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Research article

Predicting Nigeria's Petroleum Price: A Comparison between Recurrent Neural Networks, Multilayer Perceptron Neural Networks, and Generalized Regression Neural Networks

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ABSTRACT

Predicting petroleum pump prices assists in knowing when, how, and what quality to purchase. The purpose of this study is to provide an acceptable deep-learning algorithm for modeling and forecasting Premium Motor Spirits (PMS) pump prices in Nigeria. A deep learning algorithm was employed to capture the non-linear correlations present in the series, detecting patterns and for satisfactory prediction capability. The study utilized 96 monthly petroleum price data from January 2016 to December 2023 as extracted from the National Bureau of Statistics (NBS) websites. The Multifactorial deep learning algorithms like Recurrent Neural Networks (RNN), Multi-layer Perceptron Neural Networks (MLP-NN), and Generalized Regression Neural Networks (GR-NN) were employed and compared to determine the best model that provides the most accurate method for prediction. Results generated from predicting evaluation criteria like Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) suggested that the Multi-layer Perceptron Neural Network model outperforms the Recurrent Neural Networks and Generalized Regression Neural Network models in the out-of-sample prediction performances of the models. The prediction using the GR-NN model revealed a relative increase in the PMS prices. The results further projected PMS Price as high as N727 per liter at the end of 2024 and above N2,213 for the year 2025. The study therefore recommends that Multilayer Perceptron Neural Networks provide an optimal deep learning algorithm for modeling and predicting Nigeria's PMS prices.

1. Introduction

Oil has been the mainstay of the Nigerian economy for decades, profoundly impacting the country's socio-political and economic activities. While the discovery of crude oil increased government revenue and national productivity—accounting for 58.06% of total revenue and 92.6% of total exports in 2018 [1]—it also introduced significant challenges. These include environmental degradation, bunkering, and the "natural resource curse" identified by researchers such as [3], and [2]. Although agriculture was the primary revenue source before 1956, the oil industry became the dominant economic driver following the Nigerian Civil War in 1970.

The stability of an economy relies on an efficient and sustainable supply of petroleum products [14]. As a vital energy source, any shortage disrupts global economic activity, making its consumption unavoidable as industrial demand grows [8]. Consequently, petroleum plays a pivotal role in international relations, trade, and modern civilization [2, 21].

In Nigeria, domestic petroleum prices have been regulated by the government since 1973. Because the country relies heavily on imports for marginal supply, domestic prices are closely tied to international crude oil fluctuations [5]. This dependence creates a ripple effect: hikes in Premium Motor Spirit (PMS) prices increase transportation costs and the price of consumer goods, directly impacting social welfare and industrial productivity, [7, 8].

Since the 1970s, the domestic price of PMS has followed a consistent upward trend. For context, the price rose from 3 kobo in 1970 to 70 kobo by 1981, eventually reaching N22 in 2000 and N97 in 2001. Today, the price exceeds N600 per liter. [10] notes that these adjustments are often driven by government efforts to eliminate gasoline subsidies. However, such spikes pose existential challenges to businesses, particularly those struggling with rising energy costs during manufacturing.

Furthermore, these fluctuations contribute to inflation and unequal income distribution [11]. The resulting cost-management pressure on consumer industries has intensified the need for automated PMS price prediction models that provide timely information for informed decision-making. Despite its significance, the gradual rise of petrol prices across Nigeria's 36 states remains poorly understood and difficult to forecast.

Traditional time series models, such as the Box-Jenkins (ARIMA) approach, have been criticized for their inability to handle the strong randomness and lack of parameter consistency found in volatile financial contexts [4]. In contrast, machine learning (ML) algorithms are highly effective at identifying hidden patterns and non-linear relationships within historical data. While deep fully connected networks (FCN) provide a strong baseline, recent research suggests that specialized architectures like Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks are better suited for learning long sequential data [25, 16].

In light of the prevailing need for robust predictive tools, this research aims to investigate how Recurrent Neural Networks (RNN), Multilayer Perceptron Neural Networks (MLP-NN), and Generalized Regression Neural Networks (GR-NN) algorithms can be employed to predict Nigerian PMS prices.

The remainder of this study is organized as follows: Section 2 provides an empirical review of related literature. Section 3 presents the materials and methods used for modeling. Section 4 compares the three deep learning algorithms and discusses the findings. Finally, Section 5 offers conclusions, recommendations, and a discussion of the study's limitations.

2. Empirical Review of Related Literature

The application of deep learning to energy price forecasting has expanded rapidly, with researchers increasingly favoring neural networks over traditional econometric models due to their ability to capture non-linear volatility.

Recent studies highlight the efficacy of Recurrent Neural Networks (RNN), particularly Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU). [26] demonstrated that LSTM outperformed GRU in predicting aviation fuel prices, while [23] found that LSTM surpassed Modified Ensemble Empirical Mode Decomposition (MEEMD) in carbon price projections. Similarly, [21] utilized Temporal Convolutional Networks (TCN) and LSTM for Australian PMS prices, suggesting that integrating historical sequences with external influences yields higher precision.

Hybridization has become a common strategy to enhance accuracy. [13] combined Deep Belief Networks (DBN) with Particle Swarm Optimization (PSO) for natural gas pricing, while [12] developed the MOEMD-CKA-ELM model for carbon trading. In the crude oil sector, [20, 17] introduced a VMD-SE-TS/LSTM paradigm, which outperformed benchmark models across various time horizons, proving that decomposition-ensemble frameworks are robust against market noise.

While traditional frameworks like ARIMA and GARCH remain relevant for capturing autocorrelation and structural breakdowns [18, 8], they often struggle with the randomness of high-volatility markets. [27] compared econometric models (OLS, ARIMA, GARCH) against neural networks (ANN, RNN, CNN), both concluding that deep learning architectures significantly outperform traditional statistical methods in daily crude oil price forecasting.

Furthermore, the integration of alternative data sources has shown promise. [24] utilized Google Trends data within an ensemble learning framework, finding that web search sentiment acts as a significant lead indicator for price swings. In a comprehensive evaluation of fourteen ML models, [23] observed that while Support Vector Regression (SVR) excelled for weekly data, linear regression remained competitive for daily COP data, depending on the performance metric used.

