UMYU Scientifica, Vol. 1 NO. 1, September 2022, Pp 194 – 203
https://doi.org/10.56919/usci.1122.025
ISSN: 2955 – 1145 (print); 2955 – 1153 (online)
A periodical of the Faculty of Natural and Applied Sciences, UMYU, Katsina

A REVIEW ARTICLE

Forecasting Premium Motor Spirit (PMS) and Energy Commodities Prices Using Machine Learning Techniques: A Review

Agbo Sunday Ojogbane[1]*, Yemi-Peters Victoria Ifeoluwa[2], and Adewumi Sunday Eric[3]

[1]Department of Computer Science, Kogi State College of Education, Ankpa, Nigeria.
[2&3]Department of Computer Science, Federal University Lokoja, Kogi State, Nigeria.

ABSTRACT

The instability of Premium Motor Spirit (PMS/Petrol) and other energy commodities prices, occasioned by volatile and dynamic movement of prices has been found to affect the cost of production in Nigeria. As a result, this paper studies current literature on the applications of machine learning techniques in forecasting PMS (Petrol) and other energy commodities prices. The review has been done through an electronic search of the published papers in the last 4 years (2019-2022). A total number of twenty-nine (29) publications on PMS (Petrol) and other energy commodities prices forecasting using machine learning models were selected for the study to identify research gaps and future works. This paper covers a summary of reviewed published papers on forecasting PMS (Petrol) and other energy commodities prices using machine learning techniques, semantic analysis of algorithms used, and the taxonomy of the models adopted in the published papers. The results showed that there are studies that presented the application of machine learning models in forecasting the prices of PMS (Petrol) and other energy commodities in other countries. However, very few of them have proposed the construction of machine learning models for forecasting PMS (Petrol) and other energy commodities prices in Nigeria. This leads to the need to develop new models, especially deep learning hybrid models.

ARTICLE HISTORY

Received August 1, 2022
Accepted September 17, 2022
Published September 30, 2022

KEYWORDS

Premium Motor Spirit (PMS), Energy Commodities, Forecasting, Machine learning

INTRODUCTION

The importance of petroleum as a commodity to economies and civilisation cannot be overstated; it supplies a sizeable portion of the world's energy needs and hence plays a crucial role in trade, politics, international relations, and civilization (Perry, 2019). Since the government took over from the independent oil corporations in 1973, the price of petroleum on the domestic market has been regulated by the government. Because the marginal supply (litres) comes from import, the prices of petroleum products in Nigeria are theoretically derived from International Crude oil prices.

Fuel price increases have an impact on transportation, the cost of goods, and other services. Because Nigeria is import dependent, the volatility of PMS and other energy commodity prices caused by volatile and dynamic price movement has been found to affect the cost of production. This increases the cost of imported goods, which is then passed on to domestic prices by raising the general price level, having a direct impact on Nigerian society, our economy, and oil exploration, exploitation, and other activities. Additionally, increases in the price of PMS and energy commodities have led to inflation, a high cost of living, and an unequal distribution of income in Nigeria (Aji and Surjandari, 2020). Also, large fluctuation and changes in the price of PMS and other energy commodities has brought great cost management pressure to downstream related consumer industries, enterprises, and individuals, thereby leading to increased interest for an automated PMS and energy commodities price forecasting model to provide timely and useful information in making informed decision towards addressing the challenges that come with changes in price cycle in Nigeria.

However, machine learning algorithms are considered to be the most effective approaches for predicting the price of PMS and energy commodities because they are successful in identifying relationships between commodity prices, historical data, and other variables

Correspondence: Agbo S.O. Department of Computer Science, Kogi State College of Education, Ankpa, Nigeria.
sunnyreside@gmail.com; Phone number: +2348069454258

How to cite: Agbo S.O., Yemi-Peters V. I., Adewumi S. E. (2022). Forecasting Premium Motor Spirit (PMS) and Energy Commodities Prices Using Machine Learning Techniques: A Review. UMYU Scientifica, 1(1), 194 – 203.
https://doi.org/10.56919/usci.1122.025

(Bitirgen and Filik, 2020).

In the light of the prevailing need and/or interest to adopt machine learning methodologies in predicting and forecasting PMS and energy commodities prices in Nigeria, this research work seeks to investigate existing approaches for forecasting PMS and energy commodities prices to identify the weaknesses for improvement; and to propose a more accurate model for PMS and energy commodities price forecasting in Nigeria.

Several related research works have been carried out on PMS and other energy commodities price predicting and/or forecasting system using different models, but the performance and accuracy of these models have been constantly questioned (Nam, *et al.,* 2020). Thus, the objective of this paper is to review the application of machine learning techniques in forecasting the price of PMS and energy commodities to identify the research gap and to recommend a more accurate technique for future work with Nigeria in focus.

