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Time Series Analysis on Monthly Production of Crude Oil in Nigeria

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ABSTRACT

This study delves into a comprehensive time series analysis of the monthly production of crude oil, in Nigeria, a critical component of the country's economy and a significant player in the global oil market. Understanding patterns, trends, and dynamics of crude oil production is essential for policymakers, industry stakeholders, and researchers to make informed decisions and forecasts. The research utilizes monthly secondary data on crude oil production in Nigeria, collected from the Nigeria National Petroleum Cooperation (NNPC) annual statistical bulletin 2010 and 2023 respectively, to explore various aspects of the time series, including seasonality, trends, and potential forecasting models. Minitab 17.0 was applied to run the data, advanced time series model, ARIMA (Auto-regressive Integrated Moving Average) was employed using the Box-Jenkins approach for crude oil production in Nigeria from January 1999 to June 2023 to forecast future production levels based on the historical data patterns. ARIMA (2,1,1) model was the best model fitted to the crude oil production data. The pattern showed that the model fitted for this study is adequate since the P-value can be seen from table 2 is greater than 0.05. The result indicates that the forecasted values of crude oil production fluctuate steadily.

INTRODUCTION

The analyses of time series data play a crucial role in understanding and predicting trends, patterns, and fluctuations in various economic indicators and industries. In the context of the global energy market, particularly in oil-producing nations like Nigeria, examining the monthly production of crude oil through time series analysis provides valuable insight into the dynamics of the oil sector, economic performances, and broader implications for the country's economy.

One of the most popular and frequently used stochastic time series models is the Auto-regressive Integrated Moving Average (ARIMA) model. The basic assumption to implement this model is that the considered time series must be linear and follow a particular known statistical distribution, such as the normal distribution. The ARIMA model has sub-classes of other models, such as the Auto-regressive (AR) and Auto-regressive Moving Average (ARMA) models. For seasonal time series forecasting, Box and Jenkins, (2015) had proposed a quite successful variation of the ARIMA model, viz. the Seasonal ARIMA (SARIMA). The popularity of the ARIMA model is mainly due to its flexibility to represent several varieties of time series with simplicity as well as the associated Box-Jenkins model. But the severe limitation of these models is the pre-assumed linear form of the associated time series which becomes inadequate in many practical situations.

The ARIMA model, particularly ARIMA (1,1,1) has been identified as optimal for forecasting production from 2005 to 2022, demonstrating its predictive capabilities (Kelechi, et al., 2023). Usoro and Emmanuel, (2022) utilised multivariate time series analysis, confirming stationarity and fitting MARCH and MGARCH models to assess the volatility of Nigeria's crude oil production and price interactions. Akpanta et al., (2015) and Afrifa -Yamoah et al., (2016) fit SARIMA (0,0,0) x $(1,1,1)_{12}$ model to monthly rainfall in Umuahia, Abia State of Nigeria and Brong Ahafo Region of Ghana, respectively.

More so, Williams and Hoel (2003), Mombeni et al., (2013) and Farhan and Ong (2016) fitted SARIMA Models to Vehicular traffic flow, water demand in Iran and Container throughput at International Airports respectively. Nigeria is Africa's largest oil producer and fifth supplier to the United States. She is rated among the twelve biggest oil producers in the organization of petroleum Exporting Countries, (OPEC), contributing about 1.9 million barrels per week (bpd) to the OPEC basket. She is the sixth largest oil exporter, "with a total of 173 oil blocks in operation, according to the Department of Petroleum Resources (DPR)" (Eboh, 2013). The OPEC's Annual Statistical Bulletin 2012 shows that Nigeria has proven crude oil reserves of 37.2 billion barrels, while proven natural gas reserves – stands at 5.154 million cubic meters, making it the eighth in the world gas reserves and first in Africa. Yet the country depends on fuel importation to meet local demands of petroleum products. Crude oil production and export commenced in 1958. It accounted for 7.1 percent of total exports in 1961 which was dominated by cocoa, groundnut, rubber, and palm oil, in that order. In 1965, oil constituted 13.5 percent of the nation's export earnings, and by 1970, it had become the leading source of foreign exchange, accounting for 63.9 percent. By 1979, petroleum sales had completely overshadowed non-oil exports, as it then contributed about 95 percent of the country's export earnings. In 2012, oil and gas exports accounted for almost 96 percent of export earnings. Also, in 2013, "Nigeria's budget is framed on a reference of oil price of $79 per barrel, providing a wide safety margin in case of price volatility" (U.S Energy Information Administration EIA). No wonder, the Central Bank of Nigeria (CBN) reported in 2010 that petroleum accounted for approximately 96 percent of the country's foreign exchange and 76 percent of the total government revenue (CBN, 2010). It is no surprise then that it was observed that "total oil revenue generated into the federation account amounted to ₦34.2 trillion while non-oil revenue was ₦7.3 trillion, representing 82.36 percent and 17.64 percent representing 82.36 percent and 17.64 percent respectively between 2000 and 2009 Ogbonna & Ebimobowie, (2012). However, despite the above abundant oil resources and unprecedented wealth, Nigeria depends on eighty-five (85) percent and above on the importation of petroleum products Igbosewe et al., (2021). Massive infusion of subsidies,was introduced in 1973 to stabilise the fuel price and insulate Nigeria from the wild fluctuation of global market prices. Ploch (2013) observed that Nigeria imports an estimated $10 billion of fuel annually for domestic consumption. In 2012, Nigeria consumed 270, 000 bbl/d and in 2013, she imported fuel from faraway countries like United States, the United Kingdom, Venezuela, Canada, Brazil, the Netherlands, and the Persian Gulf Countries. The more worrisome is the fact that Nigeria imports fuel from non-oil producing countries, like Niger Republic, Cote d'Ivoire, Amsterdam, India, Korea, Finland, Singapore, France, Israel, Portugal, Italy, Sweden, Tunisia, and many more (Chimezie, 2009). This study aims to analyse the historical trends, patterns, and seasonality in the monthly crude oil production in Nigeria using time series techniques. Furthermore, to uncover insights into the factors influencing production levels and provide valuable information for decision-making and strategic planning in the oil industry.

MATERIALS AND METHODS

This section provides an overview of the data sources, variable selection, statistical analysis techniques, data pre-processing steps, model evaluation methods, robustness checks, and limitations that would typically be included in a research study investigating the time series analysis on monthly production of crude oil in Nigeria.

