African Journal of Mathematics and Statistics Studies

ISSN: 2689-5323

Volume 4, Issue 3, 2021 (pp. 118-134)

www.abjournals.org

MODELLING COVID-19 PANDEMIC IN NIGERIA USING MULTIVARIATE AUTOREGRESSIVE DISTRIBUTED LAG-MOVING AVERAGE MODELS

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Cite this article:

Usoro A.E., John E.E. (2021), Modelling Covid-19 Pandemic in Nigeria using Multivariate Autoregressive Distributed Lag-Moving Average Models. African Journal of Mathematics and Statistics Studies 4(3), 118-134. DOI: 10.52589/AJMSS-VFKTCGIK.

Manuscript History

Received: 7 Oct 2021

Accepted: 23 Oct 2021

Published: 19 Nov 2021

ABSTRACT: *The aim of this paper was to study the trend of COVID-19 cases and fit appropriate multivariate time series models as research to complement the clinical and non-clinical measures against the menace. The cases of COVID-19, as reported by the National Centre for Disease Control (NCDC) on a daily and weekly basis, include Total Cases (TC), New Cases (NC), Active Cases (AC), Discharged Cases (DC) and Total Deaths (TD). The three waves of the COVID-19 pandemic are graphically represented in the various time plots, indicating the peaks as (June–August, 2020), (December–February, 2021), and (July–September, 2021). Multivariate Autoregressive Distributed Lag Models (MARDLM) and Multivariate Autoregressive Distributed Lag Moving Average (MARDL-MA) models have been found to be suitable for fitting different categories of the COVID-19 pandemic in Nigeria. The graphical representation and estimates have shown a gradual decline in the reported cases after the peak in September 2021. So far, the introduction of vaccines and non-pharmaceutical measures by relevant organisations are yielding plausible results, as evident in the recent decrease in New Cases, Active Cases and an increasing number of Discharged Cases, with fewer deaths. This paper advocates consistency in all clinical and non-clinical measures as a way towards the extinction of the dreaded COVID-19 pandemic in Nigeria and the world.*

KEYWORDS: COVID-19, MARDLM, MARDL-MA.

Article DOI: 10.52589/AJMSS-VFKTCGIK

DOI URL: https://doi.org/10.52589/AJMSS-VFKTCGIK

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INTRODUCTION

Coronavirus (COVID-19) is an infectious disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-COVID-2). According to the World Health Organisation (WHO), coronavirus (COVID-19) is a newly identified virus that has caused monumental effects and has subjected the world to a health disaster, as no continent on the planet earth is free from the life-threatening and tragic pandemic. The entire human race is currently facing a tremendous health crisis with the rapid spread of the disease throughout the world. The infectious disease was first identified in December, 2019 in Wuhan, China. The countries with high vulnerability at the early stage of the outbreak were China, Spain, Italy, the USA, and the UK. As a temperate region, its effect on the African continent was not alarming as only a few cases were reported at the early stage of the outbreak.

In Africa, Nigeria recorded the first case of the coronavirus pandemic on February 27, 2020, from an Italian man who was diagnosed with the infectious disease in a laboratory in Lagos. Following the trend of the pandemic in other countries, the incidence triggered fear and reactions that the virus could be disastrous if proactive measures were not taken by the government to curb its spread (Maclean & Abdi, 2020). As part of the measures to prevent the spread of the disease in Nigeria, the federal government expressed commitment to surveillance at five international airports in Nigeria. The five airports were Enugu, Kano, Lagos, Rivers, and the FCT. This was followed by the inter-multisectoral committee which comprised stakeholders in health, security, aviation, and transport sectors as a build up for surveillance to forestall the introduction of coronavirus by foreigners and Nigerians from abroad (Oladeinde, 2020). The federal government, through the Minister of Health, Prof. Osagie Ehanire, advocated strong collaborative efforts between the relevant national and international health agencies—the Nigeria Centre for Disease Control (NCDC) and the World Health Organisation (WHO)—to strengthen surveillance. This also included the states hosting international airports. Governments at the state level equally exhibited proactive measures, especially at local airports and inter-state borders, to check the importation of the infectious disease from one state to the other. To cushion the effects of the pandemic, federal and state governments provided palliatives to vulnerable people whose means of livelihood were affected by the total lockdown directive of the federal and state governments in a bid to avert the spread of the pandemic.

To further strengthen the fight against the spread of the disease, the World Health Organization (WHO) advised national, state, and local relevant health authorities to carry out public education advocacy and campaigns against the disease through the introduction of health evasive measures, which include: (i) regular washing of hands with soap; (ii) rubbing alcohol-based hand sanitizer on hand; (iii) maintaining social distance of a minimum of 1 meter or 3 feet from someone who coughs or sneezes. The proposed measures to mitigate the rapid spread of the COVID-19 pandemic were prompted as the World Health Organisation (WHO) identified Nigeria among the 13 African countries at high risk of coronavirus. Included with Nigeria were Algeria, Angola, Ivory Coast, DR. Congo, Ethiopia, Ghana, Kenya, Mauritius, South Africa, Tanzania, Uganda and Zambia. The reason was attributed to the frequent travel of the aforementioned countries to China, which may be due to the bilateral economic relations the countries have with China and individual business transactions. Despite the efforts and trend of government activities to prevent the scourge of the coronavirus pandemic in the country, Nigeria was among the first five countries on the continent that were mostly affected by the disease. This was very worrisome and called for concern by governments, stakeholders, and individuals in society. The weekly figures published by NCDC as at September 26, 2021

Article DOI: 10.52589/AJMSS-VFKTCGIK
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recorded 204,456 Total Cases, 2,658 New Cases, 9,157 Active Cases, 192,622 Discharged Cases and 2,677 Total Deaths in Nigeria.

