

GSAR Journal of Economics and Finance
ISSN: 3107-9520 (Online)
Frequency: Monthly
Published By GSAR Publishers
Journal Homepage Link- https://gsarpublishers.com/gsarjef-home/

Statistical Modelling of Monthly Petroleum Product Sales: Trend, Seasonality and Stationarity Analysis of Premium Motor Spirit and Automotive Gas Oil in Plateau State, Nigeria

By

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Article History

Received: 09/10/2026
Accepted: 17/10/2026
Published: 19/10/2026

Vol – 2 Issue – 10

PP: -01-09

Abstract

Reliable statistical modeling of petroleum product sales requires a thorough understanding of their underlying trend, seasonal behavior, and stationarity characteristics before forecasting models can be appropriately specified. While previous studies have largely focused on crude oil prices and national-level petroleum indicators, empirical evidence on depot-level sales dynamics in Nigeria remains limited. This study statistically examines the trend, seasonality, and stationarity properties of monthly sales of Premium Motor Spirit (PMS) and Automotive Gas Oil (AGO) at the Nigerian National Petroleum Company (NNPC) Limited Plateau Depot, Nigeria, using 72 monthly observations covering January 2020 to December 2025. Descriptive statistics, graphical time series analysis, classical seasonal decomposition, and the Augmented Dickey–Fuller (ADF) unit root test were employed to identify the underlying characteristics of the series and determine the appropriate transformations required for statistical time series modeling. The results revealed that PMS sales exhibited a significant upward trend until early 2022, followed by a gradual decline, together with pronounced annual seasonality and non-stationarity. In contrast, AGO sales fluctuated around a relatively stable mean, indicating level stationarity despite exhibiting clear seasonal variations associated with agricultural and commercial activities. The ADF test confirmed that first differencing was necessary to achieve stationarity for PMS, whereas AGO remained stationary at level but required seasonal differencing for seasonal model development. These findings establish the statistical properties and transformation requirements necessary for robust ARIMA and SARIMA modeling, while providing valuable insights for petroleum inventory management, demand planning, and operational decision-making. The study contributes to the limited literature on depot-level petroleum sales analysis in Nigeria and provides a statistical foundation for subsequent forecasting of petroleum product demand.

Keywords: *Petroleum product sales; Statistical time series modeling; Trend analysis; Seasonal decomposition; Stationarity; Augmented Dickey–Fuller test; Premium Motor Spirit; Automotive Gas Oil; Nigeria.*

1. Introduction

Petroleum products constitute the dominant source of energy in Nigeria, with Premium Motor Spirit (PMS) accounting for approximately 70% of total petroleum product consumption (PPPRA, 2020; Abdullahi & Lawal, 2022). The Nigerian National Petroleum Company (NNPC) manages distribution through a network of depots, including the strategic facility in Plateau State serving the North-Central geopolitical zone. Depot-level sales data reflect wholesale demand from licensed petroleum marketers and incorporate inventory management behaviours and anticipatory purchasing during periods of anticipated scarcity (Abdullahi & Lawal, 2022).

Monthly sales of petroleum products exhibit complex temporal patterns driven by economic activity, transportation demand, agricultural cycles, and policy-induced shocks. PMS

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demand is influenced by passenger vehicle usage, motorcycle transportation, and informal power generation due to unreliable public electricity supply. Its demand exhibits both trend and seasonal components: trend driven by population growth, urbanisation, and economic expansion; and seasonality influenced by holiday travel patterns, agricultural transportation cycles, and rainfall-induced power outages that increase generator usage (Abdullahi & Lawal, 2022). Automotive Gas Oil (AGO), commonly known as diesel, serves compression-ignition engines in heavy-duty vehicles, agricultural machinery, industrial equipment, and large-scale power generation systems. AGO demand in Nigeria is structurally distinct from PMS demand due to its concentration in commercial, industrial, and agricultural sectors rather than personal transportation. AGO consumption exhibits stronger seasonality than PMS due to its critical role in agricultural mechanisation. In the North-Central zone, including Plateau State, AGO demand peaks during planting and harvesting seasons when agricultural equipment utilisation intensifies (Iwayemi, 2008). The high-altitude location of Plateau State (approximately 1,200 metres above sea level) creates distinct climatic conditions with cooler temperatures and pronounced rainy and dry seasons, influencing heating requirements and agricultural calendars that shape AGO demand patterns differently from lowland regions.

