A Hybrid Price Prediction Model For Diesel and Gasoline in Ghana

Abstract: The main purpose of this study was to develop a hybrid model that better predict the prices of petrol and diesel in Ghana by using the Box-Junkins autoregressive integrated moving average (ARIMA) and the nonlinear autoregressive neural network-LSTM (NARNN-LSTM) models. The study used a two weekly indicative prices of petrol and diesel from the website of the Bank of Ghana (BoG) and the National Petroleum Authority (NPA) from January 2016 to December 2023. A univariate ARIMA, NARNN-LSTM and a hybrid ARIMA and NARNN-LSTM models were developed and the forecasting performances were compared based on mean absolute error(MAE), mean squared error(MSE) and root mean squared error(RMSE). The ARIMA models performed better than the NARNN-LSTM models for both petrol and diesel based on the error metrics. The hybrid of ARIMA and NARNN-LSTM model far outperformed the base models of ARIMA and the NARNN-LSTM models for MAE, MSE, RMSE for both petrol and diesel in Ghana.

Keywords: ARIMA, NARNN-LSTM, Gasoline, Diesel, Hybrid,Forecasting

1 Introduction

Predictions plays an important role in the management of areas such as economics and finance. Predicting prices of petroleum product has always been the subject of contention since these product are considered volatile. Petroleum product such as petrol and diesel serve as the main source energy for businesses and companies in Ghana. A sudden change in prices of these product have a great effect on businesses and the final consumer since such increment are passed unto them in the long run. Ghana, even though an oil producing country mainly uses imported refined petroleum product. In 2022, Ghana imported \$1.79 billion in refined petroleum product mainly from Netherlands, Belgium,Malaysia United States and United kingdom constituting $796, 447, 156, 87$, and 67.5 million dollars respectively. The Oil Marketing Companies (OMCs) which are licensed and regulated by the National Petroleum Authority (NPA) are responsible for the importation, distribution and marketing of refined petroleum products in the country. Before 2005, importation, distribution and pricing of petroleum product were controlled by the state and this was occasioned by regular shortages of petroleum product in the country. To overcome this phenomenon private sector participation was welcomed and the NPA was established in 2005 (ACT 691) to regulate and monitor the activities of the downstream sector . However in 2015, Ghana implemented the price deregulation of petroleum product with the

OMCs determining the prices rather than the NPA through competitive market pricing. The competitive pricing of the petroleum product in Ghana is influenced by the import parity price of the product, the foreign exchange rate , taxes and margins. Companies and businesses always plan the their expected revenue and expenditure overtime and any sudden change in the prices of its input affect them. This paper seeks to develop a model that will help predict the prices of petrol and diesel over time.

2 Literature Review

The continues hikes in the prices of crude oil and its products has raised the concern to not just predict future prices of the petrol and diesel but also with how accurate the predictions can be .Investors in the oil sector and consumers will also want to the how prices will be in the next prices window as the aim of every investor is not to make losses[15, 3]. This prediction is very useful in an economy like Ghana where the entire energy sector is being supported by crude oil product. Thus, there is a clear necessity to forecast the fuel price trends not just for the motorists good, but to make nation and the industrial players to be be aware and be prepared for the fluctuations in prices. Several models has been used in predicting prices of commodities and Box-Jenkins models has been very useful in predicting times series data that are linear in nature[7]. The Autoregressive Integrated Moving Average (ARIMA) which is a Box-Jenkins modeling techniques has proving to be one the models that are useful in making long and short term forecast.The ARIMA models compete fairly well with rising prediction techniques in short-run prediction[9, 17]. The model also has a high prediction accuracy in a short run in predicting Bitcoin prices[22] and also has a high short term prediction potential[1]. In predicting stock prices, the ARIMA model had a high forecasting or predicting accuracy[14]. Even though the Box-Junkins technique works for both linear and nonlinear times series,neural networks has also been proven to one of the promising methods of modeling which has been introduced to solve complex classification problems[20]. They have the ability to learn from examples, then generalized to data that have been presented to them[4].The main distinguishing characteristic of neural networks is their ability to 'learn' new features from data[8, Odoi et al.]. some of these models include the Multi-layer Perceptron(MLP),Convolutional Neural Network(CNN) and the Long Short Term Memory(LSTM). The neural networks has been noted for its high prediction accuracy in forecasting prices. Neural networks can also be used to solve nonlinear problems more satisfactorily compared to conventional machine learning[23, 13, 11] .In forecasting Indian index of industrial production, the artificial neural network was used and had the best forecasting results with a mean square error (MSE) of 2.168 [19]. Stock prices was predicted using Convolutional Neural Networks on a multivariate time series , the results indicated that CNN-based multivariate forecasting model is the most effective and accurate in predicting the movement of NIFTY index values with a weekly forecast horizon[13].[21] Made an event prediction within directional change framework using a CNN-LSTM model, the CNN-LSTM network architecture incorporates the robustness of Convolutional Neural Network (CNN) in feature extraction and Long Short-Term Memory (LSTM) in predicting sequential data. The results suggest that the performance of the CNN-LSTM model improves significantly within the DC framework. The neural network models has been used in addition to other models like the Box-Junkins models in predicting and forecasting. In a comparative study of series ARIMA-MLP hybrid models for stock price forecasting, the empirical results for forecasting three benchmark data sets indicate that despite of more popularity of the conventional ARIMA-ANN model, the ANN-ARIMA hybrid model can overall achieved more accurate results[10]. Predicting prices in the petroleum sector in Ghana is such an important phenomenon not only to the sector players but whole economy, this paper seeks to predict prices of diesel and petrol in Ghana using hybrid ARIMA and nonlinear autoregressive neural network (LSTM model)

