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Original Research

Modelling Petroleum Prices in Tanzania: A Comparative Analysis between ARIMA and Holt's Method

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Abstract

Petroleum is one of the vital sources of energy for economic activities and the most traded commodity worldwide. It is crucial to industry and civilization and as it meets a substantial portion of the world's energy requirements, it has a big impact on global politics and intergovernmental relations. Given the importance of oil to the economy, projecting crude prices has received a lot of focus in the literature. The primary goal of this research is to assess how well Holt's technique and Autoregressive Integrated Moving Average (ARIMA) forecast the petroleum prices in Tanzania. To determine whether the model is more reliable at predicting the prices of petrol in Tanzania, a comparative analysis was perfumed. Monthly data on petroleum prices were extracted from the bank of Tanzania website between February, 2004 to May, 2023. The mean absolute percentage error (MAPE), mean absolute error (MAE), and mean squared error (MSE) were used to evaluate the predictive ability of the ARIMA and double exponential smoothing models. The findings indicated that ARIMA (1,1,1) outperformed double exponential smoothing model for forecasting the prices of petrol in Tanzania. The result of this study will guide policy makers and investors in the energy sector to make wise decisions through accurate prediction of the price of petroleum in the future.

Keywords: ARIMA, Holt's Model, Petroleum, Smoothing.

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Introduction

Petroleum is one of the vital sources of energy for economic activities and the most traded commodity worldwide (Kim & Jang, 2023). Petroleum is crucial to industry and civilization, and as it meets a substantial portion of the world's energy requirements, it has a big impact on global politics and intergovernmental relations (Femi Olayiwola & Matshonisa Seeletse, 2019). It remains the most significant energy source in the world, accounting for 33% of the primary energy used globally (Weldon et al., 2022). Its dominance in the transportation sector, which uses 94% of all energy, underlines how crucial it is (Weldon et al., 2022). Given that cars are one of the biggest consumers of petroleum and that petrol is the primary fuel type used in the present generation of passenger vehicles (Thakur et al., 2016), numerous studies that examine the demand for transportation fuel have focused on the demand of petrol for automobiles (Li et al., 2010).

Forecasting the use of fuel has grown in importance as an instrument for energy planning, with the main goals frequently identified as; aiding in the establishment of suitable pricing and taxation frameworks, assisting in potential investments and decision-making regarding oil reserves in order to enhance energy security, assisting in the early resolution of emission and contamination issues, and enabling the provision of future energy demands as well as the identification of national the infrastructure and energy demands (Ghazanfari, 2021). The formulation of transportation and environmental policies depends on an awareness of the factors that affect the demand for transportation fuel (Alam et al., 2019). Furthermore, in order to adopt the regulations and rules that are required to promote environmentally friendly growth, decision-makers must understand the dynamics of fuel consumption (Ajlouni & Alodat, 2021).

Given the importance of oil to the economy, projecting crude prices has received a lot of focus in the literature. The selection of when to drill as well as how much to hedge is based on forecasting, which is always an imperfect art, especially for the oil business, a worldwide sector with widely inconsistent data (Femi Olayiwola & Matshonisa Seeletse, 2019; Miao et al., 2017). Inaccurate forecasts with upside or downside bias can affect profit loss, with downside bias causing higher losses due to lower predicted prices (Ugurlu et al., 2018). Understanding the challenges of past forecasting approaches is crucial for understanding why oil prices are difficult to predict (Khan & Alghulaiakh, 2020). Crude oil prices are affected by dynamic and multifaceted elements such trade, financial markets, and physical markets, all of which can be unpredictable and have opposing effects (Polanco Martínez et al., 2018).

Various modeling techniques, including ARIMA and GARCH, have been used to estimate the demand for crude oil in the transportation and energy sectors (Gasper & Mbwambo, 2023; Mbwambo & Letema, 2023). Although studies have been done to forecast the price of oil in Tanzania's oil market, the forecasting accuracy of models used has not been examined specifically in the petroleum industry. This study tends to fill this knowledge gap in the literature by comparing the performance of various linear and nonlinear models in predicting the demand of petrol in Tanzania. In doing so, we present both the theoretical components of the various models as well as the collection of real-world factors that determine a model's appeal. To assess the forecasting accuracy of linear and nonlinear models; ARIMA, Single exponential, and Holt's linear models were developed and compared.

Literature Review

Numerous studies have been carried out for modelling and forecasting petroleum prices. However, an accurate model for predicting petroleum prices has not yet been agreed upon by researchers.

