




COMPARATIVE STUDY OF THE ERROR TREND AND SEASONAL EXPONENTIAL SMOOTHING AND ARIMA MODEL USING COVID-19 DEATH RATE IN NIGERIA

 Samuel Olorunfemi Adams^{1*}

 Godwin Somto²

^{1,2}Department of Statistics, University of Abuja, Abuja, Nigeria.

¹Email: samuel.adams@uniabuja.edu.ng Tel: +2348055249189

²Email: somtogodwin9@gmail.com Tel: +2349076968500



(+ Corresponding author)

ABSTRACT

Article History

Received: 25 April 2022

Revised: 27 May 2022

Accepted: 13 June 2022

Published: 23 June 2022

Keywords

ARIMA

COVID-19

Exponential smoothing trend

NCDC

Hannan Quinn information criterion

AMSE selection criteria.

In the last two years, COVID-19 had claimed millions of life in Nigeria and the world at large. It is an established global health emergency of our time and an ongoing threat faced by the world up till now. This study aims to determine the trend, fit an appropriate Error Trend and Seasonal (ETS) exponential smoothing and ARIMA model to the COVID-19 daily deaths in Nigeria. Dataset on the daily COVID-19 confirmed death cases were utilized in the study. The data was extracted from the Nigerian Centre for Disease Control (NCDC) online database from 10th July 2020 to 2nd December 2021. Autoregressive Integrated Moving Average (ARIMA) and twelve (12) (ETS) exponential smoothing techniques were compared based on the dataset. The performance of the ARIMA and ETS exponential smoothing methods was investigated using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Hannan Quinn Information Criterion (HQIC), and AMSE selection criteria. The best time series modeling for the coronavirus (COVID-19) epidemic in Nigeria was the ARIMA (0,1,0) because its model selection criteria showed that it had the lowest value of; AIC=2863.51, BIC= 2866.90, HQ = 2866.90, and AMSE = 0.55471. ARIMA (0,1,0) model is preferred among the thirteen (13) competing models based on daily confirmed deaths due to COVID-19 in Nigeria.

Contribution/Originality: The gap in existing literature revealed that no study on modeling of COVID-19 deaths in Nigeria had been carried out using the combination of error trend and seasonal (ETS) exponential smoothing techniques and ARIMA model. To address the gaps indicated above this study sought to determine the trend and fit an appropriate time series model to the COVID-19 reported death cases in Nigeria.

1. INTRODUCTION

Covid-19 is an infectious disease that was first found in Wuhan, China, in 2019. The World Health Organization (WHO) later assigned it as "Coronavirus," which represents Coronavirus Disease 2019. The Coronavirus outbreak is as yet recognized as one of the world's most terrible pandemics in many years. The death rate developed significantly, and the speed with which it spread was disturbing. As indicated by research, those beyond 65 years old and those with hidden ailments like cardiovascular infection, diabetes, persistent respiratory sickness, and cancer are more inclined to contract Covid-19 related disorder [1]. Sore throat, runny nose, successive coughing/sniffing, breathing hardships, and weariness are some of the signs of the of Coronavirus [2]. Covid-19 has been a significant and prominent public medical issue all around the world. Its prevalence and method of transmission have been an enormous power to deal with inside the health sector. Coronaviridae belongs to a group of viruses moved by a positive-sense RNA that contains an external viral coat. Seen with the aid of an electron magnifying instrument, there

is a noticeable corona around it. The infection causes respiratory sicknesses in people, introduced in the form of cold or pneumonia as well as major respiratory diseases. The zoonotic idea of this virus makes it feasible for them to bounce from the host then onto the next [2].

Covid illness 2019 (COVID-19) is respected to be an infectious sickness that is brought about by extreme intense respiratory disorder Covid 2 (SARS-CoV-2). The previously recognized case was viewed in Wuhan, China, in December 2019. The sickness has since spread around the world, prompting the progressing and constant pandemic. Coronavirus communicates when individuals inhale or breathe in air defiled by beads and minimal airborne particles containing the destructive infection. Nearness assumes a gigantic part in the contracting cycle of the infection. Individuals stay defenseless for as long as 20 days and can spread the infection regardless of whether they foster any indications. A few testing techniques have been taken on and created to analyze the illness. The standard indicative technique is by constant converse record polymerase chain response (rRT-PCR), the transcription-mediated amplification (TMA).

The COVID-19 pandemic is a continuous disease that has figured out how to spread to over such countless nations. More than 188 nations have been impacted internationally with north of 245,984 new cases, 25,602,665 affirmed, and 852,758 deaths recorded despite everything counting to date. Nigeria revealed its record instance of COVID-19 on the 27th of February, 2020; it just so happens, the absolute first in Nigeria and West Africa connecting with data given by the Nigerian Center of Disease Control (NCDC). A short time later, a lockdown or check-in time was started and carried out in a few conditions of the country to control and diminish the quick spread of the infection. As per the insights introduced by the NCDC, over 286,000 tests, 43,537 affirmed positive cases, 22,567 dynamic cases, 20,087 releases, and 883 demise rates was introduced and revealed as at initiation of this review, August first, 2020 across the 36 states including the country's capital, the Federal Capital Territory (FCT), Abuja [3].

