Predicting Petrol and Diesel Prices in Ghana, A Comparison of ARIMA and SARIMA Models

Abstract: Predicting prices is of great concern and important in the world of economics and finance.In this paper, a comparative analysis of gasoline and diesel in Ghana were analysed using Autoregressive Integrated Moving Average(ARIMA) and Seasonal Autoregressive Integrated Moving Average(SARIMA) .Based on their forecasting accuracy, the best model was used for predicting future prices of gasoline and diesel from January 2024 to December 2024 . A monthly data for the prices of gasoline and diesel spanning from January 2016 to December 2023 taken from the Bank of Ghana (BoG) and the National Petroleum Authority (NPA) was used for the analysis . ARIMA$(0, 1, 2)$ and ARIMA$(2, 1, 3)$ were identified as the best models for gasoline and diesel respectively, SARIMA$(0, 1, 2) \times (0, 1, 1)_{12}$ and SARIMA$(1, 1, 1) \times (0, 1, 1)_{12}$ were also identified after taking a seasonal difference of the series all based on AIC and BIC. The coefficient of the identified models were tested for its significance using the Z-test. The ARIMA and the SARIMA models were compared using RMSE, MAE, and MAPE. The SARIMA models generally performed better than the ARIMA models for both gasoline and diesel except RMSE for diesel where the ARIMA model was slightly better than the SARIMA models with values of 0.9677988 and 1.011531 respectively. The model evaluation proved that the SARIMA models for both gasoline and diesel were superior to the ARIMA and showed that, the SARIMA model is adequate and appropriate for forecasting of prices of gasoline and diesel prices in Ghana

Keywords: ARIMA, SARIMA, Gasoline, Diesel,Forecasting

1 Introduction

Pricing of petroleum product is a subject of both political and economic decision in Ghana. The petroleum industry in Ghana is categorised into upstream and downstream sector. The upstream is regulated by the Ghana National Petroleum Cooperation (GNPC) and is concerned with exploration and refinery of petroleum product. The downstream is concerned with the importation of crude oil and refined petroleum products, marketing and distribution of refined products, and all these activities are regulated by the National Petroleum Authority (NPA). Ghana's downstream sector was deregulated in 2005 to remove restriction on the establishment and operation of facilities by the private sector, remove price controls, and remove restrictions on the importation of crude oil and petroleum products [3]. Since then, the prices of petroleum product has become the subject of contention for consumers, businesses and industries. An increase or decrease in prices of petroleum products has a great impact on a volatile economy such as Ghana [13]. The value of many variables change over time and the changing nature of such variables over time is known as time series. Managing and using such data is considered as a major challenge to consumers, businesses and investors. One of such challenges is how to use the data with the observations to draw general conclusions about the trends in the data. companies, economies and global The rapid swings in prices of petrol, diesel and petroleum product in general can have serious effects on on companies, economies and global geopolitics [18, 15].Naturally forecasting is one of the main aspects of time series analysis having the art of saying that what will happen in the future rather than why [16]. It is therefore important to develop a model that will better predict the prices of petroleum product in Ghana .

2 Literature Review

Predicting and forecasting prices of a volatile products such as petrol and diesel is very important in the the world of economics since these product are some of the most important driving forces of the global economy.Volatility is one of the most significant concept in the whole of economics and finance [2, 8]. Volatility is frequently used as an indicator of the total risk of a financial assets. Estimation and forecasting of a volatile parameter is used in many value- at- risk models for gauging market risks [4].). Extensive empirical and theoretical studies have been conducted on predicting and forecasting volatility of petroleum product in the world. The Box-Jenkins approach is one of the most widely used methodologies for the analysis of time series data and it can handle any series being stationary or not, with or without seasonal elements. The ARMA model has been one of the most useful models in making predictions on stationary time series data. In modelling stock prices predictions based on ARMA model, it turns out that the data's error rates are low, indicating that the ARMA model is suitable for the short-term prediction of the prices and further [19]. The ARMA model proved to have a high prediction accuracy in forecasting stock prices [10]. Forecasting financial time series data that are very noisy and non-stationary is a major problem for market operators to invest at their best profit. In modelling stock price prediction in the New York Stock Exchange (NYSE) and the Nigeria Stock Exchange, the ARIMA model had a strong potential for short-term prediction and can compete favourably with existing techniques for stock price prediction [5]. The ARIMA model has proven to be one of the robust models in making predictions and forecasting. In predicting the exchange rate in India, the ARIMA model predicted better than the complex nonlinear models [7]. The ARIMA model has proven to be one of the robust models in making predictions and forecasting and some times has a smaller forecast error compared to other models [21]. In predicting the exchange rate in India, the ARIMA model predicted better than the complex nonlinear models [17].The ARIMA model is for non-seasonal non-stationary data. Box and Jenkins have generalised a model to deal with seasonality and this model is known as the Seasonal ARIMA (SARIMA) model. In predicting Indian electricity exchange traded market prices using the SARIMA and MLP approach, the results indicates that the SARIMA model had high prediction accuracy [9] and also supported by [6] in automatic SARIMA modelling and forecast.

