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ARIMA-based forecasting of Nigerian crude oil prices (2006–2023): Long-term dynamics, optimal model selection, and policy implications

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Abstract

The purpose of this study is to investigate Nigerian monthly crude oil prices from 2006 to 2023 using the Autoregressive Integrated Moving Average (ARIMA) model in order to provide reliable forecasts for fiscal and economic planning. Crude oil remains central to Nigeria's economy, and its unstable price patterns have significant implications for government budgeting, revenue generation, and long-term policy design. The study employs monthly price data sourced from the National Bureau of Statistics. Preliminary inspection of the series revealed sharp fluctuations without a clear long-term direction. The Augmented Dickey-Fuller test confirmed that the series was non-stationary at the level but became stationary after first differencing. Autocorrelation and partial autocorrelation plots suggested three possible models: ARIMA (0,1,1), ARIMA (1,1,0), and ARIMA (1,1,1). Model performance was compared using AIC, AICc, and BIC values, and further validated with residual diagnostics. The findings indicate that ARIMA (1,1,0) is the best-fitting model, showing that present changes in oil prices are strongly linked to immediate past changes, which reflects the short-term memory property of the oil market. Forecasts from the model point to moderate price stability around US$90–95 per barrel in the near term, though widening confidence intervals highlight rising uncertainty over longer horizons. The practical implication is that accurate short-term forecasts can guide budgetary and fiscal policies in Nigeria and other oil-dependent economies, while underscoring the importance of diversifying revenue sources to reduce vulnerability to oil price shocks.

Keywords: ARIMA, economic policy, energy economics, forecasting, model selection, Nigerian crude oil, price volatility, statistical computing, time series analysis.

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Contents

Contribution of this paper to the literature
This study contributes to the existing literature by modeling Nigerian crude oil prices with ARIMA over a long span (2006–2023). The paper's primary contribution is identifying ARIMA (1,1,0) as the best fit, documenting its accuracy in forecasting long-term price dynamics relevant for economic planning and policy decisions.

1. Introduction

Forecasting crude oil prices has become a major research focus because of their central influence on energy security, government budgeting, and overall macroeconomic performance. In highly oil-dependent economies like Nigeria, where petroleum exports dominate fiscal revenue, reliable forecasting is not only a statistical task but also an essential tool for effective economic management. Researchers have increasingly applied time-series models to this problem, with the ARIMA framework emerging as one of the most widely adopted approaches [1].

As Africa's largest oil producer and one of the world's top exporters, Nigeria, being the largest oil producer in Africa and among the major exporters worldwide, is especially vulnerable to fluctuations in international crude oil markets. Oil exports account for most government revenues and foreign exchange earnings, meaning price shocks directly affect fiscal budgets, debt servicing, and macroeconomic stability [2, 3]. Unlike more diversified economies, Nigeria has limited protection against external shocks, which makes dependable oil price forecasting vital for sound economic policy and planning [4].

Recent studies demonstrate the effectiveness of ARIMA and its extensions in modelling Nigerian crude oil price dynamics. Ngome [5], for instance, applied an ARIMA–GARCH model using monthly data from 2010 to 2021 and found that an ARIMA (2,0,5)–GARCH (1,4) model best captured volatility patterns. Similarly, Chamalwa et al. [6] reported that ARIMA (1,1,1) provided reliable short-term forecasts for data spanning 2013 to 2022, though they noted limitations in capturing broader macroeconomic shocks. These findings underscore the flexibility of ARIMA models but also point to the need for model selection tailored to the characteristics of each dataset.

While the literature provides valuable insights, most studies remain constrained by relatively narrow timeframes, limiting forecasts' robustness. For example, Suleiman et al. [1] based their analysis on data from 2006 to 2020, while Chamalwa et al. [6] focused on observations taken in less than a decade. Extending the dataset enhances the model's ability to capture long-term trends, cyclical fluctuations, and structural shifts in oil pricing. This study distinguishes itself by employing an extended dataset covering January 2006 to August 2023, providing nearly two decades of evidence for robust model identification and forecasting.

Equally important is the methodological rigor applied to ARIMA model selection. Identifying the best-fitting specification requires more than trial and error; it demands systematic application of stationarity tests, autocorrelation diagnostics, and information criteria such as AIC, AICc, and BIC. Moreover, the adequacy of the chosen model must be validated through residual analysis and statistical tests like the Box–Ljung test to ensure independence and randomness in forecast errors. Such a rigorous process strengthens confidence in the resulting forecasts and distinguishes empirical modelling from speculative prediction.

The present study employs a comprehensive framework to evaluate Nigerian crude oil price dynamics and forecasting potential. By applying ARIMA to nearly 18 years of monthly data, the analysis identifies the optimal model, assesses its adequacy, and generates forecasts of crude oil prices. The findings indicate that ARIMA (1,1,0) is the most suitable specification, capturing the stochastic properties of the series while producing stable and interpretable forecasts. The results suggest that Nigerian crude oil prices will hover around USD 93 per barrel in the near term, within a defined confidence interval, thereby providing practical insights into likely price movements.

Beyond statistical accuracy, the implications of this research extend to policy and economic planning. For Nigeria, where budgetary allocations and debt servicing are heavily tied to oil revenue, reliable forecasts can guide fiscal decisions, mitigate the risks of revenue shortfalls, and improve long-term planning. The study, therefore, contributes to the statistical literature on time-series forecasting and the broader discourse on economic resilience in resource-dependent nations.

