International Journal of Statistics and Applied Mathematics 2021; 6(2): 48-58

International Journal of Statistics and Applied Mathematics

ISSN: 2456-1452
Maths 2021; 6(2): 48-58

www.mathsjournal.com
Received: 22-01-2021
Accepted: 24-02-2021

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Otoi-NARIMA model for forecast seasonality of COVID-19 waves: Case of Kenya

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DOI: https://doi.org/10.22271/maths.2021.v6.i2a.675

Abstract

Background: Kenya has experienced three COVID-19 waves which left authorities mandated to do disease surveillance and estimate the burden of disease in a complex and uncertain environment with citizens' trust in institutions wavering having lost jobs and incomes. The citizens' vulnerability worsened with inability to connect to social support when each household wellbeing and financial ability came under threat causing much anxiety about the future. Mathematical modelling of the spread of disease informs surveillance, planning, budgeting, and response to save lives and livelihoods. In that regard, accuracy of predictions and forecasts is highly desirable. The length of duration of COVID-19 waves, the likely start and end dates, and the number of daily infections need to be estimated with precision. These inform and provide a window for authorities working in a holistic and integrated manner with researchers and experts to protect people especially the most vulnerable populations and communities to fully acquire WHO approved vaccines before the subsequent forecasted period of COVID-19 waves.

Method: Globally COVID-19 has serious health crisis with 134 million cases and 2.9 million deaths as of April 9, 2021. Kenya has experienced 392 days of COVID-19 with 136, 893 infections. The infections vary from county to county. Daily case infections data between March 13, 2020 and April 3, 2021 is used. The data is tested for stationarity and cointegration using ADF and Johansen Cointegration tests respectively. The normalized series is equally taken through these tests. A moving average of the Daily cases is estimated. The normalized series is superimposed on the moving averages. Then the combined series are used to construct Otoi-NARIMA model. The resulting model's residual is tested for autocorrelation using autocorrelation function (ACF) and partial autocorrelation function (PAFC) tests. Also, validity of the model is tested using Ljung-Box test. The model is used to forecast 45 daily cased from April 4, 2021 to May 18, 2021. The forecasted results are visualized. Likely dates for end of third wave and potential beginning of fourth wave are picked from visualization and output of Otoi-NARIMA model. The results are compared with results of standard ARIMA model.

Results: The series and normalized version are I(1) stationary. Johansen Cointegration test revealed the existence of one cointegration rank $r = 1$ between the series. Implication is that the series and superimposed normalized version would not drift apart overtime when used to estimate Otoi-NARIMA model. Whereas ACF revealed that both models show no autocorrelation PACF was inconclusive. On validity, the Ljung-Box test showed that both Otoi-NARIMA and standard ARIMA are valid, however the former is superior. The Otoi-NARIMA model has distinctly identified the seasonality of COVID-19 waves. In terms of visualization clarity Otoi-model provides restricted forecasts. There is likelihood of Kenya's third wave beginning to decline briefly between April 29, 2021 and May 9, 2021. Based on assumption that Kenya will not have fully vaccinated 51 in 100 people the wave is likely to continue between June 2, 2021 and after July 10, 2021 or the third wave will continue up to June 26, 2021, which is the likely peak. It is recommended that Kenya should aim to vaccinate 51 in 100 people before June 2, 2021.

Keywords: COVID-19, seasonality, waves, forecasting

Introduction

Since World Health Organization (WHO) declared COVID-19 epidemics as a public health emergency of international concern on 30 January 2020 (Guo *et al.* 2020) [2], various countries have experienced COVID-19 waves at different times.

The current focus has combined socioeconomic burden of the pandemic and the development of vaccine(s) and/or cure to contain the spread as well as severity of illnesses resulting from complications and case fatality rates. Whereas developed countries have harnessed capability to vaccinate majority of their populations, developing countries need resources to vaccinate even the frontline workers and most formulate a coherent plan Nazr and Shah (2020) [12]. For instance, February and March 2021 witnessed beginning of mass vaccination campaigns using approved vaccine(s) against severe COVID-19 in many parts of the world (Dagan *et al*, 2021).

At the beginning of pandemic infections in Africa several scholars observed that Africa reported fewer cases than other regions according to WHO classification (Oluwayesi *et al.*, 2020). However, a study by Shem (2020) [6, 8] established that infection rates, case fatality rates, and recovery rates in Africa were not statistically different from other regions and that with time the continent would report higher numbers of infections. On 3 January 2021 Kenya reported 136,893 cases, 3186 fatalities, 41,277 morbidity, and 93,430 recoveries suggesting that Shem (2020) [6, 8] was accurate. Kenya began vaccination campaigns on March 6, 2021 after receiving *AstraZeneca* vaccine while experiencing the third COVID-19 wave. Shem & Ndhine (2020) [6, 8] accurately predicted the first COVID-19 wave in Kenya to be from August 10, 2020 to September 4, 2020 and described mathematical possibility of multiple rotating seasonal waves.

The purpose of mathematical modelling of COVID-19 is to support disease surveillance, preparedness, budgeting, and enhanced response by estimating caseload well in advance. As such mathematical modelling assists in making informed estimation of the burden of the disease. Mathematical modelling helps to estimate with accuracy populations at risk presently and in future so that effort to mitigate transmission, including vaccines, are accelerated. Cordina *et al.* (2021) [3] observe that comprehensive recovery lies in high and equitable vaccine uptake.