The SARIMA models have also been widely used in forecasting prices. For example, in forecasting Korea Stock Prices Index (KOSPI), the SARIMA model provided more general accurate forecast for the KOSPI than the Back-propagation Neural Network [12]. Predictions have always been and will continue to be an interesting area of research, making researchers in the domain always desiring to make and improve existing predictive models. This paper seeks to predict petrol and diesel prices in Ghana, a comparison of ARIMA and SARIMA models. This paper seeks to predict petrol and diesel prices in Ghana by comparing the forecating accuracy of the ARIMA and SARIMA models

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 from 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, the ARIMA and the SARIMA models were used.

3.1 The ARIMA Models

The Autoregressive Integrated Moving Average is a Box-Junkins method used in time series modelling and forecasting [11]. 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 amount of differencing 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 differenced linear operator is giving by

$$\Delta X_t = X_t - X_{t-1} = X_t - BX_t = (1 - B)X_t \tag{1}$$

The stationary series W_t obtained as the dth differenced (Δ^d) of X_t,

$$W_t = \Delta^d X_t = (1 - B)^d X_t \tag{2}$$

Once stationality of the series is realised,the model can be defined as a combination of the Autoregressive (AR) and Moving Average (MA) models operating on the differenced series. The ARIMA (p,d,q) has the general form:

$$\phi_p(B)(1 - B)^d X_t = \mu + \theta_q(B)\epsilon_t or \phi_p(B)W_t = \mu + \theta_q(B)\epsilon_t \tag{3}$$

3.1.1 Model Identification and Estimation(ARIMA)

The first and most important step in modelling is to check for stationality of the data or series since estimation procedures are only available for stationary series. 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 Augmented Dickey Fuller test (ADF) and also with 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 test to assess the model's adequacy, 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 forecasted value with the test data

3.2 The SARIMA model

The SARIMA is an adoption of the autoregressive integrated moving average (ARIMA) models to specifically fit time series data that are seasonal in nature or have some component of seasonality. In a seasonal ARIMA model (SARIMA), seasonal differencing of appropriate order is used to remove seasonality from the time series making it non-seasonal . The seasonal ARIMA model incorporates non-seasonal and seasonal factors in a multiplicative model and is giving by:

$$ARIMA(p, d, q) \times (P, D, Q)(S)$$

p,d and q representing non-seasonal autoregressive order, non-seasonal differencing and non-seasonal moving average order respectively. P is the seasonal autoregressive order, D is the seasonal differencing and S represent the time span of the repeating seasonal pattern[14]. The seasonal ARIMA (SARIMA) is written as

$$(1 - \phi_p B)(1 - \Phi_P B^s)(1 - B)^d (1 - B^s)^D (X_t - \mu) = (1 - \theta_q B)(1 - \Theta_Q B^s)\epsilon_t \tag{4}$$

B represents the back shift operator and number of periods in a season (S) = 12. p and P are the order of nonseasonal and seasonal autoregression and q and Q are the orders of nonseasonal and seasonal moving average, respectively. ϕ the non-seasonal parameter for autoregression and θ is the non- seasonal parameter for moving average,Φ is the seasonal parameter for autoregression while Θ is the seasonal parameter for moving average

3.2.1 Model Identification and Estimation (SARIMA)

The series is differenced a number of times and this number determines the order of d. The AR and MA are determined using non-seasonal and seasonal autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. A theoretical AR model of order p has an ACF that decays and a PACF that cuts off at lag p while a theoretical MA model of order q comprises of a PACF that decays and an ACF that cuts off at lag q. The model with the minimum AIC and BIC values is therefore selected as the model that fits the data best [14] . The significance of the model parameters was tested using the t- test statistics.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 statics to assess the model's adequacy, given by

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

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 the price and validate the model's accuracy by comparing the forecasted value with the test data

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 absolute percentage error(MAPE) [20, 1] given respectively by

$$MAE = \frac{1}{N}\sum_{t=1}^{n}|x_t - \hat{x}_t| \tag{6}$$

the MAE value should be minimal

$$RMSE = \sqrt{\sum_{t=1}^{n}\frac{(x_t - \hat{x}_t)^2}{n}} \tag{7}$$

the RMSE should be relatively low

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}|\frac{x_t - \hat{x}_t}{x_t}| \tag{8}$$

The coefficient of the estimated model parameters will also evaluated to test its significance using the Z-test given by:

$$Z = \frac{(\hat{X}_t - \mu_0)}{s} \tag{9}$$

where $\hat{X}_t$ is the sample mean and μ_0 is the population mean and s is the standard deviation

5 Results And Discussion

Table 1 is the summary statistics and graph in figure 1 and 2 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.

