Mikailalsys Journal of
Mathematics and Statistics

e-ISSN : 3030-816X
p-ISSN : 3030-8399
Index : Harvard, Boston, Sydney University, Dimensions, Lens, Scilit, Semantic, Google, etc

https://doi.org/10.58578/MJMS.v4i2.9367

Non-Sinusoidal Predictive Model of Premium Motor Spirit (PMS) in Nigerian Fuel Price Hike

Akpienbi I. O., Bello M.I., Atureta M.S., Barde A.
Abubakar Tafawa Belawa University, Bauchi, Nigeria
akpienbi4u@gmail.com

Article Info:

Submitted:	Revised:	Accepted:	Published:
Feb 13, 2026	May 11, 2026	May 23, 2026	May 28, 2026

Abstract

This study investigates the dynamics of Premium Motor Spirit (PMS) prices in Nigeria using a non-sinusoidal high-order mathematical model applied to annual data spanning 1990–2022. The proposed modelling framework is designed to represent long-term price growth behaviour and structural progression rather than periodic or cyclical movements. Model parameters were estimated using the least squares estimation technique to ensure optimal fitting of the observed price series. The adequacy of the model was evaluated through validation error metrics and correlation analysis, providing quantitative measures of goodness-of-fit and predictive reliability. The findings indicate that the non-sinusoidal high-order model effectively represents the sustained upward trajectory of PMS prices over the study period, reflecting gradual economic adjustments, inflationary pressures, and long-term policy influences. However, deviations between observed and model-generated prices were evident during periods characterized by abrupt policy interventions, subsidy reforms, and regulatory shocks, which introduced short-term irregularities into the price structure. Despite these disturbances, the model maintained a strong capacity to describe the overall price evolution and underlying trend of PMS pricing in Nigeria. This study contributes to energy price modelling literature by demonstrating the relevance of non-sinusoidal growth-based approaches for analysing long-term energy price behaviour in regulated and policy-sensitive economic environments.

Keywords: Energy Price Modelling; Non-Sinusoidal Modelling; Petroleum Motor Spirit; Policy Shocks; Price Dynamics

Introduction

The Premium Motor Spirit (PMS) price persistent fluctuation in Nigeria has become a major national concern due to its adverse impact on the economy and the livelihoods of citizens. As an oil-based economy, Nigeria's dependence on petroleum revenue makes it highly vulnerable to disruptions in fuel pricing (Omoregie, 2019). This vulnerability is compounded by the country's recent decline from being Africa's top oil producer, now overtaken by Angola (Ndigwe, 2022) and later reclaims it spot as top oil producer (Ndigwe, 2022).

The surge in fuel prices has intensified economic inequality and contributed to rising poverty levels (Egbewole and James, 2018). Since PMS is central to the production and energy sectors, price volatility directly affects industrial profitability and overall productivity (Isyaka, 2014). Globally, fuel price instability influences transportation, product prices, and energy consumption (Bosler, 2010).

In Nigeria, the reliance on PMS for energy and heating makes it difficult to substitute; meaning any abrupt hike in prices can destabilize the economy (Tuo *et al.,* 2011; Moshiri *et al.,* 2006). Furthermore, pipeline vandalism has significantly curtailed production, undermining Nigeria's capacity as a leading fuel producer (Balogun, 2015; Okere, 2017), and causing environmental degradation through farmland and water pollution (Adati, 2012).

Recent studies indicate that accurate prediction of Premium Motor Spirit (PMS) prices in requires advanced modeling approaches capable of capturing strong nonlinearity, volatility, and policy-driven shocks in the petroleum market. Evidence from petroleum price forecasting shows that machine-learning and hybrid mathematical models consistently outperform traditional econometric methods in terms of predictive accuracy (Kumar, 2025; Nguyen *et al.*, 2025). In particular, Reservoir Computing models demonstrate superior performance with significantly lower forecast errors compared to classical and deep-learning benchmarks (Kumar, 2025). The incorporation of news-based sentiment indicators further enhances forecasting performance by accounting for information shocks and policy signals that strongly influence price expectations (Li *et al.*, 2025). Hybrid frameworks combining LSTM, GRU, ANN, regression techniques, and volatility-sensitive components have also been shown to improve explanatory power and reduce prediction error across short-term forecasting horizons (Bharathi and Sujatha, 2025; Amelia and Wulandhari, 2025; Cohen, 2025). Moreover, integrating deep learning with econometric volatility modeling yields superior performance under high market uncertainty (Rao *et al.,* 2025). Collectively, these findings underscore the relevance of machine-learning-driven and hybrid modelling approaches for improving PMS price prediction accuracy in deregulated and volatile petroleum market.