3 Data and Methodology

This paper uses a monthly indicative prices of diesel and petrol (gasoline) from the Bank of Ghana (BoG) and the National Petroleum Authority (NPA) spanning January 2016 to December 2023, a period of 96 months with 96 data points. In understanding the occurrence possibility of monthly prices of diesel and petrol, a hybrid ARIMA and nonlinear autoregressive neural network(LSTM) models were used.

3.1 The Autoregressive Integrated Moving Average (ARIMA)

The Autoregressive Integrated Moving Average is a Box-Junkins method used in time series modeling and forecasting. The ARIMA is a non-stationary time series model denoted by ARIMA (p,d,q) where p indicates the order of autoregressive part, d indicates the order of integration and q is the number of lagged forecast errors in the prediction equation. When the original series is stationary, d=0 the ARIMA model reduces to ARMA. The ARIMA model has an autoregressive process, integrated process and the moving average process

3.1.1 The Autoregressive Process (AR(p))

Autoregressive models assume that X_t is a linear function of the preceding values and is given by equation

$$X_t = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + ... + \alpha_p X_{t-p} + \epsilon_t \tag{1}$$

$\alpha_1, \alpha_2, \alpha_p$ are coefficient of the autoregression and ϵ_t is reisduals of the autoregression

3.1.2 The Integrated Process(d)

The behavior of the time series can be influenced by the cumulative effect of some processes. For instance, stock status is constantly modified by consumption and supply, but the average level of stocks is essentially dependent on the cumulative effect of the instantaneous changes over the period between inventories. A time series determined by the cumulative influence of an activity belongs to the class of integrated processes. Even if the behavior of a series is erratic, the differences from one observation to the other can be relatively low or even oscillate around a constant value for a process observed at different time intervals. Integrated processes are the archetype of nonstationary series. A differentiation of order one assumes that the difference between two successive values of X is constant. The integrated process is defined by;

$$X_t = X_{t-1} + \epsilon_t \tag{2}$$

3.1.3 The Moving Average Process (MA(q))

The current value of a moving averaging process is a linear combination of the current disturbance with one or more preceding perturbations. The moving average order reflects the number of previous periods contained in the current value. The moving average equation is giving by;

$$X_t = \epsilon_t - \beta_1\epsilon_{t-1} - \beta_2\epsilon_{t=2} - ... - \beta_q\epsilon_{t-q} \tag{3}$$

$\beta_1, \beta_2, \beta_q$ are the coefficient of the moving average process

The forecasting equation of ARIMA (p,d,q) is of the form ;

$$X_t = \phi + \alpha_1 X_{t-1} + ... + \alpha_p X_{t-p} + \beta_1\epsilon_{t-1} + ... + \beta_q\epsilon_{t-q} + \epsilon_t \tag{4}$$

where ϕ is a constant and $\alpha = (\alpha_1, \alpha_2, ..., \alpha_p)$ and $\beta = (\beta_1, \beta_2, ..., \beta_q)$ are vector models for the autoregressive and the moving average processes.