Related literature reviewed on machine learning algorithm

Aji and Surjandari (2020) employed a combination of two Recurrent Neural Networks (RNN) algorithm (LSTM and GRU) to develop a hybrid model for forecasting the jet fuel price. Similarly, Yang, *et al.,* (2020) adopted an ensemble machine learning approach to predict the carbon prices of Beijing, Fujian, and Shanghai. The model incorporates Modified Ensemble Empirical Mode Decomposition (MEEMD) and Long Short-Term Memory (LSTM) which is optimized by the Improved Whale Optimization Algorithm (IWOA). In a related study, time-series forecasting of petrol (PMS) prices in Australia was carried out using LSTM and a WaveNet-inspired Temporal CNN (TCN) to predict the prices of PMS (Perry, 2019). However, there is a need for future works in these studies to consider both historical price sequence and external factors and obtain more accurate forecasting results.

Further studies carried out have shown the development of Artificial Neural Network (ANN) models for the prediction and forecasting of crude oil prices (Gupta and Nigam, 2020), scheduling of gas-fired CHP plant (Żymełka and Szega, 2021), and analyzing and forecasting energy markets for the gasoline demand of Saudi Arabia (Al-Fattah, 2020). Though, Al-Fattah (2020) developed the ANN model as a hybrid model based on a Genetic Algorithm (GA), and Time-Series (TS) analysis, referred to as GANNATS. There is a need to improve the prediction performance or outcomes in subsequent studies for forecasts.

Li *et al.,* (2021) developed an integrated model to forecast monthly natural gas prices using Deep Belief Network (DBN), Variational Model Decomposition (VMD) incorporated with Particle Swarm Optimization (PSO) as a hybrid model. However, there is a need to examine the factors that influences short-term natural gas price movements to further improve the prediction accuracy of the model. While Moshkbar-Bakhshayesh (2020) in his work utilized different learning algorithms such as Feed Forward Neural Network (FFNN), Support Vector Machine (SVM), Radial Basis Network (RBN), and Decision Tree for the prediction of uranium price.

The potential of deep learning method in forecasting fuel consumption on a passenger ship and container ships were proposed by (Bui-Duy and Vu-Thi-Minh, 2021; Panapakidis and Sourtzi, 2020). The proposed forecasting model combines shallow and deep learning approaches. Also, Huang and He (2020) adopted a deep learning approach to predict the carbon trading price of China. The model combines optimization prediction method using the Mean value Optimization (MOEMD), Extreme Learning Machine (ELM) model, Kidney Algorithm (KA), and Cooperation factor (CKA) model referred to MOEMD-CKA-ELM. Though, there are improvements to be performed in future works in forecasting carbon trading prices in China. As a result, there is a need to evolve more accurate forecasting models.

Similarly, extreme learning machine model incorporated with Fast Ensemble Empirical Mode Decomposition (FEEMD) optimized by Particle Swarm Optimization (PSO-ELM) (Sun, *et al.,* 2020) and extreme learning machine, improved grey model and Hodrick-Prescott (Zhao, *et al.,* 2021) was proposed as a hybrid decomposition and integration prediction model for carbon price. But future work is required to explore the energy pricing regime in determining the effectiveness of the proposed model.

From the statistical modelling approach, Auto-Regression Integrated Moving Average (ARIMA) was adopted to foresee the future developments in Crude oil price forecasting (Shambulingappa, 2020). Also, a STL-(ELM+ARIMA) combination forecasting model as a decomposition-prediction-integration route was proposed for fuel oil price (Fangping *et al.*, 2021); while Holt-Winters additive model and ARIMA was employed to forecast the demand for total gasoline and its three components (gasoline 88, gasoline 90, and gasoline 92) for the time-series dataset over the period of 2017-2019 (Mardiana, *et al.,* 2020). Similarly, the autocorrelation analysis and spectral analysis were used for determining the trends and commercial patterns of petrol prices in South Africa to determine the continuity of past patterns of the petrol price movements into the future (Olayiwola and Seeletse, 2020).

Furthermore, Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model was employed to predicting whether information on structural breaks plays an important role in US ethanol market volatility and US biofuel industry (Bouri, *et al.,* 2020). In the same vein, GARCH was constructed as the best-fitted model to forecast daily Crude Oil Price (COP) for reducing the impact of daily COP movement using data observed from 2009 to 2018 (Gunarto *et al.,* 2020).

In another study, Smith, *et al* (2021) adopted a Global Vector Autoregressive (GVAR) model to assess the effect of the COVID-19 pandemic on global fossil fuel consumption and Carbon dioxide emissions over the two-year (2020Q1-2021Q4). While Escribano and Wang (2020) proposed a mixed Random Forest approach for modelling the weekly forecasts of gasoline prices that are co-integrated with international oil prices and exchange rates. The outcomes of these models shows that the models provide better visualization and has important advantages in terms of the generality of model specification, prediction, and forecasting. However, in future works, a comprehensive dataset needs to be created; and there is a need to understand the volatility in forecasting models. Also, there is a need to improve the accuracy of the forecasting models, thus, the performance of these models requires improvement.

A summary of reviewed publications on PMS and other energy commodities price forecasting is presented in Table 1.

Table 1: Summary of related literature reviewed.

