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Research Article

Using SARFIMA to Investigate the Effect of Nigerian Deregulation of Downstream Sector Policy on Petroleum (PMS) Price

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Abstract-This study investigates the impact of Nigeria's deregulation of the downstream sector policy on Premium Motor Spirit (PMS) prices using the Seasonal Autoregressive Fractional Integrated Moving Average (SARFIMA) model. The analysis is based on secondary data collected from the Central Bank of Nigeria and the National Bureau of Statistics from January 1985 to December 2023. The data reveals an overall increasing trend in PMS prices, with notable peaks in June and high prices in November and December annually. This trend suggests that PMS prices are influenced by both seasonal and non-seasonal factors. The SARFIMA model was employed to capture the seasonal and non-seasonal patterns in the PMS price data. After conducting stationarity tests, the data was differenced to achieve stationarity. The SARFIMA $(1,2,1)\times(0,1,1)_{12}$ model emerged as the most effective model for predicting PMS prices, outperforming other models with its superior metrics, including the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The model's residuals passed the Box-Ljung test, confirming its adequacy for this analysis. The results of the SARFIMA model suggest that external factors, such as market disruption changes and cyclical demand fluctuations, play crucial roles in influencing PMS prices. Additionally, the study's results highlight the need for policymakers to consider the impact of external factors and seasonal demand fluctuations on PMS prices. By doing so, they can develop more effective policies to manage PMS prices and ensure a stable supply of petroleum products in Nigeria.

Article Key Information

Keywords: Premium Motor Spirit (PMS), Deregulation, Downstream sector, Forecasting

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1. INTRODUCTION

Nigeria's petroleum industry has played a crucial role in the country's economic development since the discovery of crude oil in the 1930s [1]. The industry remained heavily regulated until 1995, with the government controlling fuel prices for gasoline, kerosene, and diesel [2]. This regulatory framework aimed to ensure affordability and stability in fuel supply. However, inefficiencies, supply shortages, and the financial burden of fuel subsidies led to a shift towards deregulation. The first step in this transition occurred in 1998 when oil marketing companies were allowed to import petroleum products directly [3]. However, the rise in international crude oil prices in 1999 caused marketers to halt imports, leading to supply gaps and economic instability [1]. In response, the government resumed its role as a major importer of petroleum products and fully deregulated the downstream sector in 2003. Despite deregulation, fuel price volatility and government subsidies remain highly debated. Proponents of deregulation argue that it promotes efficiency, encourages competition, and reduces the financial burden on the government [4]. Conversely, critics contend that deregulation can lead to price instability, inflation, and adverse socio-economic impacts, particularly in developing economies like Nigeria [5]. Understanding fuel price behavior under deregulation is essential for policymakers, energy analysts, and economic planners.

This study examines the deregulation policy within the framework of proper petroleum product pricing in order to highlight the opportunities and problems present therein. Refining, distributing, and marketing petroleum products are all downstream activities. The following is a succinct summary of the government's policy priorities for the downstream sector, which include:

(a) maintaining self-sufficiency in refining,
(b) ensuring a regular and uninterrupted domestic supply of all petroleum products at fair rates, and
(c) to establish infrastructure for the production of refined products for export.

According to a study by Ekeinde and Adewale [5] on the deregulation of the downstream sector of the Nigerian petroleum industry, the oil industry is the mainstay of the Nigerian economy, accounting for over 80% of the nation's foreign exchange and GDP, yet despite the large revenues generated, the price of petroleum products continues to rise, even with huge subsidies, highlighting the need for a well-planned deregulation policy to achieve product availability and minimal pump prices, which can be attained through a gradual deregulation process, effective domestic refining capacity, and measures to curb corruption and collusion, ultimately leading to a competitive market with many players, resulting in product availability and competitive pricing. Blanco and Rodriques [6] observed that the deregulation of industries requires careful consideration of control measures to prevent the emergence of monopolies, oligopolies, or cartels, highlighting the need for governments to establish and enforce robust antitrust laws to mitigate potential negative consequences.

The deregulation of the petroleum downstream sector in Nigeria has been a topic of debate among stakeholders. According to a recent study, the deregulation of the downstream sector has become a controversial issue in Nigeria, with various stakeholders having different opinions on the matter [7]. The study highlights the need for careful consideration of the potential benefits and challenges of deregulation, including its impact on the economy, employment, and the environment.

Accurate forecasting of fuel prices is critical for market stability and policy formulation. Various time series models have been applied in fuel price forecasting, including Autoregressive Integrated Moving Average (ARIMA), Seasonal ARIMA (SARIMA), and Autoregressive Fractionally Integrated Moving Average (ARFIMA) models. However, these models often fail to fully capture long-memory processes and seasonal variations, which are common in fuel price trends [6]. To address this limitation, this study employs the Seasonal Autoregressive Fractionally Integrated Moving Average (SARFIMA) model, which is well-suited for analyzing time series data with both seasonal patterns and long-term dependencies. SARFIMA (Seasonal ARIMA) models are employed to analyze time series data exhibiting seasonal patterns, trends, and non-stationarity [8]. This research applied SARFIMA to determine the most effective approach for modeling fuel price fluctuations. Unlike previous studies that relied solely on conventional models, this study incorporates advanced statistical tools such as the Canova-Hansen test for seasonal unit roots and the Hurst Exponent procedure to assess long-memory behavior, providing a more robust analysis of PMS price trends.