3.1.4 Model Identification and Estimation(ARIMA)

The first and most important step in modeling is to check for stationarity of the data or series since estimation procedures are only available for stationary series[5]. A cursory looking at the graph of the data and structure of ACF and PACF may provide clues for the presence of stationarity. If the model is found to be non-stationary, stationality therefore needs to be archived by differencing the series.The differencing is done until a plot of the data indicates the series varies about a fixed level, and the graph of ACF either cuts off fairly quickly or dies down fairly quickly . The optimal value for 'd' is therefore determined using the information criteria like AIC(Akaike information criteria) and BIC (Bayesian information criteria) to identify the best combinations for the parameters p,d,q.The model was then fitted and ARIMA(p, d, q) was selected model to the stationary time series data,estimating the model parameters (ϕ and θ) using the Maximum Likelihood Estimation(MLE). The model was then evaluated by checking the residuals behaviour, ensuring they are uncorrelated,normally distributed and have zero means . Diagnostic tests were done using the Ljung-Box Q-statistic to assess the model's adequacy. The Q-statistic is giving by

$$Q_m = n(n+2)\sum_{k=1}^{m}\frac{r_k^2(e)}{n-k} \sim \chi^2_{m-r} \tag{5}$$

where $r_k(e)$ is the autocorrelation at lag k

n is the number of residuals

m is the number of time lags included in the test. when the p-value associated with Q statistics is small (p-value$<\alpha$), the model is considered inadequate and the researcher should consider a new model but if the model diagnostics indicate a satisfactory fit,the generated model will then be used to forecast price .

The coefficient of the estimated model was also tested for its significance using the Z test at 5%.

$$Z = \frac{(X_t - \mu_0)}{s} \tag{6}$$

where X_t is the sample mean and μ_0 is the population mean and s is the standard deviation

If the model diagnostics indicate a satisfactory fit,the generated model will then be used to forecast the price and validate the model's accuracy by comparing the forecast value with the test data

3.2 Nonlinear Autoregressive Neural Network(LSTM Model)

The nonlinear autoregressive neural network is the generalization of AR process that is trained to predict a time series from the series past values $X_{t-1}, X_{t-2}, ..., X_{t-d}$ called feedback delays, where d is the feedback parameter[4] The NARNN of order p can be expressed as;

$$X_t = \alpha(X_{t-1}, X_{t-2}, ...x_{t-d}, w) + \epsilon_t \tag{7}$$

where $\alpha(.)$ is an unknown function determined by the neural network structure and connection weight,w is a vector of all parameters and ϵ_t is the error term

The Long Short Term Memory (LSTM) as a neural network model is a type of recurrent model in neural network language [24]. The recurrent neural network model as a network model was designed to process sequential data consisting of multiple time steps. The RNN model output is calculated based on the current input and the previous hidden state, where the hidden state is calculated during the previous time step [8]. In a regular RNN,it suffers from the vanishing gradient phenomenon whereby the gradient value rapidly decreases as it propagates back in time. A small gradient means that the weights of the initial layers will not be updated effectively.The LSTM resolves the vanishing gradient problem by introducing an LSTM unit into a regular RNN. The LSTM unit consists of three gates - input gate, forget gate, and output gate that control the flow of information inside the unit[12]

3.3 Hybrid ARIMA and NARNN-LSTM Model

The ARIMA and NARNN are good in modeling time series data that are linear and nonlinear in nature. A combination of the two models present a better choice of modeling time series that are linear and nonlinear in nature[6, 18] The linear component of the model will be modelled by the ARIMA model and and the residuals from the ARIMA will represent the nonlinear component which can be obtained by taking a difference of the actual values and the predicted values

$$\epsilon_t = X_t - \hat{L} \tag{8}$$

where ϵ_t is the residuals of the linear model at time t from the ARIMA and the $\hat{L}$ is the predicted value at time t.

To model the nonlinear relationship, the residuals from the ARIMA (linear model) will be used to model the NARNN-LSTM model, giving by

$$\epsilon_t = h(\epsilon_{t-1}, \epsilon_{t-2}, .., \epsilon_{t-n}) + \epsilon_t \tag{9}$$

where h is the transformational function modeled by NARRN-LSTM

The forecast equation by the hybrid ARIMA and NARNN-LSTM model is given by

$$X_t = \phi + \alpha_1 X_{t-1} + \alpha_p X_{t-p} + ... + \beta_1 \epsilon_{t-1} + \beta_q \epsilon_{t-q} + \epsilon_t + h(\epsilon_{t-1}, \epsilon_{t-2}, .., \epsilon_{t-n}) + \epsilon_t \tag{10}$$

where ϕ is a constant and $\alpha = (\alpha_1, \alpha_2, ..., \alpha_p)$ and $\beta = (\beta_1, \beta_2, ..., \beta_q)$ are vector models for the autoregressive and the moving average processes,where ϕ is a constant and $\alpha = (\alpha_1, \alpha_2, ..., \alpha_p)$ and $\beta = (\beta_1, \beta_2, ..., \beta_q)$ are vector models for the autoregressive and the moving average processes, h is the transformational function modeled by NARRN-LSTM and ϵ_t is the residual from the the hybrid model (ARIMA and NARNN-LSTM Model)

