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Original Article

A comparison of error trends, seasonal exponential smoothing, and the ARIMA model using the COVID-19 death rate in Nigeria

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Abstract

Background: COVID-19 has claimed the lives of millions of people in Nigeria and around the world during the last two years. It is a recognized global health crisis of our day, as well as a persistent threat to the earth. The goal of this study was to examine the trend and fit an Error Trend and Seasonal (ETS) exponential smoothing and Autoregressive Integrated Moving Average (ARIMA) model to Nigeria's COVID-19 daily fatalities.

Methods: A dataset of daily COVID-19 confirmed fatality cases was used in the investigation. Data was acquired from the Nigerian Centre for Disease Control (NCDC) web database between the 10th of July 2020 and the 2nd of December 2021. The ARIMA model and twelve (12) ETS exponential smoothing techniques were investigated using a dataset of COVID-19 pandemic deaths in Nigeria. The ARIMA and ETS exponential smoothing algorithms were evaluated using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Hannan Quinn Information Criterion (HQC), and Average Mean Squared Error (AMSE) selection criteria.

Result: The ARIMA (0,1,0) model was the best time series modeling for the coronavirus (COVID-19) epidemic in Nigeria since it had the lowest AIC=2863.51, BIC=2866.90, HQ = 2866.90, and AMSE = 0.55471 values.

Conclusion: The ARIMA (0,1,0) model is preferred above the other thirteen (13) competing models based on daily confirmed COVID-19 deaths in Nigeria. This research would assist the Nigerian government in better understanding the pestilence's evolution pattern and providing adequate provisions, prompt mediation, and treatment to prevent additional deaths caused by the virus.

Keywords: ARIMA; COVID-19; Exponential Smoothing Trend; NCDC; Hannan Quinn Information Criterion (HQC); AMSE selection criteria; Nigeria

Introduction

COVID-19 is an infectious disease found in 2019, in Wuhan, China. The World Health Organization (WHO) later dubbed it "Coronavirus," short for Coronavirus Disease 2019. The Coronavirus pandemic remains one of the world's most terrible pandemics in recent years. The death rate increased dramatically, and the rate at which it spread was frightening. People over the age of 65, as well as those with latent illnesses such as cardiovascular disease, diabetes, chronic respiratory sickness, and cancer, are more susceptible to developing COVID-19-related illnesses, according to studies (1). Coronavirus symptoms include sore throat, runny nose, coughing/sniffling, difficulty breathing, and exhaustion (2). COVID-19 has been a major and noticeable public health concern over the world. Its frequency and mechanism of transmission have been key pressures in the medical community to contend with. Coronaviridae is a virus family that is pushed by a positive-sense RNA that has an external viral coat. When seen using an electron microscope, it has a visible corona. Human respiratory infections, such as colds and pneumonia, as well as serious respiratory diseases, are caused by the infection. Because this virus is zoonotic, it has the potential to transfer from the host to the next recipient (2).

COVID-19 is believed to be an infectious disease caused by Covid 2, a severe respiratory disease (SARS-CoV-2). The previously acknowledged case was witnessed in Wuhan, China, in December 2019. Since then, the disease has spread around the world, culminating in an ongoing epidemic. Coronavirus spreads when people inhale or breathe in air contaminated with beads and minute airborne particles containing the fatal infection. The cycle of infection is influenced more by proximity. Individuals can be exposed for up to 20 days and still transmit the illness, even if they show no symptoms. A few diagnostic techniques have been developed to examine this illness. The main diagnostic approach is indeed the transcription-mediated amplification technique, continuous converse record polymerase chain response (rRT-PCR) (TMA).

The COVID-19 pandemic is an ongoing disease that has spread to several countries. More than 188 nations have been affected globally, with over 245,984 new cases, 25,602,665 confirmed cases, and 852,758 deaths recorded to date. On February 27th, 2020, Nigeria declared its COVID-19 record case; it just so happens to be the ultimate first in Nigeria and West Africa connecting with data offered by the Nigerian Center of Disease Control (NCDC). A lockdown or check-in period was initiated and implemented in a few sections of the country shortly afterwards to control and reduce the rapid spread of the sickness. According to the NCDC, over 286,000 tests, 43,537 confirmed positive cases, 22567 dynamic cases, 20,087 releases, and 883 death rates were introduced and revealed across the 36 states, including the country's capital, the Federal Capital Territory (FCT), Abuja, as of the start of this review on August first, 2020. (3).

