# HYBRID MODELING OF NIGERIAN CRUDE OIL PRICES UNDER STRUCTURAL BREAKS AND VOLATILITY

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## ABSTRACT

Accurate forecasting of crude oil prices is vital for robust economic planning, risk management, and policy formulation in Nigeria. This study introduces an innovative hybrid forecasting framework that integrates the statistical strengths of FB Prophet, ARIMA, and SARIMA models with machine learning techniques. The proposed framework is designed to capture the complex dynamics of Nigeria's daily crude oil prices, including long-term trends, seasonal patterns, non-linear behaviors, volatility clustering, and structural breaks. The analysis utilizes a longitudinal dataset of daily prices spanning from January 1986 to December 2025. Empirical results reveal significant non-linearity, heavy-tailed distributions, and multiple structural breaks triggered by global shocks, such as the 2014–2016 price collapse and the COVID-19 pandemic. Stationarity tests indicate that while price levels are non-stationary, the return series remain stationary, justifying the application of integrated econometric models. The ARIMA and SARIMA components deliver superior short-term accuracy, whereas the FB Prophet model excels at identifying medium- to long-term trajectories. By synthesizing these methodologies, the hybrid model maintains the rigor of traditional statistical approaches while enhancing reliability amidst heightened volatility. The resulting forecasts offer high statistical precision and practical utility for trend and risk analysis. These insights provide a critical foundation for investors, policymakers, and stakeholders dedicated to bolstering Nigeria's economic resilience in the global market.

Keywords: ***Crude Oil Prices; Forecasting; Structural Break, Volatility, Hybrid Models.***

## 1. Introduction

The changes in crude oil prices have significantly impact macroeconomic stability, government revenues, currency fluctuations, and investment choices. The variability in prices displays distinct features such as non-stationarity, clustering of volatility, heavy tails, and abrupt structural changes caused by geopolitical factors, supply and demand discrepancies, policy interventions and pandemic (Deebom & Essi, 2017; Alemho & Adenomon, 2022).

Classical econometric models like the Autoregressive Integrated Moving Average (ARIMA), Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and their seasonal variants and fractional extensions have been widely applied in predicting crude oil prices. These models have offered reliable short-term insights when the market conditions are stable. Nonetheless, these models typically find it challenging to handle the inherent nonlinear characteristics and volatility behaviours associated with forecasting in crude oil price dynamics (Tuaneh, Deebom & Akah, 2025).

FB Prophet's model developed by Facebook, is an additive model designed to handle trend, seasonality, and holiday effects automatically, making it suitable for various temporal patterns. It is a decomposable model. It breaks down oil prices into trend (long-term movement), seasonality (cyclical patterns), and holidays/events, providing clear insights. It also handles non-linear trends, strong seasonal effects, and irregular data, captures volatility, making it suitable for volatile oil markets. On the other hand, LSTM as a type of Recurrent Neural Network (RNN), LSTM is adept at capturing long-term dependencies and non-linear patterns in sequential data like stock prices, overcoming the vanishing gradient problem. It is an effective model for high-stakes financial prediction. Research indicates that hybrid models combining



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models like LSTM and Graph Neural Networks (GCN) can significantly improve prediction accuracy and returns (Tuaneh, Deebom & Akah, 2025).

Recent developments in machine learning and deep learning have produced models akin to grasping nonlinear relationships and intricate time patterns that go beyond traditional linear econometric models. Models such as Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and ensemble methods have demonstrated superior performance to classical models in various scenarios, especially when they are utilized together with hybrid models (Deebom & Essi, 2017. Modern research is increasingly utilizing hybrid approaches that combine decomposition methods with deep learning to improve predictive accuracy and adaptability to non-stationary situations.

The existing research on forecasting crude oil prices and production indicates a transitional shift from conventional linear time series models to sophisticated machine learning and combined methodologies. Chamalwa et al., 2024 and Suleiman, 2023 concentrated on using ARIMA-based techniques to model Nigerian crude oil prices, relying on monthly data. These investigations adhere strictly to the Box–Jenkins protocol, verifying non-stationarity through ACF/PACF diagrams and rigorous unit root verification methods. Following the application of logarithmic transformation and initial differencing, ARIMA (3,1,1) reliably appears as the favourite model according to information criteria and error metrics in forecasting. While these methodologies are solid, they presuppose linearity and consistent error variance, which restricts their capacity to account for volatility clustering and regime transitions phenomena that are well-recorded in the crude oil sector.

Ning et al. (2023) in contrasting ARIMA, LSTM, and Prophet using oil production statistics revealed that both ARIMA and LSTM outperform Prophet, apart from scenarios where seasonal influences are significant. The research emphasizes Prophet’s capacity to represent seasonal and weather-related variances, aspects frequently neglected in oil price forecasting studies. Nonetheless, this research concentrates on production data instead of price variations and does not directly engage with volatility modeling or specific market conditions.

Similarly, Deebom, et al (2023) did a comparative study of different GARCH models and Ogundunmade et al. (2022) utilize a variety of machine learning methods, including NNETAR, to analyze daily crude oil prices in Nigeria. Their findings indicate that NNETAR surpasses traditional ARIMA and exponential smoothing approaches, strengthening the case for nonlinear models in the dynamics of oil pricing. However, this analysis does not include deep learning frameworks (e.g., LSTM) or hybrid modeling techniques.