Method of Analysis

The non sinusoidal model equation by Ogwumu and Ataribu, (2022) was modify to the seventh order and transformation to satisfy least square method to minimize our immense data using the functional to suit the least squares method (LSM) algorithm given below as it was apply in (Ogwumu *et al.,* 2025);

$$I_{\min} = \min \sum_{i=1}^{33} \left(P_i(t) = At_i^{\,7} + Bt_i^{\,6} + C_1 t_i^{\,5} + D_1 t_i^{\,4} + E_1 t_i^{\,3} + Ft_i^{\,2} + Gt_i + H \right)^2 \qquad 1.0$$

Then, taking the partial differentiates with respect to the constants $A, B, C_1, D_1, E_1, F, G, H$. In order to obtain their values

$$
\left.\begin{aligned}
\frac{\partial I}{\partial A} &= -2\sum\left(P_i(t) - At_i^7 - Bt_i^6 - C_1t_i^5 - D_1t_i^4 - E_1t_i^3 - Ft_i^2 - Gt_i - H\right)t_i^7\\
\frac{\partial I}{\partial B} &= -2\sum\left(P_i(t) - At_i^7 - Bt_i^6 - C_1t_i^5 - D_1t_i^4 - E_1t_i^3 - Ft_i^2 - Gt_i - H\right)t_i^6\\
\frac{\partial I}{\partial C_1} &= -2\sum\left(P_i(t) - At_i^7 - Bt_i^6 - C_1t_i^5 - D_1t_i^4 - E_1t_i^3 - Ft_i^2 - Gt_i - H\right)t_i^5\\
\frac{\partial I}{\partial D_1} &= -2\sum\left(P_i(t) - At_i^7 - Bt_i^6 - C_1t_i^5 - D_1t_i^4 - E_1t_i^3 - Ft_i^2 - Gt_i - H\right)t_i^4\\
\frac{\partial I}{\partial E_1} &= -2\sum\left(P_i(t) - At_i^7 - Bt_i^6 - C_1t_i^5 - D_1t_i^4 - E_1t_i^3 - Ft_i^2 - Gt_i - H\right)t_i^3\\
\frac{\partial I}{\partial F} &= -2\sum\left(P_i(t) - At_i^7 - Bt_i^6 - C_1t_i^5 - D_1t_i^4 - E_1t_i^3 - Ft_i^2 - Gt_i - H\right)t_i^2\\
\frac{\partial I}{\partial A} &= -2\sum\left(P_i(t) - At_i^7 - Bt_i^6 - C_1t_i^5 - D_1t_i^4 - E_1t_i^3 - Ft_i^2 - Gt_i - H\right)t
\end{aligned}\right\} \qquad 2.0
$$

But at turning point $\frac{\partial I}{\partial A} = \frac{\partial I}{\partial B} = \frac{\partial I}{\partial C_1} = \frac{\partial I}{\partial D_1} = \frac{\partial I}{\partial E_1} = \frac{\partial I}{\partial F} = \frac{\partial I}{\partial G} = \frac{\partial I}{\partial H} = 0$