Coronavirus pandemic has turned into a worldwide danger to lives and security. The world overall is working diligently to discover a few answers for the battle against this destructive infection to decrease the number of passings. A few demonstrating and anticipating studies have been led on the topic utilizing so many time series models like ARIMA and Holt-Winters occasional smoothing procedures. [Bezerra and Santos \[4\]](#) thought about the presentation of ARIMA and Holt's direct remarkable smoothing models in the destruction of Coronavirus affirmed cases in Sudan, day-by-day readings of Covid-2019 confirmed cases dataset for the period 24th March 2020 to 10th t June 2020. The ARIMA model was selected as a suitable model rather than Holt parameter smoothing models. [Djakaria and Saleh \[5\]](#) contemplated the Coronavirus forecast model utilizing Holt-Winters outstanding smoothing, for a specific period. It was observed that utilizing Holt-Winters outstanding smoothing, the best prediction model is the one with smoothing boundaries $\alpha = 0.1$ and $\gamma = 0.5$ for pattern and irregularity individually, which gives the littlest MAPE worth of 6.14. [Alabdulrazzaq, et al. \[6\]](#) was keen on testing the exactness of the ARIMA procedure as the best fit model and for the forecast. The outcomes show that regardless of the powerful idea of the infection and consistent modifications made by the Kuwaiti government, the real qualities for the more often than not period noticed were well inside limits of the selected ARIMA model expectation at 95% certainty span. [Benvenuto, et al. \[7\]](#) proposed a basic econometric model that is useful in the expectation of the spread of COVID-19. ARIMA model was utilized to foresee the Johns Hopkins epidemiological information and to anticipate the pattern of the predominance and rate of COVID-19. [Chintalapudi, et al. \[8\]](#) model COVID-19 infected patient's dataset utilizing occasional ARIMA conjectures bundle in R. The expectation of contaminated patients recommended around 182, 757 and reported cases could be esteemed at 81, 635 toward the finish of May 2020 in Italy. [Panda \[9\]](#) applied ARIMA and Holt-Winters time series dramatic smoothing to foster a proficient 20-day ahead transient gauge model and anticipated the impact of COVID-19 pestilence. The displaying and estimating are finished with the openly accessible dataset from Kaggle as a point of view to India and its five states like Odisha, Delhi, Maharashtra, Andhra Pradesh, and West Bengal. The India anticipating uncovers that the COVID-19 spreading will fill further over the long haul. [Swapnarekha, et al. \[10\]](#) anticipated COVID-19 for the five most impacted territories of India like Maharashtra, Tamil Nadu, Delhi,

Gujarat, and Andhra Pradesh utilizing the constant information. Utilizing the Holt-Winters strategy, a gauge of the quantity of affirmed cases in these states was produced. The examination shows that the proposed Holt-Winters model produces RMSE worth of 76.0, 338.4, 141.5, 425.9, 1991.5 for Andhra Pradesh, Maharashtra, Gujarat, Delhi, and Tamil Nadu, which brings about more exact expectations over Holt's Linear, Auto-relapse (AR), Moving Average (MA) and Autoregressive Integrated Moving Average (ARIMA) model. Singh, et al. [11] looked at between the distinguished top 15 nations for affirmed cases, deaths, and recuperation, and a high-level ARIMA model was utilized for foreseeing the COVID-19 infection spread directions for the following 2 months. The noticed anticipated values showed that the affirmed cases, deaths, and recuperations will twofold in every one of them noticed nations except China, Switzerland, and Germany. It was additionally seen that the demise and recuperation rates were increased quicker when contrasted with affirmed cases throughout the following 2 months. Zangiacomini-Martinez, et al. [12] assessed the exhibition of the Holt's model to figure the everyday COVID-19 announced cases from the date of the main COVID-19 case to April 25, 2020, as the preparation time frame, and April 26 to May 3, 2020, as the trial in Brazil and three Brazilian states. Finding uncovers Holt's model can be a satisfactory momentary determining technique assuming their suppositions are satisfactorily checked and approved by specialists. Sharma and Nigam [13] dissected the development example of COVID-19 pandemic in India from March 4 to July 11 utilizing relapse investigation (remarkable and polynomial), auto-backward incorporated moving midpoints (ARIMA) model as well as dramatic smoothing and Holt-Winters models. It was found that the development of COVID-19 cases follows a power system of (t^2, t, \dots) after the remarkable development. The investigation further discovered that the ARIMA (5, 2, 5) model is the best-fitting model for COVID-19 cases in India. Mingzhe, et al. [14] examine the spreading, pattern, and momentary figure of the new Corona-virus in Hubei Province. From the information demonstrating, utilizing ARIMA and Holt Model it was seen that the plague circumstance in Hubei Province has fundamentally finished after May, however the scourge circumstance in the United States has become more extreme after May, so the Holt model and the ARIMA model are additionally exceptionally proper in foreseeing what is going on in the present moment. A summary of the reviewed literature revealed that no study on modeling of COVID-19 deaths in Nigeria had been carried out using the combination of error trend and seasonal (ETS) exponential smoothing techniques and ARIMA model. To address the gaps indicated above this study sought to determine the trend and fit an appropriate time series model to the COVID-19 reported death cases in Nigeria.

The remainder of this study is partitioned into four sections. In 2, we present the materials and methods for the study and section 3 gave the result. In section 4, a discussion of findings was presented and the conclusion and recommendation from the finding were presented in the last section.

2. MATERIALS AND METHODS

2.1. Data

This work is designed to study the trend pattern of COVID-19 in Nigeria from 10th July 2020 to 2nd March 2022. The essence is to fit appropriate time series models to the data using thirteen [13] time series models. Data for this study was extracted from COVID-19 confirmed deaths update released by the Nigerian Centre for Disease Control (NSDC) [3] online database from 10th July 2020 to 2nd December 2021.