Auto-correlation function (ACF)

Auto-correlation function refers to the observations in time series that are related to each other and is measured by a simple correlation between current observations (Y_t) and the observation p periods from the current one (Y_{t-p}).

$$P_k = Corr(Y_{t,} Y_{t-p}) = \frac{[cov][Y_t\, Y_{t-p}]}{\sqrt{[var][Y_t]}\sqrt{[var][Y_{t-p}]}} = \frac{Y_p}{Y_o} \quad (1)$$

Where, $Var(Y_t) = Var(Y_{t-1}) = Y_0$

As a function of K; Y_k is called the autocovariance function (ACF) of lag K, and ρ_k is the autocorrelation function of lag K.

Partial Auto-correlation Function (PACF)

Partial Auto-correlations are used to measure the degree of association between Y_t and Y_{t-p} when the effects at other time lags 1,2,3,...,p -1) are removed.

Data Collection

The Monthly production data of crude oil in Nigeria was extracted from the Annual Nigerian National Petroleum Cooperation (NNPC) Bulletin 2010 and 2023 respectively, which covers the period of twenty-four years (1999-2023).

Method of Data Analysis

The data was analyzed using MINITAB 17.0; the statistical tool employed is the auto-regressive integrated moving average (ARIMA) using the Box-Jenkins (B-J) methodology.

The Box-Jenkins methodology is a mathematical model that forecasts data ranges based on inputs from a specified time series. The pioneers who popularised an approach that combines the moving average and auto-regressive models were Box and Jenkins. Although both auto-regressive and moving average approaches were known (and were originally investigated by Yule), the contribution of Box and Jenkins was in developing a systematic methodology for identifying and estimating models that could incorporate both approaches and this makes Box-Jenkins models a powerful class of models (Dobre et al., 2014).

There are four primary stages in building a Box-Jenkins time series model. These are model identification, estimation of the model parameters, diagnostic check of the residuals, model adequacy and forecasting (Banks, and Kunisch, 1989).

Model Identification

At the identification stage, the historical data of the time series of interest is statistically analysed, and an appropriate subclass of models from the general ARIMA (*p, d, q*) family is selected. The approaches are:

i. Suitably transform the time series to remove the non-stationarity in variance (if present).
ii. Difference the time series as many times as is needed to produce mean stationarity (if required), hopefully reducing the process under study to the mixed Auto-regressive Moving Average ARMA (*p,q*) process.
iii. Identify the order of the ARMA model. That is, identify the auto-regressive order „ p" and moving average order (q) presents in the transformed and differenced data.

The basic tools for model identification (steps (ii) and (iii)) are the graphs of the estimated Sample Auto-correlation Function (ACF) and the estimated Sample Partial Auto-correlation Function (PACF) obtained from the series. These graphs are used not only to help guess the form of the model but also to obtain approximate estimates of the parameters (using Yule-Walker equations), which are useful at the estimation stage to provide starting values for iterative procedures employed during the estimation of final parameters.

For a time series Y_t, t ≥ 1, the autocorrelation coefficient at lag k is:

$$P_k = \frac{Y_k}{Y_o}, where\ Y_k = cov(Y_t, Y_{t+k})\ for\ any\ t \qquad (2)$$

Theoretically, it can be shown that an Auto-regressive (AR) process of order p has an auto-correlation function of infinite extent, dominated by damped exponential and sine waves, and a partial auto-correlation function that is zero after lag p. Conversely, the partial auto-correlation function of a Moving Average (MA) process of any order (q) is infinite in extent and its auto-correlation function is zero beyond lag q. For ARMA processes, the identification of the process order gets somewhat complicated, both the auto-correlation function and partial auto-correlation function are infinite in extent.

Model Estimation

This is the process whereby the models are estimated using non-linear time series or maximum likelihood estimation (MLE). By estimation, we make efficient use of the data to make inferences about parameter conditions on the adequacy of the entertained model by using computation algorithms to arrive at coefficients that best fit the selected ARIMA model.

Identification of parameters

Determine the order of autoregressive (p), differencing (d), and moving average (q) terms based on autocorrelation and partial auto-correlation functions.

Model Fitting

Fit the selected time series model to the crude oil production data using the statistical software minitab 17.0

Parameter Estimation

Estimate the model parameters to capture the underlying patterns in the data.

Model Validation and Diagnostics

It is a common practice in ARIMA modelling to tentatively fit more than one model to the data, estimate the parameters for each model and then perform a diagnostic check to test the validity of each model. The model that is best fits, according to various statistical tests of fit is then selected for forecasting.

Residual Analysis

Check the residuals for autocorrelation, homoscedasticity, and normality to ensure model adequacy.

ACF and PACF plots of the residuals

The ACF of the residuals obtained after fitting a proper model to the data must show no significant autocorrelations at any lag order. Similarly, the PACF plot of the residuals must show no significant spikes at any lag order. Absence of any significant spikes in the residual ACF and PACF plots demonstrate proper fitting. However, in practice, there maybe a few spikes that are close to significance. One might expect approximately 1 lag in every 20 lags to be statistically significant by chance alone for a 95% confidence limit test. Such spikes may not be a big concern; though their position of lag order also matters in deciding their importance and proper judgment should be used.

Model Diagnostic Test

Perform Ljung- Box test to evaluate model goodness of fit.

Ljung-Box Chi-Square test

Another measure of check for the randomness of residuals is using the Ljung-Box Chi-Square test. The null hypothesis is that the set of autocorrelations for residuals is white noise. This statistic measures the significance of residual auto correlation as a set and points out if they are collectively significant:

Auto-Regressive Process

This is a model in which the current value of the series is expressed as a finite linear aggregate of previous value of the process and a random shock Z_t. It is known as auto-regressive because the current value of the series can regress on its past values. Let Y_t, Y_{t-1}, Y_{t-2},... Denote the value of a process at equally spaced times $T_0, T_1, T_2, ... T_n$ Thus,

$Y_t = f(Y_{t-1}, Y_{t-2}, Y_{t-3}, ..., \mathcal{E}_t)$. We say that the process (Y_t) is autoregressive of order p (AR(p)) .

A common representation of an autoregressive model where it depends on p of its past values called as AR(p) model is represented below:

$$Y_t = \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \beta_3 Y_{t-3}, \ldots + \beta_p Y_{t-p} + \epsilon_t \quad (3)$$

Where, $\beta_1, \beta_2, ...\beta_p$ are autoregressive parameters and (ϵ_t) is a white noise process with mean, zero and constant variance, δ^2.

