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Research Article

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Measuring the Forecasting Accuracy for Masters Energy Oil and Gas Products

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Abstract The work focused on measuring the forecasting accuracy in the demand of the crude oil products in masters Energy Oil and Gas. Data of the products were collected covering a period of three years of monthly product demand. Forecasting accuracy models were used to measure and to analyze the accuracy of the forecast. Time series decomposition analyses were adapted to aid in resolving the forecasting accuracy of the master's energy oil and gas. However, the results show that the forecast is still within its control unit and is not bias. Therefore, the researcher advice the case study company to make use of the forecast in predicting their future products demands.

Keywords Forecasting accuracy, Mean Absolute Deviation, Mean Absolute Percentage Error, Mean Square Error, Root Mean Square Error, Time series, Decomposition analysis, Forecasting Errors, Seasonal Demand, seasonal Index.

Introduction

Forecasting accuracy: In statistics, the accuracy of forecast is the degree of closeness of the statement of quantity to that quantity's actual (true) value [**1**]. The actual value usually cannot be measured at the time the forecast is made because the statement concerns the future. For most businesses, more accurate forecasts increase their effectiveness to serve the demand while lowering overall operational costs.

Use of the accuracy estimates: The accuracy, when computed, provides a quantitative estimate of the expected quality of the forecasts. For inventory optimization, the estimation of the forecasts accuracy can serve several purposes:

- To choose among several forecasting models that serve to estimate the lead demand which model should be favored.
- To compute the safety stock typically assuming that the forecast errors follow a normal distribution.
- To prioritize the items that need the most dedicated attention because raw statistical forecasts are not reliable enough.

In other contexts, such as strategic planning, the accuracy estimates are used to support the what-if analysis, considering distinct scenarios and their respective likelihood.

Impact of aggregation on the accuracy: It is a frequent misconception to interpret the quality of the forecasting model as the primary factor driving the accuracy of the forecasts: this is not the case. The most important factor driving the value of the accuracy is the intrinsic volatility of the phenomenon being forecasted. In practice, in commerce or manufacturing, this volatility highly correlated to the aggregation level:

- Larger areas, such as national forecasts versus local forecasts, yield more accuracy.
- Idem for longer periods, such as monthly forecasts versus daily forecasts [2].

Anecdotal evidence: At Lokad, we routinely observe that there is no such thing as a good accuracy; it's specific of the context. When forecasting the next-day nationwide electricity consumption for a large European country, 0.5% of error was considered as relatively inaccurate; while achieving less than 80% of error for the store-level forecasts of the first day of sales of newly introduced fresh products was considered a significant achievement. Then, once a level of aggregation is given, the quality of the forecasting model plays indeed to primary role in the accuracy that can be achieved. Finally, the accuracy decreases when looking further ahead in the future.

Empirical accuracy vs. real accuracy: The term accuracy is most frequently used referring to quality of a physical measurement of some kind. Unfortunately, this vision is somewhat misleading when it comes to statistical forecasting. Indeed, unlike the physical setup where the measurement could be compared to alternative methods, the real accuracy of forecast should be strictly measured against data you don't have. Indeed, once the data is available, it is always possible to produce perfectly accurate forecasts, as it only requires mimicking the data. This single question has kept statisticians puzzled for more than a century, as a deeply satisfying viewpoint has only been found at the end of the 20th century with the advent of Vapnik-Chervonenkis theory [3]. The accuracy of the forecasts can only be practically measured against available data; however, when the data is available, those forecasts aren't true forecasts anymore, being statements about the past rather than being statements about the future. Thus, those measurements are referred as the empirical accuracy, as opposed to the real accuracy. Over fitting problems can lead to large discrepancies between the empirical accuracy and the real accuracy. In practice, a careful use of back testing can mitigate most over fitting problems when forecasting time-series.

Popular accuracy metrics: There are many metrics to measure accuracy of forecasts. The most widely used metrics are:

- MAE (mean absolute error)
- MAPE (mean absolute percentage error)
- MSE (mean square error)
- sMAPE (symmetric mean absolute percentage error)
- Pinball loss (a generalization of the MAE for quantile forecasts) [4]

In practice, a metric should be favored over another based on its capacity to reflect the costs incurred by the company because of the inaccuracies of the forecasts.

Lokad's gotcha: It's better to be approximately correct than exactly wrong. In our experience dealing with commerce or manufacturing companies, we routinely observe that too little attention is paid to the choice of the accuracy metric. Indeed, the ideal metric should not return values expressed as percentages, but should return Dollars or Euros, precisely reflecting the cost of the inefficiencies caused by the inaccurate forecasts. In particular, while most popular metrics are symmetric (the pinball loss being a notable exception), risks of over forecasting vs. under forecasting are not symmetric in practice. We suggest adopting a viewpoint where the metric is closer to an economic cost function – carefully modeled to fit the business constraints – rather than a raw statistical indicator. Also, it's quite important not to perform any planning implicitly assuming that the forecasts are exact. Uncertainty is unavoidable in business and should be accounted for [5].

Calculating demand forecast accuracy is the process of determining the accuracy of forecasts made regarding customer demand for a product.

Importance of forecasts: Understanding and predicting customer demand is vital to manufacturers and distributors to avoid stock-outs and maintain adequate inventory levels. While forecasts are never perfect, they are necessary to prepare for actual demand. In order to maintain an optimized inventory and effective supply chain, accurate demand forecasts are imperative.

Calculating the accuracy of supply chain forecasts: Forecast accuracy in the supply chain is typically measured using the Mean Absolute Percent Error or MAPE. Statistically MAPE is defined as the average of percentage errors. Most practitioners, however, define and use the MAPE as the Mean Absolute Deviation divided by Average Sales. This is in effect a volume weighted MAPE. This is also referred to as the MAD/Mean ratio.
A simpler and more elegant method to calculate MAPE across all the products forecasted is to divide the sum of the absolute deviations by the total sales of all products.
This calculation, where is the actual value and the forecast, is also known as WAPE, Weighted Absolute Percent Error. Another interesting option is the weighted. The advantage of this measure is that could weight errors, so you can define how to weight for your relevant business, ex gross profit or ABC. The only problem is that for seasonal products you will create an undefined result when sales = 0 and that is not symmetrical, that means that you can be much more inaccurate if sales are higher than if they are lower than the forecast. So sMAPE is also used to correct this, it is known as symmetric Mean Absolute Percentage Error.
Last but not least, for intermittent demand patterns none of the above are really useful. So you can consider MASE (Mean Absolute Scaled Error) as a good KPI to use in those situations, the problem is that is not as intuitive as the ones mentioned before [6].

Calculating forecast error: The forecast error needs to be calculated using actual sales as a base. There are several forms of forecast error calculation methods used, namely Mean Percent Error, Root Mean Squared Error, Tracking Signal and Forecast Bias [7].

Research Method: The use of qualitative research was adapted to analysis the collected products data of the case study company. Time series decomposition analyses were also employed to aid in the analysis of the forecasting accuracy of the data.

Table 1: Monthly Quantity Sales for Masters Energy Oil and Gas Company

Year	*Month*	**Month Code**	**KEROSINE**	**DIESEL**	**PETROLEUM**
2012	Jan	1	6180	45185	132100
	Feb	2	4000	36102	99100
	Mar	3	3122	72102	132100
	April	4	5709	40170	66100
	May	5	6092	33170	132100
	June	6	4603	33170	90100
	July	7	5406	35120	66100
	Aug	8	6404	66120	219100
	Sept	9	5833	60120	138100
	Oct	10	3326	54100	231102
	Nov	11	3540	72100	132102
	Dec	12	5709	60100	99160
2013	Jan	13	510	41100	6760
	Feb	14	789	32100	143100
	Mar	15	992	33100	99100
	April	16	3510	28102	231100
	May	17	4980	32108	99100
	June	18	3280	37100	132100
	July	19	3818	31105	99100

	Aug	20	3941	42109	232100
	Sept	21	4423	55100	99100
	Oct	22	6444	60100	68100
	Nov	23	6992	48100	132100
	Dec	24	7402	32100	165100
2014	Jan	25	3502	21100	132100
	Feb	26	2809	27102	198100
	Mar	27	3980	24102	240100
	April	28	5084	18110	99100
	May	29	5036	22110	240100
	June	30	3801	27110	66100
	July	31	3878	26110	132100
	Aug	32	4203	35110	198100
	Sept	33	4536	32110	231100
	Oct	34	3864	29810	99100
	Nov	35	3810	29002	18705
	Dec	36	4385	21700	11002

Models employed in measuring the forecasting Accuracy of the Products

Forecasting accuracy

The parameters for forecasting errors are given by equations (1) to (19) were

$$E_t = Y_t - F_t \tag{1}$$

Where E is the forecast error at period t, Y is the actual value at period t, and F is the forecast for period t.

