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Analysis and Forecasting Of the Production Quantity in a Manufacturing Industry Using Historical Data

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ABSTRACT

This research work focused on the use of forecasting techniques to model and analyze the production of plastic products in Loius carter plastic industry. Production yield data were collected from the company covering a period of three years. The applied forecasting models were used to forecast the results of the future production of the products. The applied models developed using weighted moving average method, winters model and Double exponential smoothing model show that Y1 (10litres bucket) product was to be produced for 13997.6, 15854 and 10206.5 units respectively for the month of January 2014, while for the February 2014, weighted moving average method, winters model and Double exponential smoothing model show that Y1 product was to be produced for 8554.12, 15024.1 and 9791.2 units respectively. These methods were applied on the products for monthly yield of the product types investigated. From the results, the decrease in trend showed a continuous decrease in their future production output on the product Y1. The seasonal influences were analyzed based on months using the production data of the case study company. Time series decomposition analyses were also used to study the seasonality and trend in the five products investigated.

Key Terms: *time series, forecasting, moving average, winters, double exponential, production quantity*

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I. Introduction

Forecasting is the process of making statements about events whose actual outcomes (typically) have not yet been observed. A common place 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 judgmental 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 [1].

Prediction is also known as forecasting. In an effective and efficient business organization, application of good forecasting technique is very important for the successful operations of the business in any organization. It is vital in the control of materials and goods for inventory forecasting and the control of production in the case of production or exchange of activities and services.

The principal goal of forecasting in an organization is to foreseen the future of the production quantity and for inventory management in order to balance the conflict of not wanting to hold too much stock thereby tie up capital and the desire to make items or goods available when and where required so as to avert the cost of not meeting such requirement [2]. Forecasting ensures that the problems of over production or under production of quantity of goods in an industry at the right time will be handled and elimination of forecasting can cause business failures. If a product is not available when the customer thinks it should be, the retailer and the company will lose a customer not only on that product but also likely to continue loosing more customers on the future production. Furthermore, the application of forecasting techniques is very essential for an effective management and can make a significant contribution to a business profit as well as increase its return on total assets. It is thus the management of the future production at the right time and the right proportion. The reason for greater attention to forecasting is that it helps the industry to understand whether the future is profitable or not, and also the appropriate quantity of goods necessary to produce or stock over future time. Essentially, it coordinates the activities of the production planning and control in a manufacturing industry.

The **objective** of the study is to apply some existing forecasting methods in order to show the true quantity of the products in the right proportion and at the right time in Louis Carter plastic manufacturing industry.

II. Review of Literature

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

2.2. Quantitative forecasting models are used to forecast future data as a function of past data; they are appropriate when past data are available. These methods are usually applied to short- or intermediate-range decisions. Examples of quantitative forecasting methods are last period demand, simple and weighted N-Period moving averages, simple exponential smoothing, and multiplicative seasonal indexes.

2.3. Naïve approach: Naïve forecasts are the most cost-effective objective forecasting model, and provide a benchmark against which more sophisticated models can be compared. For stationary time series data, this approach says that the forecast for any period equals the historical average. For time series data that are stationary in terms of first differences, the naïve forecast equals the previous period's actual value.

2.4. Time series methods: Time series methods use historical data as the basis of estimating future outcomes.
2.4. 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 climate patterns 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 climate, seasonality can also be due to holidays and customs; for example, one might predict that sales of college football apparel will be higher during the football season than during the off season [3].

2.5. Causal forecasting methods: These 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. Alternatively, 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 extrapolate such a relationship into the future.
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) [4].

Quantitative forecasting models are often judged against each other by comparison of their in-sample or out-of-sample mean square error, although some researchers have advised against its use [5].

2.6. Importance of Forecasting in an Organization: Vadasz [6] reviewed that forecasting is important for several reasons. First, it enables management to change operations at the right time in order to reap the greatest benefit. It also helps the company prevent losses by making the proper decisions based on relevant information. Organizations that can create high quality and accurate forecasts are able to "see what interventions are required to meet their business performance targets".
Forecasting is also important when it comes to developing new products or new product lines. It helps management decide whether the product or product line will be successful. Forecasting prevents the company from spending time and money developing, manufacturing, and marketing a product that will fail.
Stockholder expectations highlight another reason behind the importance of forecasting. Public companies experience scrutiny and pressure for short-term performance from investors. Operational results will be examined by investors and investment analysts, and actual results that differ from forecasts will be bad for the company and its stock price. This is because both meeting predictions and exceeding predictions will reduce investor confidence. This will cause investors to believe that the company does not understand its own business model.

2.7. Time Series: a time series is a sequence of data points, measured typically at successive points in time spaced at uniform time intervals. Examples of time series are the daily closing value of the dow jones industrial average and the annual flow volume of the nile river at aswan. time series are very frequently plotted via line charts. time series are used in statistics, signal processing, pattern recognition, econometrics, mathematical finance, weather forecasting, earthquake prediction, electroencephalography, control engineering, astronomy, and communications engineering.

