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Demand Forecasting of Domestic Gas Consumption: A Comparative Study of Trend Analysis, Moving Average, Single and Double Exponential Smoothing Methods

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Abstract—The increase in population and global economy has led to an increase in energy demand and consumption. Domestic gas consumption has continued to increase on a daily basis. Forecasting is essential to support decisions such as inventory management, production planning, and procurements in natural gas production and distribution. This study is aimed at forecasting natural gas demand in a selected area using trend analysis, moving average, single exponential smoothing, and double exponential smoothing techniques. 16 years (2009–2024) historical data were collected from a domestic gas distribution plant. The data were analyzed, and forecasts were made using trend analysis, moving average, single exponential smoothing, and double exponential methods. A comparative study revealed that trend analysis outperformed the other forecasting techniques, based on the lowest mean absolute percentage error (MAPE), mean absolute deviation (MAD), and mean squared deviation (MSD) as the decision criteria. The performance of double exponential smoothing is very close to that of the trend analysis. This study concludes that both trend analysis and double exponential smoothing, based on their lower MAPE and MAD, can be adopted by the gas plant in forecasting the domestic gas demand in the selected area.

Kata kunci: Natural gas, Demand forecasting, Domestic gas consumption, Single exponential smoothing, Double exponential smoothing, Trend analysis.

I. Introduction

The growth of the global economy and population growth lead to an increase in energy demand and consumption. According to many estimates, the demand for natural gas is expected to increase more than any other fossil energy source [1]. With the continuous increase of natural gas reserves and production, the demand for natural gas also continues to grow, and its status in the energy structure continues to improve [2]. Natural gas has become a critical input driving industrial activities in both developed and developing countries. The global demand for natural gas has grown rapidly, particularly in the past couple of decades, favored by consumers due to its inherent qualities as an efficient source of primary energy [3]. Natural gas represents the most competitive energy alternative and backup to the emerging renewable energies in the short and medium term [4-6]. Therefore, accurate forecasting of energy demand plays a key role in planning, setting up, and implementing networks for the renewable energy systems and continuously providing energy to consumers [7]. Understanding demand behaviour is crucial to tailoring future measures that maximize the contributions to reaching climate goals while minimizing economy distortions [5].

Energy demand forecasting is crucial for ensuring efficient resource allocation, planning infrastructure, and managing energy supply-demand balance [8-10]. The goal is to predict future trends in energy generation, consumption, and distribution using a variety of approaches and procedures [11]. In recent years, with the development of the world economy and the advancement of modernization, a contradiction between global energy supply and demand has emerged [12]. According to the Nigerian Upstream Petroleum Regulatory Commission (NUPRC) report of 2022, Nigeria's gas market is facing a growing demand that could potentially outpace supply by 2030. Moreover, there are myriads of challenging circumstances faced by the sector that invariably support this odd projection of imminent scarcity. Most of the challenging circumstances are played out in terms of sudden twists in consumers' energy consumption patterns, population increase, pipeline vandalism, security, inadequate infrastructure, regulatory inconsistencies, and a lack of an enabling environment for private sector investment, etc.

It becomes necessary to indulge in a periodic domestic gas demand forecast, and to rightly do so is by seeking efficient prediction models that are well suited for short-term forecasts. Due to the aforementioned challenges that characterize the industry, accurate gas demand forecasts are crucial for strategic planning and to meet the market demands. This study aims at forecasting domestic gas (natural gas) consumption using various univariate time series forecasting techniques. To achieve this stated purpose is to develop computationally an efficient model for short-term forecasting of natural gas consumption in Nigeria using data from various distribution outlets. It is by so doing that the nation can adequately plan objectively in areas of infrastructural development, engage in substantive trade agreements, and also express willingness to uphold renewable energy alternatives. This study pursued the following objectives: (1) to extract time series data from the sales records of XYZ Gas Distribution Plant, (2) to forecast domestic gas consumption using moving average, single exponential smoothing, double exponential smoothing, and trend analysis using data, (3) to carry out a comparative study of the forecasts made by the above forecasting techniques using the lowest MAPE, MAD, and MSD as the decision criteria, and (4) to select and recommend the most suitable forecasting technique for the selected area.

