MODELING AND FORECASTING ANTE-NATAL CARE ATTENDANCE USING BOX AND JENKINS METHOD

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ABSTRACT

Ante-natal care is a type of preventative health care in which expectant mothers are taught healthy practices during pregnancy by health professionals in order to have a solid understanding of probable indications during pregnancy and childbirth. The availability of high-quality antenatal care and its coverage, particularly in developing nations, is excellent. Furthermore, quality services, particularly in Nigeria, are a consequence of the quantity of women who require such services vs the amount of professionals available. As a result, the goal of this study was to look at the rate of ante-natal care attendance at Federal Medical Centre in Abeokuta, Ogun State, between 2010 and 2019. The data used were all secondary data, and the analysis was done using the Box-Jenkin method. The data was differencing to make it steady and then utilized for parameter estimation. The Akaike Information Criterion (AIC) was used to determine the optimal model for the series. The ARIMA (3, 1, 3) model was judged to be the best model for capturing the data at the conclusion of the investigation. As a result, the study recommends that policymakers make efforts to expand the number of staff and timely service delivery for ante-natal attendance among women in Nigeria, as the projection value shows a constant growth in the rate of attendance up to 2022.

Keywords: ANC; ARIMA; ACF;Forecasting; PACF; Stationarity.

INTRODUCTION

Antenatal care is intended to promote a healthy birth and to encourage women to adopt a healthy lifestyle before giving birth, which will benefit the unborn baby long after delivery. It's a comprehensive program that advises women on child spacing and other mother-child-related education for a healthier lifestyle. Antenatal classes are intended to educate and instruct prospective parents on a variety of topics relevant to pregnancy, labor and childbirth, and newborn baby care. Although antenatal classes are not required, they are highly recommended, especially for first-time expectant mothers. It is a type of health supervision provided to expecting mothers in order to preserve, protect, and promote the mother's and fetus' health and well-being (Ojo, 2004). The antenatal care services were provided for a set amount of time, and the important actions to be completed during that time were clearly defined. According to Adesokan (2010), prenatal services are kinds of attention, education, supervision, and treatment provided to expectant women from the time of conception in order to guarantee a healthy pregnancy and delivery. However, there have never been any safeguards in place to ensure that pregnant women receive adequate care. However, policies that have been demonstrated to be helpful in reducing maternal mortality and are widely accepted by families have always been welcomed.

Early detection during pregnancy is thought to have aided in the prevention of maternal disease, injury, maternal mortality, fetal death, infant mortality, and morbidity. This is a primary cause for prenatal pregnancy attendance in the first trimester. In Africa, antenatal care (ANC) coverage has been deemed successful since more than two out of every three pregnant women get at least one hour of interaction with health staff. It is difficult to achieve the full life-saving potential that antenatal care promises for women and babies. Four visits providing essential evidence-based interventions, referred to as focused antenatal care, are required to achieve the full life-saving potential that antenatal care promises for women and babies (WHO, 2005).. Antenatal care is the care that a woman receives during her pregnancy, and it helps to ensure that both the mother and the baby have a good outcome (WHO/UNICEF 2003). It is a vital entry point for a pregnant woman to get a wide range of health treatments, including nutritional support and anemia prevention and treatment, as well as malaria, TB, and sexually transmitted infections (STIs/HIV/AIDS) prevention, detection, and treatment.

According to Viccars and Anne (2003), using antenatal health care services is linked to better mother and newborn health outcomes. The service is thought to have a profound impact on the fetus' and infant's development.

Globally, around 303,000 women died from pregnancy-related causes in 2015, with 99 percent of deaths occurring in middle-income nations (WHO, 2018). Sub-Saharan Africa has the highest maternal mortality rates (UNICEF, 2018), and the West African area has the highest maternal mortality in Africa, accounting for almost 20% of global maternal deaths (UNICEF, 2009).

Maternal mortality in Nigeria remains high in comparison to what is available in other countries, particularly developed countries, despite the fact that antenatal care (ANC) for pregnant women provided by health professionals maintains women's health during pregnancy and improves pregnancy outcomes by identifying and managing pregnancy-related complications (Abosse et al., 2010). Women who go to ANC appointments get enough evidence-based therapeutic interventions.

Because it emphasizes the recent past over the distant past, ARIMA models are best suited for short-term forecasting including time series data. This suggests that ARIMA models' long-term projections are less dependable than short-term forecasts (Pankratz, 1983). This model has gained popularity and has proven to perform better than other models that have been evaluated. The majority of studies have shown that ARIMA models are superior to other time series models and have been explored by several studies.

