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

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Abstract

This research work makes use of the regression analysis and time series analysis for the Diesel 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 petroleum 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 probability value shows and measures the accuracy errors in the data. 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 petroleum product sales.

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

1. Introduction to Time Series Analysis

Time series methods are statistical techniques that use historical demand data to predict future demand (Stevenson, 2005). Time series methods take into account possible internal structure in the data Time series data often arise when monitoring industrial processes or tracking corporate business metrics. The essential difference between modeling data via time series methods and using the process monitoring methods discussed earlier in this chapter is the following: Time series analysis accounts for the fact that data points taken over time may have an internal structure (such as autocorrelation, trend or seasonal variation) that should be accounted for. This section will give a brief overview of some of the more widely used techniques in the rich and rapidly growing field of time series modeling and analysis (Stevenson, 2005).

2. Two Main Goals of Time Series Analysis

There are two main goals of time series analysis: (a) identifying the nature of the phenomenon represented by the sequence of observations, and (b) forecasting (predicting future values of the time series variable). Both of these goals require that the pattern of observed time series data is identified and more or less formally described. Once the pattern is established, we can interpret and integrate it with other data (i.e., use it in our theory of the investigated phenomenon, e.g., seasonal commodity prices). Regardless of the depth of our understanding and the validity of our interpretation (theory) of the phenomenon, we can extrapolate the identified pattern to predict future events.

3. Time -Series Analysis and Forecasting

A time series is a sequence of observations obtained through measurements often recorded at equally spaced intervals. Often, time series data have characteristics that facilitate forecasting. These include seasonality, underlying trends, and relationships with past observations or other causal variables. Analysts can improve time series forecasts if they understand the nature of these components and identify the model that will best exploit the data's characteristics.

The purpose of this chapter is to provide a synopsis of time series analysis and forecasting. The first section discusses the characteristics of time series data. It reviews the common components useful in creating effective forecasts such as trend, seasonality, cyclical behavior, and irregular fluctuations. The chapter concludes with an introduction to time series forecasting and an overview of the forecasting model development process (Douglas, 1990).

Characteristics of Time-Series Data: time series is a "collection of observations made sequentially in time" (Chatfield, 1996). Examples are records of local daily rainfall levels, the quarterly U.S. Gross Domestic Product, and the monthly Marine Corps personnel strength for a particular rank and MOS. Time series analysis provides tools for choosing a representative model and producing forecasts.

There are two kinds of time series data:

• Continuous, where the data contain an observation at every instant of time, e.g., seismic activity recorded on a seismogram.

• Discrete, where the data contain observations taken at intervals, e.g. monthly crime figures.

Unless the data are purely random, observations in a time series are normally correlated and successive observations may be partly determined by past values (Chatfield, 1996). For example, the meteorological factors that affect the temperature on any given day are likely to exert some influence on the following day's weather. Thus, historical temperature observations are beneficial in forecasting future temperatures.

A time series is deterministic if it contains no random or probabilistic characteristics but proceeds in a fixed, predictable fashion (Chatfield, 1996). An example of a deterministic time series would be the data collected while conducting a classical physics experiment such as one demonstrating Newton's law of motion (Gujarati, 2003). More applicable to econometric applications are stochastic time series. Stochastic variables have indeterminate or random aspects. Although the values of individual observations cannot be predicted exactly, measuring the distribution of the observations may follow a predictable pattern. Statistical models can describe these patterns. These models assume that observations vary randomly about an underlying mean value that is a function of time. Time series data can also be characterized by one or more behavioral

Components: trend, seasonality, cyclical behavior, and random noise.

Trend Component: Trend is the general drift or tendency observed in a set of data over time. It is the underlying direction (an upward or downward tendency) and the degree of change in an observation set when consideration has been made for other components. Graphing a time series can be a useful and simple method of identifying the trend of a particular data set. This indicates an upward trend of the U.S. Gross Domestic Product over a ten year span. Analysts can also discern trends by dividing the data set into a number of ranges, and calculating the mean for each span. A consistent increase or decrease in the mean for the successive ranges indicates trend.

Trends in business or economic series may be due to a growth or contraction process. Trends in service manpower levels may be attributed to external economic factors or shifts in policy due to technical innovation, downsizing, or an increased or decreased operational requirement for certain occupational specialties.

Seasonal Component: In time series data, the seasonal component is the element of variation in a data set that is dependent on the time of year. Seasonality is quite common in econometric time series. It is less common in engineering and scientific data. This component recurs annually, with possible variations in amplitude. Seasonality is attributable to the change of seasons and/or the timing of such events as holidays or the start or completion of the school term. For example, the cost of fresh produce, retail sales levels, average daily rainfall amounts, and unemployment figures all demonstrate seasonal variation.