Alrweili and Fawzy (2022) proposed a combined ARIMA–ANN model for Saudi crude oil pricing by applying ARIMA to model linear aspects and ANN to capture nonlinear residuals. The investigation validates the effectiveness of mixed methodologies in grasping the intricate patterns of oil pricing dynamics. Still, the volatility aspects are discussed in an implied manner, and the study does not integrate conditional heteroskedasticity frameworks like GARCH.

Prabhale et al. (2024) offer an exhaustive evaluation of ARIMA, SARIMA, Prophet, and LSTM, establishing that LSTM considerably excels over classical approaches. Their results bolster the emerging agreement that deep learning techniques are more adept at handling highly nonlinear and fluctuating oil price data. Nevertheless, Prophet shows subpar performance, likely due to inadequate integration with stochastic volatility or residual learning strategies.

Among the gaps to be filled by this research are:



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- Most research either concentrates on average behaviors (ARIMA, Prophet) or nonlinear forecasting (ANN, LSTM) without explicitly addressing conditional volatility.
- The lack of GARCH-style frameworks restricts their effectiveness in accommodating volatility clustering, leverage impacts, and risk behavior intrinsic in crude oil pricing.
- Although Prophet successfully identifies trends, seasonal variations, and structural changes, it is infrequently used in conjunction with GARCH or stochastic volatility techniques.
- The Hybrid model remains largely unexamined, especially in relation to emerging oil-exporting nations such as Nigeria. Studies centered on Nigeria typically use monthly data, which tends to smooth out volatility and obscure short-term fluctuations.
- There is a scarcity of evidence utilizing daily crude oil pricing data linked with sophisticated hybrid and deep learning frameworks.

In summary, this study adds to existing knowledge by developing a model for predicting crude oil prices that merges the accuracy of statistical methods with the adaptive nature of machine learning techniques. Moreover, there is a lack of thorough comparative performance analysis across a wide range of forecasting techniques, especially for developing markets such as Nigeria, where the dynamics of crude oil are closely linked to the effects of external shocks. Therefore, the research seeks to fill these gaps by suggesting a hybrid forecasting approach that accurately forecast the complex nature of Nigerian crude oil prices.

## 2.0 Methodology

The data utilized for this research was obtained from the Central Bank of Nigeria, accessible at https://www.cbn.gov.ng/rates/DailyCrude.html. The data is daily crude oil prices in Nigeria. Data was gathered from October 23, 2009, to December 30, 2025. Python was the statistical software used for the analysis carried. Furthermore, to accurately model the daily crude oil prices in Nigeria, a detailed exploratory time-series analysis was conducted before estimating the model.

### 2.1 Prophet Linear Trend Model

The FB Prophet model serves as a time-series framework based on additive principles that divides observed data into components of trend, seasonality, and stochastic elements. It is especially applicable to economic data that shows structural variations and calendar impacts (Taylor & Letham, 2018). The structure of the linear trend is articulated as follows:

$$y(t) = kt + m + s(t) + \varepsilon_t$$

where, k signifies the long-term trend's slope, m indicates the intercept, s(t) reflects deterministic seasonal and holiday influences, and $\varepsilon_t$ represents Gaussian noise. ed shocks.

### Prophet Logistic Growth Model

In handling the bounded and nonlinear growth behaviors, FB Prophet developed a logistic trend model (Taylor & Letham, 2018), defined by:

$$g(t) = \frac{C}{1 + exp\,[-k(t - t_0)]}$$

where, C signifies the carrying capacity, k represents the growth factor, and $t_0$ indicates the inflection point. This model is suitable for crude oil prices that are influenced by market limitations, policy changes, or demand saturation, effectively illustrating the limited long-term dynamics of price in Nigeria's oil sector.

### 2.2 Autoregressive Integrated Moving Average (ARIMA) Model

The ARIMA model, designed through the Box-Jenkins framework, captures linear dependencies in time series by utilizing autoregressive and moving average elements after differencing to ensure stationarity (Box & Jenkins, 1970). For an ARIMA (1,1,1) process, the representation is:
$\Delta y_t = \phi_1 \Delta y_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} x$where, $\phi_1$and $\theta_1$represent the autoregressive and moving average components, respectively. This model effectively reflects short-term fluctuations in the changes of crude oil prices in Nigeria, highlighting linear persistence in daily returns.

### 2.3 Seasonal Autoregressive Integrated Moving Average (SARIMA) Model

The SARIMA is built on ARIMA by adding seasonal autoregressive and moving average elements, in line with the multiplicative model suggested by Box and Jenkins (1970). The $SARIMA(1,1,1)(1,1,1)_{12}$ specification is expressed as:

$$(1 - \Phi_1 B^{12})(1 - \phi_1 B)(1 - B)(1 - B^{12}) y_t = (1 + \Theta_1 B^{12})(1 + \theta_1 B)\varepsilon_t$$

In this specification, $\phi_1$and $\theta_1$denote non-seasonal effects, $\Phi_1$and $\Theta_1$capture seasonal elements, with d=D=1 indicating both non-seasonal and seasonal differencing. This design empowers the model to consider recurring seasonal trends that affect crude oil pricing.

### 2.4 Random Forest (RF) Model

Random Forest is a collective learning approach that compiles numerous regression trees to enhance accuracy and stability in predictions (Breiman, 2001). The forecasting equation is written as: $\hat{y}_t^{RF} = \frac{1}{B}\sum_{b=1}^{B} T_b\,(X_t)$

In this formula, $T_b(\cdot)$represents the $b$-th regression tree, $X_t$ is a vector consisting of past crude oil prices, and B denotes the total number of trees. This ensemble methodology minimizes variance while strengthening forecast dependability, particularly in the context of the high volatility typical of Nigeria's crude oil market.