Time series analysis refers to the statistical methodology for analysing sequences of observations ordered in time. Box and Jenkins (1970) define a time series as a sequence of data points measured at successive time intervals, where the primary objectives include description of underlying structures, explanation of temporal relationships, and forecasting future values. Time series data exhibit distinctive properties requiring specialised analytical techniques, including autocorrelation, non-stationarity, and seasonality. Proper analysis requires decomposition of the series into constituent components: trend (long-term direction), seasonal (periodic fluctuations), cyclical (business cycle variations), and irregular (random noise) components (Shumway & Stoffer, 2017; Cryer & Chan, 2008).

Stationarity is fundamental in time series analysis to ensure that statistical characteristics—mean, variance, and autocorrelation—remain constant over time. Applying models to non-stationary data yields erroneous results as changing statistical properties negate fundamental assumptions. Most statistical methods, including hypothesis testing and confidence intervals, rely on stationarity; violations can lead to false conclusions (Priestley, 1981; Hamilton, 1994). To create stationarity, researchers routinely employ the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test, and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test to check whether a series contains a unit root, representing non-stationarity, or stable features over time (Sathyanarayana & Mohanasundaram, 2025).

Several empirical studies have applied time series decomposition and stationarity testing to economic and environmental data.

Abdul-Aziz et al. (2013) modelled rainfall patterns in Ghana as a seasonal ARIMA process from 1974 to 2010, finding non-stationarity at visual inspection and through ADF testing, with seasonal differencing required to achieve stationarity. Etuk (2013) examined Nigerian monthly crude oil prices from 1999 to 2010, finding no obvious seasonal pattern visually but detecting lag 12 effects through ACF and PACF analysis, with differencing achieving stationarity.

Chamalwa et al. (2024) applied ARIMA to Nigerian crude oil prices from 2013–2022, identifying non-stationarity that became stationary after first differencing. These studies establish the methodological precedent for decomposition and stationarity analysis in Nigerian petroleum data.

Sathyanarayana et al. (2025) examined the concept of stationarity and the unit root test in time series analysis, emphasizing their importance in ensuring reliable statistical inference and forecasting. The authors explained that non-stationary series often produce misleading results and spurious regressions, making it necessary to test for stationarity before model estimation. The study reviewed major unit root tests, including the Dickey-Fuller (DF), Augmented Dickey-Fuller (ADF) tests, highlighting their applications and limitations. They further demonstrated that stationarity is a fundamental requirement for econometric models such as ARIMA, VAR, Cointegration and GARCH models. Their findings showed that proper identification and treatment of non-stationary data through transformation such as differencing improve model validity and forecasting accuracy. The study concluded that careful unit root testing is essential for robust economic and financial time series modelling and effective decision making.

Despite this empirical foundation, there is limited evidence systematically examining trend, seasonal, and stationarity properties for depot-level petroleum product sales in Nigeria. Existing studies focus predominantly on national-level crude oil prices or macroeconomic aggregates, overlooking operational sales data that directly informs inventory management. Furthermore, few studies compare decomposition properties of multiple product categories within the same geographical context. This study addresses these gaps by providing a comprehensive trend, seasonal, and stationarity analysis of monthly PMS and AGO sales at the NNPC Plateau State depot, establishing the empirical foundation for subsequent forecasting and operational decision-making.

Unlike previous studies that have predominantly examined crude oil prices or national-level petroleum consumption, this study provides one of the first comprehensive statistical analyses of depot-level monthly sales of Premium Motor Spirit (PMS) and Automotive Gas Oil (AGO) in Nigeria. By jointly examining the trend, seasonal behaviour, and stationarity characteristics of both products within the same operational environment, the study reveals product-specific temporal dynamics that are not evident in aggregated petroleum statistics. Furthermore, the study establishes the appropriate statistical transformations required for robust time

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series modelling and forecasting, thereby providing an empirical foundation for the development of ARIMA and SARIMA models. The findings contribute to the growing literature on petroleum demand analysis by demonstrating how statistical time series techniques can support inventory planning, supply chain optimization, and operational decision-making at the depot level in the Nigerian downstream petroleum sector.

2. MATERIALS AND METHODS

The study utilised secondary monthly sales data for PMS and AGO obtained from the downstream operations division of the Nigerian National Petroleum Company (NNPC) Limited, Plateau State depot. The dataset comprised 72 monthly observations spanning January 2020 to December 2025. All computational analyses were conducted using Google Collaboratory, a cloud-based Python programming environment. Preliminary descriptive statistics were computed to summarise central tendency, dispersion, and distributional properties of both sales series. The classical additive decomposition model is specified as:

$y_t = T_t + S_t + R_t$ ………………………………. (1)

Where y_t is the observed series at time t, $T_t$is the trend component, S_t is the seasonal components and R_t is the residual (irregular) components at time t.