Despite the global proliferation of these models, several gaps remain. Many studies emphasize international benchmarks like WTI or Brent crude, often overlooking the domestic price complexities of specific developing economies like Nigeria. Furthermore, while hybrid models are gaining traction, the comparative performance of specific architectures—namely Recurrent Neural Networks (RNN), Multilayer Perceptron (MLP-NN), and Generalized Regression Neural Networks (GR-NN)—in the context of Nigerian PMS prices has not been rigorously explored. This study aims to fill this lacuna by providing a side-by-side performance evaluation of these three distinct algorithms.

3. Materials and Methods

3.1. Data

This study utilized secondary sourced data. The data comprised the time series of Nigeria's PMS prices. The data are a monthly series that covers the periods of 2016 to 2023. Data was sourced from the National Bureau of Statistics websites. Consequently, the analysis of the data was carried out using Excel and R programming.

3.2. *Machine Learning Modelling Approaches*

3.2.1. Recurrent Neural Network (RNN)

Estimating time series parameters, such as PMS prices, is based on the series' historical values, which vary according to the quantity of persistence components. Owing to [19], recurrent neural networks offer this functionality via the number of feedback loops. All layers of a generalized RNN can receive and deliver input in either way. Thus, the network's output is determined not only by the external inputs it receives, but also by the network's state at the previous time step. There are basically three approaches that 'memory' may be incorporated into fixed neural networks (ASCE-American Society of Civil Engineers, [19]). These are (which are, in ascending sequence of capability and complexity):

i Tapped delayed lines approaches: This uses prior inputs to calculate the response at a specific moment [15].

ii Context designs, also known as partial recurrent theories, preserve past node outputs rather than initial inputs (Kothari and Agyepong, 1997).

iii Completely recurrent models are those with full feedback and node linkages, [6].

This research used RNNs because they have several crucial features: events from the past (such as PMS pricing) can be preserved and used in present computations. They also enable the network to generate complicated, time-varying outcomes in response to basic, static inputs. RNNs have also been reported to infrequently settle at local minima, even when no measures are taken (Carling, 1995).

3.2.2. Training Methodology in RNNs

The method of training RNNs is similar to that of the Feed Forward Neural Networks (FFNN) models. The training algorithm is explained with the help of a simple example. A small Figure 1 depicts a network that has two neurons that input data, one hidden layer composed of three neurons, and a single output neuron. In addition, a neuron that receives data from the outcome layer and connects to the hidden one is added as illustrated. This neuron is an extra neuron in RNNs. Initially, weights are assigned as small random numbers. The inputs are fed into the input units, and the network's output is calculated similarly to the FFNN. The technique is performed for each of the patterns. After determining the system error, the network is trained using the steepest gradient approach, with the technique of arranged partial derivatives being used. The method of ordered partial derivatives, as given by [22], is explained briefly in the next section.

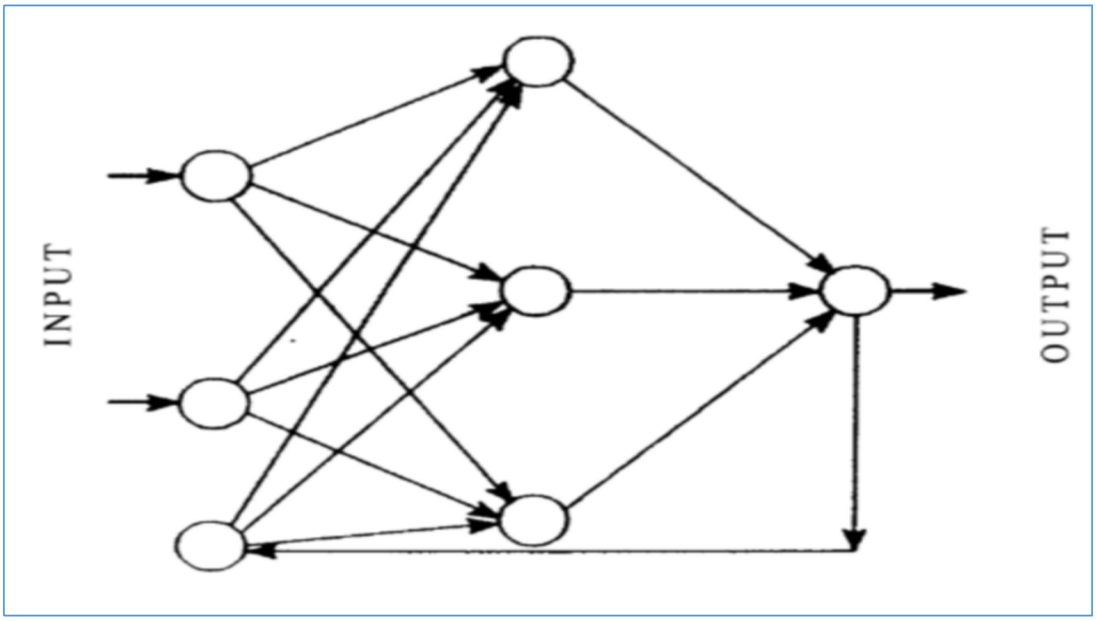

Figure 1. Typical Recurrent Neural Network

To explain the ordered partial derivatives, the composition of an ordered collection of equations can be presented as. Let $[Z_1, Z_2, Z_3, \ldots, Z_n]$ be a collection of n variables with values determined by a collection of n-equations. This equation is referred to as an arranged collection of equations if the variable Z_i is a part of the variables $[Z_1, Z_2, Z_3, \ldots, Z_{i-1}]$. Because of the arranged attributes of these equations, the variables $[Z_1, Z_2, Z_3, \ldots, Z_{i-1}]$ must be estimated before Z_i can be computed. As an illustration, the following three equations determine the form of a collection of equations that is ordered:

$$Z_1 = 1 \tag{3.1}$$

$$Z_2 = 3Z_1 \tag{3.2}$$

$$Z_3 = Z_1 + 2Z_2 \tag{3.3}$$

When estimating a partial derivative, it is important to indicate the variables that will be held constant and those allowed to change. If this is not determined,, it is suggested that all the variables are constant except the terms presented at the denominator of the partial derivative. Thus the partial derivative of Z_3 with respect to Z_1 is $\partial Z_3/\partial Z_1$. An ordered partial derivative (OPD) is a partial derivative whose constant and changing terms are determined using an ordered set of equations. The constant terms of the OPD of Z_j with respect to i (denoted as $\partial + Z_j/\partial Z_i$ to distinguish from the ordinary partial derivative) are $[Z_1, Z_2, Z_3, \ldots, Z_{i-1}]$ and the varying terms are $[Z_i, \ldots, Z_j, \ldots, Z_n]$.