2.2. Auto-Regressive Integrated Moving Average (ARIMA)

ARIMA modeling is applied to several types of time series, with or without seasonal components or trends, and to produce suitable forecasts values [15, 16]. The model is as follows;

An ARIMA model is given by:

$$\phi(\beta)(1 - \beta)^d y_i = \theta(\beta)\epsilon_i \quad (1)$$

$$\theta(\beta) = 1 - \theta_1\beta - \theta_2\beta^2 \dots \theta_p\beta^p$$

Equation 1 presents an Autoregressive integrated moving average (ARIMA) time-series model, where; ϵ_i = residual, d = differencing term, β = Backshift operator ($\beta^d Y_i = Y_{i=d}$)

2.3. Exponential Smoothing Techniques

Exponential smoothing combines error, trend, and seasonal (ETS) components in computing smoothing. Each term is the combination of either additive, multiplicative, or left out of the model. It is a popular local measurable algorithm utilized for time-series predicting. It is suitable for a time series dataset with seasonal components and prior assumptions. ETS calculates weighted means over all variables in the time series data as its prediction. The weights are exponentially diminishing after some time rather than the steady weights in the direct Moving Average (MA) technique. The weights are subject to a constant parameter called a smoothing parameter. Several ETS exponential smoothing techniques are featured in the literature. Most of these suggested techniques were applied in our study. Moreover, an exponential smoothing technique from previous studies in the literature that provides an effective performance was also introduced in this study [17-24]. Table 1 shows the existing error trend and seasonal exponential smoothing techniques criteria.

Table 1. ETS models.

Addictive error trend component	Seasonal Component		
	N (None)	A (Additive)	M(Multiplicative)
N (None)	A,N,N*	A,N,A*	A,N,M
A (Addictive)	A,A,N*	A,A,A*	A,A,M
A _d (Addictive damped)	A,A _d ,N*	A,A _d ,A*	A,A _d ,M
Seasonal Component			
Multiplicative error trend component	N (None)	A (Additive)	M (Multiplicative)
N (None)	M,N,N*	M,N,A*	M,N,M
A (Addictive)	M,A,N*	M,A,A*	M,A,M
A _d (Addictive damped)	M,A _d ,N*	M,A _d ,A*	M,A _d ,M

Note: * are the ETS models utilized in our study.

2.4. Model Selection Criteria

Akaike’s Information Criterion:

$$AIC = -2 \log(L) + 2K \tag{2}$$

Hannan –Quinn Information Criterion:

$$HQC = -2L_{max} + 2k \ln(\ln(n)) \tag{3}$$

Bayesian Information Criterion:

$$BIC = AIC + K(\log(T) - 2) \tag{4}$$

$$\text{Mean Square Error } MSE = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2$$

Where; L is the likelihood, k is the number of model parameters, Y is the vector of observed values, \hat{Y}_i is the variable being predicted, n is the number of observations, L_{max} is the log-likelihood [25-27].

3. RESULTS

From Figure 1, it can be observed that the data are not stationary following the presence of a possible upward trend from July 2020 to November 2020 and a downward trend from late November 2020 to February 2021. [3]. The graph presented in Figure 2 shows the differenced covid-19 dataset. Stationarity was achieved by differencing the covid-19 data and this is confirmed by the result of the Augmented Dickey-Fuller test with p-value = 0.01 (see Table 2) which is highly significant at all level of significance. First differencing was performed to remove the trend component of the covid-19 dataset. The result of the correlogram (ACF and PACF plot) presented in Figure 3 and 4

shows that, there is similarity between ACF and PACF with both showing a rapid decline and an exponential decay from lag 0. Hence, the model is not an Autoregressive (AR) or moving average (MA) but an ARIMA model. The only model that can be deduce from this model is ARIMA (0,1,0) (see. Figure 4, i.e. PACF plot). In Table 3, the coefficients of ARIMA (0, 1, 0) model indicates that, AIC = 879.56, MAE = 0.06546, log likelihood = -438.78, BIC (Bayesian information criterion) = 883.89 $\sigma^2 = 0.2767$.

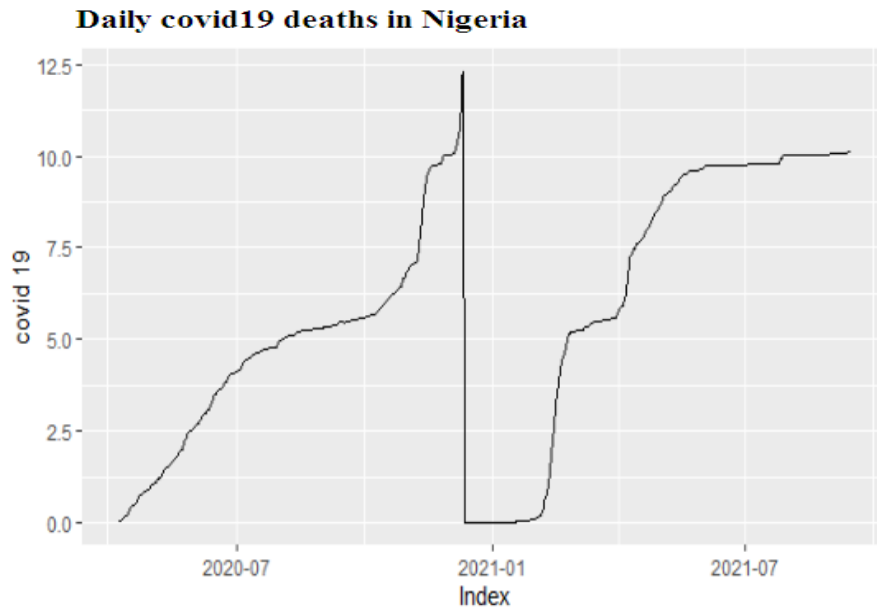


Figure 1. Trend plot of daily COVID-19 deaths.