Despite these contributions, key gaps remain in the literature. Many studies focus on shorter time spans, typically under a decade, limiting the ability to capture long-term structural changes in oil price behavior [1, 6].

Ngome [5] applied ARIMA–GARCH models and highlighted volatility persistence in Nigerian crude oil prices, while Suleiman et al. [1] concluded that ARIMA (1,1,1) offered better forecasting accuracy. Similarly, Chamalwa et al. [6] used recent data and identified ARIMA (2,1,1) as the most effective model. These studies confirm the suitability of ARIMA for modeling Nigerian crude oil prices but show that the optimal specification varies with the sample period, data frequency, and diagnostic approach.

Building on these contributions, the present study analyzes monthly Nigerian crude oil prices over an extended period from January 2006 to August 2023. This dataset captures multiple global and domestic shocks, including the 2008 financial crisis, the 2014 oil price crash, and the COVID-19 pandemic. The analysis follows the Box–Jenkins methodology, applying stationarity tests, autocorrelation (ACF and PACF) analysis, and information criteria (AIC, AICc, and BIC) for model identification. Residual diagnostics, including the Box–Ljung test, are further employed to validate model adequacy and ensure reliable forecasts [7, 8].

Unlike earlier works that often focused on short time spans, applied limited diagnostics, or overlooked policy implications [1, 5], this study not only identifies the most appropriate ARIMA specification but also emphasizes its policy relevance for Nigeria's fiscal and economic planning.

Therefore, this study aims to model and forecast Nigerian crude oil prices using ARIMA models. The specific objectives are to:

To analyze the historical trend and volatility of Nigerian monthly crude oil prices.

To test the series for stationarity and ensure robustness through formal statistical tests.

Identify and fit the most suitable ARIMA model for forecasting crude oil prices.

To evaluate the policy and economic implications of the best-fitting model for Nigeria's budgeting, fiscal management, and energy planning.

This paper is structured as follows: Section 2.2 presents the Materials and Methods. Section 2.2.1 introduces the Autoregressive Integrated Moving Average (ARIMA) model, while Section 2.2.2 describes the ARIMA model and estimation. Section 2.3 discusses the ACF and PACF plots. Section 2.4 outlines the Akaike Information Criterion (AIC), while Section 2.5 introduces the Bayesian Information Criterion (BIC). Section 2.6 presents model estimation and accuracy, where Section 2.6.1 discusses the Mean Squared Error (MSE), Section 2.6.2 the Root Mean Square Error (RMSE), Section 2.6.3 the Mean Percentage Error (MPE), Section 2.6.4 the Mean Absolute Percentage Error (MAPE), Section 2.6.5 diagnostic checking, Section 2.6.6 the Ljung-Box Q-Test, and Section 2.6.7 forecasting.

Section 3.1 provides an introduction. Section 3.2 presents the data and descriptive statistics. Section 3.3 shows the time plot, while Section 3.4 presents the stationarity test. Section 3.5 evaluates model adequacy based on residual diagnostics. Section 3.6 presents the forecasting results, and Section 3.7 shows the plot.

Finally, Section 4.1 summarizes the study. Section 4.2 concludes, and Section 4.3 provides recommendations.

2. Materials and Methods

ARIMA modeling was chosen due to its strong performance in modeling non-stationary univariate economic and financial time series [7, 8]. While other models such as VAR, ARDL, and GARCH could be applied, ARIMA provides a parsimonious and well-established framework suitable for short-term forecasting.

The dataset spans 2006–2023, representing the most recent and reliable record of Nigerian crude oil prices, capturing periods of stability and volatility.

2.1. Autoregressive Integrated Moving Average (ARIMA)

ARIMA models are widely applied in time series forecasting because they can accommodate both stationary and non-stationary data. A non-stationary series can be made stationary through differencing or, when necessary, by applying transformations such as logging or deflating. A stationary series is characterized by stable statistical properties: no persistent trend, constant variation around the mean, and repeating patterns over time. In such a series, correlations with past values and variability remain consistent. It can therefore be viewed as a combination of signal and noise, where the signal may exhibit mean reversion, cycles, alternating movements, or seasonal effects.

2.2. ARIMA Model and Estimation

Box and Jenkins are the pioneers of the ARIMA model, which is why it is referred to as the Box and Jenkins [7] methodology, but in time series literature, it is known as the ARIMA methodology. The ARIMA models allow Y_t for explanation by the past, or lagged, values of Y_t the series and stochastic error terms. The ARIMA (p, d, q) model is a combination of the AR and MA models, whose difference is given as:

$$y_t = \alpha + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_p \varepsilon_{t-p} + \varepsilon_t \quad (1)$$

y_t is the value of the time series at time t.

α is a constant term (intercept).

$\phi_1,, \ldots, \phi_p$ are the autoregressive parameters representing the relationship between the current observation and its lagged values.

$\theta_1, \theta_2, \ldots, \theta_q$ are the moving average parameters representing the relationship between the current observation and the q lagged forecast errors (Residuals)?

ε_t is the error term at time t, assumed to be white noise (independent and identically distributed with mean zero and constant variance).