Moving Average Process

A moving average model is one when Y_t depends only on the random error terms which follows a white noise process for example,

$$Y_t = f(\mathcal{E}_t, \mathcal{E}_{t-1}, \mathcal{E}_{t-2}, \ldots) \quad (4)$$

A common representation of a moving average model where it depends on q of its past values is called MA (q) model and is represented below:

$$Y_t = \mathcal{E}_t + \varphi_1 \mathcal{E}_{t-1} + \varphi_2 \mathcal{E}_{t-2} + \ldots + \varphi_q \mathcal{E}_{t-q} \quad (5)$$

The error terms $\mathcal{E}_t$ are assumed to be white noise processes with means zero and variance δ^2 and, $\phi_1, \phi_2, ... \phi_q$ are moving average parameters.

Auto-Regressive Moving Average (ARMA)

A practical way to fit the model to a time series data is to fit a model that has the fewest parameters and greatest degree of freedom among all models that fit the data, that is, parsimony, such a model is the Auto-Regression Moving Average, usually written as ARMA. The auto-regressive moving average includes both auto-regressive and moving averages. It's given as:

$$Y_t = \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \ldots + \beta_p Y_{t-p} + \epsilon_t + \varphi_1 \mathcal{E}_{t-1} + \varphi_2 \mathcal{E}_{t-2} + \ldots + \varphi_q \mathcal{E}_{t-q} \quad (6)$$

Where, $\beta_1, \beta_2, ... \beta_p$ and $\phi_1, \phi_2, ... \phi_q$ are autoregressive moving average parameters.

Data Presentation and Analysis

Data were analysed using a univariate time series to fit an Autoregressive integrated Moving average model (ARIMA). The statistical package used is Minitab version 17.0, and the data was collected from the Nigerian National Petroleum Corporation (NNPC).

RESULTS AND DISCUSSION

Data Analysis

This analysis is aimed at fitting a time series ARIMA model to the monthly Crude oil Production in Nigeria National Petroleum Corporation (NNPC). The best-fit model will also be used to estimate future production of crude oil in Nigeria. The data set contains monthly production of crude oil from 1999-2023 in Nigeria. Analysis employed uses Box-Jenkins ARIMA modeling techniques to find an appropriate model for the time series. Furthermore, our model was then assessed to determine how well it fits the data. Finally, monthly productions of crude oil for the next four years were estimated using the proposed model.

Identification

Firstly, we determine the stationarity of the time series by generating a time plot of the original data. This is presented in Figure 1.

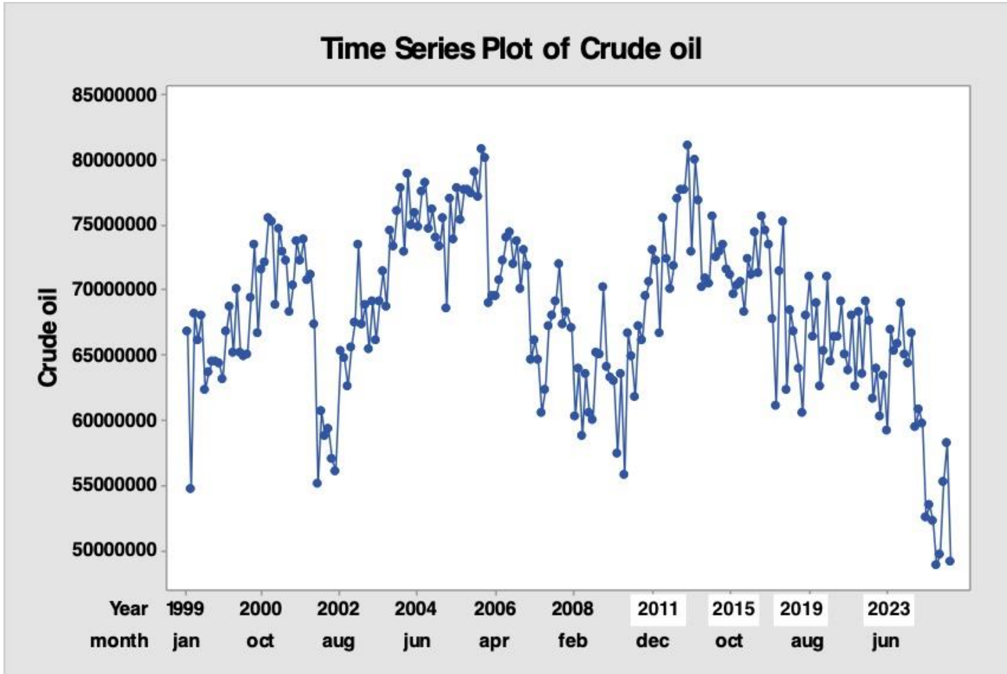

Figure 1: Time series plot of monthly Crude oil from 1999-2023

Figure 1 shows a time series plot of the original data. It is clear from this figure that there is none increasing trend in mean and variance in the time series. There is evident of seasonal pattern in the data. The original series is nonstationary and seasonal.

The next step is to examine both sample autocorrelations (ACF) and partial autocorrelations (PACF) using their respective plots for the identification of initial ARIMA model.

