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ORIGINAL RESEARCH ARTICLE

Modeling and Forecasting Crude Oil Prices in Nigeria Using ARIMA: A Time Series Analysis from 2013-2022

Hamidu Aliyu Chamalwa[1], Bashir Abdulsalam[2] and Muhammad Abbas[3]
[1]Department of Statistics, Faculty of Physical Sciences, University of Maiduguri, Nigeria
[2,3]Department of Mathematics and Computer Science, Faculty of Science, Borno State University, Maiduguri-Borno State, Nigeria

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ABSTRACT
This study utilizes Box-Jenkins ARIMA modelling to forecast crude oil prices in Nigeria from 2013 to 2022. The data, sourced from the CBN statistical bulletin, revealed non-stationarity, corrected by first differencing. The ARIMA (1, 1, 1) model was identified as the most suitable based on AIC, BIC, and HQIC criteria, providing significant information on short-term price forecasting and model adequacy. The study concludes that while ARIMA models are effective for short-term forecasting, their limitations, such as sensitivity to non-stationary data, suggest that future research should incorporate macroeconomic variables or hybrid models for improved accuracy. It was recommended that stakeholders in the Nigerian oil sector should explore other avenues in the sector, such as Liquefied Natural Gas (LNG), in order to absorb the decrease in revenue as a result of the decline in revenue from crude oil prices and sales.

INTRODUCTION
In short decades, Nigeria has experienced acute fluctuations in the prices of its most valuable and major revenue-generating natural resource, crude oil. The oil sector plays a magnificent role in the Nigerian GDP, accounting for about 82% of total government revenue and contributing immensely to the general growth and development of the Economic of the country (Suleiman et al., 2015). The Box-Jenkins modelling techniques have continued to gain more popularity in recent times as an effective and efficient tool in describing time series data, such as prices, GDP, and forex, to name but a few. The main advantage of the ARIMA model is its prowess to generate accurate forecasts of future oil prices based on the observed historical data. These forecasts can be instrumental in informing investment decisions, government policies, and risk management strategies in Nigeria's oil sector.

One of the early studies on ARIMA modeling of oil prices was conducted by Papapetrou (2001), who employed ARIMA models to forecast monthly and quarterly oil prices. The study found that ARIMA models were good at describing volatility and trends, such as oil prices, and provided accurate forecasts. However, the study was limited to using historical time series data and did not consider other factors that could influence oil prices. In contrast, Akram and Zhang (2014) applied ARIMA models to incorporate macroeconomic variables such as GDP, inflation, and exchange rates in their analysis of oil prices. The study found that incorporating these variables improved the accuracy of the ARIMA models in forecasting oil prices, suggesting that macroeconomic factors play a significant role in influencing oil prices.

Another comparative study by Caporin and Pelizzon (2006) assessed the performance of ARIMA models with GARCH models in modelling forecasting oil prices. The study found that ARIMA models outperformed GARCH models in capturing the short-term oil price volatility, while GARCH models were more effective in handling the long-term volatility. This indicated that the utilization of both models could give a more convincing analysis of oil price behaviour.

On the other hand, Saad and Tahat (2018) compared the behaviour of ARIMA models with artificial neural network models in forecasting oil prices. The study found that neural network models outperformed ARIMA models in capturing the non-linear and complex relationships in oil price data, suggesting that incorporating machine learning techniques could improve the forecasting accuracy of oil prices.

In the Nigerian view of oil prices, ARIMA modeling, in a study conducted by Adegboye (2018) the study showed that ARIMA modeling was effective in capturing the

Correspondence: Hamidu Aliyu Chamalwa. Department of Statistics, Faculty of Physical Sciences, University of Maiduguri, Maiduguri, Borno State, Nigeria. ✉ chamalwa@unimaid.edu.ng. Phone Number: +234 703 608 2523
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inherent patterns and fluctuations in oil prices, providing valuable insights for decision-makers in the industry. Similarly, Oladosun and Kolawole (2019) applied the ARIMA model to study the short-term forecasting of oil prices in Nigeria. The results obtained revealed that the ARIMA model provided accurate forecasts of oil prices, which in turn can help policymakers and market participants in making informed decisions about the subsector.

Olowe and Fasanya (2020) employed the ARIMA model to investigate the long-term trends and patterns of oil prices in Nigeria. Their results revealed the presence of significant seasonality and non-stationarity in the data, which were effectively captured by the ARIMA model and, therefore, demonstrated the usefulness of the ARIMA model in understanding the underlying dynamics of oil prices in Nigeria.

An empirical study conducted by Adewuyi and Akanbi (2016) to investigate the dynamics of crude oil prices in Nigeria via ARIMA modelling; found that the ARIMA model was effective for forecasting short-term oil prices, and they highlighted the importance of considering factors such as geopolitical events, production levels, and global demand in the modeling process. Thus, the study provided valuable insights into the applicability of ARIMA modeling in the context of Nigeria's oil market.

Similarly, Olanipekun and Olusola (2018) focused on modeling the volatility of oil prices in Nigeria using ARIMA-GARCH models. The researchers reported ARIMA-GARCH model has effectively captured the dynamics of oil prices, and they emphasized the need for policymakers to account for this volatility in their decision-making processes. This study shed light on the potential of combining ARIMA with other econometric models to enhance the accuracy of oil price forecasting in Nigeria.

One study by Adeniran and Ajilore (2016) examined the performance of various ARIMA models in predicting the prices of Brent crude oil, a benchmark for global oil prices. The study found that ARIMA models can effectively capture the volatility of oil price fluctuations in the Nigeria context, providing valuable insights for decision-making in the energy sector.