II. LITERATURE REVIEW

A. *Time series forecasting models*

Time series forecasting has gained popularity among researchers over the past few decades. Important areas of research in time series forecasting include business, economics, engineering, medicine, social sciences, and politics. Forecasting is essential to support decisions such as inventory management, production planning, procurement, and others [13]. Effective management of inventories is crucial for the growth, development, and survival of manufacturing and service industries [14, 15]. The conventional time series models that are most frequently employed are moving average, trend analysis, autoregressive integrated moving average (ARIMA), and exponential smoothing (ES). They are time series forecasting techniques, but they model the patterns of the data differently [16]. Exponential smoothing can manage non-stationary data and is appropriate for short-term forecasting [17]. Similarly, ARIMA models require steady data and may be able to capture more complicated patterns, but they may not be as appropriate for short-term or volatile data [18]. Exponential smoothing models forecast utilizing statistical descriptions of the trend and seasonality included in the data, whereas ARIMA models use autoregressive, integrated, and moving average components to capture autocorrelations [19].

Research and practice have found ES models to be highly appealing because of their transparency and simplicity [20]. ES is robust, easy to implement, and among the top-performing methods in forecasting competitions [13, 21, 22]. According to Wu et al. [23], ES forecasts are weighted combinations of historical observations, with new observations being assigned a comparatively higher weight than older ones. A weighted moving average method called exponential smoothing works particularly well when projections need to be made fast and often [24]. ES models have been widely applied in diverse fields; for instance, exponential smoothing model was used to examine the relationship between weather and economic circumstances in three European markets, as well as the long- and short-term responses of demand [25]. Repetto et al. [9] developed a robust decision rule ensemble that optimizes a predetermined loss function by employing a quadratic goal programming technique as part of their unique multi-criteria approach for distributed learning in energy forecasting. Ismail et al. [8] explained the significance, difficulties, and general approach of energy demand forecasting techniques, emphasizing their applicability and limitations. Filippov et al. [10] proposed a system's analysis-based strategy for projecting energy consumption.

Pełka [26] produced an essay that approximates the relationship between past and future demand patterns and offers a solution based on ARIMA, ES, and Prophet approaches to anticipate monthly power consumption. Forecasting models have demonstrated their effectiveness and dependability in numerous business applications concerning ES, but with certain drawbacks [13]. There has been this presumption that ARIMA is suitable for longer-term forecasting because it can capture and model more complex patterns and dependencies. ARIMA is very accurate for both short-term and long-term forecasting [16].

The simple exponential smoothing (SES) approach, the autoregressive moving average (ARMA) model, and seasonal and trend decomposition using Loess (STL) were utilized to forecast meteorological parameters at the Angra site [27]. In order to predict the oil shipping market, an exponential smoothing model with a B-criterion based on Brown's model was utilized by [28]. Sasi and Subramanian [29] utilized ARIMA and double exponential smoothing (DES) approaches to create future prediction models that greatly improved the accuracy and efficiency of demand and inventory forecasting. Nafil et al. [30] computed the energy demand projections and future consumption trends in Morocco's energy industry in 2020 by comparing three forecasting techniques: exponential smoothing, temporal causality modeling, and ARIMA. A comparative study of trend analysis, the moving average approach, simple exponential smoothing, and double exponential smoothing approaches is carried out in this study in order to make an accurate forecast of the domestic gas consumption in the selected area in Nigeria.

III. METHODS

A. *Methods of data collection*

In this study, 16 years (2009–2024) historical sales data, depicting the demand for domestic gas in a particular area in Nigeria, were collected from XYZ Gas Plant Nig. The daily time series sales data were aggregated into a yearly dataset. Table 1 shows the descriptive statistics of the data collected, showing the mean, standard error mean, standard deviation, minimum, and maximum values of the data collected.