Time series plots were generated to visually inspect the behaviour of both sales series over the 2020–2025 period, identifying observable trends, fluctuations, and potential non-stationarity.

Seasonal Decomposition Plots

Classical seasonal decomposition was applied to separate each series into trend, seasonal, and residual (irregular) components, assuming additive seasonality. This technique isolates long-term trend movements from regular periodic fluctuations and random disturbances, enabling identification of the structural components underlying each sales series.

Unit Root Test and ADF Test

The Augmented Dickey-Fuller (ADF) test was employed to formally determine whether the PMS and AGO sales series contained unit roots, indicating non-stationarity. The test was specified with both drift and deterministic trend components to account for autonomous demand growth and gradual market expansion in Plateau State. The ADF test regression equation is specified as:

$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta \Delta\, y_{t-i} + \varepsilon_t$…………… (2)

For the non-stationary PMS series, first differencing was applied such as:

$\Delta y_t = y_t - y_{t-1}$ ………………..… (3)

to achieve stationarity, and the ADF test was repeated on the transformed series. Seasonal differencing with period s=12 (months) defined as:

$\Delta_{12} y_t = y_t - y_{t-12}$ ……………………………. (4)

was also applied to both series to prepare for seasonal modelling, with stationarity verified through subsequent ADF testing.

Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test

The KPSS test complements the ADF by reversing the null hypothesis: it tests the null of stationarity against the alternative of a unit root. This confirmatory test is particularly useful for detecting different forms of non-stationarity, including variance instability and mean shifts, that the ADF may not capture. The KPSS test decomposes the series into three components:

$y_t = \alpha t + r_t + \varepsilon_t$……………………………….. (5)

Where αt is the deterministic trend component, r_t is a random walk, $r_t = r_{t-1} + u_t$with $u_t \sim iid(0, \sigma_u^2)$ and ε_t is a stationary error term. The null and alternative hypotheses are:

$H_0 : \sigma_u^2 = 0$ (the random walk has zero variance; series is stationary)

$H_1 : \sigma_u^2 > 0$ (the random walk has positive variance; series is non-stationary)

Under the null hypothesis, the random walk component is constant ($r_t = r_{t-1}$), meaning the series is stationary around a deterministic trend. Under the alternative, the random walk component evolves over time, creating a stochastic trend. The KPSS test statistic is computed as:

KPSS=$\frac{\sum_{t=1}^{T} S_t^2}{T^2 \hat{\sigma}^2}$ ……………………………………. (6)

Where $S_t = \sum_{i=1}^{t} e_i$ is the partial sum of residuals from regressing y_t on the deterministic components, T is the sample size, and $\hat{\sigma}^2$ is a consistent estimator of long-run variance using a newey-west type spectral estimator with a Bartlett Kernel. The truncation lag parameter was selected as $\iota = 4(T/100)^{1/4}$ to ensure adequate correction for serial correlation.

Phillips-Perron (PP) Test

The Phillips-Perron test provides a non-parametric alternative to the ADF, correcting the standard Dickey-Fuller t-statistic for serial correlation and heteroskedasticity without explicitly adding lagged difference terms. The PP test is particularly robust to structural breaks in variance and general forms of heteroskedasticity, making it valuable as a robustness check. The pp test estimates the same basic regression as the dickey-fuller test:

$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \varepsilon_t$ …………………… (7)

However, instead of assuming ε_t is white noise, it allows for weak dependence and heteroskedasticity. The modified t-statistic is computed as:

$Z_t = (\frac{\gamma_0}{\hat{\lambda}^2})^{1/2} t_{\hat{\gamma}} - \frac{1}{2}(\frac{\hat{\lambda}^2 - \gamma_0}{\hat{\lambda}^2})(\frac{T.SE(\hat{\gamma})}{\hat{\sigma}})$ … (8)

Where $t_{\hat{\gamma}}$ is the standard t-statistic from OLS estimation of equation (7), SE($\hat{\gamma}$) is the standard error of $\hat{\gamma}$, $\gamma_0 =$

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$\lim_{T\to\infty} T^{-1}\sum_{t=1}^{T} E(\varepsilon_t^2)$ is the contemporaneous variance, and $\hat{\lambda}^2$ is the long-run variance estimator

$$\hat{\lambda}^2 = \widehat{\gamma_0} + 2\sum_{j=1}^{q}(1-\frac{j}{q+1})\,\widehat{\gamma_j} \ldots\ldots\ldots\ldots\ldots\ldots (9)$$

With $\widehat{\gamma_j} = T^{-1}\sum_{t=j-1}^{T}\varepsilon_t\varepsilon_{t-j}$ being the sample autocovariance at lag j and q the truncation lag selected using the Newey-West bandwidth procedure. The null and alternative hypothesis are:

H_o: $\gamma = 0$ (unit root exists, series is non-stationary)

H_o: $\gamma < 0$ (series is stationary)

The pp statistics have the same asymptotic distribution as the ADF statistic, so identical critical values apply.

