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Forecasting Refined Petroleum Products Prices in Ghana

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Authors' contributions

This work was carried out in collaboration between both authors. Author AT designed the study, wrote the literature, carried out the analysis, wrote the first draft of the manuscript and reviewed the draft manuscript. Author QX supervised each section of the manuscript. Both authors read and approved the final manuscript.

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ABSTRACT

Ghanaian's demand for refined petroleum products keeps increasing although monthly prices of the product keeps rising. The paper aims to forecast refined petroleum products (gasoline, diesel, kerosene and LPG) future prices trends in Ghana. Employing benchmark techniques, cointegration, generalized autoregressive conditional heteroskedasticity (GARCH) and artificial neural network (ANN) to analyze in-sample (Jan-89 to Oct-14) and out-of-sample (Nov-14 to Dec-30) monthly data of refined petroleum products and socio-economic variables. The in-sample investigation result suggested that averagely refined petroleum products are uniformly priced in Ghana and LPG price is highly adjusted in times of refined petroleum product increment. Out-of-sample results indicates a steadily price surge of refined petroleum products in the future with ANN forecasting technique recording the best forecasting performance value.

Keywords: Ghana; refined petroleum products; price; forecast.

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1. INTRODUCTION

Ghana's Ministry of Energy operates under three diverse portfolios; power, petroleum and renewable. The petroleum portfolio is sub-divided into upstream and downstream activities: upstream activities deals with exploration, development, production and transportation of oil and gas to oil refinery but the downstream focuses on rehabilitation and expansion of petroleum refinery, storage, distribution, pricing, marketing of refined petroleum products. These activities have led to the creation of government agencies like Tema Oil Refinery (TOR), Ghana National Petroleum Corporation (GNPC), National Petroleum Authority (NAP), etc. (refer to Fig. 1) to see to the management, production, licensing oil marketing companies and other duties.

TOR is the sole oil refinery in Ghana with its crude oil input into the crude oil distillation unit mostly imported from Nigeria via pipelines and ship deliveries. The crude oil distillation unit can process 45000 barrel per stream with a two million barrel of storage capacity. The refinery predominantly processes crude oil into refined products like gasoline, diesel, kerosene, premix, LPG, and fuel oils. The refined products are then priced by NPA based on world petroleum price, various taxes and other factors. Monthly prices of refined petroleum product are surging (shown in Fig. 2) which mostly impact economic activities in Ghana negatively (Ayadi [1], Ozlale & Pakkuranez [2], Álvarez et al. [3], Raguindin & Rayers [4]). Oil price shocks destabilize economic indicators movement no matter its origination within or outside a country.

This paper aims at; (i) forecasting future prices of refined petroleum products (i.e. gasoline, kerosene, diesel and LPG) in Ghana. Gasoline, diesel, kerosene and LPG were chosen because of data availability, daily usage in every Ghanaian home and its often shortage, and (ii) analyzing which forecasting techniques forecast Ghana's refined petroleum products better. To achieve the aim of this paper, different forecasting tool to ascertain the best forecasting technique for analyzing refined petroleum product in Ghana. We found that refined petroleum products in Ghana are evenly priced for in-sample forecast, out-of-sample forecast show a steadily increment in refined petroleum products and ANN forecasting techniques performance better than logarithmic, cointegration and GARCH.

The rest of the paper is organized as follows section two covers literature on forecasting techniques, followed by methodology in sections three. Section four covers result and discussion while section five captures the concluding section of this paper.