Table 1. Descriptive Statistics of the 16 Years of Domestic Gas Consumption Data

Variable	Number of Data (Total Count)	Mean	Standard Deviation	Minimum	Maximum
Domestic Gas Consumption	16	21806	4506	13051	30665

B. *Methods of data analysis*

1. *Trend Analysis*

This technique was used to forecast the yearly demand of domestic gas for the proceeding years after sixteen (16) years of domestic gas demand data had been collected from the Sales Department of XYZ Gas Plant Nig. Using the data collected, a time series model using a linear trend equation was developed. A linear trend equation has the form [15, 31]:

$$Y_t = a + bt \tag{1}$$

Where: Y_t = forecast for period t

a = value of Y_t at t = 0

b = slope of the line

t = specified number of time periods from t = 0

a and b are determined from normal equations given below [15]:

$$\sum y = na + b\sum t \tag{2}$$

$$\sum ty = a\sum t + b\sum t^2 \quad (3)$$

Solving equations (2) and (3) simultaneously,

$$\sum t \sum y = na\sum t + b(\sum t)^2 \quad (4)$$

$$n\sum ty = na\sum t + nb\sum t^2 \quad (5)$$

Solving for a and b;

$$b = \frac{n\sum ty - \sum t \sum y}{n\sum t^2 - (\sum t)^2} \quad (6)$$

And,

$$a = \frac{\sum y - b\sum t}{n} \quad (7)$$

Where y = actual domestic gas consumption and n = number of time periods.

2. Moving Average method of forecasting

A moving average forecast uses a number of the most recent actual data values in generating a forecast. In moving average, as each new actual value becomes available, the forecast is updated by adding the newest value and dropping the oldest and recomputing the average. The moving average is computed using [15, 31]:

$$Y_t = MA_n = \frac{\sum_{i=1}^{n} Y_{t-1}}{n} = \frac{Y_{t-n} + \cdots + Y_{t-2} + Y_{t-1}}{n} \quad (8)$$

Where: Y_t = forecast for period t
MA_n = n period moving average
Y_{t-1} = actual value in period $t-1$
n= number of periods (data point) in the moving average

There are many moving average periods. In this study, five different moving average periods were examined to ascertain the one that performs better than the others. The accuracy measures – mean absolute percentage error (MAPE), mean absolute deviation (MAD), and mean squared deviation (MSE) were used to select the moving average period that gave the best result among the others.

3. Single exponential smoothing method

The single exponential smoothing method is a weighted averaging method based on the previous forecast plus a percentage of the forecast error [32]. Each new forecast is based on the previous forecast plus a percentage of the difference between that forecast and the actual value of the series at that point. The method is mathematically expressed as [32, 33]:

$$Y_t = Y_{t-1} + \alpha(A_{t-1} - Y_{t-1}) \quad (9)$$

The above equation can also be expressed as:

$$Y_t = (1-\alpha)Y_{t-1} + \alpha A_{t-1} \quad (10)$$

Where Y_t is the forecast for the period t, Y_{t-1} is the forecast for the previous period t-1, A_{t-1} is the actual demand for the previous period t-1, and α is the smoothing constant. The value of α lies between $0 < \alpha < 1$.

4. Double exponential smoothing method

The double exponential smoothing (trend-adjusted exponential smoothing) method is a variation in exponential smoothing used when a time series exhibits trend. Double exponential smoothing is composed of two elements: a smoothed error and a trend factor. The trend-adjusted forecast for the period t+1 (TAY_{t+1}) is given as [32]:

$$TAY_{t+1} = S_t + T_t \quad (11)$$

Here, S_t is the previous forecast plus smoothed error.

$$S_t = \alpha A_t + (1-\alpha)TAY_t \quad (12)$$

T_t is the estimate of trend at the end of period t.

$$T_t = T_{t-1} + \beta(TAY_t - TAY_{t-1} - T_{t-1}) \quad (13)$$

Where α and β are the smoothing constants. Just like the value of α, the value of β lies between $0 < \beta < 1$.

The testing of the double exponential smoothing parameter values was carried out in 2 stages. The first stage involved testing the α value when the β value was fixed, and then the α value with the smallest MAPE, MAD, and MSE was used to find the best β value.