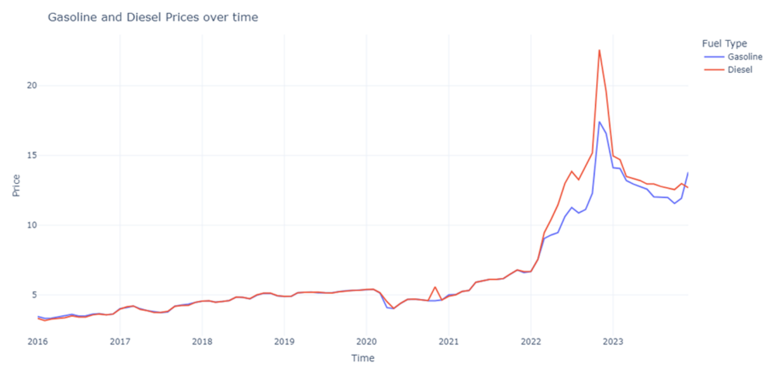

Figure 1: Times series plot of Diesel and Gasoline in Ghana

Figure 2: 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 3 and 4 respectively.Table 6 shows the Z-test for the coefficients ARIMA(2,1,3) and ARIMA(0,1,2) for 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

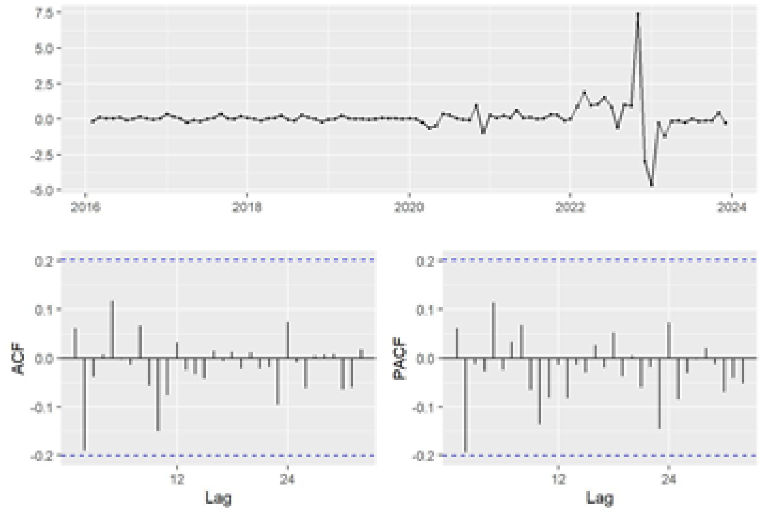

Figure 3: The ACF and PACF of the nonseasonal difference of diesel data

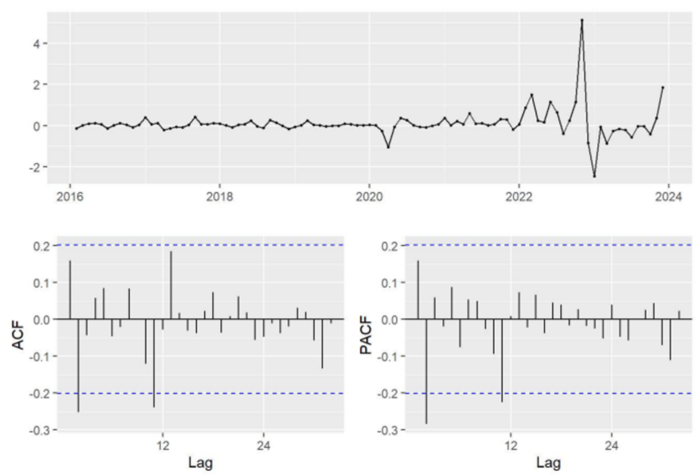

Figure 4: The ACF and PACF of the nonseasonal gasoline data

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 5 and 6 and figure 7 and 8 are the residual analysis on diesel and gasoline respectively