So, in general, the equation for an ARIMA model with d differences can be represented as:

$$(1-L)^d y_t = \alpha + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_p \varepsilon_{t-p} + \varepsilon_t \quad (2)$$

Where L is the lag operator such that $(L)^d y_t = y_{t-d}$

2.3. ACF and PACF Plot

The Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) are fundamental tools in time series analysis and forecasting. They provide a visual summary of how current values in a series relate to their past lags. The ACF measures the overall correlation between a series and its lagged values, reflecting influences from trend, seasonality, cycles, and random noise. An ACF plot displays these correlations with confidence bands, showing how strongly past values affect present behavior. The PACF, by contrast, isolates the direct correlation at each lag by removing the effects of intermediate lags. Thus, while the ACF captures total correlations across all lags, the PACF highlights the unique contribution of each lag.

2.4. Akaike Information Criteria (AIC)

Akaike Information Criterion (AIC) is the most widely used information criterion for predictive modeling. It compares the quality of a set of statistical models to each other. The basic formula for AIC is defined as:

$$\text{AIC: } 2k - 2\ln(L) \quad (3)$$

Where:

K is the number of model parameters.

Ln (L) is a measure of model fit. The higher the value, the better the fit. This is usually obtained from statistical output.

2.5. Bayesian Information Criteria

Bayesian information criterion (BIC) is a criterion for model selection among a finite set of models. It is based, in part, on the likelihood function, and it is closely related to the Akaike information criterion (AIC).

When fitting models, it is possible to increase the likelihood by adding parameters, but doing so may result in overfitting. The BIC addresses this issue by introducing a penalty term for the number of parameters in the model. The penalty term in BIC is larger than in AIC.

BIC has been widely used for model identification in time series and linear regression. It can, however, be applied quite broadly to any set of maximum likelihood-based models. BIC can be defined mathematically as follows:

$$BIC = in(n)k - 2\ln(\hat{L}) \quad (4)$$

$\hat{L}$ is the maximized value of the likelihood function of the model.
n is the number of data points.
k is the number of free parameters to be estimated.

2.6. Model Estimation and Model Accuracy

The estimation procedure involves using the model with p, d, and q orders to fit the actual time series. The phi and thetas of the selected model are estimated using maximum likelihood techniques, backcasting, etc. The maximum likelihood equation is solved by nonlinear function maximization. Backcasting is used to obtain estimates of the initial residuals.

2.6.1. Mean Squared Error (MSE)

The mean squared error is a measure of how close a fitted line is to the data points. It does this by taking the distances from the points to the regression line and squaring them. The square is done in order to remove any negative signs. A larger MSE means that the data values are dispersed widely around their central moment (mean), and a smaller MSE means otherwise. A smaller MSE is preferred and the desired choice as it shows that data values are dispersed closely to their central moment. The formula for computing MSE is given as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \quad (5)$$

MSE = Mean squared error.
n = Number of data points.
Y_i = Observed values.
$\hat{Y}_i$ = Predicted values.

2.6.2. Root Mean Square Error (RMSE)

The root mean square error is the standard deviation of the residuals. Residuals are a measure of how far from the regression line data points are; RMSE is a measure of how spread out these residuals are. In other words, root mean square error is the square root of the mean of the squares of all the errors. A larger RMSE means that the data values are dispersed widely around their central moment (mean), and a smaller RMSE means otherwise. In this case, a smaller value is always a desirable choice. The RMSE formula is given as:

$$\mathrm{R}MSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2} \quad (6)$$

2.6.3. Mean Percentage Error (MPE)

The mean percentage error in the entire series is a general measure of fit useful for comparing the fits of different models. This measure sums all of the percentage errors at each time point and divides by the number of time points. The formula is given as:

$$MPE = \frac{100}{n}\sum_{t=1}^{n}\frac{x_t - f_t}{x_t} \quad (7)$$

2.6.4. Mean Absolute Percentage Error (MAPE)

The mean absolute percentage error is a statistical measure of how accurate a forecast system is. It measures the accuracy as a percentage and can be calculated as the average of the absolute percentage errors for each time period, which is the difference between forecasted and actual values divided by the actual values. It is expressed as:

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{x_t - f_t}{x_t}\right| \quad (8)$$

x_t = Observed value.
f_t = Predicted value.
n = Number of data points.

2.6.5. Diagnostic Checking

Once a model has been fit, the final step is the diagnostic checking of the model. The checking is carried out by studying the autocorrelation plots of the residuals to see if further structure (large correlation values) can be found. If all the autocorrelations and partial autocorrelations are small, the model is considered adequate, and forecasts are generated. If some of the autocorrelations are large, the values of p and/or q are adjusted, and the model is re-estimated.

2.6.6. Ljung-Box Q-Test

This test is a portmanteau test which assesses the null hypothesis that there is an absence of serial correlation in the residuals for a fixed number of lags L, against the alternative hypothesis that some autocorrelation coefficient $\rho(k)$, $k=1, \ldots, L$, is nonzero.

The test statistic is

$$Q = T(T+2)\sum k = 1L\big(\rho(k)2(T-k)\big) \quad (9)$$

Where
T = Sample size.
L = Number of autocorrelation lags.
$\rho(k)$ = Sample autocorrelation at lag k.

2.6.7. Forecasting

Forecasting assesses the performance of the fitted model against the real dataset. There is an option to split the time series data into two parts, where the first part is considered the training set used to fit the model, and the second part is considered the test set used to evaluate the model's performance.

3. Results

This chapter contains the statistical analysis of the price of Nigerian crude oil, US$, using the time series approach to draw value insights from the dataset. The data is presented below in Table 1.