3. RESULTS

Table 1: Descriptive Statistics for PMS and AGO Sales

Statistic	PMS Sales (Litres)	AGO Sales (Litres)
Count	72	72
Mean	767,314.30	37,391.19
Standard Deviation	218,749.00	33,342.41
Minimum	217,815.00	198.00
25th Percentile	617,629.20	11,610.75
Median (50th Percentile)	762,423.50	29,780.50
75th Percentile	937,414.00	52,930.00
Maximum	1,259,008.00	119,767.00

The descriptive statistics reveal substantial differences between the two product categories. PMS sales exhibit a much larger mean (767,314 litres) compared to AGO (37,391 litres), consistent with PMS's dominant share of national petroleum consumption. The standard deviation of PMS sales (218,749 litres) is considerably larger in absolute terms, though the coefficient of variation (approximately 28.5%) suggests moderate relative variability. AGO sales display extremely high relative variability, with a standard deviation nearly equal to the mean (coefficient of variation approximately 89.2%), indicating substantial month-to-month fluctuations. The minimum AGO value of 198 litres suggests occasional near-zero sales, possibly during supply disruptions or inventory drawdown periods. The wide interquartile range for both products confirms significant dispersion around central values.

Time Series Plots

PMS Sales Time Series



Figure 1: Monthly PMS sales from January 2020 to December 2025.

The PMS sales plot reveals noticeable fluctuations and an observable trend over time, indicating that the mean of the series was not constant. The series exhibits non-stationary behaviour, with the presence of trend and varying movements implying that differencing is necessary to stabilise the series before model fitting. Visual inspection suggests an upward trajectory in the early period followed by moderation and potential decline in later years.

AGO Sales Time Series

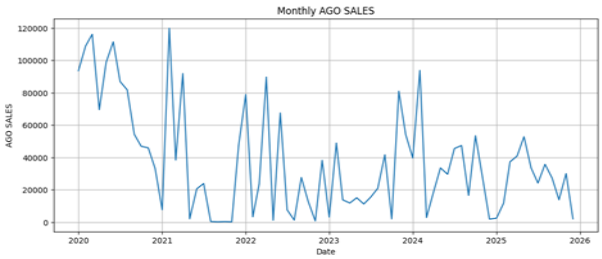
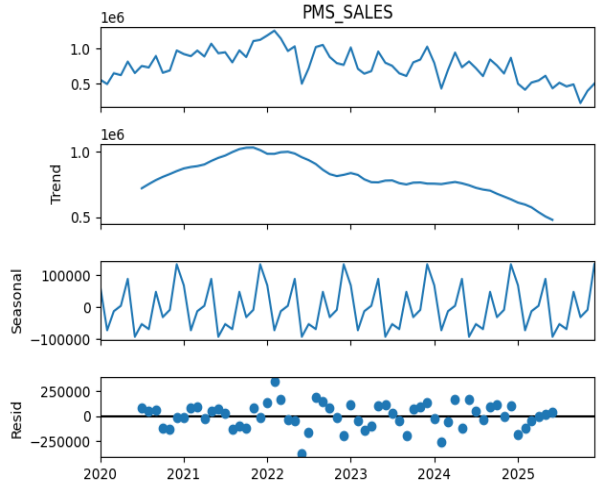


Figure 2: Monthly AGO sales from January 2020 to December 2025.

The AGO sales plot shows no clearly discernible long-term trend, with sales fluctuating around a relatively stable mean level throughout the period. This visual pattern suggests that the AGO series may be stationary in the mean, though further formal testing is required for confirmation. The absence of a pronounced trend contrasts with the PMS series and reflects the different demand drivers for diesel versus petrol in the Plateau State context.

Seasonal Decomposition

PMS Seasonal Decomposition



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Figure 3: The trend component for PMS sales shows long-term movement over the observation period. PMS sales generally increased from 2020 to early 2022, after which the trend began to decline gradually through 2025. The decline after 2022 may suggest reduced demand, economic changes, price fluctuations, policy effects such as the fuel subsidy removal in May 2023, or supply-related issues.