Theoretical View

Shem and Ndhine (2020) [6, 8] used ARIMA model to forecast COVID-19 cases, active morbidity and fatalities in Kenya and predicted the first wave. Also, Dahesh *et al*. (2020) [5] used ARIMA model to forecast confirmed cases in Pakistan. ARIMA model is a robust time series model that captures autoregression, integration, and moving averages of any series used in its estimation. The model has AR(p), Integrated (d), and moving average MA (q) components initialized as (P, D, Q). Logarithmic transformation is only done to enable various tests, including stationarity, and integration tests. Once orders of (P, D, Q) have been established appropriate ARIMA model is estimated. The residuals are test for autocorrelation using ACF and PACF. The validity of the model is tested using Ljung-Box test. The estimated model is then used to forecast daily cases.

Some of the weakness of standard ARIMA model is the large variation of lower and upper boundaries value. The interval between upper and lower boundary values at 95% confidence level is usually large. The estimation of these values is wide apart though the forecasts is always halving the sum of maximum and minimum point values. To limit this variation, Otoi-NARIMA model determines the order and estimated the moving average series. The initial series is normalized. To retain the irregularity of the underlying data pattern the normalized series is superimposed on the averaged series. The Otoi-NARIMA model is estimated by running ARIMA model of the superimposed series. All the necessary statistic tests are done on the Otoi-NARIMA model. A forecast of the novel model is done. The results are compared with that of standard ARIMA model.

Empirical Derivation of Otoi-NARIMA Model

The study used Kenyan daily COVID-19 new cases data from March 13, 2020 to April 3 2021. The series is tested for stationarity using Augmented Dickey-Fuller test as described in Dickey and Fuller (1979) [9]. The normalized and moving average series are taken through Johansen cointegration test as outlined by Johansen (1991) [10] to ascertain that the estimated model variables wont drift apart overtime. The Otoi-NARIMA model is estimated by superimposing normalized series on the moving average series as derived in equations (1) to (9). The Otoi-NARIMA and standard ARIMA models are estimated. The forecasts of both models are estimated. The results are compared, and models tested to determine the superiority and suitability of either model.

Deriving Otoi-NARIMA model Comparison of boundary Interval Between the Two Models

$$Moving\ Average = \frac{1}{M}\sum_{i=1}^{k} x_{t-j} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

$M = k + 1,$

$t - j = order\ of\ moving\ average,$

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

$$Normalization\ of\ series = \frac{x_i - \bar{x}}{x_{max} - x_{min}} \ldots\ldots\ldots\ldots\ldots\ldots \quad (2)$$

Where $\bar{x}$ $is\ mean\ of\ series,$
x_{max} $is\ maximum\ value\ in\ series$,
x_{min} $is\ minimun\ value\ in\ series,$
x_i $is\ series\ taken\ at\ random.$

$$y_t = \frac{1}{M}\sum_{i=1}^{k} x_{t-j} \cdot \frac{x_i - \bar{x}}{x_{max} - x_{min}}$$

$$y_t . \frac{x_{max} - x_{min}}{x_i - \bar{x}} = \frac{1}{M}\sum_{i=1}^{k} x_{t-j}$$

$$y_t(x_{max} - x_{min}) = (x_i - \bar{x})\frac{1}{M}\sum_{i=1}^{k} x_{t-j}$$

$$y_t(x_{max} - x_{min}) = \left(\frac{x_i - \bar{x}}{M}\right)\sum_{i=1}^{k} x_{t-j}$$

$$(x_{max} - x_{min}) = y_t^{-1}\left(\frac{x_i - \bar{x}}{M}\right)\sum_{i=1}^{k} x_{t-j}$$

$$x_{max} = y_t^{-1}\left(\frac{x_i - \bar{x}}{M}\right)\sum_{i=1}^{k} x_{t-j} + x_{min}$$

$Let\ y_t^{-1}\ be\ \omega$

$\frac{x_i - \bar{x}}{M}\ be\ \pi$

$x_{max} = x_{min} + \omega\pi \sum_{i=1}^{k} x_{t-j}$ ……………………………………………………….....(3)

$x_{min} = x_{max} - \omega\pi \sum_{i=1}^{k} x_{t-1}$……………………………………………………….……(4)

Forecast $x_f = \frac{x_{min}+\omega\pi\sum_{i=1}^{k} x_{t-j} + x_{max} - \omega\pi\sum_{i=1}^{k} x_{t-j}}{2} = \frac{x_{min}+x_{max}}{2}$……………………......(5)

Infusing the derived model into ARIMA

Let $x_{min} + \omega\pi \sum_{i=1}^{k} x_{t-j}\ \ be\ z_t$…………………………………..…………………(6)

$$z_t = \varphi_1 z_{t-1} + e_t - \vartheta_1 e_{t-1}$$

$$z_t = \varphi_1\beta_1 z_t + e_t - \vartheta_1\beta_2 e_t$$

$$z_t - \varphi_1\beta_1 z_t = e_t - \vartheta_1\beta_2 e_t$$

$$z_t(1 - \varphi_1\beta_1) = e_t(1 - \vartheta_1\beta_2)$$

$$z_t = \frac{(1 - \vartheta_1\beta_2)}{(1 - \varphi_1\beta_1)} e_t$$

$$Upper\ Interval = x_{min} + \omega\pi \sum_{i=1}^{k} x_{t-j} = \frac{(1 - \vartheta_1\beta_2)}{(1 - \varphi_1\beta_1)} e_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

$$Lower\ Interval = x_{max} - \omega\pi \sum_{i=1}^{k} x_{t-1} = \frac{(1 - \vartheta_2\beta_4)}{(1 - \varphi_2\beta_3)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