In contrast, another study by Olukosi et al. (2020) critiqued the limitations of ARIMA modelling in capturing complex patterns of oil price behaviour. The researchers argued that while ARIMA models may provide short-term predictions, the inherent limitations of the model, such as the inability to capture long-term trends and structural breaks, limit its usefulness in the context of Nigeria's oil market.

Similarly, Oloyede et al. (2018) provided a concise comparison of ARIMA modelling with other time series techniques in forecasting oil prices in Nigeria. The researchers found that while ARIMA modelling can provide accurate short-term forecasts, it may not be suitable for capturing long-term trends and structural shifts, which are prevalent in the Nigerian oil market.

Although prior studies have demonstrated the effectiveness of ARIMA models, this research builds on existing literature by focusing on Nigeria's unique economic context, which is characterized by high volatility in oil prices due to geopolitical and macroeconomic factors.

MATERIAL AND METHODOLOGY

The study employs monthly crude oil price data from 2013-2022, sourced from the CBN statistical bulletin, on a monthly basis. The data was first differenced to achieve stationarity, as confirmed by ADF and KPSS tests. ARIMA models were evaluated and compared using the AIC, BIC, and HQIC criteria. The final model selection was justified by its superior fit and the adequacy of residual diagnostics.

MODEL ESTIMATION AND EVALUATION

Once the historical data is collected, the estimation of the parameters of the tentative ARIMA model is done. This entails identifying the suitable order for the ARIMA by inspecting the ACF and PACF, respectively. The fitted models were evaluated for best fit via the criteria: The Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC).

Unit Root Test and ADF Test

The Augmented Dickey-Fuller (ADF) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test are two commonly used statistical tests for determining stationarity in time series data.

Augmented Dickey-Fuller (ADF) test was introduced in 1979 (Dickey-Fuller 1979) to test for the presence of unit root and the ADF equation is given as.

$$\Delta y_t = \alpha y_{t-1} + x_t\delta + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \_\_\_ + \beta_p \Delta y_{t-p} \quad (1)$$

The hypothesis testing is

$H_0: \alpha = 0$ (The series contains unit root)

$H_1: \alpha < 0$ (The series is stationary)

The test statistic: $t_\alpha = \hat{\alpha}/se(\hat{\alpha})$

The null hypothesis will not be rejected if the test value is greater than the critical value for a given significance level.

Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test

The hypothesis is stated as follows:

$$H_O : \sigma^2 = 0$$
$$H_A : \sigma^2 \geq 0$$

If H_o is true, then y_t is composed of a constant and a stationary process e_t, which means y_t is also stationary. The test statistic of a KPSS test is given by:

$$\text{KPSS} = \sum_{i=1}^{T} \frac{s_t^{\,2}}{\sigma_\infty^{\,2}} \qquad (2)$$

Where T denotes the number of observations $s_t = \sum_{i=1}^{t}$ for t=1,2,………T e_t denote estimated error from a regression of y_t on a constant and time and are computed as $e_t = Y_t - \bar{Y}$ and $\sigma_\infty^{\,2}$ is an estimator of long run variance of the e_t process. The null hypothesis of stationary of the test statistic is greater than the critical value at a given level of significance.

Box-Jenkins ARIMA

ARIMA model is robust tool for analysing and forecasting time series data. It brings together Autoregressive (AR), Differencing (I), and Moving Average (MA) components to account for the complex dynamics and trends present in the data.

Moving Average of order q process, is an equation with lags number up to q and is written as:

$$Y_t = \mu + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \cdots + \theta_q\varepsilon_{t-q} + \varepsilon_t \qquad (3)$$

Autoregressive Process (AR)

The Autoregressive process (AR) of order p is written as;

$$Y_t = \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \cdots + \varphi_p y_{t-p} + \varepsilon_t \qquad (4)$$

Autoregressive-Moving Average (ARMA) Process

ARMA process is an amalgamation of the AR (p) and MA (q) to form a single linear model denoted by ARMA (p, q). A time series y_t is said to follow an ARMA (p, q) process if it satisfiers with the model below.

$$y_t = \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \varphi_p y_{t-p} + \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \theta_q\varepsilon_{t-q} \ldots \quad .(5)$$

Where y_t and ε_t are the white noise process in each AR and MA respectively for an ARMA (1, 1), the model is given as

$$y_t = \varphi_0 + \varphi_1 y_{t-1} + \varepsilon_t + \theta_1\varepsilon_{t-1} \qquad (6)$$

$$y_t - \varphi_1 y_{t-1} = \varphi_0 + \varepsilon_t + \theta_1\varepsilon_{t-1} \qquad (7)$$

where φ_0 is a constant term and $\varphi_1 \neq \theta_1$

MODEL SELECTION CRITERIA

A model selection criterion of AIC, BIC and HQIC were used in selecting the best and most appropriate model:

Akaike information criteria ((AIC), Akaike, 1969). AIC (p, q)=log $[(\hat{\sigma}^2{}_{p,q}) + \frac{(p+q)2}{T}$ (8)

Schwarz Information Criteria (SIC), Schwarz, 1978)

$$\text{SIC(p, q)=log } [(\hat{\sigma}^2{}_{p,q}) + \frac{(p+q)\log(T)}{T} \qquad (9)$$

Hannan-Quinn Information Criteria (HQIC), Hannan-Quinn, 1979) were simultaneously used to assess the best fit.