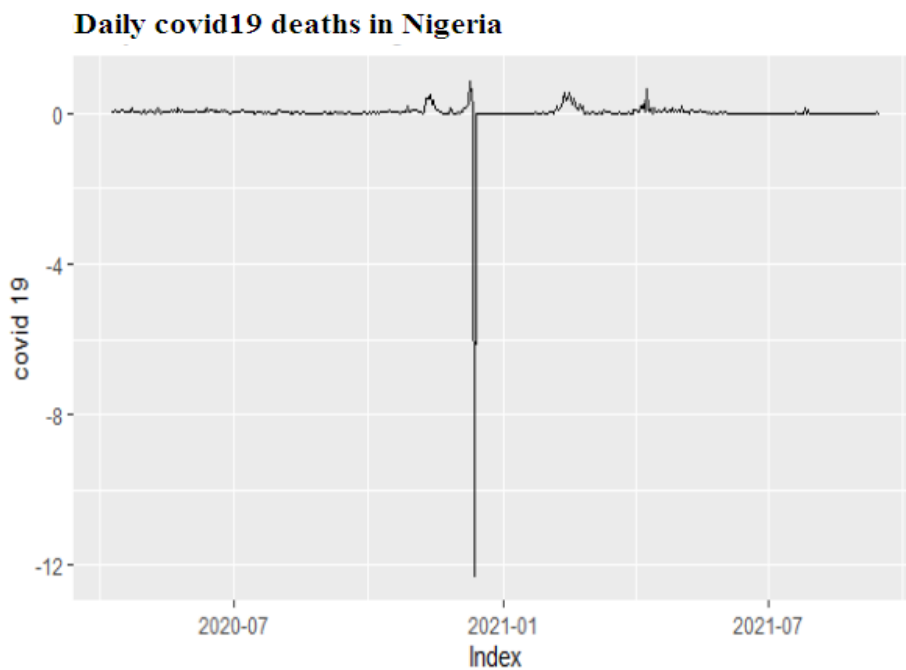


Figure 2. First differenced plot of daily COVID-19 deaths.

Series covid19

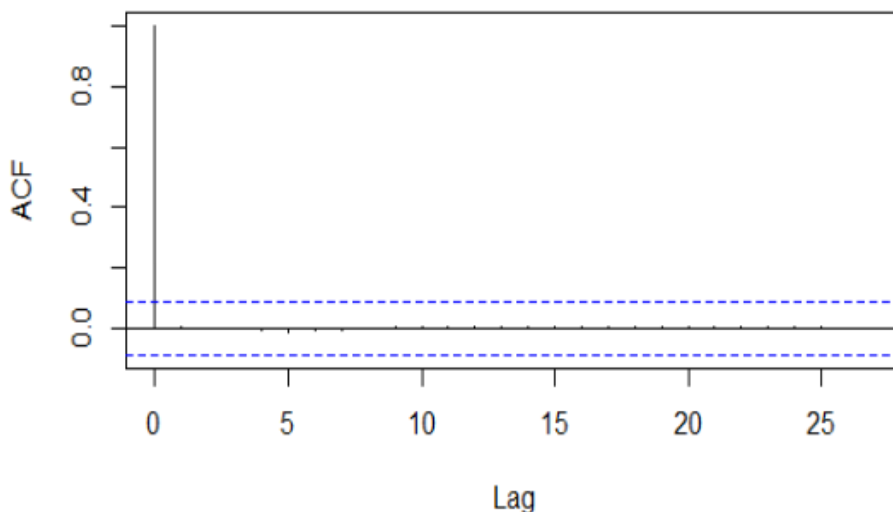


Figure 3. ACF (Auto Correlation Function) of the daily COVID-19 deaths.

Series covid19

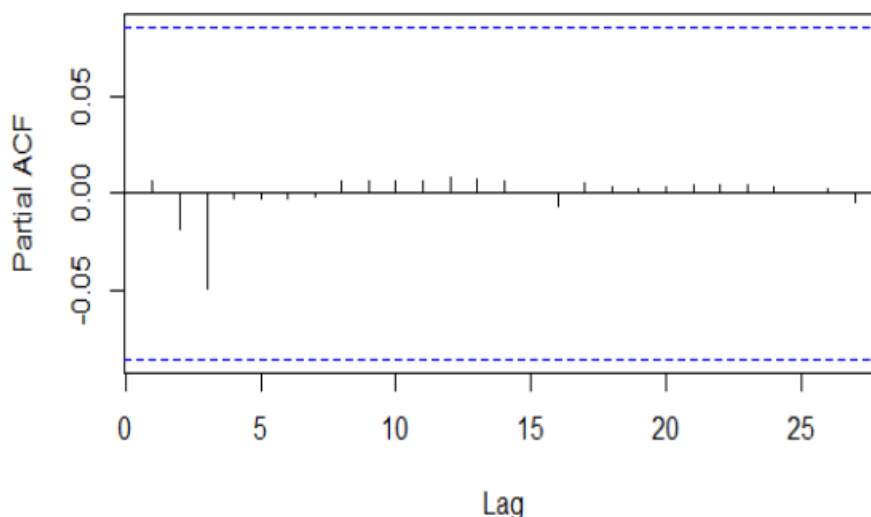


Figure 4. PACF (Auto Correlation Function) of the daily covid-19 deaths.

Table 2. ADF test result COVID-19 deaths in Nigeria.

ADF TEST	t-statistics	p-value
Covid-19	-7.55	0.01

Table 3. Coefficient of estimate for ARIMA (0,1,0) model.

