ISSN: 2278 – 7798
International Journal of Science, Engineering and Technology Research (IJSETR)
Volume 2, No 6, June 2013

# Regression and Time Series Analysis of Kerosene Product Sales in Masters Energy oil and Gas

**[1]Ogunoh Arinze Victor**
*[1]Department of Industrial and Production Engineering, Nnamdi Azikiwe University Awka, Anambra State, Nigeria Mobile: 2348030616723, E-mail: avohunoh@gmail.com*

**[2]Ezeliora Chukwuemeka Daniel**
*[2]Department of Industrial and Production Engineering, Nnamdi Azikiwe University Awka, Anambra State, Nigeria Mobile: 2348060480087, E-mail:cezeliora@gmail.com*
**[3]Chinwuko Emmanuel Chuka**
*[3]Department of Industrial and Production Engineering, Nnamdi Azikiwe University Awka, Anambra State, Nigeria Mobile: 2348037815808, E-mail:chinwukoemmanuelc@yahoo.com*
**[4] Nwosu Moses C**
*[4]Department of Industrial and Production Engineering, Nnamdi Azikiwe University Awka, Anambra State, Nigeria Mobile: 2348068261242*

**Abstract**

This research work focuses on the regression analysis and time series analysis of the Kerosene Product Sales in Masters Energy oil and Gas. The application of multiple regression model were made to show the effect of environmental factors in the Kerosene product sales. In the regression analysis, the p-value shows how the environmental factors (that is the independent variables) affect the model and how important is any of the environmental factors. The time series analysis were also used to show the trend influence in the data, detrend influence in the data, seasonal variation in the data and deseasoning of the data. Furthermore, trend estimation model was also used to forecast the product sales of the data. In conclusion, it was observed that the environmental factors have little effect on the Kerosene product sales.

**Key words:** Regression, Time Series, Trend, Seasonal index, Forecasting, Deseason, Detrend and Kerosene

## Introduction of Forecasting

**Forecasting** is the process of making statements about events whose actual outcomes (typically) have not yet been observed. A commonplace example might be estimation of some variable of interest at some specified future date. Prediction is a similar, but more general term. Both might refer to formal statistical methods employing time series, cross-sectional or longitudinal data, or alternatively to less formal judgemental methods. Usage can differ between areas of application: for example, in hydrology, the terms "forecast" and "forecasting" are sometimes reserved for estimates of values at certain specific future times, while the term "prediction" is used for more general estimates, such as the number of times floods will occur over a long period.

Risk and uncertainty are central to forecasting and prediction; it is generally considered good practice to indicate the degree of uncertainty attaching to forecasts. In any case, the data must be up to date in order for the forecast to be as accurate as possible.[2]

Although quantitative analysis can be very precise, it is not always appropriate. Some experts in the field of forecasting have advised against the use of mean square error to compare forecasting methods.[3]

**Categories of forecasting methods:** Qualitative forecasting techniques are subjective, based on the opinion and judgment of consumers, experts; appropriate when past data is not available. It is usually applied to intermediate-long range decisions. Examples of qualitative forecasting methods are: informed opinion and judgment, the Delphi method, market research, historical life-cycle analogy.

Quantitative forecasting models are used to estimate future demands as a function of past data; appropriate when past data are available. The method is usually applied to short-intermediate range decisions. Examples of quantitative forecasting methods are: last period demand, simple and weighted moving averages (N-Period), simple exponential smoothing, and multiplicative seasonal indexes.

**Naïve approach:** Naïve forecasts are the most cost-effective and efficient objective forecasting model, and provide a benchmark against which more sophisticated models can be compared. For stable time series data, this approach says that the forecast for any period equals the previous period's actual value.

**Time series methods:** Time series methods use historical data as the basis of estimating future outcomes.

- Moving average
- Weighted moving average
- Kalman filtering
- Exponential smoothing
- Autoregressive moving average (ARMA)
- Autoregressive integrated moving average (ARIMA)

  e.g. Box-Jenkins
- Extrapolation
- Linear prediction
- Trend estimation
- Growth curve

**Causal / econometric forecasting methods:** Some forecasting methods use the assumption that it is possible to identify the underlying factors that might influence the variable that is being forecast. For example, including information about weather conditions might improve the ability of a model to predict umbrella sales. This is a model of seasonality which shows a regular pattern of up and down fluctuations. In addition to weather, seasonality can also be due to holidays and customs such as predicting that sales in college football apparel will be higher during football season as opposed to the off season.[4]

Causal forecasting methods are also subject to the discretion of the forecaster. There are several informal methods which do not have strict algorithms, but rather modest and unstructured guidance. One can forecast based on, for example, linear relationships. If one variable is linearly related to the other for a long enough period of time, it may be beneficial to predict such a relationship in the future. This is quite different from the aforementioned model of seasonality whose graph would more closely resemble a sine or cosine wave. The most important factor when performing this operation is using concrete and substantiated data. Forecasting off of another forecast produces inconclusive and possibly erroneous results.

Causal methods include:

- Regression analysis includes a large group of methods that can be used to predict future values of variable using information about other variables.

These methods include both parametric (linear or non-linear) and non-parametric techniques.

- Autoregressive moving average with exogenous inputs (ARMAX)[5]

**Measuring Forecast Accuracy: Mean Forecast Error (MFE):** Forecast error is a measure of how accurate our forecast was in a given time period. It is calculated as the actual demand minus the forecast, or

$E_t = A_t - F_t$

Forecast error in one time period does not convey much information, so we need to look at the accumulation of errors over time. We can calculate the average value of these forecast errors over time (i.e., a **Mean Forecast Error**, or **MFE**).Unfortunately, the accumulation of the $E_t$ values is not always very revealing, for some of them will be positive errors and some will be negative. These positive and negative errors cancel one another, and looking at them alone (or looking at the MFE over time) might give a false sense of security. To illustrate, consider our original data, and the accompanying pair of hypothetical forecasts made with two different forecasting methods.

Based on the accumulated forecast errors over time, the two methods look equally good. But, most observers would judge that Method 1 is generating better forecasts than Method 2 (i.e., smaller misses) [6].

**Mean Absolute Deviation (MAD):** To eliminate the problem of positive errors canceling negative errors, a simple measure is one that looks at the absolute value of the error (size of the deviation, regardless of sign). When we disregard the sign and only consider the size of the error, we refer to this deviation as the absolute deviation. If we accumulate these absolute deviations over time and find the average value of these absolute deviations, we refer to this measure as the mean absolute deviation (MAD):

**Mean Squared Error (MSE):** Another way to eliminate the problem of positive errors canceling negative errors is to square the forecast error. Regardless of whether the forecast error has a positive or negative sign, the squared error will always have a positive sign. If we accumulate these squared errors over time and find the average value of these squared errors, we refer to this measure as the mean squared error (MSE).