5. Accuracy measures

The following accuracy measures were used in summarizing historical errors and in comparing the performance of the various forecasting methods examined in this study: MAPE, MAD, and MSD. The accuracy measures were calculated using the following equations:

$$MAPE = \frac{\frac{\sum|Actual\ demand - Forecast|}{Actual\ demand} \times 100}{n} = \frac{\frac{\sum|y-\hat{y}|}{y}}{n} \quad (14)$$

$$MAD = \frac{\sum|Actual\ demand - Forecast|}{n} = \frac{\sum|y-\hat{y}|}{n} \quad (15)$$

$$MSD = \frac{\sum(Actual\ demand - Mean\ value)^2}{n} = \frac{\sum(y-\bar{y})^2}{n} \quad (16)$$

IV. Results and Discussion

The 16 years of domestic gas demand data were analyzed using the moving average method, single exponential smoothing method, double exponential smoothing method, and trend analysis in Minitab 16 software. The results of the analysis are presented and discussed in this section. Figure 1 shows the time series plots of the 16 years of data obtained from the gas plant.

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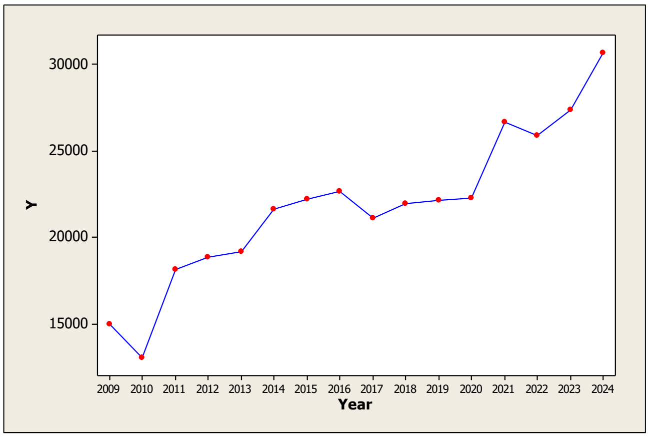

Figure 1. Time series plots of domestic gas consumption (2009 – 2024)

A. *Moving average forecasting of domestic gas consumption*

Table 2 shows the results of the moving average forecasting of the domestic gas consumption. Five moving average periods – MA_2, MA_3, MA_4, MA_5, and MA_6 were examined to ascertain the desirable MA period that will give the best forecast of the domestic gas consumption in the selected area. MAPE, MAD, and MSD were the accuracy measures used to assess the performances of the moving average periods. From the table, the larger the moving average length, the larger the MAPE, MAD, and MSD. MA_2 has the least error values (MAPE = 8%, MAD = 1897, and MSD = 5770010), showing a better performance than others. The highest error values (MAPE = 11, MAD = 2910, MSD = 12443676) occurred at MA_6, showing the least performance among the moving average periods. Hence, MA_2 is the more suitable moving average period for forecasting domestic gas demand in the area being distributed by XYZ Gas Plant Nig.

Table 2. Comparison of the accuracy measures of moving average methods

Moving Average	**Length**	**MAPE**	**MAD**	**MSD**
MA_2	2	8	1897	5770010
MA_3	3	9	2155	6473391
MA_4	4	10	2398	8855275
MA_5	5	11	2718	11349283
MA_6	6	11	2910	12443676

Figure 2 shows the actual demand (black with circular marker), the fit (red with square marker), and the forecast made (green with square marker). The forecast was made at a 95% confidence interval. The actual and the predicted (fit) are very close, showing the effectiveness of the moving average in forecasting the domestic gas demand in the selected area.