3.1. Data Presentation

This section presents the monthly Nigerian crude oil prices (in US dollars per barrel) from 2006 to 2023. The dataset covers periods of significant fluctuations, including sharp increases, sudden declines, and prolonged volatility. These variations reflect the impact of both global and domestic economic events on oil prices. The detailed yearly breakdown is displayed in Table 1.

Table 1. Monthly Nigerian crude oil prices (US$/Barrel), 2006–2023.

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2006	63.85	61.33	65	72.09	71.18	69.32	75.13	75.15	62.97	59.49	59.81	64.7
2007	55.57	59.97	64.28	70.46	70.4	73.28	79.76	73.76	79.76	83.86	95.05	93.4
2008	94.26	98.15	103.73	116.73	126.57	138.74	137.74	115.84	103.82	75.31	55.51	45.87
2009	44.95	46.52	49.7	51.16	60.02	72.24	66.52	74	70.22	78.25	78.11	75.11
2010	77.62	75.06	80.27	85.29	77.54	75.79	77.18	78.67	79.45	84.42	86.71	92.79
2011	97.96	106.57	116.56	124.49	118.43	117.03	117.86	111.99	115.73	113.12	113.92	111.46
2012	113.81	121.87	128	122.62	113.08	98.06	104.62	113.76	114.36	108.92	111.05	114.49
2013	115.24	118.81	112.79	105.55	106	106.06	109.78	107.84	113.59	112.29	111.14	112.75
2014	110.19	110.83	109.47	110.41	111.9	114.6	109.63	102.33	98.27	83.5	80.42	63.28
2015	48.81	58.09	56.69	57.45	65.08	62.06	57.01	47.09	48.08	48.86	44.82	37.8
2016	30.66	31.7	37.76	41.59	47.01	48.46	45.25	46.15	47.43	50.94	45.25	53.48
2017	55.01	46.39	52.13	52.94	50.57	47.42	49.01	51.64	56.79	58.46	63.56	65.11
2018	69.68	66.67	74.72	72.37	77.64	75.38	74.72	73.35	79.59	79.18	66.59	62
2019	60.39	64.89	67.67	73.08	73.65	66.74	66.24	61.05	65.27	59.1	63.56	68.56
2020	66.68	58.45	32.29	14.28	27.9	40.3	44.1	45.06	40.85	39.74	42.7	50.33
2021	54.87	62.48	65.62	64.3	67.83	73.46	75.93	70.72	74.55	84.11	82.16	65.41
2022	88.71	99.64	121.23	106.51	116.72	130.1	120.54	106.34	93.25	96.57	93.36	82.5
2023	84.78	86.04	81.1	76.91	76.97	82.27	89.3	98.16	94.9			

Source: National Bureau of Statistics (Online).

Interpretation: Figure 1 illustrates the descriptive statistics of Nigerian monthly crude oil prices for the period under review. The mean price of 78.660 USD per barrel provides the central value of the series, while the standard deviation of 25.900 indicates high volatility around the mean. The skewness of –0.110 reveals a slight leftward tilt, suggesting price declines occurred more frequently than upward spikes. The excess kurtosis of –0.740 shows a distribution flatter than normal, implying fewer extreme shocks than expected. Together, these characteristics confirm the unstable nature of crude oil prices and justify the use of time series methods such as ARIMA for further analysis.