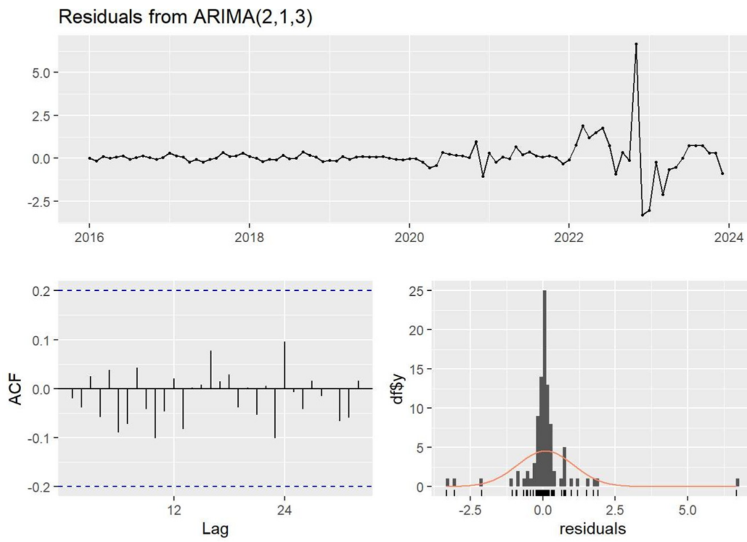

Figure 5: Residuals from Diesel, ARIMA(2,1,3)

Figure 6: residuals from Diesel, ARIMA$(2, 1, 3)$

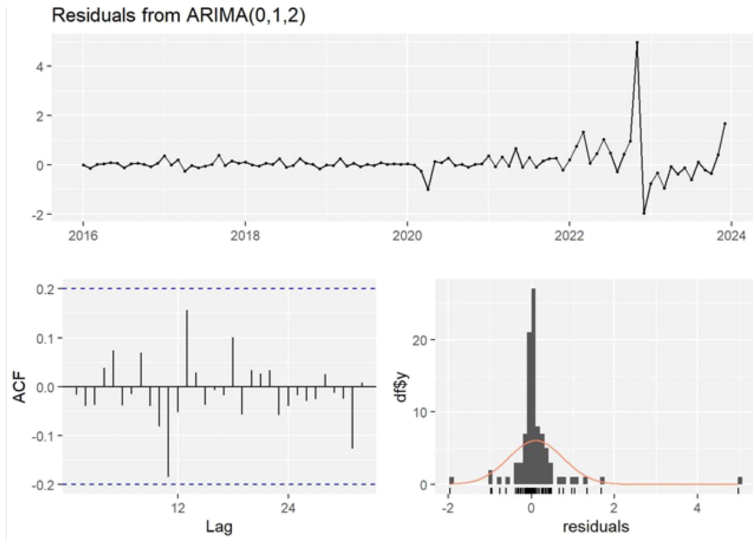

Figure 7: reiduals from Gasoline,ARIMA$(0, 1, 2)$

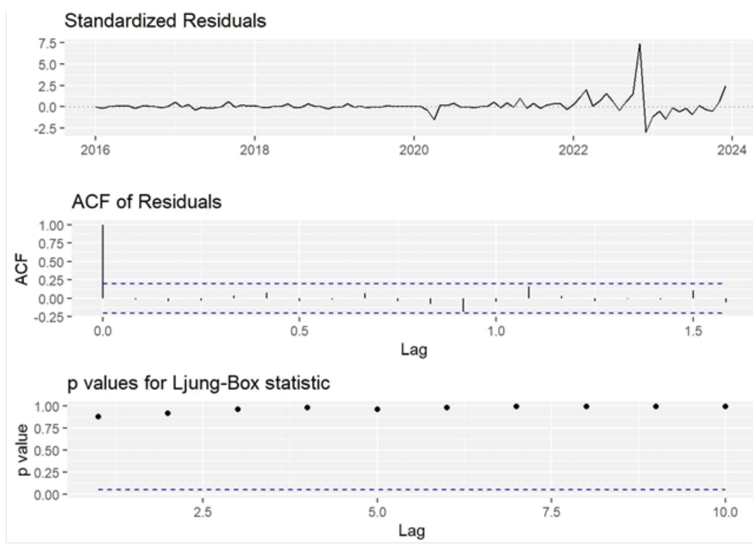

Figure 8: Residuals from Gasoline ,ARIMA(0,1,2)

5.1.2 SARIMA

As indicated earlier the series is non stationary for both diesel and gasoline per the ADF test in the ARIMA models. A seasonal differecing was carried out to make the series series stationary for both diesel and gasoline respectively. The series became stationary after the first seasonal difference and tested using the ADF test with p-values of 0.01361 and 0.01398 for diesel and gasoline respectively which are less than the significant value of 0.05 confirming that the series is stationary and does not have a root unit. Table 4 and 6 shows the SARIMA model selection based on AIC and BIC(both least) for diesel and gasoline respectively. In selecting the best SARIMA models for both diesel and gasoline, different models were analysed and the best will be used to forecast prices. $(1,1,1) \times (0,1,1)_{12}$ was considered the best model for diesel in table 4 and SARIMA $(0,1,2) \times (0,1,1)_{12}$ for gasoline in table 5 respectively. Both models had comparatively the least AIC and BIC. The adequacy of the models were then checked using the Ljung-Box test with a p-value of 0.8442 and 0.9487 for diesel and gasoline respectively . The coefficient of of the identified models were tested for its significance using the Z-test, the test results shows that both SARIMA models were significant at 5%. The test result are shown in table7The residuals of the selected models were then checked to ensure randomness and normality in order to make sure that no information is left out. Figure 9 and 10 and figure 11 and 12 are the residual analysis on SARIMA $(1,1,1) \times (0,1,1)_{12}$ and SARIMA$(0,1,2) \times (0,1,1)_{12}$ for and gasoline respectively. The models were then evaluated for its adequacy and used to make predictions in subsequent sections.