Elard (2009) investigated the attendance of pregnant women based on Antenatal Care (ANC) from 1960 to 2007 using (ARIMA) models and discovered that ANC had grown from 29% to 80%.

The Ethiopian government (MOH Ethiopia, 2000) studied patterns and built a model for forecasting health and related metrics. ARIMA models in STATA were used to identify the causes of the established patterns.

China Medical University undertook a study to see if a time series ARIMA model could be used to forecast prenatal attendance in China, in order to give a theoretical foundation for continuing to enhance antenatal attendance. The ARIMA model was shown to be quite accurate. The researchers determined that the ARIMA model's fitting result of the antenatal program's incidence is adequate. In the majority of independent studies, the ARIMA model outperforms other competent time series models in terms of forecasting. Similarly, this research looks on the viability of using time series ARIMA in the modeling and forecasting of pregnant women's attendance at ante-natal services.

MATERIALS AND METHODS

Method of Data Collection

Monthly data between January 2010 and December 2019 of ANC attendance of Federal Medical Centre Abeokuta are used in the study.

Method of Data Analysis

The presence of unit root and short memory in the dataset resulted in the application of the Box and Jenkins Methodology.

Autoregressive Integrated Moving Average Models

The order of the autoregressive, integrated, and moving average parts of the model is always referred to as an ARIMA (p,d,q) model, where p, d, and q are integers greater than or equal to zero and refer to the order of the autoregressive, integrated, and moving average parts of the model, respectively. The ARIMA model is an integral aspect of the Box-Jenkins time series modeling technique. A time series X_t is said to follow an integrated autoregressive moving average model if the d[th] difference $W_t = \nabla^d X_t$is a stationary ARMA process. If $W_t$follows an ARMA (p, q) model, we say that X_t is an ARIMA (p, d, q) process. Consider an ARIMA (p, 1, q) process where d = 1. With $W_t = X_t - X_{t-1}$ we have:

$$W_t = \emptyset_1 W_{t-1} + \emptyset_2 W_{t-2} + \cdots + \emptyset_p W_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \quad (1)$$

Or, in terms of the observed series,

$$X_t - X_{t-1} = \emptyset_1(X_{t-1} - X_{t-2}) + \emptyset_2(X_{t-2} - X_{t-3}) + \cdots + \emptyset_p\left(X_{t-p} - X_{t-p-1}\right) + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \quad (2)$$

Equation (2) may be written as:

$$X_t = (1 + \emptyset_1)X_{t-1} + (\emptyset_2 - \emptyset_1)X_{t-2} + (\emptyset_3 - \emptyset_2)X_{t-3} + \cdots + \left(\emptyset_p - \emptyset_{p-1}\right)X_{t-p} - \emptyset_p X_{t-p-1} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q}$$

This is called the difference equation form of the model. Notice that it appears to be an ARMA (p + 1, q) process.

This can be written in lag form as:

$$\left(1 - \sum_{i=1}^{p} \emptyset_i B^i\right) X_t = \left(1 + \sum_{i=1}^{q} \theta_i B^i\right) \varepsilon_t (3)$$

Where B is the lag operator, the $\emptyset_i$are the parameters of the autoregressive part of the model, the $\theta_i$are the parameters of the moving average part and $\varepsilon_t$are error terms. The error terms $\varepsilon_t$are generally assumed to be independent, identically distributed variables sampled from a normal distribution with zero mean and constant variance σ_ε^2.

Assume that the polynomial $\left(1 - \sum_{i=1}^{p} \emptyset_i B^i\right)$has a unitary root of multiplicity d. then it can be re-written as:

$$\left(1-\sum_{i=1}^{p}\emptyset_i B^i\right) = \left(1+\sum_{i=1}^{p-d}\omega_i B^i\right)(1-B)^d \quad (4)$$

An ARIMA (p,d,q) process expresses this polynomial factorization property, and is given by:

$$\left(1-\sum_{i=1}^{p}\omega_i B^i\right)(1-B)^d X_t = \left(1+\sum_{i=1}^{q}\theta_i B^i\right)\varepsilon_t \quad (5)$$

Thus, equation 5 can be thought as a particular case of an ARMA $(p+d,q)$ process having the autoregressive polynomial with some roots in the unity.