The Question often arises as to why one would use the more cumbersome MSE when the MAD calculations are a bit simpler (you don't have to square the deviations). MAD does have the advantage of simpler calculations. However, there is a benefit to the MSE method. Since this method squares the error term, large errors tend to be magnified. Consequently, MSE places a higher penalty on large errors. This can be useful in situations where small forecast errors don't cause much of a problem, but large errors can be devastating.

**Mean Absolute Percent Error (MAPE):** A problem with both the MAD and MSE is that their values depend on the magnitude of the item being forecast. If the forecast item is measured in thousands or millions, the MAD and MSE values can be very large. To avoid this problem, we can use the MAPE. MAPE is computed as the average of the absolute difference between the forecasted and actual values, expressed as a percentage of the actual values. In essence, we look at how large the miss was relative to the size of the actual value.

**Illustration of the Four forecast Accuracy Measures:** Here is a further illustration of the four measures of forecast accuracy, this time using hypothetical forecasts that were generated using some different methods than the previous illustrations (called forecasting methods A and B; actually, these forecasts were made up for purposes of illustration). These calculations illustrate why we cannot rely on just one measure of forecast accuracy.

You can observe that for each of these forecasting methods, the same MFE resulted and the same MAD resulted. With these two measures, we would have no basis for claiming that one of these forecasting methods was more accurate than the other. With several measures of accuracy to consider, we can look at all the data in an attempt to determine the better forecasting method to use. Interpretation of these results will be impacted by the biases of the decision maker and the parameters of the decision situation. For example, one observer could look at the forecasts with method A and note that they were pretty consistent in that they were always missing by a modest amount (in this case, missing by 20 units each year). However, forecasting method B was very good in some years, and extremely bad in some years (missing by 60 units in years 5 and 6). That observation might cause this individual to prefer the accuracy and consistency of forecasting method A. This causal observation is formalized in the calculation of the MSE. Forecasting method A has a considerably lower MSE than forecasting method B. The squaring magnified those big misses that were observed with forecasting method B. However, another individual might view these results and have a preference for method B, for the sizes of the misses relative to the sizes of the actual demand are smaller than for method A, as indicated by the MAPE calculations [1].

**Monitoring Forecast Accuracy over Time: Tracking Signal:** A tracking signal (T.S.) is a tool used to continually monitor the quality of our forecasting method as we progress through time. A tracking signal value is calculated each period and a determination is made as to whether it falls into an acceptable range. An upper limit and a lower limit will have been established for the tracking signal, and these values define the acceptable range. If the tracking signal drifts outside of the acceptable range, that is an indication that the forecasting method being used is no longer providing accurate forecasts. Tracking signals also help to indicate whether there is bias creeping into the forecasting process. Bias is a tendency for the forecast to be persistently under or persistently over the actual value of the data.

Tracking signal is calculated as follows:

$$\text{Tracking signal} = \frac{\text{Cumulative error}}{\text{MAD}}$$

Illustration of the computation of tracking signals to accompany a progression of hypothetical forecasts made over time some hypothetical forecasting method. (These forecasts were not made with any of the forecasting methods we illustrated – the forecasts were contrived to keep the numbers manageable.)

Keep in mind that each line in the above table would have been calculated in successive years. At the end of each year we can look back at the most recent year and compare the forecast we made with the actual demand that occurred. The next several pages show how these calculations would have unfolded through the years, and how they would have been plotted on a graph to determine whether our forecasting method still appeared to be working well.

We now begin illustrating the computation and plotting of tracking signals to accompany the progression of forecasts made over time with hypothetical forecasting Method 1. In this illustration we will assume that the upper limit has been set at a value of 3, and the lower limit has been set at a value of -3. In practice these limits may be higher or lower than these values, and they do not necessarily need to have the same numerical value [1].

## 7. Research Method Used

The data were collected for a period of three years product sales. The data were modeled and analyzed using regression and time series analysis. The regression model shows the effect of the environmental factors in its model and in the forecasting results. However, time series analyses were also used to show the seasonal and deseasonal influence and also trend and detrend influence. Time series method was also used in forecasting the results to see if there is an environmental influence in the data.

**Table 1: Presentation of Kerosene product Sales Data in Masters Energy Oil and Gas**

| Year | Month | Time | Humidity (%) | Rainfall (mm) | Temp (C) | Kerosene |
|---|---|---|---|---|---|---|
| 2010 | Jan | 1 | 28.4 | 76 | 11.2 | 6078 |
| | Feb | 2 | 30.0 | 80 | 0.7 | 3898 |
| | Mar | 3 | 30.7 | 76 | 50.6 | 3020 |
| | April | 4 | 29.2 | 81 | 121.1 | 5607 |
| | May | 5 | 28.3 | 81 | 233.1 | 5990 |
| | June | 6 | 27.6 | 85 | 248.3 | 4501 |
| | July | 7 | 26.7 | 89 | 386.6 | 5304 |
| | Aug | 8 | 26.7 | 87 | 283.3 | 6302 |
| | Sept | 9 | 26.9 | 86 | 249.4 | 5731 |
| | Oct | 10 | 26.9 | 85 | 376.0 | 3224 |
| | Nov | 11 | 27.8 | 73 | 96.3 | 3438 |
| | Dec | 12 | 28.8 | 76 | Nil | 5607 |
| 2011 | Jan | 13 | 29.0 | 72 | 0.2 | 408 |
| | Feb | 14 | 30.4 | 72 | 66.8 | 687 |
| | Mar | 15 | 30.8 | 73 | 13.6 | 890 |
| | April | 16 | 29.7 | 79 | 203.5 | 3408 |
| | May | 17 | 28.7 | 81 | 161.3 | 4878 |
| | June | 18 | 27.7 | 84 | 191.9 | 3178 |
| | July | 19 | 27.0 | 84 | 13.2 | 3716 |
| | Aug | 20 | 27.2 | 86 | 299.9 | 3839 |
| | Sept | 21 | 27.0 | 87 | 306.4 | 4321 |
| | Oct | 22 | 27.3 | 85 | 166.9 | 6342 |
| | Nov | 23 | 28.6 | 82 | 412.0 | 6890 |
| | Dec | 24 | 28.3 | 71 | Nil | 7300 |
| 2012 | Jan | 25 | 28.4 | 76 | 11.2 | 3400 |
| | Feb | 26 | 30.0 | 80 | 0.7 | 2707 |
| | Mar | 27 | 30.7 | 76 | 50.6 | 3878 |
| | April | 28 | 29.2 | 81 | 121.1 | 4982 |
| | May | 29 | 28.3 | 81 | 233.1 | 4934 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | June | 30 | 27.6 | 85 | 248.3 | 3699 |
| | July | 31 | 26.7 | 89 | 386.6 | 3776 |
| | Aug | 32 | 26.7 | 87 | 283.3 | 4101 |
| | Sept | 33 | 26.9 | 86 | 249.4 | 4434 |
| | Oct | 34 | 26.9 | 85 | 376.0 | 3762 |
| | Nov | 35 | 27.8 | 73 | 96.3 | 3708 |
| | Dec | 36 | 28.8 | 76 | Nil | 4283 |