Measures of aggregate error:

Mean absolute error (MAE)
$$MAE = \frac{\sum_{t=1}^{N} |E_t|}{N} \tag{2}$$

Mean Absolute Percentage Error (MAPE)
$$MAPE = \frac{\sum_{t=1}^{N} |\frac{E_t}{Y_t}|}{N} \tag{3}$$

Mean Absolute Deviation (MAD)
$$MAD = \frac{\sum_{t=1}^{N} |E_t|}{N} \tag{4}$$

Percent Mean Absolute Deviation (PMAD)
$$PMAD = \frac{\sum_{t=1}^{N} |E_t|}{\sum_{t=1}^{N} |Y_t|} \tag{5}$$

Mean squared error (MSE)
$$MSE = \frac{\sum_{t=1}^{N} E_t^2}{N} \tag{6}$$

Root Mean squared error (RMSE)
$$RMSE = \sqrt{\frac{\sum_{t=1}^{N} E_t^2}{N}} \tag{7}$$

Forecast skill (SS)
$$SS = 1 - \frac{MSE_{forecast}}{MSE_{ref}} \tag{8}$$

Average of Errors (E)
$$\bar{E} = \frac{\sum_{i=1}^{N} e_i}{N} \tag{9}$$

$$Tracking\ signal\ = \left(\frac{Cumulative\ \ error}{MAD}\right) \tag{10}$$

$$Seasonal\ demand\ = (seasonal\ index) \times (deseasonalized\ demand) \tag{11}$$

$$Deseasonalized\ demand\ = \left(\frac{actual\ \ seasonal\ \ demand}{seasonal\ \ index}\right) \tag{12}$$

Time Series Decomposition for Kerosene

Multiplicative Model

Data KEROSINE
Length 36
NMissing 0

Fitted Trend Equation
Yt = 5959 - 71.3903*t

Seasonal Indices

Period	Index
1	0.44175
2	0.41182
3	0.57083
4	1.07343
5	1.26184
6	0.88709
7	1.05029
8	1.20481
9	1.20762
10	1.12068
11	1.21244
12	1.55739

Accuracy Measures
MAPE 41
MAD 1085
MSD 1871402

Time	KEROSINE	Trend	Seasonal	Detrend	Deseason	Predict	Error
1	6180	5887.93	0.44175	1.04961	13989.9	2600.98	3579.02
2	4000	5816.54	0.41182	0.68769	9712.9	2395.39	1604.61
3	3122	5745.15	0.57083	0.54342	5469.2	3279.52	-157.52
4	5709	5673.76	1.07343	1.00621	5318.5	6090.38	-381.38
5	6092	5602.37	1.26184	1.08740	4827.9	7069.30	-977.30
6	4603	5530.98	0.88709	0.83222	5188.9	4906.48	-303.48
7	5406	5459.59	1.05029	0.99018	5147.2	5734.14	-328.14
8	6404	5388.20	1.20481	1.18852	5315.4	6491.74	-87.74
9	5833	5316.81	1.20762	1.09709	4830.2	6420.69	-587.69
10	3326	5245.42	1.12068	0.63408	2967.8	5878.43	-2552.43
11	3540	5174.03	1.21244	0.68419	2919.7	6273.22	-2733.22
12	5709	5102.64	1.55739	1.11883	3665.8	7946.78	-2237.78
13	510	5031.25	0.44175	0.10137	1154.5	2222.54	-1712.54
14	789	4959.86	0.41182	0.15908	1915.9	2042.58	-1253.58
15	992	4888.46	0.57083	0.20293	1737.8	2790.50	-1798.50

16	3510	4817.07	1.07343	0.72866	3269.9	5170.79	-1660.79
17	4980	4745.68	1.26184	1.04937	3946.6	5988.30	-1008.30
18	3280	4674.29	0.88709	0.70171	3697.5	4146.53	-866.53
19	3818	4602.90	1.05029	0.82948	3635.2	4834.38	-1016.38
20	3941	4531.51	1.20481	0.86969	3271.1	5459.61	-1518.61
21	4423	4460.12	1.20762	0.99168	3662.6	5386.14	-963.14
22	6444	4388.73	1.12068	1.46831	5750.1	4918.37	1525.63
23	6992	4317.34	1.21244	1.61951	5766.9	5234.54	1757.46
24	7402	4245.95	1.55739	1.74331	4752.8	6612.59	789.41
25	3502	4174.56	0.44175	0.83889	7927.6	1844.10	1657.90
26	2809	4103.17	0.41182	0.68459	6820.9	1689.78	1119.22
27	3980	4031.78	0.57083	0.98716	6972.3	2301.48	1678.52
28	5084	3960.39	1.07343	1.28371	4736.2	4251.20	832.80
29	5036	3889.00	1.26184	1.29493	3991.0	4907.30	128.70
30	3801	3817.61	0.88709	0.99565	4284.8	3386.57	414.43
31	3878	3746.22	1.05029	1.03518	3692.3	3934.61	-56.61
32	4203	3674.83	1.20481	1.14373	3488.5	4427.47	-224.47
33	4536	3603.44	1.20762	1.25880	3756.1	4351.59	184.41
34	3864	3532.05	1.12068	1.09398	3447.9	3958.30	-94.30
35	3810	3460.66	1.21244	1.10095	3142.4	4195.86	-385.86
36	4385	3389.27	1.55739	1.29379	2815.6	5278.41	-893.41