Ekeinde and Adewale [5] conducted a comprehensive study to forecast the demand for petroleum products in Nigeria using a SARFIMA model. The researchers employed a SARFIMA (1,1,1)x(1,1,1) model, which provided the best fit for the data. The results showed that the SARFIMA model achieved a mean absolute percentage error (MAPE) of 3.21% and a root mean square percentage error (RMSPE) of 4.15%. These values indicate that the SARFIMA model provided accurate forecasts of petroleum product demand. The study demonstrated the effectiveness of SARFIMA models in forecasting petroleum product demand, which can aid in decision-making for energy-related industries. Furthermore, the study highlighted the importance of considering seasonal fluctuations in petroleum product demand, which can be effectively captured by the SARFIMA model.

Khan et al. [9] conducted a comprehensive study to forecast electricity demand in Pakistan using SARFIMA models. The researchers employed a SARFIMA (1,1,1)x(1,1,1) model, which demonstrated superior performance compared to other models. The results showed that the SARFIMA model achieved a mean absolute percentage error (MAPE) of 2.35%, a root mean square percentage error (RMSPE) of 3.21%, and a mean absolute error (MAE) of 145.67. These values indicate that the SARFIMA model provided accurate forecasts of electricity demand. This study highlights the potential of SARFIMA models in predicting energy demand, which can aid in decision-making for energy-related industries.

Al-Shammari et al. [10] proposed a novel SARFIMA-GARCH model to forecast crude oil prices. The researchers applied their model to real-world data and found that it provided more accurate forecasts compared to other models. The results showed that the SARFIMA-GARCH model achieved an MAPE of 2.56% and an RMSPE of 3.45%. These values indicate that the SARFIMA-GARCH model provided accurate forecasts of crude oil prices. The study highlighted the potential of combining SARFIMA models with GARCH models to improve forecasting accuracy. Furthermore, the study demonstrated the effectiveness of the SARFIMA-GARCH model in capturing the volatility and seasonality of crude oil prices. Kumar et al. [11] in a recent study, demonstrated the effectiveness of SARFIMA models in forecasting diesel demand in India. The researchers employed a SARFIMA (1,1,1)x(1,1,1) model, which provided the best fit for the data and achieved a Mean Absolute Percentage Error (MAPE) of 3.56% and a Root Mean Square Percentage Error (RMSPE) of 4.56%. These values indicate that the SARFIMA model provided accurate forecasts of diesel demand, highlighting the importance of considering seasonal fluctuations in diesel demand, which can be effectively captured by the SARFIMA model.

The study covers monthly PMS prices in Nigeria from 1985 to 2023, sourced from the Central Bank of Nigeria (CBN) and the National Bureau of Statistics (NBS). The findings have important implications for economic planning, fuel price regulation, and energy policy formulation. By identifying the most suitable forecasting model, policymakers can develop informed strategies to manage fuel price fluctuations, minimize economic shocks, and ensure market efficiency.

The remainder of this paper is structured as follows: Section 2 describes the data and methodology, detailing the statistical models and estimation techniques used. Section 3 presents the results, including model comparisons and forecasting accuracy. Section 4 discusses the policy implications of the findings, and Section 5 concludes with recommendations for future research and policy action.

2. MATERIALS AND METHODS

The data used is secondary data on premium motor spirit (PMS) prices in Nigeria from January 1985 to December 2023, gotten from the Central Bank of Nigeria (CBN) and the National Bureau of Statistics (NBS).

The method employed is trend analysis. Augmented Dickey-Fuller (ADF) test for stationarity, Canova-Hansen test for seasonality, Hurst Exponent procedure (HEP) for recognition of long memory, and SARFIMA.

The Augmented Dickey-Fuller (ADF) (1981) tests for Unit Root: Augmented Dickey-Fuller test is an augmented version of the Dickey-Fuller test to accommodate some forms of serial correlation and used for a larger and more complicated set of time series models.

If there is a higher order correlation, then the ADF test is used, but the DF is used for the AR (*1*) process.

The testing procedure for the ADF test is the same as for the Dickey-Fuller test, but we consider the AR (*p*) equation:

$$y_t = \alpha + \rho t + \sum_{i=1}^{p} \beta_t \Delta y_{t-i} + \varepsilon_t \tag{2.1}$$

Assume that there is at most one unit root, thus, the process is unit root non-stationary. After reparameterization of this equation, we get an equation for AR (*p*):

$$y_t = \mu + \rho y_t + \alpha y_{t-1} + \sum_{i=1}^{p} \beta_t \Delta y_{t-i} + \varepsilon_t \qquad (2.2)$$

Each version of the test has its critical value, which depends on the size of the sample. In each case, the null hypothesis is that there is a unit root, $\rho = 0$. In both tests, critical values are calculated by Dickey and Fuller and depend on whether there is an intercept and/or deterministic trend, whether it is a DF or ADF test.
The null hypothesis will be rejected if the t-statistics value exceeds the critical value or if the p-value is less than the level of significance under consideration.