**Analysis of Masters Energy Kerosene Sales**

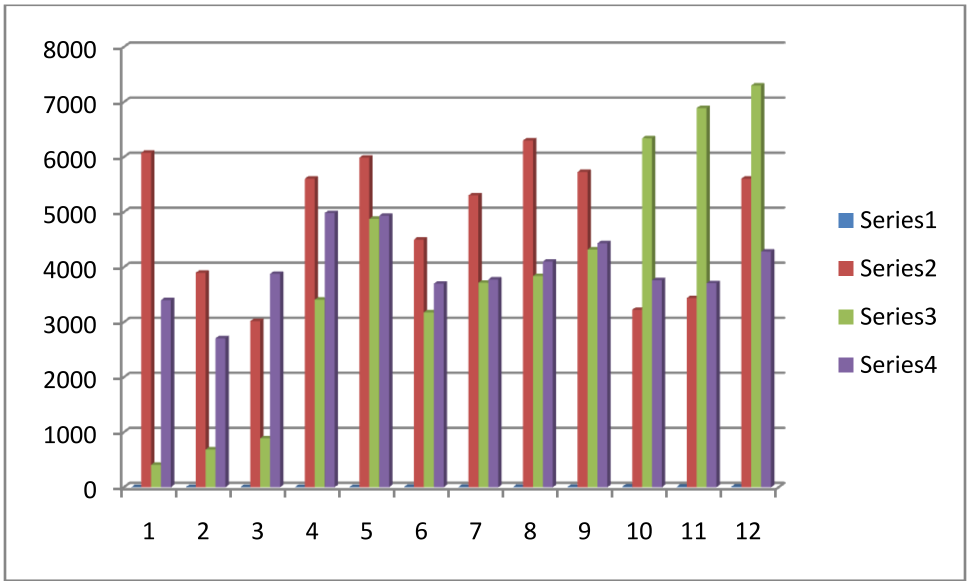


**Figure 1: KEROSINE (DPK) BAR CHART**

Figure 1 above shows the seasonal and monthly data analysis of the product sales. It shows the three years product sales from January to December months

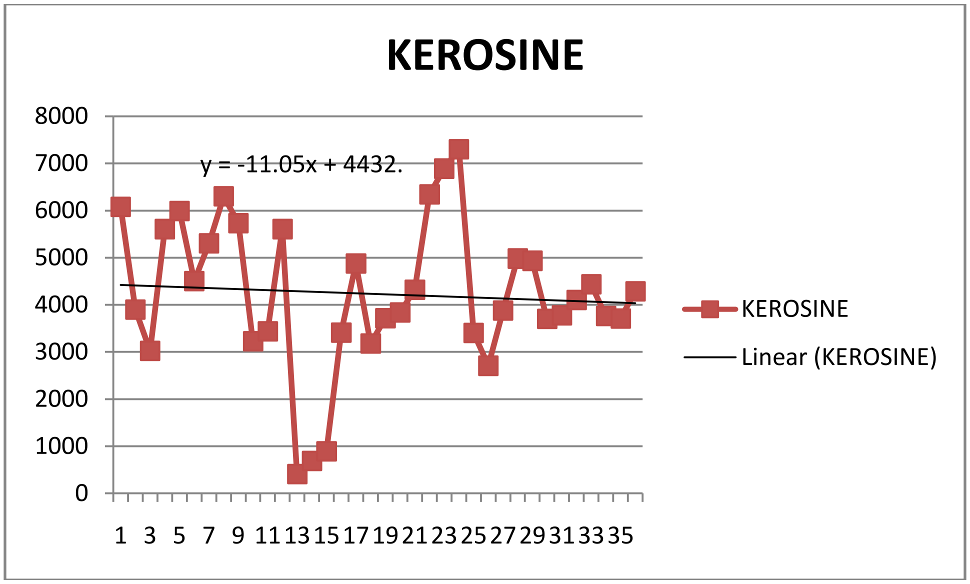


**Figure 2: Linear Trend line Model for Kerosene (From 2010 to 2012)**

The trend line shows that their product sales will be decreasing in future

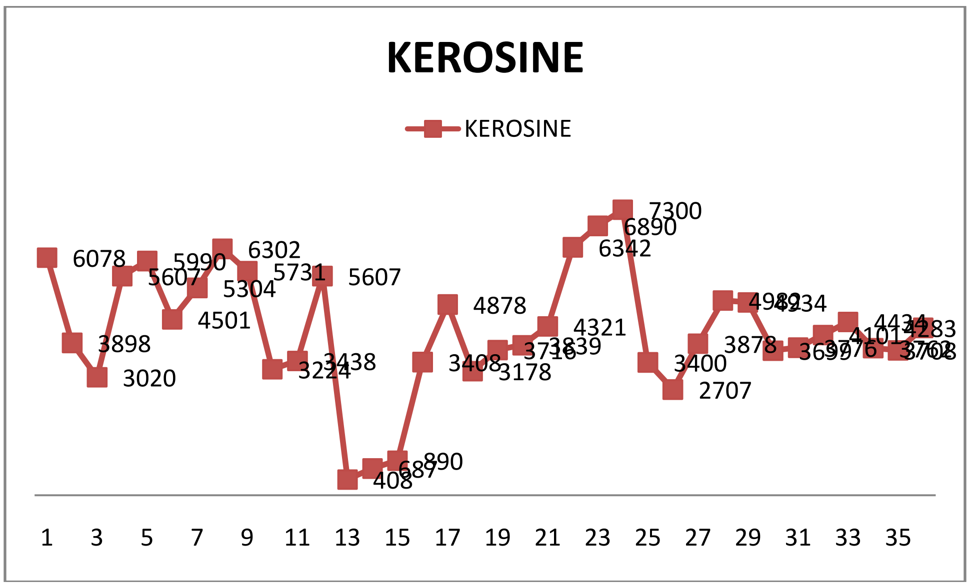


**Figure 3: Time Series Analysis of Kerosene (From 2010 to 2012)**

Figure 3 above shows the time series analysis of Kerosene product sales data, over the three years.