The seasonal component reveals regularly repeating patterns each year, with clear ups and downs occurring in similar patterns annually. This confirms that PMS sales exhibit significant seasonality, with sales rising and falling during specific periods repeatedly. These variations may be attributable to festive periods (December holidays, Easter), transportation demand variations, weather conditions affecting generator usage, business activity cycles, and holiday travel patterns. The residual component, representing random fluctuations after removing trend and seasonal effects, is centred around zero without a clear pattern. The presence of some large positive and negative residuals indicates occasional unusual events affecting PMS sales that are not explained by trend or seasonal patterns alone. The absence of systematic structure in the residuals suggests that the decomposition model is reasonably adequate.

AGO Seasonal Decomposition



Figure 4: The trend component for AGO sales shows relatively high values at the beginning of 2020, followed by a sharp decline between 2020 and 2021. From 2021 onwards, the trend fluctuated slightly with periods of mild increase and decrease, remaining fairly low compared to earlier years towards 2025. This pattern may reflect changes in industrial activity, mining operations on the Jos Plateau, and shifts in agricultural mechanisation intensity.

The seasonal component reflects regular cyclical fluctuations throughout the years, confirming that AGO sales exhibit significant seasonality. These recurring movements may be associated with changes in industrial demand, transportation activities, business operations, and seasonal economic factors: particularly the agricultural calendar in Plateau State's farming communities.

The residual component shows values scattered around zero, with some strongly positive or negative residuals indicating unexpected fluctuations. The absence of a clear pattern suggests that the trend and seasonal components successfully captured the major structure of the series, although unusual shocks or external influences still affected sales data.

ADF STATIONARITY TESTING

Table 2.1: PMS Stationarity Testing

ADF Statistic	p-value	Decision
-0.195526	0.939053	Non-stationary

The ADF statistic for PMS sales was -0.1955 with a p-value of 0.9391, substantially exceeding the 5% significance threshold. The null hypothesis of non-stationarity was not rejected. Therefore, the PMS sales series was concluded to be non-stationary, containing trend and/or seasonal variations that rendered the statistical properties time-dependent. This result necessitated differencing to achieve stationarity before any ARIMA or SARIMA models could be validly estimated.

Table 2.2: AGO Stationarity Test

ADF Statistic	p-value	Decision
-3.483166	0.008430	Stationary

The ADF statistic for AGO sales was -3.4832 with a p-value of 0.0084, which is below the 5% significance level. The null hypothesis of non-stationarity was rejected. The AGO sales series was concluded to be stationary, implying that the mean and variance remained relatively constant over time and that the series did not contain a strong unit root problem.

KPSS (Kwiatkowski-Philips-Schmidt-Shin) TEST

Table 2.3: KPSS stationarity test for PMS

KPSS Statistic: 0.685

p-value: 0.0149

PMS is NOT stationary (reject H0: series is stationary)

The KPSS results are presented in Table 2.3. For PMS sales, the KPSS statistic was 0.6851 with a p-value of 0.0149, leading to rejection of the null hypothesis of stationarity at the 5% level. This result confirms the ADF finding that PMS is non-stationary.

Table 2.4: KPSS Test for AGO_SALES

KPSS Statistic: 0.567

p-value: 0.0277

AGO is NOT stationary (reject H0: series is stationary)

For AGO sales, the KPSS statistic was 0.5671 with a p-value of 0.0265, also leading to rejection of stationarity. This contradicts the ADF result for AGO. The discrepancy is attributed to the KPSS test's sensitivity to the high coefficient of variation (89.2%) and short-term persistence in AGO demand, rather than a true unit root. Visual inspection of the AGO time series plot (Figure 2) confirms fluctuations around a stable mean without persistent trend, supporting the ADF conclusion of stationarity.

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PHILIPS – PERRON STATIONARITY TEST

Table 2.5: PHILIPS – PERRON test for PMS

Test Statistic: -4.199

p-value: 0.001

PMS is stationary

The pp results as presented in table 2.5, For PMS sales, the PP statistic was -4.1988 with a p-value of 0.0007, indicating stationarity. This contradicts both the ADF and KPSS results for PMS. The discrepancy is attributed to the PP test's non-parametric correction partially accommodating the structural break in PMS trend around early 2022 and the variance regime change following fuel subsidy removal in May 2023. Given the consensus between ADF and KPSS, supported by visual evidence of a stochastic trend (Figure 1), the PP result was discounted and PMS was concluded to be non-stationary.