Thus,

$$\text{If } j \leq i \quad \frac{\delta + Z_j}{\delta Z_i} = 0 \tag{3.4}$$

$$\text{If } j = i + 1 \quad \frac{\delta + Z_j}{\delta Z_i} = \frac{\delta Z_j}{\delta Z_i} \tag{3.5}$$

$$\text{If } j > i + 1 \quad \frac{\delta + Z_j}{\delta Z_i} = \frac{\delta Z_j}{\delta Z_i} + \sum_{k=i+1}^{j-1} \left(\frac{\delta + Z_j}{\delta Z_k} * \frac{\delta Z_k}{\delta Z_i} \right) \tag{3.6}$$

For training the network, once the system error has been calculated, the weights are changed according to the following equation.

$$\omega(k + 1) = \omega(k) - \mu * \frac{\delta + \mathrm{E}}{\delta\omega(k)} \tag{3.7}$$

where: $\omega(k)$ = thehe weight at the present iteration, k;
$\omega(k + 1)$ = the corresponding weight to be used for the next iteration, $k + 1$;
$\frac{\delta+\mathrm{E}}{\delta\omega(k)}$ = the gradient of the system error with respect to the weight $\omega(k)$.

3.2.3. Multilayer Perceptron Neural Networks (MLP-NN)

MLP-NN is a neural network based on feed forwarding having one or more layers connecting its input and layer of output. The term ”feed-forward” refers to data flowing in a single direction from the data source to the output layer. MLP-NN has three layers: an input layer, an additional hidden layer, and an outputs layer. According to Devadoss and Ligori (2013), input data are fed to neurons in the input layer, which process the input data before forwarding the output values to neurons in the layer that is concealed and finally to neurons in the output layer. Neural network training is an unrestricted nonlinear reduction process whereby a network's neural weights are iteratively changed to reduce the average or average squared error among the expected and actual output values. For training, the gradient steepest descent approach is employed with the most common backpropagation algorithm. For the slope descent method, a step size known as the learning rate must be provided. The rate of acquisition is a proportional constant that governs how much weight changes. A neuron's weight change is proportionate to its impact on the error. Incorporating a momentum element into the reverse propagation learning rule is one way to boost the learning rate and hence speed up training time without causing oscillation. The acceleration term determines how previous weight changes influence current weight changes. Many neural network software products have default settings for neural network learning speed and energy that are often effective. Initial learning rates in the literature range significantly from 0.1 to 0.9. Common practice is to begin training with a greater learning rate, such as 0.7, then gradually reduce as training progresses. As convergence approaches, many artificial neural network algorithms will automatically decrease the learning rate while increasing momentum values. Mathematically the signal processing of the network is given by equation (8).

$$y = f_s \left(\sum_{k=0}^{k} W_{1k}^{0} \left(f \sum_{n=0}^{n} W_{kn}^{i} U_n + b_n \right) \right) \tag{3.8}$$

Where network inputs are represented by U_n, the network's bias is denoted by b_n. In contrast, the f represents the activation function of the intermediate layers; the output layer activation function is denoted by f_s, and the last one, which is the output signal denoted by y.

In equation (8), it should be noted that W_{kn}^{i} are the weights for the middle layer, and W_{1k}^{o} represents the connections of the output (productivity) neurons.

The MLP-NNs methodology was used in this study because MLP methods are widely employed for pattern classification, prediction, recognition, and approximation. Weights are associated with connections among neurons, and transforming their value in a particular way results in the learning of the associated network.

The process through which weight changes occur in the network is known as a *training* or *training algorithmic structure*. The method of backpropagation is the most widely used learning approach. The process consists of two passes:

- Forward Pass: An input vector is passed through the network's nodes, yielding a set of outputs at the output layer. Throughout this phase, all weights remain fixed.

- Backward Pass: An inaccurate term is determined by comparing the network's actual answer to the desired response supplied.

3.2.4. Generalized Regression Neural Networks (GR-NN)

Specht (1991) presented a generalized regression neural network (GR-NN) as a variant of the radial basis neural network. If enough samples are available, a GR-NN may approximate any continuous function with arbitrary precision. The output for an input pattern x is computed in two steps, using a training set of n examples: n training patterns (vectors $\{x_1, x_2, \dots x_n\}$) and their corresponding training targets (scalars $\{y_1, y_n, \dots y_n\}$). First, the weights related to the training patterns are determined:

$$w_i = \frac{\exp\left(-\frac{\|x-x_i\|^2}{2\sigma^2}\right)}{\sum_{j=1}^{n} \exp\left(-\frac{\|x-x_i\|^2}{2\sigma^2}\right)} \tag{3.9}$$

The amounts of weight add up to one and signify x's closeness to the training patterns; the closer, the higher. Second, the training objectives are then averaged based on the weights needed to get the outcome:

$$\hat{y} = \sum_{i=1}^{n} w_i y_i \tag{3.10}$$

As a result, a weighted mean of the training goals is created, with weights representing the input's similarity to the patterns of the training. The smoothing component, σ, in equation (9) controls the amount of smoothness. When σ is big, all targets have tiny and similar weights, resulting in a result near to the target mean. When σ is small, only targets with patterns similar to the input receive substantial weights.

Figure 2 depicts the construction of a generalized regression neural network that was trained using n examples. As can be seen, a generalized regression neural network has three layers: input, hidden, and output. The only parameter of a generalized regression neural network is the smoothing factor.