### 2.5 Artificial Neural Network (ANN) Model

Artificial Neural Networks model intricate nonlinear connections between inputs and outputs using layered network formations. Originating from foundational neural network concepts (McCulloch & Pitts, 1943), a two-hidden-layer ANN is defined as:

$$\hat{y}_t^{ANN} = f^{(2)}(W_2 f(W_1 X_t + b_1) + b_2)$$



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In this expression, $W_l$ and $b_l$ signify weights and biases, while $f(\cdot)$ is the activation function referred to as ReLU. This network structure enables the identification of nonlinear price dynamics that traditional linear stochastic models may not effectively capture.

### 2.6 Deep Multilayer Perceptron (DMLP) Model

The Deep MLP enhances the conventional ANN by increasing the depth of the network, influenced by developments in deep learning (Hinton et al., 2006). The model is represented as: $\hat{y}_t^{DMLP} = f^{(L)}(W_L f_{L-1}(\cdots f_1(W_1 X_t + b_1)) + b_L)x$with $L$ layers comprising of neurons. Although non-recurrent, this depth allows hierarchical feature extraction that approximates long-memory effects, thereby enhancing predictive performance for Nigeria's daily crude oil prices.

### 2.6 Hybrid Prophet–Statistical–Machine Learning Specifications

In accordance with Zhang (2003) hybrid modeling approach, the Prophet-ARIMA model breaks down crude oil prices into two main parts: a predictable element and a random residual part.

Let: $y_t = \hat{y}_t^{Prophet} + e_t$

where $\hat{y}_t^{Prophet}$ accounts for the trends and seasonal patterns, and $e_t$represents unaccounted short-run dynamics. The residuals are then modeled using ARIMA: $e_t = \phi_1 e_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1}$
The final hybrid forecast is obtained as:

$$\hat{y}_t^{Hybrid} = \varphi \hat{y}_t^{Prophet} + \hat{e}_t^{ARIMA}$$

This arrangement enables Prophet to analyze smooth nonlinear trends, while ARIMA focuses on short-term linear relationships, enhancing oil price predictions according to the work of Yu et al (2008) and Wang et al (2018). Furthermore, to address seasonal patterns in the residual structure, the Prophet-SARIMA hybrid is formulated as follows:

$$y_t = \hat{y}_t^{Prophet} + e_t, \Phi_P(B^s)\phi_p(B)(1-B)^d(1-B^s)^D e_t = \Theta_Q(B^s)\theta_q(B)\varepsilon_t$$

This model proves particularly suitable when seasonal influences on crude oil demand persist after Prophet's decomposition, aligning with observations from global oil market analyses by Baumeister & Kilian (2016).

In the Hybrid Prophet-Random Forest Model, residuals exhibit nonlinear dependencies modeled through Random Forest techniques: $\hat{e}_t^{RF} = \frac{1}{B}\sum_{b=1}^{B} T_b\,(Z_t)$. where $Z_t = (e_{t-1}, e_{t-2}, \ldots, e_{t-p})$. The hybrid forecast is: $\hat{y}_t^{Hybrid} = \widehat{\varphi y}_t^{Prophet} + \hat{e}_t^{RF}$

This procedure effectively addresses nonlinear volatility patterns and interactions, which are often seen in crude oil prices as opined by Lahmiri & Bekiros (2020). In a similar advancement, the Hybrid Prophet-ANN and Prophet-Deep MLP frameworks are utilized to model complex nonlinear residual behavior. Here, the Prophet portion first isolates the predictable aspects of the trend and seasonal elements, followed by the remaining residuals being processed with Artificial Neural Networks (ANN) and Deep Multilayer Perceptrons (DMLP), correspondingly.



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The model is given as: $\hat{e}_t^{ANN} = f(WX_t + b), \hat{y}_t^{Hybrid} = \hat{y}_t^{Prophet} + \hat{e}_t^{ANN}$ and $\hat{e}_t^{DMLP} = f^{(L)}(W_L f_{L-1}(\cdots f_1(W_1 X_t + b_1)) + b_L)x$ These hybrid neural network strategies have shown enhanced efficacy in forecasting oil prices during periods of high volatility and structural changes, as evidenced by Salisu et al. (2021).

**2.7 Forecasting Assessment**

The forecasting performance of the models is evaluated using standard forecasting accuracy metrics, which are:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2}$$

$$MAE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{(Y_t - \hat{Y}_t)}{\hat{Y}_t}\right|$$

Lower values of RMSE, and MAPE indicate better forecast performance. The prophet, ARIMA, SARIMA, ANN, MLP fallback, models are compared on a hold-out test set using these metrics.