COVID-19's Economic Impact

The adverse effect of the pandemic cuts across many sectors including agriculture, oil and gas, education, services, mining, energy, and health as the worst hit sectors due to overstretching of manpower, facilities, and resources. The high risk of infection in the health sector instills fear in medical personnel, some of whom occasionally renege and break commitments in their responsibilities, failing to provide the expected services while some patients are left to their fates. Apart from the challenges in the health sector, the huge impact of the pandemic on oil and gas is very worrisome in view of the country's high reliance and dependence on oil as the major contributor to the economic growth of the nation. An instance is the envisaged negative effects on multinational companies in the era of this health crisis. This is evident as the Managing Director of Shell Nigeria Gas (SNG) Ltd expressed fears of an overwhelming economic downturn following the shutdown of its 118 customers during the peak of the lockdown. In addition to the shortfalls in the international market price of crude oil, this compelled the company to scale down its operations, reducing its production capacity (Premium Times; August 18, 2020). The negative impact of COVID-19 as a result of low turnout in production has affected the obligations of oil companies to the government and host communities in the areas of right of royalties, manpower development, and intervention in some basic amenities and infrastructure to promote economic diversification and stability. As many companies, industries, and many private organisations closed their doors during the peak of COVID-19, it resulted in an increase in the rate of unemployment across states because of the downsizing of the labor force, which is a major driving force of every nation's economy. Many businesses involved in the production of goods and services were forced to close their doors, particularly those that are not technologically advanced enough to necessitate working from home.

REVIEW OF RELATED LITERATURE

A little background literature on COVID-19 is built on the online publications and imprints on the statistics of the globally recorded cases. Despite the short period of discovery, a number of research in mathematical sciences have been established, including clinical trials for the discovery of a vaccine against the disease. This paper reviews related works published in COVID-19. Enahoro et al. (2020) adopted the Kermack-Mckendrick-Type compartmental epidemic model for the modelling and analysis of the COVID-19 pandemic in Nigeria. This model is a deterministic system of nonlinear differential equations and it reveals disease-free equilibria, which can be controlled whenever a certain epidemiological threshold has a value less than unity. Enahoro et al. (2020) split the human population at time t into mutually exclusive compartments of susceptible population, exposed population, symptotically-infectious population, asymptotically-infectious population, hospitalized population, and recovered population. The major focus of Enahoro et al. (2020) was on the effect of non-pharmaceutical intervention on COVID-19 prevalence in Nigeria, with the aim of considering the appropriate time it would be safe to relax the lockdown without exposing the human population to the risk of a second wave of the disease aside from model building, with the view of proposing a convenient and safer time to reopen the economy. Kayode et al. (2020) carried

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out a comparative analysis of models and estimators in the study of the COVID-19 pandemic in Nigeria. The paper viewed daily, cumulative, discharged, and dead cases. Their work identified the Quartic Linear Regression (QLR) model with an auto-correlated error of order 1, [AR(1)] and found OLS, Cochrane, Orcuh, Hildreth-Lu, Prais-Winsten, and Least Absolute Deviation estimators useful to estimate the parameters of the model. Vasilis (2020) carried out predictive modelling of COVID-19 data in the United States. An adaptive phase-space approach was adopted by dividing the population of study into susceptible, infectious, and recovered/removed fractions and defining their dynamic inter-relationships with first-order differential equations. The results of the work revealed a gradual reduction in the infectivity rate, although if adequate measures are not properly taken to control it, the latest waves of infection will be disastrous. Vini et al. (2020) adopted basic statistical inference to analyse COVID-19 data in Burkina Faso. The analysis involved point and interval estimations of average contamination and variance of distributions of COVID-19 cases in Burkina Faso. In Nigeria, COVID-19 cases are recorded in the categories: total cases, new cases, active cases, discharged cases, and total deaths. This gives reason to propose multivariate time series models for this work.

Johnston and Dinardo (1997) presented the general form of the univariate autoregressive distributed lag model ADL (p, q) in the form,

$$z_t = \mu + \alpha_1 z_{t-1} + \cdots + \alpha_p z_{t-p} + \beta_0 y_t + \beta_1 y_{t-1} + \cdots + \beta_q y_{t-q} + \epsilon_t \quad (1)$$

where z_t is the response time series variable, y_t is the predictor time variable, μ is the universal mean and ϵ_t is the error term, $\epsilon_t \sim ii(0, \sigma_\epsilon^2)$. From the model, z_t is a function of $z_{t-k(k=1,\dots,p)}$ and $y_{t-k(k=0,\dots,q)}$. Gujarati and Porter (2009) defined VAR models for Canadian money and interest rate as

$$M_t = \mu + \sum_{i=1}^{k} \beta_i M_{t-i} + \sum_{i=1}^{k} \gamma_i R_{t-i}$$

$$R_t = \varphi + \sum_{i=1}^{k} \pi_i M_{t-i} + \sum_{i=1}^{k} \alpha_i R_{t-i} \quad (2)$$

where M_t and R_t represent money and interest rate with associated parameters β_i, π_i and γ_i, α_i respectively. Equation "2" is a set of bivariate time series models also known as VAR models. With these models, causality between the two response variables are established.

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MODEL DERIVATION

Multivariate Autoregressive Distributed Lag Model

Proposition

Let $X_{jt(j=1,\ldots,m)}$ be $m \times 1$ matrix of response variables, $\alpha_{i.jk(i=1,\ldots,p,j=1,\ldots,m,k=1,\ldots,n)}$ be a square matrix of coefficients, $C_{j(j=1,\ldots,m)}$ be $m \times 1$ matrix of constants and $\epsilon_{jt(j=1,\ldots,m)}$ be $m \times 1$ matrix of errors; X_{kt} represents a vector of predictor variables, j *and* k are the subscripts for response and predictor variables respectively, while m *and* n are the numbers of response and predictor variables respectively. If $i = 0$ $(i \neq 1, \ldots, p)$ and $i \neq 0$ $(i = 1, \ldots, p)$, then, X_{jt} is a linear combination of $X_{kt-i(k=1,\ldots,n,\ i=0,)}$ and $X_{kt-i(k=1,\ldots,n,\ i=1,\ldots,p)}$, and X_{jt} is a Multivariate Autoregressive Distributed Lag Model in the form,

$$X_{jt} = C_j + \sum_{i=0,\ i=1}^{p} \sum_{j=1}^{m} \sum_{k=1}^{n} \alpha_{i.jk} X_{kt-i} + \epsilon_{jt} \qquad (3)$$

The above model is the aggregation of Vector Regression Models (VRM) and Vector Autoregressive Models (VARM) (Usoro, 2019).