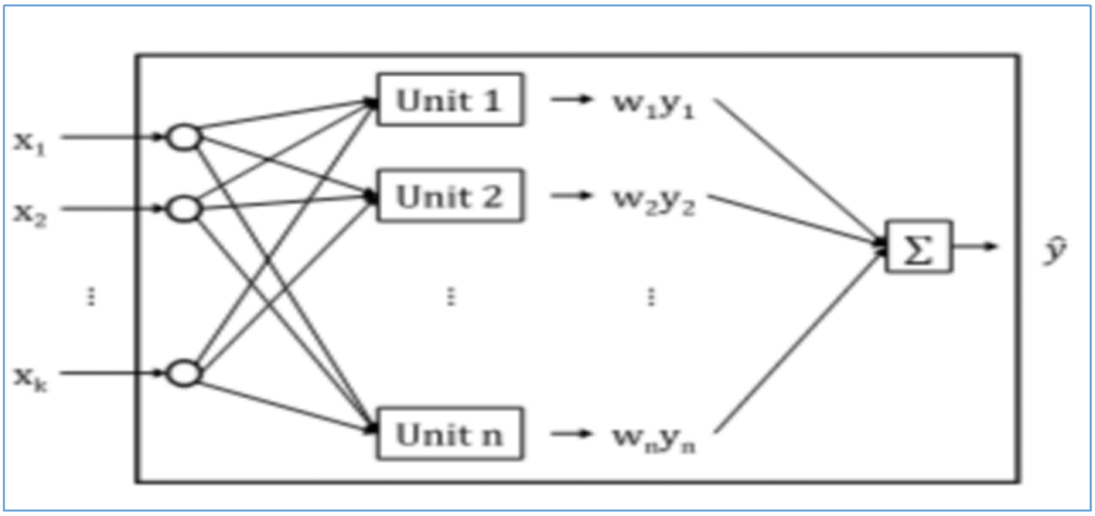

Figure 2. Structure of GR-NN

To apply GR-NN in a time series prediction environment, the training targets are the time series' historical values, and the patterns of the training are the targets' lagged (or preceding) values. Figure 2 depicts a fake quarterly time series with substantial seasonal behavior: in a year, the mean values of the initial two quarters are similar and greater than the amounts of the two most recent quarters, which are also comparable. Again, it is presumed that the training sequence contains the target's four lagged values. Figure 2 depicts the input to the GR-NN, which consists of the series's last four historical values, the most recent pattern of the training (i.e., the one with the greatest weight), and the corresponding goal. Also, the following graph shows two separate forecasts for the next predicted value for the data set (also known as the first three months of the following year). In the year of the forecast, the amount of smoothing is inadequate, along with just the goals of the patterns that were trained, which are similar to the feedback given significant weights in the weighted mean (because of variation in seasonal behavior, these objectives will probably be the first quarter parameters). In the remaining prognosis, the coefficient of smoothing is significant and, thus, all the training goals have an identical weight, therefore the outcome is close to the average of the previous values of the data set. It ought to be observed that, according to the seasonal nature of the series, the forecasting performed with the lower smoothing value is more appropriate. The present research used GR-NNs because machine learning can uncover trends in the PMS price series that are similar to its most recent preceding values, with the intention that the future values corresponding to these trends will be related to the series' future conduct. It also stems from the procedure's capacity to add a smoothing mechanism. The smoothing component establishes a level of similarity to a structure that plays an important part in the forecast.

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$$w_i = \frac{\exp\left(-\frac{\|x-x_i\|^2}{2\sigma^2}\right)}{\sum_{j=1}^{n} \exp\left(-\frac{\|x-x_j\|^2}{2\sigma^2}\right)} \tag{3.11}$$

The amounts of weight add up to one and signify x's closeness to the training patterns; the closer, the higher. Second, the training objectives are then averaged based on the weights needed to get the outcome:

$$\hat{y} = \sum_{i=1}^{n} w_i y_i \tag{3.12}$$

As a result, a weighted mean of the training goals is created, with weights representing the input's similarity to the patterns of the training. The smoothing component, σ, in equation (9) controls the amount of smoothness. When σ is big, all targets have tiny and similar weights, resulting in a result near to the target mean. When σ is small, only targets with patterns similar to the input receive substantial weights.

Figure 2 depicts the construction of a generalized regression neural network that was trained using n examples. As can be seen, a generalized regression neural network has three layers: input, hidden, and output. The only parameter of a generalized regression neural network is the smoothing factor.

3.4. Predicting Evaluation Criteria

Numerous error measures are available for model accuracy evaluation. This study evaluates the performance of the three machine learning models, namely, RNN, MLP-NN, and GR-NN, employing three different loss functions. This includes Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), which are defined as follows:

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2} \tag{3.13}$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|(A_t - F_t)| \tag{3.14}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{3.15}$$

Where A_t is the actual value in time t, and F_t is the forecast value in time t.

4. Results

4.1. Summary Statistics of the Data

Table 1 presents the descriptive statistics of the time series of Nigeria PMS prices. According to the table, the descriptive statistics for the aforementioned time series data reveal an average observed PMS Price of #194.87. The PMS Price was further revealed to range between #99.80 and #671.90 with a standard deviation of about 123.90. The table also depicts the Skewness and Kurtosis as well as the Jarque-Bera statistics for the time series normality check. The Skewness and Kurtosis as well as the Jarque-Bera statistics of the series signpost the non-normality of the series. Precisely, the Jarque-Bera probability value less than

0.05 implies the rejection of the null hypothesis of the series being normally distributed. The subsequent section presents and discusses the time series plots of the series.

Table 1. Descriptive Statistics of Nigeria PMS Prices

Statistics	PMS (Naira)
Mean	194.871
Median	150.300
Maximum	671.900
Minimum	99.800
Std. Dev.	123.896
Skewness	3.053
Kurtosis	10.943
Jarque-Bera	401.517
Probability	0.000
Observations	96

Moreover, Figure 3 presents the time series plot of the Nigerian PMS Prices between the period 2016 and 2020. As observed, the PMS Price was found to hit its lowest value of N99.80 in February 2016 for this study period (i.e., 2016-2023). The PMS Price was found to skyrocket to N162.80 in April 2016. This can be attributed to the depreciation of the Naira against the US Dollar. Afterwards, the PMS price was relatively constant between the period June 2016 and November 2017, with a PMS price of around N145.60. Again, the price rose abruptly to N190.87 in January 2018, and this can be attributed to the further fall of the Naira currency to the US Dollar. Thereafter, the price dropped to N151.40 in April 2018 and was relatively constant until July 2020, when the price was found to rise steadily, indicating instability in the PMS Price. Subsequently, the price rose sharply in June 2023 to N545.83 as a result of the removal of the fuel subsidy. It was further observed to rise to N671.86 because of the Naira depreciation as a result of the unification of the exchange rate. This is economically worrisome.