Then, expand to obtain

$$
\left.\begin{aligned}
\sum_{i=1}^{33} P_i(t)t_i^7 &= A\sum_{i=1}^{33} t_i^{14} - B\sum_{i=1}^{33} t_i^{13} - C_1\sum_{i=1}^{33} t_i^{12} - D_1\sum_{i=1}^{33} t_i^{11} - E_1\sum_{i=1}^{33} t_i^{10} - F\sum_{i=1}^{33} t_i^{9} - G\sum_{i=1}^{33} t_i^{8} - H\sum_{i=1}^{33} t_i^{7}\\
\sum_{i=1}^{33} P_i(t)t_i^6 &= A\sum_{i=1}^{33} t_i^{13} - B\sum_{i=1}^{33} t_i^{12} - C_1\sum_{i=1}^{33} t_i^{11} - D_1\sum_{i=1}^{33} t_i^{10} - E_1\sum_{i=1}^{33} t_i^{9} - F\sum_{i=1}^{33} t_i^{8} - G\sum_{i=1}^{33} t_i^{7} - H\sum_{i=1}^{33} t_i^{6}\\
\sum_{i=1}^{33} P_i(t)t_i^5 &= A\sum_{i=1}^{33} t_i^{12} - B\sum_{i=1}^{33} t_i^{11} - C_1\sum_{i=1}^{33} t_i^{10} - D_1\sum_{i=1}^{33} t_i^{9} - E_1\sum_{i=1}^{33} t_i^{8} - F\sum_{i=1}^{33} t_i^{7} - G\sum_{i=1}^{33} t_i^{6} - H\sum_{i=1}^{33} t_i^{5}\\
\sum_{i=1}^{33} P_i(t)t_i^4 &= A\sum_{i=1}^{33} t_i^{11} - B\sum_{i=1}^{33} t_i^{10} - C_1\sum_{i=1}^{33} t_i^{9} - D_1\sum_{i=1}^{33} t_i^{8} - E_1\sum_{i=1}^{33} t_i^{7} - F\sum_{i=1}^{33} t_i^{6} - G\sum_{i=1}^{33} t_i^{5} - H\sum_{i=1}^{33} t_i^{4}\\
\sum_{i=1}^{33} P_i(t)t_i^3 &= A\sum_{i=1}^{33} t_i^{10} - B\sum_{i=1}^{33} t_i^{9} - C_1\sum_{i=1}^{33} t_i^{8} - D_1\sum_{i=1}^{33} t_i^{7} - E_1\sum_{i=1}^{33} t_i^{6} - F\sum_{i=1}^{33} t_i^{5} - G\sum_{i=1}^{33} t_i^{4} - H\sum_{i=1}^{33} t_i^{3}\\
\sum_{i=1}^{33} P_i(t)t_i^2 &= A\sum_{i=1}^{33} t_i^{9} - B\sum_{i=1}^{33} t_i^{8} - C_1\sum_{i=1}^{33} t_i^{7} - D_1\sum_{i=1}^{33} t_i^{6} - E_1\sum_{i=1}^{33} t_i^{5} - F\sum_{i=1}^{33} t_i^{4} - G\sum_{i=1}^{33} t_i^{3} - H\sum_{i=1}^{33} t_i^{2}\\
\sum_{i=1}^{33} P_i(t)t_i^1 &= A\sum_{i=1}^{33} t_i^{8} - B\sum_{i=1}^{33} t_i^{7} - C_1\sum_{i=1}^{33} t_i^{6} - D_1\sum_{i=1}^{33} t_i^{5} - E_1\sum_{i=1}^{33} t_i^{4} - F\sum_{i=1}^{33} t_i^{3} - G\sum_{i=1}^{33} t_i^{2} - H\sum_{i=1}^{33} t_i^{1}\\
\sum_{i=1}^{33} P_i(t) &= A\sum_{i=1}^{33} t_i^{7} - B\sum_{i=1}^{33} t_i^{6} - C_1\sum_{i=1}^{33} t_i^{5} - D_1\sum_{i=1}^{33} t_i^{4} - E_1\sum_{i=1}^{33} t_i^{3} - F\sum_{i=1}^{33} t_i^{2} - G\sum_{i=1}^{33} t_i^{1} - H\sum_{i=1}^{33} 1
\end{aligned}\right\}(3.0)
$$

Now, solve the system of equations (1.0) simultaneously to obtain the computational table below using the collected data in appendix (A) to have the constant coefficient values of $A, B, C_1, D_1, E_1, F, G$ and H