4 Model Evaluation

There are various performance indices that can be used to measure the forecasting performance of a model . In this study, we use performance indicators or error metrics such as ,mean absolute error(MAE), the root-mean squared error(RMSE), and mean squared error (MSE) [2] given respectively by

$$MAE = \frac{1}{N} \sum_{t=1}^{n} |x_t - \hat{x_t}| \tag{11}$$

the MAE value should be minimal

$$MSE = \sum_{t=1}^{n} \frac{(x_t - \hat{x_t})^2}{n} \tag{12}$$

the MSE should be relatively low

$$RMSE = \sqrt{\sum_{t=1}^{n} \frac{(x_t - \hat{x_t})^2}{n}} \tag{13}$$

the RMSE should be relatively low

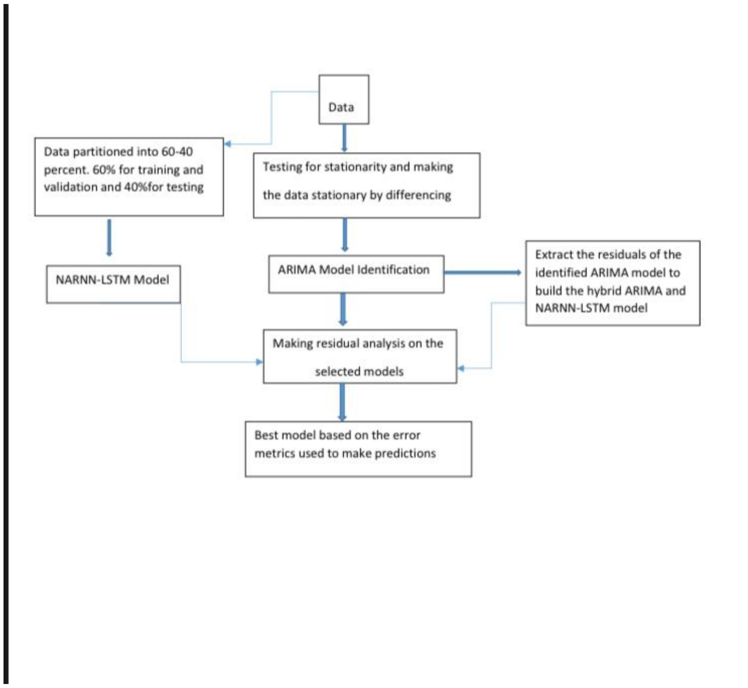

Figure 1: A flow chart for the study

5 Results And Discussion

Table 1 is the summary statistics and graph in figure 2 and 3 is monthly time and box plot of diesel and gasoline prices in Ghana from from January 2016 December 2023. The graph shows a rising trend in prices of diesel and gasoline which support the hypothesis of changes in price and signifies that the data is not stationary.

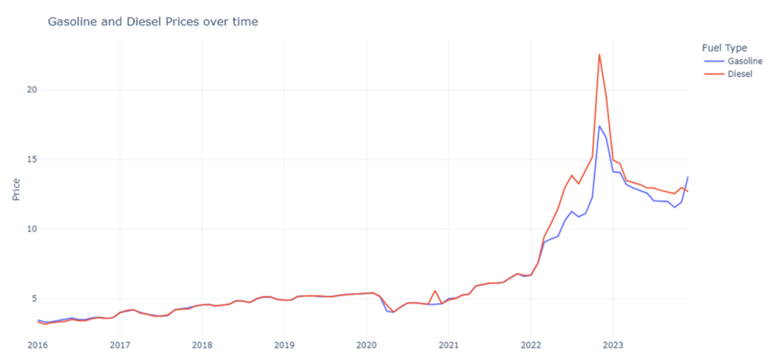

Figure 2: Times series plot of Diesel and Gasoline in Ghana

Figure 3: Box plot of gasoline and diesel

Table 1: Summary Statistics

Variable	**Observations**	**Minimum**	**Maximum**	**Mean**	**Standard Deviation**
Diesel	**96**	**3.16**	**22.58**	**6.817**	**0.418**
Gasoline	**96**	**3.32**	**17.43**	**6.486**	**0.351**