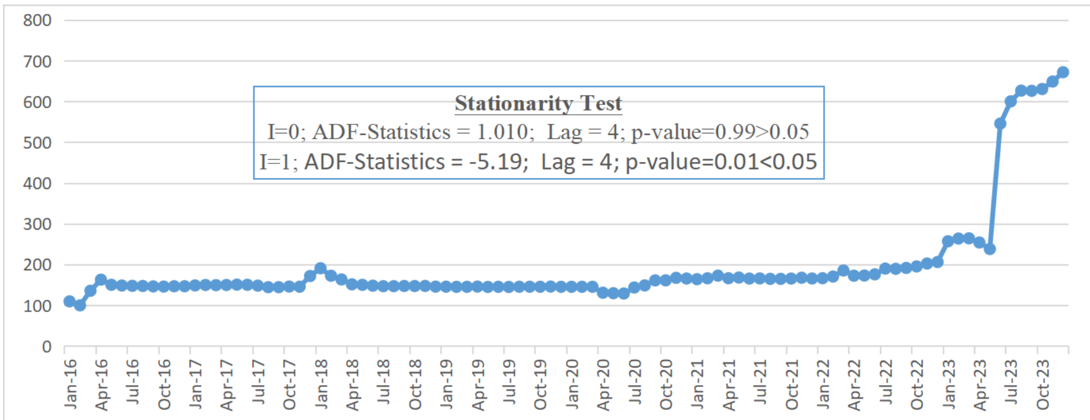

Figure 3. Time Series Plot of the Nigeria PMS Prices

Before the modeling of the PMS series, the stationarity test results (see Figure 4) depict a p-value of 0.99 which informs the non-rejection of the null hypothesis of non-stationarity for the PMS series at a 5%

level of significance. The series was found to be stationary at first difference (p-value of 0.01¡0.05). It can therefore be deduced that the PMS series was Stationary at first integration (I=1). Figure 4 presents the time series plot of the stationary PMS Price.

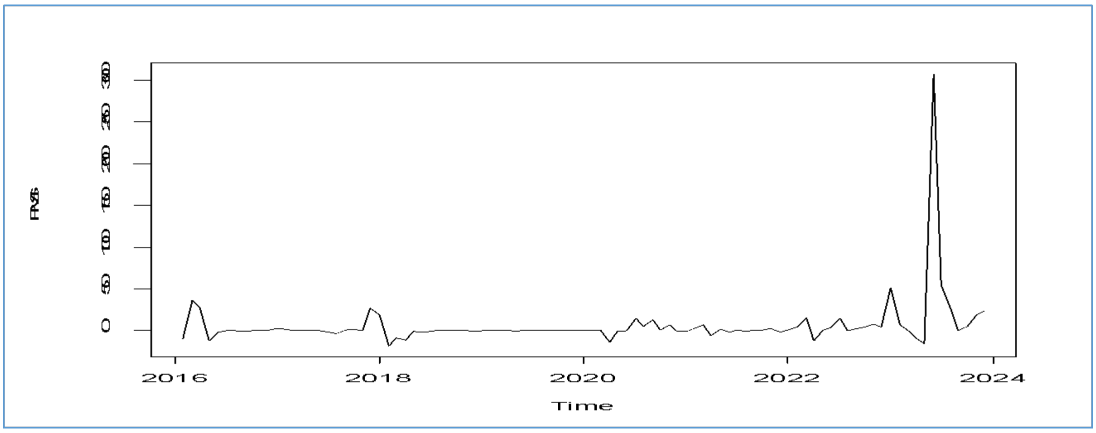

Figure 4. The Stationary Time Series Plot of the Nigeria PMS Prices

4.2. Machine Learning Modelling of Nigeria PMS Prices

This section presents and discusses the models' estimations of the country PMS prices using three classical neural network algorithms. The classical neural network algorithms to be examined include Recurrent Neural Networks (RNN), Generalized Regression Neural Networks, and Multi-layer Perceptron Neural Networks.

4.2.1. Recurrent Neural Networks Model Estimation for the Nigeria PMS Prices

This section presents and discusses the models' estimations of the country's PMS prices using the recurrent neural network algorithms. Table 2 presents the model estimations. As observed, the model estimation results returned 12, 16, and 6 parameters for the LSTM, simple RNN, and Dense, respectively, for a total of 33 parameters estimated for the recurrent neural networks. Subsequently, the estimated RNN model training set residuals were diagnosed for goodness-of-fit. Figure 6 presents the Normal Q-Q plot of RNN model residuals. According to the figure, the model's residuals are normally aligned and neither underfitted nor overfitted, as virtually all residuals seem to be on a line.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm (LSTM)                 (None, 6, 6)              12
_________________________________________________________________
simple_rnn (SimpleRNN)       (None, 10)                16
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 5
=================================================================
Total params: 33
Trainable params: 33
Non-trainable params: 0
```

Figure 5. RNN Model Estimation for the PMS Prices

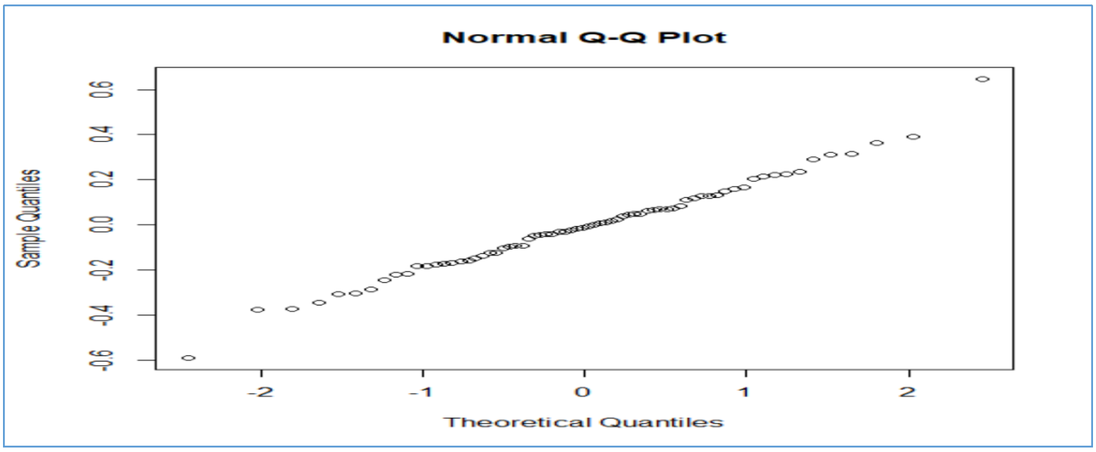

Figure 6. Normal Q-Q Plot of RNN Training Set

4.2.2. Generalized Regression Neural Networks Model Estimation for the Nigeria PMS Prices

The Generalized Regression Neural Networks (GRNN) machine learning model estimation of the PMS Price is presented in Figure 7. As observed, using the recursive multiple-step ahead strategy, the GRNN model estimation returned a Sigma (smoothing parameter) of 14.4857 over twelve (12) autoregressive lags. Consequently, the results depict a 12-month training in-sample forecast for the PMS Prices. In addition, Figure 8 presents the Normal Q-Q plots of the model residuals, the results show that the residual values are normally fitted as most of the residuals did rest on the slope line. Thus, the estimated GRNN model was properly fitted