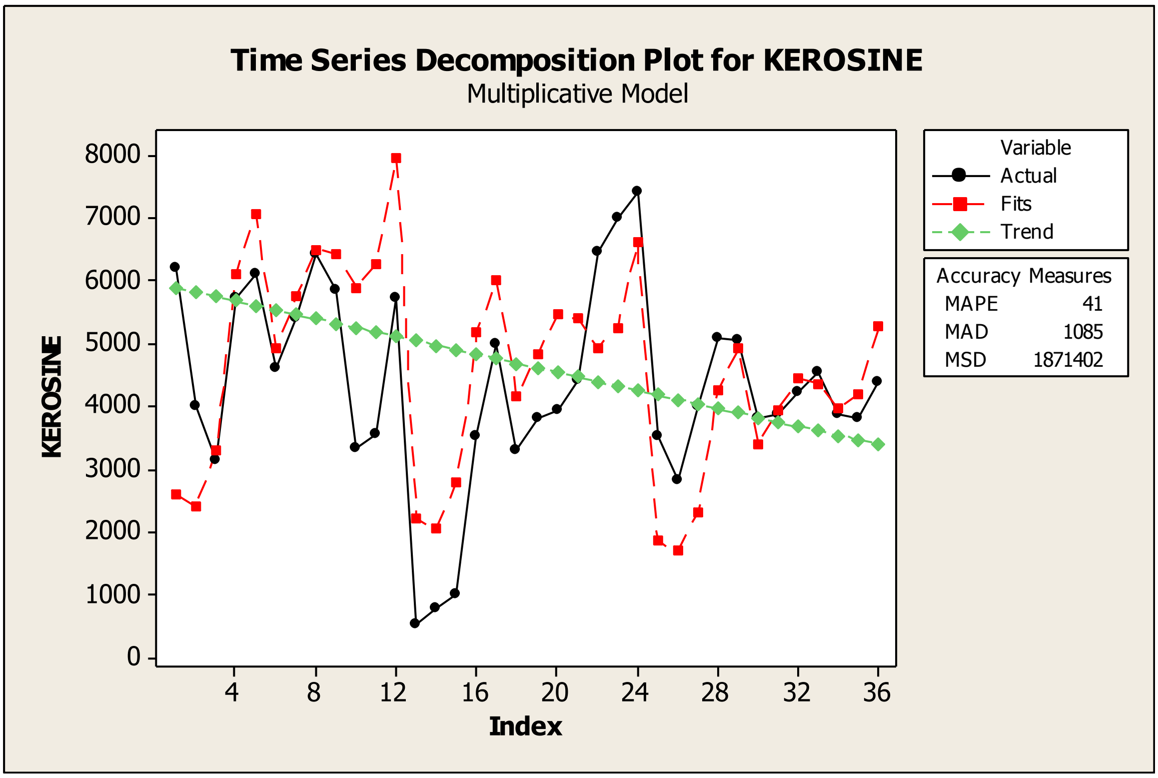

Figure 1: *Time Series Decomposition Plot for Kerosene*

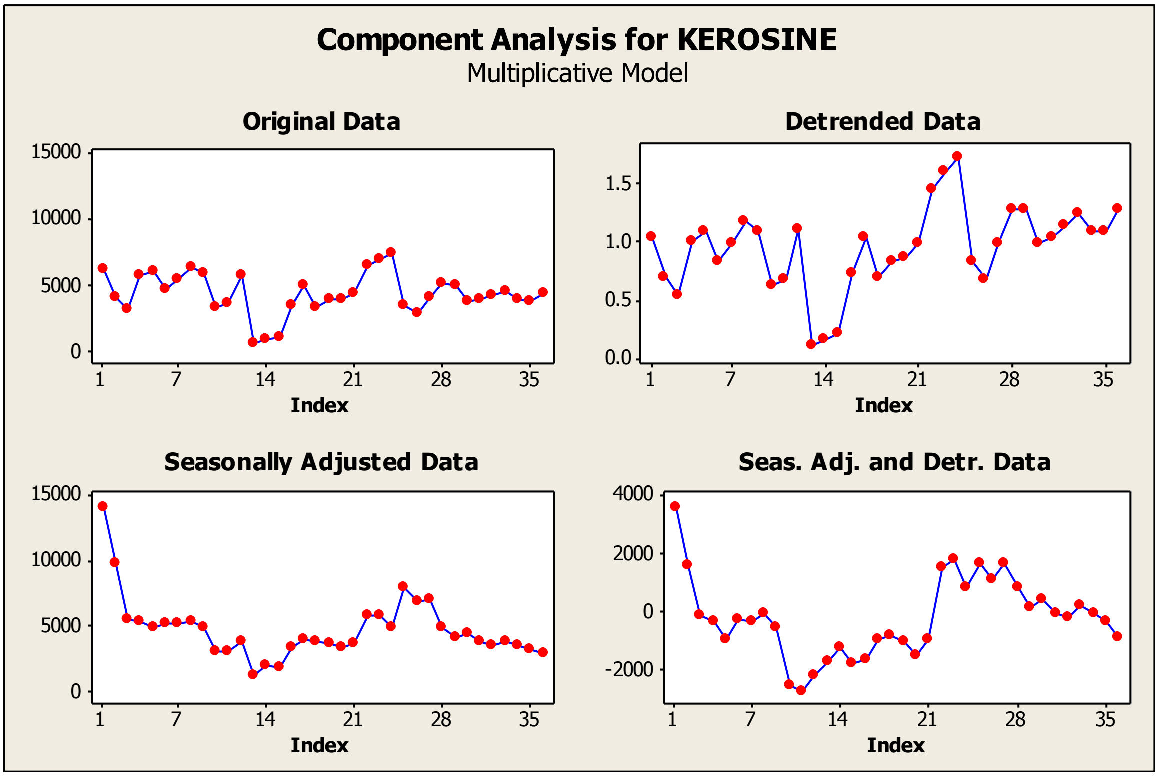

Figure 2: *Decomposition - Component Analysis for Kerosene*

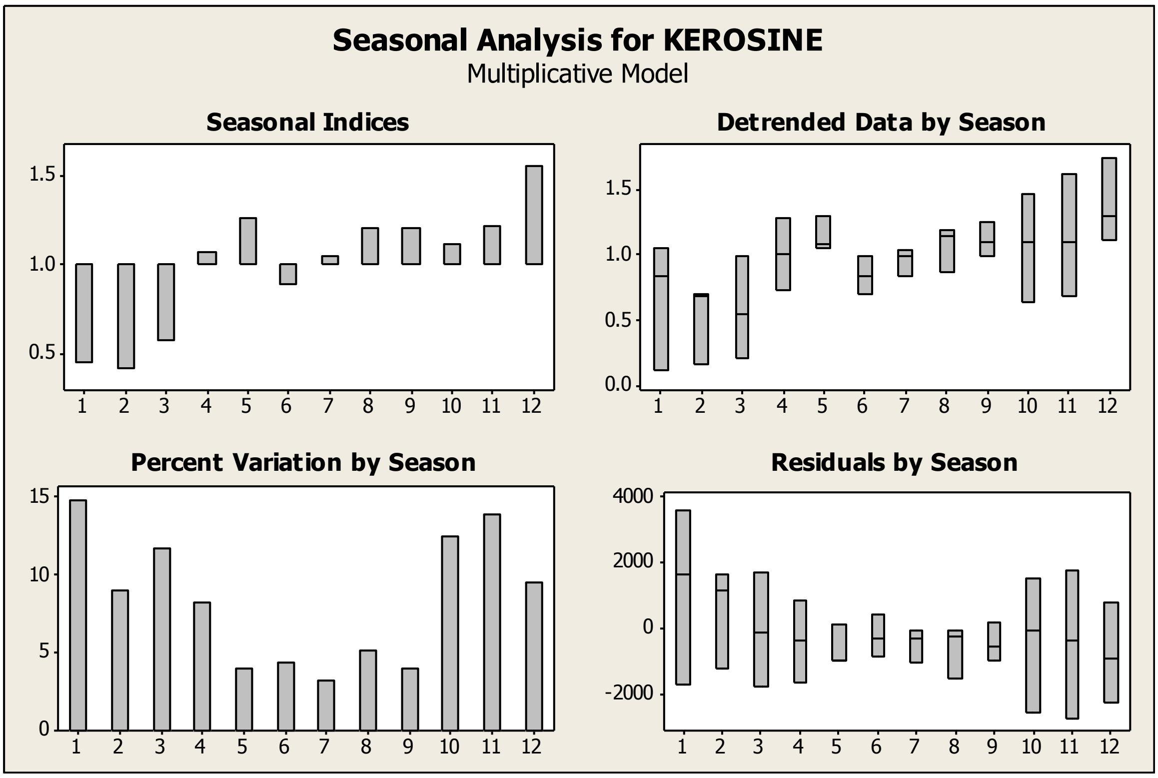

Figure 3: *Decomposition - Seasonal Analysis for Kerosene*

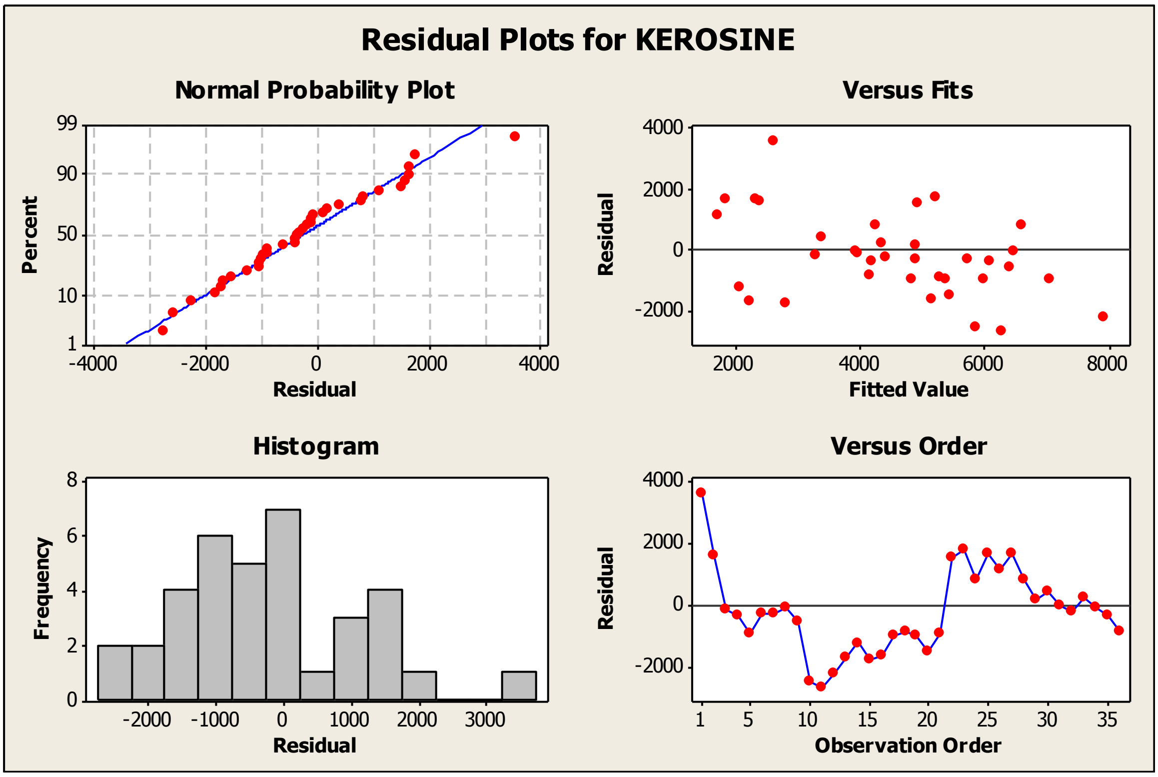

Figure 4: *Residual Plots for Kerosene*

Table 2: Measuring Forecasting Error in the Products

S/N	Product Types	MAD (MAE)	MAPE	MSD	RMSE (Standard Deviation)
1	Kerosene	1085	41	1871402	1367.992
2	Diesel	5008	12	58508114	7649.06
3	Petroleum	47947	99	3114847540	55810.82