Time series analysis comprises methods for analyzing time series data in order to extract meaningful statistics and other characteristics of the data. Time series forecasting is the use of a model to predict future values based on previously observed values. While regression analysis is often employed in such a way as to test theories that the current values of one or more independent time series affect the current value of another time series, this type of analysis of time series is not called "time series analysis", which focuses on comparing values of time series at different points in time.

Time series data have a natural temporal ordering. This makes time series analysis distinct from other common data analysis problems, in which there is no natural ordering of the observations (e.g. explaining people's wages by reference to their respective education levels, where the individuals' data could be entered in any order). Time series analysis is also distinct from spatial data analysis where the observations typically relate to geographical locations (e.g. accounting for house prices by the location as well as the intrinsic characteristics of the houses). A stochastic model for a time series will generally reflect the fact that observations close together in time will be more closely related than observations further apart. In addition, time series models will often make use of the natural one-way ordering of time so that values for a given period will be expressed as deriving in some way from past values, rather than from future values (see time reversibility.)

Time series analysis can be applied to real-valued, continuous data, discrete numeric data, or discrete symbolic data [7].

2.7.1. Methods for time series analyses: Methods for time series analyses may be divided into two classes: frequency-domain methods and time-domain methods. The former include spectral analysis and recently wavelet analysis; the latter include auto-correlation and cross-correlation analysis. In time domain correlation analyses can be made in a filter-like manner using scaled correlation, thereby mitigating the need to operate in frequency domain.

Additionally, time series analysis techniques may be divided into parametric and non-parametric methods. The parametric approaches assume that the underlying stationary stochastic process has a certain structure which can be described using a small number of parameters. In these approaches, the task is to estimate the parameters of the model that describes the stochastic process. By contrast, non-parametric approaches explicitly estimate the covariance or the spectrum of the process without assuming that the process has any particular structure.

Methods of time series analysis may also be divided into linear and non-linear, and univariate and multivariate.

III. Research Method

The research method used in this work is a quantitative research approach.

3.1. **Data Collection and Analysis:** The data gathered were the daily record of plastic pipes production over the month for three years. The method used was time series technique to model for the quantity of pipes (sizes and shapes) to be produced in the industry using predictive tools namely: Excel and Minitab tools for the development of the model and the forecasting of the results.

Table 1: Presentation of 2011-2013 Monthly Data on Quantity of finished products in the Industry

Year	*Month*	Y1			
2011	Jan	16509		June	22155
	Feb	29233		July	8750
	Mar	26649		Aug	14773
	April	52012		Sept	11958
	May	14143		Oct	5501
	June	23070		Nov	17515
	July	29873		Dec	18435
	Aug	17964	2013	Jan	22208
	Sept	3231		Feb	14106
	Oct	7028		Mar	14485
	Nov	15997		April	15997
	Dec	3154		May	24117
2012	Jan	7096		June	29080
	Feb	7267		July	16964
	Mar	22102		Aug	17281
	April	21117		Sept	5600
	May	18831		Oct	20614
				Nov	4374
				Dec	11892

Source: Louis Carter grouped data
Y1= 10litres bucket,

3.1.2. Method of data analysis: In the method of data analysis, some group of data were analyzed by using forecasting model to predict the actual quantity needed to be produce in each of the sizes of the plastic pipes over the month in the manufacturing industry. The use of Minitab tool was made to test for the fitness variables.

Table 2: Weighted Moving Average Forecasting Results of the Product types Investigated

S/N	**Weighted moving Average Forecast (0.5,0.3,0.2) Y1**	**S/N**	**Weighted moving Average Forecast (0.5,0.3,0.2) Y1**
1	13997.6	19	11169.17
2	8554.12	20	11171.05
3	11856.1	21	11176.78
4	11936.26	22	11171.25
5	10221.14	23	11172.81
6	11553.16	24	11174.33
7	11345.1	25	11172.33
8	10845.54	26	11173.17
9	11349.22	27	11173.5
10	11196.06	28	11172.82
11	11066.75	29	11173.2
12	11246.77	30	11173.23
13	11167.41	31	11173.01
14	11140.89	32	11173.17
15	11201.79	33	11173.16
16	11166.33	34	11173.09
17	11164.24	35	11173.15
18	11183.64	36	11173.13