Diagnostics

The model fitted is checked for any inadequacies by ensuring all the relevant assumptions were satisfactorily met before the model is used for forecasting.

RESULTS

Figure 1 shows a trend and no seasonal variations. This is an indication that the data is not stationary.

Figure 2 is the correlogram (ACF and PACF) of the monthly crude oil price of the data series. The autocorrelation coefficients at various lags are very high; these are individually statistically significantly different from zero and are out of the 95% confidence bounds. This implies a non-stationary time series and that a reliable model cannot be fitted on the series.

The KPSS and ADF tests Table 1 were carried out to further objectively affirm the stationarity status or otherwise of the series. From Table 1, the KPSS test confirmed that the Crude oil price was not stationary at the various levels of significance (i.e., 1%, 5%, and 10% level of significance).

This means the statistical properties (mean, variance, and covariance) of the series are unstable

Figure 3 indicates that the series is now rendered stationary after the first. As the values oscillate around a common value of zero.

The graph in Figure 4 indicated that the coefficients for both ACF and PACF are not statistically significant as they are all within the 95% confidence bound. This implies that the series is now stationary (stable) and the series is now suitable for modeling.

Unit Root Tests of first differenced series

A re-test was performed to objectively ascertain the stationarity status. The results in Table 2 statistically confirmed that the series is now stationary after the first differencing. The fluctuation in the series as a result of unstable mean, variance, and covariance has now been rendered stable and hence appropriate model can be fitted.

Model Identification and Selection

The various tentative models were fitted and identified for Crude oil prices, as shown in Table 3 below. ARIMA (1, 1, 1) was chosen as the most appropriate model that best describes the database on the smallest values of the AIC, BIC, and HQIC in relation to the other models.

Forecasting

The primary objective of the ARIMA model procedure is to generate accurate forecasts of future values of the fitted data (oil prices) based on the observed historical data. These forecasts Figure 5 can be instrumental in informing investment decisions, government policies, and risk management strategies in Nigeria's oil sector Box-Jenkins (1976)

The average crude oil prices indicated the highest average in January and the least in December 2021, as shown in Table 4

The expected average crude oil prices for 2021 show that the value will decrease with respect to monthly sales. This can be attributed to the multifaceted issues facing the international oil market.

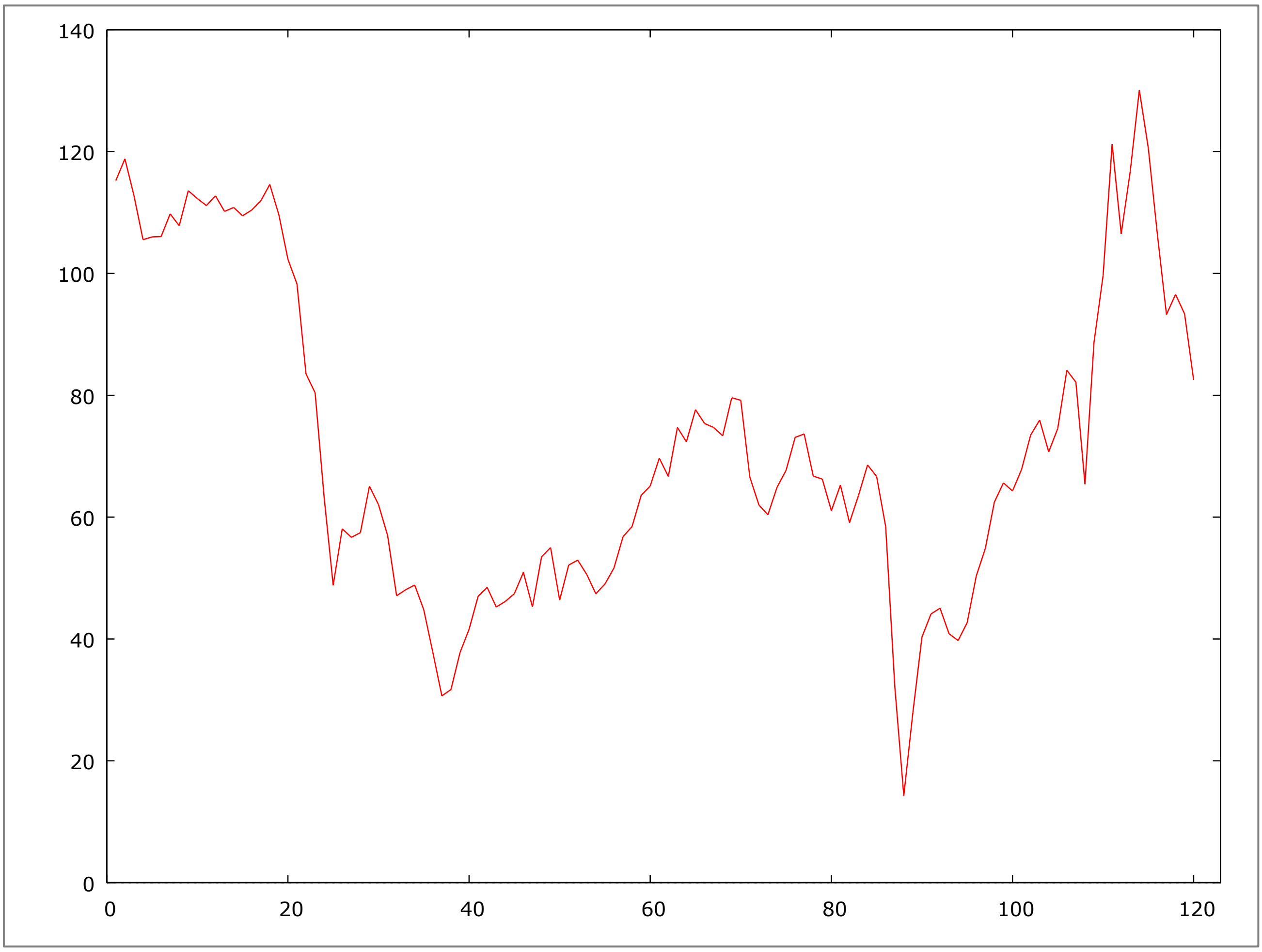

Figure 1: Time plot of the Original series.