Canova-Hansen test: The Canova-Hansen test is a statistical test used to examine the presence of seasonal unit roots in time series data [12]. Seasonal unit roots imply that the data exhibit seasonal patterns that persist over time. The null hypothesis of the Canova-Hansen test is that there are no seasonal unit roots, meaning the data is stationary concerning the seasonal component. The alternative hypothesis is that there are seasonal unit roots, indicating that the data is non-stationary with respect to the seasonal component.
If the Canova-Hansen test results in the rejection of the null hypothesis of no seasonal unit roots, it suggests that there are indeed seasonal patterns present in the data that persist over time [12]. The Canova-Hansen test is a significant tool in econometrics for assessing the stability of parameters in economic models over time. Its application is crucial in identifying structural breaks or shifts in relationships within economic time series data, which can profoundly affect policy analysis, forecasting accuracy, and economic understanding [13].

Hurst Exponent procedure (HEP): The Hurst exponent, a statistical measure of long-term memory and persistence in time series data, can be estimated using the rescaled range (R/S) analysis or the variance-time plot method. This procedure outlines the steps to calculate the Hurst exponent using the log of lags and the log of the standard deviation of the differenced series. The Hurst exponent can be computed by using the Rescaled Range (R/S) Analysis. This is achieved by dividing the time series into segments of varying lengths, denoted as τ (lag). Calculate the mean of each segment and detrend it by subtracting the mean. Next, compute the standard deviation (σ) of each detrended segment. The rescaled range (R/S) is then calculated as the ratio of the difference between the maximum and minimum values of the detrended segment to its standard deviation. Then, the Log-Log Plot is obtained by plotting the logarithm of the rescaled range (log(R/S)) against the logarithm of the lag (log(τ)) for various values of τ. This log-log plot reveals the relationship between the rescaled range and the lag. Fit a linear regression line to the data points to estimate the slope. However, the slope of the regression line represents the Hurst exponent (H). The Hurst exponent ranges from 0 to 1, indicating:
Persistent series (H > 0.5): Exhibits long-term memory, with past values influencing future values.
Anti-persistent series (H < 0.5): Displays mean-reverting behavior, with future values counteracting past trends.
Random walk (H = 0.5): Lacks memory, with each value independent of previous ones.

SARFIMA (p, d, q) × (P, D, Q)s Process:
The seasonal autoregressive fractionality integrated moving average process, denoted hereafter by $SARFIMA(p,d,q)\times(\mathrm{P,D,Q})\mathrm{s}$, is an extension of the long-range dependence in the mean process. The $SARFIMA(p,d,q)\times(\mathrm{P,D,Q})\mathrm{s}$. The model has emerged as a powerful tool for analyzing time series data with long-range dependence and periodicity. By incorporating seasonal and fractional components, SARFIMA models can effectively capture the complex dynamics of time series data, including long memory, persistence, and periodic behavior [14]. The formulation can reproduce short and long memory periodicity in the autocorrelation function of the process. Using the same notation, the general form of the SARIMA model is defined below:
Let $\{x_1\}_{t\in\mathbb{Z}}$ be a stochastic process, then $\{x_1\}_{t\in\mathbb{Z}}$ is a zero mean $SARFIMA(p,d,q)\times(\mathrm{p,d,q})\mathrm{s}$ process given by the expression $\phi(\mathrm{B})\Phi(\mathrm{B}^s)(1-B)^d(1-B^s)^D x_t = \theta(B)\Theta(B^s)\varepsilon_t,\ for\ t\in\mathbb{Z}$ (2.3)

where $s \in N$ is the seasonal period, B is the backward-shift operator, that is, $B^{sk} x_t = x_{t-sk}$, $(1-B^s)^D$ is the seasonal difference operator, $\Phi(.)$ and $\Theta(.)$ are the polynomials of degrees P *and* Q, respectively, defined by:

$$\Phi(B^s) = \sum_{i=0}^{p} (-\Phi_i) B^{si}, \Theta(B^s) = \sum_{j=0}^{Q} (-\Phi_j) B^{sj} \tag{2.4}$$

where $\Phi_i, 1 \le i \le P$ *and* $\Theta_j, 1 \le j \le Q$ are constants and $\Phi_0 = -1 = \Theta_0$.