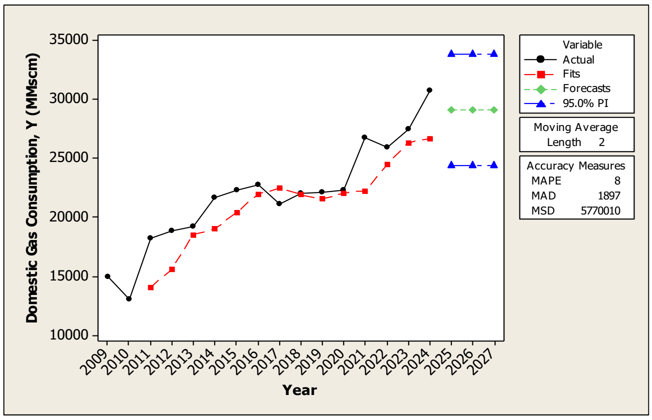

Figure 2. Moving Average (MA_2) forecast

B. *Single exponential smoothing forecast of domestic gas consumption*

Table 3 shows the results of the single exponential smoothing method at different values of the smoothing constant. Different values of the smoothing constant, ranging from 0.1 to 0.9, were examined to ascertain the value of the smoothing constant of the single exponential smoothing method that will give the best forecast of the domestic gas demand in the selected area. The lowest MAPE, MAD, and MSD were used as the criteria to select the best-performing smoothing constant for the single exponential smoothing method. From the table, smoothing constant $\alpha = 0.9$ has the lowest MAPE (8), MAD (1725), and MSD (5072386), showing it to be the best-performing smoothing constant among the examined constants. The highest MAPE, MAD, and MSD of 18, 3965, and 19850032, respectively, occurred at the smoothing constant of 0.1. The exponential smoothing with the smoothing constant of 0.1 is the least performing among the various exponential smoothing examined. Based on the lowest MAPE, MAD, and MSD criteria, the table also shows that the higher the smoothing constant, the better the performance of the exponential smoothing method in forecasting the domestic gas demand. Hence, a smoothing constant of 0.9 is the more suitable exponential smoothing constant for forecasting domestic gas demand in the selected area.

Table 3. Comparison of the performance of various single exponential smoothing models at different smoothing constants

S/N	Smoothing constant, α	MAPE	MAD	MSD
1	0.1	18	3965	19850032
2	0.2	15	3205	12649945
3	0.3	13	2700	9321610
4	0.4	11	2392	7576942
5	0.5	11	2196	6545194
6	0.6	10	2037	5890171
7	0.7	9	1902	5469217
8	0.8	9	1784	5210852
9	0.9	8	1725	5072386

Figure 3 shows the actual demand (black with circular marker), the fit (red with square marker), and the forecast made (green with square marker) using the exponential smoothing method with a smoothing constant of 0.9. The forecast was made at a 95% confidence interval.

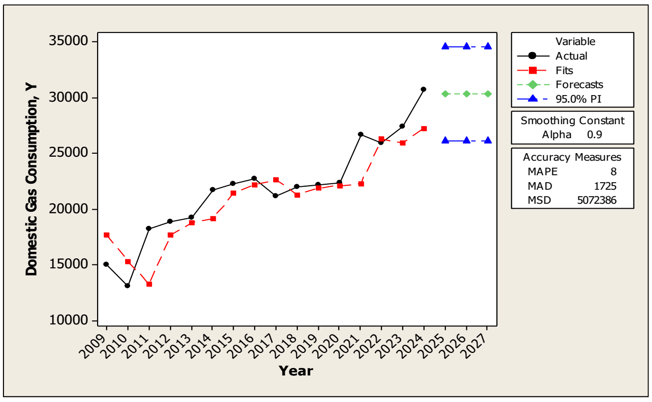

Figure 3. Exponential Smoothing method's forecast at smoothing constant of 0.9

C. *Double exponential smoothing forecast of domestic gas consumption*

Table 4 shows the results of the double exponential smoothing forecast of domestic gas demand at different values of the smoothing constants α and β. Different values of the smoothing constants α and β, ranging from 0.1 to 0.9, were examined to ascertain the values of the smoothing constants of the double exponential smoothing method that will give the best forecast of the domestic gas demand. The testing of the double exponential smoothing parameter values was carried out in 2 stages. The first stage involved testing the α value (0.1 to 0.9) when the β value (0.1) was fixed, and then the α value with the lowest MAPE and MAD was used to find the best β value. From the first stage of the testing, an α value of 0.7 gave the lowest MAPE and MAD at a fixed value of β (0.1). The second stage of the testing showed that the smoothing constants α = 0.7 and β = 0.4 gave the lowest MAPE and MAD among the different smoothing constants examined. Hence, double exponential smoothing with smoothing constants of α = 0.7 and β = 0.4 is a more suitable double exponential smoothing method for forecasting domestic gas demand in the selected area.