The Coronavirus epidemic has become a global threat to lives and security. To lessen the number of deaths, the entire world is working hard to find a few remedies to the struggle against this lethal sickness. Several demonstrations and predicting studies on the subject have been undertaken, utilizing a variety of time series models such as ARIMA and Holt-Winters periodic smoothing approaches. (4) Taken into account the presentation of ARIMA and Holt's direct significant smoothing models in the destruction of Coronavirus confirmed cases in Sudan, day-by-day readings of Covid-2019 confirmed cases dataset from March 24th to June 10th, 2020. Over Holt parameter smoothing approaches, the ARIMA model was picked as an appropriate model. (5) For a specific time period, the Coronavirus forecast model with Holt-Winters exceptional smoothing was investigated. When employing Holt-Winters exceptional smoothing, it was revealed that the optimal prediction model has smoothing bounds = 0.1 and = = 0.5 for pattern and irregularity individually, producing the minimum MAPE worth of 6.14. (6) was eager to validate the ARIMA process's accuracy as the most matched model and forecast. The findings show that, despite the strong belief in the illness and the consistent modifications implemented by the Kuwaiti government, the true attributes for the vast majority of the time studied were well within the confines of the specified ARIMA model expectation at 95% certainty. (7) proposed a basic econometric model for predicting the spread of COVID-19. The ARIMA model was used to forecast the epidemiological data from Johns Hopkins and estimate the pattern of predominance and rate of COVID-19. (8) Model a COVID-19-infected patient's dataset in R using the ARIMA hypotheses bundle on occasion. By the end of May 2020, the number of impacted patients in Italy is estimated to reach about 182, 757, with 81, 635 documented cases. (9) developed a capable 20-day ahead transient gauge model using ARIMA and Holt-Winters time series extreme smoothing and anticipated the impact of the COVID-19 pandemic. The estimating and exhibiting are accomplished using a Kaggle publicly available dataset with a focus on India and its five states of Odisha, Delhi, Maharashtra, Andhra Pradesh, and West Bengal. The distribution of COVID-19 is expected to grow in the long run, according to India. (10) projected COVID-19 for the five most impacted Indian states of Maharashtra, Tamil Nadu, Delhi, Gujarat, and Andhra Pradesh using constant data. The number of confirmed cases in these states was calculated using the Holt-Winters method. According to the investigation, the proposed Holt-Winters model has RMSE values of 76.0, 338.4, 141.5, 425.9, and 1991.5 for Andhra Pradesh, Maharashtra, Gujarat, Delhi, and Tamil Nadu, resulting in more precise predictions than Holt's Linear, Auto-relapse (AR), Moving Average (MA), and Autoregressive Integrated Moving Average (ARIMA) models. (11) looked at the top 15 countries in terms of confirmed cases, deaths, and recovery, and a high-level ARIMA model was used to anticipate COVID-19 infection distribution trends over the next two months. With the exception of China, Switzerland, and Germany, the observed predicted values suggested that the confirmed cases, deaths, and recuperations would more than quadruple in each of the studied countries. It was also discovered that the death and recovery rates increased faster when compared to confirmed cases over the subsequent two months. (12) evaluated the use of the Holt's model to