Using a variety of trend models, including a linear trend model, a quadratic trend model, an exponential trend model, a single exponential smoothing model, a Holt's linear model, a Holt-Winters' model, a partial adjustment model (PAM), and an autoregressive integrated moving average (ARIMA) model, Li et al. (2010) conducted a research to forecast Automobile Petrol Demand in Australia. Moreover, to assess forecasting accuracy, the study examined the variation between forecasts and actual observations of petrol demand. Based on the identified best-forecasting model "business as usual" scenario was suggested for predicting Australia's automotive fuel demand.

Using ARIMA, Mishra et al., (2022) conducted research to model and forecast the price of crude oil in India. He used monthly data and Box Jenkins methodology to generate. The ARIMA model clearly shows that between December 2019 and November 2020, the average monthly percentage increase in crude oil output 0.01% leading into a 0.36% increase in crude oil prices during the same period. The study's findings were beneficial to the commodity market investors as they develop their investment plans while taking future changes into account. Additionally, it helped the Indian government to implement the required measures to absorb the volatility and manage crude oil prices.

In his research, Zulu et al. (2022) applied a Box Jenkins methodology to forecast the price of fuel in Zambia. To forecast the price of fuel he used data from 1998 to 2022. Because of its accuracy, mathematical soundness, and adaptability, the ARIMA model was selected for forecasting. As a result of its smaller errors when compared to Simple Exponential Smoothing (SES), Holt's method and Holt Winter's method, ARIMA (1, 1, 2) was found to be the best fit for the price of fuel. The study's findings also indicated that fuel prices in Zambia will keep rising from 2022 to 2032.

Using a range of GARCH models, Mbwambo & Letema (2023) predicted the returns of Brent crude oil prices from January 2002 to February 2022. The GJRGARCH (1,1) model was the most effective model in the family of GARCH models at predicting the erratic nature of crude oil prices. The GJRGARCH model was chosen because it has a lower information criteria value and a higher likelihood value. A diagnostic analysis was done to determine whether the suggested model could accurately predict the volatility of crude oil. The study suggested to use the GJRGARCH model to predict future changes in exceptional circumstances.

Gasper & Mbwambo (2023) carried out a study for addressing the issue of forecasting crude oil prices in a situation with unexpected circumstances. Monthly data from January 2002 to February 2022 on Brent oil price were examined using Box Jenkins approach. The accuracy of numerous models was assessed, and it was found that ARIMA (0, 1, 1) was the most accurate model for predicting crude oil prices. Additionally, the study demonstrates that even if the Ukraine conflict and the corona virus had a significant impact on crude oil prices, a model of this type is still able to accurately represent the underlying volatility in crude oil prices.

Methodology

The primary goal of this study is to establish a framework that supports the validity of several forecasting techniques and identify the method that is most effective with the least prediction errors. In order to help investors and the government in the energy sector to make informed decisions, forecasting is a potential tool. Several quantitative forecasting techniques, including the ARIMA model, Single exponential smoothing and Holt's method have been used in this study. The Mean Absolute Error (MAE), Mean Absolute Percent Error (MAPE), and Root Mean Square Error (RMSE) error determination techniques were used to find the optimal model. Historical data collected from the bank of Tanzania website between February 2004 and May 2023 was analyzed using by R software to obtain the optimal model. The following sections provide a comprehensive description of each technique employed in this research.

ARIMA model

In 1970, Box and Jenkins developed the Autoregressive Integrated Moving Average (ARIMA) model, which forecasts future values using historical data (Chyon et al., 2022). Most time series patterns without a seasonal component employ the ARIMA model to obtain the predicted values. In order to generate a short-term predictions, ARIMA models usually outperforms complex structural models (Khan & Alghulaiakh, 2020). A mathematical representation of the ARIMA model is denoted by (2).

$$x_t = \mu + \phi_1 x_{t-1} + \phi_2 x_{t-2} + \cdots + \phi_p x_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} \quad (2)$$

Where μ is a constant term, ϕ_1 ,...., ϕ_p and θ_1 ,..., θ_q are coefficients, ε_t is the random term, p and q are orders of autoregressive and moving average terms respectively and x_t are the actual values.