Table 3: Measuring Forecasting Error and seasonal Demand in Kerosene Product

Month Code	FE	$(FE)^2$	Seasonal Index	Deseasonal Demand	Seasonal Demand
1	3579.02	12809384	0.44175	13989.9	6180.038
2	1604.61	2574773	0.41182	9712.9	3999.966
3	157.52	24812.55	0.57083	5469.2	3121.983
4	381.38	145450.7	1.07343	5318.5	5709.037
5	977.3	955115.3	1.26184	4827.9	6092.037
6	303.48	92100.11	0.88709	5188.9	4603.021
7	328.14	107675.9	1.05029	5147.2	5406.053
8	87.74	7698.308	1.20481	5315.4	6404.047
9	587.69	345379.5	1.20762	4830.2	5833.046
10	2552.43	6514899	1.12068	2967.8	3325.954
11	2733.22	7470492	1.21244	2919.7	3539.961
12	2237.78	5007659	1.55739	3665.8	5709.08
13	1712.54	2932793	0.44175	1154.5	510.0004
14	1253.58	1571463	0.41182	1915.9	789.0059
15	1798.5	3234602	0.57083	1737.8	991.9884
16	1660.79	2758223	1.07343	3269.9	3510.009

17	1008.3	1016669	1.26184	3946.6	4979.978
18	866.53	750874.2	0.88709	3697.5	3280.015
19	1016.38	1033028	1.05029	3635.2	3818.014
20	1518.61	2306176	1.20481	3271.1	3941.054
21	963.14	927638.7	1.20762	3662.6	4423.029
22	1525.63	2327547	1.12068	5750.1	6444.022
23	1757.46	3088666	1.21244	5766.9	6992.02
24	789.41	623168.1	1.55739	4752.8	7401.963
25	1657.9	2748632	0.44175	7927.6	3502.017
26	1119.22	1252653	0.41182	6820.9	2808.983
27	1678.52	2817429	0.57083	6972.3	3979.998
28	832.8	693555.8	1.07343	4736.2	5083.979
29	893.41	798181.4	1.26184	3991	5036.003
30	414.43	171752.2	0.88709	4284.8	3801.003
31	56.61	3204.692	1.05029	3692.3	3877.986
32	224.47	50386.78	1.20481	3488.5	4202.98
33	184.41	34007.05	1.20762	3756.1	4535.941
34	94.3	8892.49	1.12068	2815.6	3155.387
35	385.86	148887.9	1.21244	3142.4	3809.971
36	128.7	16563.69	1.55739	3447.9	5369.725

Time Series Decomposition for Diesel

Multiplicative Model
Data DIESEL
Length 36
NMissing 0

Fitted Trend Equation
Yt = 60186 - 1090.20*t

Seasonal Indices

Period	Index
1	0.76050
2	0.76613
3	0.75675
4	0.62651
5	0.77348
6	0.96762
7	0.75129
8	1.22060
9	1.36783
10	1.41691
11	1.47056
12	1.12182

Accuracy Measures
MAPE 12
MAD 5008
MSD 58508114

Time	DIESEL	Trend	Seasonal	Detrend	Deseason	Predict	Error
1	45185	59096.2	0.76050	0.76460	59415.1	44942.5	242.5
2	36102	58006.0	0.76613	0.62238	47122.8	44439.9	-8337.9
3	72102	56915.8	0.75675	1.26682	95277.9	43071.3	29030.7
4	40170	55825.6	0.62651	0.71956	64116.8	34975.5	5194.5
5	33170	54735.4	0.77348	0.60601	42884.1	42336.8	-9166.8
6	33170	53645.2	0.96762	0.61832	34279.9	51908.3	-18738.3
7	35120	52555.0	0.75129	0.66825	46746.4	39484.0	-4364.0
8	66120	51464.8	1.22060	1.28476	54170.0	62818.0	3302.0
9	60120	50374.6	1.36783	1.19346	43952.9	68903.8	-8783.8
10	54100	49284.4	1.41691	1.09771	38181.7	69831.5	-15731.5
11	72100	48194.2	1.47056	1.49603	49029.1	70872.2	1227.8
12	60100	47104.0	1.12182	1.27590	53573.5	52842.3	7257.7
13	41100	46013.8	0.76050	0.89321	54043.6	34993.4	6106.6
14	32100	44923.6	0.76613	0.71455	41899.1	34417.1	-2317.1
15	33100	43833.4	0.75675	0.75513	43739.4	33171.1	-71.1
16	28102	42743.2	0.62651	0.65746	44854.6	26779.2	1322.8
17	32108	41653.0	0.77348	0.77084	41511.1	32217.8	-109.8
18	37100	40562.8	0.96762	0.91463	38341.4	39249.5	-2149.5
19	31105	39472.6	0.75129	0.78802	41402.2	29655.3	1449.7
20	42109	38382.4	1.22060	1.09709	34498.6	46849.6	-4740.6
21	55100	37292.2	1.36783	1.47752	40282.8	51009.3	4090.7
22	60100	36202.0	1.41691	1.66013	42416.3	51294.9	8805.1
23	48100	35111.8	1.47056	1.36991	32708.7	51633.8	-3533.8
24	32100	34021.6	1.12182	0.94352	28614.1	38166.2	-6066.2
25	21100	32931.4	0.76050	0.64073	27745.0	25044.2	-3944.2
26	27102	31841.2	0.76613	0.85116	35375.4	24394.4	2707.6
27	24102	30751.0	0.75675	0.78378	31849.2	23271.0	831.0
28	18110	29660.8	0.62651	0.61057	28906.0	18582.9	-472.9
29	22110	28570.6	0.77348	0.77387	28585.1	22098.8	11.2
30	27110	27480.4	0.96762	0.98652	28017.1	26590.7	519.3
31	26110	26390.2	0.75129	0.98938	34753.6	19826.7	6283.3
32	35110	25300.0	1.22060	1.38775	28764.5	30881.2	4228.8
33	32110	24209.8	1.36783	1.32632	23475.2	33114.9	-1004.9
34	29810	23119.6	1.41691	1.28938	21038.8	32758.3	-2948.3
35	29002	22029.4	1.47056	1.31651	19721.8	32395.4	-3393.4
36	21700	20939.2	1.12182	1.03633	19343.5	23490.1	-1790.1

Forecasts

Period	Forecast
37	15095.1
38	14371.6
39	13370.8
40	10386.6
41	11979.8
42	13931.8
43	9998.0
44	14912.8
45	15220.4

46	14221.8
47	13157.1
48	8813.9
49	5146.0
50	4348.8
51	3470.6
52	2190.3
53	1860.8
54	1273.0
55	169.3
56	-1055.6
57	-2674.1
58	-4314.8
59	-6081.3
60	-5862.2
61	-4803.1
62	-5673.9
63	-6429.5
64	-6006.0
65	-8258.1
66	-11385.8
67	-9659.3
68	-17024.0
69	-20568.6
70	-22851.3
71	-25319.7
72	-20538.3