calculate the daily COVID-19 announced cases from the date of the main COVID-19 case to April 25, 2020, as the preparatory time frame, and April 26 to May 3, 2020, as the trial in Brazil and three Brazilian states. Finding reveals Holt's model can be a sufficient temporary determining approach if their assumptions are evaluated and confirmed by specialists. (13) examined the COVID-19 epidemic in India from March 4 to July 11 using relapse analysis (remarkable and polynomial), the auto-backward included moving midpoints (ARIMA) model, and dramatic smoothing and Holt-Winters models. Following the extraordinary development, it was discovered that the development of COVID-19 cases follows a power system of (t2, t,...) According to the findings, the ARIMA (5, 2, 5) model is the best-fitting model for COVID-19 instances in India. (14) investigate the new Covid's dissemination, pattern, and temporary figure in Hubei Province. According to the data presented, the plague situation in Hubei Province has essentially ended after May, while the scourge situation in the United States has become more severe after May, implying that the Holt model and the ARIMA model are also extremely accurate in predicting what is happening right now.
A review of the literature indicated that no study on modeling COVID-19 deaths in Nigeria has been conducted using a mix of error trend and seasonal (ETS) exponential smoothing approaches and the ARIMA model. To fill the deficiencies identified above, the purpose of this work is to determine the trend and fit an appropriate time series model to COVID-19 reported mortality cases in Nigeria.

Materials and Methods

Data

This paper is intended to investigate the COVID-19 trend pattern in Nigeria from July 10, 2020 to March 2, 2022. The goal is to use thirteen (13) time series models to fit appropriate time series models to the data. Data for this study were gathered from the Nigerian Centre for Disease Control (NSDC) (3) internet database from the 10th of July 2020 to the 2nd of December 2021.

Auto-Regressive Integrated Moving Average (ARIMA)

ARIMA modeling is used to anticipate values for various types of time series, with or without seasonal components or trends (15-16). The model is as follows:
An ARIMA model is given by:

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

(1)

$\theta(\beta) - 1 - \theta_i\beta - \theta_2\beta^2 \dots \theta_p\beta^q$

ϵ_i = residual, d = differencing term, β = Backshift operator ($\beta^d Y_i = Y_{i=q}$)

Exponential Smoothing Techniques

In computing smoothing, exponential smoothing incorporates error, trend, and seasonal (ETS) components. Each term is a combination of additive, multiplicative, or omitted terms from the model. It is a well-known local measurable algorithm used for time-series prediction. It is appropriate for a seasonal time series dataset with prior assumptions. As a prediction, ETS computes weighted means across all variables in the time series data. Rather with the constant weights in the direct Moving Average (MA) technique, the weights diminish exponentially over time. The weights are affected by a constant value known as the smoothing parameter. The literature contains several ETS exponential smoothing approaches. The majority of the strategies mentioned were used in our investigation. This study also introduced an exponential smoothing technique from earlier studies in the literature that gives effective performance (17 - 24). The criteria for the existing error trend and seasonal exponential smoothing approaches are shown in Table 1. In our investigation, we used asterisk models.

Model Selection Criteria

Akaike's Information Criterion

$$AIC = -2\log(L) + 2K \qquad (2)$$

Hannan –Quinn Information Criterion

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

Bayesian Information Criterion

$$BIC = AIC + K(\log(T) - 2$$

(4)

Mean Square Error $MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \widehat{Y_\iota}\right)^2$

Where; L is the likelihood, k is the number of model parameters, Y is the vector of observed values, $\widehat{Y_\iota}$ is the variable being predicted, n is the number of observations, L_{max} is the log-likelihood (25-27).

Table 1. Error Trend and Seasonal Exponential Smoothing 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 (Additive 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 (Additive damped)	M,A_d,N*	M,A_d,A*	M,A_d,M