Single Exponential Smoothing (SES)

This is a type of weighted average technique which predicts the future values based on historical forecasts and a proportion of anticipated error (Sidqi & Sumitra, 2019). Because it does not need retaining the history of earlier input data, it is simple to implement and compute (Cadenas et al., 2010). It equally diminishes the impact of unusual data. The following is the SES equation:

$$F_t = \alpha A_t + (1 - \alpha) F_{t-1}$$

where F_t represents the forecast for the time period t, F_{t-1} represents the forecast for the prior period, $A_t$represents the actual petroleum price for the prior period, and α represents the smoothing constant between 0 and 1 inclusive.

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Double Exponential Smoothing (Holt's) Method

To forecast data with a linear trend, Holt (1957) developed the Holt's approach, sometimes known as double exponential smoothing (Dharmawan & Indradewi, 2021). Holt's approach is an improvement of simple exponential smoothing (Liantoni & Agusti, 2020). Using two separate smoothing constants (beta for the trend and alpha for the level), Holt's approach smooths the given time series.

Level equation: $l_t = \alpha x_t + (1-\alpha)(l_{t-1} + b_t)$

Trend equation: $b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1}$

Forecast equation: $h_{t+m} = l_t + mb_t$

where h_{t+m} is a prediction for m periods into the future, l_t is an estimate of the level at time t, b_t is an estimate of the trend (slope) at time t, m are the forecasted future periods, and α is a smoothing constant for the level between 0 and 1 inclusive and β is a smoothing constant for the trend between 0 and 1 inclusive.

Measures of forecasting accuracy

Forecasting accuracy is a crucial factor to take into account when deciding between different forecasting approaches. The forecasting error in this context refers to the discrepancy between the observed value and the predicted value for a specific period (Karmaker et al., 2017). The three factors used in this study to determine forecasting error are mean absolute error (MAE), mean squared error (MSE), and mean absolute percentage error (MAPE) (Prayudani et al., 2019). The abbreviations MSE, MAPE, and MAE stand for mean squared error, mean absolute percent error, and mean absolute error between actual value and estimated value for a certain period, respectively. The following computations were MAE in this study to obtain the most robust forecasting model among several models.

$$MAD = \sum \frac{|A_t - F_t|}{n} \quad (4)$$

$$MSE = \sum \frac{(A_t - F_t)^2}{n-1} \quad (5)$$

$$MAPE = \sum \frac{|^{\varepsilon_t}/_{A_t}|}{n} \quad (6)$$

where A_t is the observed value at time t, F_t is the predicted value at time t, n is specified number of time periods, and ε_t is the forecast error.

Result

The trend of petroleum price

Figure 1 illustrates a time series representation of the petroleum data from Feb, 2004 to May, 2023. Figure 1 suggests that petroleum prices fluctuate from time to time.

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Figure 1. Observed values

Stationarity

Table 1 shows the p-value of the ADF statistic at 5% significance level. We can conclude based on the generated result that the data set is not stationary because the p-values is larger than 5%.

Table 1: ADF test for stationarity

	Dickey-Fuller	p-value
Before differencing	-2.4461	0.3884
After differencing	-6.2779	0.01

After the first order differencing, the p-value for the ADF statistic was lower at 5% thus it may be decided that petroleum price became stationary after first order differencing.

ARIMA model

The ACF plot suggests four different Autoregressive Integrated Moving Average models: ARIMA (0,1,0), ARIMA (0,1,1), ARIMA (1,1,0), and ARIMA (1,1,1). The ARIMA (1,1,1) model outperformed other models in predicting the price of petroleum in Tanzania after examining log likelihood and the AIC criterion. The AIC value of the model was the lowest when compared to other models. Table 2 displays the outcome of the four ARIMA combinations.

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Table 2. ARIMA combinations

	ARIMA (0,1,0)	ARIMA (0,1,1)	ARIMA (1,1,0)	ARIMA (1,1,1)
Log likelihood	-1344.39	-1337.15	-1338.07	-1334.42
AIC	2690.79	2678.3	2680.15	2676.84
$Sigma^2$	6647	6241	6291	6174

The accurate prediction for petrol price was achieved using the ARIMA (1,1,1) model with drift. The output of the ARIMA (1,1,1) model for predicting the price of petroleum is shown in Table 3.

Table 3. Estimates of ARIMA (1,1,1) model

	Coefficient	Std error	RMSE	MAE	MAPE
AR1	-0.3961	0.1491	77.893	48.33198	2.382028
MA1	0.6531	0.1213			
Drift	9.4376	6.0788			

Diagnostic test

This was done to see the extent to which the chosen model fit the data. The residuals should be normally distributed and serial correlation among residuals. Histograms were applied to check if residuals are normally distributed. Additionally, the Box-Ljung test and ACF of the residuals were plotted as indicated in figure 2 to ascertain whether or not the residuals are correlated.