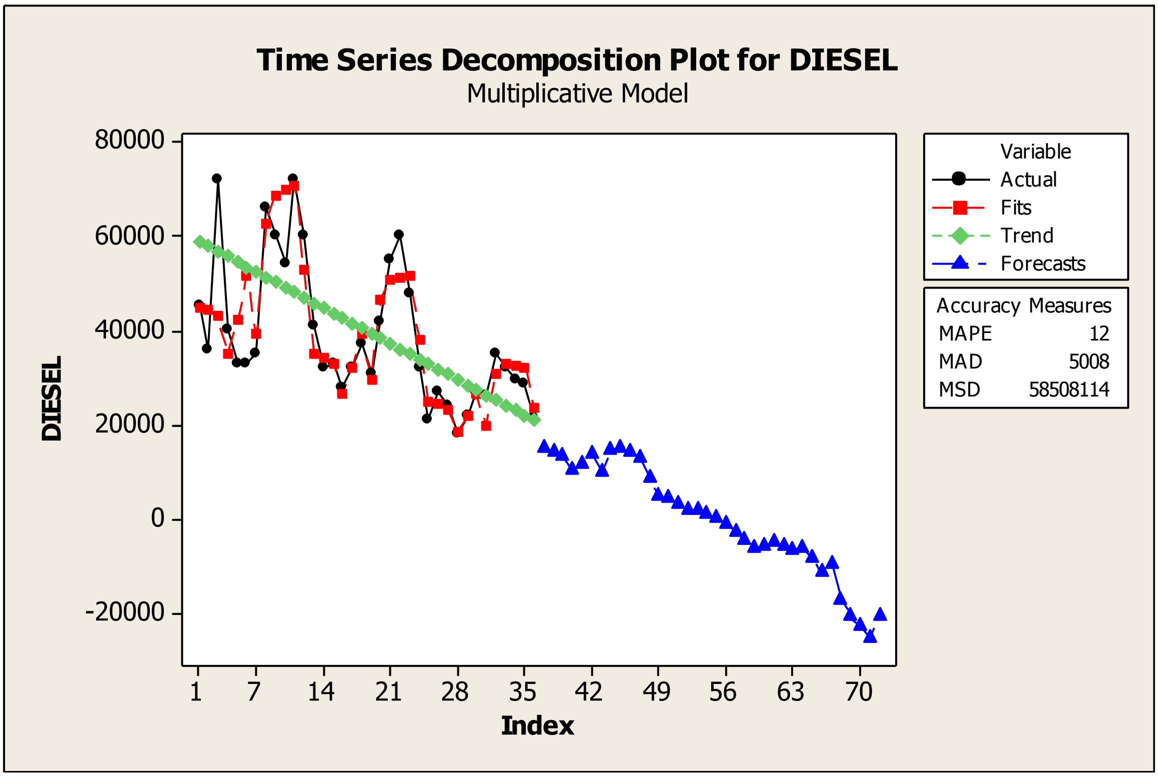

Figure 5: *Time Series Decomposition Plot for Diesel*

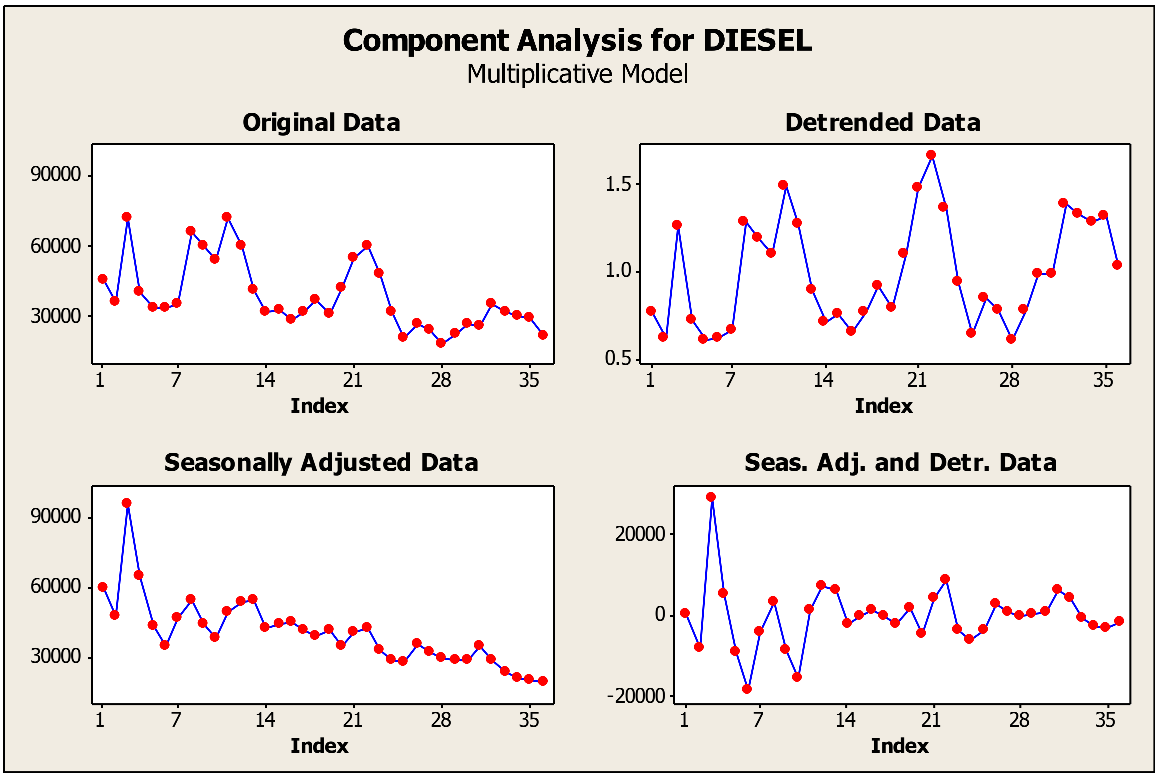

Figure 6: Decomposition - Component Analysis for Diesel

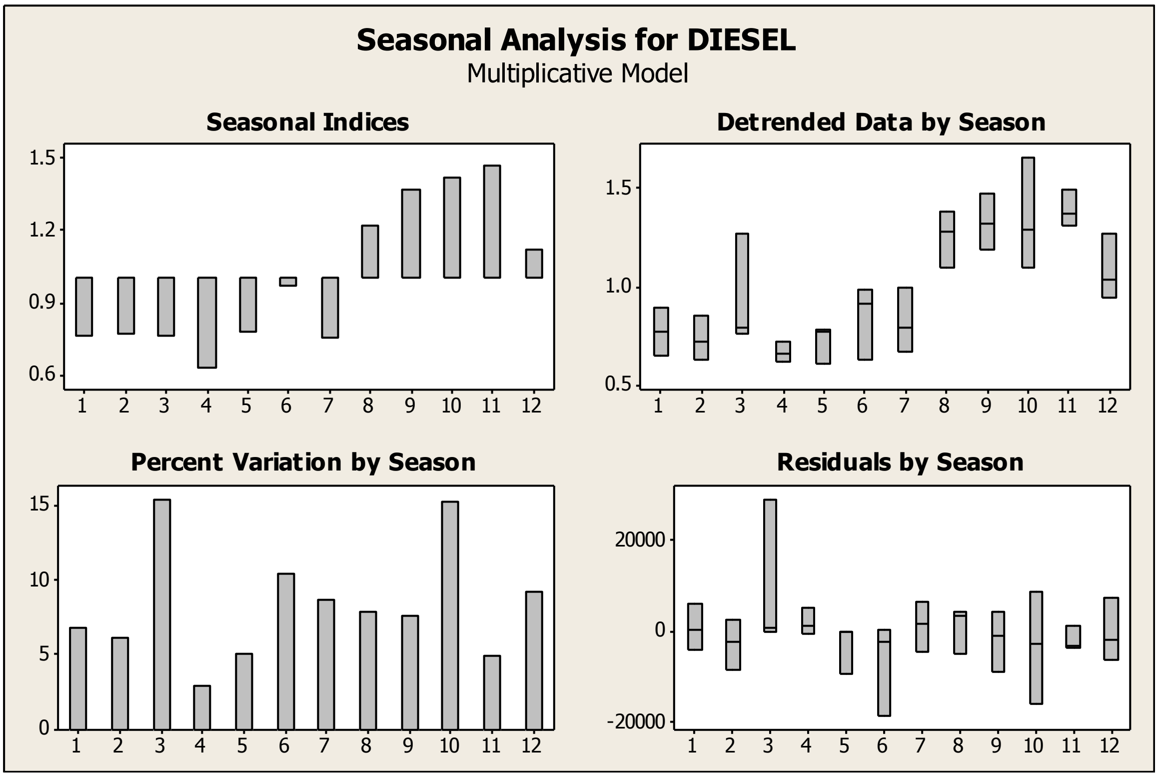

Figure 7: Decomposition - Seasonal Analysis for Diesel

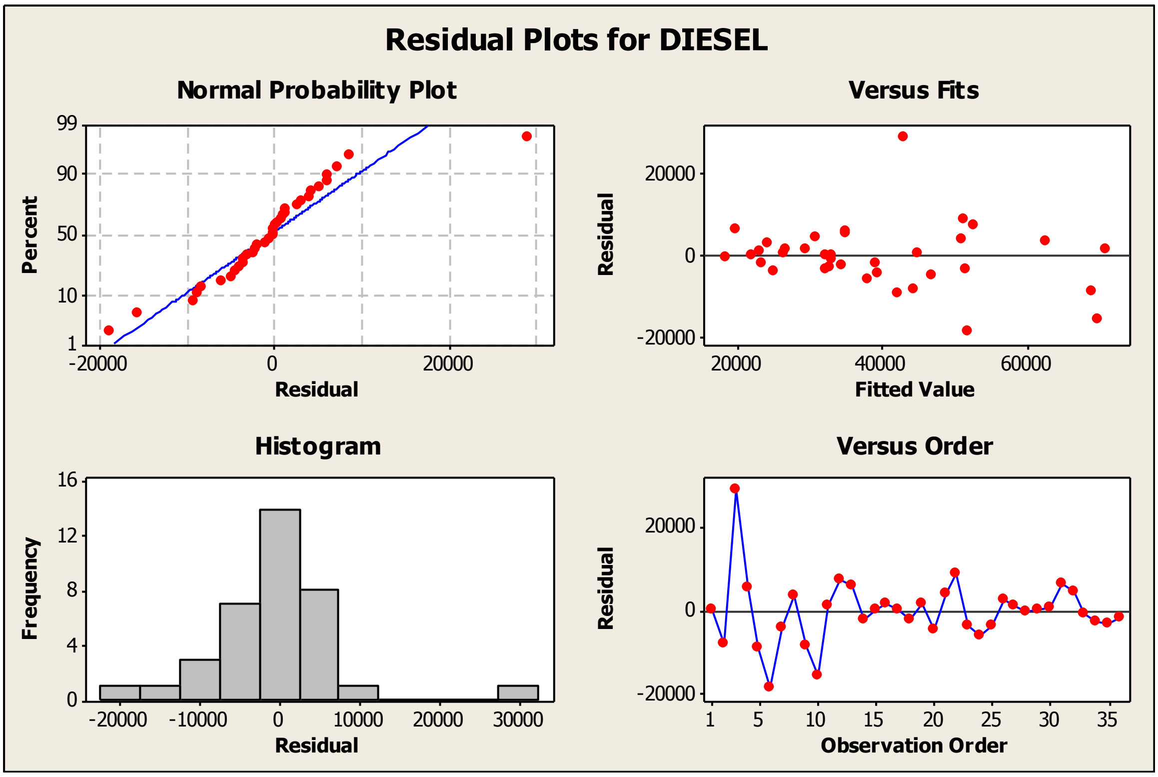

Figure 8: *Residual Plots for Diesel*

Table 4: Measuring Forecasting Error and seasonal Demand in Diesel Product

Month Code	FE	$(FE)^2$	Seasonal Index	Deseasonal Demand	Seasonal Demand
1	242.5	58806.25	0.7605	59415.1	45185.18
2	8337.9	69520576	0.76613	47122.8	36102.19
3	29030.7	8.43E+08	1.12182	95277.9	106884.7
4	5194.5	26982830	0.62651	64116.8	40169.82
5	9166.8	84030222	0.77348	42884.1	33169.99
6	18738.3	3.51E+08	0.75675	34279.9	25941.31
7	4364	19044496	0.75129	46746.4	44637.97
8	3302	10903204	1.2206	54170	66119.9
9	8783.8	77155142	1.36783	43952.9	60120.1
10	15731.5	2.47E+08	1.41691	38181.7	54100.03
11	1227.8	1507493	1.47056	49029.1	72100.23
12	7257.7	52674209	0.96762	53573.5	51838.79
13	6106.6	37290564	0.7605	54043.6	41100.16
14	2317.1	5368952	0.76613	41899.1	32100.16
15	71.1	5055.21	1.12182	43739.4	49067.73
16	1322.8	1749800	0.62651	44854.6	28101.86
17	109.8	12056.04	0.77348	41511.1	32108.01
18	2149.5	4620350	0.75675	38341.4	29014.85
19	1449.7	2101630	0.75129	41402.2	31105.06
20	4740.6	22473288	1.2206	34498.6	42108.99
21	1790.1	3204458	1.36783	40282.8	55100.02
22	8805.1	77529786	1.41691	42416.3	60100.08
23	3533.8	12487742	1.47056	32708.7	48100.11
24	6066.2	36798782	0.96762	28614.1	27687.58

25	3944.2	15556714	0.7605	27745	21100.07
26	2707.6	7331098	0.76613	35375.4	27102.16
27	831	690561	1.12182	31849.2	35729.07
28	472.9	223634.4	0.62651	28906	18109.9
29	11.2	125.44	0.77348	28585.1	22110
30	519.3	269672.5	0.75675	28017.1	21201.94
31	6283.3	39479859	0.75129	35375.4	26577.18
32	4228.8	17882749	1.2206	28764.5	35109.95
33	1004.9	1009824	1.36783	23475.2	32110.08
34	2948.3	8692473	1.41691	21038.8	29810.09
35	3393.4	11515164	1.47056	19721.8	29002.09
36	4090.7	16733826	0.96762	19343.5	45232.75

Time Series Decomposition for PETROLEUM

Multiplicative Model
Data PETROLEUM
Length 36
NMissing 0

Fitted Trend Equation