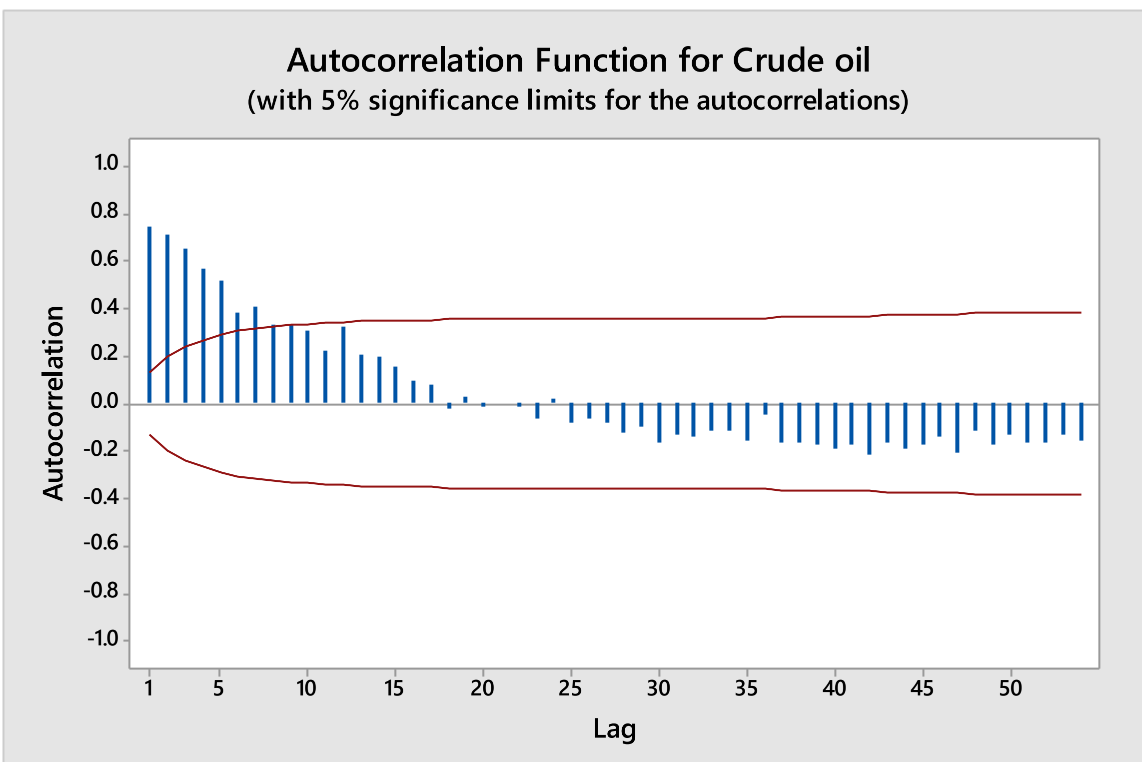

Figure 2: Autocorrelation plot of the original data

The autocorrelation plot has 5% confidence band which is constructed based on the assumption that the process is a moving average (MA) process. The autocorrelation plot shows that seven spikes were significant at lag 1,2,3,4,5,6,7 and other autocorrelations were within the confidence band and near zero. The autocorrelation plot indicates that the process is nonstationary where q lies between 1 and 7.

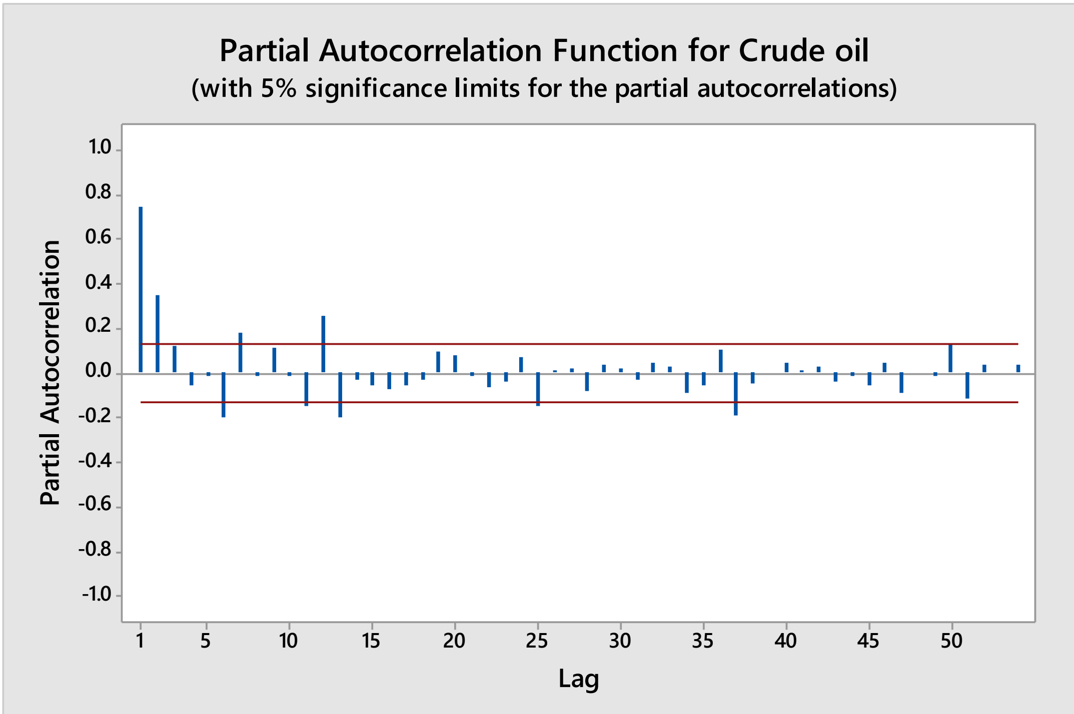

Figure 3: Partial correlation function plot of the original data

The partial auto-correlation plot has a 5% confidence level which is constructed based on the assumption that the process is an auto-regressive (AR) process. The partial auto-correlation plot shows nine significant spikes at lag 1,2,5,6,10,11,12,25,37. Other autocorrelations were within the confidence band and near zero. The partial auto-correlation plot indicates that the process is non stationary because it decays quickly after lag 1,2,5,6,10,11,12,25,37, indicating that an AR (1) model is appropriate for the data. Since the data is a nonstationary one. There is a need to transform the data. The natural logarithm is employed in this research work for the transformation, also the difference of the natural logarithm (In crude oil) was carried out before we plotted the time series plot to verify that the data is stationary.