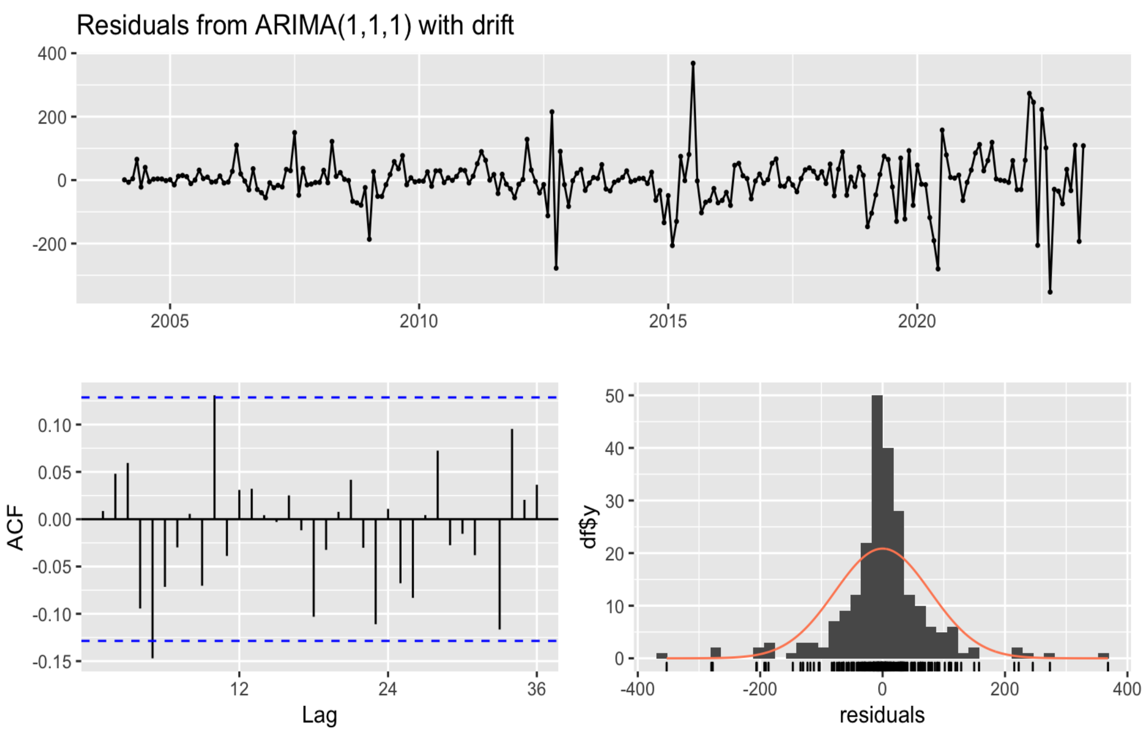

Figure 2. Residual plots

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The histogram in figure 2 shows that the residuals appear to be normally distributed and the mean of residuals is approximately zero. The fact that there are no significant spikes in the ACF plot of residuals in figure 2 further proves that the residuals are not correlated at the 5% significance level. Furthermore, the Box-Ljung test's p-value is higher than 5%, indicating that there is no proof of serial correlation between the residuals. As a result, we can say that the model accurately predicts the data. Figure 3 displays a comparison between actual demand and fitted values using the ARIMA approach.

Figure 3. Comparison of actual versus fitted values using ARIMA method.

Single exponential smoothing (SES) method

Nine trials were conducted to find the ideal smoothing constant. For the single exponential smoothing approach, the lower the forecasting errors the larger the smoothing constant parameters as shown in Table 4.

Table 4. Forecasting errors under SES method

Smoothing parameter (alpha)	RMSE	MAE	MAPE
0.1	201.4380	154.7046	8.064540
0.2	151.4854	112.0557	5.921869
0.3	128.2998	92.60400	4.856049
0.4	114.1289	80.90050	4.200748
0.5	104.1820	71.94649	3.702314
0.6	96.76422	64.95819	3.317372
0.7	91.11899	60.00806	3.040840
0.8	86.83176	56.64902	2.849745
0.9	83.63787	53.88280	2.691734

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Table 4 displays various predicting error levels for various smoothing constants. Table 4 makes it evident that when the smoothing constant value increases, the values of MAPE, MAE, and RMSE gets smaller. We found that the optimal smoothing constant (alpha= 0.9) achieved the lowest errors.