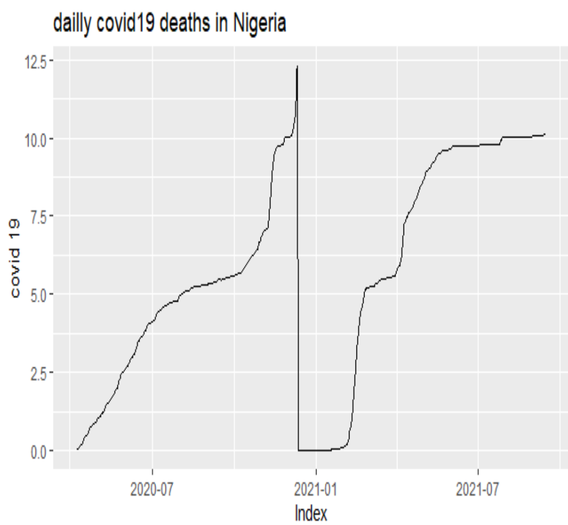


Figure 1. Trend plot of daily COVID-19 deaths deaths

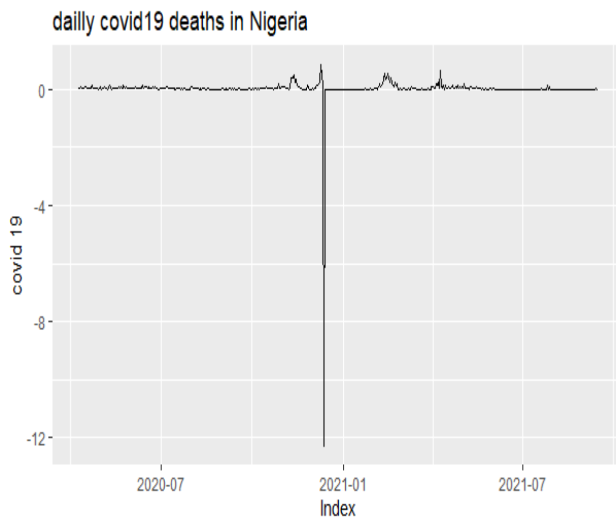
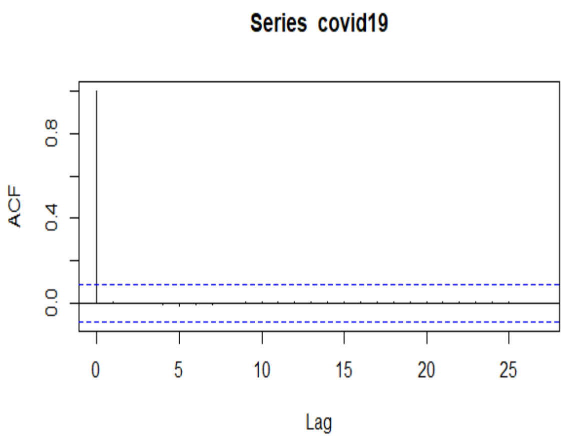


Figure 2. First differenced plot of daily COVID-19



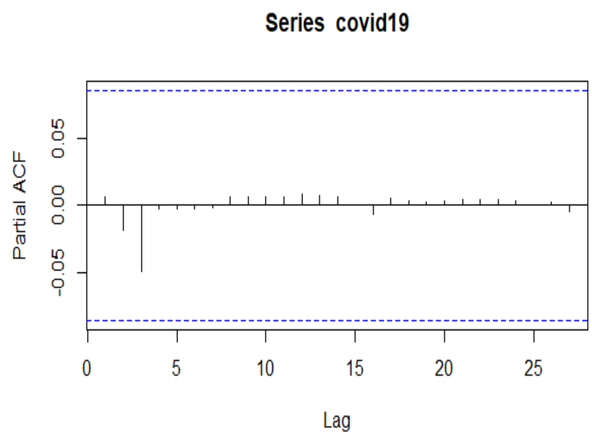


Figure 3. ACF (Auto Correlation Function) of COVID-19 deaths

Figure 4. PACF (Auto Correlation Function) of COVID-19 deaths

Table 2. ADF Test Result COVID-19 Deaths in Nigeria

ADF TEST	t-statistics	p-value
COVID-19	-7.5503	0.01

ADF: Augmented Dickey-Fuller test

Table 3. Coefficient of Estimate for ARIMA (0,1,0) Model

AIC	MAE	LogL	AICc	σ^2	RMSE	BIC	MASE	ME
879.56	0.06545588	-438.	879.56	0.2767	0.52559	883.89	0.9982	0.02201418

AIC: Akaike Information Criterion
MAE: Mean Absolute Error
LogL: Log likelihood
AICc: Akaike Information statistics corrected
σ^2 = Variance
RMSE: Root Mean Square Error
BIC: Bayesian Information Citerion
MASE: Mean Absolute Scaled Error
ME: Margin of Error