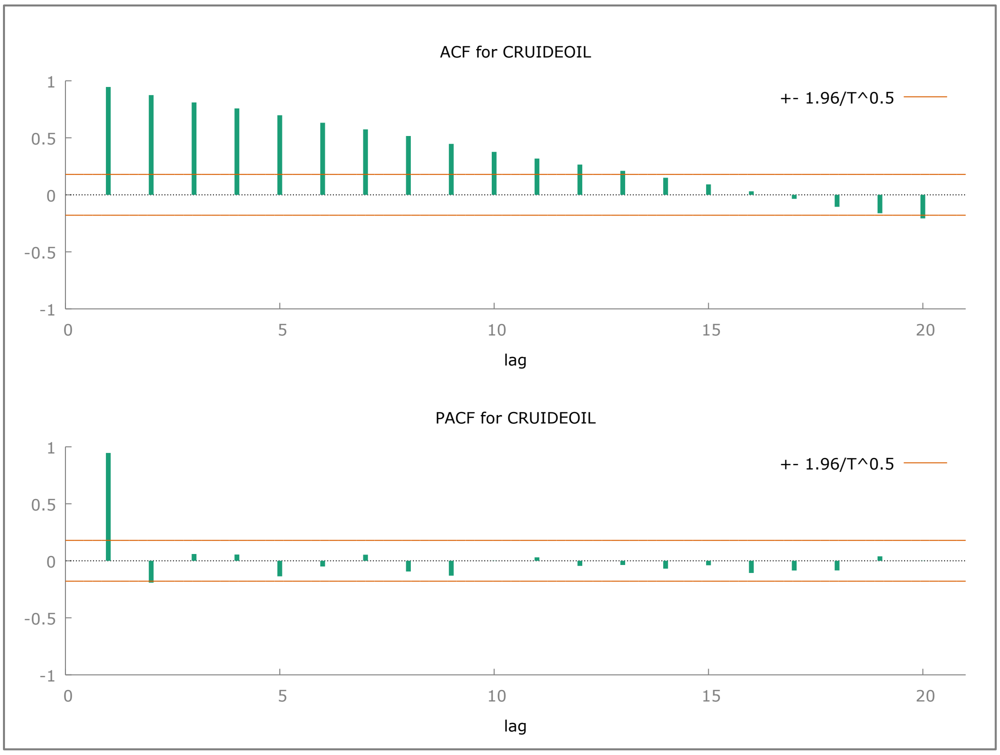

Figure 2: ACF and PACF for the crude oil data at levels

Table 1 KPSS and ADF tests of monthly Crude oil price

Test	**Without trend**		**With trend**	
KPSS	**Test statistic**	**Critical value**	**Test statistic**	**Critical value**
	0.424005	1% 5% 10% 0.735 0.465 0.349	0.370015	1% 5% 10% 0.216 0.148 0.120
ADF	**Constant**		**Constant + trend**	
	Test statistic	**P-value**	**Test statistic**	**P-value**
	-2.22553	0.1487	-3.41551	0.06927