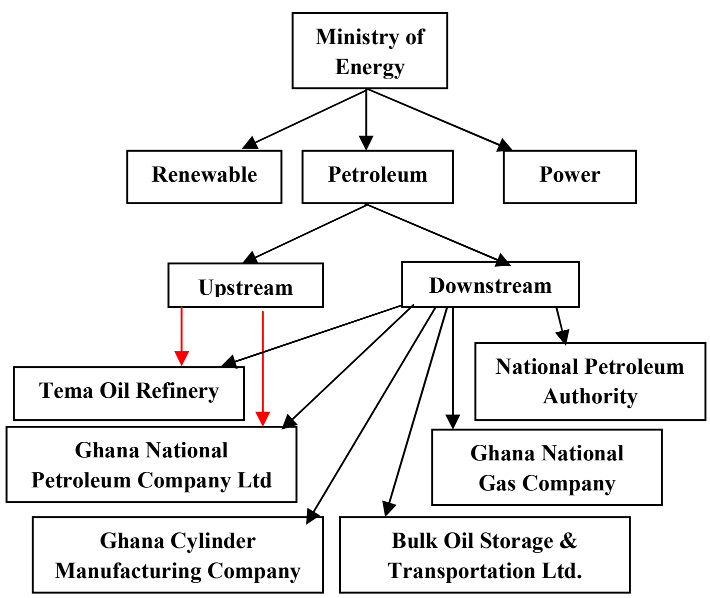

Fig. 1. Ministry of energy operation

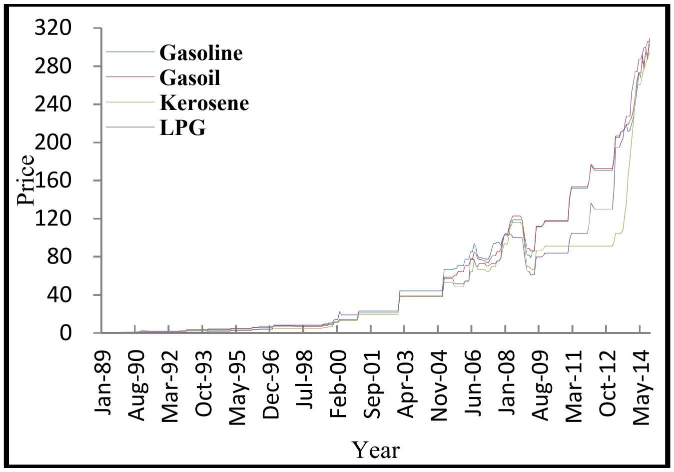

Fig. 2. Monthly price of refined petroleum products trend in Ghana

2. LITERATURE REVIEW

Forecasting is the procedure for estimating a future event by casting forward past data that are combined in a predetermined way (Manipaz [5]). Most often economic variable forecasting invites hot debates from scholars since innumerable variables can be used to forecast an economic variable resulting in different forecasting trend or predictions. Ye et al. [6] utilized two non-linear inventory variables to forecast short-run crude oil prices; they concluded that fusing low and high-inventory variables improves short-run forecasting ability. Besides in the short-run, nominal and real crude oil price prediction can be improved if oil price movements are forecasted with oil-sensitivity (Chen [7]). In their quest to determine asymmetric relationship between price of crude oil and refined petroleum product in US, Kaufmann & Laskowski [8] used two-stage econometric methodology and established that price asymmetric is ignited by contractual agreement between retailers and consumers which can be traced to petroleum product pricing market efficiency. Using linear and non-linear model as a feed into artificial neural network (ANN) to forecast energy usage in Iranian metal industry, Piltan et al. [9] concludes logarithmic non-linear evaluation performs better than linear and exponential feeds.

Forecasting electrical energy consumption using ANN has proved it superiority as a better forecasting technique over linear or quadratic forecasting models (Azadeh et al. [10], Azadeh & Faiz [11]). Ardakani & Ardehali [12] simulation result (of 10.81%, 5.48% and 4.57% for linear regression, quadratic regression and ANN optimization method respectively) verifies ANN forecasting performance ability dominance over linear and quadratic regressions. Jammazi & Aloui [13] work on crude oil price forecasting using a combination of ANN modeling and wavelet decomposition concluded that the combined methodology improves forecasting denoising by 3% drawing it closer to real anticipated future oil price fluctuations. Yu et al. [14] proposed empirical mode decomposition (EMD) base neural network to forecast crude oil price. Their empirical results obtained illustrate how EMD-based neural network predict world crude oil spot price efficiently.

Forecasting energy market volatility efficiency, Efimova & Serletis [15] utilized univariate and multivariate GARCH models established that univariate and multivariate GARCH techniques react alike but univariate forecast energy volatility more efficiently. Wei et al. [16] research on crude oil market forecasting volatility concludes that non-linear GARCH model is capable of capturing long-memory and/ or asymmetric volatility. But Wei [17] paper improves Wei et al. [16] studies by introducing stochastic volatility-GARCH model which captures long-memory and/or asymmetric volatility better than non-linear GARCH model. Auers [18] article on daily seasonality of crude oil returns and volatility using a dummy augmented GARCH argued that: (i) seasonality often occurs during Monday trading; (ii) these seasonality lowers Monday’s trading returns; and (iii) GARCH-M, TGARCH and CGARCH produces robust seasonality result.

Lanza et al. [19] forecast heavy oil and product prices using cointegration with error correction model (CECM) with sample size spanning from 1994 to 2002 suggested that CECM produce a better forecast performance than the naïve model (ARMA (1, 1)). In order to analyze asymmetric price transmission from crude oil to gasoline prices Chen et al. [20] used threshold cointegration they observed traces of asymmetric not only in the short- and long-run but also across the spot and future market which occurs at the downstream stages of gasoline distribution. Finally, Shoesmith [21] concluded that Bayesian error correction model models short-run dynamic better than vector autoregression.

From the literature review, it can be deduce that crude oil forecasting has been extensively studied with less attention given to refined petroleum product. Besides, ANN forecasting method has been compared to linear, quadratic and exponential forecasting but not to cointegration and GARCH and this paper addresses these lapses. The next section touches on the methodology employed for the forecasting analysis.

3. METHODOLOGY

3.1 Data Collection and Processing

A monthly historical data set for population (POP), exchange rate (XRATE), gross domestic product (GDP), world petroleum price (WPP), motor gasoline (GASOL), gas oil or diesel (GOIL), kerosene (KERO) and liquefied petroleum gas (LPG) were constructed from Jan-89 to Dec-13 equaling 300 observations. These historical data were divided into train data (Jan-89 to Dec-08) and test data (Jan-09 to Dec-13) for in-sample analysis. The forecast data for out-of-sample analysis (from Jan-15 to Dec-30) were mainly obtained by extrapolation, autoregressive integrated moving average and predicted future data source. Data for our investigations (in-sample and out-of-sample) were acquired from Bank of Ghana, World Bank, National Petroleum Authority Ghana, West Texas Intermediate and US Energy Information. The data comes in diverse form mainly annually and monthly: the annual data (example, GDP) were converted into monthly data set using entropy weight method (Tetteh [22]) as shown in Appendix A.1.