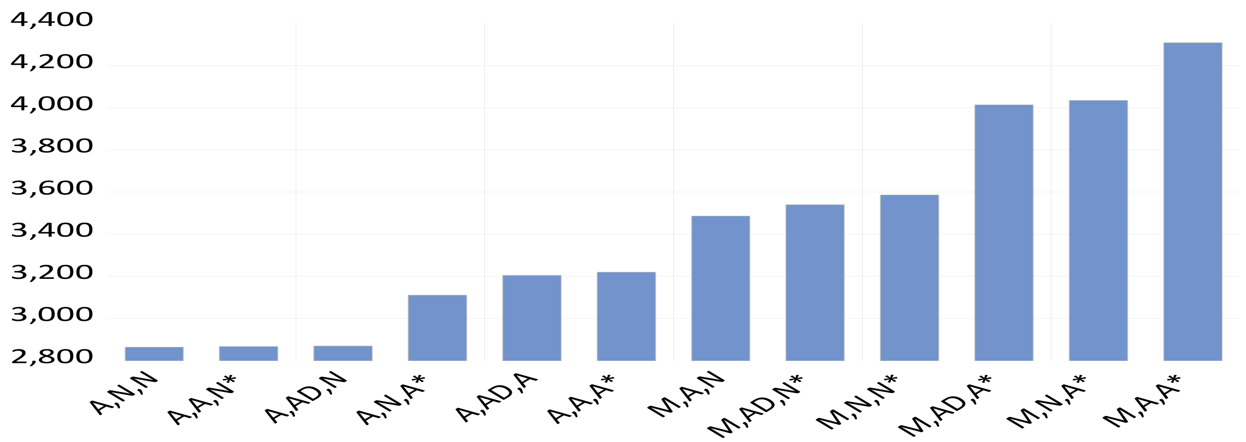


Figure 5. Model comparison graph

Table 4. Error Trend and Seasonal Model comparison table

Model	Compact LL	Likelihood	AIC	BIC	HQ	AMSE
A,N,N	-1429.76	-439.054	2863.51	2872.19	2866.90	0.55471
A,A,N	-1429.26	-438.556	2866.52	2883.87	2873.29	0.55246
A,AD,N	-1429.73	-439.029	2869.46	2891.16	2877.93	0.00022
A,N,A*	-1541.04	-550.341	3110.09	3170.83	3133.79	0.70021
A, AD, A*	-1585.01	-594.311	3204.03	3277.78	3232.81	0.00011
A, A, A*	-1593.60	-602.897	3219.20	3288.62	3246.29	0.98072
M, A, N*	-1738.76	-748.056	3485.52	3502.87	3492.29	0.74725
M, AD, N*	-1764.63	-773.924	3539.25	3560.95	3547.72	0.00001
M, N, N	-1791.09	-800.387	3586.18	3594.86	3589.57	0.79023
M, AD, A*	-1989.83	-999.124	4013.65	4087.41	4042.44	0.00023
M, N,A*	-2003.26	-1012.55	4034.51	4095.25	4058.22	0.67597
M, A, A*	-2138.40	-1147.70	4308.80	4378.22	4335.90	0.98157

Note: * 8 models failed to converge.
A,N,N: Additive, None, None
A,A,N: Additive, Additive, None
A,AD,N: Additive, Additive damped, None
A,N,A: Additive, None, Additive
A,AD,A: Additive, Additive damped, Additive
A,A,A: Additive, Additive, Additive
M,A,N: Multiplicative, Additive, None
M,AD,N: Multiplicative, Additive damped, None
M,N,N: Multiplicative, None, None
M,AD,A: Multiplicative, Additive damped, Additive
M,N,A: Multiplicative, None, Additive
M,A,A: Multiplicative, Additive, Additive