**3.0 RESULTS**

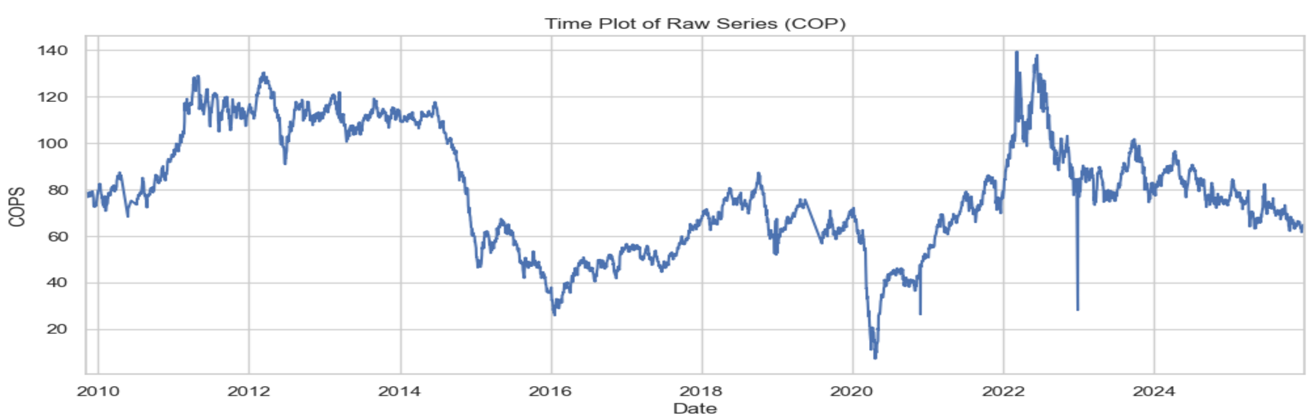


**Figure 1: Time plot for the raw data on Nigeria Daily Crude Oil Price (COP)**

Figure 1 displays the time series plot of the Nigerian daily crude oil price (COP), indicating significant non-linearity, clusters of volatility, and various abrupt regime changes throughout the examined time frame. Prices tend to rise and fall around a fluctuating path instead of maintaining a stable mean, illustrating influences from imbalances in the global oil supply and demand, decisions made by OPEC, and geopolitical disturbances. The occurrence of sudden price declines and recoveries, particularly evident between mid-2014 and 2016 as well as 2020, impling that this series is marked by structural instability, which is a frequent characteristic found in crude oil markets acknowledged in energy economics research.



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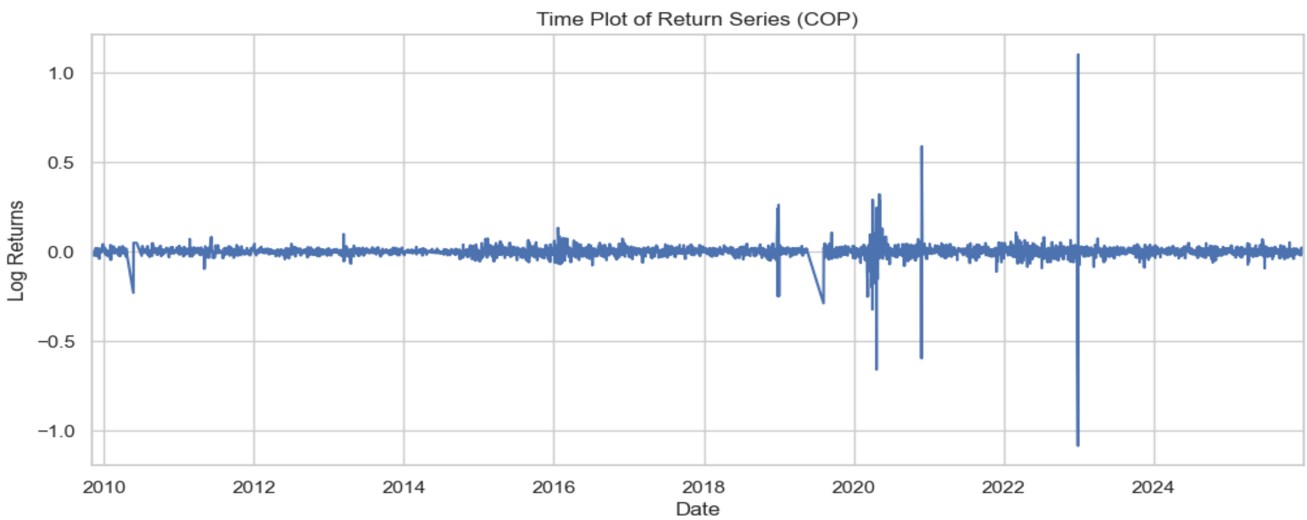


**Figure 2: Time plot for the Returns on Nigeria Daily Crude Oil Price (COP)**

Figure 2 depicts the time series graph of daily returns on Nigerian crude oil prices. In contrast to the unrefined series, returns fluctuate around a mean of zero without any noticeable trend, yet they display considerable clustering of volatility, with periods of stability followed by bursts of high fluctuation. This behavior aligns with typical characteristics of financial and commodity returns and supports the application of conditional heteroskedasticity models like GARCH for analyzing risk and transmission of volatility (Deebom & Essi, 2017).