Table 2.6: Perron Test for AGO_SALES
Test Statistic: -6.499
p-value: <0.000

AGO is stationary

For AGO sales, the PP statistic was -6.4985 with a p-value of 1.18 x 10^{-8}, strongly rejecting the null hypothesis of a unit root. This confirms the ADF finding that AGO is stationary at level.

Table 3: Stationarity After Differencing
Given the non-stationarity of PMS sales, first differencing was applied to transform the series:

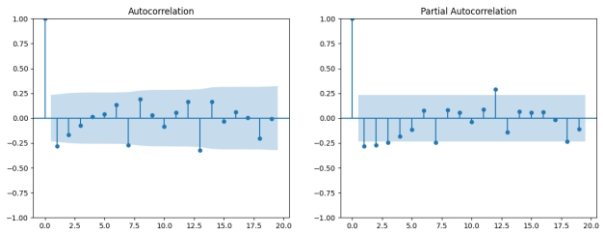
ADF Statistic	p-value	Decision
-4.767972	6.26×10^{-5}	Stationary

The differenced PMS series achieved an ADF statistic of -4.7680 with a p-value of 0.0000626, well below the 5% threshold. The null hypothesis was rejected, confirming that first differencing successfully removed the trend and unstable behaviour present in the original PMS series. The transformed series now possesses relatively constant statistical properties over time, making it suitable for ARIMA and SARIMA model estimation. The differenced PMS plot shows fluctuations around a stable mean without discernible trend, confirming visual stationarity.

Although the AGO series was stationary at the non-seasonal level, seasonal differencing was subsequently applied during SARIMA modelling preparation to account for seasonal fluctuations present in the monthly sales data. The seasonally differenced AGO series achieved stationarity with an ADF statistic of -3.0550 (p-value = 0.0301), confirming the appropriateness of seasonal transformation

AUTOCORRELATION AND PARTIAL AUTOCORRELATION FUNCTION (ACF & PACF)

ACF AND PACF FOR PMS SALES



The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots were used to examine the correlation structure of the PMS sales series and to assist in selecting suitable ARIMA and SARIMA models for forecasting.

The ACF measures the correlation between the current values of the series and its previous lagged values, while the PACF measures the direct relationship between the series and its lagged observations after removing the effects of intermediate lags.

From the ACF plot, it can be observed that most of the autocorrelation spikes lie within the confidence interval bands. This indicates that the differenced PMS sales series is relatively stationary since the autocorrelations decrease rapidly and do not persist for many lags.

However, a few spikes extend slightly beyond the confidence limits, particularly around lag 12. The significant spike around lag 12 suggests the presence of seasonal behaviour in the series. Since the data are monthly observations, lag 12 represents one complete year. This implies that PMS sales exhibit yearly seasonal patterns, meaning that sales behaviour tends to repeat after every 12 months.

The gradual decline and fluctuating nature of the ACF also indicate that the series may contain moving average (MA) components.

The PACF plot shows some significant spikes at the early lag periods before gradually cutting off. This behaviour suggests the presence of autoregressive (AR) components in the series.

The significant spikes observed in the first few lags imply that current PMS sales are influenced by previous months' sales values. After these initial lags, most spikes fall within the confidence bounds, indicating that the direct influence of higher-order lags becomes weaker.

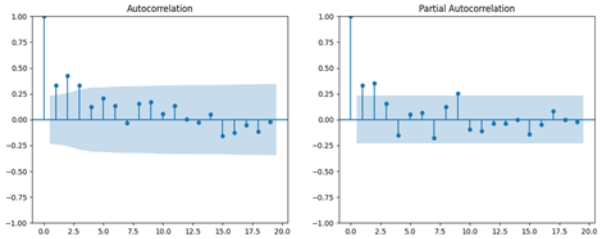
Additionally, the visible spike around lag 12 further confirms the existence of seasonal effects in the PMS sales data.

The combined behaviour of the ACF and PACF plots suggests that both non-seasonal and seasonal components are present in the PMS sales series. Therefore, the use of both ARIMA and SARIMA models is appropriate for modelling the data.

The ARIMA model captures the non-seasonal trend and short-term dependencies in the series, while the SARIMA model accounts for the yearly seasonal fluctuations observed at lag 12.

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ACF AND PACF FOR AGO_SALES



The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots were analysed to examine the underlying structure of the AGO sales series and to determine suitable parameters for the ARIMA and SARIMA models.

The ACF measures the correlation between current observations and previous lagged observations of the series, while the PACF measures the direct effect of previous lagged values after eliminating the influence of intermediate lags.