Diagnostic Check of the Residuals and Model Adequacy

It is pertinent to check the adequacy of the fitted ARIMA model for white noise through its residuals. The ACF and PACF plots of the residuals are examined for no significant autocorrelations at any lag order thereby demonstrating proper fitting. The model which fits the best according to various statistical tests of fit is then selected for forecasting. In doing this, the following tests are carried out;

• **Ljung-Box chi-square test:** The Ljung-Box chi-square test is another way to check for residual unpredictability. The null hypothesis states that the set of residual autocorrelations is white noise. This statistic assesses the relevance of residual autocorrelations as a group and determines if they are significant collectively. The statistic was proposed by Box and Pierce (1970):

$$Q = n(\hat{\rho}_1^2 + \hat{\rho}_2^2 + \dots + \hat{\rho}_k^2) = n\sum_{k=1}^{n}\hat{\rho}_k^2 \quad (6)$$

which was modified on a null distribution which is much closer to chi-square for typical sample sizes as;

$$Q_* = n(n+2)\left(\frac{\hat{\rho}_1^2}{n-1} + \frac{\hat{\rho}_2^2}{n-2} + \dots + \frac{\hat{\rho}_k^2}{n-k}\right) = n(n+2)\sum_{k=1}^{n}\frac{\hat{\rho}_k^2}{n-k} \quad (7)$$

The sample size is n, $\hat{\rho}_k^2$ reopresents the sample autocorrelation at lag k, and the number of lags being examined is h. For significance level α, the critical region for rejection of the hypothesis of randomness is $Q_* > \chi^2_{1-\alpha,h}$ Where $\chi^2_{1-\alpha,h}$ is the α Quantile of the chi-squared distribution with h degrees of freedom. Notice that since (n+2)(n – k) >1 for every k ≥ 1, we have $Q_* > Q$ which partly explains why the original statistic Q tended to overlook inadequate models.

The Akaike Information Criterion (AIC)

This is computed as:

$$\text{AIC} = -2\,l/T + 2\,K/T \quad (8)$$

Where l is the log likelihood computed as:

$$l = -\frac{T}{2}\left[1 + \log(2\pi) + \log\left(\frac{\hat{e}'\hat{e}}{T}\right)\right] \quad (9)$$

For non-nested alternatives, the AIC is frequently employed in model selection, and smaller AIC values are preferable. It also tries to select the model with the fewest free parameters that best explains the data.

SBC (Schwarz's Bayesian Criteria): Bayesian Information Criteria is another name for it (BIC). SBC is also a model selection statistical tool that penalizes overfitting of estimation. In most cases, the model with the lowest SBC is the best fit.

It's calculated as follows:

$$SBC = -\ 2\log(\text{likelihood})\ +\ k\ln(n) \qquad (10)$$

For normally and independently distributed residuals

$$SBC = n\left[ln\frac{R}{n}\right] + kln(n) \qquad (11)$$

The SBC criterion penalizes free parameters more heavily than the AIC criterion. It must be noted that both AIC and SBC tests may not generally point to a common model as the best fit. In such cases, proper judgment is required in choosing the best fit for the model.

Forecasting Using ARIMA Models

Once an adequate and satisfactory model is fitted to the series of interest, forecasts can be generated using the model. Consider the general ARIMA model of equation (1).

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} \qquad (12)$$

The one-step ahead forecast for time t+1 is given by:

$$y_t = \phi_1 y_t + \phi_2 y_{t-1} + \ldots + \phi_p y_{t-p+1} + e_{t+1} - \theta_1 e_t - \theta_2 e_{t-1} - \cdots - \theta_q e_{t-q+1} \qquad (13)$$

Except e_{t+1} the random shock at time t+1, all other parameters are known.

Thus, setting $e_{t+1} = 0$, its true expected values, the one-step ahead forecasts can be generated.

RESULTS AND DISCUSSION

Table 1: Descriptive Statistics of studied variable

Minimum	Median	Mean	Maximum
250	500	490	1000

Source: Extracted from R-Studio Output

On the descriptive statistics of frequency of pregnant women attendance to ante-natal care in table 1, minimum, median, maximum and mean of the data location can be depicted. Analysis indicated that the range of the sampled data fall within250 to 1000 on average of490 within the study period.

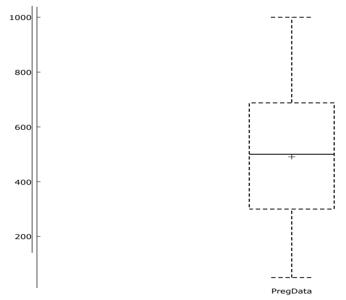

Fig1: Box-plot ofpregnancy data

From the box plot of fig. 1, it can be observed that the dataset is normal and there are no evidences of extreme values in the datasets of all the cases.