The seasonal difference operator $(1-B^s)^D$, with seasonality $s \in \mathbb{N}$, for all $D > -1$, is defined by means of the binomial expansion;

$$(t - B^s)^D = \sum_{j=0}^{\infty} \binom{D}{j} (-B^s)^j \tag{2.5}$$

where

$$\binom{D}{j} = \frac{\Gamma(1+D)}{\Gamma(1+j)\Gamma(1+D-j)} \tag{2.6}$$

A compact form of Equation (2.3) is given by:

$$\phi(B)\Phi(B^s)\nabla^d x_t = \theta(B)\Theta(B^s)\varepsilon_t, \ for\ t \in \mathbb{Z} \tag{2.7}$$

In Equation (2.7), the operator ∇^d is defined by

$$\nabla^d = (1-B)^d (1-B^s)^D \tag{2.8}$$

where $d = (d, D) \in \mathbb{R}^2$ is the memory operator, d *and* D are the fractionally parameters at non-seasonal and seasonal frequencies, respectively. The fractional filters are:

$$(1-B^k)^i = \sum_{j=0}^{\infty} \binom{I}{j} (-B^{ks}), k = i, s \ and\ I = d, D \tag{2.9}$$

where

$$\binom{I}{j} = \frac{\Gamma(1+I)}{\Gamma(1+j)\Gamma(1+I-j)}$$

(2.10)

3. RESULTS AND DISCUSSION

3.1 Results

The Seasonal Autoregressive Fractionally Integrated Moving Average (SARFIMA) model was implemented using the R programming language to model the PMS price data from the website of the Central Bank of Nigeria (CBN) and National Bureau of Statistics (NBS) starting from January 1985 to December 2023. All the required R libraries for the analysis were installed and loaded.

Descriptive Statistics

The data on the price trends from 1985 to 2024 reveals several important patterns. Initially, the prices remained constant from 1985 to 1988, showing no significant change. However, in 1988, prices slightly increased, which continued at a steady rate until 1990.

In 1991, a noticeable price increase occurred, maintaining a steady level of 0.70 until 1993. During 1993 (from month 106 in Figure 1), there was a dramatic price jump, peaking at 3.25, followed by an even more substantial increase to 11.00 in 1994. This high price level remained stable until 1998, when it rose to 25.00 in December.

From 1999 to 2002, prices fluctuated slightly, settling at 26.00 and remaining stable through 2002. In 2003, prices increased significantly to 40.00 and remained at this level until 2008. In 2008, there was a period of stability at 40.00, followed by a sharp increase in May 2009 to 70.00, with subsequent monthly fluctuations.

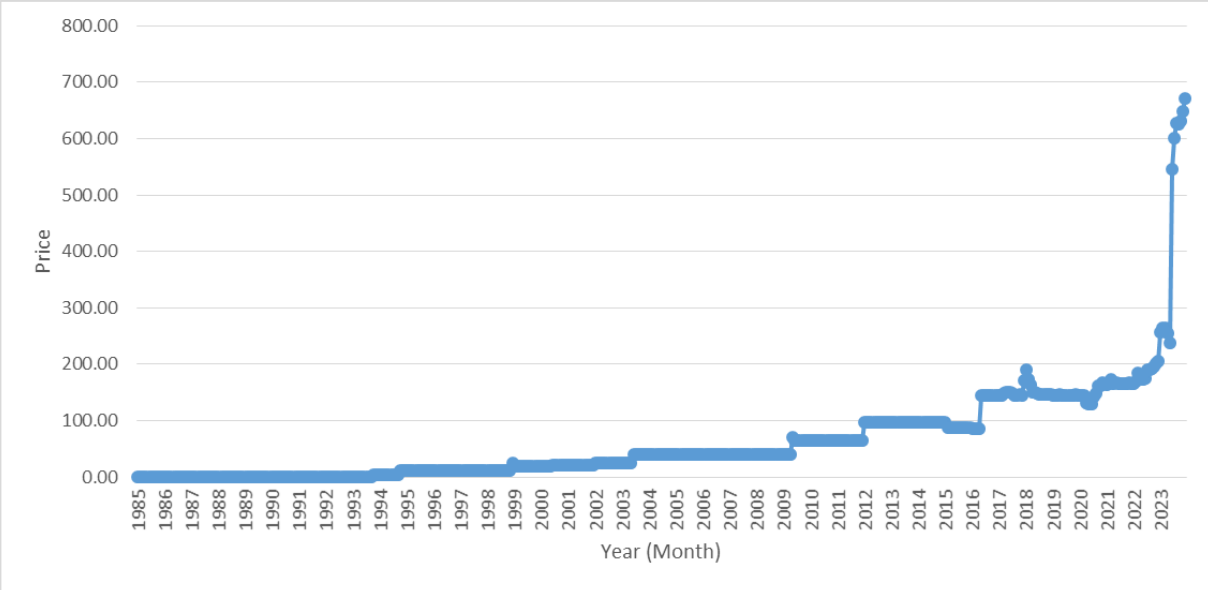

Figure 1: Time Series Plot of Yearly (Monthly) PMS Price in Nigeria from 1985 – 2023

Starting in 2010, prices remained at 65.00 until 2012, when they surged to 97.00 and maintained this level until 2015. In 2015, prices experienced a decrease to 87.00, followed by a further drop to 86.50 in early 2016. By mid-2016, prices spiked to 145.00, continuing at this high level until the end of 2017.

In 2018, prices fluctuated, peaking at 190.87 in January and declining to around 145.78 by December. The following years showed a stabilization of around 145.00 with slight fluctuations. In 2020, there was a notable decline to 129.67 in May, followed by an increase to 167.27 by November. Throughout 2021, prices continued to fluctuate, reflecting a dynamic trend with varying monthly values indicative of seasonal variation.