$$Forecast = \frac{x_{max} + x_{min}}{2} = \frac{(1 - \vartheta_3\beta_5)}{(1 - \varphi_3\beta_6)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (9)$$

$$\beta_1 \neq \beta_2\ > \beta_5$$

$$\beta_3 \neq \beta_4 > \beta_6$$

$$\beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq \beta_6$$

$\varphi_1 \neq \vartheta_1 > \vartheta_3$

$\varphi_2 \neq \vartheta_2 > \vartheta_3$

$\varphi_1 \neq \varphi_2 \neq \vartheta_1 \neq \vartheta_2 \neq \vartheta_3$

Where,
$\omega, \pi, \varphi_1, \beta_1, \vartheta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$ coefficients of variables and parameters used in the model.
e_t is stochastic error.
$z_t = Autoregressive\ series$
e_{t-1} lag of stochastic errors for moving average.

Results

The estimated models

The estimated Otoi-NO-RIMA model is ARIMA (3,1,2). The basic ARIMA model is also (3,1,4)
Otoi-NARIMA (3, 1, 2)

$$\hat{y}_t = \varphi_1 \hat{y}_{t-1} + \varphi_2 \hat{y}_{t-2} + \varphi_3 \hat{y}_{t-3} - \vartheta_1 \hat{e}_t - \vartheta_2 \hat{e}_{t-2}$$

$$NEW\ CASES_t = 1.0424_{(0.0771)} NEW\ CASES_{t-1} - 0.5993_{(0.0775)} NEW\ CASES_{t-2} - 0.1348_{(0.0735)} NEW\ CASES_{t-3} + 1.5557_{(0.0569)} MA_{t-1} - 0.8162_{(0.0375)} MA_{t-2} \quad (10)$$

Standard ARIMA

$$\hat{y}_t = \varphi_1 \hat{y}_{t-1} + \varphi_2 \hat{y}_{t-2} + \varphi_3 \hat{y}_{t-3} - \vartheta_1 \hat{e}_{t-1} - \vartheta_2 \hat{e}_{t-2} - \vartheta_3 \hat{y}_{t-3} - \vartheta_4 \hat{y}_{t-4}$$

$$NEW\ CASES_t = 2.1092_{(0.0421)} NEWCASES_{t-1} - 2.0611_{(0.0535)} NEW\ CASES_{t-2} + 0.8818_{(0.0372)} NEW\ CASES_{t-3} + 3.658_{(0.1253)} MA_{t-1} - 2.9003_{(0.0568)} MA_{t-2} - 2.3939_{(1.151)} MA_{t-3} + 0.6839_{(0.0447)} MA_{t-4} \quad (11)$$

Table 1: Stationarity test results

	At Level	1st Difference
Dickey-Fuller	-0.44202	-8.0225
Lag Order	7	7
P-value	0.9842	0.01

Table 2: Johansen Cointegration Test

Rank	Test	10%	5%	1%
$r \leq r$	**3.35**	**7.52**	**9.24**	**12.97**
$r \leq 0$	11123.59	13.75	15.67	20.20

Lag selection FPE=3, the Final Prediction Error criteria chose 3 lags for the model.
The series of daily COVID-19 cases in Kenya is I(1) stationary, that is, after the first difference. The normalized and moving average series are equally I (1) stationary. The Johansen cointegration test finds 1 cointegration rank at 95% confidence level. $H_0: r \leq 1$. We reject the null hypothesis and conclude that there is 1 cointegrating vector. It means that when the model is estimated the variables will not drift apart over time.

Comparison of Otoi-NARIMA and Standard ARIMA Models

Otoi-NARIMA

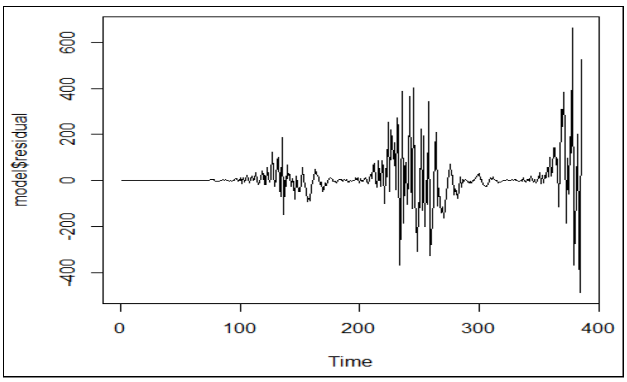

Fig 1: Otoi-NARIM residuals showing wave seasonality.

Standard ARIMA

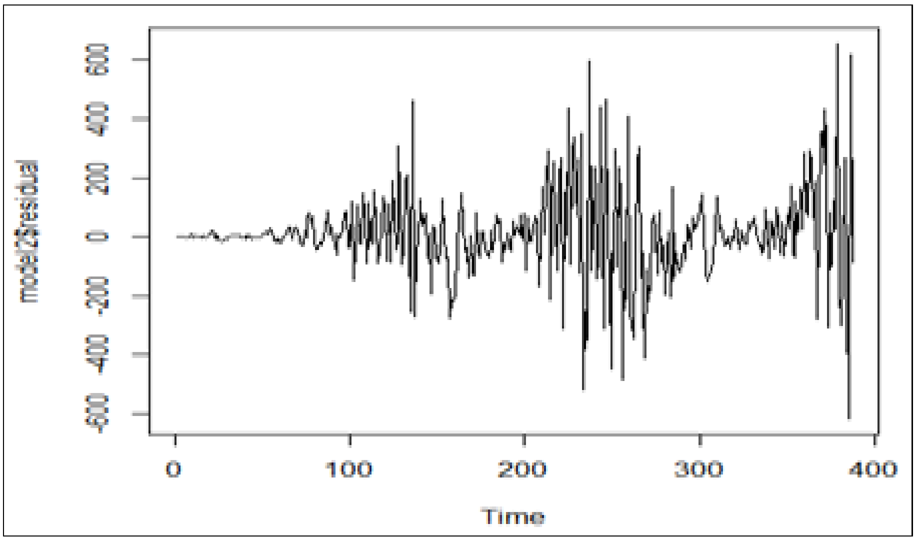

Fig 2: Standard ARIMA showing indistinct seasonality.