Derivation:

Given X_j and X_k to be two time series variables, with $\alpha_{i.jk}$ as the parameter of contribution of X_k to X_j at lag i, let $\alpha_{i.jk(j=k)}$ be associated with the lag polynomials,

$$(1 - \sum_{i=1}^{p} \alpha_{i.11} L^i), (1 - \sum_{i=1}^{p} \alpha_{i.22} L^i), \ldots, (1 - \sum_{i=1}^{p} \alpha_{i.mn} L^i), where\ m = n$$

and

$\alpha_{i.jk(j \neq k)}$, with the lag polynomials,

$$(-\sum_{i=1}^{p} \alpha_{i.11} L^i),$$

$$for\ j = 1, k = 2,3, \ldots, n$$

$$j = 2, k = 1,3, \ldots, n$$

$$j = 3, k = 1, 2, \ldots, n$$

$$j = m, k = 1, 2, 3, \ldots, n - 1$$

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www.abjournals.org

Let $\alpha(L)$ be a linear combination of

$$(1-\sum_{i=1}^{p} \alpha_{i.jk(j=k)}L^i) \; and \; (-\sum_{i=1}^{p} \alpha_{i.jk(k\neq)}L^i),$$

such that for each response variable,

$$\alpha_1(L) = (1-\sum_{i=1}^{p} \alpha_{i.11}L^i) - \sum_{i=0}^{p} \alpha_{i.12}L^i - \sum_{i=0}^{p} \alpha_{i.13}L^i - \cdots - \sum_{i=0}^{p} \alpha_{i.1n}L^i = 0 \qquad (4)$$

$$\alpha_2(L) = -\sum_{i=0}^{p} \alpha_{i.21}L^i + \left(1-\sum_{i=1}^{p} \alpha_{i.22}L^i\right) - \sum_{i=0}^{p} \alpha_{i.23}L^i - \cdots - \sum_{i=0}^{p} \alpha_{i.2n}L^i = 0 \qquad (5)$$

$$\vdots \qquad\qquad\qquad\qquad \vdots$$

$$\alpha_m(L) = -\sum_{i=0}^{p} \alpha_{i.m1}L^i - \sum_{i=0}^{p} \alpha_{i.m2}L^i - \sum_{i=0}^{p} \alpha_{i.m3}L^i - \cdots + \left(1-\sum_{i=1}^{p} \alpha_{i.mn}L^i\right) = 0 \qquad (6)$$

The multiplications of (4), (5) and (6) by $X_{1t}, X_{2t}, \dots, X_{mt}$ respectively produce Multivariate Autoregressive Distributed Lag Models, which are reduced to the form,

$$X_{jt} = C_j + \sum_{i=0,\; i=1}^{p} \sum_{j=1}^{m} \sum_{k=1}^{n} \alpha_{i.jk}X_{kt-i} + \epsilon_{jt} \qquad (7)$$

where X_{jt} is an $m \times 1$ vector matrix, $\alpha_{i.jk}$ (i =1,…, p, j=1,…,m, $k = 1, \dots, n$) are matrices of coefficients, C_j is an $m \times 1$ vector of constants and ϵ_{jt} is an error term, $\epsilon_{jt} \sim iid(0, \sigma_\epsilon^2)$. The difference between X_{kt} and X_{jt} is that each subscripted "k" in X_{kt} defines a contributor (predictor term) to each subscripted "j" in X_{jt}, with the associated parameter α_{jk} indicating the contribution of "k" to "j".

From (7), if $i = 0$, it defines Multi-Dependent Linear Regression Models (MLRM), and if $i =$ 1,…, p, it defines the Vector Autoregressive Model (VARM). The linear combination of MLRM and VARM produces MARDLM as derived. Assuming ϵ_{jt} is not identically and independently distributed with zero mean and constant variance, it describes the autocorrelation of the residual term. Therefore, the component of the error term assumed to follow the moving average process needs to be filtered out, leaving an uncorrelated residual of

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the model. This justifies an extension of the Multivariate Autoregressive Distributed Lag Model with additional components.

From (7), we have

$$X_{jt} = C_j + \sum_{i=0,\ i=1}^{p} \sum_{j=1}^{m} \sum_{k=1}^{n} \alpha_{i.jk} X_{kt-i} + \sum_{s=1}^{q} \varphi_s \epsilon_{jt-s} \quad (8)$$

where ϵ_{jt-s} is the s lag moving average component of the error term in MARDLM with the parameter φ_s. The additional moving average component for the autocorrelated error term modifies (Usoro, 2019).

In this paper, we consider Multivariate Autoregressive Distributed Lag Moving Average Models for modelling Total Cases, New Cases, Active Cases, Discharged Cases and Total Deaths of the COVID-19 pandemic, where each response variable is a linear combination of the predictor variables at time t and both response and predictor variables at time $(t-k)$. The suitability of Usoro (2019) will be investigated using the error term of each response model. The justification of the additional component to the MARDLM is based on the behaviour of each error term in the MARDLM.

ANALYSIS AND RESULTS

Graphical presentations of COVID-19 Cases

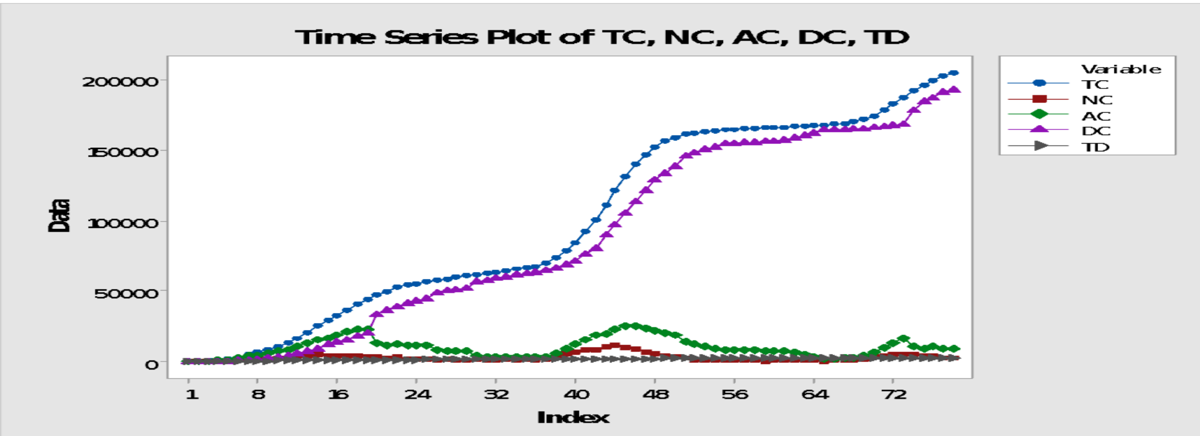

Figure 1: Multiple Time Graphs of All Reported Cases

Figure 1 is a multiple time plot of all cases, with total cases as the highest, followed by discharged cases, active cases, new cases, and total deaths as the least. From the graph, it is clear that the total and discharged cases compete favourably, which implies significant recovery of infected persons in comparison with the total cases. The weekly cumulative cases of COVID-19 at time added to the new cases at time gives the total cases at (where is the week-ended total confirmed cases)—Appendix 1.