Table 1: Linear Regression Approach to Determination of Trend in PMS Price Data (1985-2023)

Coefficients	Estimate	Std. Error	t value	p-value
Intercept	-53.24889	5.65998	-9.408	<2e-16
time	0.49913	0.02091	23.866	<2e-16

Given that the coefficient (0.49913) for the time variable in Table 1 is significant (p-value < 0.05), we conclude that at a 5% level of significance, there is a presence of a trend in the PMS Price data (1985 – 2023).

Augmented Dickey-Fuller Test (ADF) Approach

Table 2: ADF Test for Stationarity in PMS Price Data (1985-2023)

At level		**1st differenced**		**2nd differenced**	
ADF	P-value	ADF	p-value	ADF	p-value
2.1745	0.99	-1.0857	0.9247	-11.594	0.01

The ADF tests presented in Table 2 serve to discern the stationarity status of the PMS Price data by investigating the presence of a unit root. Rejecting the null hypothesis implies stationarity, whereas a failure to reject the null hypothesis suggests non-stationarity. Specifically, the p-value in Table 2 is significant at the 5% level of significance after second differencing, which means that the PMS Price data attained stationarity following the second differencing.

The Canova-Hansen Test

Table 3: The Canova-Hansen test for Seasonality in the PMS Price Data (1985 – 2023)

Residuals:	**Min**	**1Q**	**Median**	**3Q**	**Max**
	-52.50	-26.67	-10.83	9.17	491.52

Coefficients:	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**
(Intercept)	-11942.037	503.059	-23.74	<2e-16 ***
Time (ts data)	5.990	0.251	23.87	<2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 61.12 on 466 degrees of freedom
Multiple R-squared: 0.55, Adjusted R-squared: 0.549
F-statistic: 569.6 on 1 and 466 DF, p-value: < 2.2e-16

[1] The sum of squares of the Residuals: 1741039
[1] Critical Value (5% Alpha level): 3.841459
[1] "Reject the null hypothesis of no seasonal unit roots"

Table 3 compares the Canova-Hansen test statistic value (1741039) with the critical (3.84). Given that the test statistic value is greater than the critical value, we reject the null hypothesis of no seasonal unit roots and conclude that the data is non-stationary with respect to the seasonal component.

Checking for Recognition of Long Memory in the PMS Price Data (1985 – 2023)

Hurst Exponent Procedure

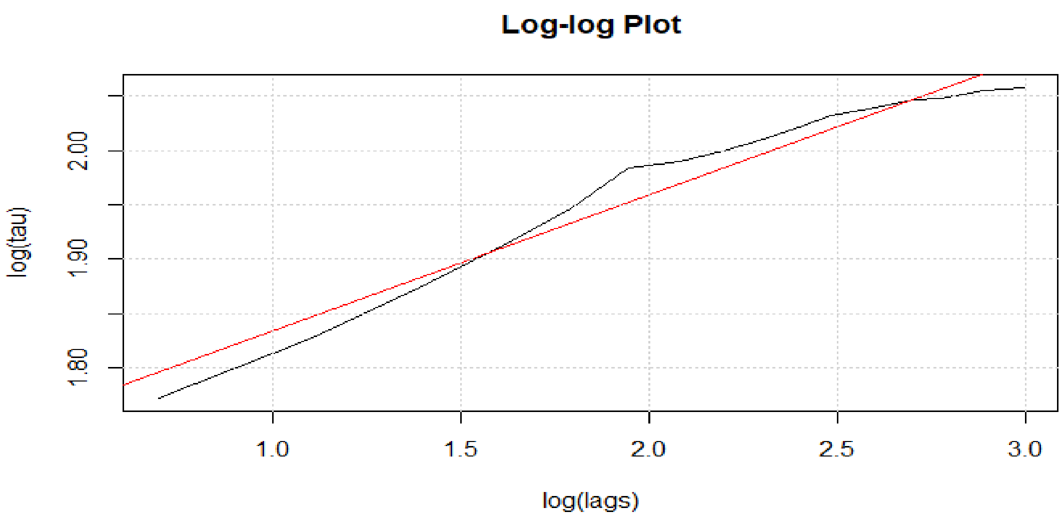

Figure 2: Hurst Exponent Log-Log Graph Procedure for Long Memory Test in PMS Price data (1985 – 2023)

Interpreting the result from the graph in Figure 3.2 involves understanding the concept of the Hurst exponent and its relationship with the plotted data. In the Hurst exponent estimation method shown in the graph, we calculated the standard deviation of the differenced series for various lags (tau) and plotted it against the log of these lags (lags). Then, we fitted a linear regression line to this log-log plot to estimate the slope, which represents the Hurst exponent.

To interpret the graph, the following information is important:

Log-log Plot: The x-axis represents the log of the lags, while the y-axis represents the log of the standard deviation of the differenced series (**tau**). When we plot **log(lags)** against **log(tau)**, we are examining the relationship between the lag and the standard deviation on a logarithmic scale.