```
Call:  grnn_forecasting(timeS = PMSts, h = 12, lags = 1:12)

Multiple-Step Ahead Strategy: recursive
Sigma (smoothing parameter): 14.48567
Autoregressive lags: 1 2 3 4 5 6 7 8 9 10 11 12
Type of training samples transformation: additive
Forecasting horizon: 12
Forecast:
           Jan       Feb       Mar       Apr       May       Jun
2024  710.7083  748.5090  788.9014  846.8183  982.9594 1045.0422
           Jul       Aug       Sep       Oct       Nov       Dec
2024 1086.6029 1090.2035 1097.0121 1118.2714 1144.7107 1186.0283
```

Figure 7. GRNN Model Estimation for the PMS Prices

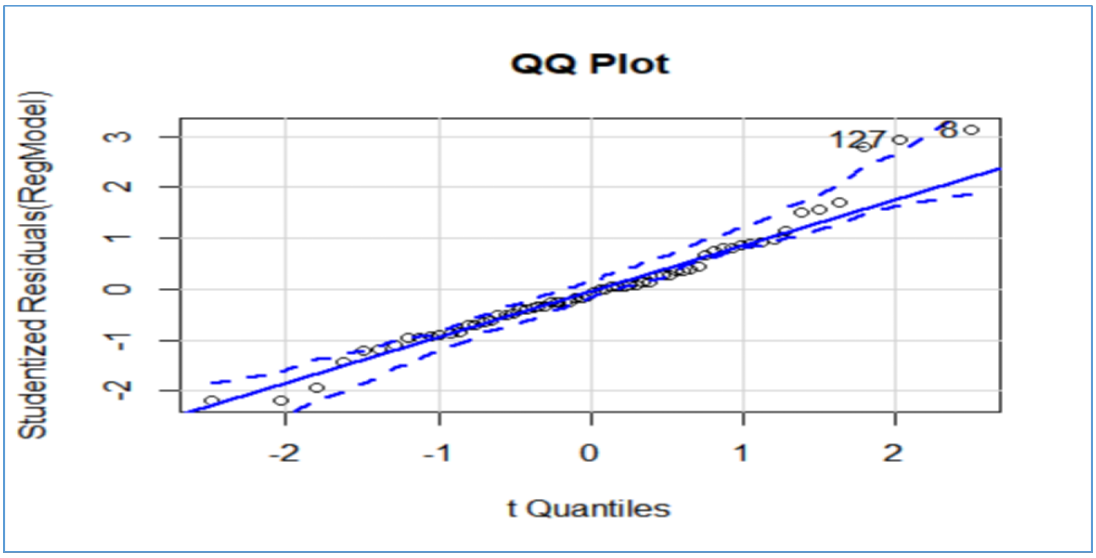

Figure 8. Normal Q-Q Plot of the GRNN Model Residuals

4.2.3. Multi-Layer Perceptron Neural Networks Model Estimation for the Nigeria PMS Prices

The multi-layer perceptron neural networks (MLP-NN) machine learning model estimation of the PMS Price is presented in Figure 9. Both results revealed a total of 5 hidden nodes with 20 repetitions were estimated for the prediction of PMS Prices using the median operator. It is interesting to note that the MLP-NN model utilized the series univariate lag 5, lag 7, and lag 11, to model the PMS Prices. Figure 10 demonstrates the estimated MLP-NN model structure with three (3) nodes for the Inputs (namely training dataset and testing dataset) and five (5) hidden nodes.