The Otoi-NARIMA model has clearly illustrated separation between the waves and respective lengnths.

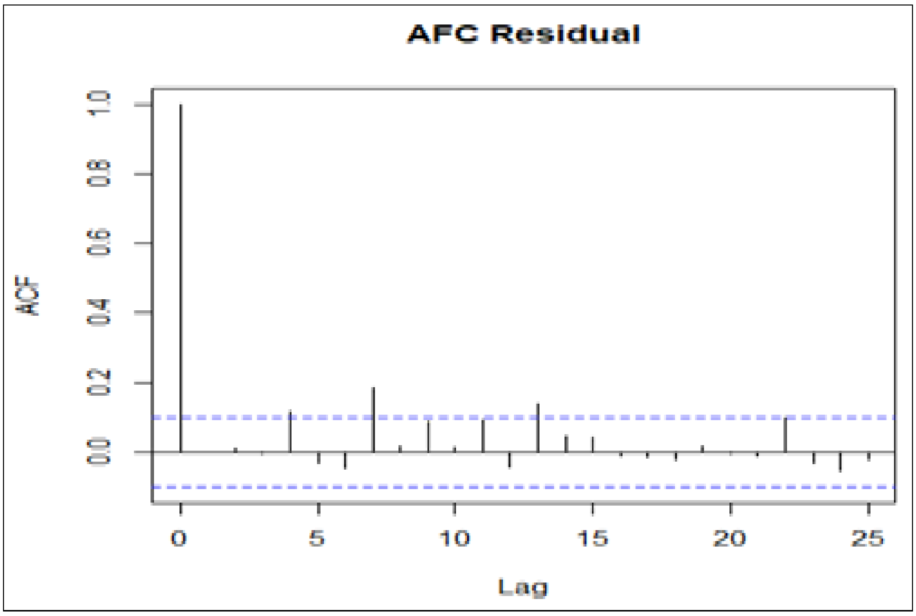

Fig 2: ACF of Otoi-NARIMA

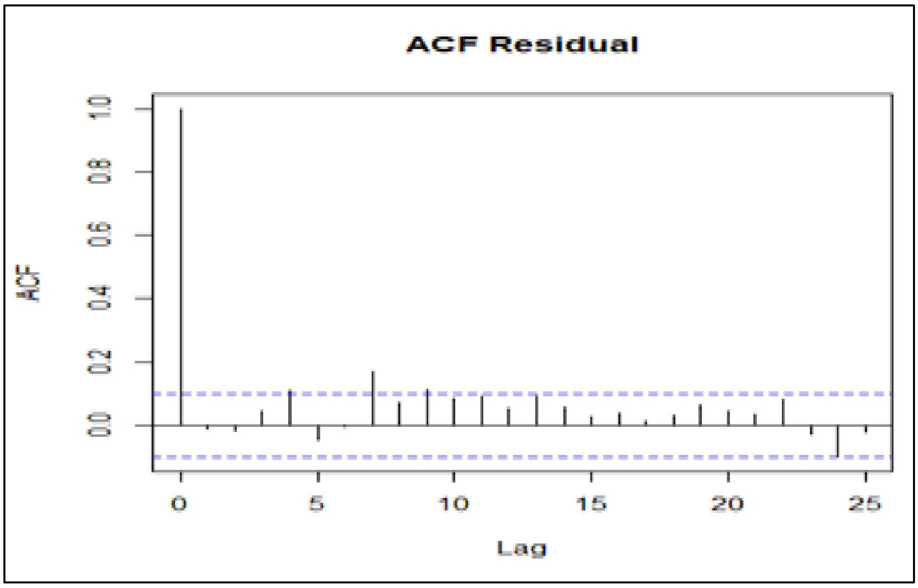

Fig 4: ACF of standard ARIMA

Otoi-NARIMA

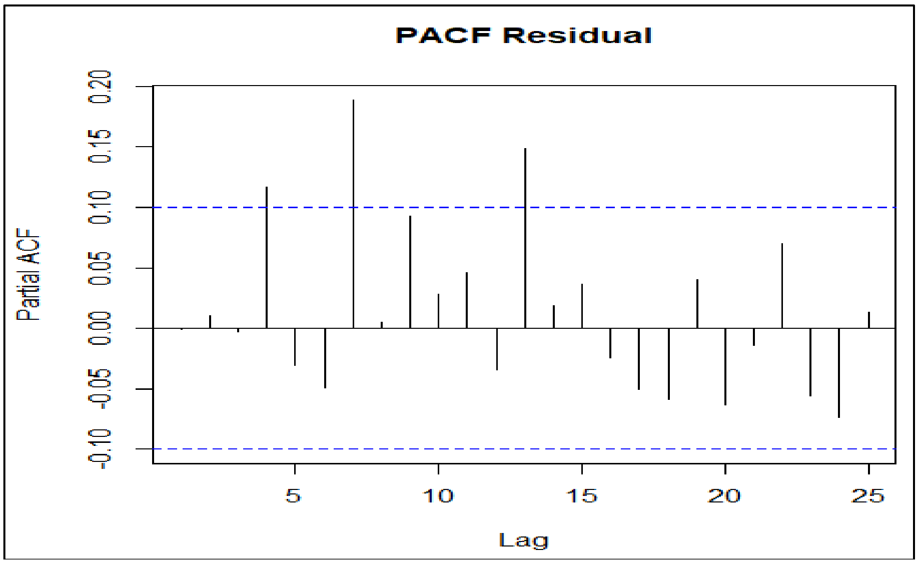

Fig 5: PACF of Otoi-NARIMA model

The standard ARIMA show more autocorrelation

Standard ARIMA

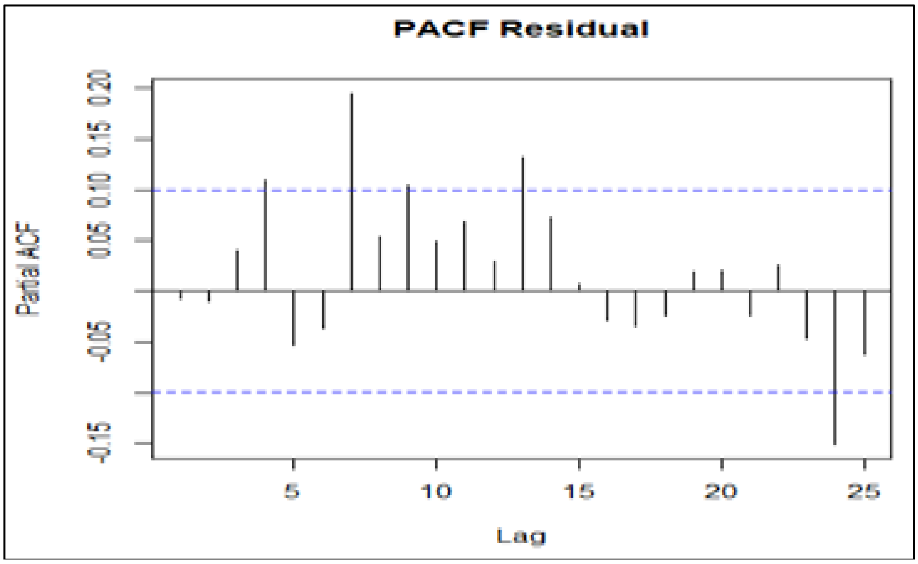

Fig 6: PACF of standard ARIMA

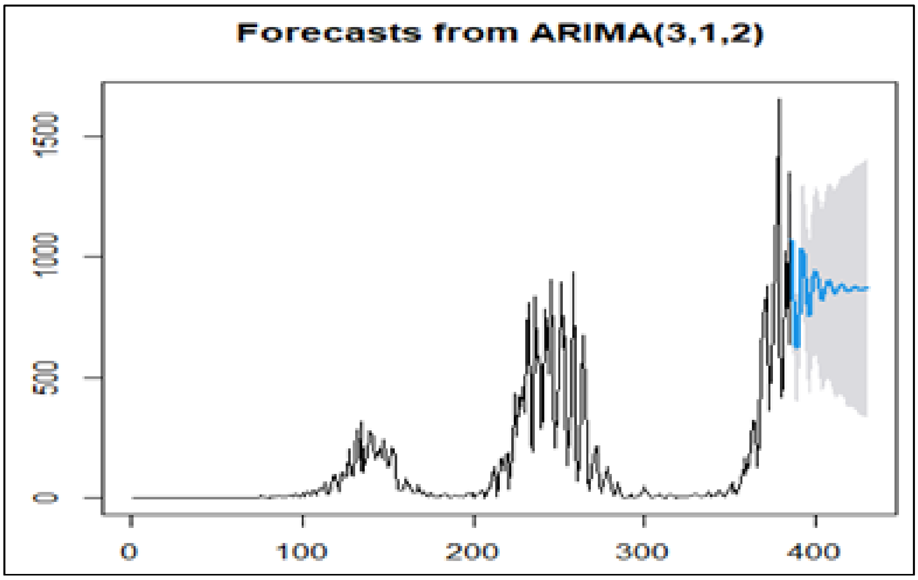

Fig 7: Otoi-NARIMA clear forecasts visualization and

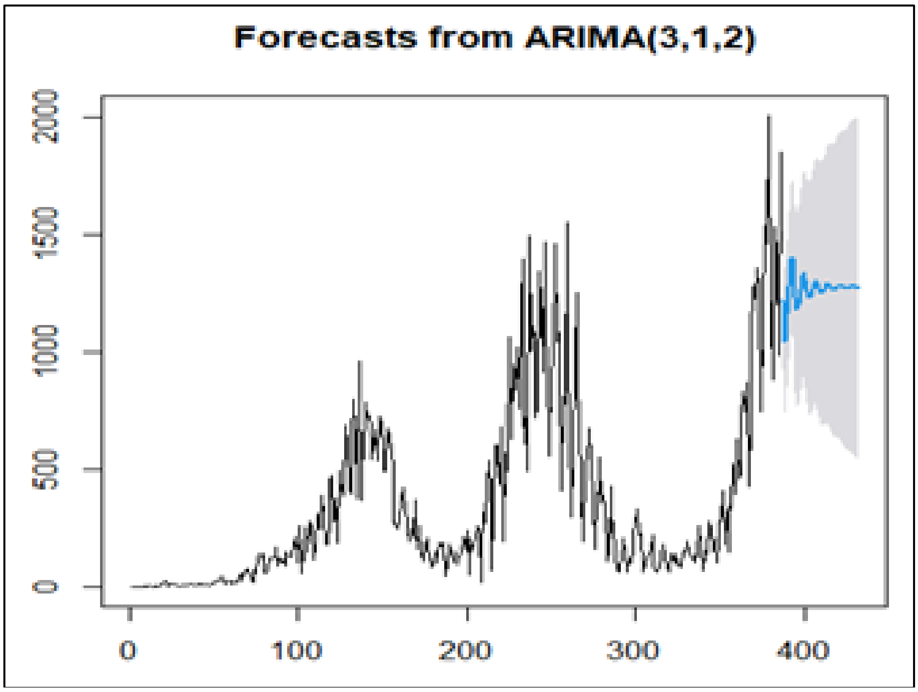

Fig 8: ARIMA Crowded visualization of forecasts and seasonality.

Table 3: *Ljung-Box Test of the model validity*

Otoi-NARIMA Model	Standard ARIMA
p-value=0.9973	P-value=0.8688
Df=3	Df=3
X-squared=0.047859	X-squared=0.71856

H_0: Model doesn't show lack of fit
H_1: Model Shows lack of it.

In the Ljung-Box test a significant p-value reject null hypothesis that the series isn't autocorrelated, i.e., shows lack of fit. A significant p-value means we fail to reject alternative hypothesis that the model shows lack of fit.
In our case the p-value for both models are not significant and we fail to reject the hull hypothesis that the model doesn't show lack of fit. We take note that $0.9973 > 0.8688$, that is, Otoi-NARIMA is a superior model.