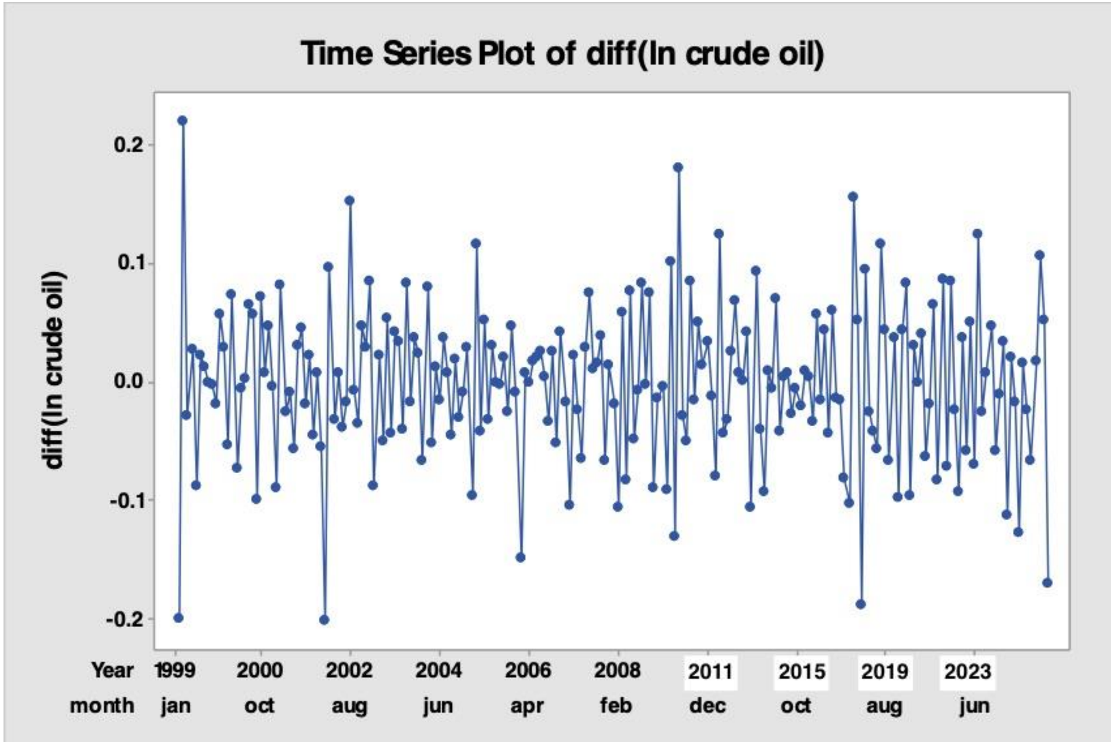

Figure 4: Time Series plot

The Time Series plot shows that the data is now stationary.

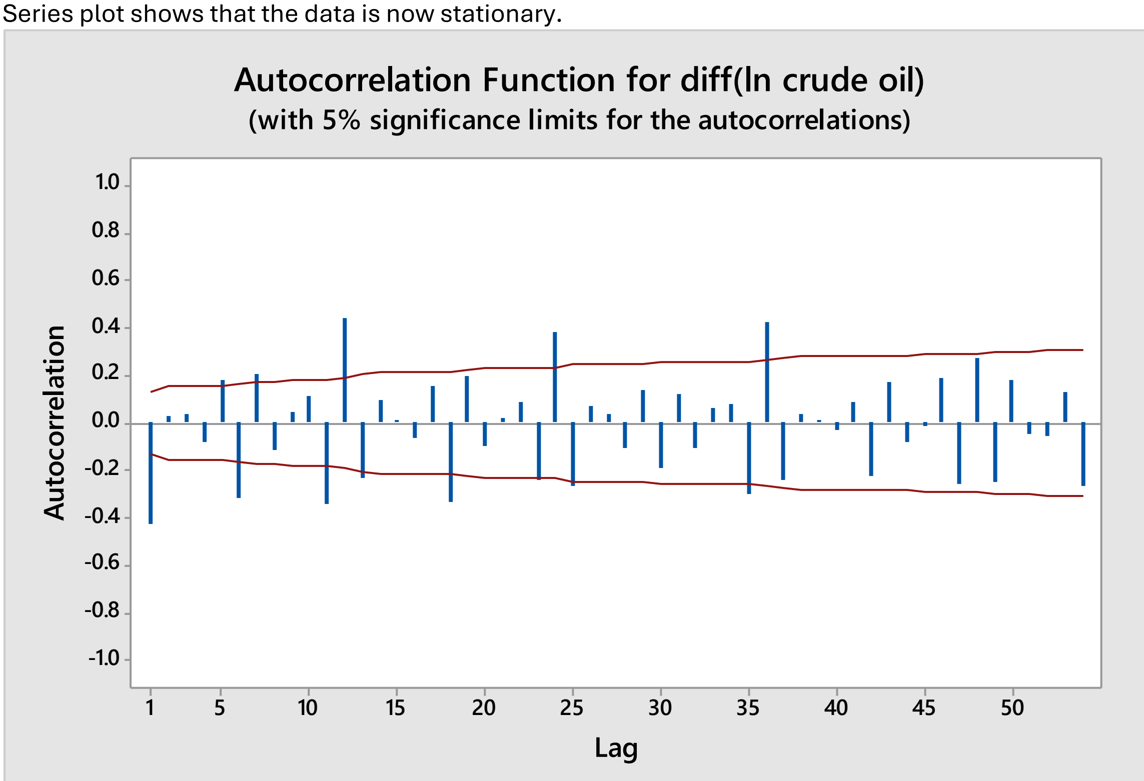

Figure 5: Autocorrelation function for diff(ln crude oil)