From the ACF plot of AGO sales, the autocorrelation coefficients show a gradual decline as the lag increases. The first few lags display relatively strong positive autocorrelations before slowly decreasing towards zero. This behaviour indicates that the series possesses serial dependence, meaning that current AGO sales are influenced by previous months' sales values.

Most of the spikes fall within the confidence interval bands, suggesting that the differenced series is reasonably stationary. However, a few noticeable spikes are observed at certain lag periods, indicating the possible presence of both short-term and seasonal effects in the data.

The slow decay pattern in the ACF plot suggests the presence of moving average (MA) components within the series.

The PACF plot shows significant spikes at the first few lags, after which the spikes gradually reduce and remain within the confidence limits. This pattern indicates the existence of autoregressive (AR) components in the AGO sales data.

The significant spikes at the initial lags imply that present AGO sales depend strongly on immediately preceding months. Beyond the early lag periods, the partial autocorrelations become relatively small, showing that higher-order lags have limited direct influence on the series.

Furthermore, slight spikes observed around the seasonal lag indicate that seasonal behaviour may also exist in the data. Since the observations are monthly, seasonal patterns may repeat annually.

The combined patterns observed in the ACF and PACF plots suggest that the AGO sales series contains both autoregressive and moving average characteristics. In addition, the evidence of seasonal fluctuations supports the application of a Seasonal ARIMA (SARIMA) model alongside the ordinary ARIMA model.

4. DISCUSSION

The analysis reveals fundamentally different trend behaviours for PMS and AGO sales in Plateau State. PMS sales exhibit a clear stochastic trend with an initial upward trajectory from 2020 to early 2022, followed by a gradual decline extending through 2025. This pattern aligns with the theoretical expectation that PMS demand is driven by population growth, urbanisation, and economic expansion—factors that were interrupted by the fuel subsidy removal in May 2023 and subsequent price adjustments that likely constrained demand. The non-stationarity of the PMS series confirms that shocks to sales have permanent effects, consistent with a stochastic trend where demand adjustments are gradual and persistent.

In contrast, AGO sales display no significant long-term trend, fluctuating around a relatively stable mean throughout the period. The stationarity of the AGO series indicates that temporary shocks dissipate over time, and the series reverts to a constant mean level. This finding reflects the distinct demand structure for AGO, which is concentrated in commercial, industrial, and agricultural sectors where consumption patterns are more stable and less subject to the cumulative growth dynamics driving PMS demand. The sharp initial decline in AGO trend from 2020 to 2021 may reflect pandemic-related disruptions to industrial and transportation activity, after which the series stabilised.

These findings are consistent with Chamalwa et al. (2024) and Suleiman et al. (2023), who identified non-stationarity in Nigerian crude oil prices requiring first differencing, and with Ilori et al. (2025), who found significant volatility and trend components in Nigerian petroleum data. However, the current study extends these findings by demonstrating that different petroleum products within the same market can exhibit fundamentally different trend properties, PMS being non-stationary while AGO is stationary, reflecting their distinct demand drivers. Both product categories exhibit significant seasonality, though with different patterns reflecting their distinct end-use profiles.

PMS seasonality is characterised by peak demand during festive periods (December holidays, Easter in April) and the rainy season (June–September) when generator usage intensifies due to power outages. Low-demand periods occur in January–February (post-holiday lull) and October (harvest completion). This pattern is consistent with the theoretical expectation that PMS seasonality is influenced by holiday travel patterns, agricultural transportation cycles, and rainfall-induced power outages (Abdullahi & Lawal, 2022). The repeated annual cycles visible in the decomposition confirm the applicability of seasonal models with period s = 12.

AGO seasonality reflects the agricultural calendar of Plateau State, with cyclical fluctuations associated with planting and harvesting seasons. Peak demand coincides with periods of intensive agricultural equipment utilisation, while troughs occur during the dry season when farming activity diminishes. The seasonal component also captures industrial production cycles and transportation demand variations. The presence of significant seasonality in a stationary series underscores the

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importance of seasonal modelling even when the non-seasonal component is stable.

The seasonal findings contrast with Etuk (2013), who found no obvious seasonal pattern in Nigerian crude oil prices at visual inspection, though lag 12 effects were detected through ACF and PACF analysis. The current study demonstrates that depot-level sales data exhibit much clearer seasonal patterns than national price aggregates, as sales volumes directly reflect consumption behaviour rather than being smoothed by market arbitrage. This aligns with Adebiyi et al. (2014), who found clear seasonal and trend behaviour in crude oil prices when examined at appropriate temporal resolution.