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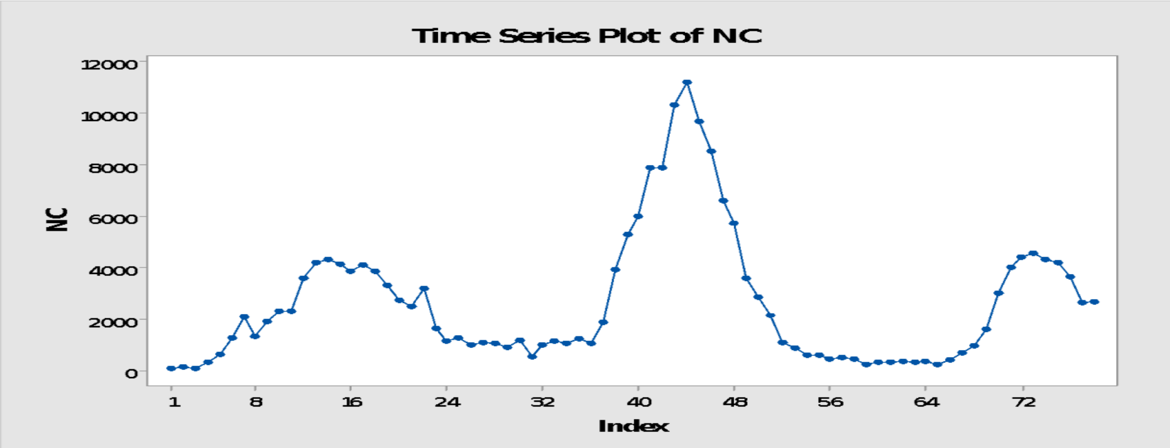

Figure 2: Time Plot of New Cases

Figure 2 presents three peaks from the COVID-19 pandemic in Nigeria. The first peak of the incidence after the discovery of the pandemic in March 2020 was within June and August 2020; the second peak was recorded between December 2020 and February 2021, being the second wave of the pandemic. The third wave of the scourge struck between July and the first week of September 2021. As shown in the graph, there is evidence of a decline in the last month i.e., in the 2nd, 3rd and 4th weeks of September 2021.

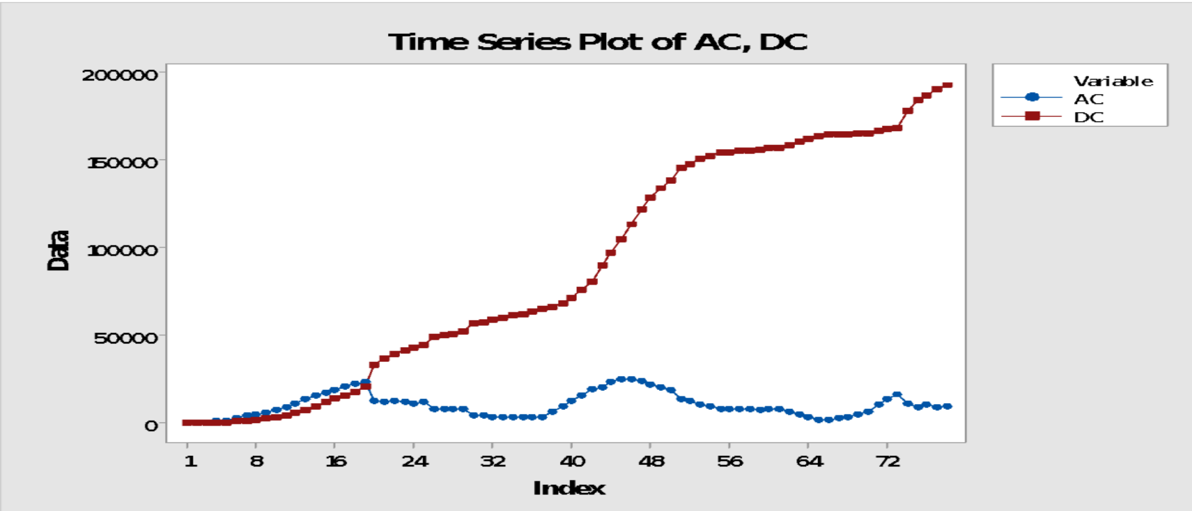

Figure 3: Time Plots of Active and Discharged Cases

Figure 3 presents the bivariate plots of active and discharged cases. There is a significant difference in the trends of the discharged cases versus active cases. The number of discharged cases increased with an increase in the number of active cases from August 3, 2020.

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Analysis and Interpretation of Results

This section looks at estimating the parameters of multivariate autoregressive distributed lag models with and without the error term's moving average process.

Estimation of Parameters of MARDLM

Table 1: Parameter Estimates of MARDLM

Total Cases (TC)	Coefficient	SE. Coeff	T-Value	P-value
Constant	3.81	6.18	0.62	0.540
NC	0.7888	0.0528	14.95	0.000
AC	0.2091	0.0526	3.98	0.000
DC	0.2101	0.0525	4.0	0.000
TD	0.2097	0.0585	3.59	0.001
TC-1	0.7968	0.0810	9.84	0.000
NC-1	0.00232	0.00365	0.64	0.527
AC-1	-0.0067	0.0585	-0.11	0.909
DC-1	-0.0069	0.00584	-0.12	0.907
TD-1	-0.0062	0.0628	-0.10	0.921
ϵ_{TCt-1}	-0.2474	0.1111	-2.23	0.029
New Cases (NC)	**Coefficient**	**SE. Coeff**	**T-Value**	**P-value**
Constant	-5.16	6.86	-0.75	0.455
TC	0.9755	0.0652	14.95	0.000
AC	0.0256	0.0650	0.39	0.695
DC	0.0243	0.0650	0.37	0.710
TD	0.0296	0.0709	0.42	0.678
TC-1	-1.0220	0.0651	-15.70	0.000
NC-1	-0.00024	0.00408	-0.06	0.952
AC-1	0.0215	0.0650	0.33	0.742
DC-1	0.0221	0.0649	0.34	0.734
TD-1	0.0222	0.0698	0.32	0.752
ϵ_{NCt-1}	-0.3237	0.1085	-2.98	0.004
Active Cases (AC)	**Coefficient**	**SE. Coeff**	**T-Value**	**P-value**
Constant	2.6	12.9	0.20	0.838
TC	0.912	0.230	3.98	0.000
NC	0.090	0.229	0.39	0.695
DC	-0.99966	0.00256	-390.52	0.000
TD	-1.0174	0.0484	-21.04	0.000
TC-1	0.135	0.264	0.51	0.612
NC-1	-0.00626	0.00762	-0.82	0.414
AC-1	-0.046	0.122	-0.38	0.708