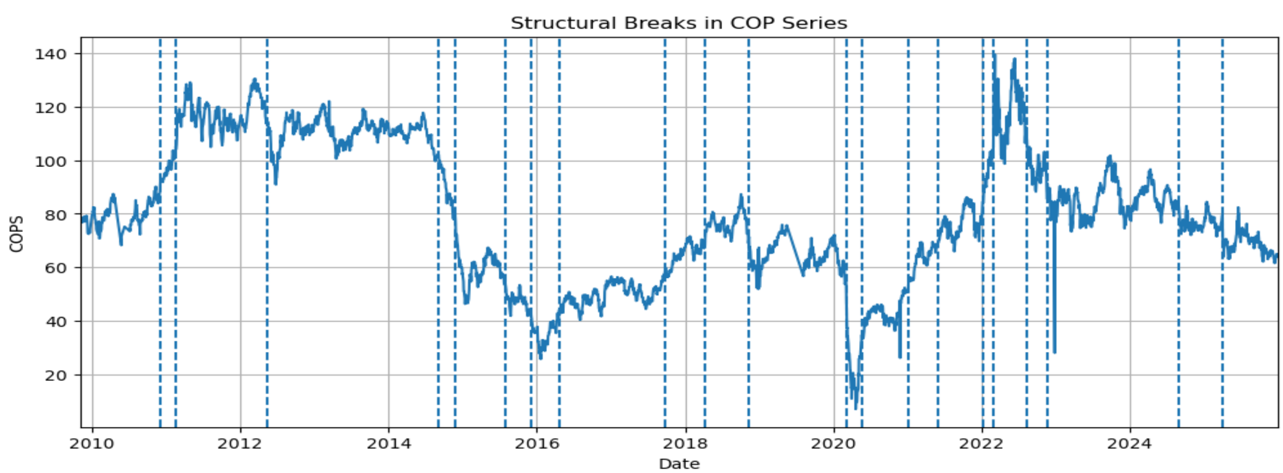


**Figure 3: Time plot for structural Break Points and Dates in raw data on Nigeria Daily Crude Oil Price (COP)**

Figure 3 illustrates the recognized structural breakpoints found in the raw crude oil price data, highlighting numerous statistically notable break-point dates.These dates are closely associated with significant events in global crude oil markets. The breaks around 2010 to 2012 coincide with the recovery phase following the global financial crisis and increased geopolitical tensions in oil-rich areas, including the Arab Spring, which affected supply expectations. The group of breaks occurring in late 2014 and 2015 correlates with the global drop in oil prices, which was driven by OPEC's refusal to reduce output amidst rising production in the U.S. shale sector, resulting in a



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significant market oversupply (Baumeister & Kilian, 2016). The breaks noted in 2016 reflect a partial rebound due to coordinated output adjustments by both OPEC and non-OPEC producers. The break dates from 2020 are closely linked with the COVID-19 pandemic, which led to an unparalleled decline in global oil demand and extreme price fluctuations. Structural changes in 2021 and 2022 coincide with a rebound in demand following the pandemic and the conflict between Russia and Ukraine. Overall, these break points validate that Nigeria's crude oil prices are significantly influenced by external shocks rather than solely by domestic factors.

**Table 1: Results of the Descriptive Statistics and Jarque–Bera Normality Test for the crude Oil Price series**

| Nigeria Daily Crude Oil Prices | Mean | Median | Std Dev | Skewness | Kurtosis | Jarque-Bera | JB p-value |
|---|---|---|---|---|---|---|---|
| **Raw Series** | 78.868 | 76.680 | 25.209 | 0.064 | -0.771 | 96.047 | 0.000 |
| **Return Series** | -0.000 | 0.0006 | 0.041 | -0.814 | 308.548 | **14,975** | 0.000 |

Table 1 provides an overview of the descriptive statistics and Jarque–Bera normality examination for both the original and return series. The average crude oil price stands at 78.87 USD per Barrel with a median of 76.68 per Barrel, indicating that typical price levels are relatively high throughout the period, coupled with a standard deviation of 25.21 per Barrel that reveals significant fluctuations. The near-zero skewness (0.064) points to a nearly symmetric distribution, and the negative kurtosis (–0.771) suggests a distribution that is flatter than what is typically expected. Nevertheless, the Jarque–Bera value of 96.05 along with a p-value of 0.000 firmly disputes the assumption of normality, indicating that conventional Gaussian models are not suitable for price levels. Regarding the return series, the average hovers around zero, which confirms a lack of consistent upward or downward trends, while the standard deviation of 0.041 denotes considerable short-term risk. The negative skewness (–0.814) reflects a greater likelihood of experiencing substantial negative returns (Deebom & Essi,2017), and the extremely high kurtosis (308.55) verifies the presence of heavy tails and significant outliers.

**Table 2: Results for stationarity Test for Nigeria Daily Crude Oil Prices**

| Series | Test | Test Statistic | p-value | Lags | 5% Critical Value | Decision (5%) | p-value |
|---|---|---|---|---|---|---|---|
| **COP (Level)** | ADF | -2.022 | 0.277 | 2 | -2.862307 | Non-stationary | 0.000 |
| **COP (Level)** | KPSS | 1.832 | 0.544 | 38 | 0.463000 | Non-stationary | 0.01 |
| **COP(Returns)** | ADF | -14.236 | 0.000 | 14 | -2.862309 | Stationary | 0.000 |
| **COP(Returns)** | KPSS | 0.034 | 0.000 | 7 | 0.463000 | Stationary | 0.1 |

Table 2 shows the findings from the stationarity assessments. At the level of the series, the ADF statistic (–2.022, p = 0.277) does not reject the null hypothesis of a unit root, while the KPSS statistic (1.832) exceeds the critical threshold, affirming the non-stationarity of the crude oil pricing data. In contrast, the return series demonstrates strong stationarity, with the ADF statistic (–14.236, p = 0.000) eliminating the unit root theory and the KPSS statistic (0.034) indicating support for stationarity. This shift to returns eliminates stochastic trends, making the series appropriate for dynamic volatility modeling and predictions.