**Trend Equation:** A trend equation has the form

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

Where t = Specified number of time periods from t=o

$F_t$ =Forecast for period t

$a$ =Value of $F_t$ at t = 0

$b$ = Slope of the line

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

$$a = \frac{\sum y - b\sum t}{n} \text{ or } \bar{y} - b\bar{t} \quad (3)$$

Where, n = Number of periods

y = Value of the time series

**Table 2: Forecasting Results of Kerosene Product Sales using Trend Estimation Method**

| year | month | time | Kerosene |
|---|---|---|---|
| 2013 | Jan | 37 | 4023.15 |
| | Feb | 38 | 4012.1 |
| | Mar | 39 | 4001.05 |
| | April | 40 | 3990 |
| | May | 41 | 3978.95 |
| | June | 42 | 3967.9 |
| | July | 43 | 3956.85 |
| | Aug | 44 | 3945.8 |
| | Sept | 45 | 3934.75 |
| | Oct | 46 | 3923.7 |
| | Nov | 47 | 3912.65 |
| | Dec | 48 | 3901.6 |
| 2014 | Jan | 49 | 3890.55 |
| | Feb | 50 | 3879.5 |
| | Mar | 51 | 3868.45 |
| | April | 52 | 3857.4 |
| | May | 53 | 3846.35 |
| | June | 54 | 3835.3 |
| | July | 55 | 3824.25 |
| | Aug | 56 | 3813.2 |
| | Sept | 57 | 3802.15 |
| | Oct | 58 | 3791.1 |
| | Nov | 59 | 3780.05 |
| | Dec | 60 | 3769 |
| 2015 | Jan | 61 | 3757.95 |

ISSN: 2278 – 7798
International Journal of Science, Engineering and Technology Research (IJSETR)
Volume 2, No 6, June 2013

| | | | |
|---|---|---|---|
| | Feb | 62 | 3746.9 |
| | Mar | 63 | 3735.85 |
| | April | 64 | 3724.8 |
| | May | 65 | 3713.75 |
| | June | 66 | 3702.7 |
| | July | 67 | 3691.65 |
| | Aug | 68 | 3680.6 |
| | Sept | 69 | 3669.55 |
| | Oct | 70 | 3658.5 |
| | Nov | 71 | 3647.45 |
| | Dec | 72 | 3636.4 |

# General Regression Analysis for Forecasting

## General Regression Analysis: KEROSINE versus Temp (C), Humidity (%), ...

```
Regression Equation

KEROSINE = 14212.4 - 422.209 Temp (C) + 29.6395 Humidity (%) - 0.208318
           Rainfall (mm) - 21.9765 MONTH/TIME


Coefficients

Term               Coef   SE Coef         T       P          95% CI             VIF
Constant        14212.4   13012.0   1.09225   0.283  (-12325.8, 40750.6)
Temp (C)         -422.2     298.0  -1.41690   0.166  ( -1029.9,   185.5)   2.17436
Humidity (%)       29.6      86.9   0.34092   0.735  (  -147.7,   207.0)   3.23077
Rainfall (mm)      -0.2       3.2  -0.06523   0.948  (    -6.7,     6.3)   2.82573
MONTH/TIME        -22.0      25.4  -0.86596   0.393  (   -73.7,    29.8)   1.05142
Summary of Model

S = 1542.66        R-Sq = 16.57%         R-Sq(adj) = 5.81%

Analysis of Variance

Source             DF    Seq SS    Adj SS    Adj MS        F         P
Regression          4  14657094  14657094   3664273  1.53975  0.215115
  Temp (C)          1  12339900   4777664   4777664  2.00760  0.166485
  Humidity (%)      1    497866    276600    276600  0.11623  0.735461
  Rainfall (mm)     1     34767     10125     10125  0.00425  0.948412
  MONTH/TIME        1   1784560   1784560   1784560  0.74988  0.393166
Error              31  73773428  73773428   2379788
Total              35  88430522

Fits and Diagnostics for All Observations
Obs  KEROSINE      Fit   SE Fit  Residual  St Resid
  1      6078  4449.96  640.763   1628.04   1.16017
```

```
 2    3898  3873.19  711.095     24.81   0.01812
 3    3020  3426.71  646.578   -406.71  -0.29038
 4    5607  4171.56  496.979   1435.44   0.98290
 5    5990  4506.24  481.989   1483.76   1.01251
 6    4501  4895.20  467.264   -394.20  -0.26813
 7    5304  5342.96  611.471    -38.96  -0.02751
 8    6302  5283.23  532.025   1018.77   0.70357
 9    5731  5154.23  490.024    576.77   0.39430
10    3224  5076.24  594.933  -1852.24  -1.30135
11    3438  4376.87  749.589   -938.87  -0.69634
12    5607  4041.66  451.565   1565.34   1.06118
13     408  3816.64  557.923  -3408.64  -2.37003  R
14     687  3189.70  605.518  -2502.70  -1.76389
15     890  3039.56  580.254  -2149.56  -1.50386
16    3408  3620.29  523.376   -212.29  -0.14629
17    4878  4088.60  291.571    789.40   0.52111
18    3178  4571.37  327.973  -1393.37  -0.92436
19    3716  4882.17  827.168  -1166.17  -0.89558
20    3839  4775.31  374.208   -936.31  -0.62563
21    4321  4866.06  404.418   -545.06  -0.36613
22    6342  4687.20  448.585   1654.80   1.12114
23    6890  3976.37  807.297   2913.63   2.21643  R
24    7300  3840.85  711.878   3459.15   2.52754  R
25    3400  3922.52  483.865   -522.52  -0.35671
26    2707  3345.75  715.549   -638.75  -0.46738
27    3878  2899.28  665.862    978.72   0.70333
28    4982  3644.12  494.371   1337.88   0.91554
29    4934  3978.80  417.345    955.20   0.64317
30    3699  4367.77  432.286   -668.77  -0.45161
31    3776  4815.53  570.479  -1039.53  -0.72527
32    4101  4755.79  518.332   -654.79  -0.45066
33    4434  4626.79  516.561   -192.79  -0.13263
34    3762  4548.80  607.278   -786.80  -0.55483
35    3708  3849.43  774.924   -141.43  -0.10603
36    4283  3514.23  629.564    768.77   0.54587

R denotes an observation with a large standardized residual.
```