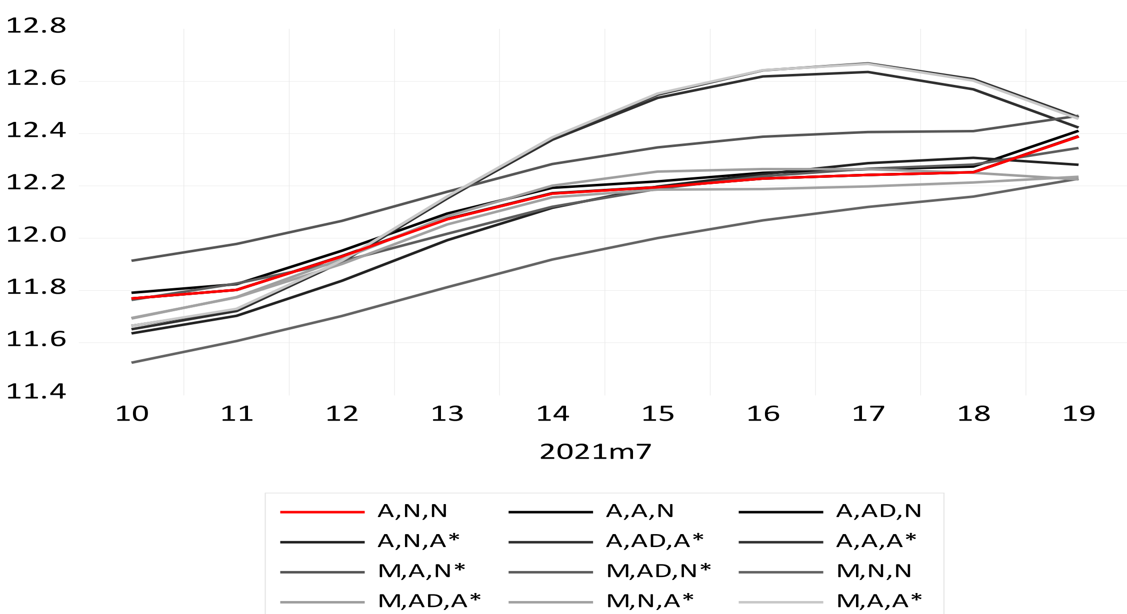


Figure 6. Forecast comparison graph

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

AIC	MAE	MASE	AICc	σ^2	RMSE	BIC	MASE	ME
2662.123	0.066025	0.99820	2662.184	0.5456	0.5445	267.934	0.999	0.02281

AIC: Akaike Information Criterion
MAE: Mean Absolute Error
LogL: Log likelihood
AICc: Akaike Information statistics corrected
σ^2 = Variance
RMSE: Root Mean Square Error
BIC: Bayesian Information Citerion
MASE: Mean Absolute Scaled Error
ME: Margin of Error

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

Model	AIC	MAE	BIC
ARIMA(0,1,0)	879.56	0.06545588	883.89
ETS(A,N,N)	2662.138	0.06602579	2674.934

AIC: Akaike Information Criterion
MAE: Mean Absolute Error
BIC: Bayesian Information Criterion
ARIMA: Autoregressive Intergrated Moving Average
ETS(A,N,N): Error Trend and Seasonal