Otoi-NARIMA is (3, 1, 2), that is, AR (3), I (1), and MA (2) while standard ARIMA is (3, 1, 4) . The autocorrelation function (ACF) of both models shows no autocorrelation while the PACF are inconclusive. The residual time plot of Otoi-NARIMA model shows clear, distinct separation of waves of infections on observable seasonality of occurrence. However, the residual time plot of standard ARIMA is crowed and lack clear separation between the waves. The seasonality is not well defined by standard ARIMA model.
The visualization of forecasts of both models looks similar briefly. On scrutiny, Otoi-NARIMA illustrates distinct and clear data points. The standard ARIMA is indistinct and shows unclear crowded data points. Also, the interval between lower and upper boundaries is smaller in Otoi-ARIMA. The standard ARIMA on the other hand exhibits wide intervals which makes longer forecasts more inaccurate.

Table 4: Comparison of boundary Interval Between the OTOI-NARIMA and Standard ARIMA Models

Interval Length (OTOI-NARIMA)	Intevel Length (Standard ARIMA)	Interval Reduction	% Reduction
396.7595	592.2191	195.4596	33.00461
441.2527	612.8965	171.6438	28.00535
446.2889	627.4549	181.166	28.87315
446.3054	627.7642	181.4588	28.90557
448.2069	636.9582	188.7513	29.63323
468.1015	671.1343	203.0328	30.25219
516.7326	736.1544	219.4218	29.80649
571.8692	796.6274	224.7582	28.21372
608.9932	832.3458	223.3526	26.83411
626.0821	847.9497	221.8676	26.16518
633.4426	856.8425	223.3999	26.07246
639.5843	868.5113	228.927	26.35855
650.4196	890.3144	239.8948	26.94495
669.9563	922.9121	252.9558	27.40844
695.8318	957.2773	261.4455	27.31137
