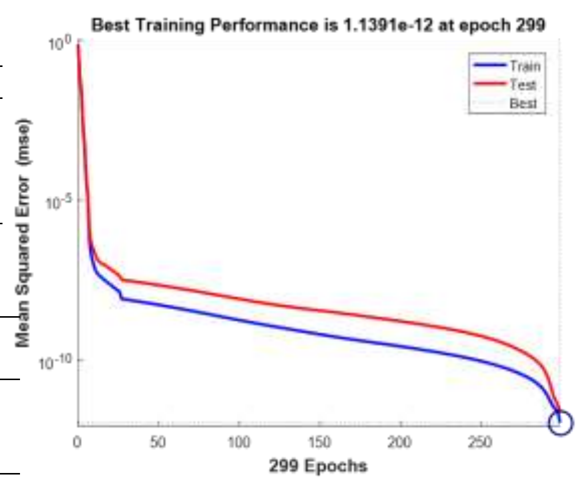

Figure 3.7: Bayesian Regularization (BR) training performance

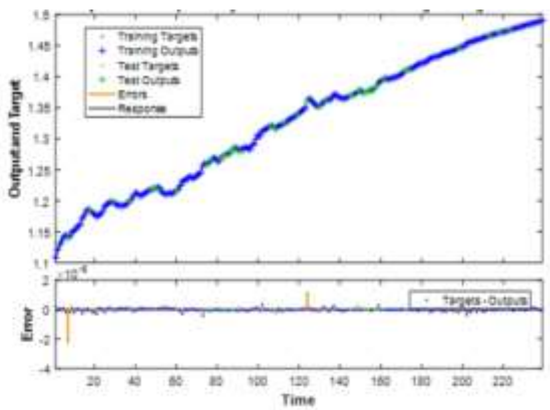

Figure 3.8: Bayesian Regularization (BR) response plot.

Table 3.6: Ten days ahead forecasts by the selected models

Date	Actual Data	ARIMA (1,2,1)	ANN Trained by BR Algorithm
1st July,2020	26484	26308.7	26481.0
2nd July,2020	27110	26926.2	27001.01
3rd July,2020	27564	27548.9	27552.002
4th July,2020	28167	28176.7	28181.5
5th July,2020	28711	28809.5	28716.1
6th July,2020	29286	29447.4	29255.9
7th July,2020	29789	30090.4	30000.7
8th July,2020	30249	30738.5	30150.6
9th July,2020	30748	31391.6	30405.6
10th July,2020	31323	32049.8	31265.7

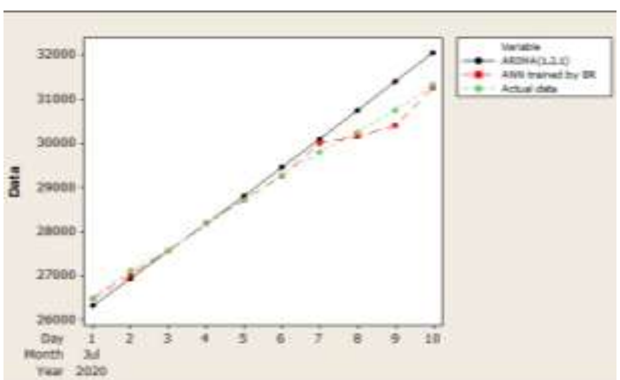

Figure 3.9: Ten days ahead forecasts by the selected models

Similarly, PACF displaying sharp cut at lag 4 (Figure 3.4), is indicating that up to lag 4 of AR terms can be included in the forecasting equation of the model. Table 3.2 presents ARIMA model selection. ARIMA (1,2,1) is chosen because it minimized all three information selection criteria**,** and in Table 3.3, the parameters of ARIMA (1,2,1) coefficients were estimated. From the t statistic results in the Table, it can be observed that the AR and MA coefficients are significant at 5% and 0.1% respectively since their P-values are 0.0448 and 0.0000.

Model of the equation according to series ARIMA (1,2,1) is given as follows from Table 3.3.

$$\Phi_p(1-B)^2X_t = \Theta_q(B)W_t \quad (13)$$

$$-0.211591(1-B)^2X_t = -0.769021W_t \quad (14)$$

Figure 3.5 is a series parallel architecture which was used to train the network. Parallel configuration in Figure 3.6, was used after the training step for multi-step-ahead prediction task. During the training, the dataset has been divided randomly into training (70%), validation (15%) and testing (15%). Similarly, the model was trained with variant of backpropagation algorithms. For each algorithm the best trained network is retrained in Table 3.4. Bayesian Regularization (BR) was trained to have lowest MSE (see Table 3.4 and Figure 3.7) and mimic target output closely for training and testing sets (Figure 3.8), and hence chosen for the prediction. The prediction performance for the ARIMA (1, 2, 1) and ANN trained by Bayesian algorithm were compared using Root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) in Table 3.5. The results have shown that the ANN model performed better than ARIMA model. Similarly, the two selected models were used to forecast ten days ahead COVID-19 cases as shown Table 3.6 and Figure 3.9. The forecasts clearly showed that ANN trained by BR algorithms compares more closely to the actual value than the ARIMA (1,2,1) which confirms the earlier predicted results.

4. Conclusion

The study used Box-Jenkins time series and backpropagation gradient based Artificial Neural Network Approaches for the prediction of daily cumulative confirmed Covid-19 cases in Nigeria. The research further identified ARIMA (1,2,1) and Bayesian Regularization models as the best and used them for the prediction. The empirical results showed that the daily cumulative confirmed Covid-19 cases in Nigeria is significantly trending upward. The results have also indicated that good prediction for the data can be achieved using both ARIMA and ANN models. However, ANN trained by BR gives better predictions and forecasts than the ARIMA model. In future studies, fractionally integrated ARIMA model can be considered to avoid over differencing of the data.

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