## Table 3: Forecasting results for Kerosene product Sales using Regression model

| Year | Month | Temp (C) | Humidity (%) | Rainfall (mm) | Time | Kerosene |
|---|---|---|---|---|---|---|
| 2013 | Jan | 28.8 | 76 | 0 | 37 | 3492.252 |
| | Feb | 28.8 | 76 | 0 | 38 | 3470.276 |
| | Mar | 28.8 | 76 | 0 | 39 | 3448.299 |
| | April | 28.8 | 76 | 0 | 40 | 3426.323 |
| | May | 28.8 | 76 | 0 | 41 | 3404.346 |
| | June | 28.8 | 76 | 0 | 42 | 3382.37 |
| | July | 28.8 | 76 | 0 | 43 | 3360.393 |
| | Aug | 28.8 | 76 | 0 | 44 | 3338.417 |
| | Sept | 28.8 | 76 | 0 | 45 | 3316.44 |
| | Oct | 28.8 | 76 | 0 | 46 | 3294.464 |
| | Nov | 28.8 | 76 | 0 | 47 | 3272.487 |
| | Dec | 28.8 | 76 | 0 | 48 | 3250.511 |
| 2014 | Jan | 28.8 | 76 | 0 | 49 | 3228.534 |
| | Feb | 28.8 | 76 | 0 | 50 | 3206.558 |
| | Mar | 28.8 | 76 | 0 | 51 | 3184.581 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | April | 28.8 | 76 | 0 | 52 | 3162.605 |
| | May | 28.8 | 76 | 0 | 53 | 3140.628 |
| | June | 28.8 | 76 | 0 | 54 | 3118.652 |
| | July | 28.8 | 76 | 0 | 55 | 3096.675 |
| | Aug | 28.8 | 76 | 0 | 56 | 3074.699 |
| | Sept | 28.8 | 76 | 0 | 57 | 3052.722 |
| | Oct | 28.8 | 76 | 0 | 58 | 3030.746 |
| | Nov | 28.8 | 76 | 0 | 59 | 3008.769 |
| | Dec | 28.8 | 76 | 0 | 60 | 2986.793 |
| 2015 | Jan | 28.8 | 76 | 0 | 61 | 2964.816 |
| | Feb | 28.8 | 76 | 0 | 62 | 2942.84 |
| | Mar | 28.8 | 76 | 0 | 63 | 2920.863 |
| | April | 28.8 | 76 | 0 | 64 | 2898.887 |
| | May | 28.8 | 76 | 0 | 65 | 2876.91 |
| | June | 28.8 | 76 | 0 | 66 | 2854.934 |
| | July | 28.8 | 76 | 0 | 67 | 2832.957 |
| | Aug | 28.8 | 76 | 0 | 68 | 2810.981 |
| | Sept | 28.8 | 76 | 0 | 69 | 2789.004 |
| | Oct | 28.8 | 76 | 0 | 70 | 2767.028 |
| | Nov | 28.8 | 76 | 0 | 71 | 2745.051 |
| | Dec | 28.8 | 76 | 0 | 72 | 2723.075 |

**Table 4: Forecasting Results of Kerosene Product Sales**

| year | month | time | Trend estimation | Regression |
|---|---|---|---|---|
| 2013 | Jan | 37 | 4023.15 | 3492.252 |
| | Feb | 38 | 4012.1 | 3470.276 |
| | Mar | 39 | 4001.05 | 3448.299 |
| | April | 40 | 3990 | 3426.323 |
| | May | 41 | 3978.95 | 3404.346 |
| | June | 42 | 3967.9 | 3382.37 |
| | July | 43 | 3956.85 | 3360.393 |
| | Aug | 44 | 3945.8 | 3338.417 |
| | Sept | 45 | 3934.75 | 3316.44 |
| | Oct | 46 | 3923.7 | 3294.464 |
| | Nov | 47 | 3912.65 | 3272.487 |
| | Dec | 48 | 3901.6 | 3250.511 |
| 2014 | Jan | 49 | 3890.55 | 3228.534 |
| | Feb | 50 | 3879.5 | 3206.558 |
| | Mar | 51 | 3868.45 | 3184.581 |
| | April | 52 | 3857.4 | 3162.605 |
| | May | 53 | 3846.35 | 3140.628 |
| | June | 54 | 3835.3 | 3118.652 |
| | July | 55 | 3824.25 | 3096.675 |
| | Aug | 56 | 3813.2 | 3074.699 |

| | | | | |
|---|---|---|---|---|
| | Sept | 57 | 3802.15 | 3052.722 |
| | Oct | 58 | 3791.1 | 3030.746 |
| | Nov | 59 | 3780.05 | 3008.769 |
| | Dec | 60 | 3769 | 2986.793 |
| 2015 | Jan | 61 | 3757.95 | 2964.816 |
| | Feb | 62 | 3746.9 | 2942.84 |
| | Mar | 63 | 3735.85 | 2920.863 |
| | April | 64 | 3724.8 | 2898.887 |
| | May | 65 | 3713.75 | 2876.91 |
| | June | 66 | 3702.7 | 2854.934 |
| | July | 67 | 3691.65 | 2832.957 |
| | Aug | 68 | 3680.6 | 2810.981 |
| | Sept | 69 | 3669.55 | 2789.004 |
| | Oct | 70 | 3658.5 | 2767.028 |
| | Nov | 71 | 3647.45 | 2745.051 |
| | Dec | 72 | 3636.4 | 2723.075 |

The little difference between the two results was due to external or environmental influence on the data. This shows that the independent variable (that is the environmental factors that influence the data) has little effect on the product sales.

**Moving Average for KEROSINE**

```
Data      KEROSINE
Length    36
NMissing  0

Moving Average
Length  2

Accuracy Measures
MAPE        70
MAD       1383
MSD    3018471

Time  KEROSINE      MA  Predict    Error
1         6078       *        *        *
2         3898  4988.0        *        *
3         3020  3459.0   4988.0  -1968.0
4         5607  4313.5   3459.0   2148.0
5         5990  5798.5   4313.5   1676.5
6         4501  5245.5   5798.5  -1297.5
7         5304  4902.5   5245.5     58.5
8         6302  5803.0   4902.5   1399.5
9         5731  6016.5   5803.0    -72.0
10        3224  4477.5   6016.5  -2792.5
11        3438  3331.0   4477.5  -1039.5
12        5607  4522.5   3331.0   2276.0
13         408  3007.5   4522.5  -4114.5
14         687   547.5   3007.5  -2320.5
15         890   788.5    547.5    342.5
```

| | | | | |
|---|---|---|---|---|
| 16 | 3408 | 2149.0 | 788.5 | 2619.5 |
| 17 | 4878 | 4143.0 | 2149.0 | 2729.0 |
| 18 | 3178 | 4028.0 | 4143.0 | -965.0 |
| 19 | 3716 | 3447.0 | 4028.0 | -312.0 |
| 20 | 3839 | 3777.5 | 3447.0 | 392.0 |
| 21 | 4321 | 4080.0 | 3777.5 | 543.5 |
| 22 | 6342 | 5331.5 | 4080.0 | 2262.0 |
| 23 | 6890 | 6616.0 | 5331.5 | 1558.5 |
| 24 | 7300 | 7095.0 | 6616.0 | 684.0 |
| 25 | 3400 | 5350.0 | 7095.0 | -3695.0 |
| 26 | 2707 | 3053.5 | 5350.0 | -2643.0 |
| 27 | 3878 | 3292.5 | 3053.5 | 824.5 |
| 28 | 4982 | 4430.0 | 3292.5 | 1689.5 |
| 29 | 4934 | 4958.0 | 4430.0 | 504.0 |
| 30 | 3699 | 4316.5 | 4958.0 | -1259.0 |
| 31 | 3776 | 3737.5 | 4316.5 | -540.5 |
| 32 | 4101 | 3938.5 | 3737.5 | 363.5 |
| 33 | 4434 | 4267.5 | 3938.5 | 495.5 |
| 34 | 3762 | 4098.0 | 4267.5 | -505.5 |
| 35 | 3708 | 3735.0 | 4098.0 | -390.0 |
| 36 | 4283 | 3995.5 | 3735.0 | 548.0 |