Checking for Stationarity and Determination of The Appropriate ARIMA Order

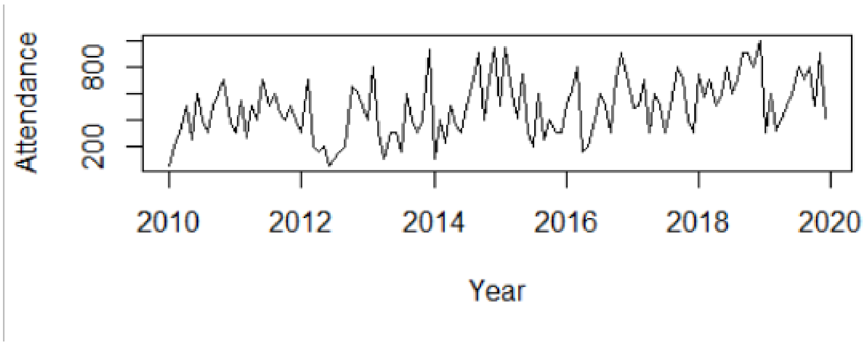

***Figure* 2: Time plot of attendance of pregnant women to antenatal care at Federal Medical Centre Abeokuta**

Time plot of the attendance of pregnant women to antenatal care in figure 2 indicated that the series was found to be non-stationary in its mean and variance. This is as a result of the irregular pattern displayed. However, this is a problem, as our intent is to adopt the conventional techniques of modeling time series data. Hence, we adopt the principle of ARIMA modeling algorithm.

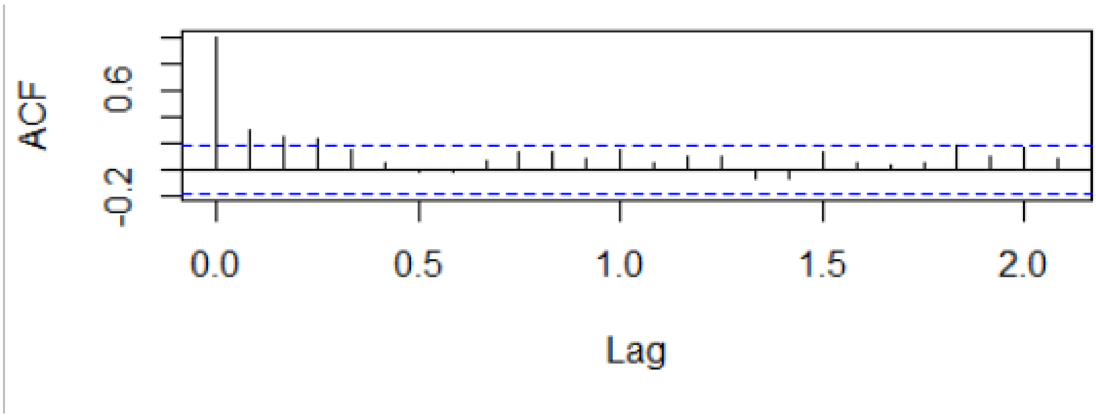

***Figure 3:* Sample ACF plot of attendance of pregnant women to antenatal care at Federal Medical Centre Abeokuta**

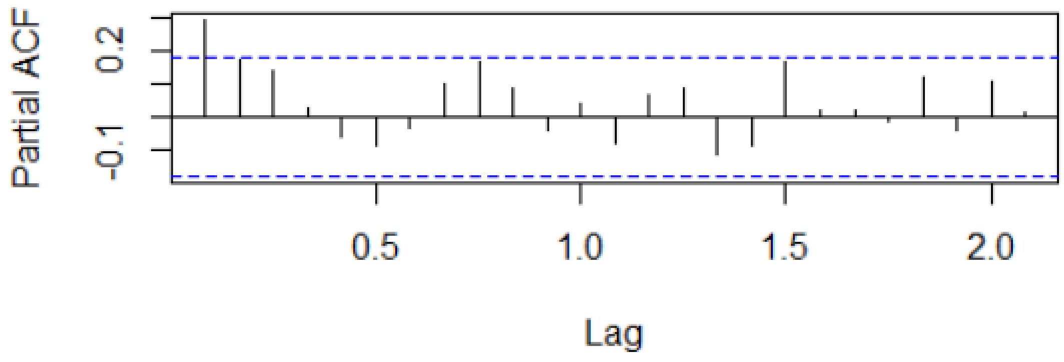

Figure 4: **Sample PACF plot of attendance of pregnant women to antenatal care at Federal Medical Centre Abeokuta**