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DC-1	-0.047	0.122	-0.39	0.700
TD-1	-0.047	0.131	-0.36	0.723
Discharged Cases (DC)	**Coefficient**	**SE. Coeff**	**T-Value**	**P-value**
Constant	2.2	12.9	0.17	0.866
TC	0.917	0.229	4.00	0.000
NC	0.086	0.229	0.37	0.710
AC	-0.999	0.00256	-390.52	0.000
TD	-1.0163	0.0487	-20.85	0.000
TC-1	0.132	0.264	0.50	0.619
NC-1	-0.00621	0.00762	-0.82	0.418
AC-1	-0.048	0.122	-0.39	0.696
DC-1	-0.049	0.122	-0.40	0.690
TD-1	-0.049	0.131	-0.38	0.708
Total Deaths (TD)	**Coefficient**	**SE. Coeff**	**T-Value**	**P-value**
Constant	13.0	11.8	1.10	0.274
TC	0.768	0.214	3.59	0.001
NC	0.087	0.210	0.42	0.678
AC	-0.8537	0.0406	-21.04	0.000
DC	-0.8525	0.0409	-20.85	0.000
TC-1	0.136	0242	0.56	0.576
NC-1	-0.00465	0.00699	-0.67	0.508
AC-1	-0.048	0.112	-0.43	0.666
DC-1	-0.050	0.118	-0.45	0.653
TD-1	0.054	0.120	0.45	0.655

From Table 1, MARDLM with and without moving average components of the error terms were estimated. In each of the response variable models, some parameter estimates are significant while some are not, including positive and negative coefficients. The results revealed significant contributions of New Cases (NC), Active Cases (AC), Discharged Cases (DC) and Total Deaths (TD) to the Total Cases (TC). As a time series variable, one time lag of the Tocal Cases is significant. MA(1) model is fitted to the error term to capture the presence of the moving average component in the model. The present and the preceding Total Cases of COVID-19 have an impact on the New Cases as shown in the second set of the model estimates. The autocorrelation structure of the error term justifies the inclusion of MA(1) model to capture the moving average component of the model. As evident in Figures 1 and 3, an increase in the current time of the Discharged Cases and Total Deaths decreases the Active Cases. This explains the negative coefficients of the Discharged and Total Deaths in the model of the Active Cases. Apart from the Total Cases which has significantly contributed to every response variable, evidence has it that Active Cases and Total Deaths have negative impact on the Discharged Cases. This implies an increase in the Active Cases and Total Deaths decreases the number of the Discharged Cases and vice versa. Finally, Active and Discharged Cases have a

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ISSN: 2689-5323
Volume 4, Issue 3, 2021 (pp. 118-134)
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strong negative impact on the Total Deaths, which accounts for the decrease in the Total Deaths as Active and Discharged Cases increase.