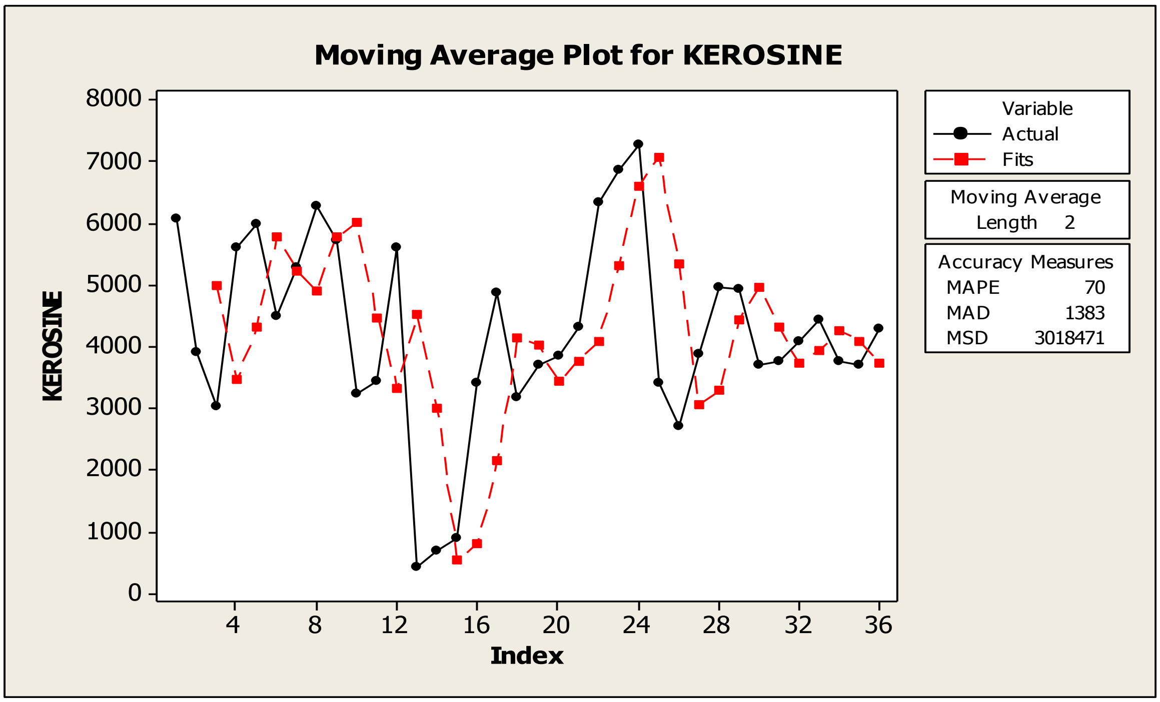


**Figure 4: Moving Average Plot for KEROSINE**

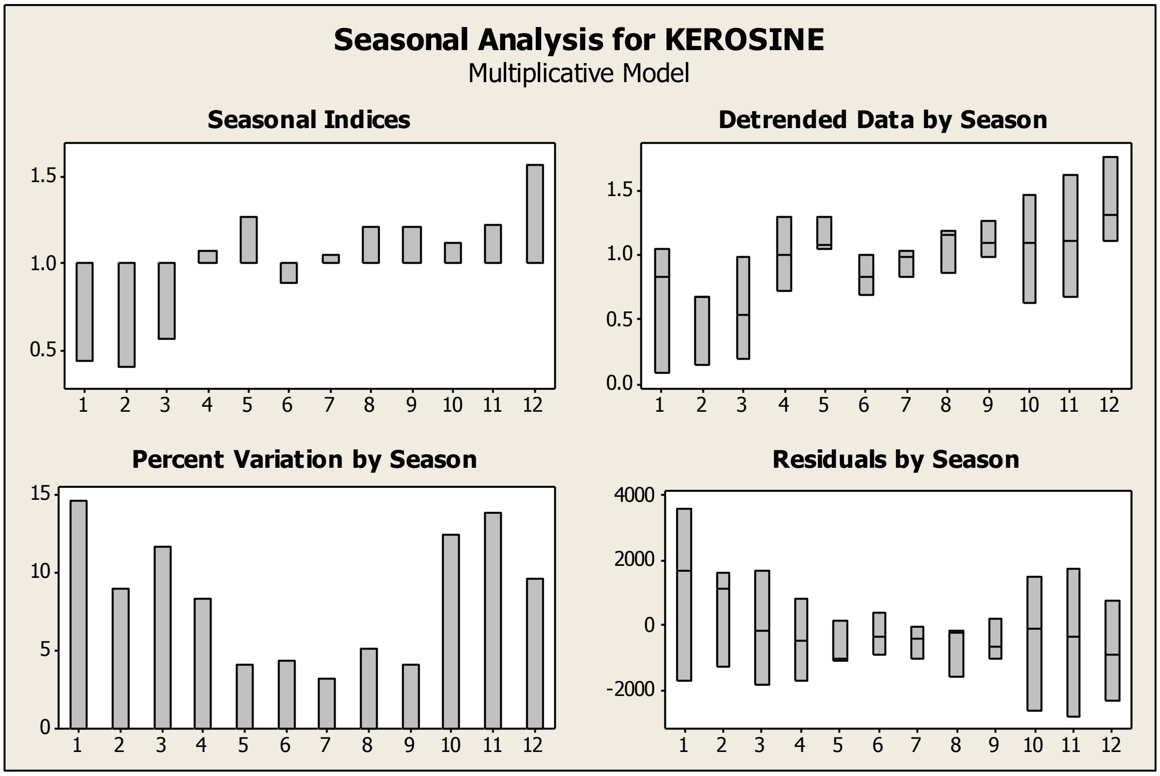


**Figure 5: Decomposition - Seasonal Analysis for KEROSINE**

Figure 5 shows a seasonal analysis of the data for the Kerosene product sales. The chart also shows the movement of the data periodically. From the seasonal indices plot, it shows that the influence of the season was more within the months of December, this is due to high increase in product sales and also slightly influence within the month of January and February over the period of three years data. This is due to little or no product sales during those seasons. However, detrend data by season was the plot of the seasonal influence of the absolute changes in values and removal of the effects of accumulating data sets from a trend by season. It was also observed that the seasonal influence of detrend data were high in the month of December and low in the month of January. Furthermore, the percent variation of detrend data by season were also plotted to show the percent variation of the data seasonally and it was noted that it was high in the month of January with about 15% variation. The residual plot by season was the error plot by season and was also high in the month of January.