AIC	MAE	LogL	AICc	σ^2	RMSE	BIC	MASE	ME
879.563	0.065	-438.00	879.56	0.277	0.526	883.891	0.998	0.022

3.1. Exponential Smoothing

The model comparison bar chart above shows that ETS (A,N,N) model was the best model because it had the smallest value in the chart. Table 4 presents the autocorrelation function of the daily confirmed cases of COVID-19 in Nigeria. It can be seen that there is exponential decay in the ACF plot, the result also shows that the Akaike

information criterion selected ETS model is an A,N,N (Additive Error, No Trend, No season) specification with smoothing parameter $\alpha = 0.999$ and initial parameter 0.0281 estimated on the boundary. The summary statistics indicate that this specification is superior to other models. Based on all the three information criteria, the average mean squared error and the likelihood is lower in the selected model. In Figure 6, The exponential smoothing plot shows both the last few observations of the in-sample forecast and the out-of-sample forecasts for each of the possible ETS specifications and it is shown that A,N,N will provide a better forecast.

Table 5 shows the coefficients of ETS (A,N,N) model with AIC = 2662.138, MAE = 0.06602579 and log-likelihood = -438.78, the model also shows that BIC = 2674.934 and σ^2 estimated = 0.5456 with level smoothing parameter $\alpha = 0.999$ and initial parameter 0.0281. Having identified the models above, we now compare the ARIMA (0,1,0) and ETS (A, N, N) models using the model selection criteria with the least Bayesian information criterion (BIC), Mean Absolute Error (MAE), and least Akaike Information. From the results provided in Table 6, it is clearly shown that ARIMA (0, 1, 0) model possess the minimum BIC, MAE, and Akaike Information criteria.

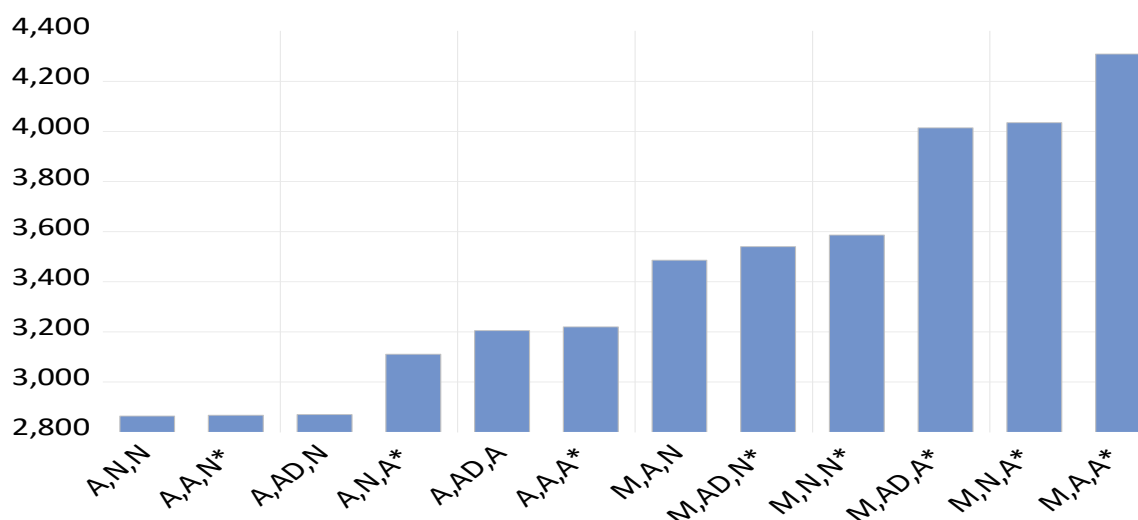


Figure 5. Model comparison graph.

Table 4. Model comparison table.

Model	Compact LL	Likelihood	AIC	BIC	HQ	AMSE
A,N,N	-1429.76	-439.054	2863.51	2872.19	2866.90	0.554
A,A,N	-1429.26	-438.556	2866.52	2883.87	2873.29	0.552
A,AD,N	-1429.73	-439.029	2869.46	2891.16	2877.93	0.000
A,N,A*	-1541.04	-550.341	3110.09	3170.83	3133.79	0.700
A, AD, A*	-1585.01	-594.311	3204.03	3277.78	3232.81	0.000
A, A, A*	-1593.60	-602.897	3219.20	3288.62	3246.29	0.980
M, A, N*	-1738.76	-748.056	3485.52	3502.87	3492.29	0.747
M, AD, N*	-1764.63	-773.924	3539.25	3560.95	3547.72	0.000
M, N, N	-1791.09	-800.387	3586.18	3594.86	3589.57	0.790
M, AD, A*	-1989.83	-999.124	4013.65	4087.41	4042.44	0.000
M, N,A*	-2003.26	-1012.55	4034.51	4095.25	4058.22	0.675
M, A, A*	-2138.40	-1147.70	4308.80	4378.22	4335.90	0.982

Note: * 8 models failed to converge.

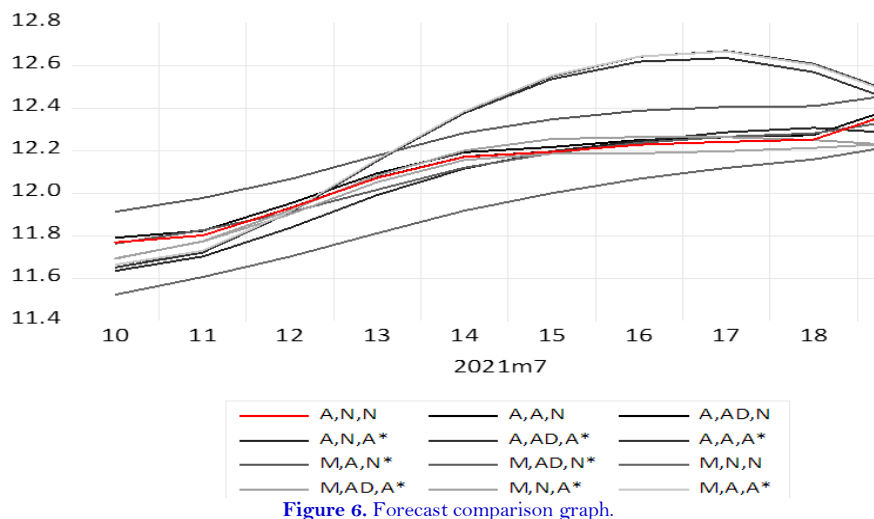


Figure 6. Forecast comparison graph.