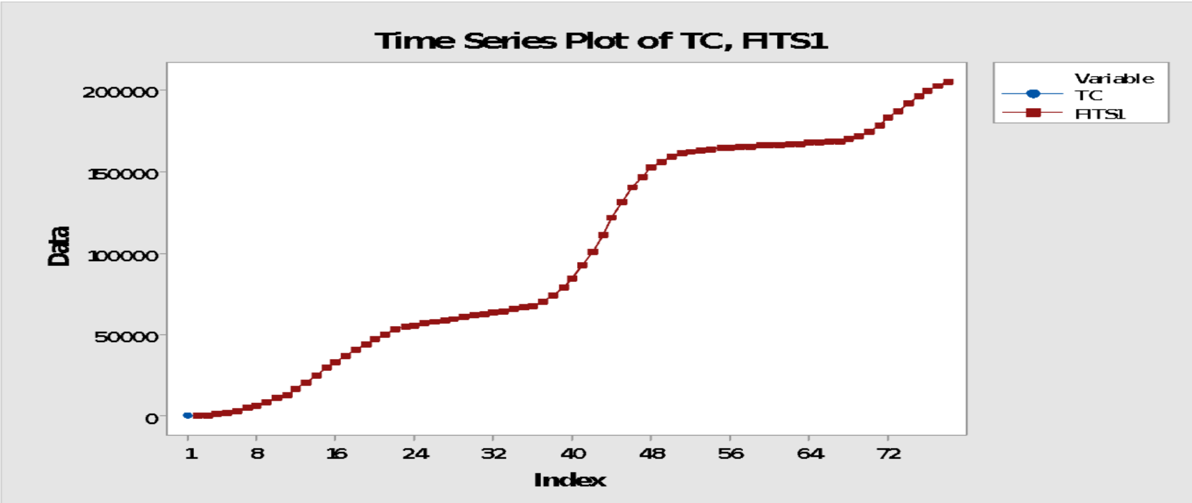

Figure 4A: Time Plots of Actual and Estimates of Total COVID-19 Cases

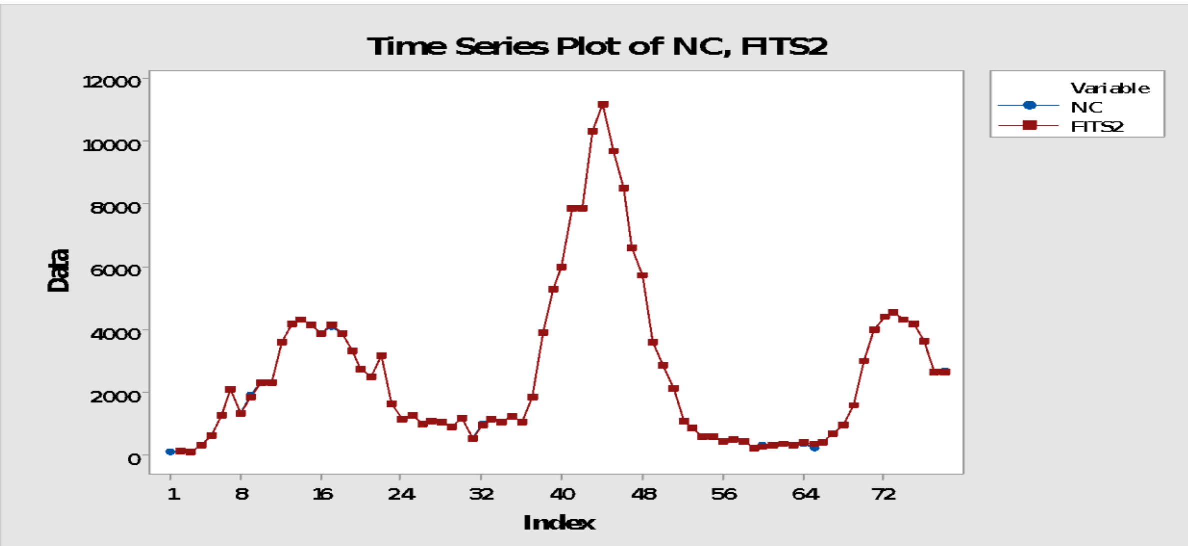

Figure 4B: Time Plots of Actual and Estimates of New COVID-19 Cases

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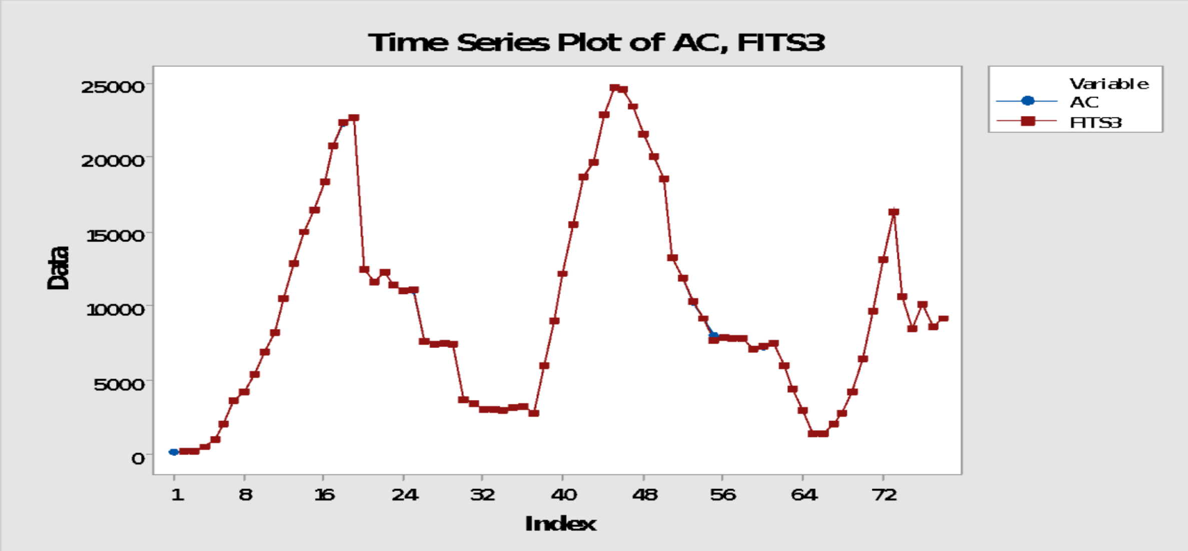