Testing for unit root for non-stationarity in Ghana's refined petroleum product we applied Augmented Dickey-Fuller [23] (ADF) and Phillips & Perron [24] (PP) test. Both were run with trend with ADF set to Schwarz information criteria (SIC) and PP set to bandwidth with Bartlett Kernel regression (Table 1). For these test the null hypothesis is a non-stationary time series and the alternative is a stationary. Non-stationarity for refined petroleum products were achieved at first difference and that of socio-economic variables were also achieved at first difference with the exception of population which was significant at second difference. The unit root test analysis set the basis for the cointegration and GARCH analysis and support them at first difference.

3.2 Forecasting Techniques

In order to accomplish the aim of this paper (i.e. forecasting refined petroleum products future price and analyzing the best forecasting technique for refined petroleum products) four divergent forecasting techniques were applied. These techniques have the ability to capture refined petroleum products future trends. They are;

3.2.1 Benchmark technique (BT)

The BT applied here is a simple logarithmic linear regression (Plitan et al. [9], Chen [7], Kaufmann & Laskowski [8]). From equation (1), Y_t, X_t, λ's and ε_t represents refined petroleum products, socio-economic variables, parameters and residual of the logarithmic linear regression respectively.

$$logY_t = \lambda_0 + \lambda_1 logX_{1t} + \lambda_2 logX_{2t} + \lambda_3 logX_{3t} + \lambda_4 logX_{4t} + \varepsilon_t \qquad (1)$$

3.2.2 Cointegration

The cointegration relationship (Chen et al. [20], Lanza et al. [19]) is given by:

$$logY_t = \lambda_0 + \lambda_1 logX_{1t} + \lambda_2 logX_{2t} + \lambda_3 logX_{3t} + \lambda_4 logX_{4t} + \varepsilon_t \qquad (2)$$

where Y_t and X_t stands for refined petroleum product and socio-economic variable respectively, λ's are the attributed weight of each socio-economic variables explaining refined petroleum product movements in Ghana, ε_t measures the equilibrium deviation between refined petroleum product and socio-economic variables. For refined petroleum product and socio-economic variables to be cointegrated ε_t

Table 1. Unit root test

Log level	ADF (with trend)			PP fisher test (with trend)		
	Statistics	P-value	Lag	Statistics	P-value	Bandwidth
LGASOL	-2.721407	0.2287	0	-2.796675	0.1997	5
LGOIL	-2.949294	0.1486	0	-3.032610	0.1251	4
LKERO	-2.365868	0.3967	0	-2.382422	0.3880	1
LLPG	-2.255716	0.4565	0	-2.254956	0.4569	3
LWPP	-3.293334	0.0857	1	-2.829119	0.1880	6
LGDP	-1.384889	0.8637	0	-1.283045	0.8900	7
LPOP	-3.3599010	0.0316	12	-4.271398	0.0040	19
LXRATE	-1.279217	0.8908	4	-0.827918	0.9609	12
First Difference						
ΔLGASOL	-17.63381	0.0000	0	-17.74594	0.0000	9
ΔLGOIL	-17.75313	0.0000	0	-17.90392	0.0000	9
ΔLKERO	-17.06551	0.0000	0	-17.10750	0.0000	3
ΔLLPG	-17.12303	0.0000	0	-17.48128	0.0000	7
ΔLWPP	-12.78144	0.0000	0	-12.26368	0.0000	12
ΔLGDP	-17.25500	0.0000	0	-17.39382	0.0000	9
ΔLPOP*	-1.482725	0.8335	10	-20.32614	0.0000	41
ΔLXRATE	-4.893192	0.0004	3	-10.66096	0.0000	10

*Note: * Population (POP) was significant at second difference (Δ^2POP; -46.20513: 0.0001: 10)*

should be I (0). The estimation used for εt is error correction model given by;

$$\Delta logY_t = \lambda_0 + \sum_{j=1}^{p} \beta_j \, \Delta logX_{1t-j} + \sum_{k=1}^{p} \gamma_k \, \Delta logX_{2t-k} + \sum_{l=1}^{p} \theta_l \, \Delta logX_{3t-l} + \sum_{m=1}^{p} \vartheta_m \, \Delta logX_{4t-m} + \sum_{n}^{p} \omega_n \, \Delta logY_{t-n} + \psi_t \tag{3}$$

$\Delta logY_t$ and $\Delta logX_{1t}$ to $\Delta logX_{4t}$ are the lagged of refined petroleum product and socio-economic variables, with β_j, γ_k, θ_l, ϑ_m, and ω_n are the coefficient of the error correction model and ψ_t the error term.

3.2.3 Generalized autoregressive conditional heteroskedasticity (GARCH)

The generalized GARCH (1, 1) model (We et al., [16], Wei [17], Çelik & Ergin [25]) is given by;

$$Y_t = \lambda_t + \varepsilon_t \;\Rightarrow\; Y_t = \lambda_t + \sigma_t \delta_t, where\ \delta_t \sim NID\,(0{,}1)$$

$$\sigma_t^2 = \tau + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{4}$$

λ_t is the conditional mean, ε_t^2 account for volatility and σ_t^2 is the conditional variance with $\tau > 0$, $\alpha > 0$, $\beta > 0$ and $\alpha + \beta < 0$. GARCH (1, 1) models often account for volatility clustering which is particular with future data and yield best performance. GARCH (1, 1) for refined petroleum products is given by;

$$logY_t = \lambda_0 + \lambda_1 logX_{1t} + \lambda_2 logX_{2t} + \lambda_3 logX_{3t} + \lambda_4 logX_{4t} + \lambda_5 \sigma_t + \varepsilon_t$$

$$\sigma_t^2 = \tau + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \lambda_6 logX_{1t} + \lambda_7 logX_{2t} + \lambda_8 logX_{3t} + \lambda_9 logX_{4t} \tag{5}$$