Table 1 Non-sinusoidal model computation analysis

(t)	$p(t)$	t^{14}	t^{13}	t^{12}	t^{11}	t^{10}	t^{9}
0	0.7	0	0	0	0	0	0
1	0.7	1	1	1	1	1	1
2	3.25	16384	8192	4096	2048	1024	512
3	11	4782969	1594323	531441	177147	59049	19683
4	11	2.68E+08	67108864	16777216	4194304	1048576	262144
5	11	6.1E+09	1.22E+09	2.44E+08	48828125	9765625	1953125
6	11	7.84E+10	1.31E+10	2.18E+09	3.63E+08	60466176	10077696
7	11	6.78E+11	9.69E+10	1.38E+10	1.98E+09	2.82E+08	40353607
8	11	4.4E+12	5.5E+11	6.87E+10	8.59E+09	1.07E+09	1.34E+08
9	20	2.29E+13	2.54E+12	2.82E+11	3.14E+10	3.49E+09	3.87E+08
10	22	1E+14	1E+13	1E+12	1E+11	1E+10	1E+09
11	26	3.8E+14	3.45E+13	3.14E+12	2.85E+11	2.59E+10	2.36E+09
12	30	1.28E+15	1.07E+14	8.92E+12	7.43E+11	6.19E+10	5.16E+09
13	40	3.94E+15	3.03E+14	2.33E+13	1.79E+12	1.38E+11	1.06E+10
14	55	1.11E+16	7.94E+14	5.67E+13	4.05E+12	2.89E+11	2.07E+10
15	60	2.92E+16	1.95E+15	1.3E+14	8.65E+12	5.77E+11	3.84E+10
16	65	7.21E+16	4.5E+15	2.81E+14	1.76E+13	1.1E+12	6.87E+10
17	70	1.68E+17	9.9E+15	5.83E+14	3.43E+13	2.02E+12	1.19E+11
18	65	3.75E+17	2.08E+16	1.16E+15	6.43E+13	3.57E+12	1.98E+11
19	65	7.99E+17	4.21E+16	2.21E+15	1.16E+14	6.13E+12	3.23E+11
20	65	1.64E+18	8.19E+16	4.1E+15	2.05E+14	1.02E+13	5.12E+11
21	65	3.24E+18	1.54E+17	7.36E+15	3.5E+14	1.67E+13	7.94E+11
22	141	6.22E+18	2.83E+17	1.29E+16	5.84E+14	2.66E+13	1.21E+12
23	97	1.16E+19	5.04E+17	2.19E+16	9.53E+14	4.14E+13	1.8E+12
24	97	2.1E+19	8.76E+17	3.65E+16	1.52E+15	6.34E+13	2.64E+12
25	87	3.73E+19	1.49E+18	5.96E+16	2.38E+15	9.54E+13	3.81E+12
26	86.50	6.45E+19	2.48E+18	9.54E+16	3.67E+15	1.41E+14	5.43E+12
27	86.5	1.09E+20	4.05E+18	1.5E+17	5.56E+15	2.06E+14	7.63E+12
28	86.5	1.82E+20	6.5E+18	2.32E+17	8.29E+15	2.96E+14	1.06E+13
29	145	2.98E+20	1.03E+19	3.54E+17	1.22E+16	4.21E+14	1.45E+13
30	145	4.78E+20	1.59E+19	5.31E+17	1.77E+16	5.9E+14	1.97E+13
31	165	7.57E+20	2.44E+19	7.88E+17	2.54E+16	8.2E+14	2.64E+13
32	198.7	1.18E+21	3.69E+19	1.15E+18	3.6E+16	1.13E+15	3.52E+13
$\sum =$	2053.85	3.15E+21	1.04E+20	3.45E+18	1.15E+17	3.87E+15	1.31E+14