S/N	Author(s)	Aim of the Study	Methods Utilized	Research Gaps
1.	(Aji & Surjandari, 2020)	Jet fuel price monitoring	Recurrent Neural Network (RNN) algorithm, Long Short-Term Memory (LSTM), and Gate Recurrent Units (GRU)	To increase parameters. To introduce metaheuristic algorithms into neural networks.
2.	(Gupta & Nigam, 2020)	Crude oil price prediction.	ANN	To consider more future sets for better prediction outcome.
3.	(Perry, 2019)	Retail petrol price prediction.	Simple LSTM, a sequence-to-sequence LSTM seq2seq LSTM, and a WaveNet-inspired Temporal (TCN)	More datasets. Performance on lesser input data.
4.	(Bouri *et al.*, 2020)	Ethanol price volatility forecasting.	GARCH models	More allied market variables are to be considered.
5.	(Fangping *et al.*, 2021)	Price of fuel oil forecasting.	STL (ELM + ARIMA)	Accuracy of the forecasting model to be improved.
6.	(Escribano & Wang, 2020)	Gasoline prices forecasting	Mixed Random Forest Error Correction Models.	To improve the performance of the forecasting model for Gasoline prices.
7.	(Bui-Duy & Vu-Thi-Minh, 2021)	Fuel consumption forecasting	Deep learning and ATSP.	To include more datasets and economic variabilities.
8.	(Sun *et al.*, 2020)	Carbon price forecasting	Fast ensemble empirical mode decomposition (FEEMD) and extreme learning machine optimized by particle swarm optimization (PSO-ELM)	To improve the performance of the forecasting model for energy prices.
9.	(Zhao *et al.*, 2021)	Carbon price forecasting	Hodrick-Prescott filter and an extreme learning machine	Irregular fluctuation of datasets impacts the results.
10.	(Smith *et al.*, 2021)	Global fossil consumption forecasts.	Global vector autoregressive model.	Dataset unavailability
11.	(Huang & He, 2020)	Carbon price forecasting	Deep learning techniques	Ineffectiveness of models.
12.	(Gunarto *et al.*, 2020)	Crude oil price forecasting	Autocorrelation functions and GARCH model.	Instability of datasets.
13.	(Herlina, 2020)	Oil fuel price and agricultural commodity.	Panel Cointegration and Granger Causality Model	Performance improvements of the model needed.
14.	(Panapakidis *et al.*, 2020)	Fuel consumption forecasting	Shallow and deep learning approaches.	To improve the forecasting model to obtain better prediction outcomes.
15.	(Shambulingappa, 2020)	Crude oil price forecasting	Machine learning of ARIMA	To enhance the performance of prediction.

Table 1: Continued

S/N	Author(s)	Aim of the Study	Methods Utilized	Research Gaps
16.	(Olayiwola & Seeletse, 2020)	Petrol price forecasting	Autocorrelation and spectral analyses.	Limited to the South African market.
17.	(Berrisch & Ziel, 2021)	Natural gas prices forecasting	Risk and portfolio management (Day-Ahead/Month-Ahead)	To focus on specific natural gas commodities such as petrol.
18.	(Mardiana *et al.*, 2020)	Gasoline demand forecasting	Time Series: ARIMA, NN, linear regression, Holt-Winters addictive.	Model for predicting supply chain factors deviation impacts.
19.	(Ricardianto *et al.*, 2020)	Fuel price and exchange rate on aviation sector determination	Descriptive qualitative technique	To model low-cost carrier airline industry.
20.	(van Bentem, 2020)	Aviation fuels sustainability forecasts.	Net Present Value, computerized model	To evolve information realized into models to overcome uncertainties.
21.	(García Jolly & Martín del Campo, 2021)	Automotive fuels model of supply chain growth	Refinery model with a small model.	Suitable for tree supply chain networks rather than the grid.
22.	(Żymełka & Szega, 2021)	Gas-fired CHP plant thermal storage forecasts.	Optimization algorithm and forecasting models: ANN, ARIMA, multi-layer perceptron, triple exponential smoothing methods.	To minimize risks of errors for electricity price or heat demand prediction.
23.	(Westarp, 2020)	bunker fuel speed–consumption relation.	Exponent of the function variable and stochastic criteria (Variances, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Cook's Distance).	Unsuitable for small-scale datasets. To extend the scope of the study. To improve accuracy of the model.
24.	(Li *et al.*, 2021)	Natural gas spot prices forecasting.	Variational mode decomposition (VMD), particle swarm optimization (PSO), and deep belief network (DBN).	To further improve the prediction accuracy of the model.
25.	(Khan *et al.*, 2020)	Hydrogen fuel cell consumer preference forecasts.	Mixed logit model	To compare different models' performances
26.	(Al-Fattah, 2020)	Gasoline demand prediction	AI model based on a genetic algorithm (GA), artificial neural network (ANN), and data mining (DM) approach for time-series (TS) (known as GANNATS)	The predictive model can be extended to price forecasting.
27.	(Yang *et al.*, 2020)	Carbon price forecasting.	Modified ensemble empirical mode decomposition (MEEMD) and LSTM optimized by the improved whale optimization algorithm (IWOA).	Influence of Historical carbon price sequence and external factors on better accuracy.