Yt = 135738 - 28.2898*t

Seasonal Indices

Period	Index
1	0.45612
2	1.15830
3	1.12041
4	1.18858
5	1.14916
6	0.74511
7	0.63068
8	1.70945
9	0.88978
10	1.12248
11	0.92784
12	0.90210

Accuracy Measures
MAPE 99
MAD 47947
MSD 3314847540

Time	PETROLEUM	Trend	Seasonal	Detrend	Deseason	Predict	Error
1	132100	135710	0.45612	0.97340	289616	61900	70200
2	99100	135681	1.15830	0.73039	85556	157160	-58060
3	132100	135653	1.12041	0.97381	117904	151987	-19887
4	66100	135625	1.18858	0.48737	55613	161201	-95101
5	132100	135597	1.14916	0.97421	114953	155823	-23723
6	90100	135568	0.74511	0.66461	120922	101013	-10913
7	66100	135540	0.63068	0.48768	104808	85482	-19382

8	219100	135512	1.70945	1.61683	128170	231651	-12551
9	138100	135483	0.88978	1.01931	155207	120550	17550
10	231102	135455	1.12248	1.70612	205886	152045	79057
11	132102	135427	0.92784	0.97545	142376	125654	6448
12	99160	135399	0.90210	0.73236	109922	122143	-22983
13	6760	135370	0.45612	0.04994	14821	61745	-54985
14	143100	135342	1.15830	1.05732	123543	156767	-13667
15	99100	135314	1.12041	0.73237	88450	151606	-52506
16	231100	135285	1.18858	1.70824	194434	160798	70302
17	99100	135257	1.14916	0.73268	86237	155433	-56333
18	132100	135229	0.74511	0.97686	177290	100760	31340
19	99100	135201	0.63068	0.73299	157133	85268	13832
20	232100	135172	1.70945	1.71707	135775	231070	1030
21	99100	135144	0.88978	0.73329	111376	120248	-21148
22	68100	135116	1.12248	0.50401	60669	151664	-83564
23	132100	135087	0.92784	0.97789	142374	125339	6761
24	165100	135059	0.90210	1.22243	183018	121836	43264
25	132100	135031	0.45612	0.97830	289616	61590	70510
26	198100	135002	1.15830	1.46738	171026	156374	41726
27	240100	134974	1.12041	1.77886	214297	151226	88874
28	99100	134946	1.18858	0.73437	83377	160394	-61294
29	240100	134918	1.14916	1.77960	208934	155043	85057
30	66100	134889	0.74511	0.49003	88712	100507	-34407
31	132100	134861	0.63068	0.97953	209458	85054	47046
32	198100	134833	1.70945	1.46923	115885	230490	-32390
33	231100	134804	0.88978	1.71434	259728	119946	111154
34	99100	134776	1.12248	0.73529	88287	151283	-52183
35	18705	134748	0.92784	0.13881	20160	125024	-106319
36	11002	134720	0.90210	0.08167	12196	121530	-110528