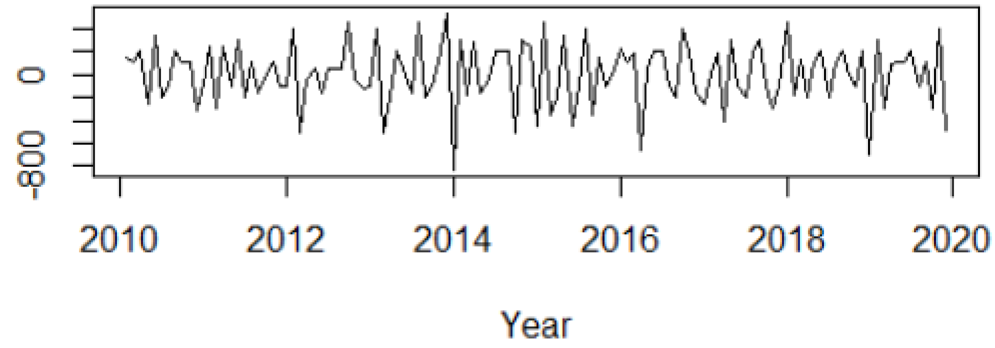

Figure 5: Time plot of first differenced attendance of pregnant women to antenatal care at Federal Medical Centre Abeokuta

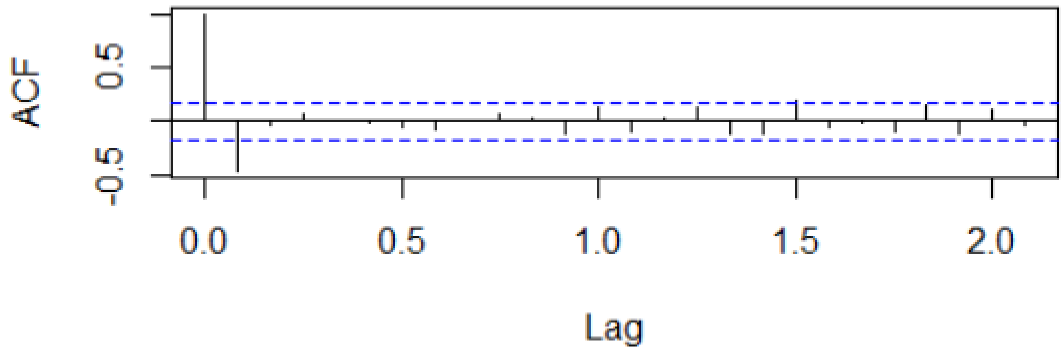

Figure 6: **Sample ACF plot of first differenced attendance of pregnant women to antenatal care at Federal Medical Centre Abeokuta**

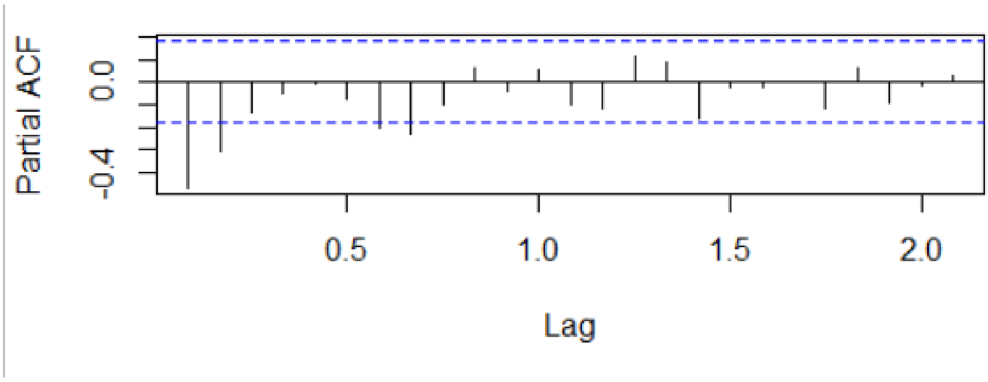

Figure 7: **Sample PACF plot of first differenced attendance of pregnant women to antenatal care at Federal Medical Centre Abeokuta**

Fig. 5-7 above shows the time plot, ACF and PACF of the differenced series and it was seen to possess stationarity. From the ACF, there is a significant spike at lag1, 15, 17 and 18 which dies off up to lag 24. Also, there is a slow decay in the PACF up to lag 3, with significant spikes in 1, 2, 7, 8 and 17 which dies off up to lag 24.