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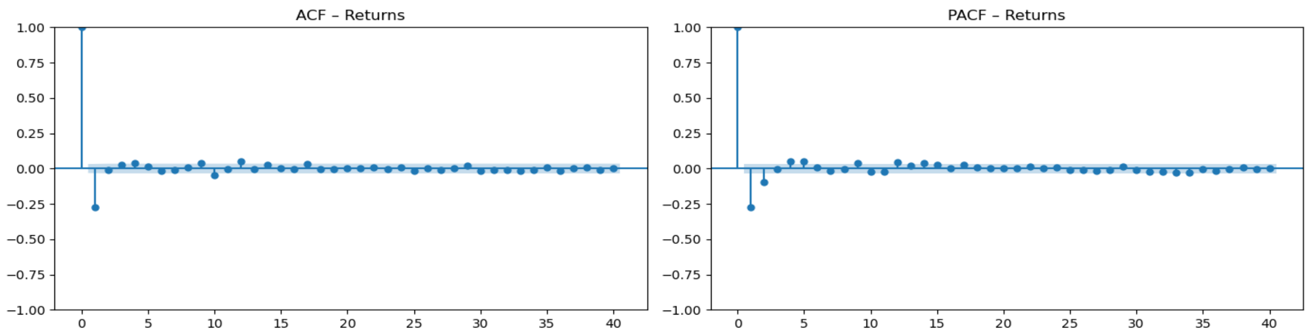


**Figure 4: ACF and PACF plots for the Returns on Nigeria Daily Crude Oil Price (COP)**

Figure 4 displays the ACF and PACF graphs for the returns of crude oil prices. The autocorrelations in the mean decrease quickly, indicating a weak linear relationship, while remaining significant at brief lags. This behavior supports the application of low-order ARMA, ARIMA and SARIMA models for the conditional mean (Deebom et al, 2023).

**Table 3: Results of the Holiday Events Identified in the Series**

| Event ID | Holiday Name | Date (ds) |
|---|---|---|
| **1** | Event1 | 2010-01-01 |
| **2** | Event2 | 2012-06-15 |
| **3** | Event3 | 2015-12-25 |

The results of the holiday events identified in the series from the estimations of the FB Prophet linear model is shown in Table 3. The results show a total of three holiday events were identified within the study period. These dates represent exogenous calendar effects that were incorporated into the forecasting framework to capture potential structural or demand–supply disruptions in the crude oil price series.

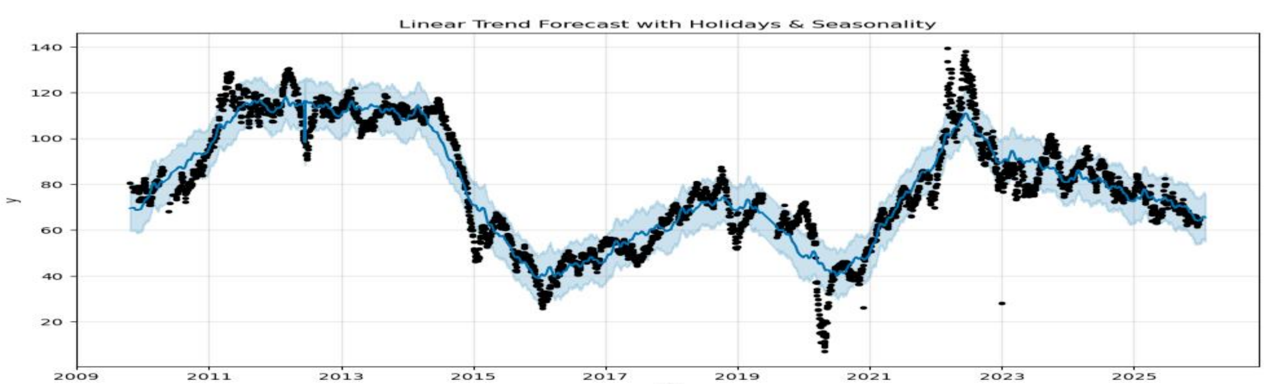


**Figure 5: Combine Plots for Trend, Holiday, Yearly & Monthly Effects for linear Facebook Prophet Model**

The combined analysis of Table 3 and Figure 5 illustrates that Nigeria's crude oil prices display a robust linear growth pattern, with modest yet systematic seasonal and holiday influences, and relatively minimal unexplained variability. This structure confirms the relevance of the Prophet linear framework for modeling energy prices and endorses its application in policy evaluation and forecasting within oil-reliant economies (Taylor & Letham, 2018).