5.1 Model Identification

5.1.1 ARIMA

Stationarity of the of the dataset was tested for both diesel and gasoline using the ADF test and p-values for diesel and gasoline were 0.6326 and 0.7818 respectively which is higher than the significance level of 0.05 . This indicates non stationarity of the data set. The data was then differenced, and it became stationary after the first difference for both diesel and gasoline with p-vaues of 0.0136 and 0.01398 respectively from the ADF test which is less than the significance level of 0.05. The best model for diesel and gasoline was identified using AIC and BIC, and ACF and PACF. Table 2 and 3 shows the model identification for both diesel and gasoline using the AIC and BIC after the first difference. From table 2, the ARIMA (0,1,2) was the best model in terms of AIC and BIC(both least) for diesel, the coefficient of the model was tested using the Z-test and the test results were not significant. The ARIMA(2,1,0) and (2,1,3) were then considered and tested ,the ARIMA(2,1,3) had all the model coefficient significant and considered to be the best model for diesel even though ARIMA(0,1,2) had the least AIC and BIC values, that is the difference between the two models is not significant in terms of AIC and BIC values .The ARIMA (0,1,2) had the least values in terms of AIC and BIC from table3 and considered to be the best model for gasoline. the model coefficient were then tested and all the test results were significant using the Z-test .The ACF and the PACF for the differenced dataset for diesel and gasoline are in Figure 4 and 5 respectively.Table **??** shows the Z-test for the coefficients ARIMA(2,1,3) and ARIMA(0,1,2) diesel and gasoline respectively.

Table 2: Model Identification for Diesel

			AIC	AICc	BIC
1	1	0	280.8634	280.9060	285.9712
0	0	0	546.1132	546.1558	551.2419
1	1	1	280.6927	280.8218	288.3544
2	1	0	279.6118	279.7409	287.2735
0	1	2	279.5115	279.6405	287.1731
2	1	1	281.6118	281.8727	291.8273
2	1	1	281.6118	281.8727	291.8273
1	2	2	284.4606	284.7215	294.6338
2	2	2	285.4036	285.8432	298.1201
2	1	3	280.5347	281.2014	295.8580
3	1	2	285.2749	285.9415	300.5981
0	1	3	281.4951	281.7560	291.7106
0	1	4	283.4916	283.9312	296.2610

Table 3: Model Identification for Gasoline

			AIC	AICc	BIC
1	1	1	284.7997	284.8422	209.9074
1	1	1	512.5319	512.5745	517.66.6
2	1	0	199.4055	199.5346	207.0672
0	1	2	198.4348	198.5638	206.0964
2	1	1	200.4917	200.7526	210.7072
1	2	2	203.2121	203.4729	213.3852
2	2	2	203.5936	204.0331	216.3101
2	1	3	201..6131	202.2798	216.9364
3	1	2	204.0777	204.7444	219.4010
0	1	3	200.4273	200.6882	210.6428
0	1	4	202.2809	202.7205	215.0503