Forecasts

Period	Forecast
37	61436
38	155980
39	150846
40	159991
41	154652
42	100254
43	84839
44	229910
45	119644
46	150902
47	124709
48	121224
49	61281
50	155587
51	150465
52	159587
53	154262

54	100001
55	84625
56	229329
57	119342
58	150521
59	124394
60	120918
61	61126
62	155194
63	150085
64	159184
65	153872
66	99748
67	84411
68	228749
69	119040
70	150140
71	124079
72	120611

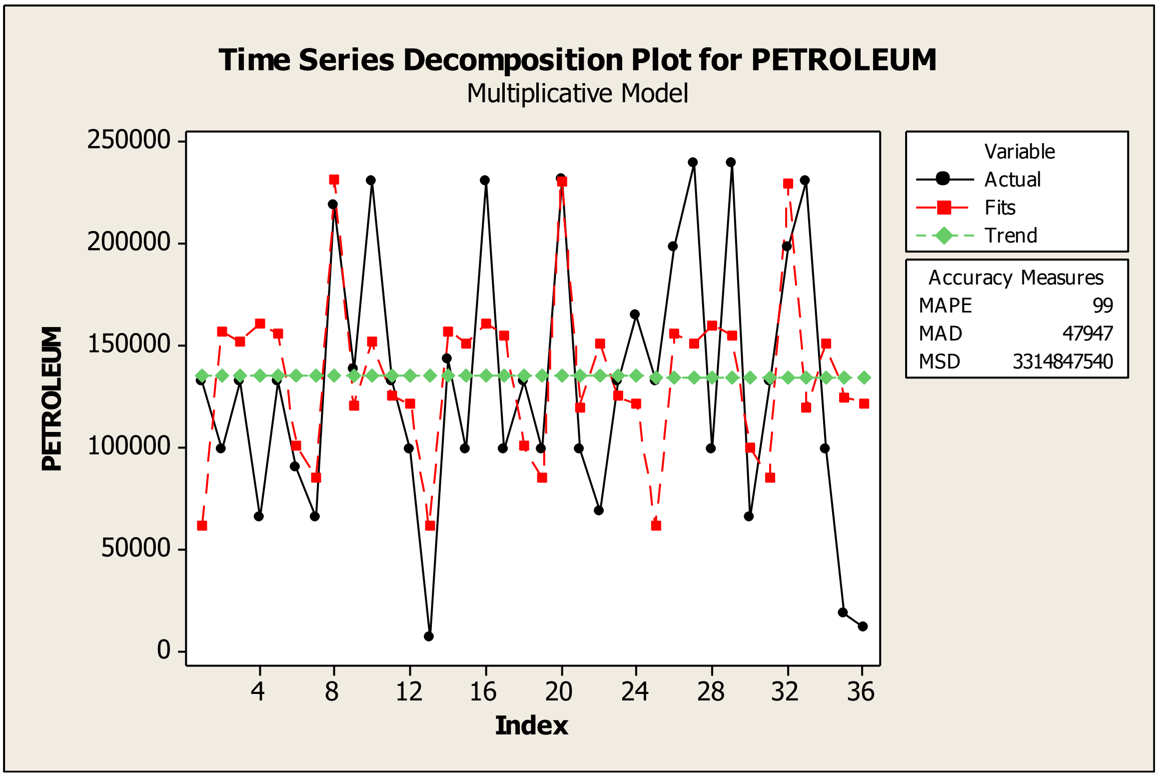

Figure 9: *Time Series Decomposition Plot for Petroleum*

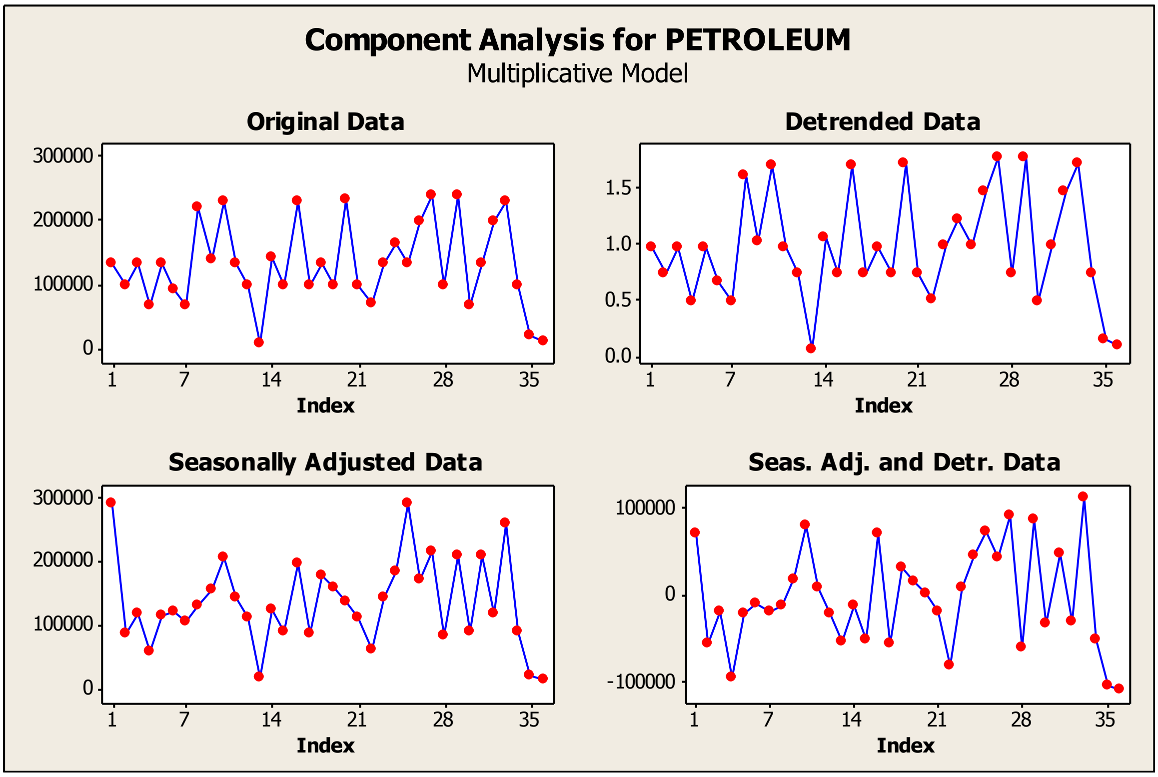

Figure 10: *Decomposition - Component Analysis for Petroleum*

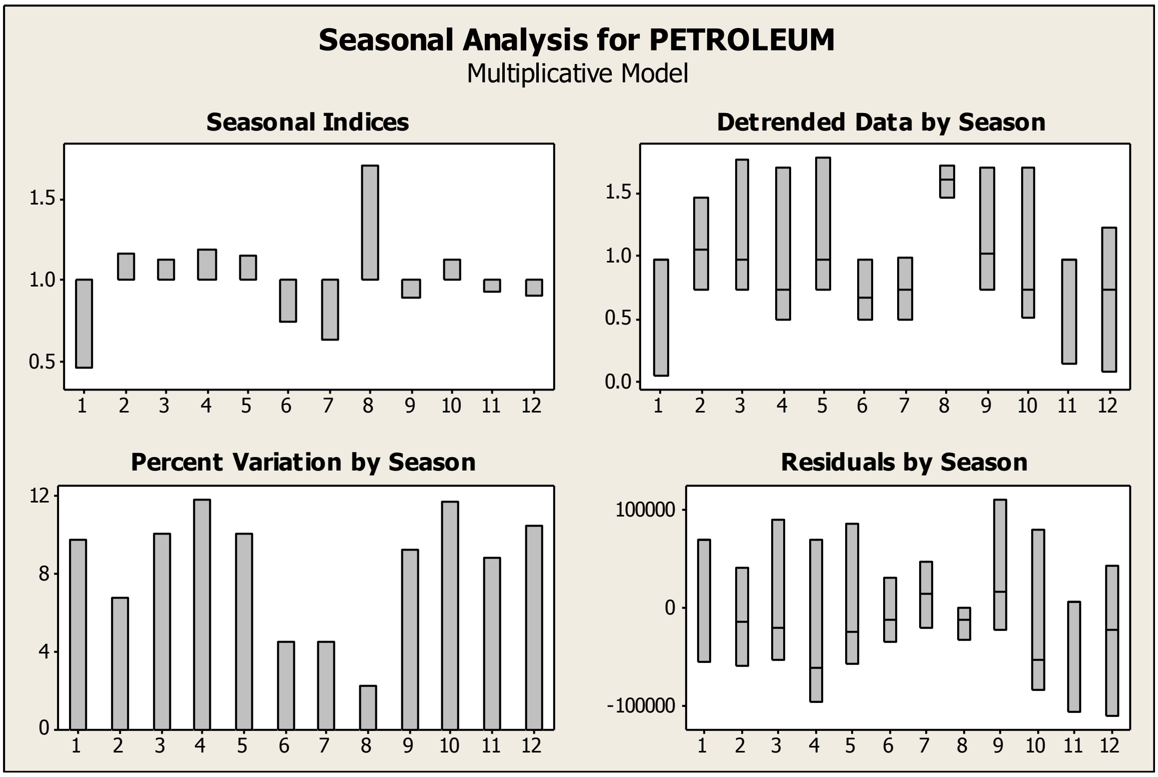

Figure 11: *Decomposition - Seasonal Analysis for Petroleum*

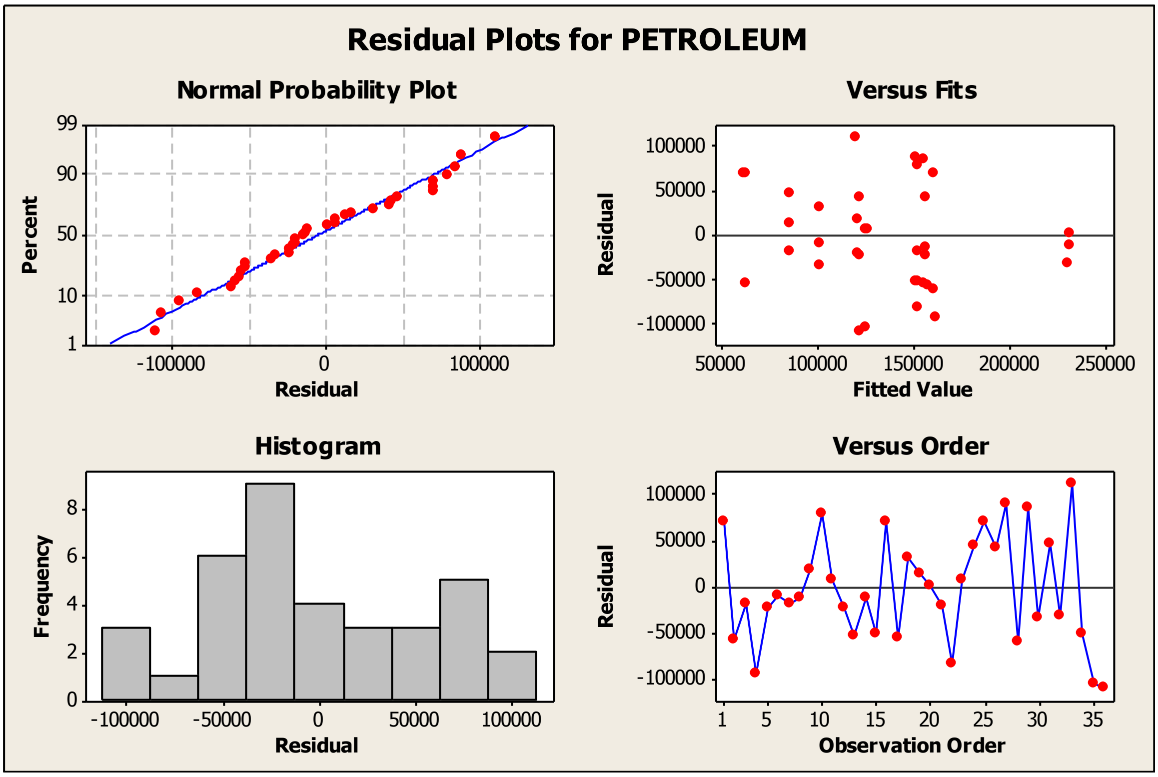

Figure 12: *Residual Plots for Petroleum*

Table 5: Measuring Forecasting Error and seasonal Demand in Petroleum Product

Month Code	FE	$(FE)^2$	Seasonal Index	Deseasonal Demand	Seasonal Demand
1	70200	4.93E+09	0.45612	289616	132099.6
2	58060	3.37E+09	1.1583	85556	99099.51
3	19887	3.95E+08	1.12041	117904	132100.8
4	95101	9.04E+09	1.18858	55613	66100.5
5	23723	5.63E+08	1.14916	114953	132099.4
6	10913	1.19E+08	0.74511	120922	90100.19
7	19382	3.76E+08	0.63068	104808	182655
8	12551	1.58E+08	1.70945	128170	219100.2
9	17550	3.08E+08	0.88978	155207	138100.1
10	79057	6.25E+09	1.12248	205886	231102.9
11	6448	41576704	0.92784	142376	132102.1
12	22983	5.28E+08	0.9021	109922	99160.64
13	54985	3.02E+09	0.45612	14821	6760.155
14	13667	1.87E+08	1.1583	123543	143099.9
15	52506	2.76E+09	1.12041	88450	99100.26
16	70302	4.94E+09	1.18858	194434	231100.4
17	56333	3.17E+09	1.14916	86237	99100.11
18	31340	9.82E+08	0.74511	177290	132100.6
19	13832	1.91E+08	0.63068	157133	99100.64
20	1030	1060900	1.70945	135775	232100.6
21	21148	4.47E+08	0.88978	111376	99100.14
22	110528	1.22E+10	1.12248	60669	68099.74
23	6761	45711121	0.92784	142374	132100.3
24	43264	1.87E+09	0.9021	183018	165100.5

25	70510	4.97E+09	0.45612	289616	132099.6
26	41726	1.74E+09	1.1583	171026	198099.4
27	88874	7.9E+09	1.12041	214297	240100.5
28	61294	3.76E+09	1.18858	83377	99100.23
29	85057	7.23E+09	1.14916	208934	240098.6
30	34407	1.18E+09	0.74511	88712	66100.2
31	47046	2.21E+09	0.63068	209458	132101
32	32390	1.05E+09	1.70945	115885	198099.6
33	111154	1.24E+10	0.88978	259728	231100.8
34	52183	2.72E+09	1.12248	88287	99100.39
35	106319	1.13E+10	0.92784	12196	11315.94
36	83564	6.98E+09	0.9021	20160	94547.3

Discussion and Conclusion