Figure 4C: Time Plots of Actual and Estimates of Active COVID-19 Cases

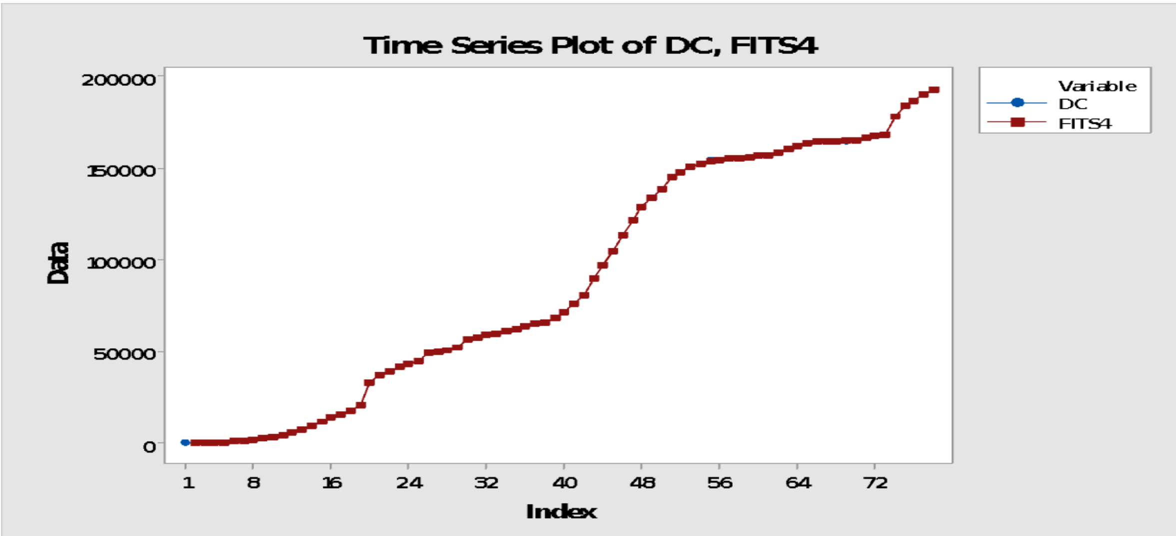

Figure 4D: Time Plots of Actual and Estimates of Discharged COVID-19 Cases

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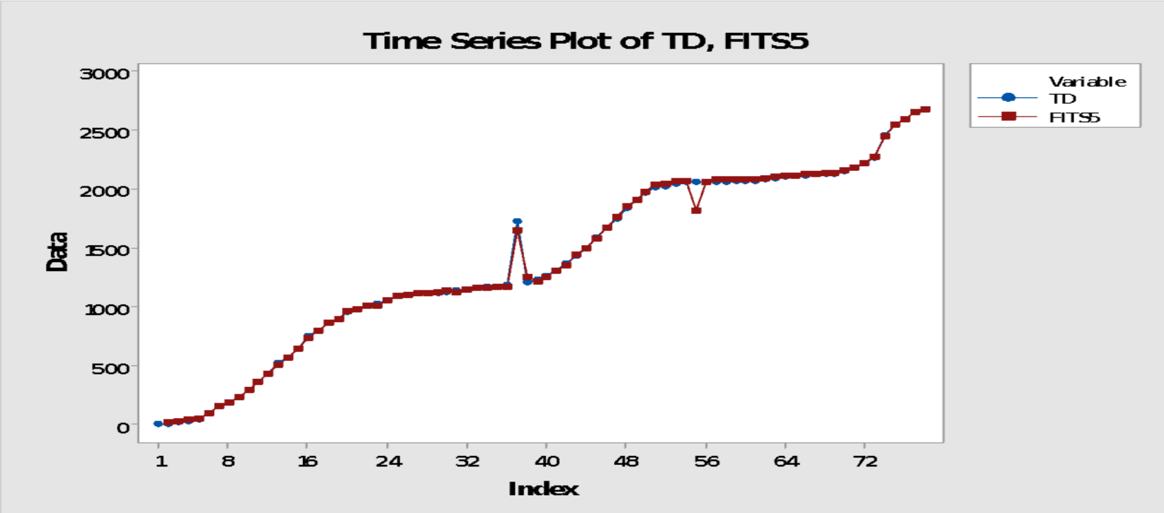

Figure 4E: Time Plots of Actual and Estimates of Total COVID-19 Cases of Deaths

The time plots of actual and estimated cases of the COVID-19 pandemic in Figures 4A-4E reveal suitability of the estimated MARDL-MA Models in fitting different cases of the pandemic in Nigeria. Appendix 1 contains the actual and estimated weekly data of COVID-19 Cases in Nigeria beginning from April 5, 2020 to September 26, 2021. The plots of the actual and estimates compete favourably as shown in the figures. The findings affirm MARDLM models for Active, Discharged and Total Deaths, while MARDL-MA Models have an advantage over MARDL Models for the estimation of Total and New Cases of COVID-19 in Nigeria.

DISCUSSION AND CONCLUSION

The emergence of the COVID-19 disease in almost all the nations in the world has been very threatening in view of its vulnerabilities in humanitarian settings, therefore subjecting the entire human race to distress and calamity, before the global enlightenment and awareness on possible means of transmission and non-pharmaceutical interventions as strategies to control the spread of the dreaded disease in the world. The daily mortality reports at the initial discovery of the pandemic in continents such as Europe, Asia and America were very devastating, overwhelming, and constituted serious panic as many nations mostly affected by COVID-19 appeared to have been overpowered by the pandemic. The effects of the novel coronavirus, which included human deaths and total closure of the world economy triggered global concern, thereby posing huge burdens on the economy of many nations in the era. In a bid to curb the spread of the disease in Nigeria, governments at all levels exhibited proactive measures, especially in the area of public enlightenment, creation of awareness and educating the human population on the possible ways of contracting the disease and the non-pharmaceutical measures to prevent and control the spread of the disease, while advocating for epidemiological investigations and clinical research to finding solution to the world health challenge. Governments at the state and federal levels have channelled huge resources in the fight against the disease in Nigeria. This is evidenced in the construction of special health facilities across

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many states in the country, building and strengthening the capacity of the existing tertiary health facilities, some of which serve as isolation centres for the COVID-19 infected persons. The good news about the prevalence of the novel COVID-19 is that, while many countries in the world today are engaged in clinical investigations and medical research to proffer solution to the life threatening pandemic, the humanitarian settings in Nigeria are very much acquainted with the trendy health challenges through governmental and non-governmental organisations to properly educate the public about the disease, as much as illuminating citizens on how to contain the coronavirus pandemic in the country.

Today, many nations in the world have built up capacity to overcome the scourge through extensive enlightenment campaigns, medical research and procurement of vaccines against the global pandemic. Despite the resurgence of the global pandemic in July 2021 as the third wave of the disease, the efforts of Nigerian government at all levels are reputed to have plausible impacts, as the country is experiencing a gradual decrease in the active and dead cases, while observing a significant increase in the daily discharged cases in September 2021. In spite of the pharmaceutical and non-pharmaceutical trials to fight against the disease, the need to have statistics view of the COVID-19 pandemic in Nigeria became pertinent in the sense that statistical research on the disease reveals the patterns of different categories of the life-threatening pandemic with a view to assess and appraise the effects of government, non-governmental organisations and other major stakeholders in the war against the dreaded disease. Sequel to the recent plausible development and the society's hope for a gradual extinction of the pandemic, it is encouraging to advocate more capacity building in the health sector, and strengthen the synergy between the private and public health organisations as a panacea for the global health challenge in our society. Statistically, Multivariate Autoregressive Distributed Lag Models (MARDLM) have been applied, and are found suitable for modelling and estimation of Active Cases, Discharged Cases and Total Deaths, while the modified model, MARDL-MA Model, is the best for Total and New Cases. Further findings from the research have it that every category of the COVID-19 pandemic, be it total cases, new cases, active cases, discharged cases or deaths, is dependent on the newly confirmed cases. Therefore, the COVID-19 pandemic will gradually go to extinction as the number of discharged cases increases with a drastic reduction in community transmission in Nigeria.

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APPENDIX

Appendix 1: Actual and Estimated Weekly Covid 19 Data From March 2020 to September 2021.