Table 1: Continued

S/N	Author(s)	Aim of the Study	Methods Utilized	Research Gaps
28.	(Moon & Jung, 2020)	Renewable energy prices forecasts.	Fixed-price contract.	To evolve stronger technology for determining volatility of commodity.
29.	(Moshkbar-Bakhshayesh, 2020)	Uranium price estimation.	Feed-forward neural network with Bayesian regularization and supervised learning algorithms (SVM, Radial Basis Network, decision tree).	To prevent overfitting problems (memorization and generalization).

MATERIALS AND METHODS

This section presents the methodology for review and analysis on the related research publications on PMS and other energy commodities. The published papers involved journals, conference proceeding and technical reports. The focus of this paper is on the application of machine learning techniques in forecasting the price of PMS and other energy commodities, to identify research gap and propose a more accurate machine learning techniques for future work.

Search process

In reviewing previous studies, a search was performed in reputable scientific electronic databases using two approaches. The first approach used keywords such as price forecasting, premium motor spirit price, energy commodities price, machine learning. The second approach used the search string: "price forecasting using machine learning techniques" OR "premium motor spirit price forecasting" OR "energy commodities price forecasting" OR "premium motor spirit and energy commodities price forecasting using machine learning techniques" to download research papers published from 2019 to March, 2022. The databases searched were Google Scholar, Springer, IEEE Xplore, ACM digital library and ScienceDirect.

Criteria for inclusion and exclusion

The articles screening was based on inclusion criteria with consideration on some factors such as studies published from 2019 to 2022, studies presented on application of machine learning techniques in forecasting the price of crude oil and petroleum products, and articles that have concentrated on forecasting the prices of premium motor spirit (PMS) and energy commodities using machine learning techniques.
Similarly, the exclusion criteria were also used to eliminate publications that were published earlier than the year 2019, and articles that have not concentrated on forecasting the price of non-petroleum products.
Based on the keywords and search string supplied for articles search from the electronic databases, a total number of 127 publications were accessed from various electronic databases. After applying inclusion and exclusion criteria considering the papers which were published online from 2019 to March, 2022; and eliminating the inappropriate papers, a total number of twenty nine (29) publication papers were selected, reviewed and analyzed to obtain needed information.

RESULTS

The findings from the reviewed publications are presented under the following sub-headings.

Energy commodities forecasting

The analysis of the reviewed publications based on PMS and other energy commodities is presented in Table 2.

Table 2: Analysis of review publications based on PMS and other energy commodities

Commodities	Number publications	Reviewed publications
Crude oil	3	(Gupta & Nigam, 2020; Gunarto *et al.*, 2020; Shambulingappa, 2020)
Jet fuel	3	(Aji & Surjandari, 2020; Ricardianto *et al.*, 2020; Bentem *et al.*, 2020)
Gasoline	6	(Escribano & Wang, 2020; Berrisch & Ziel, 2021; Mardiana *et al.*, 2020; Żymełka & Szega, 2021; Li *et al.*, 2021; Al-Fattah, 2020)
Petrol (PMS)	6	(Perry, 2019; Fangping *et al.*, 2021; Bui-Duy & Vu-Thi-Minh, 2021; Herlina, 2020; Panapakidis & Sourtzi, 2020; Olayiwola & Seeletse, 2020)
Carbon fuel	4	(Sun *et al.*, 2020; Zhao *et al.*, 2021; Huang & He, 2020; Yang *et al.*, 2020)
Ethanol	1	(Bouri *et al.*, 2020)
Fossil fuel	1	(Smith *et al.*, 2021)
Hydrogen fuel	1	(Khan *et al.*, 2020)
Uranium	1	(Moshkbar-Bakhshayesh, 2020)

A graphical representation of the analysis of PMS and other energy commodities considered in the reviewed publications is shown in Figure 1.