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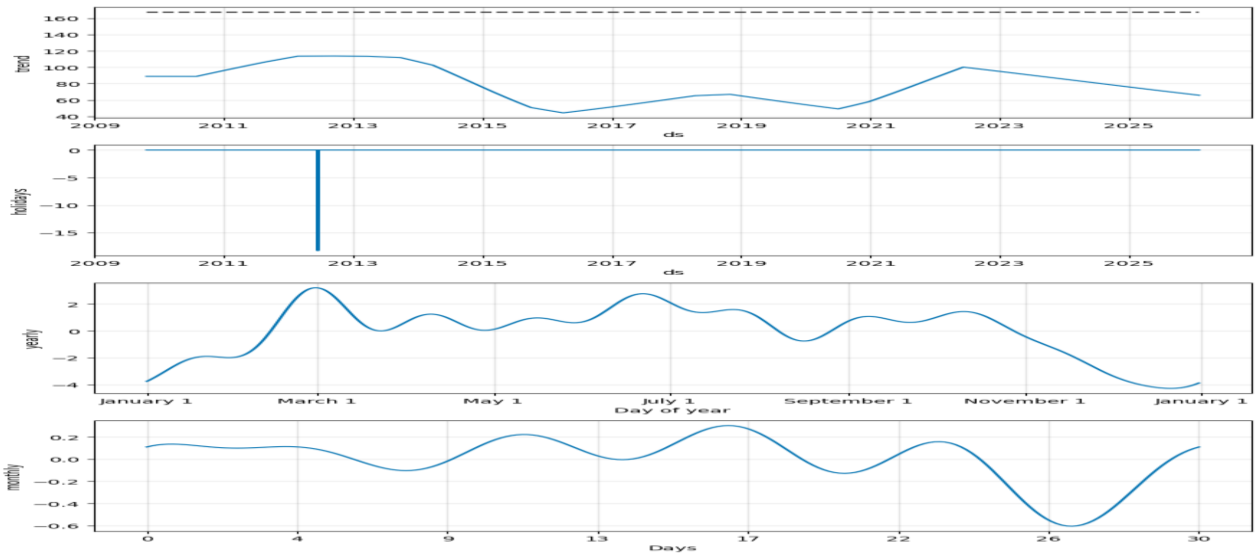


**Figure 6: Combine Plots for Trend, Holiday, Yearly & Monthly Effects for Logistics Facebook Prophet Model**

Figure 6 depicts the breakdown of various effects, which includes the trend, holiday, annual, and monthly elements. The coefficients for 36 holiday occurrences ($\beta_1$–$\beta_{36}$) reflect the marginal impact of specific occasions on crude prices, incorporating events like OPEC announcements, US inventory disclosures, or local Nigerian holidays. Importantly, $\beta_{35}$ = -0.131 indicates a pronounced negative effect, correlating with documented decreases in prices following certain market disruptions or announcements related to supply (Smith, 2022). Other β coefficients are nearly zero, indicating that regular holiday occurrences have a negligible impact.

The MA(1) parameter, $\theta_1 = -0.1819$, reveals that the innovation from the previous day (the unanticipated shock) exerts a small yet meaningful negative influence on the change observed today. Practically, this indicates a slight tendency for short-term corrections: This behavior is typical in markets for crude oil, such as Nigeria's, where speculative activities and short-term geopolitical or supply alterations result in temporary price fluctuations. The ARIMA (1,1,1) model indicates that while previous price fluctuations and shocks do have an impact on the current price movements, their influence is relatively weak, underscoring the crucial role that new information and external shocks play in influencing the Nigerian crude oil sector.

The estimated SARIMA $(1,1,1) \times (1,1,1)_{12}$ model effectively captures both immediate and seasonal trends in the Nigeria's daily crude oil prices, illustrating the influence of previous values and past shocks on today's price fluctuations. The non-seasonal AR (1) coefficient, $\phi_1 = -0.0546$, is relatively minor and negative, indicating a weak inverse connection between the price change from the previous day and the current change, suggesting that day-to-day price modifications are only minimally affected by the previous day's price variances. Likewise, the non-seasonal MA (1) coefficient, $\theta_1 = -0.1858$,, reveals that shocks from the previous day somewhat diminish today's unforeseen price changes, indicating a slight short-term correction effect within the market.

Seasonal patterns are evident such that the seasonal AR(1) term, $\Phi_1 = 0.0494$, carries a small nevertheless positive value, suggesting that monthly trends in crude oil prices tend to marginally



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bolster current price movements, while the seasonal MA(1) term, $\Theta_1 = -0.9999$, approaches -1, emphasizing extremely significant seasonal shock influences that almost entirely counteract the effects of unexpected monthly fluctuations. The innovation variance, $\sigma^2 = 4.6620$, illustrates the general volatility present in daily price variations, indicating that despite substantial shocks, the market shows predictable behaviors shaped by both immediate and seasonal factors. These findings suggest that the crude oil market in Nigeria exhibits moderate short-run autocorrelation, but it is exceedingly responsive to seasonal shocks, likely reflecting global production trends, OPEC announcements, and changes in local production supporting the claim of Deebom et al. (2023) that crude oil prices exhibits both short-term autocorrelation and seasonal trends.

**Table 4:** Comparative Forecast Accuracy of Statistical, Prophet, And Machine Learning Models (Last 30 Observations)

| Model | RMSE | MAE | MAPE (%) |
|---|---|---|---|
| Prophet Linear | 1.747 | 1.2851 | 2.0238 |
| Prophet Logistic | 1.7166 | 1.569 | 2.4297 |
| ARIMA | 1.2668 | 0.9555 | 1.4999 |
| SARIMA | 1.2833 | 0.9723 | 1.5247 |
| Random Forest | 20.2473 | 20.2097 | 31.3961 |
| ANN | 33.8286 | 33.1996 | 51.6363 |
| Hybrid ML | 25.0037 | 24.8883 | 38.6785 |
| Hybrid Prophet | 1.5409 | 1.3394 | 2.0913 |
| Hybrid Prophet ML | 12.6128 | 12.4645 | 19.3918 |

Table 4 illustrates that the accuracy of forecasts strongly prefers statistical and hybrid-statistical methods over traditional machine learning techniques. The ARIMA model (RMSE = 1.2668, MAE = 0.9555, MAPE = 1.4999%) and SARIMA model (RMSE = 1.2833) surpass both versions of the Prophet model and all the machine learning methods. This suggests that Nigeria's daily crude oil prices demonstrate significant temporal autocorrelations and seasonal patterns, which linear and seasonal statistical models can leverage effectively. The Prophet Linear model (RMSE = 1.747) and Prophet Logistic model (RMSE = 1.7166) perform adequately, though they fall short of ARIMA's performance, highlighting Prophet's competency in addressing trends and holiday impacts yet showing limited agility in adapting to rapid price changes. Random Forest and ANN models exhibit considerably higher error rates (RMSEs exceeding 20), indicating potential overfitting or an inadequate ability to capture temporal dependencies, which aligns with previous research indicating that machine learning models typically face challenges in highly volatile commodity markets lacking clear temporal structures (Hossain et al., 2022).