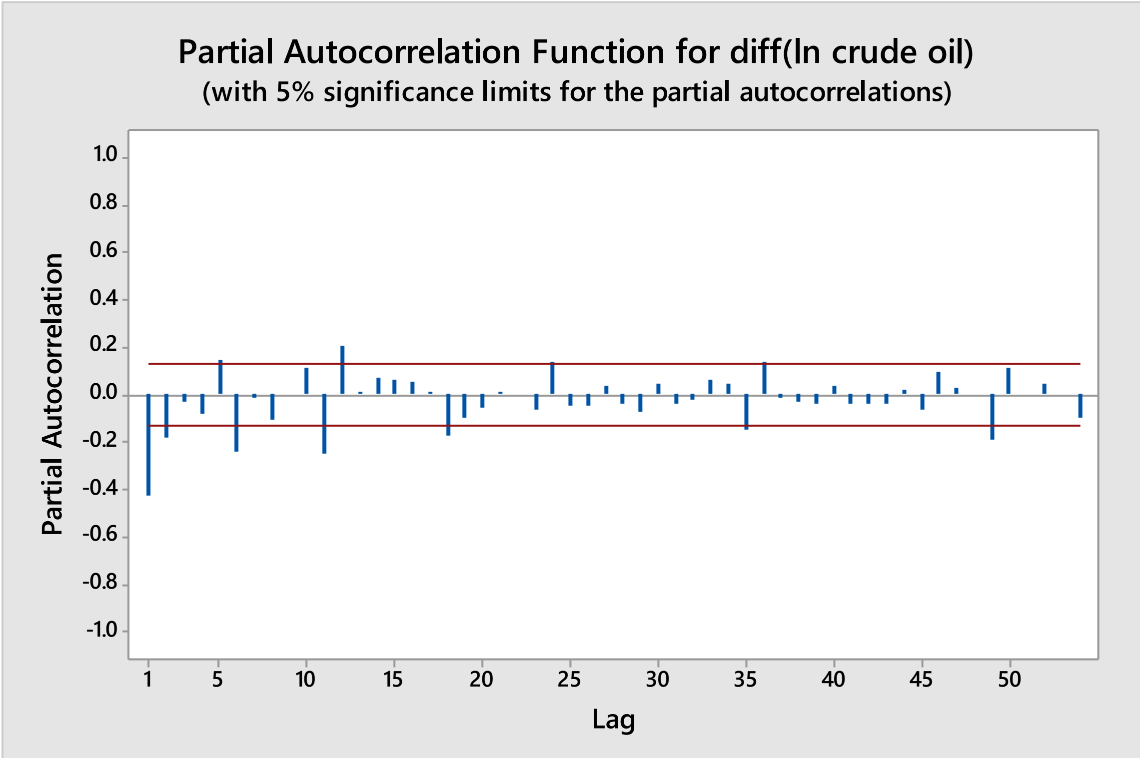

Figure 6: Partial Autocorrelation function for diff (ln crude oil)

Since there is spike in between the data as shown in Figure 5 and 6, it implies that there is a presence of seasonality in the data since it is a monthly data. Also, the autocorrelation function and partial correlation function determine the order of the data.

The next step in the process is the estimation stage.

Estimation Stage

This involves starting with a preliminary estimate and refining the estimate iteratively until the sum of squared errors is minimised. Parameters that are significantly different from zero are dropped from the model. The Ljung-Box statistic should give non-significant values for an efficient model. Hence, the following parameters were estimated for ARIMA (2,1,1) with a seasonal moving average of $(0,0,1)^{12}$ based on our plot. The result is presented below in table 1.

Table 1: Final Estimates of Parameters

Type	Coef	SE coef	T	P
AR 1	-0.2930	0.0705	-4.16	0.000
AR 2	-0.2389	0.0712	-3.35	0.001
SAR 12	0.9921	0.0132	75.27	0.000
MA 1	-0.2930	0.0201	47.84	0.000
SAM 12	0.8827	0.0619	14.25	0.000
Constant	-0.00002317	0.00006806	-0.34	0.734

Source: Researchers Output (2024)

Differencing: 1 regular difference

Number of observations: Original series 215, after differencing 214

Residuals: SS = 0.463948 (backforecasts excluded)

MS = 0.002231DF = 208

From figure 6 and table 1 above, it was deduced that the final estimate parameters are significance with P-value less than 0.05

From the output (table 1) we can confirm that all the parameters excluding the constant are significantly different from zero, because they have p-values that are significantly smaller to 0.05.

Table 2: Modified Box-Pierce (Ljung-Box) Chi-Square statistic

Lag	12	24	36	48
Chi-square	6.1	17.6	24.6	45.2
Df	6	18	30	42
P-value	0.411	0.483	0.744	0.339

Source: Researchers output (2024)

The Box-pierce Chi-Square p-values in Table 2 are non-significant ($p > 0.05$) indicating that the model fits the data well and the residuals appear to be uncorrelated. Therefore, the appropriate model is ARIMA (2,1,1). Furthermore, the model contains minimal parameters. The model for this data is given as

$$Y_t = -0.00002317 - 0.2930Y_{t-1} - 0.2930\,\epsilon_{t-1} \quad (7)$$

The result in figure 7 shows a probability plot and a histogram of the residual reveals that the residuals are Normal, and the time series plot of the residual, contains only noise. These diagnostics indicate that a reasonable model has been found.

Residual Plots for diff (ln crude oil)

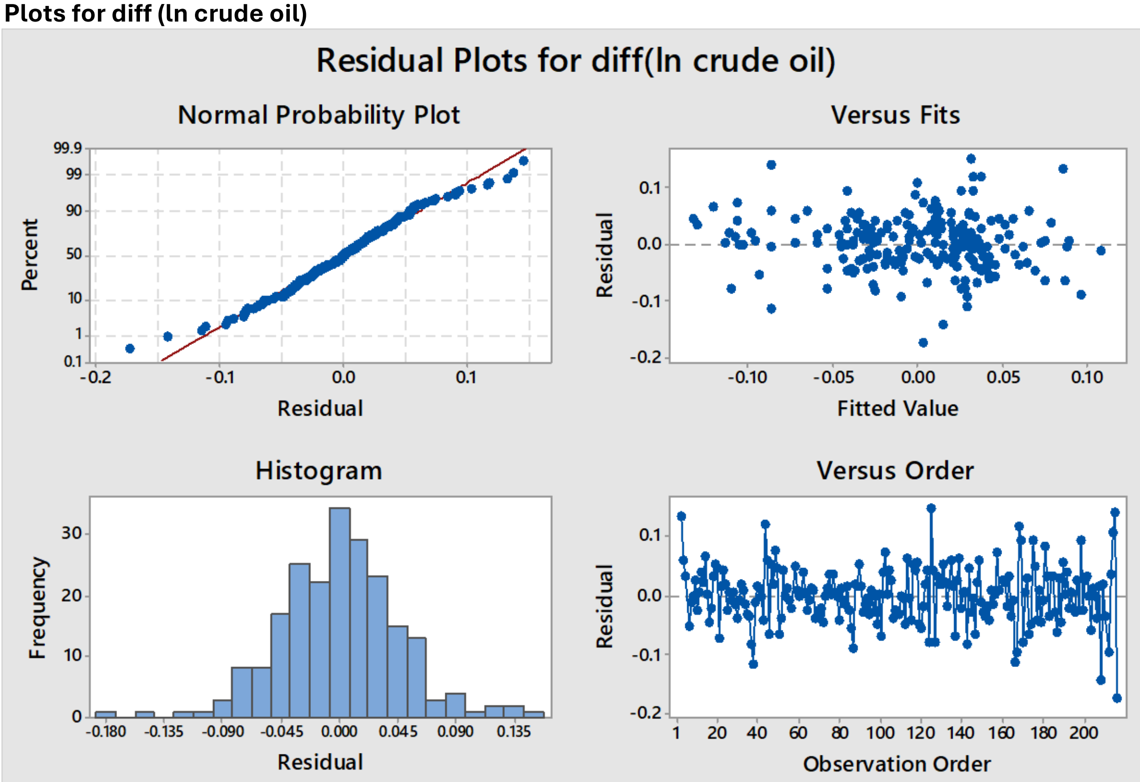

Figure 7: Residual Plots for diff(ln crude oil)

Model Diagnostic / Validation

A diagnostic check was carried out to validate the model, or possibly realise that a tentative model may need to be modified. For a model to be considered "good" it should have the following properties:

The residual should be approximately normal.