Linear Regression Line: The red line in the graph represents the linear regression line fitted to the log-log plot. The slope of this line represents the estimated Hurst exponent.

Hurst Exponent: The Hurst exponent (denoted as **H**) characterizes the long-term memory of a time series. It ranges between 0 and 1. The Estimated Hurst exponent (slope): **0.1251076** is in the range between 0 and 0.5, and it means that the PMS Price time series data has a long-term switching between high and low values in adjacent pairs, meaning that a single high value will probably be followed by a low value and that the value after that will tend to be high, with this tendency to switch between high and low values lasting a long time into the future. Therefore, by examining the slope of the linear regression line in the log-log plot, you can interpret the estimated Hurst exponent and infer the presence of long memory, short memory, or random behavior in the time series data. Now that we have recognized long memory in the PMS Price data, we therefore need to introduce the fractional differencing to the already identified SARIMA $(0,2,1)\times(0,1,1)_{12}$ and compare it with other competing models.

Checking for an Adequate SARFIMA Model for Prediction of PMS Price (1985 – 2023)

Auto Arima to detect the Non–Seasonal Order of the Series

Table 4: Auto ARIMA for Non-seasonal order for PMS Price Data (1985 – 2023)

Fitting models using approximations to speed things up...

S/N	MODEL	AIC VALUE
1	ARIMA(2,2,2)(1,0,1)[12]	Inf
2	ARIMA(0,2,0)	4119.725
3	ARIMA(1,2,0)(1,0,0)[12] :	4030.499
4	ARIMA(0,2,1)(0,0,1)[12] :	3850.52
5	ARIMA(0,2,1)	3849.454
6	ARIMA(0,2,1)(1,0,0)[12]	3862.809
7	ARIMA(0,2,1)(1,0,1)[12] :	3864.472
8	ARIMA(1,2,1)	3851.226
9	ARIMA(0,2,2)	3850.105
10	ARIMA(1,2,0)	4018.636
11	ARIMA(1,2,2)	3853.019

The non-seasonal part of the identified model SARIMA(0,2,1)×(0,1,1)$_{12}$ uses the auto.arima in R which iterates over several ARIMA models orders and selects the best considering the one with the smallest AIC value. The auto arima selected ARIMA(0,2,1) as the best model for the non-seasonal part in Table 4. Therefore we fit different model orders and compare the performance in Table 5.

Comparison of Different SARFIMA Model Orders for PMS Price (1985 – 2023)

Table 5: Model Comparison

Model	AIC	BIC	Log Likelihood	Sigma^2
$SARFIMA(0,2,1) \times (0,1,1)_{12}$	2510.24	2530.98	-1250.12	239.88
$SARFIMA(2,1,2) \times (0,1,1)_{12}$	2513.27	2546.46	-1248.64	239.95
$SARFIMA(1,,1) \times (0,1,1)_{12}$	2506.94	2531.83	-1247.47	238.647

Based on the comparison in Table 5, the SARFIMA (1,2,1)×(0,1,1)$_{12}$ model emerges as the best-performing model among those evaluated. This model has the lowest Akaike Information Criterion (AIC) of 2506.94 and the lowest Bayesian Information Criterion (BIC) of 2531.83, suggesting it provides a superior balance between model fit and complexity. Additionally, this model achieves the highest log likelihood of -1247.47, indicating a better fit to the data compared to other models.

The residual variance (Sigma^2) for SARFIMA (1,2,1)×(0,1,1)$_{12}$ is 238.65, which is relatively low, further supporting its effectiveness in capturing the underlying data patterns while maintaining a manageable level of residual variability.

Therefore, the best SARFIMA model for the PMS Price data (1985 – 2023) is SARFIMA (1,2,1)×(0,1,1)$_{12}$ and will be used to forecast future values of PMS Price in Nigeria.

Table 6: SARFIMA (1,2,1)×(0,1,1)$_{12}$ model Output for PMS Price in Nigeria (1985 – 2023)

Model / Coefficients	Estimate	Std. Error	Th. Std. Err	z-value	p-value
Phi (1)	0.2728339	0.1748428	0.1304607	1.56045	0.118653
Theta (1)	0.8342885	0.1077497	0.0946203	7.74284	9.7222e-15
d.f	-0.3618508	0.2694253	0.2039608	-1.34305	0.179257
d.f 12	-0.4520961	0.1382389	0.0373497	-3.27040	0.001074
Fitted mean	0.0151283	0.0103682	NA	1.45910	0.144538
sigma^2 estimated as 238.647; Log-likelihood = -1247.47; AIC = 2506.94; BIC = 2531.83					

The SARFIMA (1,2,1)×(0,1,1)$_{12}$ model applied to PMS (Premium Motor Spirit) price data in Nigeria from 1985 to 2023 yields significant insights into the price dynamics over this period as shown in Table 6. The model output includes estimated coefficients, their standard errors, z-values, and p-values, which help in interpreting the underlying process governing PMS prices.