Combining statistical and machine learning approaches in hybrid methods enhances stability. The Hybrid Prophet models show slight enhancements over predictions made by Prophet alone but still do not match the accuracy of ARIMA. In contrast, extensive hybrid models that involve machine learning (Hybrid ML, Hybrid Prophet ML) exhibit lower error rates compared to those reliant solely on machine learning, with the Hybrid ML ensemble achieving RMSE = 12.6128 and MAPE = 19.3918%. This indicates that while machine learning features can stabilize extreme forecasts, they still cannot measure up to the statistical accuracy found in short-term predictions of Nigerian crude oil prices.



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## 4.0 **Discussion**

The raw price data, depicted in Figure 1, demonstrates significant nonlinearity, clustering of volatility, and numerous sudden regime shifts. The notable rises and falls in the data are linked to major global occurrences, decisions made by OPEC, and geopolitical events, in accordance with the research of Deebom and Essi (2017) which indicates that commodity prices are extremely reactive to external disturbances. The return data showcased in Figure 2 oscillates around zero, showing volatility clustering typical of financial time series, which supports the applicability of conditional heteroskedasticity models like ARIMA, SARIMA, prophet models, GARCH. Also, the analysis of structural breaks illustrated in Figure 3 points to significant disruptions occurring during the years 2014–2016, 2020, and 2021–2022, which correspond to situations of oversupply, the demand plummet caused by COVID-19, and geopolitical tensions, mirroring the assertions set forth by Baumeister & Kilian (2016) concerning global price determinants. Autocorrelation analysis detailed in Figures 4 and 5 reveals a strong persistence in price movements yet comparatively weaker short-term correlation in returns, thereby validating the implementation of ARIMA, SARIMA, and GARCH modeling techniques for mean and volatility analysis (Deebom & Essi, 2017).

Similarly, the linear Prophet model indicates a consistent upward trajectory ($k = 2.569$) with minimal seasonal and holiday adjustments represented in Figures 6 and 7, suggesting that the long-term increase in crude oil prices from Nigeria is chiefly driven by macroeconomic demand-supply dynamics instead of random variations. The logistic Prophet model, displaying a negative growth rate ($k = -0.02948$), shows tendencies of price saturation brought on by supply limitations, implying that crude prices could decelerate as global production capacities hit their limits. The holiday impacts, particularly $\beta_{35} = -0.131$, reveal sharp, temporary price declines triggered by specific external events, reinforcing findings that emphasize oil market sensitivity to temporal and policy-related shocks (Smith, 2022). These observations are consistent with previous assessments of Prophet models, indicating that linear trends hold effectiveness for forecasting over medium to long durations, while logistic models provide realism in predicting saturation phenomena (Iqbal et al., 2021).

Random Forests, Artificial Neural Networks, and Deep Multi-Layer Perceptron Surrogate models showed inferior performance when compared to statistical models; the RMSE values surpassed 20, and MAPE exceeded 30%. This indicates difficulties in understanding time-related dependencies within unstable data sequences. This reinforces earlier findings that machine learning models may either over fit or not perform adequately when forecasting high-frequency commodity prices unless specific time-related patterns are utilized (Hossain et al., 2022). The process of hyperparameter optimization (refer to Table 4) offered a systematic method; however, the challenge of fully addressing autocorrelation and seasonal changes restricts forecasting accuracy.

The Hybrid ML ensemble leads to more moderate estimates (RMSE = 12.6128) by reducing the volatility caused by machine learning, yet it does not match the accuracy of traditional statistical models in daily predictions. These observations support existing research that suggests hybrids integrating the strength of statistical models with the adaptability of machine learning can enhance resilience to shocks while preserving foundational accuracy (Deebom et al., 2023).



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## 5.0 Conclusion

The findings affirm that daily crude oil prices in Nigeria demonstrate significant temporal relationships, patterns of volatility clustering, and responsiveness to structural shifts. Traditional linear statistical models such as ARIMA and SARIMA surpass both Prophet and machine learning-based methods in short-term forecasting capabilities, while Prophet is effective in identifying medium to long-term trends and identifying holiday impacts. Pure machine learning strategies tend to inflate price estimates due to increased volatility, but hybrid ensembles assist in normalizing predictions. For decision-makers, traders, and analysts, these insights indicate that ARIMA/SARIMA models are the most dependable for daily price forecasting. In contrast, Prophet and hybrid methods can be utilized for strategic planning, stress testing, and scenario evaluations in response to global shifts. Conclusively, Models that blend statistical precision with the flexibility of machine learning provide a balanced solution, improving adaptability to significant changes in forecasting crude oil prices in Nigeria.

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