720.5516	984.15	263.5984	26.78437

738.9982	1002.202	263.2034	26.26252
751.5734	1015.685	264.1111	26.00326
761.4914	1029.557	268.0652	26.03696
771.9882	1047.387	275.3992	26.29392
785.253	1069.741	284.4879	26.59409
801.5106	1093.592	292.0818	26.70847
818.8326	1115.077	296.244	26.56714
834.7724	1132.718	297.9456	26.3036
848.2358	1147.722	299.4862	26.09397
859.7729	1162.34	302.5673	26.03087
870.7105	1178.407	307.6963	26.11121
882.2676	1196.406	314.1384	26.25684
894.9856	1215.284	320.2979	26.35582
908.5167	1233.399	324.8819	26.34038
921.9648	1249.827	327.8624	26.23262
934.5752	1264.823	330.248	26.11021
946.1832	1279.338	333.1549	26.04119
957.1563	1294.293	337.1369	26.04795
968.0496	1310.039	341.9895	26.10529
979.2634	1326.229	346.9659	26.16183
990.8544	1342.16	351.3058	26.17465
1002.5647	1357.33	354.7648	26.13697
1014.0406	1371.732	357.6917	26.07591
1025.0728	1385.748	360.6748	26.02745
1035.6915	1399.823	364.1313	26.01267
1046.0929	1414.183	368.0903	26.02847
1056.4914	1428.731	372.2395	26.05386
1066.9957	1443.171	376.1753	26.06589
1077.5683	1457.245	379.6768	26.05442

The Otoi-NARIMA model reduces variation between the upper and lower intervals of ARIMA model. *Table 4* shows the magnitude and percentage reduction of the intervals. It is this reduction that sharpens the forecasts of Otoi-NARIMA model. The reduction value becomes smaller with increase in time, that is, far forecasts exhibit smaller reduction of intervals. The largest reduction is 33% which decreases with increase in time.