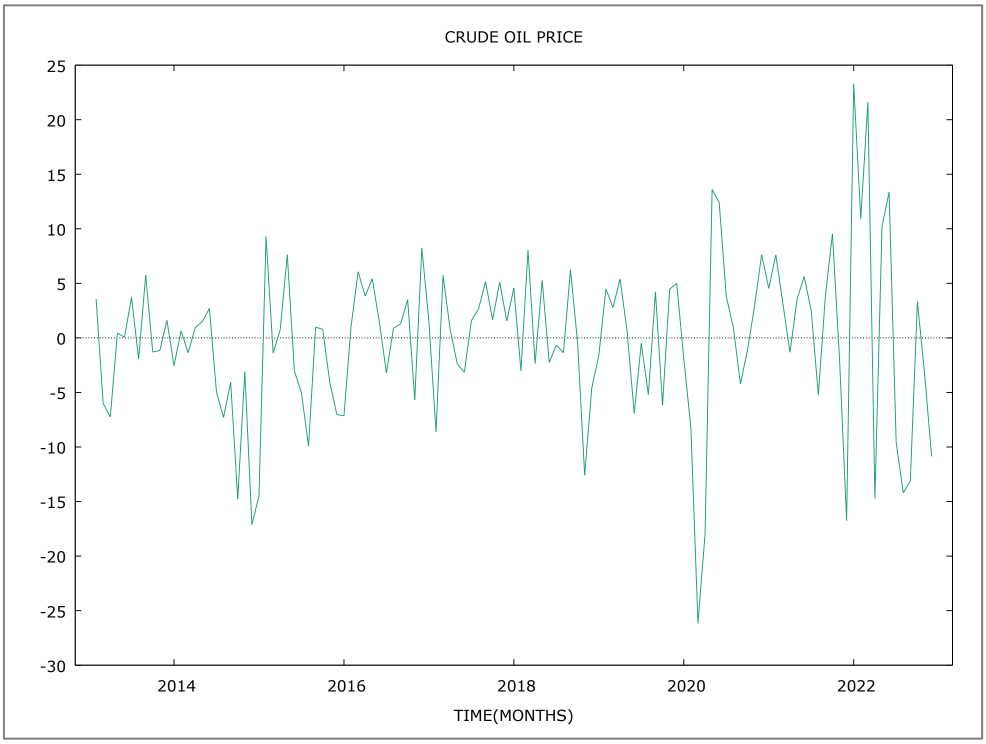

Figure 3: The graph of the first differences of the series

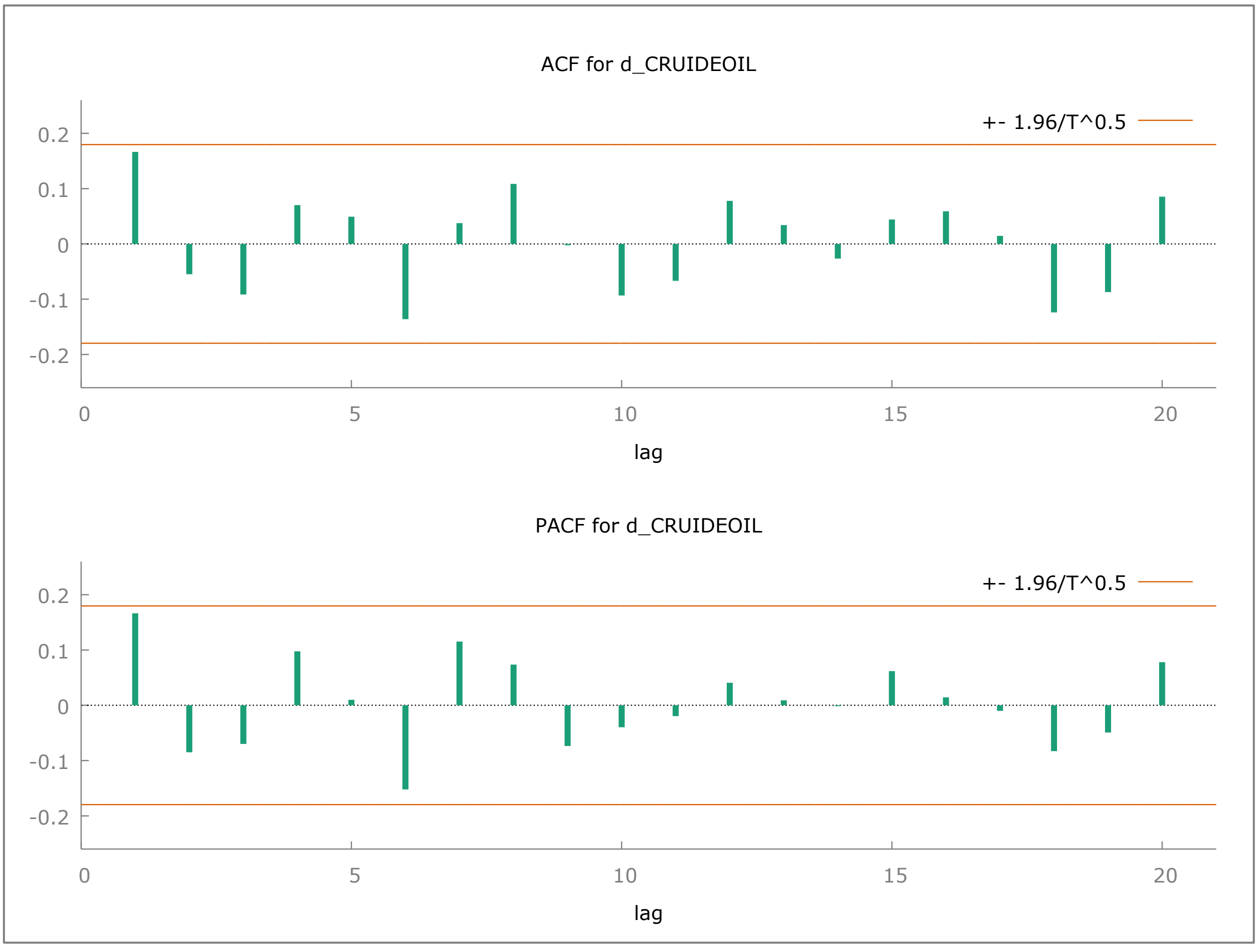

Figure 4: ACF and PACF first differenced series

Table 2 KPSS and ADF tests of monthly Crude oil price

Test	**Without Trend**		**With Trend**	
KPSS	**Test statistic**	**Critical value**	**Test statistic**	**Critical value**
	0.0271148	1% 5% 10% 0.735 0.465 0.349	0.0255169	1% 5% 10% 0.216 0.148 0.120
ADF	**Constant**		**Constant + Trend**	
	Test statistic	**P-value**	**Test statistic**	**P- value**
	-4.25599	0.0005243	-4.23682	0.003872

Table 3: Model Identification

MODEL	**AIC**	**HQIC**	**BIC**
ARIMA (1,1,1)	**821.4739**	**825.9879**	**832.590**
ARIMA(1,1,2)	823.2037	828.8462	837.099
ARIMA(2,1,1)	822.8189	828.4615	836.714
ARIMA(2,1,2)	819.5623	826.3333	836.237
ARIMA(3,1,1)	823.9764	829.4523	840.651
ARIMA(3,1,2)	821.5527	828.7679	841.006