Incorporating seasonality in a forecast is useful when the time series has a discernible seasonal component. When the data contain a seasonal effect, it is useful to separate the seasonality from the other components in the time series. This enables the analyst to estimate and account for seasonal patterns.

Cyclical Component: Cyclical behavior describes any non-seasonal component that oscillates in a recognizable pattern. The 11-year sunspot cycle has been long recognized as naturally occurring cyclical activity. More ambiguous is the 5 to 7 year business cycle that a number of economists hypothesize influence global economic activity. If the data include a discernible cyclical component, the time series should span enough cycles to accurately model and forecast its effects (Yaffee, 2000). Cyclical behavior in which the oscillations extend over a very long period (such as 20 years) can often be accurately modeled as a trend for short-term forecasts (Chatfield, 1996).

General linear model: The general linear model (GLM) is a statistical linear model. It may be written as (Christensen, 2002).

$$\mathbf{Y} = \mathbf{X}\mathbf{B} + \mathbf{U},$$

where **Y** is a matrix with series of multivariate measurements, **X** is a matrix that might be a design matrix, **B** is a matrix containing parameters that are usually to be estimated and **U** is a matrix containing errors or noise. The errors are usually assumed to follow a multivariate normal distribution. If the errors do not follow a multivariate normal distribution, generalized linear models may be used to relax assumptions about **Y** and **U**.

The general linear model incorporates a number of different statistical models: ANOVA, ANCOVA, MANOVA, MANCOVA, ordinary linear regression, t-test and F-test. The general linear model is a generalization of multiple linear regression model to the case of more than one dependent variable. If **Y**, **B**, and **U** were column vectors, the matrix equation above would represent multiple linear regression.

Hypothesis tests with the general linear model can be made in two ways: multivariate or as several independent univariate tests. In multivariate tests the columns of **Y** are tested together, whereas in univariate tests the columns of **Y** are tested independently, i.e., as multiple univariate tests with the same design matrix (Wichura, 2006).

4. Linear Regression Models

In statistics, linear regression models often take the form of something like this:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2 + \beta_4 x_1^2 + \beta_5 x_2^2 + \varepsilon$$

Here a response variable y is modeled as a combination of constant, linear, interaction, and quadratic terms formed from two predictor variables x_1 and x_2. Uncontrolled factors and experimental errors are modeled by ε. Given data on x_1, x_2, and y, regression estimates the model parameters β_j (j = 1... 5).

More general linear regression models represent the relationship between a continuous response y and a continuous or categorical predictor **x** in the form:

$$y = \beta_1 f_1(\boldsymbol{x}) + ... + \beta_p f_p(\boldsymbol{x}) + \varepsilon$$

The response is modeled as a linear combination of (not necessarily linear) functions of the predictor, plus a random error ε. The expressions $f_j(\mathbf{x})$ (j = 1, ..., p) are the terms of the model. The β_j (j = 1... p) are the coefficients. Errors ε are assumed to be uncorrelated and distributed with mean 0 and constant (but unknown) variance.

Whether or not the predictor **x** is a vector of predictor variables, multivariate regression refers to the case where the response $\mathbf{y} = (y_1, ..., y_M)$ is a vector of M response variables. See Multivariate Regression for more on multivariate regression models (Rawlings, 1998).

5. Multiple Linear Regression

Multiple linear regression, is a generalization of linear regression (Mardia, 1979), by considering more than one independent variable, and a specific case of general linear models formed by restricting the number of dependent variables to one. The basic model for linear regression is

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_p X_{ip} + \epsilon_i.$$

In the formula above we consider n observations of one dependent variable and p independent variables. Thus, Y_i is the i^{th} observation of the dependent variable, X_{ij} is i^{th} observation of the j^{th} independent variable, j = 1, 2, ..., p. The values β_j represent parameters to be estimated, and ε_i is the i^{th} independent identically distributed normal error (Friston, 1995).

6. 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.

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

Year	Month	Time	Humidity (%)	Rainfall (mm)	Temp (C)	Diesel
2010	Jan	1	28.4	76	11.2	45000
	Feb	2	30.0	80	0.7	36000
	Mar	3	30.7	76	50.6	72000
	April	4	29.2	81	121.1	40000
	May	5	28.3	81	233.1	33000
	June	6	27.6	85	248.3	33000
	July	7	26.7	89	386.6	35000
	Aug	8	26.7	87	283.3	66000
	Sept	9	26.9	86	249.4	60000
	Oct	10	26.9	85	376.0	54000
	Nov	11	27.8	73	96.3	72000
	Dec	12	28.8	76	Nil	60000
2011	Jan	13	29.0	72	0.2	41000
	Feb	14	30.4	72	66.8	32000
	Mar	15	30.8	73	13.6	33000
	April	16	29.7	79	203.5	28000
	May	17	28.7	81	161.3	32000
	June	18	27.7	84	191.9	37000
	July	19	27.0	84	13.2	31000
	Aug	20	27.2	86	299.9	42000
	Sept	21	27.0	87	306.4	55000
	Oct	22	27.3	85	166.9	60000
	Nov	23	28.6	82	412.0	48000
	Dec	24	28.3	71	Nil	32000
2012	Jan	25	28.4	76	11.2	21000
	Feb	26	30.0	80	0.7	27000
	Mar	27	30.7	76	50.6	24000
	April	28	29.2	81	121.1	18000
	May	29	28.3	81	233.1	22000
	June	30	27.6	85	248.3	27000