Table 4: SARIMA Model Identification for Diesel

						AIC	AICc	BIC
1	1	1	0	1	1	267.5036	267.7644	277.1789
2	1	0	0	1	0	302.0445	302.1735	309.3010
2	1	0	0	1	1	268.0160	268.2769	277.6914
0	1	2	0	1	0	302.0561	302.1851	309.3126
0	1	2	0	1	1	267.6841	267.9449	277.3294
2	1	1	0	1	0	303.5143	303.7752	313.1897
2	1	1	0	1	1	269.4267	269.8662	2811.5209
2	1	1	0	1	0	303.5143	303.7752	313.1897
2	1	1	0	1	1	269.4267	269.8662	281.5219

Table 5: SARIMA Model Identification for Gasoline

						AIC	AICc	BIC
1	1	0	1	1	1	207.9373	208.1981	217.6126
1	1	0	0	1	0	239.1481	239.1906	220.6745
1	1	1	1	1	1	202.8060	203.2456	214.9003
0	1	2	1	1	1	201.9781	202.3876	214.0423
0	1	2	0	1	1	201.0043	201.2652	210.6797
2	1	1	1	1	1	204.3997	205.0663	218.9127
2	1	1	0	1	0	240.3564	240.6173	250.0318
0	1	3	0	1	0	240.5220	240.7829	250.1974
0	1	3	0	1	1	202.9896	203.4292	215.0839