The discussion was based on the charts, tables, results and the analyses of the products data developed. Time series decomposition analyses and residual plots were used to show the forecasting accuracy of the kerosene, diesel and the petroleum products demand in the case study company. The decomposition analysis plots show the times series analysis, component analysis and the seasonal analysis of each of the products under review. The time series decomposition analyses show the observation order of the actual products demand over a period of time. It also shows the upward or downward movement of the trend. The upward movement of the trend shows an increase in the future demands, while the downward movement shows the reduction of the future products demand. The decomposition component analyses show the effect of trend and seasonal influence in the data. It shows the effect of removing trend (i.e. detrend) and the effect of removing seasonal influence (i.e. deseasonal or seasonal adjustment) in the original products data. The decomposition seasonal analyses show the seasonal indices of the product demand data over the twelve months in year. It also shows the removal of the trend data by the season and also shows the percentage variation of the detrend data by season. Furthermore, the residuals or the errors of the products data were also observed by season. The residual plots show the normal probability plots of the predicted products data. It shows in histogram plots and the frequency accumulation of the residuals or the errors in the products demand. It also shows the residuals in the predictions versus the predicted or fitted values and also the errors in the predictions versus the observed or the periods of the products data. Table 2 shows the tools used for accuracy measures in the products demand of the case study company. Tables 3, 4 and 5 show the seasonal demand and the errors in the products demand. From the findings, results show that the kerosene and the Diesel products demands in future will diminish while the Petroleum product demand in future will slightly increase. However, the company is strictly advice to checkmate their Kerosene and Diesel Products have seen their failure in the future and always measure their products forecasting accuracy. Finally, this study and the techniques of measuring the forecasting accuracy were recommended to the case study company.

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