	July	31	26.7	89	386.6	26000
	Aug	32	26.7	87	283.3	35000
	Sept	33	26.9	86	249.4	32000
	Oct	34	26.9	85	376.0	29700
	Nov	35	27.8	73	96.3	28900
	Dec	36	28.8	76	Nil	21600

7. Analysis of the Data

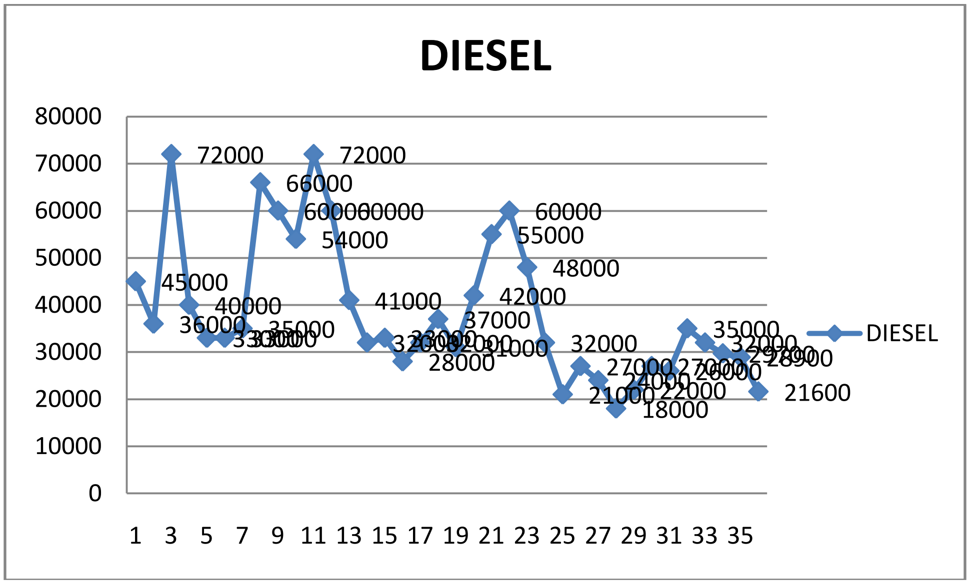

Figure 1: Time Series Analysis of Diesel

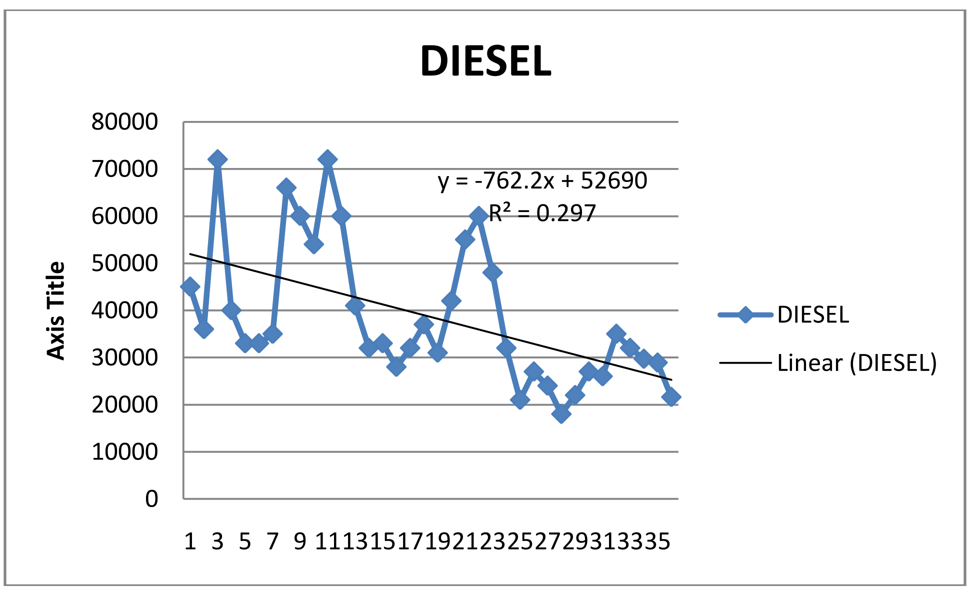

Figure 2: Forecasting Trend Model

Trend Equation: A trend equation has the form

$$F_t = a + bt \quad (1)$$

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 Diesel Product Sales using Trend estimation method