Table 2 Non-sinusoidal model computation analysis continuation

t^8	t^7	t^6	t^5	t^4	t^3	t^2	t
0	0	0	0	0	0	0	0
1	1	1	1	1	1	1	1
256	128	64	32	16	8	4	2
6561	2187	729	243	81	27	9	3
65536	16384	4096	1024	256	64	16	4
390625	78125	15625	3125	625	125	25	5
1679616	279936	46656	7776	1296	216	36	6
5764801	823543	117649	16807	2401	343	49	7
16777216	2097152	262144	32768	4096	512	64	8
43046721	4782969	531441	59049	6561	729	81	9
1E+08	10000000	1000000	100000	10000	1000	100	10
2.14E+08	19487171	1771561	161051	14641	1331	121	11
4.3E+08	35831808	2985984	248832	20736	1728	144	12
8.16E+08	62748517	4826809	371293	28561	2197	169	13
1.48E+09	1.05E+08	7529536	537824	38416	2744	196	14
2.56E+09	1.71E+08	11390625	759375	50625	3375	225	15
4.29E+09	2.68E+08	16777216	1048576	65536	4096	256	16
6.98E+09	4.1E+08	24137569	1419857	83521	4913	289	17
1.1E+10	6.12E+08	34012224	1889568	104976	5832	324	18
1.7E+10	8.94E+08	47045881	2476099	130321	6859	361	19
2.56E+10	1.28E+09	64000000	3200000	160000	8000	400	20
3.78E+10	1.8E+09	85766121	4084101	194481	9261	441	21
5.49E+10	2.49E+09	1.13E+08	5153632	234256	10648	484	22
7.83E+10	3.4E+09	1.48E+08	6436343	279841	12167	529	23
1.1E+11	4.59E+09	1.91E+08	7962624	331776	13824	576	24
1.53E+11	6.1E+09	2.44E+08	9765625	390625	15625	625	25
2.09E+11	8.03E+09	3.09E+08	11881376	456976	17576	676	26
2.82E+11	1.05E+10	3.87E+08	14348907	531441	19683	729	27
3.78E+11	1.35E+10	4.82E+08	17210368	614656	21952	784	28
5E+11	1.72E+10	5.95E+08	20511149	707281	24389	841	29
6.56E+11	2.19E+10	7.29E+08	24300000	810000	27000	900	30
8.53E+11	2.75E+10	8.88E+08	28629151	923521	29791	961	31
1.1E+12	3.44E+10	1.07E+09	33554432	1048576	32768	1024	32
4.48E+12	1.55E+11	5.46E+09	1.96E+08	7246096	278784	11440	528

Table 3 Non-sinusoidal model computation analysis continuation

$P(t)t^7$	$P(t)t^6$	$P(t)t^5$	$P(t)t^4$	$P(t)t^3$	$P(t)t^2$	$P(t)t$
0	0	0	0	0	0	0
0.7	0.7	0.7	0.7	0.7	0.7	0.7
416	208	104	52	26	13	6.5
24057	8019	2673	891	297	99	33
180224	45056	11264	2816	704	176	44
859375	171875	34375	6875	1375	275	55
3079296	513216	85536	14256	2376	396	66
9058973	1294139	184877	26411	3773	539	77
23068672	2883584	360448	45056	5632	704	88
95659380	10628820	1180980	131220	14580	1620	180
2.2E+08	22000000	2200000	220000	22000	2200	220
5.07E+08	46060586	4187326	380666	34606	3146	286
1.07E+09	89579520	7464960	622080	51840	4320	360
2.51E+09	1.93E+08	14851720	1142440	87880	6760	520
5.8E+09	4.14E+08	29580320	2112880	150920	10780	770
1.03E+10	6.83E+08	45562500	3037500	202500	13500	900
1.74E+10	1.09E+09	68157440	4259840	266240	16640	1040
2.87E+10	1.69E+09	99389990	5846470	343910	20230	1190
3.98E+10	2.21E+09	1.23E+08	6823440	379080	21060	1170
5.81E+10	3.06E+09	1.61E+08	8470865	445835	23465	1235
8.32E+10	4.16E+09	2.08E+08	10400000	520000	26000	1300
1.17E+11	5.57E+09	2.65E+08	12641265	601965	28665	1365
3.52E+11	1.6E+10	7.27E+08	33030096	1501368	68244	3102
3.3E+11	1.44E+10	6.24E+08	27144577	1180199	51313	2231
4.45E+11	1.85E+10	7.72E+08	32182272	1340928	55872	2328
5.31E+11	2.12E+10	8.5E+08	33984375	1359375	54375	2175
6.95E+11	2.67E+10	1.03E+09	39528424	1520324	58474	2249
9.05E+11	3.35E+10	1.24E+09	45969647	1702580	63058.5	2335.5
1.17E+12	4.17E+10	1.49E+09	53167744	1898848	67816	2422
2.5E+12	8.62E+10	2.97E+09	1.03E+08	3536405	121945	4205
3.17E+12	1.06E+11	3.52E+09	1.17E+08	3915000	130500	4350
4.54E+12	1.46E+11	4.72E+09	1.52E+08	4915515	158565	5115
6.83E+12	2.13E+11	6.67E+09	2.08E+08	6511002	203468.8	6358.4
2.18E+13	7.43E+11	2.56E+10	9.02E+08	32517083	1214220	47777.1

Thus, substitute the constant coefficients of $A, B, C_1, D_1, E_1, F, G, H$ in equation (1.0) and likewise substitute the values of (t) in table 1 and 3 above, by solving simultaneously the system using Maple 18 software to obtain the constant coefficients in appendix (B). Hence, substitute the constant coefficients values into the non-sinusoidal model equation (1.0) with the values of (t) and it becomes.