Table 7. Ljung-Box Q test

Statistics	DF	Sig
1.6634	10	0.9983

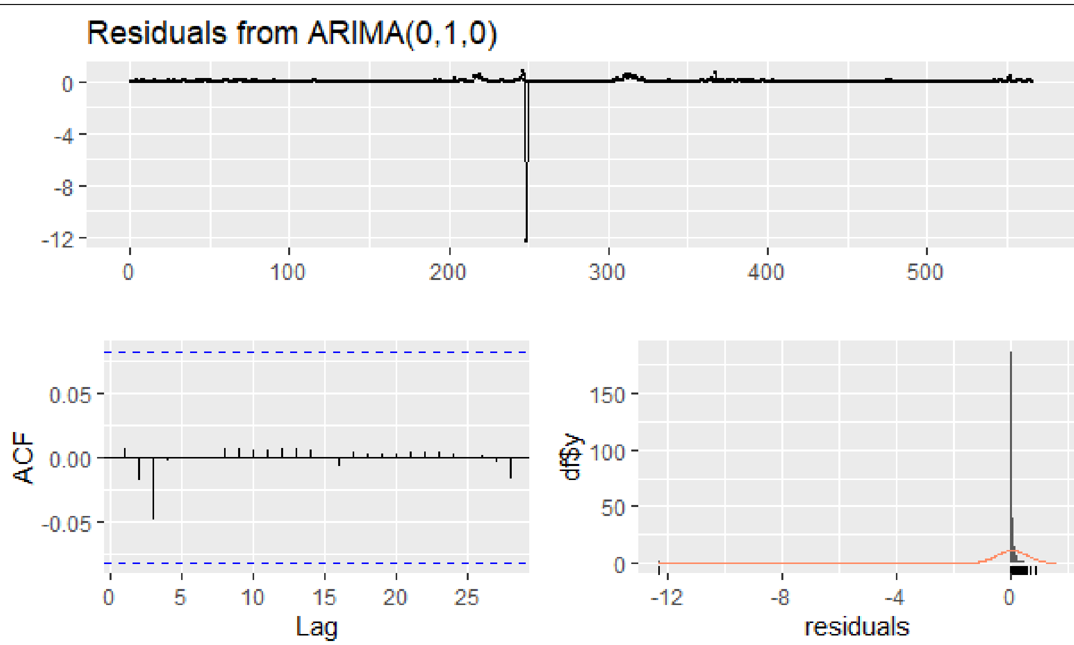


Figure 7. Plot of residuals

Results

Figure 1 shows that the data are not stationary, with a likely increase trend from July 2020 to November 2020 and a decrease tendency from late November 2020 to February 2021. (3). The graph in Figure 2 depicts the differenced COVID-19 dataset. Stationarity was attained by differentiating the COVID-19 data, as confirmed by the p-value of 0.01 in the Augmented Dickey-Fuller test (see Table 2), which is highly significant at all levels of significance. The trend component of the COVID-19 dataset was first removed using differencing. The results of the correlogram (ACF and PACF plot) shown in Figure 3 and 4 reveal that ACF and PACF are similar, with both showing a quick drop and an exponential decay from lag 0. As a result, the model is an ARIMA model rather than an Autoregressive (AR) or Moving Average (MA) model. ARIMA (0,1,0) is the only model that can be deduced from this model (see. Figure 4, i.e. PACF plot). The coefficients of the ARIMA (0, 1, 0) model are shown in Table 3: AIC = 879.56, MAE = 0.06546, log likelihood = -438.78, BIC (Bayesian information criterion) = 883.89 2 = 0.2767.

Exponential smoothing

According to the model comparison bar chart, the ETS (A,N,N) model was the best because it had the smallest value on the chart. Table 4 shows the autocorrelation function of daily confirmed COVID-19 cases in Nigeria. The ACF plot demonstrates exponential decay; the result also shows that the ETS model chosen by the Akaike information criteria is an A,N,N (Additive Error, No Trend, No Season) specification with smoothing value = 0.999 and initial parameter 0.0281 computed on the boundary. The summary statistics show that this specification outperforms other models. The selected model has a reduced average mean squared error and likelihood based on all three information criteria. Figure 6 displays the last few observations of the in-sample forecast as well as the out-of-sample forecast for each of the available ETS specifications, and it is proven that A,N,N will produce a better forecast. Table 5 displays the coefficients of the ETS (A,N,N) model with AIC = 2662.138, MAE = 0.06602579, and log-likelihood = -438.78, as well as BIC = 2674.934 and 2estimated = 0.5456 with level smoothing parameter = 0.999 and initial parameter 0.0281. We now examine the ARIMA (0,1,0) and ETS (A, N, N) models using the model selection criteria using the least Bayesian information criterion (BIC), Mean Absolute Error (MAE), and Akaike Information. The results in Table 6 clearly show that the ARIMA (0, 1, 0) model meets the lowest BIC, MAE, and Akaike Information requirements.

Residual checking

Table 7 displays the test for model fitness for forecasting, with p = 0.9983 indicating that the suggested model ARIMA (0,10) is a good fit, implying that it is suitable for forecasting. Figure 7 indicates that the residual process is white noise, implying that the ARIMA (0,1,0) model is appropriate for forecasting.