Table 5. ETS (A, N, N) Model.

AIC	MAE	MASE	AICc	σ^2	RMSE	BIC	A	ME
2662.123	0.066	0.998	2662.138	0.546	0.545	267.934	0.999	0.023

Table 6. Comparison between ARIMA (0, 1, 0) and ETS (A,N,N).

Model	AIC	MAE	BIC
ARIMA(0,1,0)	879.563	0.065	883.891
ETS(A,N,N)	2662.123	0.066	2872.19

3.2. Residual Checking

Table 7, presents the test for model fitness for forecast, it was observed that $p = 0.9983$, these result shows that the suggested model ARIMA (0,10) is a good fit, which implies that it is suitable for a forecast. Figure 7 shows that the residual process is white noise, this implies that the ARIMA (0,1,0) model is adequate and can be used to make the forecast.

Table 7. Ljung-Box Q test.

Statistics	DF	Sig
1.6634	10	0.998

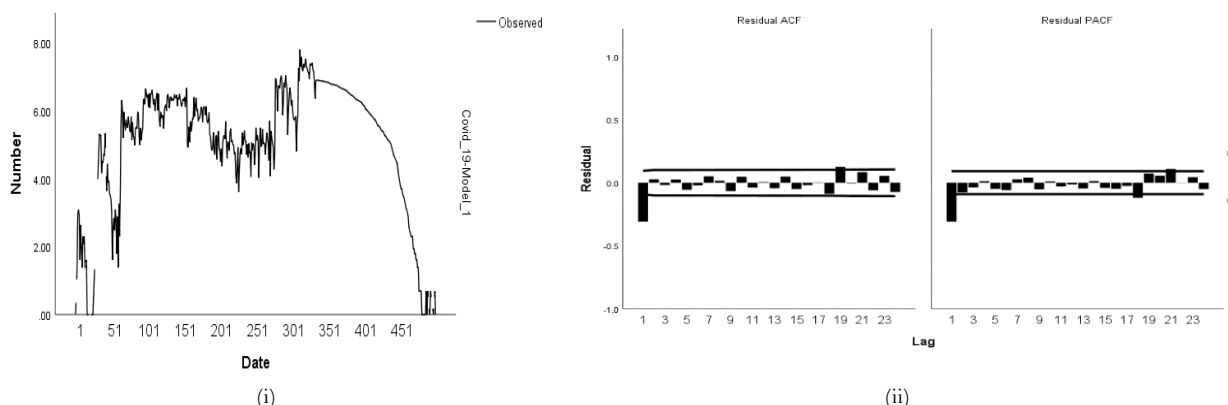


Figure 7. (i) The Standardized Residual Plot of the ARIMA (0,1,0) model and (ii) The standardized Residual plot for the ACF and PACF Respectively.

4. DISCUSSION OF FINDINGS

Nigeria is one of the countries in Africa that is worst hit with the problem of the COVID-19 pandemic. In this study, the ARIMA model and twelve (12) Error Trend and Seasonal (ETS) Exponential Smoothing Techniques have been applied to the dataset of Nigeria daily COVID-19 death for the period 10th July 2020 to 2nd December 2021. The aim was to compare 13 time series models, determine the COVID-19 trend and fit appropriate time series models to the COVID-19 daily deaths. The finding from the result indicated that; generally, there is a sharp reduction in the number of COVID-19 confirmed death cases between the years December 2020 and December 2021 in Nigeria. Other findings indicated that; there was an upward trend in the daily confirmed death cases in Nigeria from July 2020 to November 2020. The finding regarding the upwards trend is similar to the findings of the study from Chu [28]; Hongchao, et al. [29]; Adams, et al. [30]; Maleki, et al. [31], while the downward trend is consistent with discoveries from studies like; Benvenuto, et al. [7] and Anastassopoulou, et al. [32]; Adejumo, et al. [33].

Findings from the study indicated that ARIMA (0,1,0) was the best model selected among thirteen (13) competing models. This was inferred from the values of the model selection criteria like AIC, BIC, HQ, and AMSE that was utilized in the study. All these criteria established ARIMA (0,1,0) as the best model because it had the smallest value of all four (4) selection criteria. This finding is in line with Panda [9]; Sharma and Nigam [13]; Ceylan [34]; Kalekar [35]; Gupta and Pal [36]; Yonar, et al. [37]. One of the results showed that ARIMA models are suitable for predicting the prevalence of COVID-19 in the future for European countries. Another study applied Holt-Winters and Autoregressive integrated moving average (ARIMA) time series parameter smoothing to produce an effective 20-day ahead short-time technique and forecast the impact of the COVID-19 pandemic. The modeling and prediction are computed with the public dataset from Kaggle as a point of view to India and its five states like Odisha, Delhi, Maharashtra, Andhra Pradesh, and West Bengal. The India prediction indicated that the COVID-19 spreading will increase in the long run.

5. CONCLUSION AND RECOMMENDATION

The purpose of this study is to establish the trend and the appropriate time series technique for modeling the daily COVID-19 deaths. It was observed that the data showed the presence of a possible upward trend from July 2020 to November 2020 and a downward trend from late November 2020 to February 2021. This is an indication of non-stationarity and seasonality in the data set. Stationarity was achieved by differencing the covid-19 data with a confirmation of this seasonality by the result of the Augmented Dickey-Fuller test (p-value = 0.01).