year	month	time	Diesel
2013	Jan	37	24488.6
	Feb	38	23726.4
	Mar	39	22964.2
	April	40	22202
	May	41	21439.8
	June	42	20677.6
	July	43	19915.4
	Aug	44	19153.2
	Sept	45	18391
	Oct	46	17628.8
	Nov	47	16866.6
	Dec	48	16104.4
2014	Jan	49	15342.2
	Feb	50	14580
	Mar	51	13817.8
	April	52	13055.6
	May	53	12293.4
	June	54	11531.2
	July	55	10769
	Aug	56	10006.8
	Sept	57	9244.6
	Oct	58	8482.4
	Nov	59	7720.2
	Dec	60	6958
2015	Jan	61	6195.8
	Feb	62	5433.6

	Mar	63	4671.4
	April	64	3909.2
	May	65	3147
	June	66	2384.8
	July	67	1622.6
	Aug	68	860.4
	Sept	69	98.2
	Oct	70	-664
	Nov	71	-1426.2
	Dec	72	-2188.4

8. General Regression Analysis: DIESEL versus Temp (C), Humidity (%), ...

```
Regression Equation

DIESEL  =  247235 - 4571.15 Temp (C) - 819.789 Humidity (%) + 16.8096 Rainfall
           (mm) - 866.187 MONTH/TIME

Coefficients

Term               Coef  SE Coef          T      P        95% CI           VIF
Constant         247235   101875    2.42683  0.021  (39458.4, 455011)
Temp (C)          -4571     2333   -1.95935  0.059  (-9329.3,     187)  2.17436
Humidity (%)       -820      681   -1.20438  0.238  (-2208.0,     568)  3.23077
Rainfall (mm)        17       25    0.67225  0.506  (  -34.2,      68)  2.82573
MONTH/TIME         -866      199   -4.35938  0.000  (-1271.4,    -461)  1.05142

Summary of Model
S = 12078.0         R-Sq = 40.48%        R-Sq(adj) = 32.79%

Analysis of Variance
Source            DF      Seq SS      Adj SS      Adj MS        F         P
Regression         4  3074978918  3074978918   768744729   5.2698  0.002342
  Temp (C)         1   220985119   560030153   560030153   3.8390  0.059118
  Humidity (%)     1    59049661   211599286   211599286   1.4505  0.237558
  Rainfall (mm)    1    22667677    65924980    65924980   0.4519  0.506404
  MONTH/TIME       1  2772276461  2772276461  2772276461  19.0042  0.000133
Error             31  4522196638  4522196638   145877311
Total             35  7597175556

Fits and Diagnostics for All Observations
Obs  DIESEL      Fit   SE Fit  Residual  St Resid
  1   45000  54432.1  5016.74   -9432.1  -0.85850
  2   36000  42796.4  5567.40   -6796.4  -0.63410
  3   72000  42848.4  5062.27   29151.6   2.65839  R
  4   40000  45925.1  3891.01   -5925.1  -0.51820
  5   33000  51055.6  3773.65  -18055.6  -1.57370
  6   33000  50365.6  3658.37  -17365.6  -1.50866
  7   35000  52659.0  4787.41  -17659.0  -1.59253
  8   66000  51696.0  4165.40   14304.0   1.26171
  9   60000  50165.5  3836.56    9834.5   0.85872
 10   54000  52247.2  4657.92    1752.8   0.15729
 11   72000  52402.8  5868.78   19597.2   1.85645
 12   60000  42887.3  3535.45   17112.7   1.48175
 13   41000  44389.4  4368.17   -3389.4  -0.30101
 14   32000  38243.2  4740.80   -6243.2  -0.56201
 15   33000  33834.5  4543.01    -834.5  -0.07457
 16   28000  36269.9  4097.68   -8269.9  -0.72788
 17   32000  37626.0  2282.81   -5626.0  -0.47435
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```
 18   37000  39385.9  2567.81    -2385.9  -0.20217
 19   31000  38715.7  6476.17    -7715.7  -0.75682
 20   42000  40115.0  2929.80     1885.0   0.16087