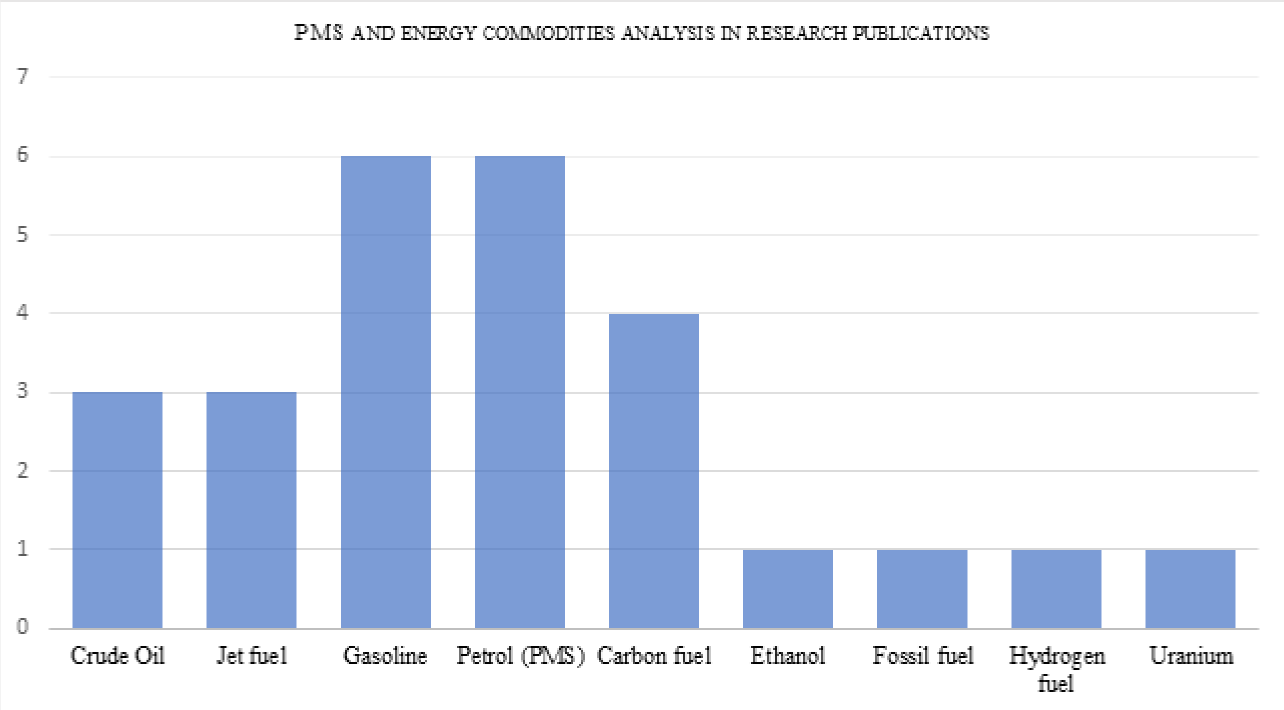

Figure 1: Graphical representation of PMS and other energy commodities in reviewed publications.

Machine learning methods for forecasting

Semantic analysis of machine learning methods utilized, and taxonomy of models adopted in reviewed publications are presented in Table 3 and Table 4.

Table 3: Semantic analysis of machine learning methods utilized in reviewed publications

Machine learning methods	Number publications	Reviewed publications
ANN	3	(Gupta & Nigam, 2020; Żymełka & Szega, 2021; Al-Fattah, 2020)
ARIMA	5	(Fangping *et al.*, 2021; Shambulingappa, 2020; Olayiwola & Seeletse, 2020; Mardiana *et al.*, 2020; Żymełka & Szega, 2021)
GARCH	2	(Bouri *et al.*, 2020; Gunarto *et al.*, 2020)
GVAR	1	(Smith *et al.*, 2021)
LSTM	3	(Aji & Surjandari, 2020; Perry, 2019; Yang *et al.*, 2020)
Random Forest	1	(Escribano & Wang, 2020)
Deep Learning unspecified	3	(Bui-Duy & Vu-Thi-Minh, 2021; Huang & He, 2020; Panapakidis & Sourtzi, 2020)
Gate Recurrent Units (GRU)	1	(Aji & Surjandari, 2020)
Extreme Learning	2	(Sun *et al.*, 2020; Zhao *et al.*, 2021)
Deep Belief Network (DBN)	1	(Li *et al.*, 2021)
Support Vector Machine (SVM)	1	(Moshkbar-Bakhshayesh, 2020)
Particle Swarm Optimization (PSO)	2	(Sun *et al.*, 2020; Li *et al.*, 2021)
Improved Wale Optimization Algorithm (IWOA)	1	(Yang *et al.*, 2020)
Genetic Algorithm (GA)	1	(Al-Fattah, 2020)
Feed-Forward Neural Network (FFNN)	1	(Moshkbar-Bakhshayesh, 2020)
Wavenet-Inspired Temporal Network (TCN)	1	(Perry, 2019)
Radial Basis Network (RBN)	1	(Moshkbar-Bakhshayesh, 2020)
Decision Tree	1	(Moshkbar-Bakhshayesh, 2020)

A graphical representation of semantic analysis of machine learning methods utilized in the reviewed publications is shown in **Figure 2.**