On the objective of determining the appropriate time series technique among the thirteen (13) competing models; i.e. ANN, AAN, AADN, ANA, AADA, AAA, MAN, MADN, MNN, MADA, MNA, MAA and ARIMA. The smallest values of; AIC=2863.51, BIC= 2866.90, HQ = 2866.90, and AMSE = 0.55471 proved that ARIMA (0,1,0) is the preferred time series techniques among thirteen (13) competing methods for modeling the daily COVID-19 deaths in Nigeria. It is recommended that; ARIMA (0, 1, 0) provides the best-fit method for modeling the daily COVID-19 death in Nigeria for the period 10th July 2020 to 2nd December 2021.

Funding: This study received no specific financial support.

Competing Interests: The authors declare that they have no competing interests.

Authors' Contributions: Both authors contributed equally to the conception and design of the study.

Acknowledgement: Authors are thankful to the Department of Statistics, Faculty of Science, University of Abuja, Nigeria, for their support and encouragement throughout the period of writing this work

REFERENCES

- [1] World Health Organization, "Coronavirus disease 2019 (COVID-19), Weekly Epidemiological Update and Weekly Operational Update December Situation report, 2020. [Accessed December 2020]," 2020.
- [2] World Health Organization, "Rolling updates on coronavirus disease (COVID-19), Interactive Timeline, 2020. [Accessed December 2020]," 2020.

- [3] Nigeria Centre for Disease Control NCDC, "COVID-19 outbreak in Nigeria: Situation report." Retrieved from: <http://covid19.ncdc.gov.ng/>, 2020.
- [4] A. K. L. Bezerra and É. M. C. Santos, "Prediction the daily number of confirmed cases of COVID-19 in Sudan with ARIMA and Holt Winter exponential smoothing," *International Journal of Development Research*, vol. 10, pp. 39408-39413, 2020.
- [5] I. Djakaria and S. E. Saleh, "Covid-19 forecast using holt-winters exponential smoothing," presented at the Journal of Physic Conference Series, IOP Publishing, 2021.
- [6] H. Alabdulrazzaq, M. N. Alenezi, Y. Rawajfih, B. A. Alghannam, A. A. Al-Hassan, and F. S. Al-Anzi, "On the accuracy of ARIMA based prediction of COVID-19 spread," *Results in Physics*, vol. 27, p. 104509, 2021. Available at: <https://doi.org/10.1016/j.rinp.2021.104509>.
- [7] D. Benvenuto, M. Giovanetti, L. Vassallo, S. Angeletti, and M. Ciccozzi, "Application of the ARIMA model on the COVID-2019 epidemic dataset," *Data in Brief*, vol. 29, p. 105340, 2020. Available at: <https://doi.org/10.1016/j.dib.2020.105340>.
- [8] N. Chintalapudi, G. Battineni, and F. Amenta, "COVID-19 disease outbreak forecasting of registered and recovered cases after sixty day lockdown in Italy: A data driven model approach," *Journal of Microbiology, Immunology and Infection*, vol. 53, pp. 396-403, 2020. Available at: <http://dx.doi.org/10.1016/j.jmii.2020.04.004>.
- [9] M. Panda, "Application of ARIMA and Holt-Winters forecasting model to predict the spreading of COVID-19 for India and its states," *medRxiv*, pp. 1-26, 2020. Available at: <https://doi.org/10.1101/2020.07.14.20153908>
- [10] H. Swapnarekha, H. S. Behera, J. Nayak, B. Naik, and P. S. Kumar, "Multiplicative holt's winter model for trend analysis and forecasting of COVID-19 spread in India," *SN Computer Science*, vol. 2, pp. 1-15, 2021. Available at: <https://doi.org/10.1007/S42979-021-00808-0>.
- [11] R. K. Singh, M. Rani, A. S. Bhagavathula, R. Sah, A. J. Rodriguez-Morales, H. Kalita, C. Nanda, S. Sharma, Y. D. Sharma, and A. A. Rabaan, "Prediction of the COVID-19 pandemic for the top 15 affected countries: Advanced autoregressive integrated moving average (ARIMA) model," *JMIR public health and surveillance*, vol. 6, p. e19115, 2020. Available at: <https://doi.org/10.2196/19115>.
- [12] E. Zangiacomini-Martinez, D. C. Aragon, and A. A. Nunes, "Short-term forecasting of daily COVID-19 cases in Brazil by using the Holt's model," *Journal of the Brazilian Society of Tropical Medicine*, vol. 53, 2020. Available at: <https://doi.org/10.1590/0037-8682-0283-2020>.
- [13] V. K. Sharma and U. Nigam, "Modeling and forecasting of COVID-19 growth curve in India," *Transactions of the Indian National Academy of Engineering*, vol. 5, pp. 697-710, 2020. Available at: <https://doi.org/10.1007/S41404-020-00165-Z>.
- [14] E. Mingzhe, B. Zhao, and J. Cao, "Time series analysis of Holt model and the ARIMA Model facing Covid-19," *Annals of Mathematics and Physics*, vol. 3, pp. 023-029, 2020. Available at: <https://doi.org/10.17352/Amp.000014>.
- [15] G. E. Box and G. M. Jenkins, *Time series analysis: Forecasting and control*. Taiwan: Republic of China: Holden-Day, 1976.
- [16] G. E. P. Box and G. M. Jenkins, *Time series analysis: Forecasting and control*. San Francisco: Holden-Day, 1970.
- [17] J. K. Ord, A. B. Koehler, and R. D. Snyder, "Estimation and prediction for a class of dynamic nonlinear statistical models," *Journal of the American Statistical Association*, vol. 92, pp. 1621-1629, 1997. Available at: <https://doi.org/10.1080/01621459.1997.10473684>.
- [18] S. Roberts, "A general class of holt-winters type forecasting models," *Management Science*, vol. 28, pp. 808-820, 1982. Available at: <https://doi.org/10.1287/Mnsc.28.7.808>.
- [19] P. R. Winters, "Forecasting sales by exponentially weighted moving averages," *Management Science*, vol. 6, pp. 324-342, 1960. Available at: <https://doi.org/10.1287/mnsc.6.3.324>.
- [20] R. J. Hyndman, A. B. Koehler, J. K. Ord, and R. D. Snyder, *Forecasting with exponential smoothing*. Berlin Heidelberg: Springer, 2008.
- [21] C. C. Pegels, "Exponential forecasting: Some new variations," *Management Science*, vol. 15, pp. 311-315, 1969. Available at: <https://www.jstor.org/stable/2628137>.