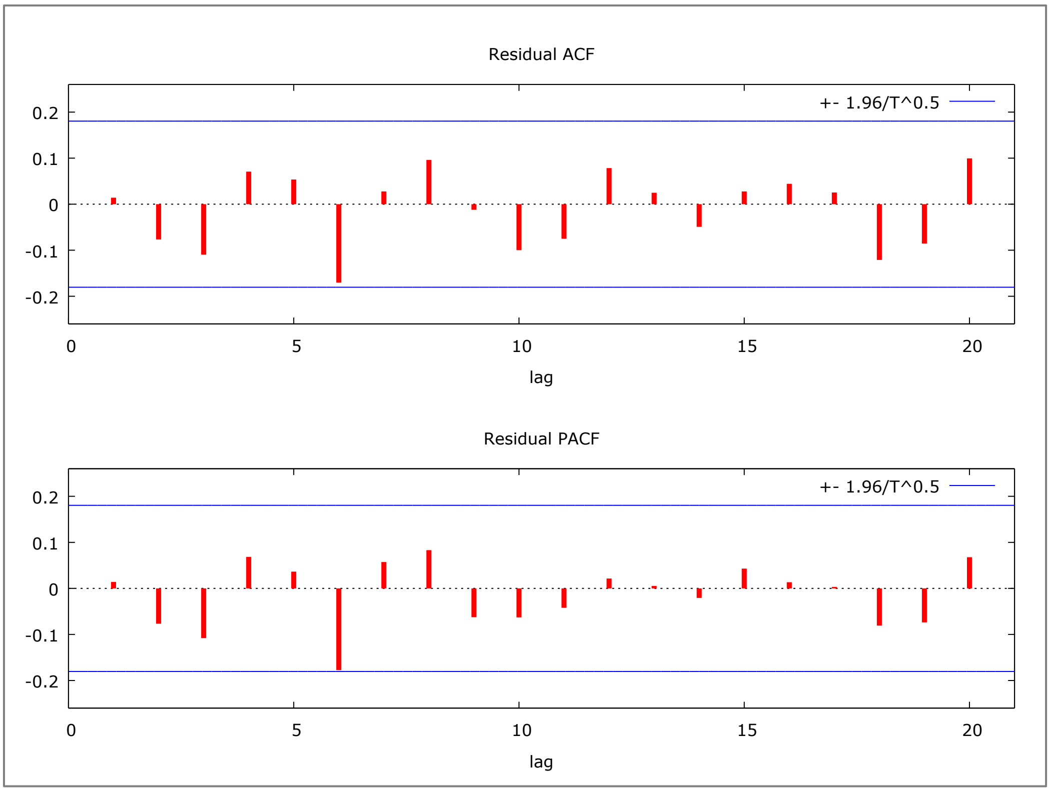

Figure 5: The Residual ACF and PACF of ARIMA (1,1,1) model

Table 4: Ljung-Box Test and ARCH-LM Test of ARIMA (1, 1, 1) Model for CLIOBAS

Model	Lag	Ljung-Box Test		ARCH-LM Test	
		Test statistic	P-value	Test Statistic	P-value
ARIMA (1,1,1)	12	6.1295	0.909	8.85371	0.715372
ARIMA (1,1,1)	24	20.0956	0.691	21.7308	0.595329
ARIMA (1,1,1)	36	30.1716	0.742	25.6552	0.899689
ARIMA (1,1,1)	48	40.245	0.864	35.5599	0.908234

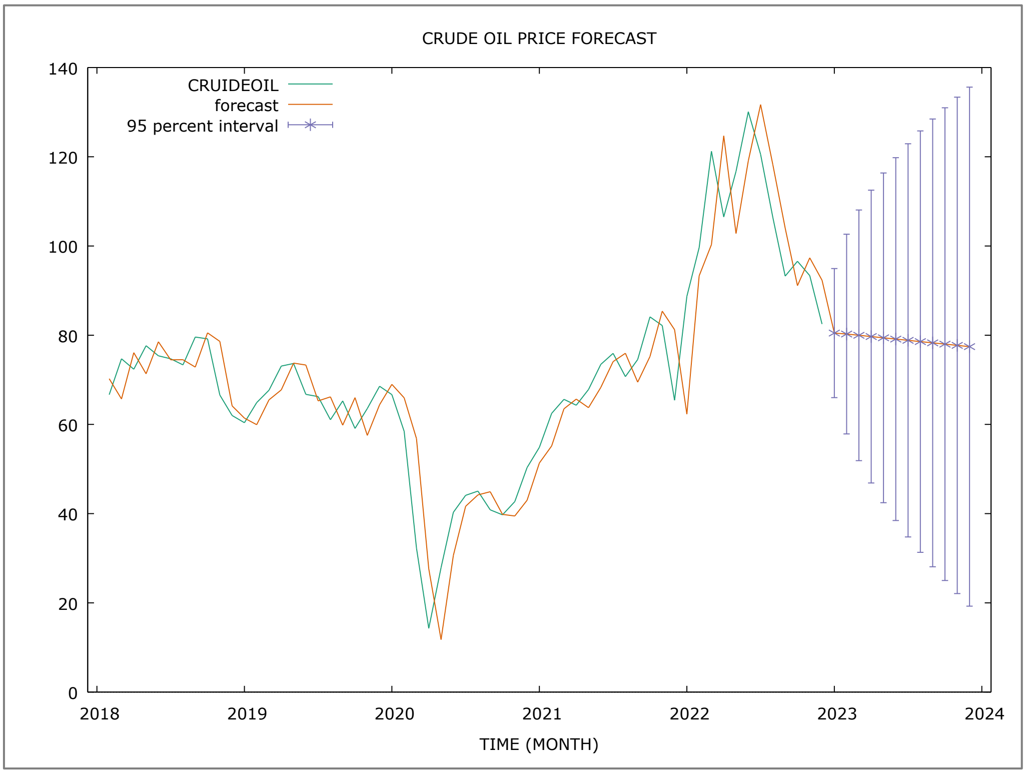

Figure 6: Graph for actual, fitted, and forecasted values using the selected model