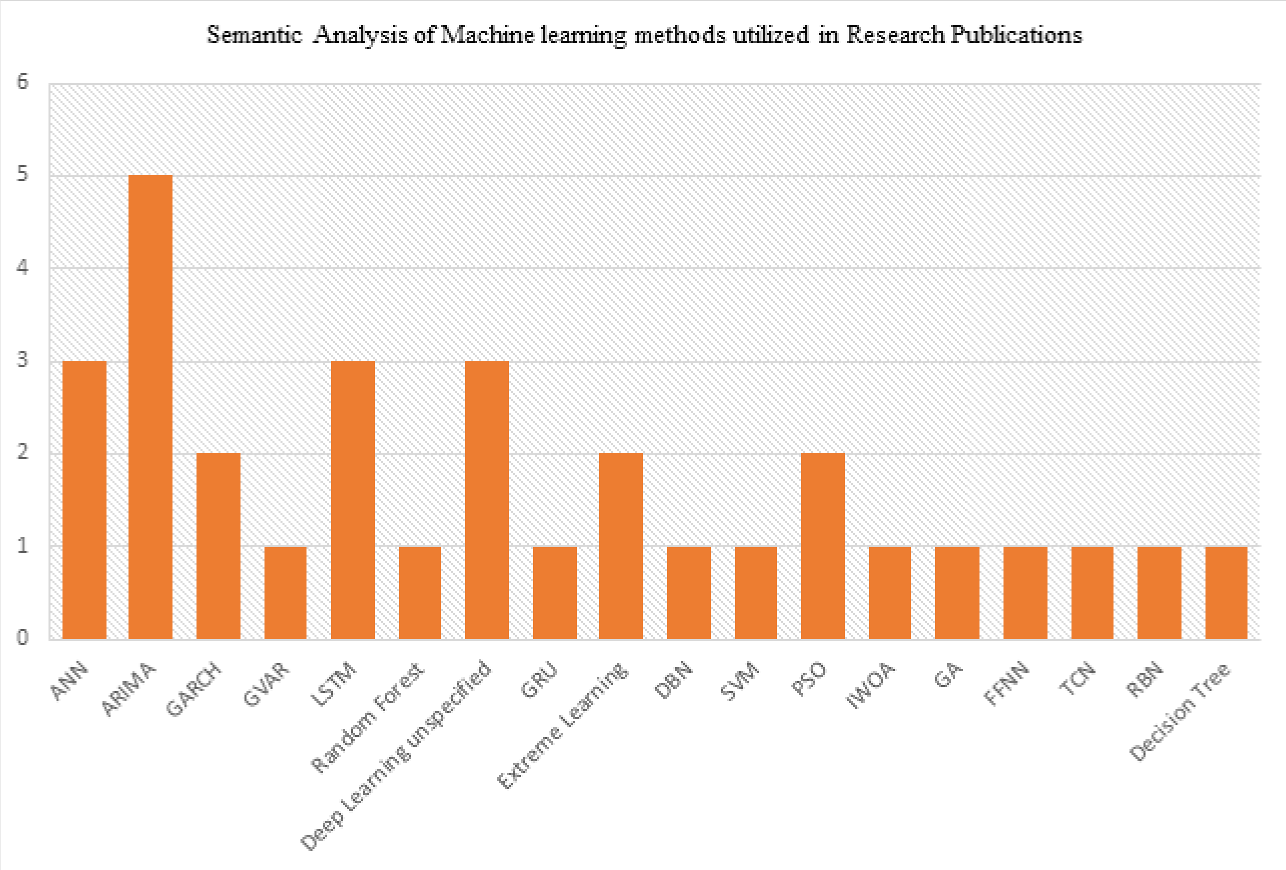

Figure 2: Graphical representation of semantic analysis of machine learning methods utilized in research publications.

Table 4: Taxonomy of Models adopted in reviewed publications

Machine learning approaches	Number publications	Reviewed publications
Deep learning models	8	(Aji & Surjandari, 2020; Perry, 2019), (Bui-Duy & Vu-Thi-Minh, 2021; Sun *et al.*, 2020; Zhao *et al.*, 2021; Huang & He, 2020; Panapakidis & Sourtzi, 2020; Yang *et al.*, 2020)
Shallow learning models	9	(Gupta & Nigam, 2020; Escribano & Wang, 2020; Sun *et al.*, 2020; Panapakidis & Sourtzi, 2020; Żymełka & Szega, 2021; Li *et al.*, 2021; Al-Fattah, 2020; Yang *et al.*, 2020; Moshkbar-Bakhshayesh, 2020)
Statistical learning models	14	(Bouri *et al.*, 2020; Fangping *et al.*, 2021; Smith *et al.*, 2021; Gunarto *et al.*, 2020; Herlina, 2020; Shambulingappa, 2020; Olayiwola & Seeletse, 2020; Berrisch & Ziel, 2021; Mardiana *et al.*, 2020; Ricardianto *et al.*, 2020; Żymełka & Szega, 2021; Westarp, 2020; Khan *et al.*, 2020; Moon & Jung, 2020)

A graphical representation of the taxonomy of models adopted in the reviewed publications is shown in Figure 3.