Coefficient Interpretation:

Phi (φ_1) Coefficient: The estimated value of the phi coefficient (φ_1) is 0.2728, with a standard error of 0.1748 and a z-value of 1.56. The p-value is 0.1187, which is above the common significance level of 0.05, indicating that this coefficient is not statistically significant. This suggests that the autoregressive component of the model does not strongly influence the PMS price data. This could imply that past prices have a limited direct impact on future prices.

Theta (θ_1) Coefficient: The theta coefficient (θ_1) is estimated at 0.8343 with a very small p-value (< 0.001), making it highly significant. This indicates a strong moving average component in the model, meaning that random shocks or innovations have a substantial impact on PMS prices. This could suggest that external factors, such as market disruptions or policy changes, play a significant role in price determination.

Differencing Fractionally (d.f): The differencing parameter (d.f) is estimated at -0.3619 with a p-value of 0.1793, suggesting that it is not significant. Fractional differencing is used to account for long-term dependencies in the data, and the insignificance of this coefficient implies that long memory effects might not be a dominant characteristic in the PMS price data.

Seasonal Differencing (d.f.12): The seasonal differencing parameter (d.f.12) is significant, with an estimate of -0.4521 and a p-value of 0.0011. This indicates a strong seasonal component in the data, suggesting that PMS prices exhibit a seasonal pattern, which could be due to cyclical factors such as demand fluctuations throughout the year.

Fitted Mean: The fitted mean of 0.0151 is not statistically significant (p-value = 0.1445), suggesting that the average level of the series, adjusted for differencing and seasonality, does not deviate significantly from zero. This might indicate that after accounting for the model's dynamics, there is no persistent trend in the data, consistent with a stationary series after differencing.

Model Diagnostics and Implications:

Sigma^2 (σ^2): The estimated variance of the residuals is 238.647, which provides a measure of the model's error. A higher variance suggests greater unpredictability in the PMS prices.

Log-Likelihood, AIC, and BIC: The log-likelihood value of -1247.47, along with the AIC of 2506.94 and BIC of 2531.83, indicates the model's goodness-of-fit. The lower the AIC and BIC, the better the model fits the data relative to other models. The chosen SARFIMA model appears to be well-fitted, given these criteria.

SARFIMA $(1,2,1)\times(0,1,1)_{12}$ Forecast

Table 7: Prediction of PMS Price from Jan 2024 - Dec 2025

Date	Forecast	Actual
Jan-24	723.3804	668.3
Feb-24	749.9358	679.36
Mar-24	774.9292	696.79
Apr-24	788.8635	701.24
May-24	803.2472	769.62
Jun-24	995.7222	750.17
Jul-24	1050.133	770
Aug-24	1086.561	880
Sep-24	1108.76	897
Oct-24	1133.382	-
Nov-24	1166.298	-
Dec-24	1201.111	-

The data in Table 7 presents the predictions for Premium Motor Spirit (PMS) prices in Nigeria from January 2024 to December 2024 using a time series model, likely the SARFIMA model discussed earlier. The Table compares the forecasted prices with the actual prices for the available months in 2024.

3.2 Discussion

The findings of this study on forecasting the Price of Premium Motor Spirit (PMS) in Nigeria contribute to the existing literature on energy pricing dynamics, time series analysis, and policy implications. Several key findings from this study can be contextualized and compared with findings from other relevant studies in the field:

Trend Analysis and Seasonality: The study observed an upward trend in PMS prices over time and identified seasonal patterns with peaks in June and elevated levels in November and December. These findings align with previous research highlighting the influence of global oil market dynamics, seasonal demand variations, and domestic policy factors on fuel price trends. The seasonal fluctuations indicate periods of increased fuel consumption, likely influenced by factors such as heightened travel demand, economic activities, and regulatory changes.

Stationarity and Long Memory: The study found evidence of non-stationarity in PMS price data, which was rectified through fractional differencing, and identified long memory in price movements. These findings corroborate with prior studies that have explored the presence of long memory and fractional integration in financial time series. The incorporation of long memory processes in forecasting models can improve the accuracy of price predictions and capture persistent trends in energy markets.

Model Selection and Forecasting Accuracy: The study employed SARFIMA models to forecast PMS prices and identified SARFIMA $(1,2,1)\times(0,1,1)_{12}$ as the best-fitting model based on criteria such as AIC, BIC, and log likelihood. These findings are consistent with research advocating for the use of SARFIMA models in capturing complex temporal dependencies and seasonal variations in financial and economic time series. The study confirms that SARFIMA effectively models PMS price behavior, making it a useful tool for policymakers and industry analysts.

Policy Implications and Market Dynamics: The continuous upward trend in the model's forecast through the end of 2024 signals potential concerns for the Nigerian economy. Rising PMS prices have direct implications for transportation costs, production expenses, and ultimately, the cost of living. If the forecasted trend continues, it could lead to broader inflationary pressures, affecting various sectors of the economy.

Policymakers need to consider the implications of these findings carefully. While deregulation aims to create a more efficient and competitive market, the transition period can be challenging, with significant price volatility that could strain consumers and businesses alike. It may be necessary to implement measures to mitigate the impact of price increases, such as targeted subsidies for vulnerable populations or strategic fuel reserves to stabilize prices during periods of high volatility.