3.2.4 Feed-forward artificial neural network (FFANN)

The feed forward artificial neural network (FFANN) with error back-propagation algorithm (Yu et al., [14], Chattopadhyay & Rangarajan [26]) was employed due to its nature of subduing seasonality in data characteristics. The three layers of FFANN is shown in Fig. 3; (i) four socio-economic inputs, (ii) ten sigmoid function hidden layer, and (iii) one linear function output layer. Where W_1 and W_2 are weight vectors from input layer to hidden layer and from hidden layer to output layer respectively, $X_1$to X_4 are socio-economic variables vector input data, B_1 and B_2 are bias value for hidden and output layer and $f_1(t)$, $f_2(t)$ and input data are define in equations 6, 7 and 8.

$$f_1(t) = W_1 * X + B_1 \tag{6}$$

$$f_2(t) = \frac{1}{1 + exp(-\phi * (W_2 * f_1(t) + B_2))} \tag{7}$$

$$logY_t = f(logX_1(t), logX_2(t), logX_3(t), \log X_4(t)) \tag{8}$$

3.2.5 Evaluating forecast performance

In order to determine the forecasting techniques performance we employed mean square error (MSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) as given below where N is the sample size.

$$MSE = \sqrt{N^{-1}\sum_{t=1}^{n}(logY_t - log\bar{Y}_t)^2} \tag{9}$$

$$MAPE = 100N^{-1}\sum_{t=1}^{n}\left|\frac{logY_t - log\bar{Y}_t}{logY_t}\right| \tag{10}$$

4. RESULTS AND DISCUSSION

Using equations (1), (3) and (5) to estimate the predictive in-sample regression model, including coefficient, p-value and t-statistics as reported in Table 2, residual analysis and forecasting performance are reported in Tables 3 and 4 respectively. These techniques were applied to investigate whether Ghana's refined petroleum products pricing are normally distributed about its pricing mean and if they are under- or over-priced. The baseline results, the estimate of λ_0 (Table 2) using the benchmark technique, cointegration and GARCH for monthly refined petroleum product were all negative and statistically significant at 1% for gasoline, gasoil, kerosene and LPG. The socio-economic variables world petroleum price, gross domestic product, population and exchange rate were all positive and statistically significant at 1%, 5% and 10%. The result implies that a 1% increase (decrease) of world petroleum price, gross domestic product, population and exchange rate increase (decrease) gasoline, gasoil, kerosene and LPG prices in Ghana. Besides, LPG experiences high price rise in times of refined petroleum product increment and vice-versa. The pricing increasing dynamics of Ghana's refined petroleum is consistent with our expectation and also confirms National Petroleum Authority monthly pricing mechanism. Cointegration technique performs better than benchmark technique and GARCH model.

The residual analysis for gasoline, gasoil, kerosene and LPG (Table 3) does not follow a normally distributed pattern since it skewness are less or greater than zero and kurtosis statistics less or greater than 3. Gasoline price are skewed to the left with kurtosis following platykurtic features whereas gasoil price displays leptokurtic features which show shaper pricing than the mean with thicker tail and skewed to the left. That of kerosene price is mainly skewed to the left with platykurtic features that is flatter than normal distributed pricing with a wider peak but LPG pricing follows leptokurtic features which is skewed to the left. These distribution phenomena are due to refine petroleum products pricing in Ghana rising most often with an intermittent price reduction although world petroleum price, gross domestic product, population and exchange rate remains partially stable. The outcome reflects how gasoline and kerosene products are over-priced and gasoil and LPG are under-priced in Ghana. These prices average up to a fair pricing strategy for refined petroleum products in Ghana. GARCH technique outshines benchmark technique and cointegration model.

The in-sample forecasting performance results for gasoline, gasoil and kerosene and LPG measured using mean square error and mean absolute percentage error (refer to Table 4). Both forecasting performance techniques account that, GARCH forecast gasoline, gasoil and kerosene in-sample monthly price better than benchmark and cointegration analysis whereas LPG monthly price is forecasted accurately by benchmark technique. First of all, the results correspond with our pervious in-sample analysis results. Besides, the results signify that monthly refine petroleum product price in Ghana does not deviate much from its expected trend when forecasted using socio-economic variables. Finally, it may be concluded that GARCH forecast in-sample monthly refined petroleum product price in Ghana more consistently.

The subsequent analysis is focused on the result obtained from the out-of-sample forecasting test of refine petroleum product price in Ghana. This was achieved by applying all the forecasting methods plus forecasting performance evaluation techniques described at the methodology section. The outcome suggests that artificial neural network (ANN) techniques forecast gasoline, gasoil, kerosene and LPG out-of-sample future price better than benchmark, cointegration and GARCH (refer to Table 5). Besides, the error gaps for the refine petroleum products were quite high for benchmark, cointegration and GARCH but negligible for ANN due to the error trend of prediction decreasing with increasing in epoch. Using benchmark, cointegration and GARCH techniques, out-of-sample forecast from 2015 to 2030 for gasoline, gasoil, kerosene and LPG followed a rise and fall pattern whereas that of ANN showcase a gradual rise (refer to Figs. 4 to 7). These results indicate that future price of Ghana's refined petroleum product will be increasing (decreasing) steadily if and only if socio-economic variable increases (decreases) gradually. Furthermore, forecasting with diverse forecasting techniques helps create out-of-sample forecast trend band which act as an equilibrium zone for future refined petroleum price monitoring. Within the equilibrium zone, lowest price rise refined petroleum product may be pegged to ANN future price forecast with the highest future price linked to the weak predictions techniques (gasoline and gasoil, benchmark technique; kerosene, cointegration and LPG, GARCH). Finally, ANN forecast Ghana's out-of-sample refined petroleum product price prudently.