 21   55000  39452.5  3166.32    15547.5   1.33391
 22   60000  36509.6  3512.12    23490.4   2.03273  R
 23   48000  36280.3  6320.60    11719.7   1.13871
 24   32000  38877.6  5573.53    -6877.6  -0.64186
 25   21000  33643.6  3788.34   -12643.6  -1.10247
 26   27000  22008.0  5602.27     4992.0   0.46654
 27   24000  22059.9  5213.25     1940.1   0.17807
 28   18000  25136.6  3870.59    -7136.6  -0.62377
 29   22000  30267.1  3267.53    -8267.1  -0.71099
 30   27000  29577.1  3384.51    -2577.1  -0.22228
 31   26000  31870.5  4466.47    -5870.5  -0.52314
 32   35000  30907.5  4058.19     4092.5   0.35976
 33   32000  29377.0  4044.33     2623.0   0.23048
 34   29700  31458.7  4754.58    -1758.7  -0.15840
 35   28900  31614.3  6067.14    -2714.3  -0.25990
 36   21600  22098.9  4929.07     -498.9  -0.04524

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

Table 3: Forecasting results for Diesel product Sales using Regression model

Year	Month	Temp (C)	Humidity (%)	Rainfall (mm)	Time	Diesel
2013	Jan	28.8	76	0	37	21233
	Feb	28.8	76	0	38	20366.81
	Mar	28.8	76	0	39	19500.62
	April	28.8	76	0	40	18634.44
	May	28.8	76	0	41	17768.25
	June	28.8	76	0	42	16902.06
	July	28.8	76	0	43	16035.88
	Aug	28.8	76	0	44	15169.69
	Sept	28.8	76	0	45	14303.5
	Oct	28.8	76	0	46	13437.31
	Nov	28.8	76	0	47	12571.13
	Dec	28.8	76	0	48	11704.94
2014	Jan	28.8	76	0	49	10838.75
	Feb	28.8	76	0	50	9972.566
	Mar	28.8	76	0	51	9106.379
	April	28.8	76	0	52	8240.192
	May	28.8	76	0	53	7374.005
	June	28.8	76	0	54	6507.818
	July	28.8	76	0	55	5641.631
	Aug	28.8	76	0	56	4775.444
	Sept	28.8	76	0	57	3909.257
	Oct	28.8	76	0	58	3043.07
	Nov	28.8	76	0	59	2176.883
	Dec	28.8	76	0	60	1310.696
2015	Jan	28.8	76	0	61	444.509
	Feb	28.8	76	0	62	-421.678
	Mar	28.8	76	0	63	-1287.87
	April	28.8	76	0	64	-2154.05

	May	28.8	76	0	65	-3020.24
	June	28.8	76	0	66	-3886.43
	July	28.8	76	0	67	-4752.61
	Aug	28.8	76	0	68	-5618.8
	Sept	28.8	76	0	69	-6484.99
	Oct	28.8	76	0	70	-7351.17
	Nov	28.8	76	0	71	-8217.36
	Dec	28.8	76	0	72	-9083.55

Table 4: Forecasting Results of Diesel Product Sales

year	month	time	Trend estimation	Regression
2013	Jan	37	24488.6	21233
	Feb	38	23726.4	20366.81
	Mar	39	22964.2	19500.62
	April	40	22202	18634.44
	May	41	21439.8	17768.25
	June	42	20677.6	16902.06
	July	43	19915.4	16035.88
	Aug	44	19153.2	15169.69
	Sept	45	18391	14303.5
	Oct	46	17628.8	13437.31
	Nov	47	16866.6	12571.13
	Dec	48	16104.4	11704.94
2014	Jan	49	15342.2	10838.75
	Feb	50	14580	9972.566
	Mar	51	13817.8	9106.379
	April	52	13055.6	8240.192
	May	53	12293.4	7374.005
	June	54	11531.2	6507.818
	July	55	10769	5641.631
	Aug	56	10006.8	4775.444
	Sept	57	9244.6	3909.257
	Oct	58	8482.4	3043.07
	Nov	59	7720.2	2176.883
	Dec	60	6958	1310.696
2015	Jan	61	6195.8	444.509
	Feb	62	5433.6	-421.678
	Mar	63	4671.4	-1287.87
	April	64	3909.2	-2154.05
	May	65	3147	-3020.24
	June	66	2384.8	-3886.43
	July	67	1622.6	-4752.61
	Aug	68	860.4	-5618.8
	Sept	69	98.2	-6484.99

	Oct	70	-664	-7351.17
	Nov	71	-1426.2	-8217.36
	Dec	72	-2188.4	-9083.55

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 DIESEL