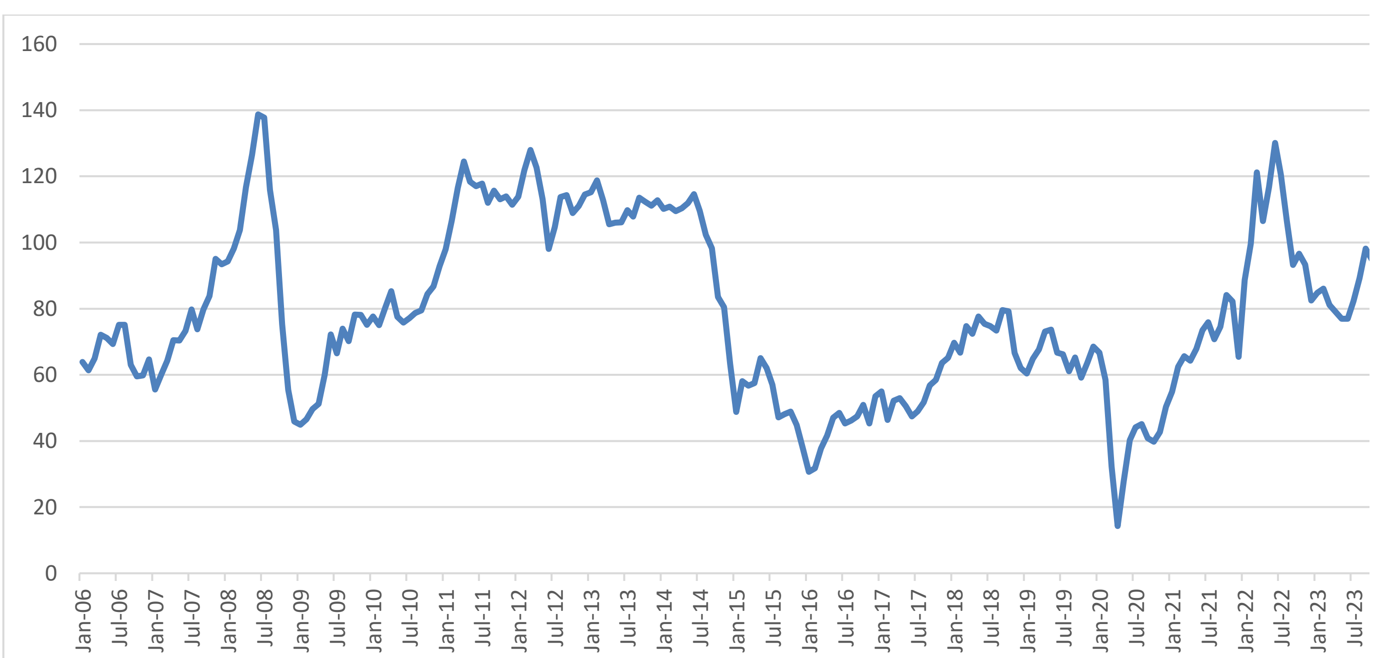

Figure 1. Time plot of the price of Nigerian crude oil, US$.

3.2. Time Plot

Interpretation: Figure 1 illustrates the trend of Nigerian crude oil prices from 2006 to 2023, showing pronounced fluctuations without a consistent long-term pattern. The plot reveals sharp rises, such as the peak in mid-2008, followed by a sudden decline during the global financial crisis in 2009. Subsequent years display repeated cycles of increases and declines, reflecting the volatile nature of the oil market. This instability confirms the presence of randomness and short-term shocks in the series, thereby justifying the use of time-series models such as ARIMA for forecasting.

3.3. Stationary Test

Following the time plot, it is important to verify whether the mean and variance generating the series do not vary with time (stationarity). The Dickey-Fuller test was employed to verify this, and the results are shown in the Table 2.

H_0 : Stationery=0.

H_1: Stationery≠0.

Table 2. Augmented Dickey-Fuller Test Results.

Variable	t-statistic	Lag	p-value
Level (Observed)	-2.8099	5	0.2364
First difference	-6.8309	5	0.01

Interpretation: The Augmented Dickey-Fuller Test with a statistic value of -2.872 and a p-value of 0.1997 implies that we do not reject the null hypothesis, which suggests that the series is not stationary. The conclusion following the test result indicates that the series is not stationary at the level. The series was differenced once to attain stationarity, followed by the Dickey-Fuller test on the differenced series. The p-value for the ADF statistic for the first difference series (0.01) is less than α=0.05, thus we reject the null hypothesis and conclude that the series is stationary after first differencing.

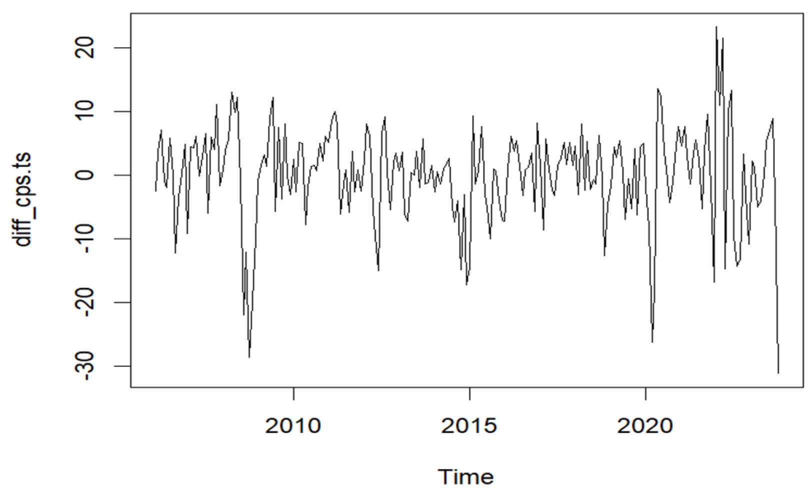

Figure 2. First-order differencing on the Price of Nigerian crude oil, US$.

Interpretation: Figure 2 shows the time plot of the price of Nigerian crude oil in US dollars after first differencing. It is well observed from the plot that no trend or seasonal component can be observed in the series; thus, the mean and variance generating the series do not vary with time after first differencing.

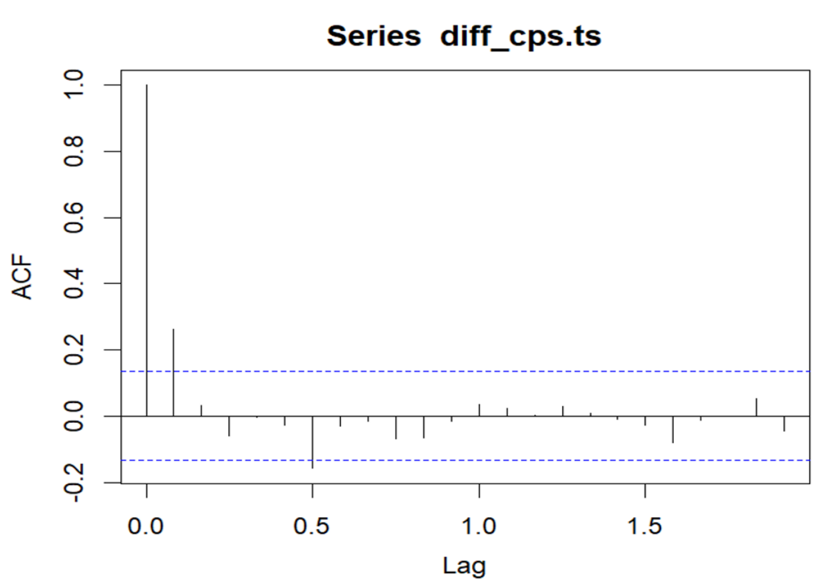

Figure 3. Autocorrelation function (ACF) plot.