Notwithstanding, let Compare the results of the non-sinusoidal (polynomial) model with the source data of the Nigerian fuel prices in appendix (A).

Table 4 Validation of the non-sinusoidal model result

Year(s)	(t)	P(t)	P(t) model	Absolute Error
1990	0	0.7	-8.45459	9.15459
1991	1	0.7	3.390392	2.690392
1992	2	3.25	9.884445	6.634445
1993	3	11	12.70095	1.700947
1994	4	11	13.2667	2.2667
1995	5	11	12.76096	1.760959
1996	6	11	12.12007	1.120068
1997	7	11	12.04715	1.047146
1998	8	11	13.02629	2.026288
1999	9	20	15.34074	4.659261
2000	10	22	19.0945	2.905499
2001	11	26	24.23682	1.763181
2002	12	30	30.58903	0.589028
2003	13	40	37.87319	2.12681
2004	14	55	45.742	9.257996
2005	15	60	53.80943	6.190567
2006	16	65	61.68151	3.318489
2007	17	70	68.98679	1.013213
2008	18	65	75.40587	10.40587
2009	19	65	80.6995	15.6995
2010	20	65	84.73469	19.73469
2011	21	65	87.50829	22.50829
2012	22	141	89.16745	51.83255
2013	23	97	90.02657	6.973431
2014	24	97	90.58	6.420002
2015	25	87	91.51008	4.510079
2016	26	86.50	93.68995	7.189947
2017	27	86.5	98.18055	11.68055
2018	28	86.5	106.2213	19.72133
2019	29	145	119.2141	25.78593
2020	30	145	138.6993	6.300686
2021	31	165	166.3248	1.324815
2022	32	198.7	203.8056	5.105555
				$\cong$ 275.4188

Validation results indicate moderate absolute errors throughout the study period. Errors are smallest during stable periods such as 1995–2005 and 2014–2017, but increase significantly during volatile years like 2012 and 2019. The cumulative absolute error is higher indicating reduced precision.

Table 5 Computation of the non-sinusoidal Model correlation

x	y	xy	y^2	x^2
0.7	-8.45459	-5.918213	71.48009207	0.49
0.7	3.390392	2.3732744	11.49475791	0.49
3.25	9.884445	32.12444625	97.70225296	10.5625
11	12.70095	139.71045	161.3141309	121
11	13.2667	145.9337	176.0053289	121
11	12.76096	140.37056	162.8421001	121
11	12.12007	133.32077	146.8960968	121
11	12.04715	132.51865	145.1338231	121
11	13.02629	143.28919	169.6842312	121
20	15.34074	306.8148	235.3383037	400
22	19.0945	420.079	364.5999303	484
26	24.23682	630.15732	587.4234437	676
30	30.58903	917.6709	935.6887563	900
40	37.87319	1514.9276	1434.378521	1600
55	45.742	2515.81	2092.330564	3025
60	53.80943	3228.5658	2895.454757	3600
65	61.68151	4009.29815	3804.608676	4225
70	68.98679	4829.0753	4759.177195	4900
65	75.40587	4901.38155	5686.04523	4225
65	80.6995	5245.4675	6512.4093	4225
65	84.73469	5507.75485	7179.967689	4225
65	87.50829	5688.03885	7657.700819	4225
141	89.16745	12572.61045	7950.83414	19881
97	90.02657	8732.57729	8104.783306	9409
97	90.58	8786.26	8204.7364	9409
87	91.51008	7961.37696	8374.094742	7569
86.5	93.68995	8104.180675	8777.806731	7482.25
86.5	98.18055	8492.617575	9639.420398	7482.25
86.5	106.2213	9188.14245	11282.96457	7482.25
145	119.2141	17286.0445	14212.00164	21025
145	138.6993	20111.3985	19237.49582	21025
165	166.3248	27443.592	27663.9391	27225
198.7	203.8056	40496.17272	41536.72259	39481.69
$\sum = 2053.85$	$\sum = 2053.864$	$\sum = 209753.7$	$\sum = 210272.47$	$\sum = 214919$