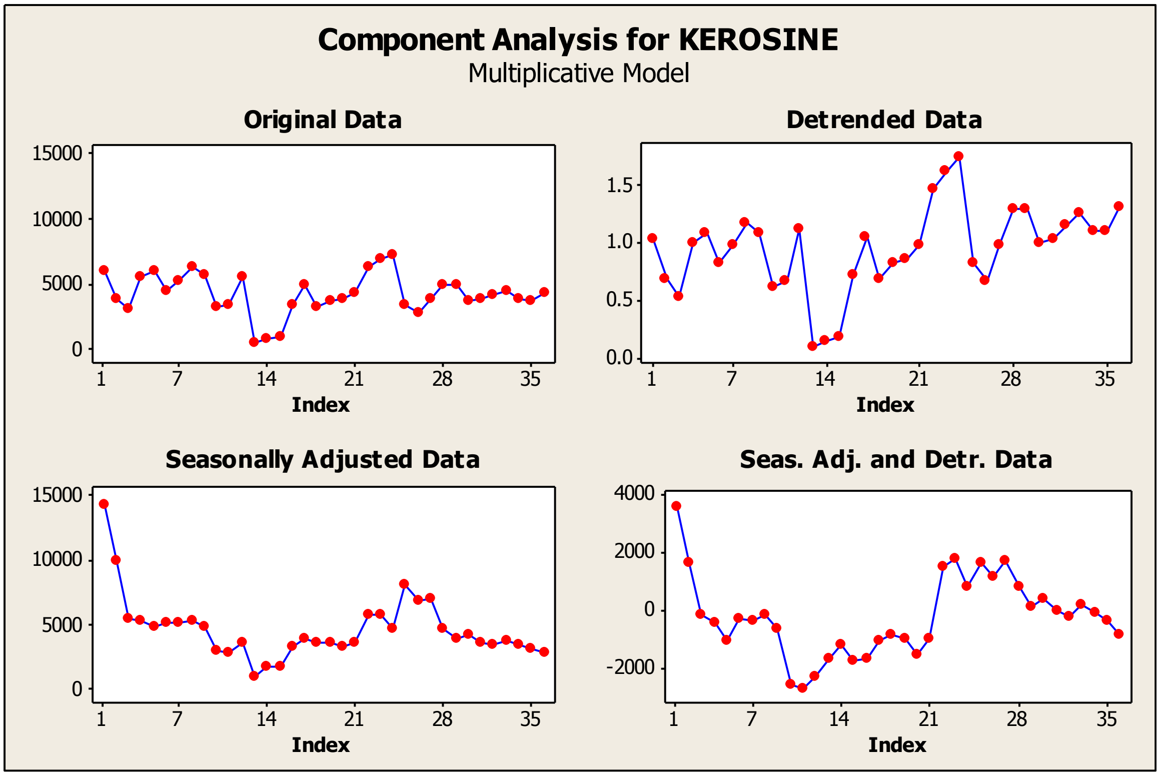


**Figure 6: Decomposition - Component Analysis for KEROSINE**

The decomposition component analysis plot was used to show the time series data plot of the values for the 36 months period of time. The detrend data plot was the plot of the data after the removal of the effects of accumulating data sets from a trend and to show only the absolute changes in values to allow potential cyclical patterns to be identified. Seasonal adjusted data plot was the plot of the data after the removal of the seasonal effects on the data. Seasonal adjusted and detrend data plot were used to show the data plot when they have already removed the seasonal effects and also remove the effects of accumulating data sets from a trend, to show only the absolute changes in values.

| Time | KEROSINE | Trend | Seasonal | Detrend | Deseason | Predict | Error |
|---|---|---|---|---|---|---|---|
| 1 | 6078 | 5838.23 | 0.42658 | 1.04107 | 14248.3 | 2490.46 | 3587.54 |
| 2 | 3898 | 5765.03 | 0.39574 | 0.67615 | 9850.0 | 2281.43 | 1616.57 |
| 3 | 3020 | 5691.84 | 0.55812 | 0.53058 | 5411.0 | 3176.71 | -156.71 |
| 4 | 5607 | 5618.64 | 1.07588 | 0.99793 | 5211.6 | 6044.97 | -437.97 |
| 5 | 5990 | 5545.45 | 1.26974 | 1.08017 | 4717.5 | 7041.29 | -1051.29 |
| 6 | 4501 | 5472.25 | 0.88455 | 0.82251 | 5088.5 | 4840.48 | -339.48 |
| 7 | 5304 | 5399.06 | 1.05188 | 0.98239 | 5042.4 | 5679.17 | -375.17 |
| 8 | 6302 | 5325.86 | 1.21036 | 1.18328 | 5206.7 | 6446.23 | -144.23 |
| 9 | 5731 | 5252.67 | 1.21354 | 1.09107 | 4722.5 | 6374.33 | -643.33 |
| 10 | 3224 | 5179.47 | 1.12372 | 0.62246 | 2869.1 | 5820.25 | -2596.25 |
| 11 | 3438 | 5106.28 | 1.21766 | 0.67329 | 2823.5 | 6217.70 | -2779.70 |
| 12 | 5607 | 5033.08 | 1.57224 | 1.11403 | 3566.3 | 7913.20 | -2306.20 |
| 13 | 408 | 4959.89 | 0.42658 | 0.08226 | 956.4 | 2115.78 | -1707.78 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 14 | 687 | 4886.69 | 0.39574 | 0.14059 | 1736.0 | 1933.84 | -1246.84 |
| 15 | 890 | 4813.50 | 0.55812 | 0.18490 | 1594.6 | 2686.49 | -1796.49 |
| 16 | 3408 | 4740.30 | 1.07588 | 0.71894 | 3167.6 | 5099.98 | -1691.98 |
| 17 | 4878 | 4667.11 | 1.26974 | 1.04519 | 3841.7 | 5926.02 | -1048.02 |
| 18 | 3178 | 4593.91 | 0.88455 | 0.69179 | 3592.8 | 4063.55 | -885.55 |
| 19 | 3716 | 4520.72 | 1.05188 | 0.82199 | 3532.7 | 4755.26 | -1039.26 |
| 20 | 3839 | 4447.52 | 1.21036 | 0.86318 | 3171.8 | 5383.12 | -1544.12 |
| 21 | 4321 | 4374.33 | 1.21354 | 0.98781 | 3560.7 | 5308.42 | -987.42 |
| 22 | 6342 | 4301.13 | 1.12372 | 1.47450 | 5643.8 | 4833.25 | 1508.75 |
| 23 | 6890 | 4227.93 | 1.21766 | 1.62964 | 5658.4 | 5148.18 | 1741.82 |
| 24 | 7300 | 4154.74 | 1.57224 | 1.75703 | 4643.1 | 6532.24 | 767.76 |
| 25 | 3400 | 4081.54 | 0.42658 | 0.83302 | 7970.4 | 1741.10 | 1658.90 |
| 26 | 2707 | 4008.35 | 0.39574 | 0.67534 | 6840.4 | 1586.25 | 1120.75 |
| 27 | 3878 | 3935.15 | 0.55812 | 0.98548 | 6948.4 | 2196.28 | 1681.72 |
| 28 | 4982 | 3861.96 | 1.07588 | 1.29002 | 4630.6 | 4155.00 | 827.00 |
| 29 | 4934 | 3788.76 | 1.26974 | 1.30227 | 3885.8 | 4810.76 | 123.24 |
| 30 | 3699 | 3715.57 | 0.88455 | 0.99554 | 4181.8 | 3286.61 | 412.39 |
| 31 | 3776 | 3642.37 | 1.05188 | 1.03669 | 3589.8 | 3831.35 | -55.35 |
| 32 | 4101 | 3569.18 | 1.21036 | 1.14900 | 3388.2 | 4320.01 | -219.01 |
| 33 | 4434 | 3495.98 | 1.21354 | 1.26831 | 3653.8 | 4242.52 | 191.48 |
| 34 | 3762 | 3422.79 | 1.12372 | 1.09910 | 3347.8 | 3846.24 | -84.24 |
| 35 | 3708 | 3349.59 | 1.21766 | 1.10700 | 3045.2 | 4078.66 | -370.66 |
| 36 | 4283 | 3276.40 | 1.57224 | 1.30723 | 2724.1 | 5151.28 | -868.28 |