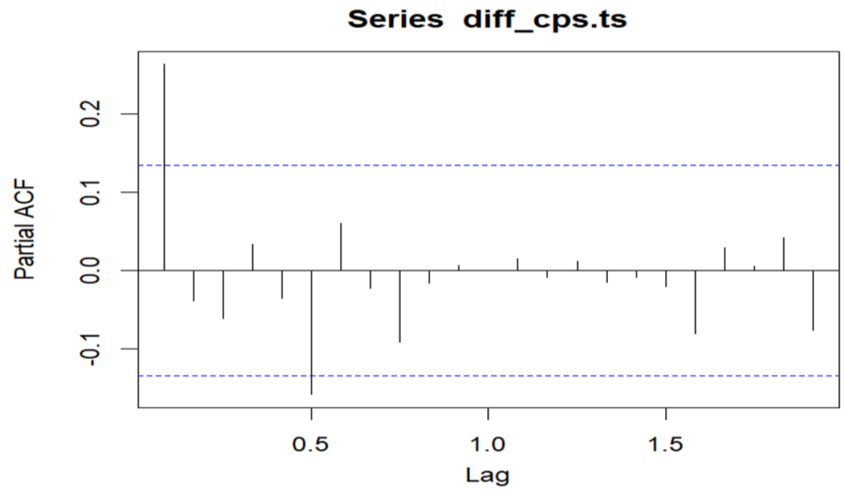

Figure 4. Partial autocorrelation function (ACF) Plot.

Interpretation: Figure 3 and Figure 4 show the ACF and PACF plots, respectively. Based on the plots, the ACF shows a cut-off, suggesting an MA model of order 1, while the PACF suggests an AR of order 0. Thus, the following models were considered: ARIMA (0,1,1); ARIMA (1,1,0), and ARIMA (1,1,1).

Table 3. Information criteria based on the suggested models.

Models	AIC	AICc	BIC
ARIMA (1,1,0)	1437.92	1437.98	1444.64
ARIMA (0,1,1)	1439.06	1439.12	1445.77
ARIMA (1,1,1)	1439.87	1439.99	1449.94

Interpretation: Table 3 shows the values of information criteria used to select a suitable optimal model, and the model ARIMA (1,1,0) has the lowest values of AIC, AICc, and BIC. The fitted model is given as:

$$\hat{y}_t = -0.297 + 0.2756 * y_{t-1}$$

The identification of ARIMA (1,1,0) implies that Nigerian crude oil prices follow a first-order autoregressive process in their differenced form, suggesting that current price changes are strongly influenced by immediate past changes. This reflects the short-term memory characteristic of oil price movements in Nigeria. From a policy perspective, this finding suggests that oil price shocks tend to transmit quickly but may not persist over long horizons, providing opportunities for timely fiscal intervention.

3.4. Model Adequacy Based on Residual Diagnostician

The adequacy of the ARIMA (1,1,0) model is assessed through residual analysis. A good model should produce residuals that behave like white noise, meaning they are randomly distributed with constant variance and no autocorrelation. The residual plots show that the values are scattered around zero without a systematic pattern, suggesting that the model has captured the main dynamics of the series. Furthermore, the autocorrelation and partial autocorrelation functions of the residuals exhibit no significant spikes outside the confidence bounds, reinforcing the absence of serial correlation. These results are supported by the Box–Ljung test, which fails to reject the null hypothesis of no autocorrelation. Together, these diagnostics confirm that the ARIMA (1,1,0) model is statistically adequate and reliable for forecasting Nigerian crude oil prices.