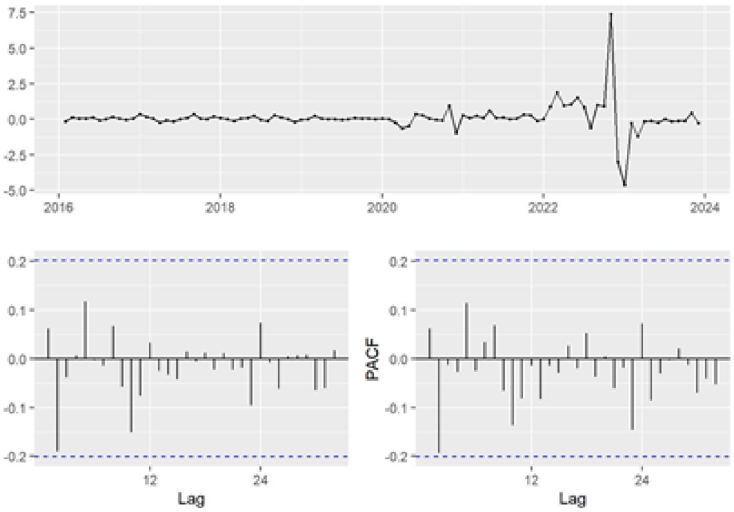

Figure 4: The ACF and PACF of nonseasonal difference of diesel

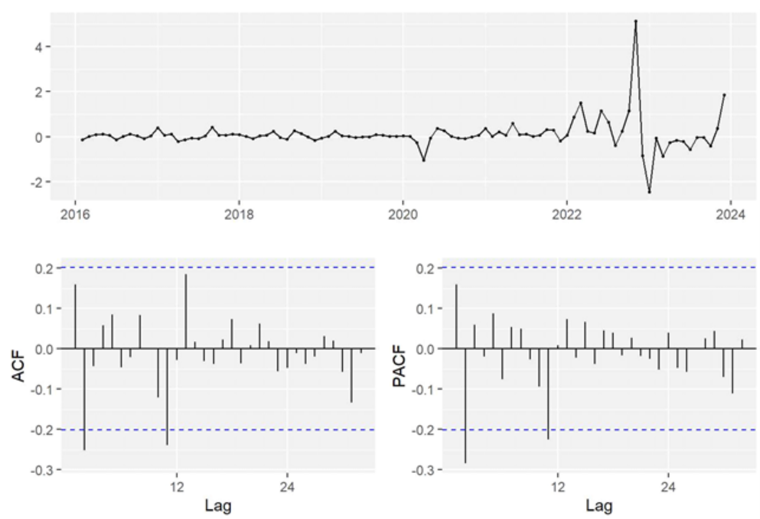

Figure 5: The ACF and PACF of nonseasonal difference of gasoline data

The adequacy of ARIMA(2,1,3) and ARIMA(0,1,2) for diesel and gasoline were tested using the Ljung-Box test with a p-value 0.9441 and 0.8336 for diesel and gasoline respectively,which shows that both models are adequate and significant.The ACF and the PACF plot for the best model on the residuals for both diesel and gasoline were also checked to ensure that no more information are left out, the results indicates the residuals were random and do not contain any information.Figure 6 and 7 and figure 8 and 9 are the residual analysis on diesel and gasoline respectively