Table 5: OTOI-NARIMA Model 45 days forecasts of infections

DAY	Lower interval	Prediction	Upper interval	Interval length
4/4/2021	874.5237	1072.9035	1271.2832	396.7595
5/4/2021	601.1801	821.8065	1042.4328	441.2527
6/4/2021	408.6703	631.8147	854.9592	446.2889
7/4/2021	398.8039	621.9566	845.1093	446.3054
8/4/2021	535.275	759.3785	983.4819	448.2069
9/4/2021	700.0936	934.1443	1168.1951	468.1015
10/4/2021	776.9338	1035.3001	1293.6664	516.7326
11/4/2021	731.5594	1017.494	1303.4286	571.8692
12/4/2021	610.262	914.7586	1219.2552	608.9932
13/4/2021	491.661	804.702	1117.7431	626.0821
14/4/2021	437.2214	753.9427	1070.664	633.4426
15/4/2021	461.0377	780.8299	1100.622	639.5843
16/4/2021	528.8995	854.1093	1179.3191	650.4196
17/4/2021	586.2478	921.2259	1256.2041	669.9563
18/4/2021	595.736	943.6519	1291.5678	695.8318
19/4/2021	556.6562	916.932	1277.2078	720.5516
20/4/2021	497.0944	866.5935	1236.0926	738.9982
21/4/2021	451.3228	827.1095	1202.8962	751.5734
22/4/2021	438.9723	819.718	1200.4637	761.4914
23/4/2021	456.4649	842.459	1228.4531	771.9882
24/4/2021	483.2892	875.9157	1268.5422	785.253
25/4/2021	497.4047	898.16	1298.9153	801.5106
26/4/2021	488.8171	898.2334	1307.6497	818.8326
27/4/2921	463.0842	880.4704	1297.8566	834.7724
28/4/2021	434.7939	858.9118	1283.0297	848.2358
29/4/2021	417.1872	847.0736	1276.9601	859.7729
30/4/2021	414.6914	850.0467	1285.4019	870.7105
1/5/2021	422.0119	863.1457	1304.2795	882.2676
2/5/2021	429.1215	876.6143	1324.1071	894.9856
3/5/2021	428.1453	882.4037	1336.662	908.5167
4/5/2021	417.6195	878.6019	1339.5843	921.9648

5/5/2021	402.0666	869.3542	1336.6418	934.5752
6/5/2021	388.1206	861.2122	1334.3038	946.1832
7/5/2021	380.2009	858.7791	1337.3572	957.1563
8/5/2021	378.3435	862.3683	1346.3931	968.0496
9/5/2021	379.0336	868.6653	1358.297	979.2634
10/5/2021	377.9792	873.4064	1368.8336	990.8544
11/5/2021	372.809	874.0913	1375.3737	1002.5647
12/5/2021	364.0951	871.1154	1378.1357	1014.0406
13/5/2021	354.4274	866.9638	1379.5002	1025.0728
14/5/2021	346.4814	864.3271	1382.1729	1035.6915
15/5/2021	341.4212	864.4676	1387.5141	1046.0929
16/5/2021	338.508	866.7537	1394.9994	1056.4914
17/5/2021	335.9101	869.4079	1402.9058	1066.9957
18/5/2021	332.0017	870.7858	1409.57	1077.5683

Table 6: Basic ARIMA forecasts for 45 days from 29 March 2021

Day	Lower Interval	Prediction	Upper Interval	Intevel Length
4/4/2021	925.9999	1222.109	1518.219	592.2191
5/4/2021	741.2145	1047.663	1354.111	612.8965
6/4/2021	849.2751	1163.002	1476.73	627.4549
7/4/2021	965.9388	1279.821	1593.703	627.7642
8/4/2021	1076.356	1394.835	1713.314	636.9582
9/4/2021	1064.214	1399.781	1735.348	671.1343
10/4/2021	958.8316	1326.909	1694.986	736.1544
11/4/2021	832.6846	1230.998	1629.312	796.6274
12/4/2021	765.9072	1182.08	1598.253	832.3458
13/4/2021	778.0423	1202.017	1625.992	847.9497
14/4/2021	837.4515	1265.873	1694.294	856.8425
15/4/2021	889.3687	1323.624	1757.88	868.5113
16/4/2021	893.6766	1338.834	1783.991	890.3144
17/4/2021	847.8359	1309.292	1770.748	922.9121
18/4/2021	783.8587	1262.497	1741.136	957.2773
19/4/2021	740.062	1232.137	1724.212	984.15
20/4/2021	733.9264	1235.027	1736.128	1002.2016
21/4/2021	755.3535	1263.196	1771.038	1015.6845
22/4/2021	778.8554	1293.634	1808.412	1029.5566
23/4/2021	782.3636	1306.057	1829.751	1047.3874
24/4/2021	760.7831	1295.653	1830.524	1069.7409
25/4/2021	726.5926	1273.389	1820.185	1093.5924
26/4/2021	698.4274	1255.966	1813.504	1115.0766
27/4/2921	687.512	1253.871	1820.23	1132.718
28/4/2021	691.807	1265.668	1839.529	1147.722
29/4/2021	699.9448	1281.115	1862.285	1162.3402
30/4/2021	700.2582	1289.461	1878.665	1178.4068
1/5/2021	688.356	1286.559	1884.762	1196.406
2/5/2021	668.7175	1276.359	1884.001	1215.2835
3/5/2021	650.1564	1266.855	1883.555	1233.3986
4/5/2021	639.2098	1264.123	1889.037	1249.8272
5/5/2021	636.2958	1268.707	1901.119	1264.8232
6/5/2021	636.6079	1276.277	1915.946	1279.3381
7/5/2021	634.1988	1281.345	1928.492	1294.2932
8/5/2021	626.0419	1281.062	1936.081	1310.0391
9/5/2021	613.4757	1276.59	1939.705	1326.2293
10/5/2021	600.5358	1271.616	1942.696	1342.1602
11/5/2021	590.8125	1269.477	1948.142	1357.3295
12/5/2021	585.1857	1271.052	1956.918	1371.7323
13/5/2021	581.7584	1274.632	1967.506	1385.7476
14/5/2021	577.6032	1277.515	1977.426	1399.8228
15/5/2021	570.8538	1277.945	1985.037	1414.1832
16/5/2021	561.7261	1276.092	1990.457	1428.7309
17/5/2021	551.996	1273.581	1995.167	1443.171
18/5/2021	543.5509	1272.173	2000.796	1457.2451