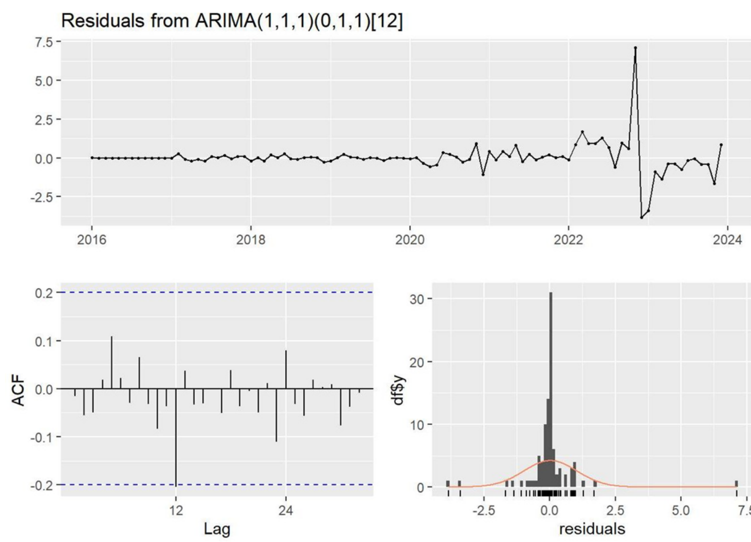

Figure 9: residuals from SARIMA$(1, 1, 1,) \times (0, 1, 1)$

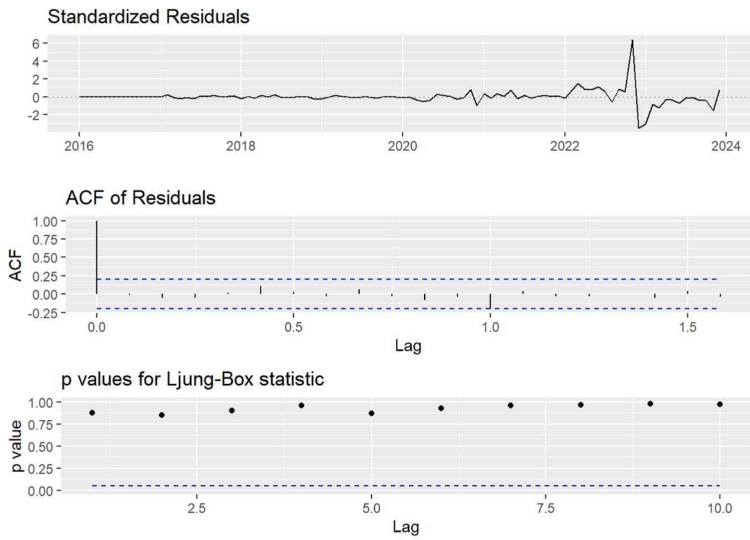

Figure 10: residuals from Diesel, $\text{SARIMA}(1,1,1) \times (0,1,1)$

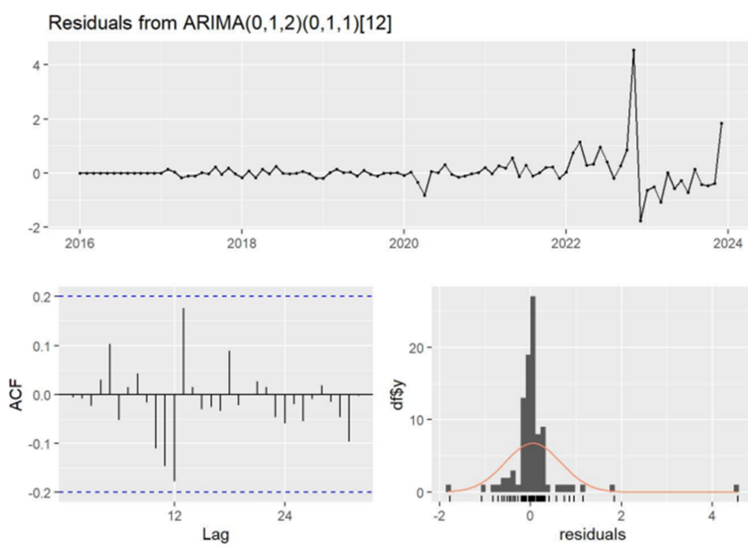

Figure 11: residuals from Gasoline,$\text{SARIMA}(0,1,2) \times (0,1,1)$

Figure 12: residuals from Gasoline, SARIMA$(0, 1, 2) \times (0, 1, 1)$

The coefficient of of the selected models were also tested using the Z-test for ARIMA and SARIMA models for diesel and gasoline.The test results shown in Table6 and 7 indicates that ,all models coefficient were significant at 5%

Table 6: Test of significance on the coefficient of the identified ARIMA model

	ARIMA						
	DIESEL					GASOLINE	
	AR1	AR2	MA1	MA2	MA3	MA1	MA2
Z Value	14.7997	-8.3685	-9.9823	2.5885	2.0277	**2.6503**	**-2.3773**
P Value	2.2e-16	2.2e-16	2.2e-16	0.009639	0.042587	**0.008041**	**0.017439**

Table 7: Test of significance on thr identified SARIMA models

	SARIMA					
	DIESEL			GASOLINE		
	MA1	MA2	SMA1	MA1	MA2	SMA1
Z-value	2.4751	-2.5513	-2.3952	2.4751	-2.5513	-2.3952
p-value	**0.01332**	**0.01073**	**0.01661**	**0.01332**	**0.01073**	**0.01661**

6 Model Evaluation

The identified ARIMA and SARIMA models were evaluated and compared for both diesel and gasoline based on root mean spuare errors (RMSE),mean absolute errors (MAE) and mean absolute percentage errors(MAPE).From table 8, it can be seen that the SARIMA models for both diesel and gasoline performed better than than the ARIMA models in all the parameters except the RMSE for diesel where the ARIMA slightly performed better than the SARIMA. The SARIMA model was then used to make a 12 months forecast for prices of diesel and gasoline in Ghana. Table 9 and 10 for diesel and gasoline respectively.

Table 8: Model evaluation for the ARIMA and SARIMA modesl

Diesel					**Gasoline**		
	RMSE	**MAE**	**MAPE**		**RMSE**	**MAE**	**MAPE**
ARIMA	**0.967788**	**0.43561**	**4.84027**	**ARIMA**	**0.6618888**	**0.2930457**	**3.58355**
SARIMA	**1.011531**	**0.4281961**	**4.463798**	**SARIMA**	**0.6184579**	**0.2719587**	**3.10523**

Table 9: 12 months forecast of Diesel prices in Ghana

2024 Diesel Forecast					
Month	**Point Forecast**	**Low 80**	**High 80**	**Low 95**	**High 95**
January	**11.84444**	**10.418916**	**13.23995**	**9.664295**	**14.02458**
February	**11.77479**	**9.602498**	**13.94709**	**8.452554**	**15.09704**
March	**11.99073**	**9.353517**	**14.62794**	**7.957461**	**16.02400**
April	**11.98446**	**8.904465**	**15.06446**	**7.274012**	**16.69491**
May	**12.24502**	**8.907123**	**15.68292**	**6.987210**	**17.50283**
June	**12.51496**	**8.735631**	**16.29429**	**6.734974**	**18.29495**
July	**12.74211**	**8.660503**	**16.82373**	**6.499829**	**18.98440**
August	**12.56892**	**8.199220**	**16.93862**	**5.886039**	**19.25180**
September	**12.80558**	**8.169869**	**17.44128**	**5.715874**	**19.898528**
October	**13.01181**	**8.121853**	**17.90177**	**5.533266**	**20.49035**
November	**14.72173**	**8.586245**	**19.85159**	**6.876278**	**22.56718**
December	**13.94647**	**8.586245**	**19.30670**	**5.748711**	**22.14424**