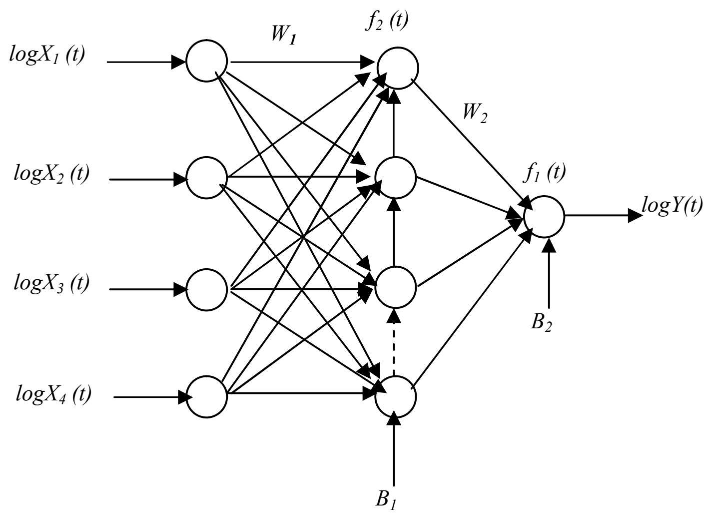

Fig. 3. FFANN model with socio-economic variables data as input

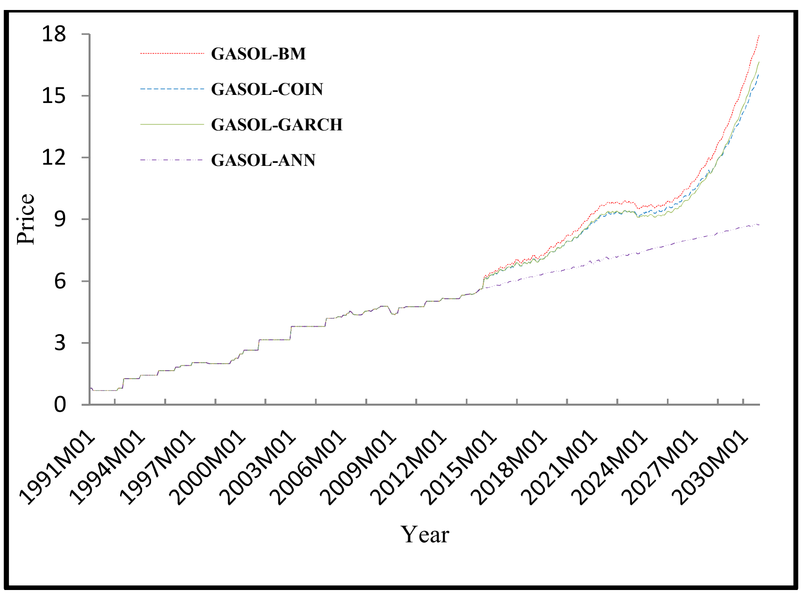

Fig. 4. Gasoline predicted future price trend

Table 2. In-Sample forecast of monthly price refine petroleum product

	GASOL			GOIL			KERO			LPG		
	BM.	**COIN.**	**GARCH**	**BM.**	**COIN.**	**GARCH**	**BM.**	**COIN.**	**GARCH**	**BM.**	**COIN.**	**GARCH**
λ_0	-21.8081	-19.0884	-19.930	-16.897	-13.354	-9.2354	-26.158	-22.708	-17.682	-11.694	-19.968	-7.9002
	[-8.9262]*	[-4.4777]*	[-19.213]*	[-7.3807]*	[-3.2926]*	[-17.407]*	[-10.931]*	[-6.1086]*	[-14.844]*	[-5.1204]*	[-5.1365]*	[-10.995]*
	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0011}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}
LWPP	0.0161	0.0043	0.2076	0.0381	0.0340	0.3161	0.1911	0.1934	0.4361	0.4164	0.4457	0.1583
	[0.2807]	[0.0381]	[7.5133]*	[0.7070]	[0.3336]	[21.224]*	[3.3917]*	[1.8557]**	[13.591]*	[7.7427]*	[5.4845]*	[9.2874]*
	{0.7792}	{0.9696}	{0.0000}	{0.4802}	{0.7390}	{0.0000}	{0.0008}	{0.0648}	{0.0000}	{0.0000}	{0.0000}	{0.0000}
LGDP	0.5084	0.1599	0.3521	0.6350	0.2537	0.5161	0.3309	-0.0689	0.2787	0.5304	0.0805	0.6690
	[9.9497]*	[0.9748]	[14.602]*	[13.262]*	[1.6176]***	[32.516]*	[6.6108]*	[-0.4727]	[12.486]*	[11.104]*	[0.4017]	[53.708]*
	{0.0000}	{0.3307}	{0.0000}	{0.0000}	{0.1017}	{0.0000}	{0.0000}	{0.6369}	{0.0000}	{0.0000}	{0.6883}	{0.0000}
LPOP	1.9675	1.8418	1.8597	1.3810	1.1855	0.6649	2.4502	2.2714	1.6105	-1.3388	-1.9690	-1.0127
	[9.9331]*	[4.4838]*	[17.393]*	[5.9423]*	[3.0009]*	[11.982]*	[10.086]*	[6.4581]*	[13.450]*	[-5.7747]*	[-5.0465]*	[-14.146]*
	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0030}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}
LXRATE	0.8382	0.4107	0.7663	0.8705	0.4021	0.7911	0.8428	0.3590	0.7712	1.1174	0.5722	1.1138
	[46.387]*	[2.0426]**	[83.107]*	[51.407]*	[2.1234]**	[128.16]*	[47.616]*	[2.0631]**	[74.111]*	[66.152]*	[2.5726]*	[203.38]*
	{0.0000}	{0.0422}	{0.0000}	{0.0000}	{0.0348}	{0.0000}	{0.0000}	{0.0402}	{0.0000}	{0.0000}	{0.0107}	{0.0000}
Adj.-R^2	98.08%	98.25%	97.44%	98.36%	98.52%	97.32%	98.34%	98.56%	97.50%	98.56%	98.77%	98.35%