Discussion

Nigeria is one of the African countries that has been hardest hit by the COVID-19 pandemic. The ARIMA model and twelve (12) Error Trend and Seasonal (ETS) Exponential Smoothing Techniques were applied to the Nigeria daily COVID-19 death dataset from 10th July 2020 to 2nd December 2021 in this study. The goal was to analyze 13 time series models, establish the COVID-19 trend, and fit suitable time series models to COVID-19 daily deaths. According to the findings, there is a significant decrease in the number of COVID-19 confirmed fatality cases in Nigeria between December 2020 and December 2021. Other data revealed an increase in daily confirmed fatality cases in Nigeria from July 2020 to November 2020. The ascending trend is compatible with the findings of the study from (28-31), whereas the declining trend is consistent with findings from studies such as (7) and (32-33).

According to the study's findings, ARIMA (0,1,0) was the best model chosen out of thirteen (13) competing models. This was deduced from the values of the model selection criteria used in the study, such as AIC, BIC, HQ, and AMSE. ARIMA (0,1,0) was determined to be the best model by all four (4) selection criteria since it had the least value. This finding is consistent with the findings of Ceylan (2020) [34], who used Auto-Regressive Integrated Moving Average (ARIMA) models to estimate the epidemiological trend of COVID-19 prevalence in Italy, Spain, and France, Europe's most impacted countries. He created multiple ARIMA models with various ARIMA parameters. The best models for Italy, Spain, and France were ARIMA (0,2,1), ARIMA (1,2,0), and ARIMA (0,2,1) models with the lowest MAPE values (4.7520, 5.8486, and 5.6335). This study demonstrates that ARIMA models can be used to forecast the prevalence of COVID-19 in the future. Panda (2020) [9] found similar results to ours, demonstrating that ARIMA models are suitable for projecting the incidence of COVID-19 in European countries in the future. Another study used Holt-Winters and Autoregressive integrated moving average (ARIMA) time series parameter smoothing to create an effective 20-day ahead short-time technique and forecast the COVID-19 pandemic's effects. The modeling and prediction are performed using a public dataset from Kaggle with a focus on India and its five states, including Odisha, Delhi, Maharashtra, Andhra Pradesh, and West Bengal. According to the India estimate, COVID-19 dissemination will expand in the long run. Gupta and Pal (2020) [36] verified our findings by using exploratory data analysis to report the current status and time-series forecasting approaches to predict future changes. Their major findings show that the number of infected patients is fast increasing in India, with the average number of infected cases each day increasing from 10 to 73 between the first and 300th case. In the worst-case scenario, the number of infected people in India might reach 700,000 in the next 30 days, while the most hopeful scenario could restrict the number to 1000-1200. Furthermore, the ARIMA model indicates that there will be approximately 7000 patients in the next 30 days, up from the current number of 536. According to the forecasting model developed by Holt's linear trends, an estimated 3 million people may get infected if control measures are not implemented soon. ARIMA model superiority over alternative time series models was also proven in research by (13), (35), and (37).

Conclusion and Recommendation

The goal of this study is to determine the trend and the best time series technique for modeling daily COVID-19 deaths. The data revealed the presence of a probable increase trend from July 2020 to November 2020 and a possible decreasing trend from late November 2020 to February 2021. This indicates that the data set is non-stationary and seasonal. Stationarity was produced by differencing the COVID-19 data, with the Augmented Dickey-Fuller test (p-value = 0.01) confirming this seasonality.

The goal was to select the best time series technique from among the thirteen (13) competing models, namely ANN, AAN, AADN, ANA, AADA, AAA, MAN, MADN, MNN, M,AD,A, MNA, MAA, and ARIMA. The lowest values of AIC=2863.51, BIC=2866.90, HQ=2866.90, and AMSE = 0.55471 demonstrated that ARIMA (0,1,0) is the optimal time series technique among thirteen (13) competing methods for modeling daily COVID-19 fatalities in Nigeria. ARIMA (0, 1, 0) is selected as the best-fit method for modeling daily COVID-19 deaths in Nigeria from 10th July 2020 to 2nd December 2021.

Conflict of Interest: None

Authors' Contributions: Conception and design: SOA; Analysis and interpretation of the data: SOA, SG; Drafting of the article: SOA; Critical revision of the article for important intellectual content: SOA, SG; Final approval of the article: SOA; Provision of study materials or patients: SG; Statistical expertise: SOA.

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