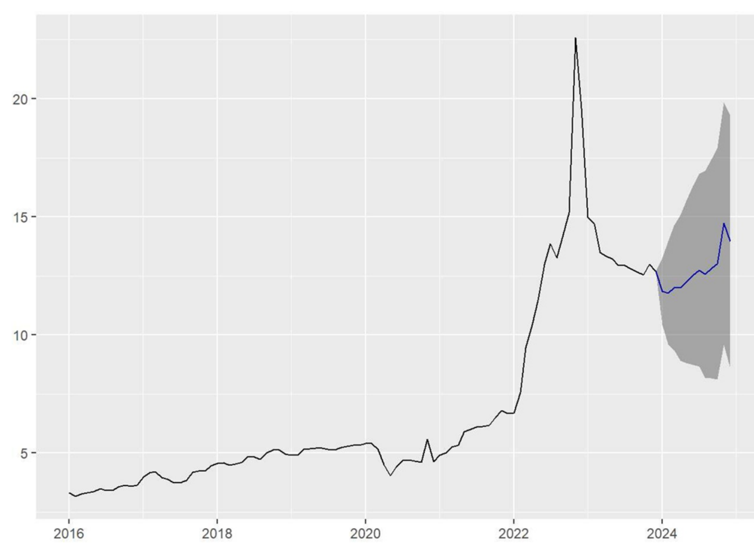

Figure 13: Diesel forecast for 2024

Table 10: 12 months forecast of Gasoline prices in Ghana

2024 Gasoline Forecast					
Month	**Point Forecast**	**Low 80**	**High 80**	**Low 95**	**High 95**
January	**14.24528**	**13.31866**	**15.17189**	**12.028138**	**15.66242**
February	**13.78070**	**12.28543**	**15.27597**	**11.493886**	**16.06751**
March	**13.89195**	**12.14348**	**15.64006**	**11.218449**	**16.56545**
April	**13.766695**	**11.79821**	**15.73569**	**10.756020**	**16.7788**
May	**13.83945**	**11.67243**	**16.00648**	**10.525271**	**17.15363**
June	**14.0445**	**11.69582**	**16.39309**	**10.452534**	**17.63638**
July	**14.07696**	**11.55979**	**16.59412**	**10227282**	**17.92663**
August	**14.02321**	**11.34810**	**16.39831**	**9.93198**	**18.11443**
September	**14.16321**	**11.33899**	**16.98744**	**9.843931**	**18.48249**
October	**14.32571**	**11.35986**	**17.29157**	**9.789827**	**18.86160**
November	**15.04947**	**11.94844**	**18.15049**	**10.306856**	**19.79208**
December	**15.16571**	**11.93396**	**18.39746**	**10.22317**	**20.10825**

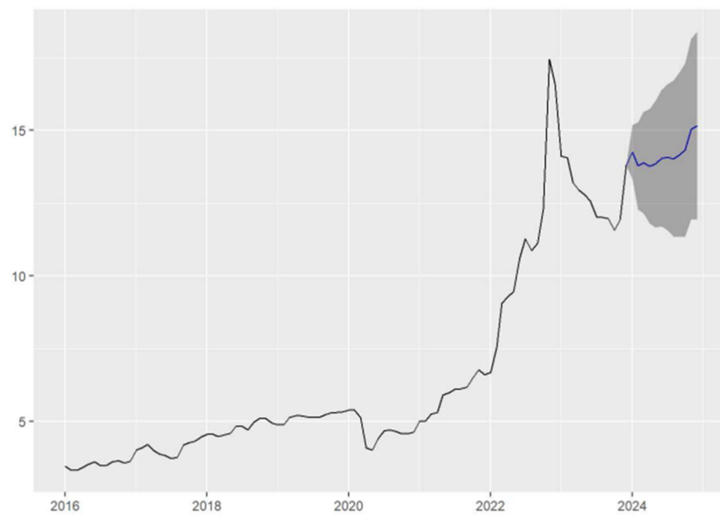

Figure 14: Enter Caption333333333

7 Conclusion

this paper proposes to predict Gasoline and Diesel prices in Ghana,A comparion of ARIMA and SARIMA models. The results obtained from the study shows that prices of Gasoline and diesel were not stationary and stationality was achieved at the first seasonal and non-seasonal differences of the series. In predicting prices, the ARIMA (0,1,2) and ARIMA(2,1,3) were identified as the best ARIMA MODELS for gasoline and diesel respectively. SARIMA$(0,1,2) \times (0,1,1)_{12}$ and SARIMA$(1,1,1) \times (0,1,1)_{12}$ were also considered to be the best models for gasoline and diesel respectively. The forecasting accuracy of the ARIMA and SARIMA for gasoline and diesel were compared based on