```
MLP fit with 5 hidden nodes and 20 repetitions.
Series modelled in differences: D1.
Univariate lags: (5,7,11)
Forecast combined using the median operator.
MSE: 118.6153.
```

Figure 9. MLP-NN Model Estimation for the PMS Prices

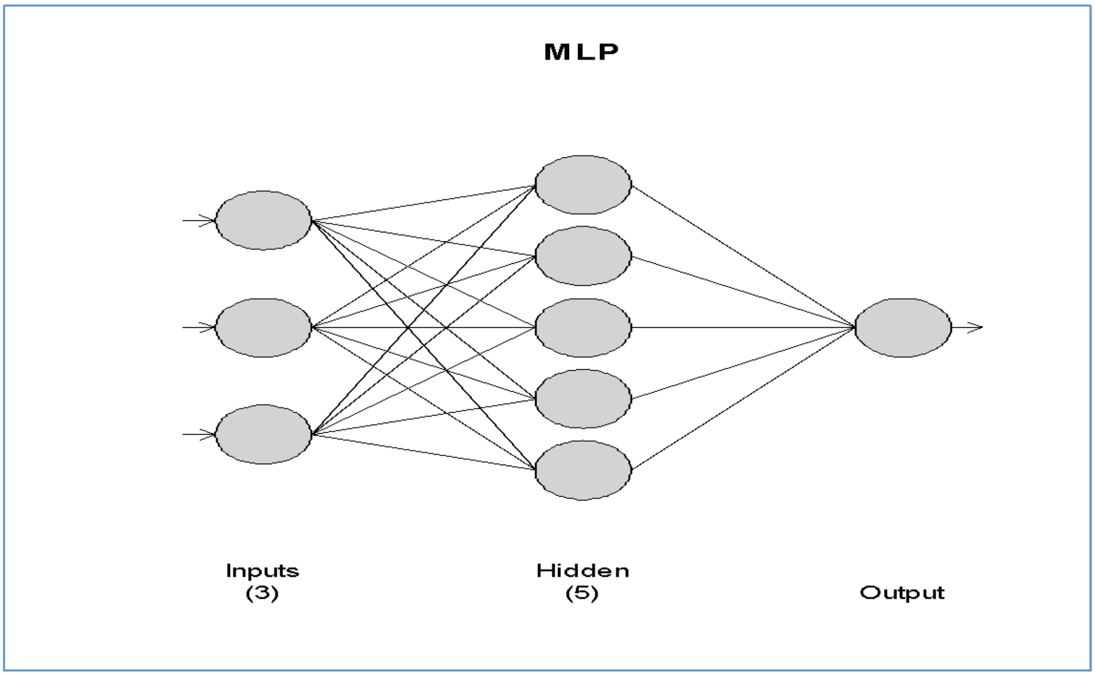

Figure 10. Plot of the MLP-NN Model Structure

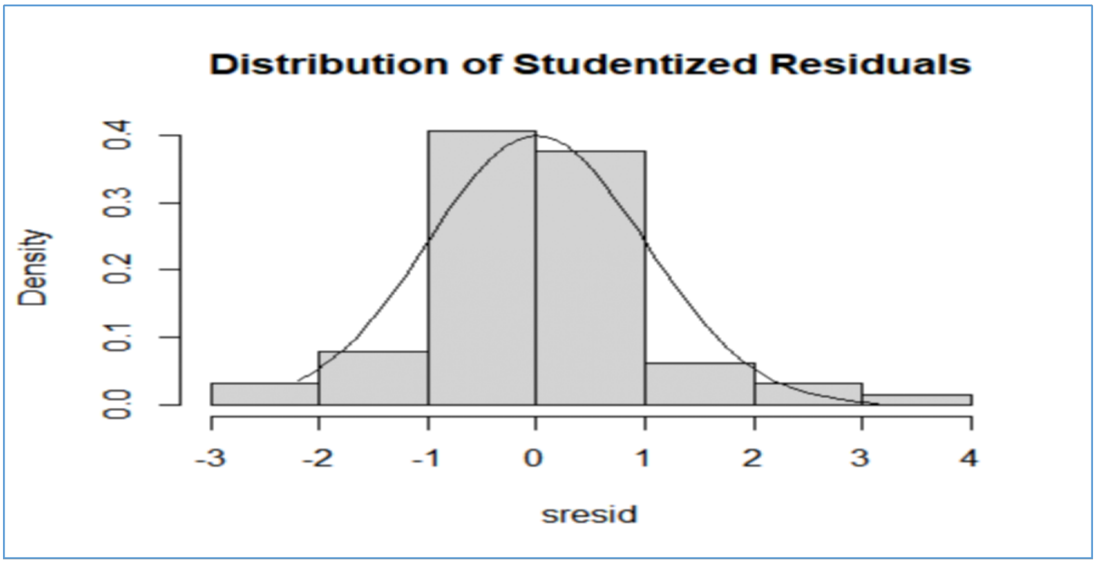

Figure 11. Distribution of the MLP-NN Model Residuals

Similarly, the MLP model residuals were diagnosed. Figure 11 reveals the studentized distribution of the MLP model residuals. The plot reveals the skewness and kurtosis of the residuals, which further supports the kurtosis of the residuals approaching zero. Thus, it can be inferred that the fitted MLP model has appropriately accommodated the stochastic process behaviour observed in the PMS Prices of the country.

4.3. Prediction Performance of the Estimated RNN, GRNN, and MLP Models

Following that, all the goodness of fit tests are in support of the assumption that there is no pattern in the residuals of the three estimated models for the prediction of PMS Prices. The study goes ahead to assess the accuracy performances of the three models in the pursuit to identify the optimal model. Eighty percent of the total data series was obtainable for the modeling of the PMS prices series. Afterward, in-sample prediction performance errors were evaluated for the three models. The employed prediction performance error criteria include: price Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The in-sample prediction performance (see Table 5 and Figure 9) reveals the MLP-NN model with the lowest RMSE, MAE, and MAPE prediction errors. This directly infers that the estimated MLP-NN model outperformed RNN and GR-NN. Thus, based on the prediction error criteria the estimated MLP-NN model returns as the optimal model for the prediction of the Nigerian PMS Prices.

Table 2. Accuracy Measures of the RNN, GRNN, and MLP Models

	RNN	**GRNN**	**MLP-NN**
Trainable %	80	80	80
	In-Sample Prediction Errors		
RMSE	18.1871	282.2010	10.8911
MAE	11.1256	209.0112	6.1220
MAPE	8.1241	39.4963	3.8717

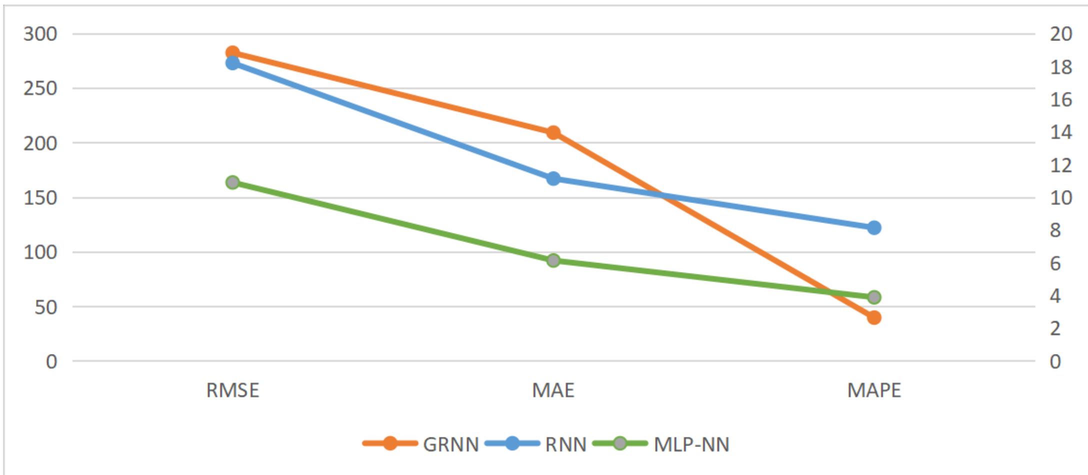

Figure 12. Accuracy Plots of the RNN, GRNN, and MLP-NN Models

> MLP_pred

	Jan	Feb	Mar	Apr	May	Jun
2024	785.5216	801.1963	809.7809	835.7445	415.7428	536.3460
2025	330.0664	334.8237	548.3998	1057.4900	1237.8179	1566.5979

	Jul	Aug	Sep	Oct	Nov	Dec
2024	547.3082	572.8430	580.0047	621.8297	727.2044	285.8034
2025	639.4919	1062.6974	901.5528	1205.8339	2092.6873	2212.7433

Figure 13. MLP-NN Out-Sample Prediction of PMS Prices

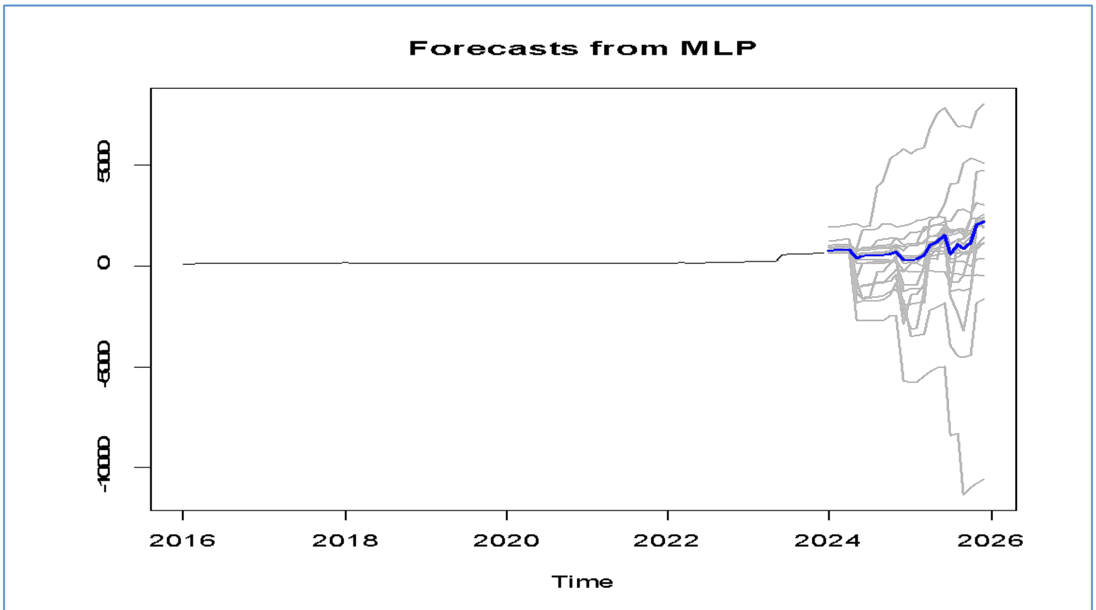

Figure 14. MLP-NN Out-Sample Prediction Plot of PMS Prices

Consequently, the study provides the out-of-sample forecast for the PMS price series using the optimal model, which is the MLP-NN. The selected MLP-NN was used to forecast twenty-four (24) months of PMS prices, i.e., January 2024 to December 2025. The prediction results are presented in Figures 13 and 14. The results show the PMS Prices projection, which includes the point predictions and interval predictions, while the table only presents the point projection of PMS Prices. The point prediction results revealed a relative increase in the PMS Prices across the out-of-sample predictions. The results further projected as high as N1000 and above N2000 for the PMS Prices in the year 2025.

4.4. Discussion of Findings