Figure 7: Sample PACF of First Order and Seasonal Differencing of ASI

Table 2: Augmented Dickey-Fuller Test for Series Stationarity

Dickey-Fuller test statistic	Lag order	P-value
-4.07956	24	0.0000

Source: R-studio Output

Table 2 further validated the series' stationarity, with an ADF value of -4.07956 and a p-value of 0.000 < 0.05 significance level. However, after we've established series stationarity, we may go on to model identification. It's critical to figure out the different orders for the AR(p) and MA(q) components at this point. The gradual decay up until lag 3 showed an AR of order 3. We hope to arrive at the best feasible model for the ANC data after a few iterations on this model-building technique.

Table 3: Model Iterations for the differenced pregnancy data

Model	AIC	BIC	LOG LIKELIHOOD
(1, 1, 1)	1617.659	1628.776	- 804.8296
(1, 1, 2)	1618.245	1632.141	- 804.1227
(1, 1, 3)	1621.762	1638.437	- 804.8809
(3, 1, 3)	**1615.121**	**1637.354**	**- 799.5603 ***
(2, 1, 1)	1618.731	1632.627	- 804.3657
(2, 1, 3)	1616.308	1635.762	- 801.1540
(3, 1, 1)	1618.326	1635.000	- 803.1629
(3, 1, 2)	1619.017	1638.471	- 802.5086

Source: Extracted from R-Output

Table 3 above shows the model iterations of different ARIMA models of various orders. In order to choose the best model, we look for the model with the least AIC and that maximizes log-likelihood.Only one model fits these conditions, ARIMA (3, 1, 3).We proceed to estimate the parameters of the best fitted model in table 4.3 as shown in Table 4.

Table 4: Table showing parameter estimates of ARIMA (3, 1, 3)

Coefficients	Estimates	Standard Error	$\|Z\|\ value$	P-VALUE
ϕ_1	-0.542993	0.0989558	5.487	0.0000
ϕ_2	-0.662609	0.0963392	6.878	0.0000
ϕ_3	0.303061	0.0905748	3.346	0.0000
θ_1	-0.220179	0.0640704	3.437	0.0000
θ_2	0.187308	0.0543966	3.443	0.0000
θ_3	-0.967128	0.0615409	15.72	0.0000

Source: Extracted from R-output

The model specification for ARIMA(3,1, 3) in table 4 is written in form of backshift operator as;

$$(1-\phi_1 B-\phi_2 B^2-\phi_3 B^3 B)Y_t=(1-\theta_1 B-\theta_2 B^2-\theta_3 B^3)\varepsilon_t \quad (15)$$

Expanding in linear form, we have

$$Y_t=\phi_1 Y_{t-1}+\phi_2 Y_{t-2}-\phi_3 Y_{t-3}+\varepsilon_t-\theta_1\varepsilon_{t-1}-\theta_2\varepsilon_{t-2}-\theta_3\varepsilon_{t-3} \quad (16)$$

Substituting the coefficients, we have:

$$Y_t=-0.542993Y_{t-1}-0.662609Y_{t-2}+0.303061Y_{t-3}+0.220179\varepsilon_{t-1}-0.187308\varepsilon_{t-2}+0.967128\varepsilon_{t-3}+\varepsilon_t \quad (16)$$

From table 4, it shows that all the AR(p) and MA(q) estimated parameters are statistically significant since their corresponding p-values are <0.05 level of significance. This indicates that the model coefficient is efficient in forecasting ANC attendancein FMC Abeokuta. The model parameters have been parsimoniously fitted, the standard errors and log-likelihood have improved while the model has a smaller AIC and variance which confirms that it captures the dependence in the series more than any other iterative models suggested by the sample ACF and PACF of first order differencing.In addition, since it is essential to check whether the model is correctly specified, that is, whether the model assumptions are supported by the data, the residual of the fitted model was subjected to normality check by plotting the ACF of residuals, and dependence test by plotting the p-values for Ljung-Box test statistic.