S/N	TC	NC	AC	DC	TD	EST(TC)	EST(NC)	EST(AC)	EST(DC)	EST(TD)
1	111	69	107	3	1					
2	232	121	194	33	5	235.66	115.988	196.6	35.158	17.4096
3	323	91	228	85	10	326.8	85.9861	230.23	86.788	21.9713
4	627	304	436	170	21	630.3	299.235	438.87	172.44	32.4777
5	1273	646	994	239	40	1275.9	641.755	996.41	241.06	49.7329
6	2551	1278	2071	393	87	2553.1	1274.73	2072.9	394.66	92.2102
7	4641	2090	3587	902	152	4642.4	2087.86	3587.5	902.35	153.012
8	5959	1318	4183	1594	182	5962.8	1315.61	4177.9	1588.7	183.052
9	7839	1880	5350	2263	226	7839.4	1878.88	5351.4	2264.3	229.441
10	10162	2323	6868	3007	287	10162	2322.98	6867.6	3006.8	286.335
11	12486	2324	8173	3959	354	12486	2324.72	8170.8	3957.1	350.663
12	16085	3599	10445	5220	420	16082	3601.61	10447	5222.5	418.777
13	20244	4159	12847	6879	518	20241	4162.97	12844	6876.7	508.712
14	24567	4323	14995	9007	565	24564	4327.86	14992	9004.5	561.597
15	28711	4144	16401	11665	645	28707	4149.29	16398	11663	638.586
16	32558	3847	18371	13447	740	32553	3854.15	18369	13446	730.82
17	36663	4105	20769	15105	789	36655	4113.87	20772	15109	788.005
18	40532	3869	22300	17374	858	40524	3878.27	22303	17378	855.499
19	43841	3309	22645	20308	888	43833	3317.7	22650	20314	892.646
20	46577	2736	12446	33186	945	46578	2731.44	12456	33193	959.225
21	49068	2491	11596	36497	975	49067	2491.92	11596	36497	973.945
22	52227	3159	12280	38945	1002	52224	3161.12	12283	38948	1001.82
23	53865	1638	11339	41513	1013	53867	1638.42	11335	41509	1010.87
24	55005	1140	10935	43013	1057	55004	1141.06	10937	43016	1054.59
25	56256	1251	11022	44152	1082	56253	1252.53	11027	44158	1082.78
26	57242	986	7575	48569	1098	57243	982.988	7580.1	48573	1102.46
27	58324	1082	7422	49794	1108	58324	1080.98	7424.6	49797	1107.68
28	59345	1021	7464	50768	1113	59346	1020.03	7465.8	50770	1112.57
29	60266	921	7416	51735	1115	60267	919.89	7418.2	51737	1115.48
30	61440	1174	3704	56611	1125	61444	1168	3708.9	56614	1129.89
31	61992	552	3397	57465	1130	61997	547.976	3393.9	57462	1125.56
32	62964	972	3028	58790	1146	62967	967.76	3029.6	58791	1143.83
33	64090	1126	3026	59910	1154	64094	1121.79	3025.1	59909	1150.52
34	65148	1058	2912	61073	1163	65152	1053.55	2910.1	61071	1158.84
35	66383	1235	3140	62076	1167	66387	1230.8	3139	62075	1164.04
36	67412	1029	3184	63055	1173	67417	1024.62	3181.8	63053	1169.25
37	69255	1843	2755	64774	1726	69258	1840.69	2747.2	64766	1645.62

Article DOI: 10.52589/AJMSS-VFKTCGIK
DOI URL: https://doi.org/10.52589/AJMSS-VFKTCGIK

African Journal of Mathematics and Statistics Studies
ISSN: 2689-5323
Volume 4, Issue 3, 2021 (pp. 118-134)
www.abjournals.org

38	73173	3918	5886	66090	1197	73173	3916.32	5888	66092	1250.78
39	78434	5261	8910	68303	1221	78435	5260.09	8906.4	68299	1215.2
40	84414	5980	12126	71034	1254	84415	5980.44	12120	71028	1246.97
41	92251	7837	15413	75532	1306	92249	7838.65	15412	75531	1302.58
42	100087	7836	18699	80030	1358	100087	7838.82	18690	80022	1350.91
43	110387	10300	19635	89317	1435	110384	10300.9	19638	89319	1438.56
44	121566	11179	22834	97228	1504	121565	11181.9	22826	97220	1500.06
45	131242	9676	24667	104989	1586	131244	9678.66	24654	104976	1579.37
46	139748	8506	24556	113525	1667	139748	8507.43	24553	113521	1669.74
47	146354	6606	23408	121193	1753	146355	6606.35	23407	121192	1757.23
48	152074	5720	21567	128668	1839	152073	5719.15	21574	128675	1849.05
49	155657	3583	20008	133742	1907	155658	3581.83	20013	133747	1915.18
50	158535	2878	18511	138055	1969	158533	2876.54	18526	138070	1983.45
51	160657	2122	13245	145399	2013	160659	2114.94	13261	145414	2032.91
52	161737	1080	11808	147899	2030	161739	1074.76	11820	147911	2044.44
53	162593	856	10237	150308	2048	162594	849.927	10253	150324	2065.13
54	163195	602	9139	151998	2058	163197	595.586	9154.4	152014	2074.29
55	163793	598	7926	154107	2060	163858	598	7642.1	153823	1821.83
56	164233	440	7840	154332	2061	164233	440	7840	154332	2061
57	164719	486	7731	154926	2062	164721	479.263	7746.3	154942	2078.12
58	165181	462	7757	155361	2063	165183	455.316	7771.9	155376	2078.8
59	165419	238	7057	156297	2065	165422	230.415	7071.7	156312	2081.18
60	165709	290	7230	156413	2066	165711	283.108	7245.4	156429	2081.9
61	166019	310	7476	156476	2067	166021	303.274	7491.3	156492	2082.91
62	166367	348	5946	158344	2077	166370	339.131	5962	158360	2093.93
63	166687	320	4385	160213	2089	166692	310.101	4399.1	160227	2103.69
64	167105	362	2929	162073	2103	167067	407.223	2936.9	162081	2110.93
65	167467	209	1399	163949	2119	167353	350.207	1396.1	163946	2116.1
66	167859	392	1356	164382	2121	167866	381.129	1366.1	164392	2130.71
67	168552	693	1989	164439	2124	168558	682.831	1998.6	164449	2132.86
68	169518	966	2694	164697	2127	169524	956.141	2703.3	164706	2135.96
69	171097	1579	4178	164787	2132	171102	1570.32	4188	164797	2141.25
70	174088	2991	6399	165537	2152	174091	2983.68	6410.7	165549	2161.24
71	178086	3998	9575	166328	2183	178088	3992.63	9583	166337	2188.55
72	182503	4417	13152	167132	2219	182504	4413.67	13158	167139	2223.61
73	187023	4520	16300	168455	2268	187022	4518.15	16308	168464	2273.68
74	191345	4322	10613	178278	2454	191351	4311.27	10623	178286	2451.57
75	195511	4166	8435	184524	2552	195518	4156.22	8439	184527	2547.89
76	199151	3640	10140	186413	2598	199156	3633.82	10140	186414	2592.36
77	201798	2647	8580	190563	2655	201805	2638.01	8583.3	190566	2652.67
78	204456	2658	9157	192622	2677	204460	2650.83	9164.6	192630	2679.51

Article DOI: 10.52589/AJMSS-VFKTCGIK
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