```
Data      DIESEL
Length    36
NMissing  0

Moving Average
Length  2

Accuracy Measures
MAPE          25
MAD         9866
MSD    175309779
```

Time	DIESEL	MA	Predict	Error
1	45000	*	*	*
2	36000	40500	*	*
3	72000	54000	40500	31500
4	40000	56000	54000	-14000
5	33000	36500	56000	-23000
6	33000	33000	36500	-3500
7	35000	34000	33000	2000
8	66000	50500	34000	32000
9	60000	63000	50500	9500
10	54000	57000	63000	-9000
11	72000	63000	57000	15000
12	60000	66000	63000	-3000
13	41000	50500	66000	-25000
14	32000	36500	50500	-18500
15	33000	32500	36500	-3500
16	28000	30500	32500	-4500
17	32000	30000	30500	1500
18	37000	34500	30000	7000
19	31000	34000	34500	-3500
20	42000	36500	34000	8000
21	55000	48500	36500	18500
22	60000	57500	48500	11500
23	48000	54000	57500	-9500
24	32000	40000	54000	-22000
25	21000	26500	40000	-19000
26	27000	24000	26500	500
27	24000	25500	24000	0
28	18000	21000	25500	-7500
29	22000	20000	21000	1000
30	27000	24500	20000	7000
31	26000	26500	24500	1500
32	35000	30500	26500	8500