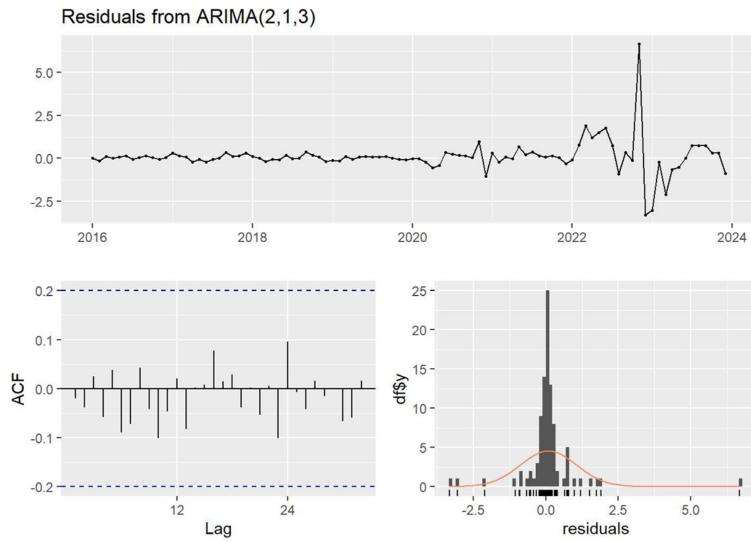

Figure 6: Residuals from diesel,ARIMA $(2, 1, 3)$

Figure 7: Residuals from diesel ARIMA $(2, 1, 3)$

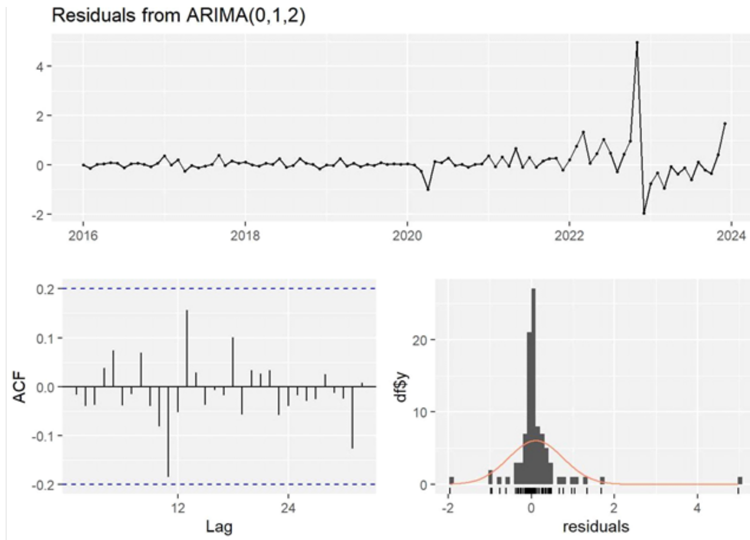

Figure 8: Residuals from gasoline,ARIMA $(0, 1, 2)$

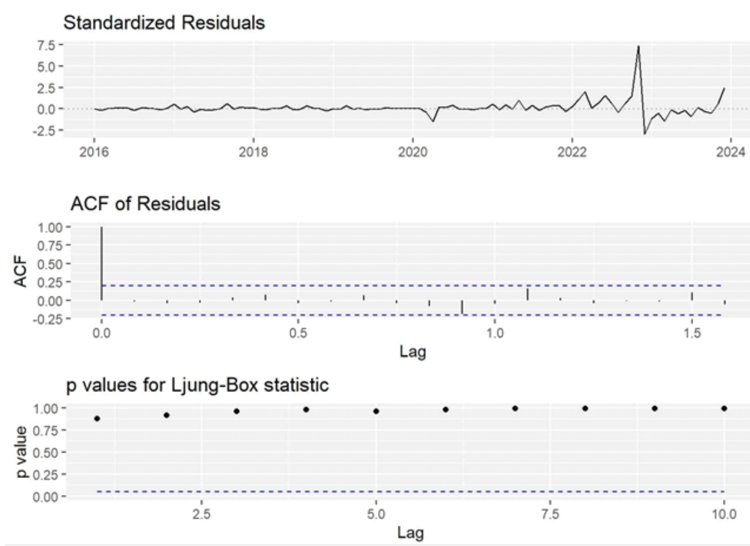

Figure 9: Residuals from gasoline ,ARIMA $(0, 1, 2)$

5.1.2 NARNN-LSTM Models

The dataset for the analysis for both diesel and gasoline was partitioned to (60-40)%. 60% was used for training and validation and 40% for testing . In developing an optimal architecture for the NARNN-LSTM model,determination of time delays ,the number of hidden neurons and an effective training algorithm are required. The developed NARNN-LSTM model is a sequential model with one LSTM hidden layers and three dense layers with 120, 100 and 1 neurons using Adam algorithm as an optimizer for diesel and the LSTM model for gasoline had sequential LSTM model with one dense layer of and two dense layers of 120 and 1 neurons with a total parameter of 73201 at one time step. 10 and 11 shows the training and validation loses for diesel and gasoline respectively