- [22] J. W. Taylor, "Exponential smoothing with a damped multiplicative trend," *International journal of Forecasting*, vol. 19, pp. 715-725, 2003. Available at: [https://Doi.Org/10.1016/S0169-2070\(03\)00003-7](https://Doi.Org/10.1016/S0169-2070(03)00003-7).
- [23] C. C. Holt, "Forecasting seasonals and trends by exponentially weighted moving averages," *International journal of Forecasting*, vol. 20, pp. 5-10, 2004. Available at: <https://Doi.Org/10.1016/J.Ijforecast.2003.09.015>.
- [24] E. S. Gardner and E. Mckenzie, "Forecasting trends in time series," *Management Science*, vol. 31, pp. 1237-1246, 1985. Available at: [https://Doi.Org/10.1016/0169-2070\(86\)90056-7](https://Doi.Org/10.1016/0169-2070(86)90056-7).
- [25] K. P. Burnham and D. R. Anderson, *Model select ion and multi-model inference: A practical information-theoretic approach*, 2nd ed. New York: Springer-Verlag, 2002.
- [26] H. Akaike, "Information theory and an extension of the maximum likelihood principle, In Petrov, B.N. Csaki, F(Eds.)," presented at the 2nd International Symposium On Information Theory, Tsahkadsor, Armenia, USSR, 1973.
- [27] G. E. Schwarz, "Estimating the dimension of a model," *Annals of Statistics*, vol. 6, pp. 461 – 464, 1978. Available at: <https://Doi.Org/101214/Aos/1176344136>.
- [28] J. Chu, "A statistical analysis of the novel coronavirus (COVID-19) in Italy and Spain," *PloS one*, vol. 16, p. e0249037, 2021. Available at: <https://doi.org/10.1371/journal.pone.0249037>.
- [29] Q. Hongchao, S. Xiao, R. Shi, M. P. Ward, Y. Chen, W. Tu, Q. Su, W. Wang, X. Wang, and Z. Zhang, "COVID-19 transmission in Mainland China is associated with temperature and humidity: A time-series analysis," *Science of the Total Environment*, vol. 728, p. 138778, 2020. Available at: <https://doi.org/10.1016/j.scitotenv.2020.138778>.
- [30] S. O. Adams, M. A. Bamanga, S. O. Olanrewaju, H. U. Yahaya, and R. O. Akano, "Modeling COVID-19 cases in Nigeria using some selected count data regression models," *International Journal of Healthcare and Medical Sciences*, vol. 6, pp. 64-73, 2020. Available at: <https://doi:10.5923/j.ajms.20201001.02>.
- [31] M. Maleki, M. R. Mahmoudi, D. Wraith, and K.-H. Pho, "Time series modelling to forecast the confirmed and recovered cases of COVID-19," *Travel Medicine and Infectious Disease*, vol. 37, p. 101742, 2020. Available at: <https://doi.org/10.1016/j.tmaid.2020.101742>.
- [32] C. Anastassopoulou, L. Russo, A. Tsakris, and C. Siettos, "Data-based analysis, modelling and forecasting of the COVID-19 outbreak," *PloS One*, vol. 15, p. e0230405, 2020. Available at: <https://doi.org/10.1371/journal.pone.0230405>.
- [33] T. J. Adejumo, A. A. Akomolafe, A. T. Owolabi, A. I. Okegbade, O. J. Oladapo, J. I. Idowu, and G. S. D., "Modeling fatality rate of COVID – 19 in Nigeria using multiple linear regression analysis," *Global Scientific Journals*, vol. 8, pp. 439 – 449, 2020.
- [34] Z. Ceylan, "Estimation of COVID-19 prevalence in Italy, Spain, and France," *Science of the Total Environment*, vol. 729, p. 138817, 2020. Available at: <https://doi.org/10.1016/j.scitotenv.2020.138817>.
- [35] P. S. Kalekar, "Time series forecasting using holt-winters exponential smoothing," *Kanwal Rekhi school of information Technology*, vol. 4329008, pp. 1-13, 2004.
- [36] R. Gupta and S. K. Pal, "Trend analysis and forecasting of COVID-19 outbreak in India," *MedRxiv Preprint*, pp. 1-19, 2020. Available at: <https://doi.org/10.1101/2020.03.26.20044511>.
- [37] H. Yonar, A. Yonar, M. A. Tekindal, and M. Tekindal, "Modeling and Forecasting for the number of cases of the COVID-19 pandemic with the Curve Estimation Models, the Box-Jenkins and Exponential Smoothing Methods," *EJMO*, vol. 4, pp. 160-165, 2020.

Views and opinions expressed in this article are the views and opinions of the author(s), International Journal of Natural Sciences Research shall not be responsible or answerable for any loss, damage or liability etc. caused in relation to/arising out of the use of the content.