33	32000	33500	30500	1500
34	29700	30850	33500	-3800

35	28900	29300	30850	-1950
36	21600	25250	29300	-7700

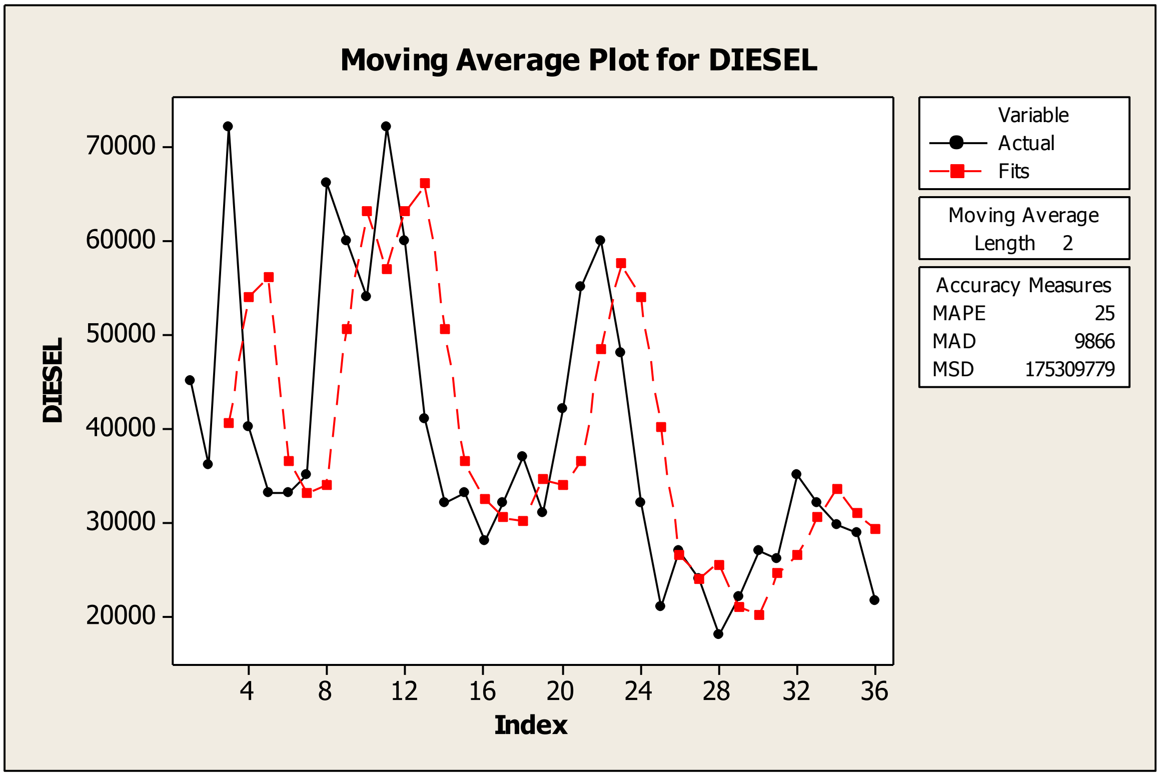

Figure 3: Moving Average Plot for DIESEL

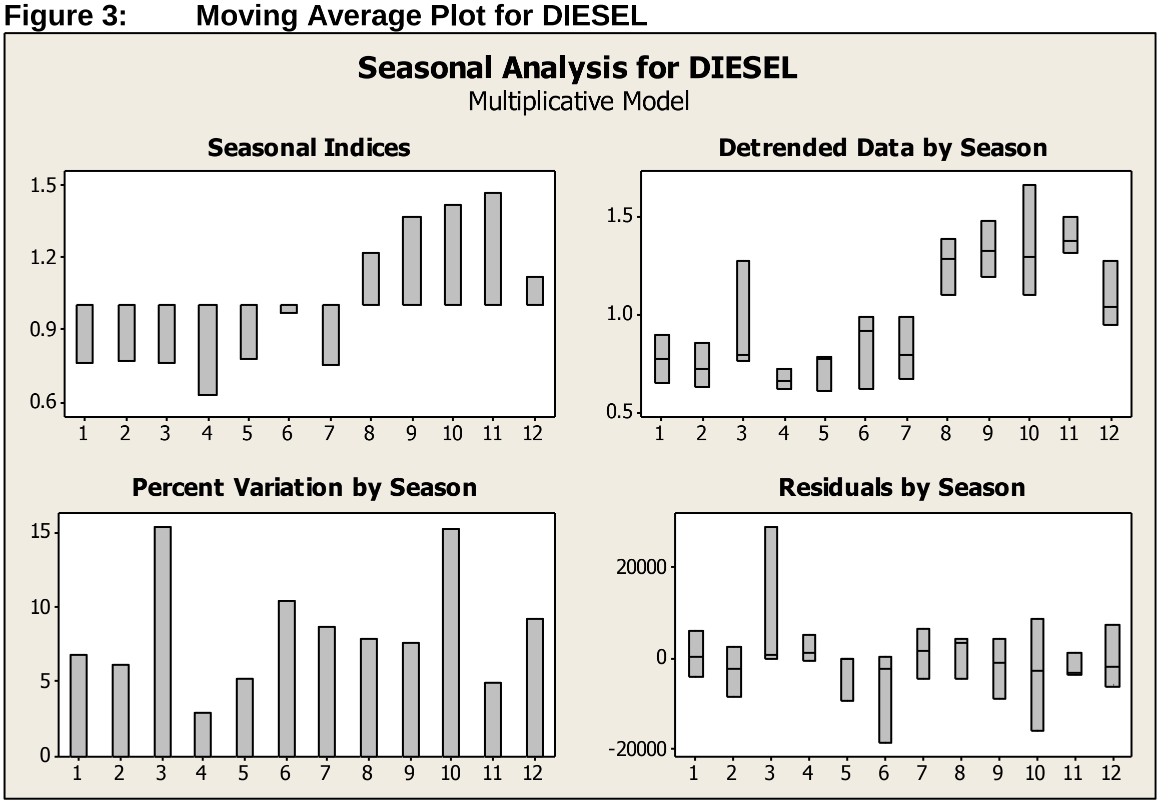

Figure 4: Decomposition - Seasonal Analysis for DIESEL

Figure 4 shows a seasonal analysis of the data for the diesel 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 November, this is due to high increase in product sales and also slightly influence within the month of April 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 October and low in the month of Aprl. 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 months of March and October with about 15% variation. The residual plot by season was the error plot by season and was also high in the month of March.

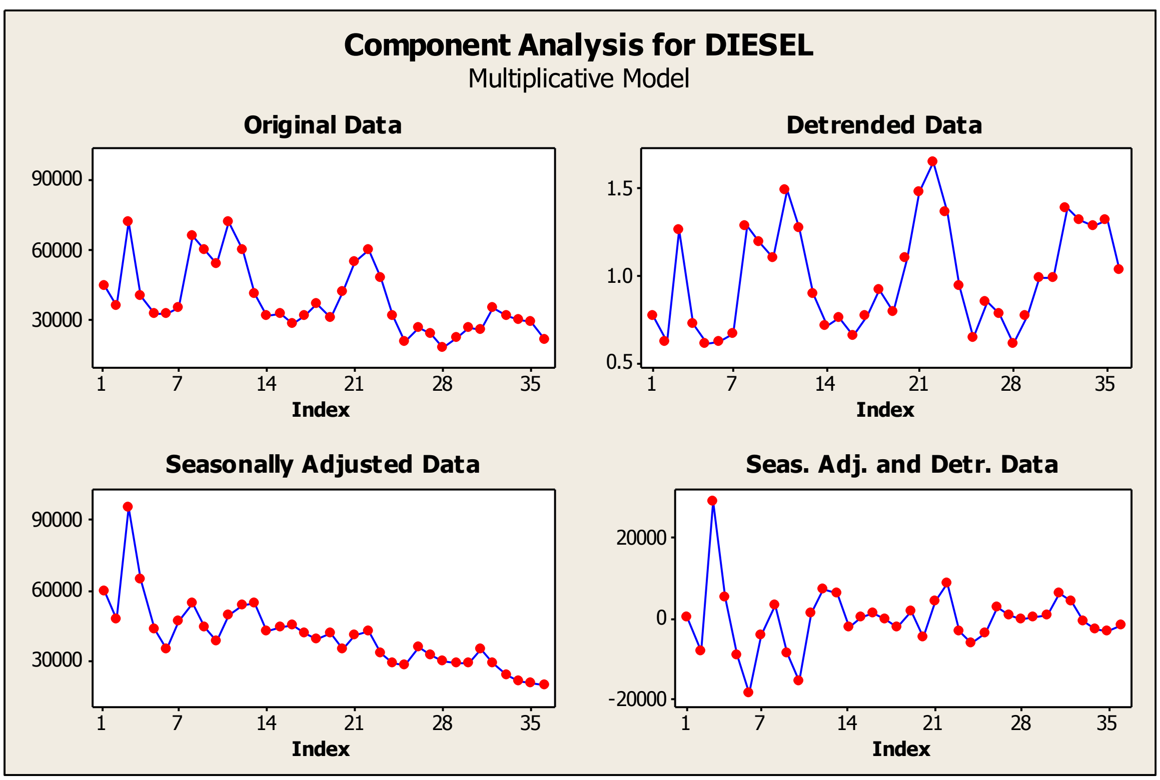

Figure 5: Decomposition - Component Analysis for DIESEL

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.

Trend Analysis for DIESEL