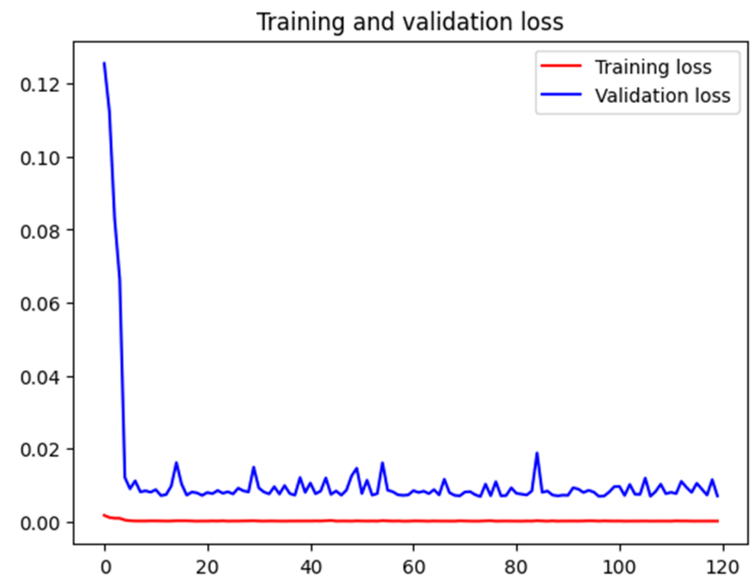

Figure 10: NARNN-LSTM training and Validation loses for diesel

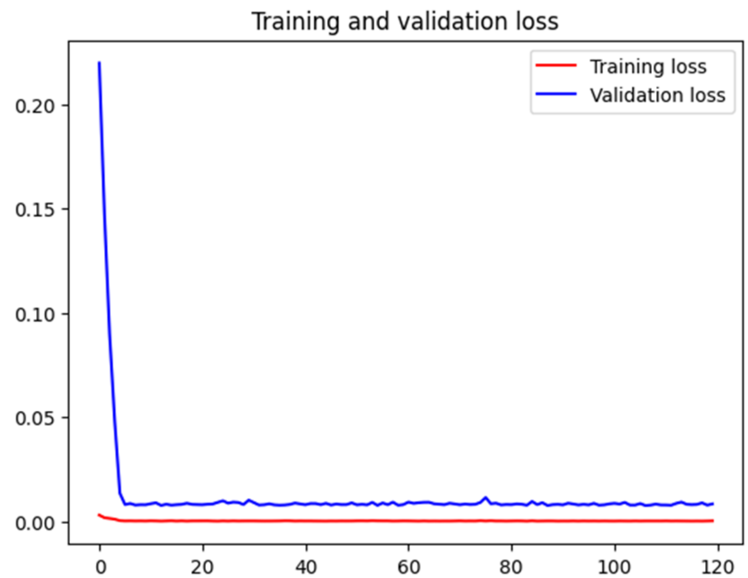

Figure 11: NARNN-LSTM training and Validation loses for gasoline

5.2 Hybrid ARIMA and NARNN-LSTM Model

The hybrid model was developed by applying the NARNN-LSTM model to time series prediction using past values of the univariate residual times series from the ARIMA models from diesel and gasoline respectively. The optimal architecture of the LSTM hybrid model is a sequential model with two hidden layers of LSTM models and three dense layers of 120, 100 and 1 neurons with a total parameter of 171281 using the Adam optimising algorithm for diesel. The LSTM models for gasoline is also a sequential model with two hidden layers of LSTM s with three dense layers of 120, 100 and 1 neurons with a total parameter of 171281 all at one time delay .The training and the validation loses for the hybrid models for diesel and gasoline from 12 and 13 all shows a decreasing functions suggesting that the models are optimally performing

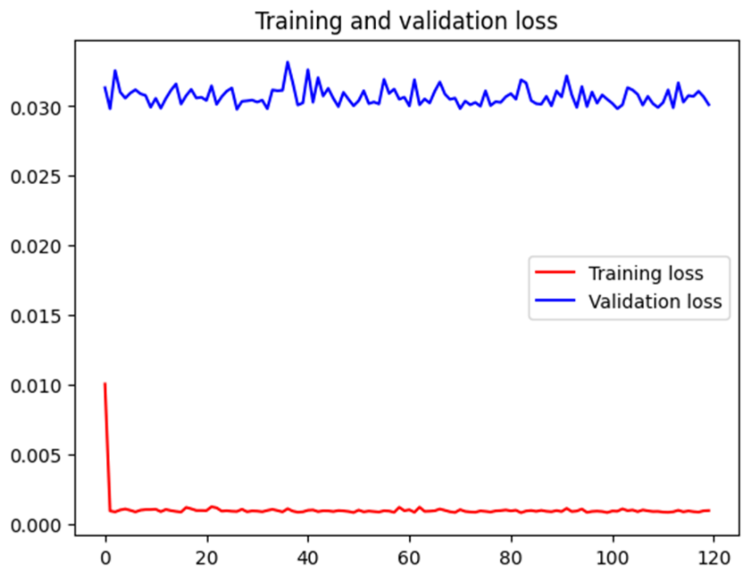

Figure 12: ARIMA and NARNN-LSTM training and validation loses for gasoline

Figure 13: ARIMA and NARNN-LSTM training and validation loses for diesel

6 Model Evaluation

The potency of the ARIMA,NARNN-LSTM and the combination of the ARIMA and NARNN-LSTM models were compared using the error metrics such as the MSE, MAE and RMSE and the best model used for prediction . The results are shown in table 3

Table 4: Model Evaluation

	Diesel				Gasoline		
	MSE	MAE	RMSE		MSE	MAE	RMSE
ARIMA	**0.9366136**	**0.4281963**	**0.967788**		**0.4380967**	**0.2930457**	**0.661888**
NARNN-LSTM	**2.6457287**	**0.82935371**	**1.626569**		**1.6846709**	**0.7424710**	**1.2979487**
ARIMA and NARNN-LSTM	**0.1375025**	**0.1764055**	**0.37081341**		**0.18104225**	**0.2726928**	**0.4259406**

Figure 14: ARIMA and NARNN-LSTM 12 Month forecast for diesel in Ghana

Figure 15: ARIMA and NARNN-LSTM 12 Month forecast for gasoline in Ghana

7 Conclusion

This paper proposes to predict gasoline and diesel in Ghana using hybrid model of ARIMA and NARNN-LSTM model. First the ARIMA and the NARNN-LSTM were developed for gasoline and diesel respectively. ARIMA $(0, 1, 2)$ and ARIMA $(2, 1, 3)$ were considered the best models based on AIC and BIC for gasoline and diesel. The residuals from th ARIMA models were used to develop the hybrid models. The models were compared based on its forecasting accuracy, the ARIMA models for gasoline and diesel performed better than the LSTM model but the hybrid of ARIMA and NARNN-LSTM model performed far better than the the individual models for both gasoline and diesel based on MSE,MAE,RMSE. The forecast information presented in this study can be considered by Consumers, petroleum industry players and the government as a whole in making policies and decisions in Ghana

8 Limitation Of The Study

The findings of this study is limited to Ghana as the pricing formula of petroleum product prices may not be the same in other countries.

9 Recommendation

we recommend that, future studies should consider comparing the developed non-linear modesl to other non-linesr models such as TAR or Markov switching.

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