Table 5: Months forecasted values for the Crude Oil ARIMA (1, 1, 1) (for 95% CI, z(0.025) = 1.96)

TIME	Prediction	std. error	95% interval
2021:01	80.4750	7.38076	(66.0090, 94.9411)
2021:02	80.2611	11.4194	(57.8795, 102.643)
2021:03	79.9762	14.3325	(51.8850, 108.067)
2021:04	79.6940	16.7474	(46.8698, 112.518)
2021:05	79.4118	18.8554	(42.4558, 116.368)
2021:06	79.1295	20.7504	(38.4595, 119.800)
2021:07	78.8472	22.4862	(34.7750, 122.919)
2021:08	78.5650	24.0974	(31.3350, 125.795)
2021:09	78.2827	25.6073	(28.0933, 128.472)
2021:10	78.0005	27.0331	(25.0166, 130.984)
2021:11	77.7182	28.3873	(22.0801, 133.356)
2021:12	77.4360	29.6799	(19.2645, 135.607)

DISCUSSION

The data was differenced once in order to achieve stationary, being one of the requirements for a befitting model. ARIMA (1, 1, 1) model satisfies the best fit as having the smallest values of the AIC, BIC and HQIC in relation to the other competing models. This was in agreement with the results of Acha et al. (2023), while Suleiman et al. (2015) and Mujtala (2023) reported an ARIMA (3,1,1) model as most appropriate. ARIMA (0, 1, 1) model was found to be the best model for forecasting crude Oil prices (Gasper et al 2023).

The ARIMA (1, 1, 1) model's superiority was supported by residual diagnostics, which indicate no significant autocorrelations as indicated in Figure 5 above and are in line with the theory of parsimony (i.e., keep it simple). However, the model's performance should be compared with other advanced techniques like ARIMA-GARCH or machine learning models to assess its robustness. In a study by Suleman (2015), it was suggested that the hybrid model of ARIMA and GARCH was the best model for oil price data. However, we observed that the forecasting ability of ARIMA models is still better as it indicated a decline in the oil price.

The model adequacy test revealed that the residuals do not deviate from the white noise assumption. Since the assumption for a good model is that the residuals must follow a white noise process, that is, if the model fits the data well, the residuals are expected to be random, independent, and identically distributed following the normal distribution (Bollerslev et al., 1992); Muhammad et al., 2002 and Ngailo E. 2011). There is no ARCH effect in the residuals on the selected model.

Forecasting provides a basis for economic and business planning, inventory and production control, and optimization of industrial processes, as described by Box and Jenkins (1976)

CONCLUSION

The study is on Modeling and forecasting of monthly crude oil prices in Nigeria an ARIMA techniques. From the results obtained and presented in the preceding sections, ARIMA (1, 1, 1) was the best-selected model for crude oil prices, being the one with the smallest of the information criteria and insignificant autocorrelations. Therefore, the study concludes that while ARIMA models are effective for short-term forecasting, their limitations, such as sensitivity to non-stationary data, suggest that future research should incorporate macroeconomic variables or hybrid models for improved accuracy, as reported in a study by Suleiman et al, 2015, Alrweili1 and Fawzy 2022, Aamir and Shabri 2016, Mombeini and Chamzini 2014. The study strongly recommended that a more sustained effort should be on to keep the sector buoyant and attractive to investors for more revenue generation for both government and investors. The oil sector stakeholders in Nigeria should explore other avenues in the sector, such as liquefied Natural Gas (LNG), in order to absorb the decrease in revenue as a result of the decline in revenue from crude oil sales.

REFERENCES

Aamir A. and Shabri A. (2016) Modelling and Forecasting Monthly Crude Oil Price of Pakistan: A Comparative Study of ARIMA, GARCH and ARIMA. **[Crossref]**

Acha C. K., Amalahu C.C. and Ezilkwu C. E. (2023): Modeling and Forecasting of Nigeria Crude Oil Production. *Journal of Mathematics and Statistics Studies 4(1):58-67*. **[Crossref]**

Adegboye, R. (2023): ARIMA modeling Oil prices for Nigeria. *Journal of Management and Social Sciences, 6, 364-349*.

Adeniran, M. A., & Ajilore, O. T. (2016). Forecasting Crude Oil Price for the Next 6 Months: A Case of ARIMA Model. *Journal of Economics and Sustainable Development*, 7(2), 92-98.

Adewuyi, A. O., & Akanbi, A. (2016). Dynamics of crude oil prices in Nigeria: An ARIMA analysis. *Journal of Applied Sciences,* 16(4), 190-195. Akram, Q. F., & Zhang, L. (2014). Oil price fluctuations and Saudi Arabia's economy. *Economic Modelling*, 38, 215-234.

