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

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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 cases 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) [10] 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 = \[ \frac{1}{M} \sum_{t=1}^{k} x_{t-j} \] ....... (1)

\[ M = k + 1, \]
\[ t - j = order \ of \ moving \ average, \]
\[ k = 1,2,3,...,j \]

Normalization of series = \[ \frac{x_{\bar{t}}}{x_{\text{max}} - x_{\text{min}}} \] .......................................................... (2)

Where \( \bar{t} \) is mean of series,
\( x_{\text{max}} \) is maximum value in series,
\( x_{\text{min}} \) is minimum value in series,
\( x_{t} \) is series taken at random.
\[ y_t = \frac{1}{M} \sum_{i=1}^{k} x_{t-j} \cdot \frac{x_i - \bar{x}}{x_{\text{max}} - x_{\text{min}}} \]

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

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

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

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

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

Let \( y_t^{-1} \) be \( \omega \)

\[ \frac{x_i - \bar{x}}{M} = \pi \]

\[ x_{\text{max}} = x_{\text{min}} + \omega \pi \sum_{i=1}^{k} x_{t-j} \] \hspace{1cm} (3)

\[ x_{\text{min}} = x_{\text{max}} - \omega \pi \sum_{i=1}^{k} x_{t-1} \] \hspace{1cm} (4)

Forecast \( x_f = x_{\text{min}} + \omega \pi \sum_{i=1}^{k} x_{t-j} + x_{\text{max}} - \omega \pi \sum_{i=1}^{k} x_{t-j} = x_{\text{min}} + \frac{x_{\text{max}} x_{\text{min}}}{z} \] \hspace{1cm} (5)

Infusing the derived model into ARIMA

Let \( x_{\text{min}} + \omega \pi \sum_{i=1}^{k} x_{t-j} \) be \( z_t \) \hspace{1cm} (6)

\[ z_t = \varphi_1 z_{t-1} + e_t - \theta_1 e_{t-1} \]

\[ z_t = \varphi_1 \beta_1 \bar{x} + e_t - \theta_1 \beta_2 e_t \]

\[ z_t - \varphi_1 \beta_1 \bar{x} = e_t - \theta_1 \beta_2 e_t \]

\[ z_t (1 - \varphi_1 \beta_1) = e_t (1 - \theta_1 \beta_2) \]

\[ z_t = \frac{e_t (1 - \theta_1 \beta_2)}{(1 - \varphi_1 \beta_1)} \]

Upper Interval \( = x_{\text{min}} + \omega \pi \sum_{i=1}^{k} x_{t-j} = (1 - \theta_1 \beta_2) \frac{e_t}{(1 - \varphi_1 \beta_1)} \] \hspace{1cm} (7)

Lower Interval \( = x_{\text{max}} - \omega \pi \sum_{i=1}^{k} x_{t-1} = (1 - \theta_2 \beta_4) \frac{e_t}{(1 - \varphi_2 \beta_3)} \] \hspace{1cm} (8)

Forecast \( = \frac{x_{\text{max}} + x_{\text{min}}}{2} = (1 - \theta_3 \beta_6) \frac{e_t}{(1 - \varphi_3 \beta_5)} \) \hspace{1cm} (9)

\[ \beta_1 \neq \beta_2 \neq \beta_5 \]

\[ \beta_3 \neq \beta_4 \neq \beta_6 \]

\[ \beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq \beta_6 \]
\( \varphi_1 \neq \varphi_2 > \varphi_3 \)
\( \varphi_2 \neq \varphi_3 > \varphi_4 \)
\( \varphi_1 \neq \varphi_2 \neq \varphi_1 \neq \varphi_2 \neq \varphi_3 \)

Where,
\[ \omega, \pi, \varphi_1, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6 \] coefficients of variables and parameters used in the model.
\( \varepsilon_t \) is stochastic error.
\( z_t = Autoregressive\ series \)
\( \varepsilon_{t-1} \) 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)

\[
\hat{y}_t = \varphi_1 \hat{y}_{t-1} + \varphi_2 \hat{y}_{t-2} + \varphi_3 \hat{y}_{t-3} - \vartheta_1 \varepsilon_t - \vartheta_2 \varepsilon_{t-2}
\]

**NEW CASES** = \(1.0424 (0.0773) \) **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**\(_{t-2}\) ..........................................................(10)

Standard ARIMA

\[
\hat{y}_t = \varphi_1 \hat{y}_{t-1} + \varphi_2 \hat{y}_{t-2} + \varphi_3 \hat{y}_{t-3} - \vartheta_1 \varepsilon_t - \vartheta_2 \varepsilon_{t-1} - \vartheta_3 \varepsilon_{t-2} - \vartheta_4 \varepsilon_{t-3}
\]

**NEW CASES** = \(2.1092 (0.0421) \) **NEW CASES**\(_{t-1}\) \(- 2.0611 (0.0535) \) **NEW CASES**\(_{t-2}\) \(+ 0.8818 (0.0372) \) **NEW CASES**\(_{t-3}\) + \(3.658 (0.1253) \) **MA**\(_{t-1}\) \(- 2.9003 (0.0569) \) **MA**\(_{t-2}\) \(- 2.3939 (0.151) \) **MA**\(_{t-3}\) + \(0.6839 (0.0447) \) **MA**\(_{t-4}\) ..........................................................(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**

![Fig 1: Otoi-NARIM residuals showing wave seasonality.](image_url)
The Otoi-NARIMA model has clearly illustrated separation between the waves and respective lengths.
Otoi-NARIMA

**Fig 5:** PACF of Otoi-NARIMA model

The standard ARIMA show more autocorrelation

**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|

H₀: Model doesn’t show lack of fit  
H₁: Model Shows lack of fit.

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 null 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 crowded 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-NARIMA. 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) | Interval Length (Standard ARIMA) | Interval Reduction | % Reduction |
|-------------------------------|----------------------------------|--------------------|-------------|
| 396.7595                      | 592.2191                         | 195.4596           | 33.0061     |
| 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           | 29.63232    |
| 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    |
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      | 636.0281        |
| 14/4/2021| 437.2214       | 753.9427   | 1070.644       | 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| 436.4649       | 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        |
| 27/4/2021| 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   | 1336.6662      | 908.5167        |
| 4/5/2021 | 417.6195       | 878.6019   | 1339.5843      | 921.9649        |
| Day      | Lower Interval | Prediction | Upper Interval | Interv 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     |
| 27/4/2021| 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        | 1268.559   | 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   | 1913.946      | 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     |
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 response1.

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 responders 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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