## Trend Analysis for KEROSINE

```
Data      KEROSINE
Length    36
NMissing  0

Fitted Trend Equation
Yt = 4433 - 11.0503*t
```

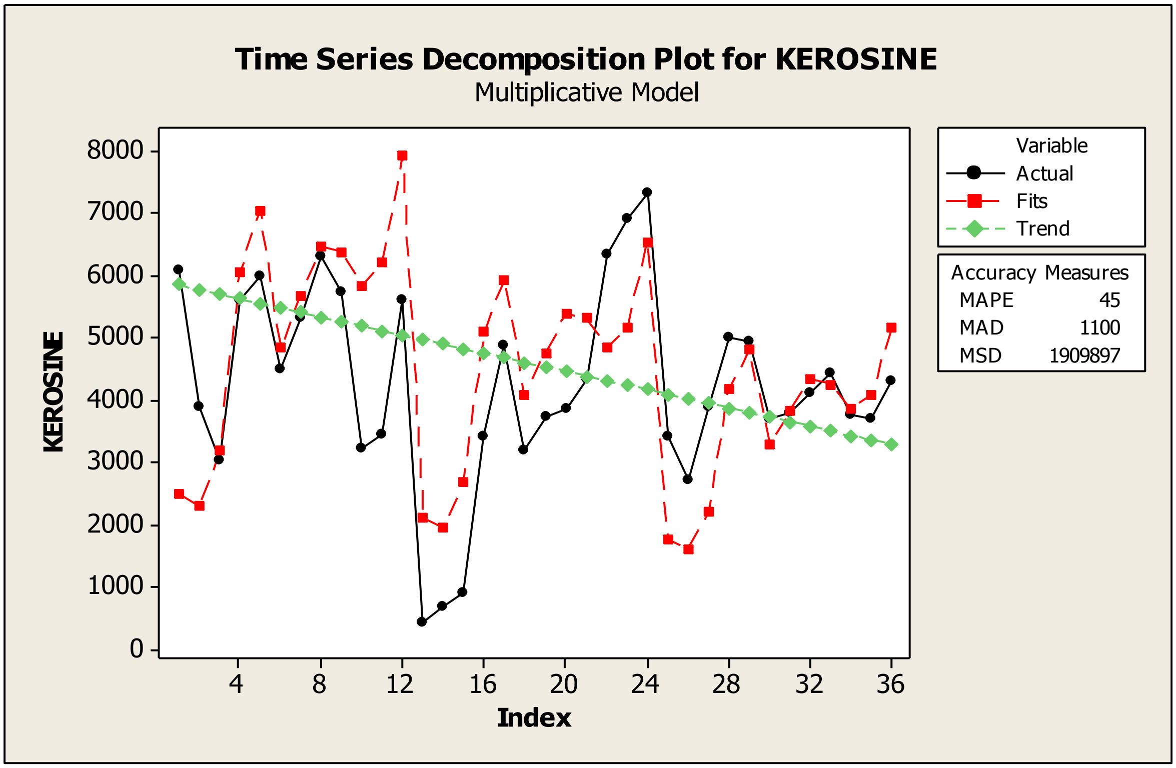


**Figure 7: Time Series Decomposition Plot for KEROSINE**

Figure 7 shows a trend forecasting analysis of the data for the Kerosene product sales. The chart also shows the movement of the data periodically. The trend line shows that the data contains seasonal influence and trend influence that is responsible for slightly reducing the yield by value at the trend component per month. The accuracy measures of the data were evaluated as shown. The mean absolute deviation is the measure of the average of the forecasting errors in the data and this was shown in the chart as 1100. It expresses accuracy in the same units as the data. However, the mean absolute percent error measures the percentage average of the sum of the forecasting errors divided by the sum of the values of the data and this is 45 percent in the chart. Furthermore, the mean squared deviation is the average squared deviation of the forecasting error in the data and is 1909897.

## Reference

1. Abraham B. & Ledolter J., 1983, *Statistical Methods for Forecasting*, John Wiley & Sons
2. Scott Armstrong, Fred Collopy, Andreas Graefe and Kesten C. Green (2010 (last updated)). "Answers to Frequently Asked Questions".
3. J. Scott Armstrong and Fred Collopy (1992). "Error Measures For Generalizing About Forecasting Methods: Empirical Comparisons". *International Journal of Forecasting* **8**: 69–80.
4. Nahmias, Steven (2009). *Production and Operations Analysis*.
5. Ellis, Kimberly (2008). *Production Planning and Inventory Control Virginia Tech*. McGraw Hill. ISBN 978-0-390-87106-0.
6. Yaffee, R., 2000, *Time Series Analysis and Forecasting*, Academic Press