The correlation coefficient $(r) = \dfrac{n\sum xy - \sum x \sum y}{\sqrt{\left(n\sum x^2 - \left(\sum x\right)^2\right)\left(n\sum y^2 - \left(\sum y\right)^2\right)}}$

$$r = \frac{33\times(209753.7376)-(2053.85)(2053.864427)}{\sqrt{\left(33\times(214918.9825)-(2053.85)^2\right)\left(33\times(210272.4754)-(2053.864427)^2\right)}}$$

$$r = \frac{2.\ 7035\times10^6}{\sqrt{(2.\ 874\times10^6)(2.\ 7206\times10^6)}}$$

$$r = \frac{2.\ 7035\times10^6}{\sqrt{7.\ 819\times10^{12}}} = \frac{2.\ 7035\times10^6}{2.\ 7962\times10^6}$$

$$\therefore r = 0.96685$$

The correlation coefficient between observed PMS prices and non-sinusoidal model predictions is approximately 0.967, indicating a strong linear association. However, it shows greater dispersion around the line of best fit which reflect the model's difficulty in capturing cyclical price reversals.

Results and Discussion

As shown in table 2, the non-sinusoidal model produces a smooth, steadily increasing price trajectory over time. From 1990 to 2005, the model aligns reasonably well with observed prices, reflecting gradual growth. However, from 2008 onward, discrepancies become more pronounced.

During 2012, the model underestimates the sharp price jump to ₦141, and between 2018 and 2019, it overestimates prices when government intervention temporarily stabilized the market. Despite these deviations, the model correctly captures the long-term upward direction of PMS prices.

The non-sinusoidal model is effective in describing the general growth trajectory of PMS prices but fails to adequately capture the oscillatory behavior induced by policy interventions. PMS pricing in Nigeria is not governed solely by smooth economic growth; instead, it experiences repeated upward and downward adjustments. Consequently, while useful for long-term trend analysis, the non-sinusoidal model is less suitable for detailed forecasting in regulated fuel markets.

Conclusion

The findings indicate that PMS price movements in Nigeria are largely non-periodic and dominated by abrupt, policy-driven changes rather than smooth cyclical behaviour. Major price adjustments are closely associated with subsidy reforms, exchange-rate instability, deregulation policies, and global oil market shocks, leading to structural breaks in the price series. While the non-sinusoidal model captures the general long-term trend of PMS prices, its accuracy declines during periods of economic and regulatory instability. The study concludes that non-sinusoidal modelling offers a more realistic representation of PMS price dynamics, especially for short-term forecasting and policy analysis, and highlights the necessity of hybrid models that incorporate economic and institutional factors.

Acknowledgement

The author acknowledges the Tertiary Education Trust Fund (TETFund), Nigeria, for the financial support provided for this research under its Institution-Based Research intervention.

Conflict of Interests

The authors declare that there is no conflict of interests

References

Adati, A. K. (2012). Oil exploration and spillage in the Niger Delta of Nigeria. *Civil and Environmental Research, 2*(3), 38–51. https://www.iiste.org/Journals/index.php/CER/article/view/1789

Amelia, R., & Wulandhari, L. A. (2025). Crude oil price forecasting using LSTM and GRU feature extractor and machine learning regressor. *Journal of Advances in Information Technology, 16*(8), 1100–1117. https://doi.org/10.12720/jait.16.8.1100-1117

Balogun, T. F. (2015). Mapping impacts of crude oil theft and illegal refineries on mangrove of the Niger Delta of Nigeria with remote sensing technology. *Mediterranean Journal of Social Sciences, 6*(3), 150–153. https://doi.org/10.5901/mjss.2015.v6n3p150

Bharathi, S., & Sujatha, P. (2025). Oil and gas industry price prediction using hybrid machine learning techniques. *Journal of Information Systems Engineering and Management, 10*(41s), 56–68. https://doi.org/10.52783/jisem.v10i41s.7652

Bosler, F. T. (2010). *Models for oil price prediction and forecasting* [Master's thesis, San Diego State University].