RMSE, MAE, MAPE . The SARIMA models for both gasoline and diesel performed better than ARIMA models in all the parameters except the RMSE for the ARIMA model for diesel which slightly outperformed the SARIMA model. Consumers, petroleum industry players and the government as a whole can use the price forecast information to protect the vulnerable consumers by reducing taxes which is an element of the price build up 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.

References

[1] Agyare, O. R., Odoi, B., and Asamoah, M. (2021). Electricity consumption forecast for tarkwa using autoregressive integrated moving average and adaptive neuro fuzzy inference system. *Serbian Journal of Electrical Engineering*, 18(1):75–94.

[2] Agyarko, K., Frempong, N. K., and Wiah, E. N. (2023). Hybrid model for stock market volatility. *Journal of Probability and Statistics*, 2023.

[3] Akesse, S. G. (2016). *Exploring the potential benefits of strengthening institutions to Ghana's economy: The case of full petroleum downstream sector deregulation in Ghana*. PhD thesis.

[4] Alberg, D., Shalit, H., and Yosef, R. (2008). Estimating stock market volatility using asymmetric garch models. *Applied Financial Economics*, 18(15):1201–1208.

[5] Ariyo, A. A., Adewumi, A. O., and Ayo, C. K. (2014). Stock price prediction using the arima model. In *2014 UKSim-AMSS 16th international conference on computer modelling and simulation*, pages 106–112. IEEE.

[6] Arlt, J. and Trcka, P. (2021). Automatic sarima modeling and forecast accuracy. *Communications in Statistics-Simulation and Computation*, 50(10):2949–2970.

[7] Babu, A. and Reddy, S. (2015). Exchange rate forecasting using arima. *Neural Network and Fuzzy Neuron, Journal of Stock & Forex Trading*, 4(3):01–05.

[8] Christiansen, C., Schmeling, M., and Schrimpf, A. (2012). A comprehensive look at financial volatility prediction by economic variables. *Journal of Applied Econometrics*, 27(6):956–977.

[9] Gupta, S., Chakrabarty, D., and Kumar, R. (2023). Predicting indian electricity exchange-traded market prices: Sarima and mlp approach. *OPEC Energy Review*, 47(4):271–286.

[10] Koh, W. S., Heng, H. S., Wong, C. Z., Lai, P. L., and Dass, C. (2020). Forecasting stock price using arma model. *INTI JOURNAL*, 2020(59).

[11] Mani, V., Subramanian, S., Shanmugasundaram, S., et al. (1995). Forecasting of egg production and wholesale egg price in coimbatore district of tamil nadu. *The Indian Journal of Animal Sciences*, 65(10).

[12] Na, S. H. and Sohn, S. Y. (2011). Forecasting changes in korea composite stock price index (kospi) using association rules. *Expert Systems with Applications*, 38(7):9046–9049.

[13] ODOI, B. (2017). Modeling price volatility in petroleum products in ghana. *Ghana Journal of Technology*, 1(2):40–44.

[14] Pepple, S. U. and Harrison, E. E. (2017). Comparative performance of garch and sarima techniques in the modeling of nigerian board money. *CARD Int J Soc Sci Confl Manag*, 2(4):258–270.

[15] Selley, N. (2013). *The New Economy of Oil: Impacts on Business, Geopolitics and Society.* Routledge.

[16] Sharma, H. and Burark, S. (2015). Bajra price forecasting in chomu market of jaipur district: An application of sarima model. *Agricultural situation in India*, 71(11):7–12.

[17] Sharma, S. and Yadav, M. (2020). Analyzing the robustness of arima and neural networks as a predictive model of crude oil prices. *Theoretical and Applied Economics*, 27(2):289–300.

[18] Stevens, P. (2019). The geopolitical implications of future oil demand. *Chattam House*, pages 1–32.

[19] Tang, H. (2021). Stock prices prediction based on arma model. In *2021 International Conference on Computer, Blockchain and Financial Development (CBFD)*, pages i–iv. IEEE.

[20] Twumasi-Ankrah, S., Odoi, B., Adoma Pels, W., and Gyamfi, E. H. (2019). Efficiency of imputation techniques in univariate time series.

[21] Zulua, J., Mwansab, G., and Wakumeloc, M. (2022). Forecasting price of fuel using time series autoregressive integrated moving average model: A zambian review from 1998 to 2022. *International Journal*, 78(8/1).