Table 4. Accuracy measures of double exponential smoothing method at different values of smoothing constants α and β

S/N	α	β	MAPE	MAD
1	0.1	0.1	7	1473
2	0.2	0.1	7	1532
3	0.3	0.1	7	1522
4	0.4	0.1	7	1493
5	0.5	0.1	7	1442
6	0.6	0.1	7	1411
7	0.7	0.1	7	1393
8	0.8	0.1	7	1397
9	0.9	0.1	7	1405
10	0.7	0.1	7	1393
11	0.7	0.2	7	1413
12	0.7	0.3	7	1407
13	0.7	0.4	7	1388
14	0.7	0.5	7	1423
15	0.7	0.6	7	1499
16	0.7	0.7	7	1560
17	0.7	0.8	7	1609
18	0.7	0.9	7	1658

Figure 4 shows the actual demand (black with circular marker), the fit (red with square marker), and the forecast made (green with square marker) using the double exponential smoothing method with the smoothing constants of α = 0.7 and β = 0.4. The forecast was made at a 95% confidence interval. The figure shows the closeness of the predicted (fit) with actual demand, inferring the robustness of the double exponential smoothing method in forecasting the domestic gas demand.

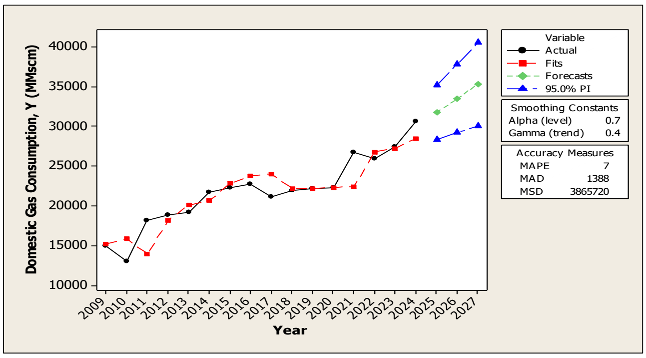

Figure 4. Double Exponential Smoothing forecast of domestic gas consumption at α = 0.7 and β = 0.4

D. *Trend analysis forecast of domestic gas consumption*

Equation (17) shows the linear trend model generated for forecasting domestic gas consumption in the selected area. The forecast made using the linear trend is shown in Figure 8. The black line with circular markers shows the actual demand for domestic gas, the red line with square markers shows the fit, and the green line with square markers shows the forecast. An upward trend is observed, showing a likely increase in the domestic gas demand in the area. The values of accuracy measures are MAPE = 7, MAD = 1370, and MSD = 2523997.

$$Y_t = 14313 + 882t \quad (17)$$

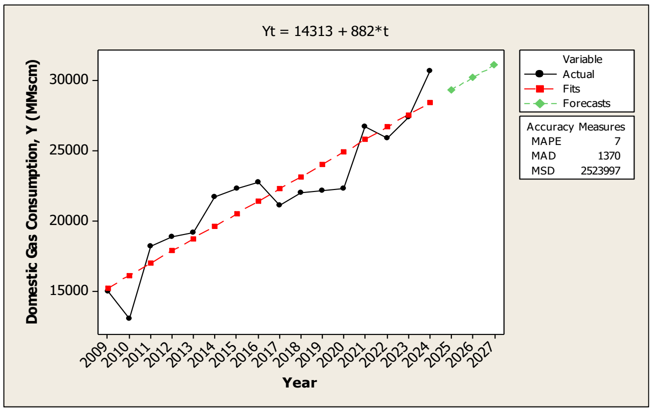

Figure 5: Trend Analysis forecast of domestic gas consumption

E. *Comparison of the time Series forecasting methods*

Table 5 compares the performances of four forecasting methods – moving average, single exponential smoothing, double exponential smoothing, and trend analysis – using the lowest MAPE, MAD, and MSD as the decision criteria. The comparison of the performances of the various methods is pictorially shown by Figure 6. Trend analysis with MAPE of 7%, MAD of 1370, and MSD of 2523997 outperformed others when compared with the accuracy measures of others. This is followed by double exponential smoothing with the same MAPE as trend analysis, but with higher MAD and MSD than those of trend analysis. The least performed method, viewing from their accuracy measures, is the moving average method.