The entire parameters estimate should have a significant p-value

The LBQ Statistics should be non – significant and relatively large (i.e, $p > 0.05$)

Both ACF and PACF plots of residual should be within the limits $=1.96/\sqrt{N}$; where N is the number of observations upon which the model is based.

ACF of Residuals for diff(ln crude oil)

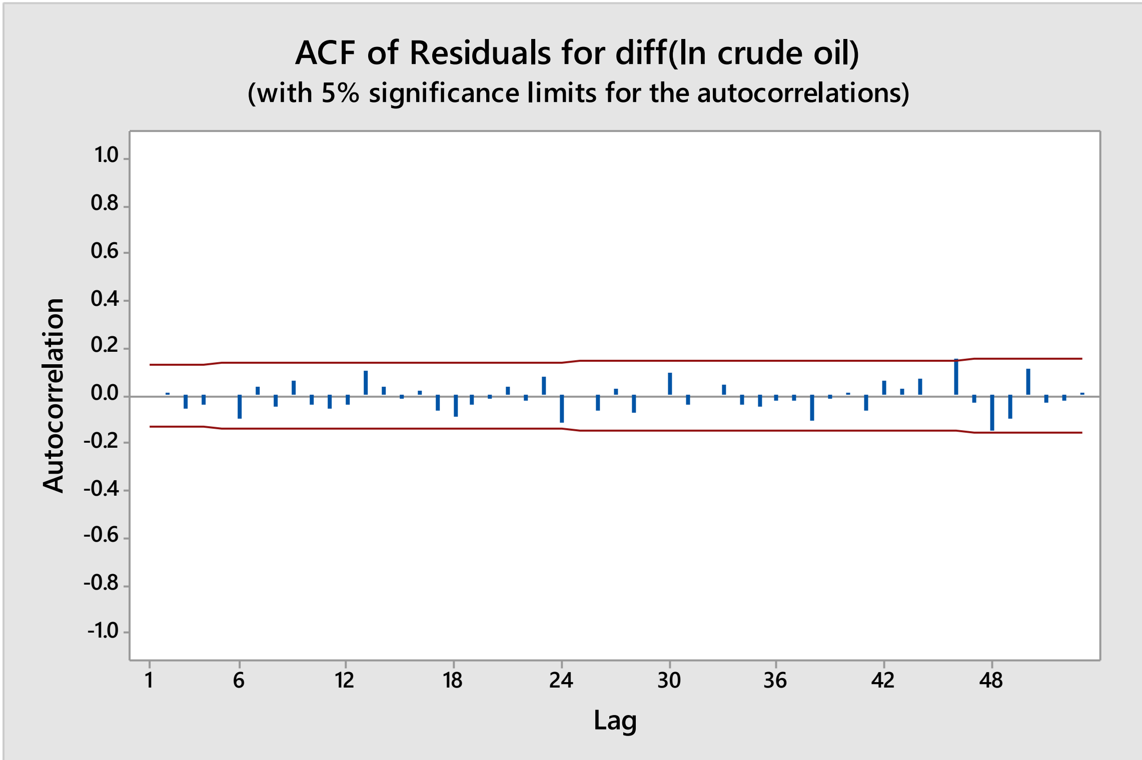

Figure 8: ACF of Residuals for diff(ln crude oil)

PACF of Residuals for diff(ln crude oil)

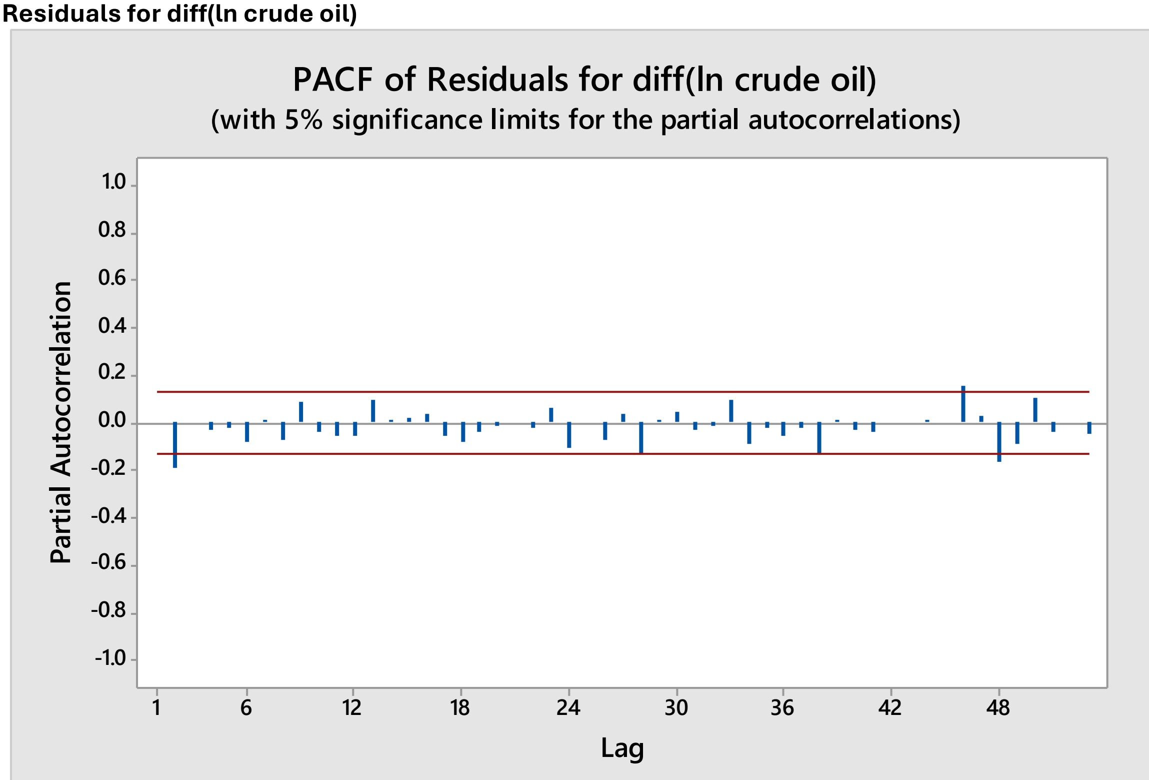

Figure 9: PACF of Residuals for diff(ln crude oil)