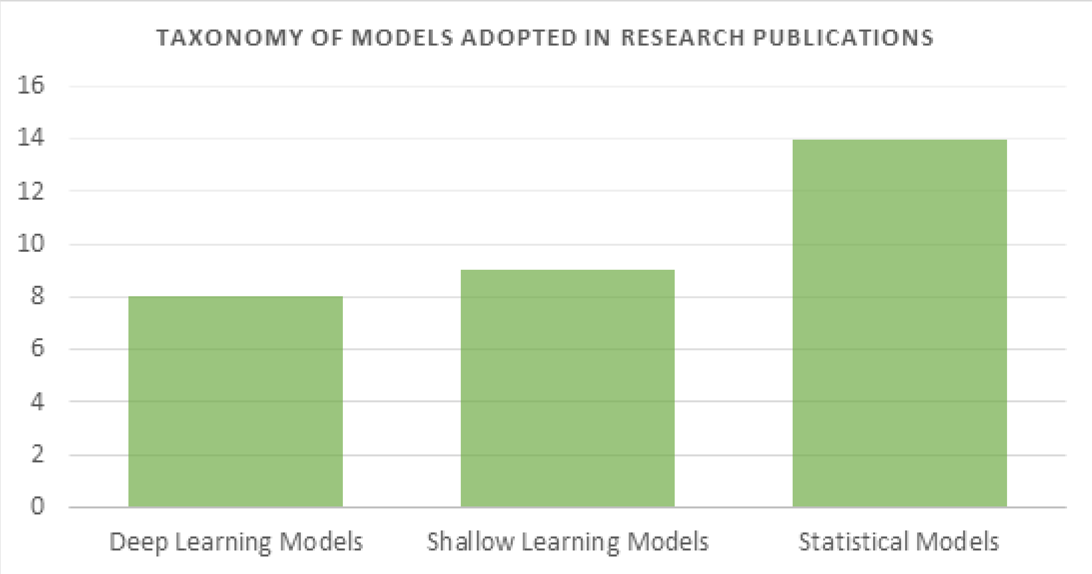

Figure 3: Graphical representation of taxonomy of models adopted in research publications

DISCUSSION

The reviewed publications in this study have shown that a combination of statistical tools and machine learning approaches have been utilized in forecasting the prices of PMS and other energy commodities. However, research focus on evolving models for PMS and energy commodities price forecasting has not been significant. Also, the taxonomy of the models used showed that Deep learning models, Shallow learning models, and Statistical models have been applied for forecasting the prices of PMS and other energy commodities. Though, statistical models have been used significantly rather than machine learning models in forecasting the prices of PMS and other energy commodities.

Furthermore, the performance and accuracy of the machine learning forecasting models developed in the reviewed related research works can better be improved in future works, through the development and integration of more sophisticated hybrid (ensemble) models for accurate forecasting outcome. This is achievable with availability of historical dataset, input data mining and extraction, data pre-processing, evolving stronger technology, and benchmarking of comparable models.

The reviewed publications further showed that there is no significant research work on PMS and energy commodities price forecasting in Nigeria. Hence, identifying a research gap in our country assert the need to evolve machine learning techniques in forecasting the price of PMS and other energy commodities in Nigeria. This can be achieved through the development of a hybrid (ensemble) forecasting model using a real, reliable, relevant, efficient, and up-to-date time-series dataset.

CONCLUSION

This paper has established the application of machine learning techniques in forecasting the price of PMS and other energy commodities. Based on the review, Nigeria is lacking behind in advancing research on the development and application of machine learning techniques in the area of forecasting PMS and energy commodities prices. This is due to irregular fluctuation of datasets and economic variabilities which will impacts the prediction and forecasting outcome. Therefore, this study identified the need to promote research work centered on the implementation of machine learning techniques in our petroleum sector. As a result, we recommend the development and implementation of an ensemble forecasting model using artificial intelligence approaches such as Deep learning algorithms in forecasting the price of PMS and energy commodities in Nigeria. This will provide needed and prompt information to consumers, businesses, manufacturers, and government about upcoming changes in the price of PMS and energy commodities to enhance efficient planning of actions and decision making; and to handle cost management pressure arising from price movements of petroleum products in Nigeria. It is hoped that this goal will be achieved using a historical dataset of the price of PMS and other energy commodities.

ACKNOWLEDGEMENT

The editors, anonymous reviewers, and referees are gratefully acknowledged by the authors for their contributions to the success of this study.

REFERENCES

Aji, A.B., and Surjandari, I. (2020). Hybrid vector autoregression-recurrent neural networks to forecast multivariate time series jet fuel transaction price. *IOP Conf. Series: Materials Science and Engineering*, 909, 012079. **[Crossref]**

Al-Fattah, S.M. (2020). A new artificial intelligence GANNATS model predicts gasoline demand of Saudi Arabia. *Journal of Petroleum Science and Engineering*, 194(June), 107528. **[Crossref]**

Berrisch, J., and Ziel, F. (2021). *Distributional Modeling and Forecasting of Natural Gas Prices*. 1–26. **[Crossref]**

Bitirgen, K., and Filik, Ü.B. (2020). Electricity Price Forecasting based on XGBooST and ARIMA Algorithms. *Journal of Engineering Research and Technology*, 1(1), 1–13.

Bouri, E., Dutta, A., and Saeed, T. (2020). Modeling and Analysis: Forecasting ethanol price volatility under structural breaks. *Biofuels, Bioproducts & Biorefining*, 1–7. **[Crossref]**

Bui-Duy, L., and Vu-Thi-Minh, N. (2021). Utilization of a deep learning-based fuel consumption model in choosing a liner shipping route for container ships in Asia. *Asian Journal of Shipping and Logistics*, 37(1), 1–11. **[Crossref]**

Escribano, Á., and Wang, D. (2020). Forecasting gasoline prices with mixed random forest error correction models. *Economics*, 1–32.

Fangping, Y., Yanqing, L., and Chenxi, Z. (2021). *Forecasting the Price of Fuel Oil : A STL- (ELM + ARIMA) Combination Approach Forecasting the Price of Fuel Oil : A STL-(ELM + ARIMA) Combination Approach*. **[Crossref]**

García Jolly, R., and Martín del Campo, C. (2021). A practical model for the supply chain growth optimization for automotive fuels in Mexico. *Canadian Journal of Chemical Engineering*, 99(4), 898–914. **[Crossref]**

Gunarto, T., Azhar, R., Tresiana, N., and Ahadiat, A. (2020). *Accurate Estimated Model of Volatility Crude Oil Price*. 10(5), 228–233.