```
Data       DIESEL
Length     36
NMissing   0

Fitted Trend Equation
Yt = 52690 - 762.239*t
```

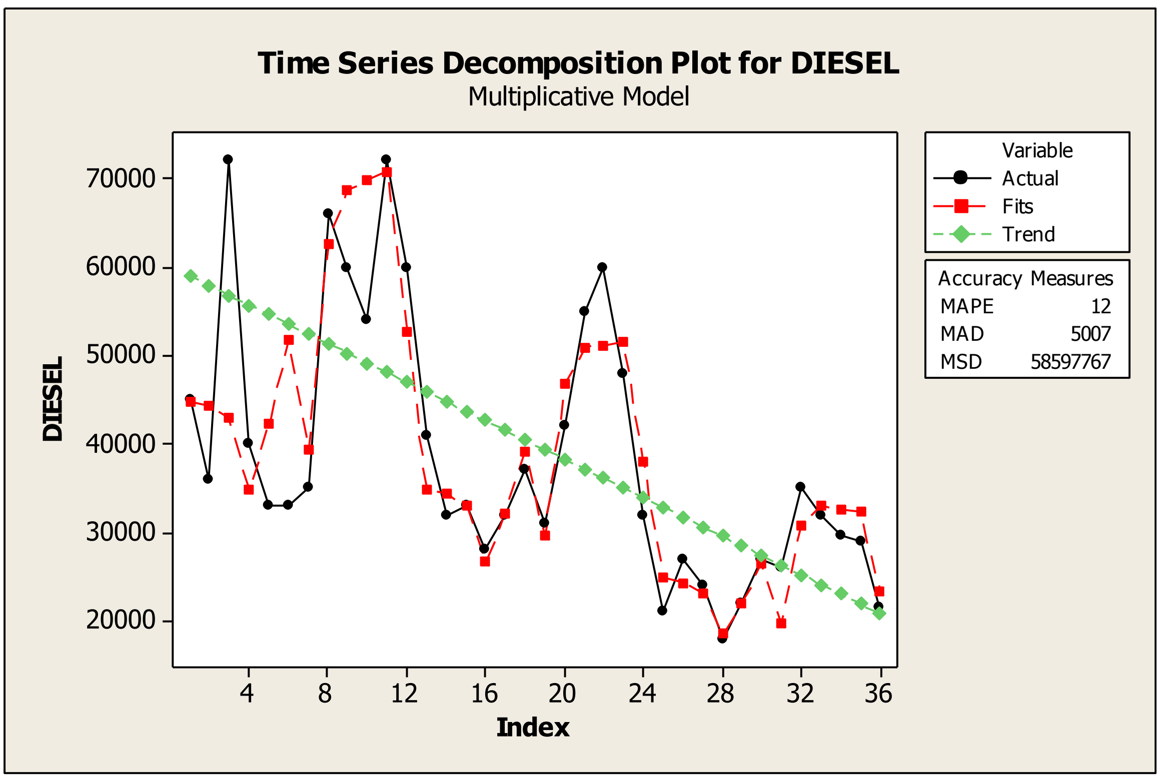

Figure 6: Time Series Decomposition Plot for DIESEL

Figure 6 shows a trend forecasting analysis of the data for the diesel 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 5007. 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 12 percent in the chart. Furthermore, the mean squared deviation is the average squared deviation of the forecasting error in the data and is 58597767.

In conclusion, it shows that time series analysis explain the analysis of trend and seasonal influence on the data. It was also used to forecast the future product sales of the case study company. While the regression analysis was used to show the effect of the external (i.e. independent variables) factors in the forecast.

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