Cohen, G. (2025). A comprehensive study on short-term oil price forecasting using econometric and machine learning techniques. *Machine Learning and Knowledge Extraction, 7*(4), Article 127. https://doi.org/10.3390/make7040127

Egbewole, Z. T., & Rotowa, O. J. (2018). Hike in pump price: Major doom to Nigerian forest. *Journal of Energy, Environmental & Chemical Engineering, 3*(2), 19–26. https://doi.org/10.11648/j.jeece.20180302.11

Isyaka, M. S. (2014). The implications of price changes on petroleum products distribution in Gwagwalada, Abuja, Nigeria. *Journal of Energy Technologies and Policy, 4*(7), 1–15. https://www.iiste.org/Journals/index.php/JETP/article/view/14278

Kumar, K. (2025). Forecasting crude oil prices using reservoir computing models. *Computational Economics, 66*, 2543–2563. https://doi.org/10.1007/s10614-024-10797-w

Li, M., Xiao, Y., Ding, S., Zhang, Q., Xiong, H., & Ding, J. (2025). Crude oil price fluctuation forecasting incorporating news sentiment based on improved sentiment lexicon. *Journal of King Saud University - Computer and Information Sciences, 37*, Article 262. https://doi.org/10.1007/s44443-025-00289-8

Moshiri, S., & Foroutan, F. (2006). Forecasting nonlinear crude oil futures prices. *The Energy Journal, 27*(4), 81–96. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol27-No4-4

Ndigwe, C. (2022, June 14). *Angola overtakes Nigeria as Africa's biggest oil producer*. BusinessDay. https://businessday.ng/energy/article/angola-overtakes-nigeria-as-africas-biggest-oil-producer/

Ndigwe, C. (2022, December 14). *Nigeria pumped 1.18m bpd oil in November*. BusinessDay. https://businessday.ng/energy/article/nigeria-pumped-1-18m-bpd-oil-in-november/

Nguyen, T. H., Nguyen, N. M. T., Le, T. P. T., Nguyen, T. H. P., & Hoang, T. H. (2025). Application of ARIMA and LSTM models for crude oil price forecasting. *International Journal of Scientific Engineering and Science, 9*(4), 31–34. https://ijses.com/wp-content/uploads/2025/04/121-IJSES-V9N3.pdf

Ogwumu, O. D., Ataribu, O. S., Akpienbi, I. O., Otti, E. E., Ogofotha, M. O., Philemon, M. E., & Shaiki, I. R. (2022). A mathematical model for estimating an intelligence quotient (IQ) of retiree and humans above 65 years: A study of Federal University Wukari community members of Nigeria. *International Journal of Engineering and Manufacturing, 12*(2), 41–51. https://doi.org/10.5815/ijem.2022.02.05

Ogwumu, O. D., & Ataribu, O. S. (2022). Determination of a better non-linear mathematical model with trigonometric sinusoidal behaviour for the pricing of local rice in Nigeria market. *Engineering Mathematics Letters, 2022*, Article 1. https://doi.org/10.28919/eml/6643

Okere, R. (2017, April 18). *Nigeria loses Africa's top oil producer position to Angola*. The Guardian. https://guardian.ng/news/nigeria-loses-africas-top-oil-producer-position-to-angola/

Omoregie, U. (2019). Nigeria's petroleum sector and GDP: The missing oil refining link. *Journal of Advances in Economics and Finance, 4*(1), 1–8. https://doi.org/10.22606/jaef.2019.41001

Rao, A., Sharma, G. D., Tiwari, A. K., Hossain, M. R., & Dev, D. (2025). Crude oil price forecasting: Leveraging machine learning for global economic stability. *Technological Forecasting and Social Change, 216*, Article 124133. https://doi.org/10.1016/j.techfore.2025.124133

Tuo, J., & Yanbing, S. (2011). Summary of world oil price forecasting model. In *2011 Fourth International Symposium on Knowledge Acquisition and Modeling (KAM)* (pp. 327–330). IEEE. https://doi.org/10.1109/KAM.2011.94