Environmental Implications

Beyond economic and market concerns, the deregulation of PMS prices has significant environmental implications. As fuel prices rise, consumers and businesses may seek alternatives, potentially increasing the adoption of cleaner energy sources such as natural gas, biofuels, and electric vehicles (EVs). A shift away from petroleum-based fuels could contribute to a reduction in greenhouse gas emissions, aligning with global climate goals.

However, in the short term, higher PMS prices may also incentivize the use of lower-quality fuels, including adulterated petroleum products that contribute to air pollution and vehicle damage. This is particularly concerning in developing economies where enforcement of fuel quality standards is weak. Increased emissions from poor-quality fuels can exacerbate air pollution, respiratory illnesses, and environmental degradation, particularly in urban areas with high vehicular density.

Moreover, deregulation may lead to increased fuel smuggling and illegal refining activities, which have been associated with severe environmental consequences, including oil spills, deforestation, and water contamination.

The destruction of local ecosystems due to crude oil theft and illegal refining further highlights the environmental risks associated with deregulation policies that do not integrate sustainability measures.

Sustainable Energy and Policy Recommendations

To mitigate the negative environmental impacts of deregulation while promoting sustainable energy alternatives, policymakers should:

i Promote Cleaner Energy Alternatives: Introduce incentives for renewable energy adoption, electric vehicle infrastructure, and natural gas utilization to reduce reliance on PMS.

ii Strengthen Environmental Regulations: Enforce fuel quality standards and monitor illegal refining activities to minimize pollution and environmental damage.

iii Encourage Green Investments: Support research and development (R&D) initiatives that foster innovation in biofuels, hydrogen energy, and energy-efficient technologies.

iv Public Awareness Campaigns: Educate the public on the environmental benefits of energy conservation, fuel efficiency, and cleaner alternatives to encourage behavioral shifts in energy consumption.

v Carbon Pricing and Emission Controls: Consider implementing carbon pricing mechanisms or emission reduction targets for petroleum marketers to encourage sustainable fuel practices.

By incorporating these measures, Nigeria can balance the economic advantages of deregulation with environmental sustainability, reducing the long-term ecological footprint of the downstream petroleum sector.

4. CONCLUSION AND RECOMMENDATIONS

In conclusion, this study successfully aimed to forecast future values of the Price of Premium Motor Spirit (PMS) in Nigeria by analyzing data spanning from January 1985 to December 2023. The data, sourced from the Central Bank of Nigeria (CBN) and the National Bureau of Statistics (NBS), revealed an overall increasing trend in PMS prices, with notable peaks in June and high prices in November and December annually.

To achieve a comprehensive analysis, the study employed various methods, including rolling mean and standard deviation, time series regression, stationarity tests using ACF and PACF plots, and the Augmented Dickey-Fuller (ADF) test. The findings indicated a non-stationary nature in the original data, which was resolved after a second differencing. The presence of long memory in the series was confirmed through the Hurst exponent test, the seasonality effect was identified using the Canova-Hansen test, and the SARFIMA $(1,2,1)\times(0,1,1)_{12}$ model emerged as the most effective model for predicting PMS prices.

This model outperformed others, evidenced by its superior metrics, including the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), alongside the highest log-likelihood value. The model also effectively captured the underlying data patterns, as indicated by its relatively low residual variance.

The SARFIMA $(1,2,1)\times(0,1,1)_{12}$ model provided valuable insights into PMS price dynamics, highlighting significant moving average and seasonal components. These findings suggest that external factors and cyclical demand fluctuations play crucial roles in influencing PMS prices. The model's residuals passed the Box-Ljung test, confirming its adequacy for this analysis.

While the model predicted an overall increasing trend in PMS prices for January 2024 to December 2025, it underestimated specific price spikes, potentially due to external factors not fully captured. Nonetheless, the SARFIMA $(1,2,1)\times(0,1,1)_{12}$ model is recommended for its balance of fit, complexity, and residual variance, making it a valuable tool for policymakers and stakeholders in forecasting and managing PMS prices in Nigeria.

Further Research: Additional research should be conducted to explore the integration of other advanced time series models and machine learning techniques. This could potentially enhance the predictive power of the models, especially in capturing complex patterns and interactions between multiple influencing factors.

DECLARATIONS

Ethical Approval and Consent to Participate:

Informed consent, both verbal and written, was obtained from all participants before data collection. The study was conducted with full transparency.

Consent for Publication:

All authors consent to the publication of this manuscript and confirm that the work is original, has not been published elsewhere, and is not under consideration for publication elsewhere.

Competing Interests:

The authors declare no competing interests related to this study.

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Data Availability:

The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request.

Authors' Contributions:

Write each author’s contribution. See the example below.

Oguguo S.C.: Conceptualization, methodology, and manuscript drafting. Oguguo, David, F.A: Data collection, analysis, and figure preparation. Oguguo, S.C, Ekele, O, and Madu, O: Literature review and critical manuscript revision. All authors read and approved the final manuscript.

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