*[ ] represent t-statistics, at ***, **, * 10%, 5% and 1% respectively and { } represent probability value.*

Table 3. Refine petroleum product residual analysis

	GASOL			GOIL			KERO			LPG		
	BM.	**COIN.**	**GARCH**	**BM.**	**COIN.**	**GARCH**	**BM.**	**COIN.**	**GARCH**	**BM.**	**COIN.**	**GARCH**
Mean	-2.6e-15	4.14e-15	-0.1884	-5.78e-15	8.48e-16	-0.2360	-1.01e-15	7.62e-15	-0.1891	-2.67e-15	-6.25e-15	-0.1411
Median	0.0345	0.0228	-0.2526	0.0237	0.0167	-0.4537	0.0071	0.0071	-0.2842	0.0185	-0.0008	-0.1294
Maximum	0.4434	0.4810	3.4129	0.4347	0.4361	3.2444	0.5697	0.5078	2.5997	0.4816	0.4477	2.9881
Minimum	-0.6032	-0.5541	-3.3009	-0.5490	-0.5036	-2.8951	-0.6267	-0.5718	-2.6252	-0.5236	-0.4759	-3.3240
Std. Dev.	0.2081	0.1976	0.9827	0.1950	0.1837	0.9735	0.2038	0.1884	0.9840	0.1945	0.1792	0.9920
Skewness	0.5553	-0.5464	0.2395	-0.4304	-0.4387	0.3289	-0.2945	-0.3037	0.0997	-0.4024	-0.1612	0.1469
Kurtosis	3.2178	3.1574	3.0762	3.0287	2.9307	2.8250	3.5864	3.6884	2.3256	2.7670	2.7471	2.7738
Jarque-Bera	12.808	12.141	2.3533	7.4166	7.7131	4.6324	6.9084	8.3922	4.9454	7.0211	1.6721	1.3744
Probability	0.0017	0.0023	0.3083	0.0245	0.0211	0.0986	0.0316	0.0151	0.0844	0.0299	0.0151	0.5030

Table 4. In-Sample forecasting performance

Techniques	Mean square error (MSE)				Mean absolute percentage error (MAPE)			
	GASOL	GOIL	KERO	LPG	GASOL	GOIL	KERO	LPG
Benchmark Analysis	0.240998(2)	0.252842(2)	0.418023(2)	0.549528(1)	4.331558(2)	4.808546(2)	8.661614(2)	11.40603(1)
Cointegration	0.329046(3)	0.365198(3)	0.537321(3)	0.719044(3)	6.341662(3)	7.130599(3)	11.26156(3)	14.91395(3)
GARCH	0.148738(1)	0.148101(1)	0.368758(1)	0.571965(2)	2.484083(1)	2.753926(1)	7.383576(1)	11.99128(2)

( ) represent forecast ranking

Table 5. Out-of Sample forecasting performance

Techniques	Mean square error (MSE)				Mean absolute percentage error (MAPE)			
	GASOL	GOIL	KERO	LPG	GASOL	GOIL	KERO	LPG
Benchmark Analysis	3.2460(4)	3.3836(4)	2.5919(3)	4.1338(2)	34.1271(4)	35.8590(4)	23.1442(3)	44.7409(2)
Cointegration	2.6494(3)	2.9521(3)	3.2772(4)	4.4666(4)	28.1152(3)	31.5331(3)	30.2511(4)	48.4334(3)
GARCH	2.7422(2)	2.7764(2)	2.1401(2)	4.1919(3)	27.8934(2)	29.0002(2)	17.6568(2)	51.2001(4)
ANN	0.0742(1)	0.0818(1)	0.1224(1)	0.0700(1)	3.2992(1)	3.3594(1)	3.9628(1)	2.5178(1)