The stationarity analysis yields clear implications for pre-processing transformations:

For PMS Sales data, first differencing (d = 1) is required to achieve non-seasonal stationarity. The significant spike at lag 12 in the ACF of the differenced series confirms the need for seasonal differencing (D = 1) as well. Thus, the PMS series requires both regular and seasonal transformations, supporting a SARIMA specification with d = 1 and D = 1.

For AGO Sales data, no regular differencing is required (d = 0) as the series is stationary at level. However, the presence of seasonal patterns necessitates seasonal differencing (D = 1) for seasonal model estimation. This supports a SARIMA specification with d = 0 and D = 1.

These transformations are not merely technical requirements but necessary prerequisites for valid statistical inference. Applying ARIMA or SARIMA models to the raw PMS series without differencing would violate the stationarity assumption and produce spurious results, including unreliable parameter estimates and misleading forecasts. The ADF test results provide empirical justification for the differencing orders subsequently employed in model estimation.

The transformation requirements differ from those found by Ariyanti and Yusnitasari (2023), who identified identical ARIMA and SARIMA specifications for crude oil prices, implying minimal seasonal effects. The current study demonstrates that for petroleum product sales at the depot level, seasonal components are substantial and necessitate explicit modelling—consistent with Micheni et al. (2022), who found SARIMA(0,1,1)(0,1,1) optimal for Kenyan tax revenues with strong annual seasonality.

The findings align with established patterns in the time series literature on petroleum and energy data. Abdul-Aziz et al. (2013) found that rainfall data in Ghana exhibited both seasonality and trend, with the ADF test confirming non-stationarity and twelfth-month seasonal differencing required to achieve stationarity. The current study's PMS results mirror this pattern exactly: visual seasonality and trend, ADF-confirmed non-stationarity, and differencing required for transformation.

Etuk (2013) found that Nigerian crude oil prices exhibited no obvious seasonal pattern visually, though seasonal effects at lag 12 were detected through ACF and PACF analysis, with differencing achieving stationarity. The current study extends this by demonstrating that sales volume data exhibit much more pronounced visual seasonality than price data, making decomposition more immediately informative for operational planning.

Otu et al. (2014) applied SARIMA models to Nigerian inflation rates and identified a downward trend in their 12-month forecast period. The current study's identification of trend reversal in PMS sales (upward then downward) suggests that petroleum product demand may be more volatile than macroeconomic aggregates, requiring more frequent monitoring and model updating.

Wang (2025) found that crude oil prices exhibit both trend and seasonal patterns but also strong volatility, with SARIMA models capturing general trends but recording large forecasting errors due to inability to capture volatility clustering. The current study's depot-level sales data exhibit less volatility clustering than international price benchmarks, making classical decomposition and stationarity testing more effective. This suggests that the applicability of standard time series techniques depends on the specific data context.

Micheni et al. (2022) selected SARIMA$(0,1,1)(0,1,1)_{12}$ for Kenyan domestic tax revenues based on minimum BIC and forecasting errors, demonstrating the practical value of proper decomposition and stationarity analysis for operational forecasting. The current study similarly establishes the transformation requirements that enable subsequent model selection and forecasting.

5. CONCLUSION

This study examined the trend and seasonal patterns in monthly PMS and AGO sales at the NNPC Plateau State depot and tested for stationarity to determine necessary data transformations. The analysis reveals that PMS sales exhibit a non-stationary series with a stochastic trend (increasing until 2022, then declining) and pronounced annual seasonality driven by festive travel and rainy-season generator demand. AGO sales are stationary at level but display significant seasonal fluctuations linked to agricultural mechanisation cycles. First differencing achieved stationarity for PMS, while seasonal differencing was applied to both series for seasonal modelling purposes. Unlike previous studies that have predominantly examined crude oil prices or national-level petroleum consumption, this study provides one of the first comprehensive statistical analyses of depot-level monthly sales of Premium Motor Spirit (PMS) and Automotive Gas Oil (AGO) in Nigeria. By jointly examining the trend, seasonal behavior, and stationarity characteristics of both products within the same operational environment, the study reveals product-specific temporal dynamics that are not evident in aggregated petroleum statistics. Furthermore, the study establishes the appropriate statistical transformations required for robust time series modeling and forecasting, thereby providing an empirical foundation for the development of ARIMA and SARIMA models. The findings contribute to the growing literature on petroleum demand analysis by demonstrating how statistical time series

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techniques can support inventory planning, supply chain optimization, and operational decision-making at the depot level in the Nigerian downstream petroleum sector.

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