The results in figure 7 shows that the residual plots follow a normal distribution curve thereby making the data stationary and adequate, also figure 8 and 9 shows that ACF and PACF plots of the residuals are well within their two standard error limits. Hence, the residuals are white noise model classified as ARIMA (0, 0, 0) that constitutes:
There is no differencing involved.
No Moving average (MA) part since Y_t *does not depend on* ε_{t-1}*, therefore, the model is efficient or a good fit.*
Therefore, we can conclude that we have produced an adequate model for forecasting the future values of this series. However, we are uncertain how well this model will perform in the next four years because of the interval for which it was tested. It is suspected that the variability may increase as the forecast is extended to a longer period.

Forecasting

Once an adequate and satisfactory model is fitted to the series of interest, forecasts can be generated using the model.
Forecasts of future production of monthly crude oil are of particular interest to the researcher. We may now use the final form of the best-fit ARIMA model for the time series to estimate the future production of crude oil. The forecasted barrels of crude oil monthly, for the next four years are displayed in table 3 (alongside the confidence intervals of the estimates)

Table 3: Forecasted values using ARIMA (2,1,1) 95% Limits

MONTHS	YEAR	FORECAST	LOWER	UPPER
January	**2026**	0.002561	-0.095517	0.100639
February		-0.105207	-0.203284	-0.007129
March		0.039290	-0.058795	0.137375
April		-0.045940	-0.144100	0.052220
May		-0.002880	-0.101079	0.095318
June		-0.040621	-0.138850	0.057608
July		0.017916	-0.080352	0.116185
August		0.001326	-0.096981	0.099634
September		-0.032279	-0.13063	0.066065
October		0.022636	-0.075745	0.12108
November		0.051955	-0.150374	0.046464
December		0.002757	-0.095700	0.101213
January	**2027**	-0.000061	-0.099342	0.099219
February		-0.106998	-0.206279	-0.007718
March		0.036330	-0.062961	0.135621
April		-0.048234	-0.147610	0.051141
May		-0.005531	-0.104953	0.093890
June		-0.042989	-0.142447	0.056469
July		0.015069	-0.084436	0.119346
August		-0.001404	-0.100955	0.098147
September		-0.034758	-0.134353	0.064837
October		0.019706	-0.079933	0.112891
November		-0.054308	-0.153993	0.045376
December		-0.000046	-0.99775	0.099683
January	**2028**	-0.002857	-0.103423	0.097709
February		-0.108960	-0.209528	-0.008393
March		0.033216	-0.067366	0.133798
April		-0.050693	-0.151369	0.049983
May		-0.008344	-0.109073	0.092386
June		-0.045519	-0.146293	0.055254
July		0.012063	-0.088765	0.112891
August		-0.004294	-0.105176	0.096587
September		-0.037399	-0.138332	0.063534
October		0.016618	-0.084367	0.117604
November		-0.056825	-0.157862	0.044213
December		-0.003007	-0.10497	0.098082

January	**2029**	-0.005811	-0.107750	0.096128
February		-0.111088	-0.213030	-0.009147
March		0.029945	-0.072017	0.131907
April		-0.053313	-0.155379	0.048752
May		-0.011315	-0.155379	0.048752
June		-0.048211	-0.150389	0.053968
July		0.008900	-0.093341	0.111141
August		-0.007343	-0.109646	0.094959
September		-0.040200	-0.142562	0.062162
October		0.013373	-0.142562	0.062162
November		-0.059502	-0.161984	0.042980
December		-0.006127	-0.108669	0.096415

Source: Researchers output (2024).

It is clear from these forecasts that the production of crude oil on a monthly basis in Nigeria is expected to follow the fluctuation trend.

The time series plot of the data reveals non increasing trend by mean and variance. There is an element of seasonal pattern, and the data is nonstationary. The auto-correlation plot shows that seven spikes were significant at lag 1,2,3,4,5,6, and 7 which also indicates that the process is nonstationary. The partial auto-correlation plot shows nine significant spikes at different lag. This indicates nonstationary process meaning that AR (1) model is visible. Since the data shows non stationary, it was made stationary by transformation. The analysis reveals ARIMA (2,1,1) as the appropriate model. The pattern showed that the model fitted for this study is adequate since the p-value in table 2 above is greater than 0.05. The results indicate that the forecasted values of crude oil production fluctuate steadily. Future production of crude oil on monthly basis were estimated for four years using this model and we found out that the forecasted values followed the seasonality trend present in the data, The ARIMA model developed for predicting the monthly production of crude oil is given as ARIMA (2,1,1):

$$Y_t = -0.00002317 - 0.2930Y_{t-1} - 0.2930 \in_{t-1} \quad (8)$$

The findings from the ARIMA (2.1.1) analysis offer valuable insights into the future trajectory of crude oil production in Nigeria. Also, stakeholders can use these forecasts to anticipate changes in production levels, optimize resource allocation, and mitigate risks associated with fluctuations in the oil sector.

CONCLUSION

In this study, we employed an ARIMA (2,1,1) model to analysed the time series data of monthly production of crude oil for a period of twenty-four years in Nigeria. The estimated equation derived from the model is given as, equation (8). The ARIMA (2,1,1) model provides valuable insights into the dynamics and patterns observed in the time series data. The coefficient estimates indicate that both the lagged value of the variable (Y_{t-1}) and the error term ($\in_{t-1}$) have a significant impact on the current value of the variable Y_t. The negative coefficients suggest a negative relationship between these components and the monthly production of crude oil. By utilizing this ARIMA model, we have been able to capture important trends, seasonality, and auto-correlation presents in the data, allowing for meaningful forecasting and analysis of the variable Y_t. The model not only helps in understanding the historical patterns but also provides future values of the variable with a reasonable degree of accuracy. The ARIMA (2,1,1) model, along with the derived equation, serves as a valuable tool for understanding and analysing the dynamics of the time series data and can guide future analysis and forecasting efforts in this domain of crude oil production in Nigeria.

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