( ) represent forecast ranking

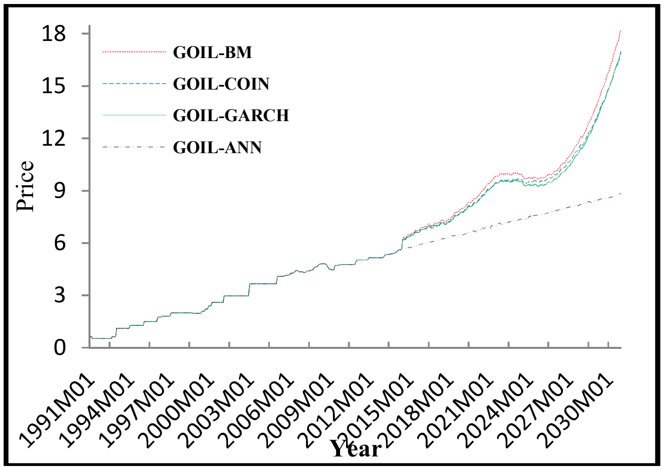

Fig. 5. Gasoil predicted future price trend

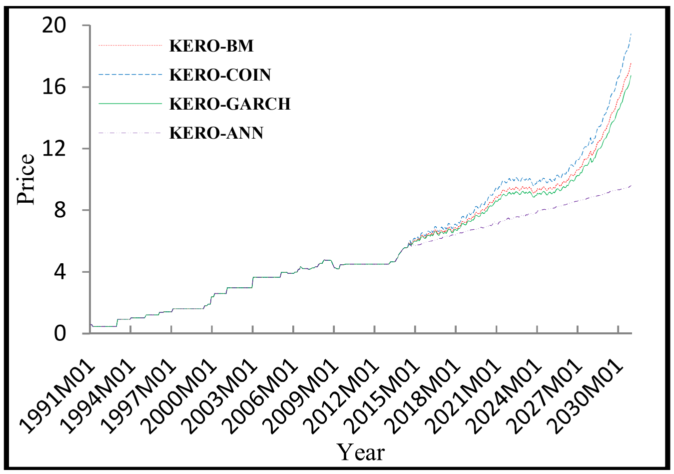

Fig. 6. Kerosene predicted future price trend

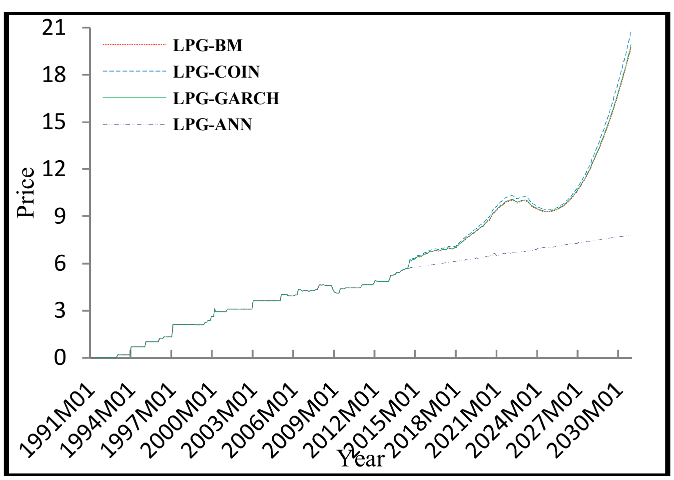

Fig. 7. Liquefied Petroleum Gas (LPG) predicted future price trend

5. CONCLUSION

Ghana's refined petroleum products' pricing under the watch of National Petroleum Authority is in it growing stage although monthly pricing of the product keeps soaring. This paper focused on forecasting future price of refined petroleum products and the best forecasting techniques appropriate for in-sample and out-of-sample forecasting. Using monthly data spanning from Jan-89 to Oct-14 for in-sample analysis and Nov-15 to Dec-30 for out-of-sample analysis which were mainly obtained by extrapolations, autoregressive integrated moving average and predicted future data sources. The in-sample result indicated that socio-economic variable increment (decrement) triggers refined petroleum products price increment (decrement) in Ghana with LPG experiencing the highest price increment (decrement). Furthermore, it was observed that gasoline and kerosene were over-priced whereas gasoil and LPG were under-priced and GARCH predicts in-sample refined petroleum product more consistently. That of out-of-sample analysis echoed that future price of refined petroleum products will be soaring steadily depending on socio-economic variable performance in Ghana. Implying in times of world petroleum price decreasing coupled with unstable performance of other socio-economic variables refined petroleum products price reduction would not be swift. ANN forecasting technique forecasted out-of-sample refined petroleum product better compared to benchmark technique (Azadeh et al. [10], Azadeh & Faiz [11]) cointegration and GARCH. The main limitation of this paper stems from our entropy weight apportionment used to convert annual data into monthly data since different weight values may alter the adjusted weight values which may either maintained or sway the forecasting results.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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APPENDIX

A.1. Derivation of Monthly Figures from Annual Data:

The mean or average of a data is defined as **∑f = ∑fX / N**, where N = number of observation (in our case 12 months in a year), ∑*f* = the sum of monthly variables (i.e. from January to December), and ∑*fX* = the average annual value (eg. in 1989 Ghana's GDP is $30million). In order to find the corresponding values of each month (January, February, to December) ∑*fX* is collapse into $X_1 + X_2 + X_3 + ...+ X_{12}$: where X_1 to X_{12} varies in weight and represent a monthly records in a year. To unearth these weights, I used MATLAB R2011 to generate a 12 by 12 matrix by entering magic 12 as shown below.