Gupta, N., and Nigam, S. (2020). Crude Oil Price Prediction using Artificial Neural Network. *Procedia Computer Science*, 170, 642–647. **[Crossref]**

Herlina, M. (2020). Panel cointegration analysis in determining relationship of agricultural commodity and oil fuel price in Indonesia. *Indonesian Journal of Statistics and Its Applications*, 4(2), 341–358.

Huang, Y., and He, Z. (2020). Science of the Total Environment Carbon price forecasting with optimization prediction method based on unstructured combination. *Science of the Total Environment*, 725, 138350. **[Crossref]**

Khan, U., Yamamoto, T., and Sato, H. (2020). Consumer preferences for hydrogen fuel cell vehicles in Japan. *Transportation Research Part D: Transport and Environment*, 87, 102542. **[Crossref]**

Li, J., Wu, Q., Tian, Y., and Fan, L. (2021). Monthly Henry Hub natural gas spot prices forecasting using variational mode decomposition and deep belief network. *Energy*, 227, 120478. **[Crossref]**

Mardiana, S., Saragih, F., and Huseini, M. (2020). Forecasting gasoline demand in Indonesia using time series. *International Journal of Energy Economics and Policy,* 10(6), 132–145. **[Crossref]**

Moon, J., and Jung, T.Y. (2020). A critical review of Korea's long-term contract for renewable energy auctions: The relationship between the import price of liquefied natural gas and system marginal price. *Utilities Policy*, 67(October), 101132. **[Crossref]**

Moshkbar-Bakhshayesh, K. (2020). Performance study of bayesian regularization based multilayer feed-forward neural network for estimation of the uranium price in comparison with the different supervised learning algorithms. *Progress in Nuclear Energy*, 127, 103439. **[Crossref]**

Nam, K.J., Hwangbo, S., and Yoo, C.K. (2020). A deep learning-based forecasting model for renewable energy scenarios to guide sustainable energy policy: A case study of Korea. *Renewable and Sustainable Energy Reviews*, 122(December 2019), 109725. **[Crossref]**

Olayiwola, M.F., and Seeletse, S.M. (2020). Statistical forecasting of petrol price in South Africa. *Journal of Engineering and Applied Sciences,* 15(2): 602-606. **[Crossref]**

Panapakidis, I., Sourtzi, V. and Dagoumas, A. (2020). Forecasting the fuel consumption of passenger ships with a combination of shallow and deep learning. *Electronics*, *9*(5): 776. **[Crossref]**

Perry, M. (2019). Predicting Retail Petrol Prices in Australian Restorative Markets (Time Series Forecasting). *Deep Learning, Spring 2019, Stanford University, CA*. 1–6.

Ricardianto, P., Agushinta, L., Sari, M., and Ikhsan, R.B. (2020). The strategy of the Indonesian aviation industry to face fluctuate exchange rate and the increase of aviation fuel price. *Journal of Xi'an University of Architecture & Technology*, 12(4), 4538–4546.

Shambulingappa, H.S. (2020). Crude oil price forecasting using machine learning. *International Journal of Advanced Scientific Innovation*, 1(1), 1–11. **[Crossref]**

Smith, L.V., Tarui, N., and Yamagata, T. (2021). Assessing the impact of COVID-19 on global fossil fuel consumption and CO2 emissions. *Energy Economics*, 97, 105170. **[Crossref]**

Sun, W., Sun, C., and Li, Z. (2020). A hybrid carbon price forecasting model with external and internal influencing factor considered comprehensively: A case study from china. *Polish Journal of Environmental Studies*, 29(5), 3305–3316. **[Crossref]**

van Bentem, K.J.P. (2020). Techno-economic Analysis of Sustainable Aviation Fuels by Using Traffic Forecasts and Fuel Price Projections: a Case Study at TUI Aviation. M.Sc. Thesis. Department of Transport, Infrastructure & Logistics, Delft University of Technology Delft, the Netherlands.

Westarp, A.G von. (2020). A new model for the calculation of the bunker fuel speed-consumption relation. *Ocean Engineering*, 204, 107262. **[Crossref]**

Yang, S., Chen, D., Li, S., and Wang, W. (2020). Carbon price forecasting based on modified ensemble empirical mode decomposition and long short-term memory optimized by improved whale optimization algorithm. *Science of the Total Environment*, 716, 137117. **[Crossref]**

Zhao, L.T., Miao, J., Qu, S., and Chen, X.H. (2021). A multi-factor integrated model for carbon price forecasting: Market interaction promoting carbon emission reduction. *Science of the Total Environment*, 796, 149110. **[Crossref]**

Żymełka, P., and Szega, M. (2021). Short-term scheduling of gas-fired CHP plant with thermal storage using optimization algorithm and forecasting models. *Energy Conversion and Management*, 231. **[Crossref]**