4.1 Diagnostic Check of fitted ARIMA(3,1,3) model

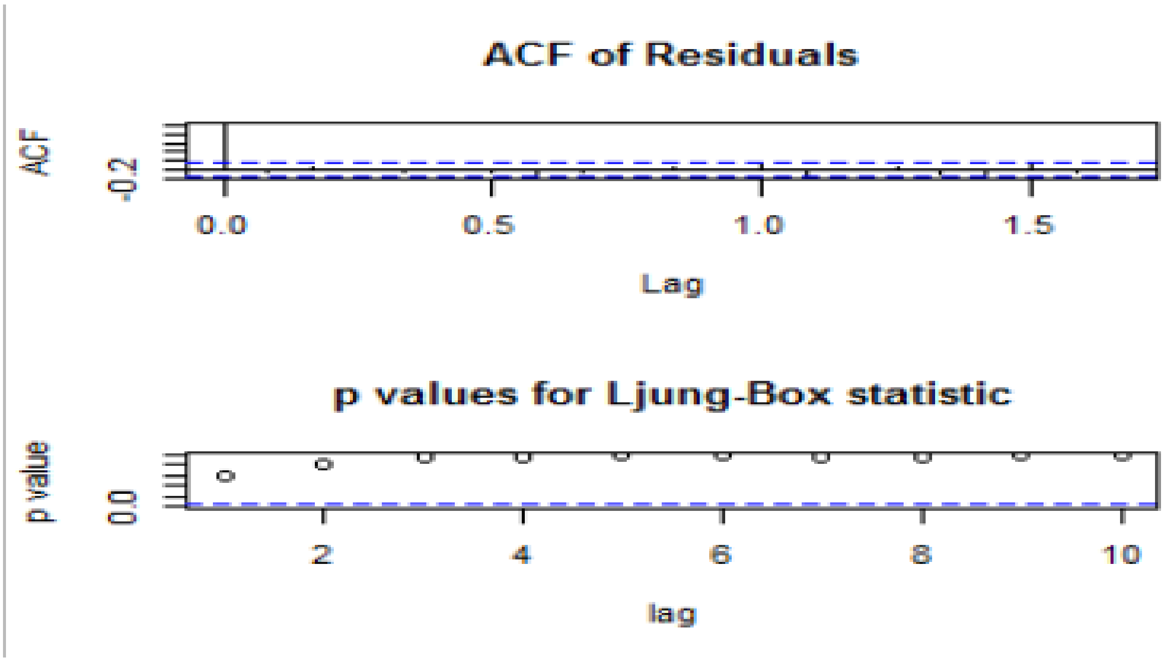

Fig. 8: ACF of Residuals and p-values for Ljung-Box statistic

It can be depicted in figure 8 that all the spikes in the ACF of residuals were not statistically significant and the p-values of the Ljung Box test statistic are above the threshold, implying that the autocorrelation functions are zero and the model have achieved white noise.

Table 5: Shapiro-Wilk's Test of normality

Shapiro-Wilk statistic (w)	p-value	Lag value
3.093	0.21300	12

Source: Extracted from R-Output

Table 5 below shows that the Shapiro-Wilk test has a test statistics w = 3.093 leading to p-value of 0.21300. This indicated that normality is not rejected at 1%, 5%, and 10% significant levels implying that the residuals of the chosen model are normally distributed.

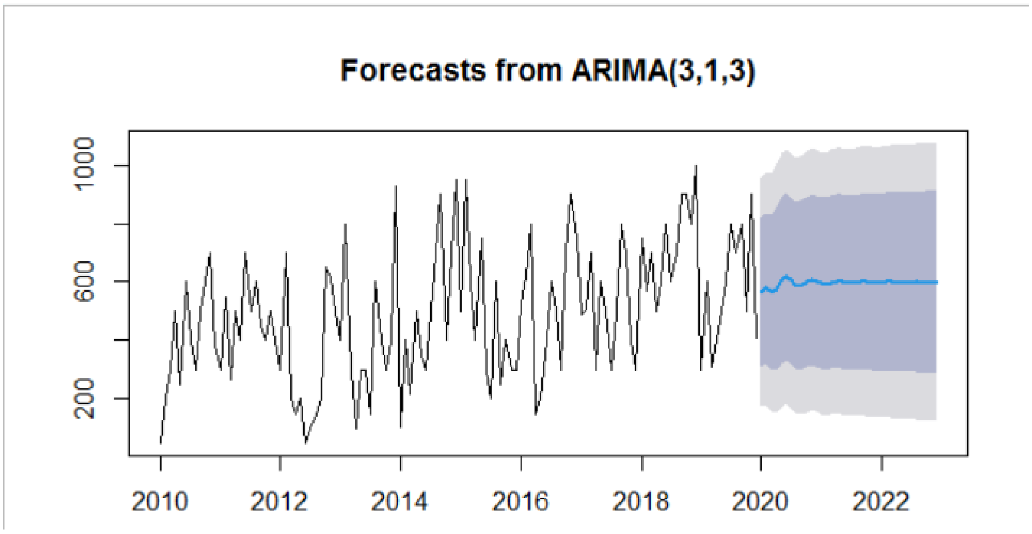

Fig. 9: Forecasts from ARIMA(3,1,3)