$$\begin{bmatrix} 1227 & 1287 & 1329 & 1380 & 1431 & 1482 & 1533 & 1584 & 1635 & 1686 & 1737 & 1788 \\ 1277 & 1328 & 1379 & 1430 & 1481 & 1532 & 1583 & 1634 & 1685 & 1736 & 1787 & 1838 \\ 1327 & 1378 & 1429 & 1480 & 1531 & 1582 & 1633 & 1684 & 1735 & 1786 & 1837 & 1888 \\ 1377 & 1428 & 1479 & 1530 & 1581 & 1632 & 1683 & 1734 & 1785 & 1836 & 1887 & 1938 \\ 1427 & 1478 & 1529 & 1580 & 1631 & 1682 & 1733 & 1784 & 1835 & 1886 & 1937 & 1988 \\ 1477 & 1528 & 1579 & 1630 & 1681 & 1732 & 1783 & 1834 & 1885 & 1936 & 1987 & 2038 \\ 1527 & 1578 & 1629 & 1680 & 1731 & 1782 & 1833 & 1884 & 1935 & 1986 & 2037 & 2088 \\ 1577 & 1628 & 1679 & 1730 & 1781 & 1832 & 1883 & 1934 & 1985 & 2036 & 2087 & 2138 \\ 1627 & 1678 & 1729 & 1780 & 1831 & 1882 & 1933 & 1984 & 2035 & 2086 & 2137 & 2188 \\ 1677 & 1728 & 1779 & 1830 & 1881 & 1932 & 1983 & 2034 & 2085 & 2136 & 2187 & 2238 \\ 1727 & 1778 & 1829 & 1880 & 1931 & 1982 & 2033 & 2084 & 2135 & 2186 & 2237 & 2288 \\ 1777 & 1828 & 1879 & 1930 & 1981 & 2032 & 2083 & 2134 & 2185 & 2236 & 2287 & 2338 \end{bmatrix}$$

We utilize entropy to find the weight; Entropy is a concept use to measure information that is the average amount of information (Ding & Shi [27]). In this paper we calculated the *magic 12* index weight by using entropy. Entropy method of weight calculation is highly reliable, free of decision makers' biasness and can be easily adopted (Zou et al. [28]).

If a decision matrix B shown below with *m* alternatives and *n* indicators entropy steps of weight calculation are as follows:

$$B = \begin{array}{c} * \\ A_1 \\ A_2 \\ A_3 \\ \vdots \\ A_m \end{array} \begin{bmatrix} C_1 & C_2 & C_3 & \dots & C_n \\ X_{11} & X_{12} & X_{13} & \dots & X_{1n} \\ X_{21} & X_{22} & X_{23} & \dots & X_{2n} \\ X_{31} & X_{32} & X_{33} & \dots & X_{3n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{1m} & X_{2m} & X_{3m} & \dots & X_{mn} \end{bmatrix} \qquad (A.1)$$
$$W = \quad [w_1, \; w_2, \; w_3, \; \cdots \; w_n]$$

w_j is the weight of criterion.

(i) In matrix B, feature weight $\boldsymbol{p_{ij}}$ is of the ***i***th alternatives to the ***j***th factor,

$$p_{ij} = X_{ij} \Big/ \sum_{i=1}^{m} X_{ij} \; (1 \le i \; \le m, 1 \le j \; \le n) \qquad (A.2)$$

(ii) The output entropy $\boldsymbol{e_j}$ of the ***j***th factor becomes,

$$e_j = -k \left[\sum_{i=1}^{m} p_{ij} \, In \, p_{ij} \right] \; (k = \; 1/In \, m \, ; 1 \le j \; \le n) \qquad (A.3)$$

(iii) Variation coefficient of the ***j***th factor $\boldsymbol{g_j}$ can be defined by the following equation,

$$d_j = 1 - e_j (1 \le j \le n) \quad (A.4)$$

Note that the larger $\boldsymbol{g_j}$ is the higher the weight should be.

(iv) Calculate the weight of entropy $\boldsymbol{w_j}$,

$$w_j = d_j \Big/ \sum_{j=1}^{m} d_j \; (1 \le j \le n) \quad (A.5)$$

(v) Calculate the adjusted weight $\boldsymbol{\beta_j}$,

$$\beta_j = \lambda_j w_j \Big/ \sum_{j=1}^{n} \lambda_j w_j \quad (A.6)$$

The resulted weight is presented in the table below;

Table A.1. Entropy weight result

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
e_j	0.9973	0.9975	0.9977	0.9978	0.9979	0.9981	0.9982	0.9983	0.9984	0.9984	0.9985	0.9986
d_j	0.0027	0.0025	0.0023	0.0022	0.0021	0.0019	0.0018	0.0017	0.0016	0.0016	0.0015	0.0014
w_j	0.1140	0.1066	0.0999	0.0939	0.0883	0.0833	0.0786	0.0743	0.0704	0.0668	0.0634	0.0603
λ_j	0.0570	0.0600	0.0660	0.0686	0.0754	0.0846	0.0879	0.0900	0.0920	0.0973	0.1070	0.1139
	0.0065	0.0064	0.0066	0.0064	0.0067	0.0070	0.0069	0.0067	0.0065	0.0065	0.0068	0.0069
β_j	0.0814	0.0801	0.0826	0.0806	0.0833	0.0882	0.0865	0.0838	0.0811	0.0814	0.0850	0.0861

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