Figure 4 illustrates that for a single exponential smoothing method, the variation of the observed and fitted values is almost the same.

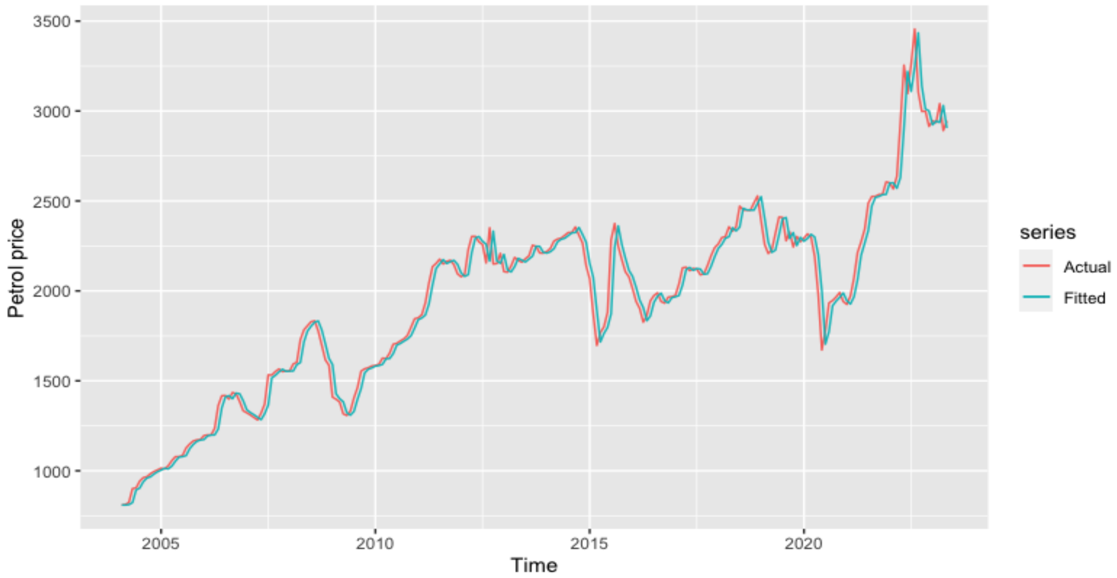

Figure 4. Comparison of actual versus fitted values using SES method.

Double exponential (Holt's) method

In line with Holt's procedure, nine trials were also carried out with different smoothing constants (both level and trend), ranging from 0.1 to 0.3, as shown in Table 5. At alpha= 0.9 and beta= 0.1, we achieved the lowest errors.

Table 5. Forecasting errors under Holt's method

Smoothing parameter, alpha (Level)	Smoothing constant, beta (Trend)	RMSE	MAE	MAPE
0.1	0.1	213.3621	158.9657	8.228098
0.2	0.1	162.926	117.2084	5.981383
0.2	0.2	181.4535	123.7842	6.314036
0.3	0.1	136.8296	95.42364	4.845245
0.3	0.2	146.4521	98.2135	4.982532
0.3	03	146.8052	100.8356	5.043209
0.9	0.1	85.30201	54.89941	2.717236
0.9	0.2	86.55263	56.07995	2.781121
0.9	0.3	87.53581	56.26348	2.786955

Figure 5 compares the actual and predicted price of petroleum using Holt's technique with the best possible the combination of smoothing constants