Ahmed, R. A., & Shabri, A. Bin. (2014). Daily crude oil price forecasting model using arima, generalized autoregressive conditional heteroscedastic and Support Vector Machines. *American Journal of Applied Sciences*, *11* (3), 425–432. **[Crossref]**

Akaike H. (1969): fitting autoregressive models for prediction. *Annals of the Institute of statistical Mathematics* 21, 243-247. **[Crossref]**

Akram, Q. F., & Zhang, L. (2014). Oil price fluctuations and Saudi Arabia's economy. *Economic Modelling*, 38, 215-234. Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). *Time series analysis: forecasting and control*. John Wiley & Sons.

Alrweili H and Fawzy H (2022): forecasting Crude Oil Prices Using an ARIMA-ANN Hybrid Model. J. Stat. Appl. Pro. 11, No. 3, 845- 855 (2022). **[Crossref]**

Bollerslev T., Chou R. Y, Kroner K F (1992) Arch Modeling in Finance: Review of The Theory and Empirical Evidence; *Journal of Econometrics* vol. 52(1-2). **[Crossref]**

Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). *Time series analysis: forecasting and control*. John Wiley & Sons.

Brooks, C. (2014). Introductory econometrics for finance. Cambridge University Press. **[Crossref]**

Caporin, M., & Pelizzon, L. (2006). Volatility spillovers, comovements and market interdependencies. *The European Journal of Finance*, 12(6-7), 537-557. Hyndman, R. J., & Athanasopoulos, G. (2018). *Forecasting: principles and practice*. OTexts.

Dickey, D. A., and Fuller, W. A. (1979), „Distribution of the Estimators for Autoregressive Time Series with a Unit Root", *Journal of the American Statistical Association,* 74, 427–31. **[Crossref]**

Gasper L. H. M. (2023): Forecasting Crude Oil Prices By Using ARIMA Model: Evidence From Tanzania. *Journal of Accounting, Finance and Auditing Studies 9/2 (2023): 158-175.* **[Crossref]**

Hannan e. j. and Quinn b. g. (1979); determination of the order of an Autoregression. *Journal of the Royal Statistical Society, Series B, 41.* **[Crossref]**

Laban Gaspera Haika Mbwambo (2023): Forecasting Crude Oil Prices By Using ARIMA Model: Evidence From Tanzania. *Journal of Accounting, Finance and Auditing Studies 9/2 (2023): 158-175.* **[Crossref]**

Mombeini H. Yazdani-Chamzini A. (2014): Developing a new approach for forecasting the trends of oil price. *The Business & Management Review*, Volume 4 Number 3. **[Crossref]**

Muhammad Aamir and Ani Shabri(2016) Modelling and Forecasting Monthly Crude Oil Price of Pakistan: A Comparative Study of ARIMA, GARCH and ARIMA Kalman Model. *Advances in Industrial and Applied Mathematics* AIP Conf. Proc. 1750, 060015-1–060015-7; Published by AIP Publishing. 978-0-7354-1407-5/$30.00. **[Crossref]**

Mujtaba Suleiman, Isah Muhammad, Adamu Zakar Adamu, Yahaya Zakari, Rufai Ali Muhammad, Ibrahim Adamu and Mannir Abdu (2023) "Modelling Nigeria Crude Oil Prices using ARIMA Time Series Models" NIPES *Journal of Science and Technology Research* 5(1), pp.230-241, ISSN-2682-582

Ng'ang'a, F. W., & Oleche, M. (2022). Modelling and Forecasting of Crude Oil Price Volatility Comparative Analysis of Volatility Models. *Journal of Financial Risk Management*, *11* (01), 154–187. **[Crossref]**

Ngailo, E. (2011). Modelling and Forecasting using time series GARCH models: An Application of Tanzania inflation rate data. (Unpublished Master's Thesis). University of Dares Salaam.

Oladosun, M., & Kolawole, M. (2019). Short-term forecasting of the dynamics of crude oil prices in Nigeria using ARIMA model. *Cogent Economics & Finance*, 7(1), 1554539.

Olanipekun, A. E., & Olusola, O. (2018). Modeling volatility of crude oil price using ARIMA-GARCH models. *Energy Exploration & Exploitation,* 36(1), 83-101.

Olowe, R. A., & Fasanya, I. O. (2020). Application of ARIMA Model in Long-Term Trend Analysis of Crude Oil Prices in Nigeria. *International Journal of Economics and Financial Issues*, 10(1), 7-16.

Oloyede, J.A., Obadiaru, D.E., Omankhanlen, A.E., Asaleye, A.J. (2018), Stock market volatility spillover in West Africa: Regional and global perspectives. Journal of Applied Economic Sciences, 6(60), 1597-1604.

Olukosi, J. O., Yusuf, A., & Ogunleye, O. O. (2020). Volatility Forecast of Crude Oil Price in Nigeria using ARIMA and ARCH Family Models. *Journal of Mathematical Finance*, 10(1), 1-18.

Papapetrou, E. (2001). Oil price and the dollar. Energy Economics, 23(2), 213-233.

Saad, W., & Tahat, B. (2018). Forecasting crude oil prices using a combination of stochastic and neural network models. *Energy Economics*, 74, 64-71. **[Crossref]**

Schwarz G. (1978); Estimating The Dimension of a Model. *The Annals of Statistics vol. 6(2).* **[Crossref]**

Suleiman, S., Usman, U., & Adamu, U. (2015). Modelling and Forecasting the Crude Oil Price in Nigeria. *International Journal of Novel Research in Marketing Management and Economics*, *2*(1), 1–13. Available at: **www.noveltyjournals.com**