Hence, trend analysis is recommended for demand forecasting of domestic gas consumption in the selected area.

Also, comparing the two exponential smoothing techniques – simple and double – it can be observed that double exponential smoothing is a better forecasting method for the domestic gas consumption than the single exponential smoothing method using the least values of the accuracy measures as the decision criteria. This finding is in agreement with the previous findings on time series forecasting methods [34].

In comparing the performance of double exponential smoothing and moving average, this study found that double exponential smoothing performs better than the moving average. This does not agree with the findings of [35], which found that the two-period moving average is better than the double exponential smoothing.

Table 4. Comparison of various time series forecasting techniques

Forecasting method	Accuracy measures		
	MAPE	MAD	MSD
Moving Average (MA_2)	8	1897	5770010
Single Exponential Smoothing	8	1725	5072386
Double Exponential Smoothing	7	1388	3865720
Trend Analysis	7	1370	2523997

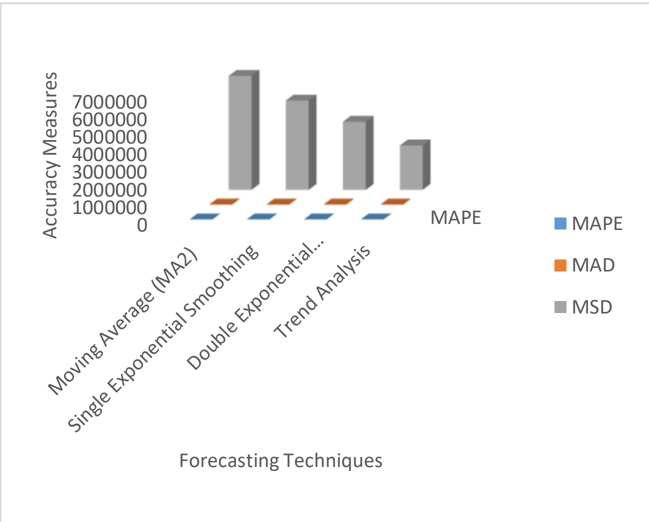

Figure 6. Comparison of various time series forecasting techniques

V. Conclusion

In this study, demand forecasting of domestic gas consumption in a selected area using trend analysis, moving average, single exponential smoothing, and double exponential smoothing methods was carried out. The results revealed the following:

An upward trend in the demand of domestic gas in the selected area as shown in the sales records of XYZ Gas Plant Nig.

Moving average method, single exponential smoothing, double exponential smoothing, and trend analysis are all good univariate time series forecasting techniques that can be used in forecasting domestic gas consumption, as can be seen in the closeness of their mean absolute percentage errors.

Among all the smoothing constants examined for forecasting domestic gas demand using the single exponential smoothing method, a smoothing constant of 0.9 gave a better forecast than other smoothing constants when compared using the lowest MAPE, MAD, and MSD as the criteria.

The double exponential smoothing method with a smoothing constants of $\alpha = 0.7$ and $\beta = 0.4$ is the most suitable double exponential smoothing for forecasting the domestic gas consumption in the selected area.

Trend analysis outperformed the other forecasting techniques when compared using the lowest MAPE, MAD, and MSD as the performance criteria.

This study concludes that trend analysis and double exponential smoothing can be adopted by XYZ Gas Plant Nig. in forecasting the domestic gas demand in the selected area. The forecast will enable the company to plan ahead in terms of inventory management, logistics, procurement of natural gas, and distribution. It becomes pertinent that short-term prediction model for domestic gas demand in the company and the selected area, and by extension Nigeria, be developed and be frequently updated due to the dynamic nature of markets and other uncertain situations that are bound to emanate.

Declaration of Conflict of Interests

The authors declare that there is no conflict of interest. They have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethical Considerations

No ethical approval is required for publication of this research work.

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