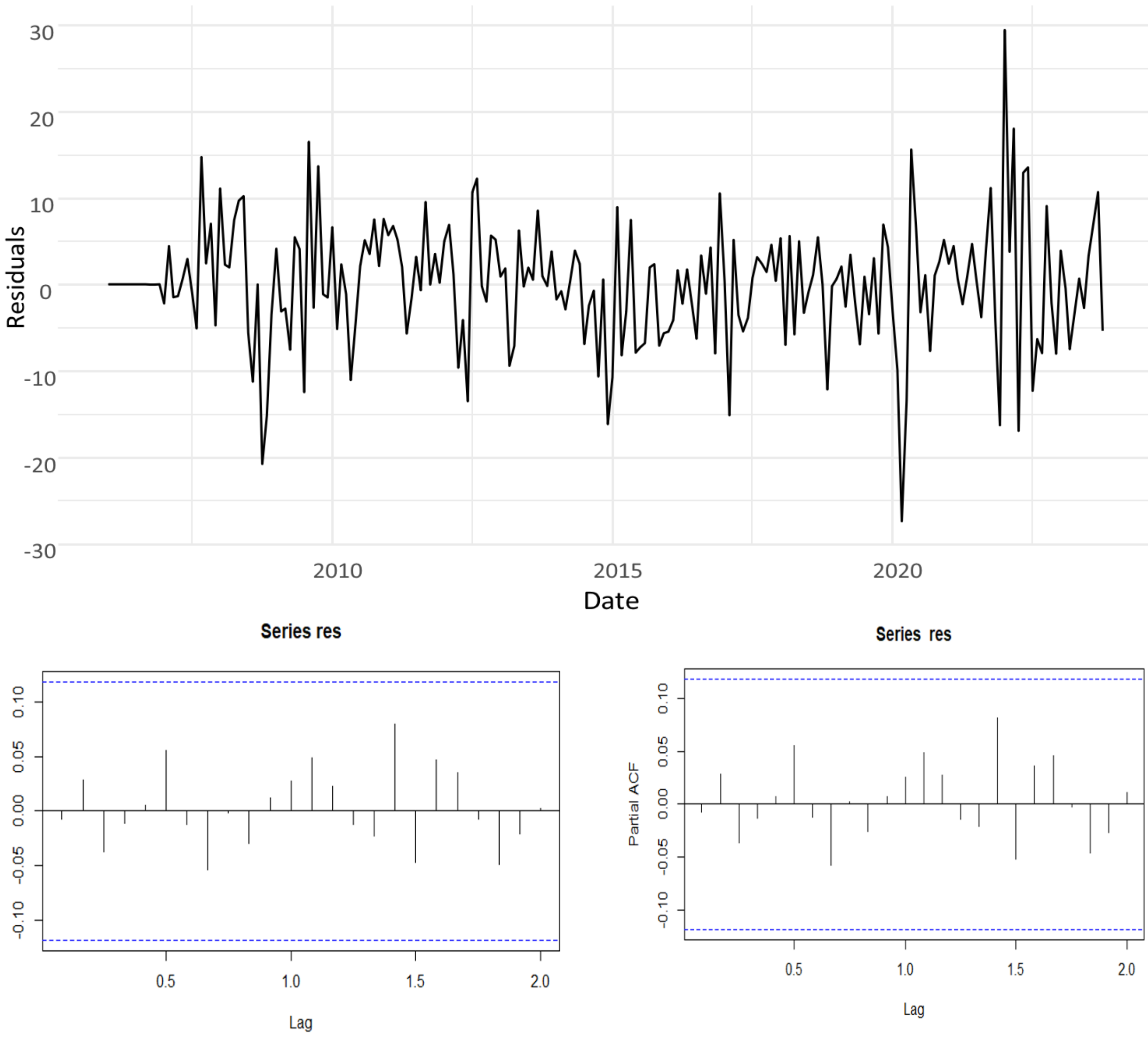

Figure 5. Residual Plot.

Interpretation: Figure 5 illustrates the residual diagnostics of the fitted ARIMA (1,1,0) model. The residual plot shows that values are randomly scattered around zero without a visible pattern, while the ACF and PACF of the residuals display no significant spikes outside the confidence limits. These results confirm that the residuals behave like white noise, indicating that the model is well specified and adequate for forecasting Nigerian crude oil prices.

Hypothesis 2 (Test for Presence of Autocorrelation).

Null Hypothesis-H_0: There is no residual autocorrelation.

Alternative Hypothesis-H_1: There is residual autocorrelation.

Table 4. Test: Box-Ljung test.

Q*	Df	p-value
17.948	24	0.8055

Note: Q^* denotes the Ljung–Box modified chi-square statistic used to test for autocorrelation in the residuals.

Interpretation: Table 4 shows that the Box-Ljung test was conducted on the residuals to check for the presence of autocorrelation, and there was not enough evidence to indicate the presence of autocorrelation in the residuals; thus, the model is adequate.

3.5. Forecasting

The ARIMA model forecast shows expected future values with confidence intervals, suggesting the model captures the data's trends and seasonality effectively, as indicated by residual analysis showing no significant patterns or autocorrelations. The point forecast in the prediction table below shows a point forecast for the year 2023/2024 with the lower and higher confidence intervals of 95% for the range of the crude oil price in US dollars, which will fall if it does not meet the point forecast.

Table 5. The prediction table.

Period	Point forecast	Lo 95	Hi 95
Oct 2023	94.000	80.010	108.200
Nov 2023	93.812	71.100	116.312
Dec 2023	93.723	64.212	123.213
Jan 2024	93.757	58.510	128.121
Feb 2024	93.743	53.523	133.036
March 2024	93.727	49.123	138.001
April 2024	93.725	45.143	142.231
May 2024	93.710	41.421	145.213
June 2024	93.737	38.025	149.321
July 2024	93.721	34.727	152.211
August 2024	93.726	31.632	155.091

Interpretation: Table 5. illustrates the point forecasts and 95% confidence intervals for Nigerian crude oil prices from October 2023 to August 2024. The forecasts show that prices are expected to remain relatively stable around US$93–94 per barrel in the short term. The progressive widening of the confidence intervals indicates that while the short-term predictions are reliable, the level of uncertainty increases over longer horizons, reflecting the unpredictable nature of oil price movements.

3.6. Forecast Plot

The forecast plot generated from the ARIMA (1,1,0) model provides a visual representation of predicted Nigerian crude oil prices from October 2023 to August 2024. The model projects relatively stable price movements, clustering around USD 93–94 per barrel in the near term. While the central forecast indicates moderate stability, the confidence intervals widen progressively over the forecast horizon. This widening reflects increasing uncertainty in long-term projections, a common feature in time-series forecasting where future shocks or market disruptions cannot be fully captured by the model. The forecast, therefore, suggests that although short-term price expectations are reliable, policymakers and market participants should treat longer-term projections with caution and incorporate complementary risk-management strategies.