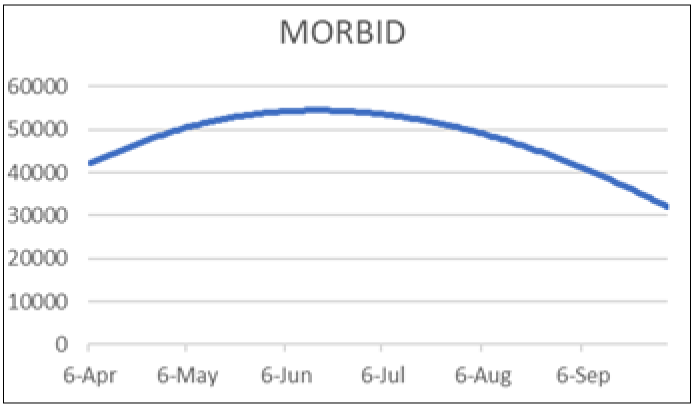

Chart 1: Peak of third waves based on forecast.

Discussion

The series used to forecast COVID-19 new infections are I(1) stationary according to Augmented Dickey-Fuller test and have a cointegration rank $r = 1$. The Ljung-Box test as well as ACF and PACF show that Otoi-NARIMA is superior to standard ARIMA model. *Table 5* and *Table 6* present 45 days forecasts on Otoi-NARIMA and standard ARIMA models from April 4, 2021 to May 18, 2021. The Otoi-NARIMA model reduces the interval between maximum and minimum values by 33%, which reduces with time increase as shown in *table 4*. The reduction phenomenon enhances and sharpens the forecasts.

Whereas standard ARIMA model predicts the likelihood of Kenya's third wave to begin declining after May 9, 2021, the Otoi-NARIMA model sets decline after April 29, 2021. It means that Kenya's third wave will likely decline briefly between April 29, 2021 and May 9, 2021. Otoi-NARIMA model also forecast the likelihood of Kenya's fourth wave or continuation of the third wave 15 days after April 29, 2021 which is May 15, 2021. There is strong likelihood of the wave to begin declining after July 10, 2021. The third wave will likely decline and begin to rise after 15. days and will likely have peak intensity after June 26,2021.

The wave as predicted by Otoi-NARIMA model assumes that government will not have fully vaccinated 51 in 100 Kenyans. Where full vaccination implies two doses of vaccine. There are countries like Chile which had vaccinated 47 in 100 Chileans by March 2021 but relapsed into a second wave. Kenya received 1.2 million doses of AstraZeneca vaccines against 55 million Kenyans. On April 4, 2021 Kenya had vaccinated 282,315 people which is 0.00513%. If all the first batch of vaccines are used, Kenya will have vaccinated almost 2 in 100 Kenyans. It is recommended that 26.52 million Kenyans need to be fully vaccinated before May 15, 2021 to avoid the health risk of a higher COVID-19 peak intensity. The occurrence of reinfection and protection by immune response with or without vaccine is discussed by Hansen *et al*. (2021) [13] which found that individuals can be reinfected during infection surges. The longevity of immune response after the first and second doses of vaccines requires populations to take a third dose or boosters. Whereas some scholars treat variants as new epidemic which require new vaccines others advocate for three doses to boost immune response[1].

There is also the risk of post-acute COVID-19 syndrome which include multiorgan reinfections and re-hospitalization if not given multispecialty management (Nalbandian *et al*., 2021) [11]. Kenya may need to take a position on either three doses or boosters to protect most vulnerable people and communities, and specific population groups (children, women and the elderly) and first respondents at the front line in the fight against the pandemic to evade the looming crisis. The existing health inequality and burden of disease management to families who use out of pocket hospital bill payment, may necessitate decision makers to come to that conclusion soon. In Kenya, health insurance policies including NHIF do not cover COVID-19 and families and households living with reduced mitigation sources and facing vulnerability associated with job loss, poor quality housing, poor environmental quality, mental and other health challenges and social isolation are strained. The study builds a case study to predict the impact of lockdown on widespread households living in highly populated urban slum settlements and may not afford restrictive measure of individuals quarantined on a mandatory basis. More aware of the successive waves, competent authorities may be more tactful in handling and build deeper interactions within the health systems in response to COVID-19 and related pandemics for the future.

There are currently many COVID-19 variants around the globe including Kenya and as the virus continues to mutate more strains may be reported. In this regard, mathematical modeling help to predict the spread of the disease and the expected impact of mitigation is reported. to enable a timely and efficient response.

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