Table 6: Short Time Forecasts from ARIMA(3,1,3)

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95

Jan 2020	563.9605	309.0010	818.9199	174.0336	953.8873
Feb 2020	578.8240	319.3775	838.2704	182.0349	975.6131
Mar 2020	564.7340	299.9525	829.5156	159.7856	969.6825
Apr 2020	576.7793	298.3700	855.1886	150.9890	1002.5696
May 2020	605.9018	321.1517	890.6520	170.4140	1041.3897
Jun 2020	618.7257	333.9546	903.4968	183.2059	1054.2455
Jul 2020	606.0215	320.7738	891.2692	169.7728	1042.2702
Aug 2020	588.8571	303.3842	874.3299	152.2640	1025.4501
Sep 2020	587.8952	299.1089	876.6814	146.2347	1029.5556
Oct 2020	600.3060	308.4360	892.1760	153.9294	1046.6826
Nov 2020	608.7896	316.4155	901.1637	161.6420	1055.9371
Dec 2020	604.7161	312.3319	897.1003	157.5531	1051.8792
Jan 2021	595.7728	303.1337	888.4119	148.2200	1043.3256
Feb 2021	593.2716	299.1528	887.3905	143.4556	1043.0876
Mar 2021	598.4643	302.5205	894.4081	145.8573	1051.0712
Apr 2021	603.5910	306.8383	900.3436	149.7469	1057.4350
May 2021	602.8677	305.8492	899.8863	148.6170	1057.1185
Jun 2021	598.5461	301.1501	895.9421	143.7181	1053.3740
Jul 2021	596.3970	298.0708	894.7233	140.1464	1052.6477
Aug 2021	598.3196	298.7694	897.8699	140.1970	1056.4423
Sep 2021	601.1412	300.7261	901.5563	141.6959	1060.5865
Oct 2021	601.4492	300.5267	902.3717	141.2280	1061.6704
Nov 2021	599.5110	298.0873	900.9348	138.5232	1060.4988
Dec 2021	598.0698	295.8921	900.2475	135.9288	1060.2108
Jan 2022	598.6343	295.5153	901.7533	135.0538	1062.2148
Feb 2022	600.0745	296.1244	904.0246	135.2230	1064.9260
Mar 2022	600.5464	295.9604	905.1324	134.7224	1066.3704
Apr 2022	599.7534	294.5758	904.9309	133.0246	1066.4822
May 2022	598.9025	293.0253	904.7797	131.1037	1066.7013
Jun 2022	598.9706	292.2860	905.6553	129.9370	1068.0043
Jul 2022	599.6555	292.1870	907.1241	129.4229	1069.8881
Aug 2022	600.0312	291.8748	908.1875	128.7467	1071.3157
Sep 2022	599.7484	290.9469	908.5499	127.4773	1072.0195
Oct 2022	599.2884	289.8012	908.7756	125.9686	1072.6082
Nov 2022	599.2151	288.9846	909.4455	124.7585	1073.6716
Dec 2022	599.5166	288.5404	910.4928	123.9196	1075.1136

Source: Extracted from R-Output

Table 6 shows the three years forecast. A close look indicates that there is going to be a steadily constant rate in the reported cases of pregnancy in Federal Medical Centre, Abeokuta from the start of 2020 to the end of 2022. It can be seen that the forecast has no seasonal effect as the seasonal period do not exhibit larger variation compared to other periods as evidenced in table 6 and fig. 8 respectively.

CONCLUSION

ARIMA order (3, 1, 3) was found to be the most appropriate for fitting model for pregnant women ante-natal care attendance, and the prediction of ante-natal care attendance is on the rise, after using all necessary and relevant procedures in line with the study's goals. As a result, policymakers should make efforts to increase the quality and number of people as well as timely ANC service delivery to reduce mother and child morbidity and mortality. In academia, the fitted model can be evaluated and built upon, laying the groundwork for future research by incorporating exogenous variables such as pregnant women's socio-economic status in the absence of white noise to boost ante-natal care attendance in the study area.

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