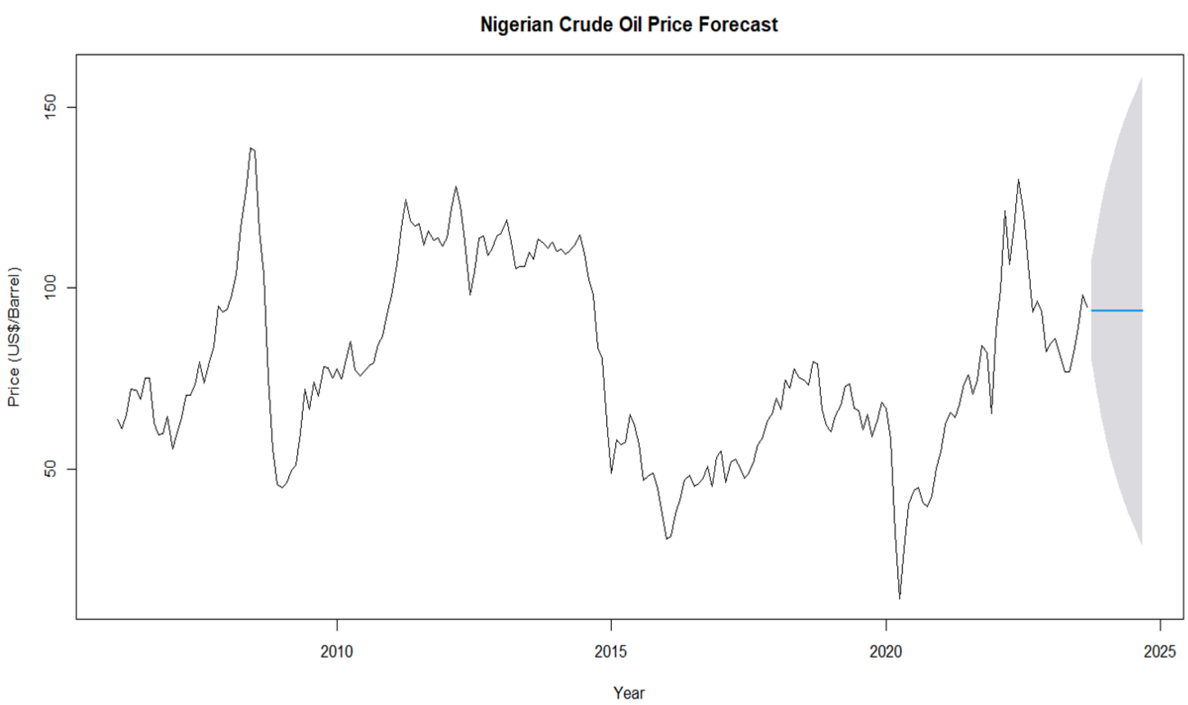

Figure 6. Plot of ARIMA (1, 1, 0).

Interpretation: Figure 6 displays the ARIMA (1,1,0) forecast, indicating that Nigerian crude oil prices are expected to remain stable around US$93–94 per barrel from October 2023 through August 2024. The wider confidence bands in the plot remind us that predictions further into the future are less specific.

4. Discussion

The results show that Nigerian crude oil prices exhibit significant short-term fluctuations influenced by immediate past values, as captured by the ARIMA (1,1,0) specification. This finding reflects the short-term memory property of oil price movements, consistent with the view that global commodity prices react quickly to shocks but may not persist indefinitely [9, 10].

For Nigeria, this has strong fiscal and policy implications. Since oil revenue accounts for a major share of government income, sudden price drops translate into revenue shortfalls, budget deficits, and exchange rate instability [2, 4]. The ARIMA (1,1,0) model highlights that such shocks are often temporary, suggesting that appropriate stabilization policies such as countercyclical fiscal measures or the use of sovereign wealth funds can cushion the immediate impact without over-adjusting long-term plans.

This result also underscores the importance of accurate short-term forecasts for budgetary planning. Reliable projections of crude oil prices enable policymakers to anticipate revenue inflows, adjust expenditure, and reduce the risks of procyclical spending. Moreover, the study's findings emphasize the need to reduce Nigeria's dependence on oil revenue by diversifying into non-oil sectors, thereby reducing exposure to external shocks [11, 12].

Overall, the empirical evidence not only validates ARIMA as a robust forecasting tool but also highlights its relevance in designing proactive fiscal policies, strengthening stabilization funds, and guiding macroeconomic management in oil-dependent economies.

5. Conclusion

This study applied ARIMA modeling to Nigerian monthly crude oil prices and identified ARIMA (1,1,0) as the most suitable model, based on AIC and BIC criteria. The results indicate that short-term crude oil price changes in Nigeria are highly dependent on immediate past fluctuations. This highlights the sensitivity of the Nigerian economy to short-term oil price shocks. Beyond methodological adequacy, the findings demonstrate that reliable forecasting of oil prices is crucial for macroeconomic stability, as oil revenues remain the backbone of Nigeria's fiscal system. In light of these findings, it is recommended that future modeling of crude oil prices should incorporate error variance and information criteria such as AIC and BIC to ensure accurate forecasts. Students and researchers are encouraged to adopt ARIMA modeling in the study of economic time series, particularly for commodities prone to volatility like crude oil. Policymakers should also integrate crude oil price forecasts into budgetary and fiscal planning in order to minimize the risks of revenue shortfalls and excessive borrowing. Furthermore, greater attention should be given to economic diversification as a way to reduce Nigeria's vulnerability to oil price fluctuations.

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