This study investigated Nigeria's PMS prices using machine learning approaches such as RNNs, GR-NNs, and MLP-NNs to determine the most reliable model for PMS price prediction. Prior to the modeling findings, the empirical results from the descriptive study (i.e., the trend investigation) revealed that the PMS price was mostly stable until July 2020, when the price began to grow significantly, showing PMS price instability. This finding is consistent with research conducted by [3, 5], all of which found the recent rise in PMS prices to be economically concerning and problematic. Empirical findings from PMS price modeling showed that MLP-NN outperformed the RNNs and GR-NNs models based on the minimal prediction criterion. Thus, this study identified MLP-NN as the best model for predicting Nigerian PMS prices. This finding reinforced the superiority of MLP (a form of deep learning algorithm) over other neural network algorithms, such as RNNs and GR-NNs, in time series prediction. While this conclusion is unique in terms of model comparison, i.e., MLP-NNs versus RNNs versus GR-NNs, the efficiency performance of the MLP-NNs is similar to the study findings of [9] and [20]. Their studies revealed deep learning machine learning approaches to outperform the Feed Forward Neural Network (FFNN), Support Vector Machine (SVM), Radial Basis Network (RBN), and Decision Tree in the prediction of uranium prices. In addition, empirical findings from the out-of-sample predictions of the PMS prices uniquely projected as high as N1000 and above N2000 for the PMS Prices in the year 2025.

5. Conclusion

According to the empirical findings from the descriptive analysis, which demonstrated that PMS prices have been continuously growing in recent years, the study concludes that the country's PMS price is unstable. This study used three (3) models (one traditional time series model, namely RNN, GRNN, and ML-NN), and the outcomes were compared. The diagnostic goodness-of-fit results for the selected models showed no evidence of non-normality in their residuals. Thus, the three estimated models were completely fitted and revealed no non-normality features in the models' residuals. Furthermore, according to the estimated model performance criteria, the machine learning model Multi-Layer Perceptron Neural Network performed better than the Recurrent Neural Networks and Generalized Regression Neural Networks models in terms of both in-sample prediction and performance. As a result, this study suggests that MLP-NN is the best model for modeling and predicting Nigeria's PMS prices. Lastly, empirical findings from the out-of-sample predictions of the PMS prices, which uniquely projected as high as N1000 and above N2000 for the PMS Prices in the year 2025, this study concludes skyrocketing prices of PMS will skyrocket shortly. It is therefore evident that the application of artificial intelligence and econometric models provides a sufficient overview of predicting the PMS price dynamics. However, the machine learning model is insufficient to understand the macroeconomic dynamics and account for structural events (breaks) in the series. Following the empirical results of the analysis, this study deduced that among the examined neural network models, the Multilayer Perceptron Neural Networks model displayed robustness in predicting the PMS Prices' series dynamics. Thus, it can be inferred that the MLP-NN model demonstrated high appropriateness of modeling such unstable time series data. Therefore, it is on this note this study recommends that a machine learning approach, particularly MLP-NN to be employed when considering using the Neural Networks model to model and predict the dynamics in time series data.

Conflict of Interest

The authors declare there is no existing conflict of interest.

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