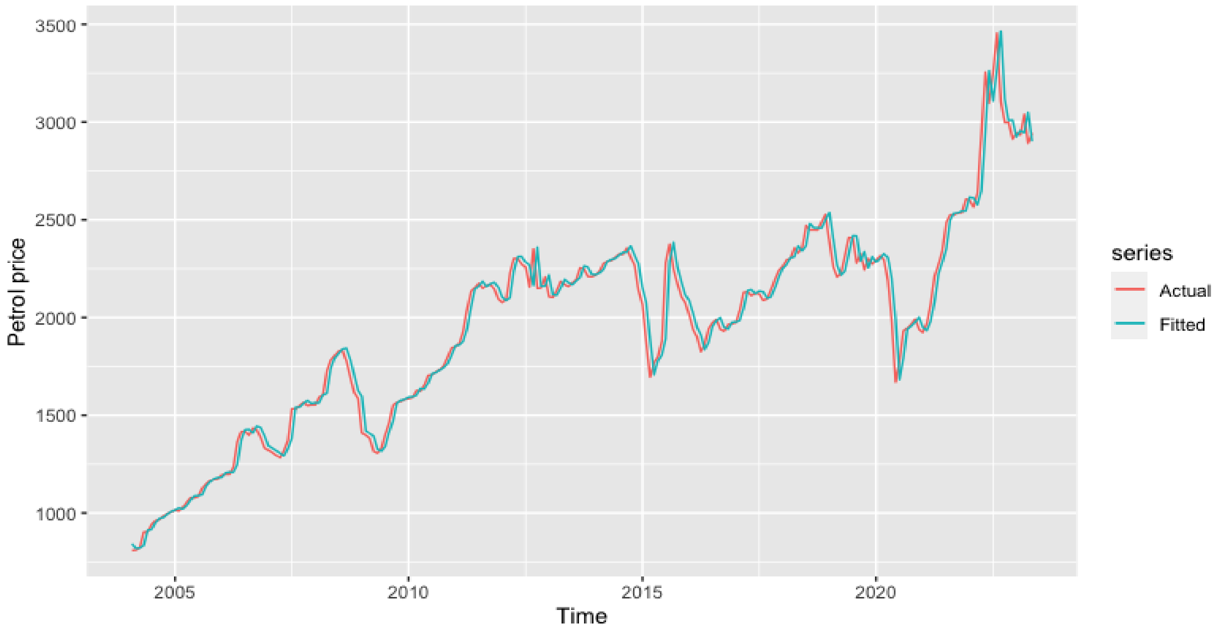

Figure 5. Comparison of actual versus fitted values using Holt's method.

Summary of the three models

Table 6 provides a summary of the results from all computations and analyses considering the three distinct forecasting methods. Results show that there are variations in the methods used. When comparing the results from various methods, ARIMA (1,1,1) with drift showed the lowest values of forecasting error thus, denoting the greatest accuracy which implies the suitability of this method in forecasting Petroleum prices in Tanzania.

Table 6: Comparison of ARIMA (1,1,1) and VAR models

	ARIMA (1,1,1)	SES	Holt's method
Root Mean Square Error	77.89300	83.63787	85.30201
Mean Absolute Error	48.33198	53.88280	54.89941
Mean Absolute Percentage Error	2.382028	2.691734	2.717236

Conclusion and Discussion

Finding the best forecasting model for petrol prices in Tanzania was a major goal of this study. To determine whether the model is more reliable at predicting the prices of petrol in Tanzania, a comparative analysis was perfumed using monthly data on petroleum prices which were extracted from the bank of Tanzania website between February, 2004 to May, 2023. The mean absolute percentage error (MAPE), mean absolute error (MAE), and mean squared error (MSE) were used to evaluate the predictive ability of the ARIMA and double exponential smoothing models. The findings indicated that ARIMA (1,1,1) outperformed double exponential smoothing models in forecasting the prices of petrol in Tanzania

The result of this study is contrary to study done by Fondo et al. (2021) and in line with the study conducted by Sokkalingam et al. (2021). This study can help policymakers, investors as well as other sectors to make an optimal selection of the contingent forecasting method.

Limitation of the study

Perfect foresight in the oil market is challenged by unpredictable factors such as global economic shifts, supply disruptions, changes in oil production and inventory demand, and geopolitical events. These events create uncertainty about future supply or demand, leading to higher volatility in prices. Accidental events like power outages or pipeline problems further complicate the situation. Market participants assess the possibility of future events and their potential impact on prices, considering factors like size, duration, current stock levels, and producers' ability to set potential shocks. The forward-looking behavior of speculators and quantification of speculative oil demand shocks can invalidate standard econometric models. Additionally, it is difficult to relate changes in real oil prices to macroeconomic outcomes due to reverse causality from macro aggregates to oil prices.

Recommendation and rea for further studies

Further research may be done to compare the accuracy of various models, such as Generalized Autoregressive Conditional Heteroscedasticity (GARCH), Vector Error Correction Model, and machine learning models with that of ARIMA and exponential smoothing models in predicting the petroleum prices in Tanzania. In addition, Multivariate GARCH models can be utilized for further research by incorporating various explanatory factors like production capacity, international crude oil price, exchange rate, and inflation to estimate the price of petroleum.

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