3.1.3. Trend Analysis for Y1

Data Y1
Length 36
NMissing 0

Fitted Trend Equation
Yt = 21388 - 238.595*t

Accuracy	Measures
MAPE	75
MAD	6908
MSD	83549358

Time	Y1	Trend	Detrend
1	16509	21149.9	-4640.9
2	29233	20911.3	8321.7
3	26649	20672.7	5976.3
4	52012	20434.1	31577.9
5	14143	20195.5	-6052.5
6	23070	19956.9	3113.1
7	29873	19718.3	10154.7
8	17964	19479.7	-1515.7
9	3231	19241.1	-6010.1
10	7028	19002.5	-1974.5
11	15997	18763.9	-2766.9
12	3154	18525.3	-5371.3
13	7096	18286.7	-1190.7
14	7267	18048.2	-10781.2
15	22102	17809.6	4292.4
16	21117	17571.0	3546.0
17	18831	17332.4	1498.6
18	22155	17093.8	5061.2
19	8750	16855.2	-8105.2
20	14773	16616.6	-1843.6
21	11958	16378.0	-4420.0
22	5501	16139.4	-10638.4
23	17515	15900.8	1614.2
24	18435	15662.2	2772.8
25	22208	15423.6	6784.4
26	14106	15185.0	-1079.0
27	14485	14946.4	-461.4
28	15997	14707.8	1289.2
29	24117	14469.2	9647.8
30	29080	14230.6	14849.4
31	16964	13992.0	2972.0
32	17281	13753.4	3527.6
33	5600	13514.8	-7914.8
34	20614	13276.2	7337.8
35	4374	13037.7	-8663.7
36	11892	12799.1	-907.1

Forecasts

Period	Forecast
37	12560.5
38	12321.9
39	12083.3
40	11844.7
41	11606.1
42	11367.5
43	11128.9
44	10890.3
45	10651.7
46	10413.1
47	10174.5
48	9935.9
49	9697.3
50	9458.7
51	9220.1
52	8981.5
53	8742.9
54	8504.3
55	8265.7
56	8027.2
57	7788.6
58	7550.0
59	7311.4
60	7072.8
61	6834.2
62	6595.6
63	6357.0
64	6118.4
65	5879.8
66	5641.2
67	5402.6
68	5164.0
69	4925.4
70	4686.8
71	4448.2
72	4209.6

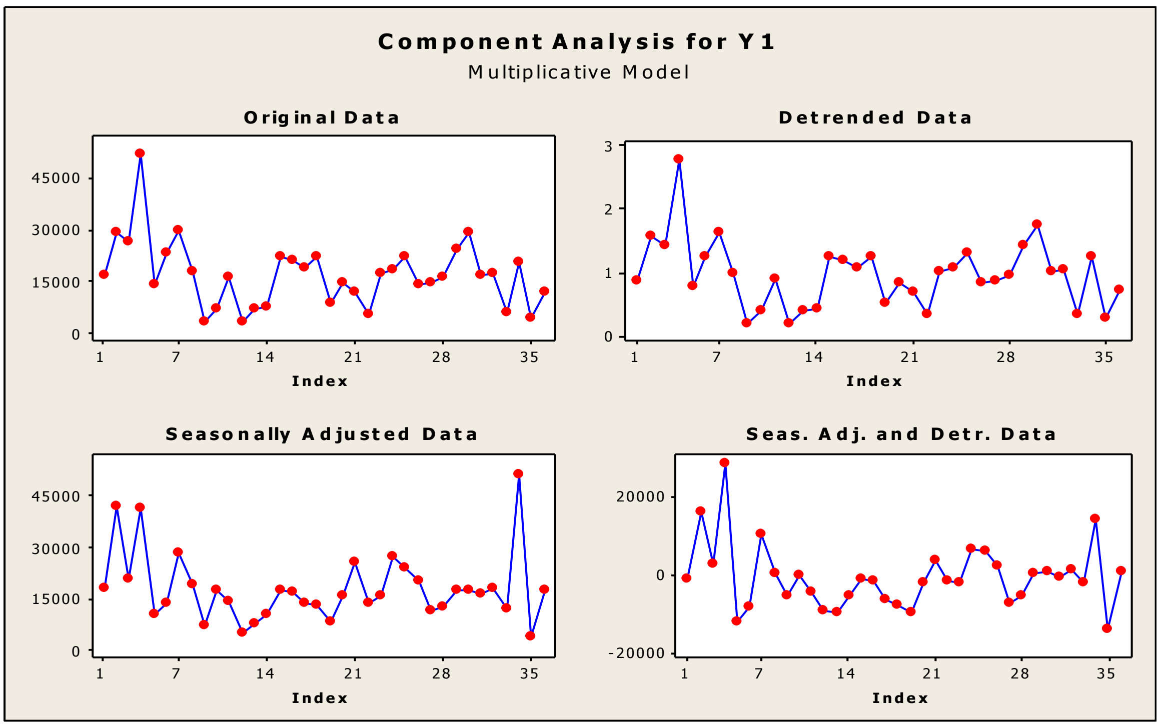

Figure 1: **Decomposition - Component Analysis for Y1**

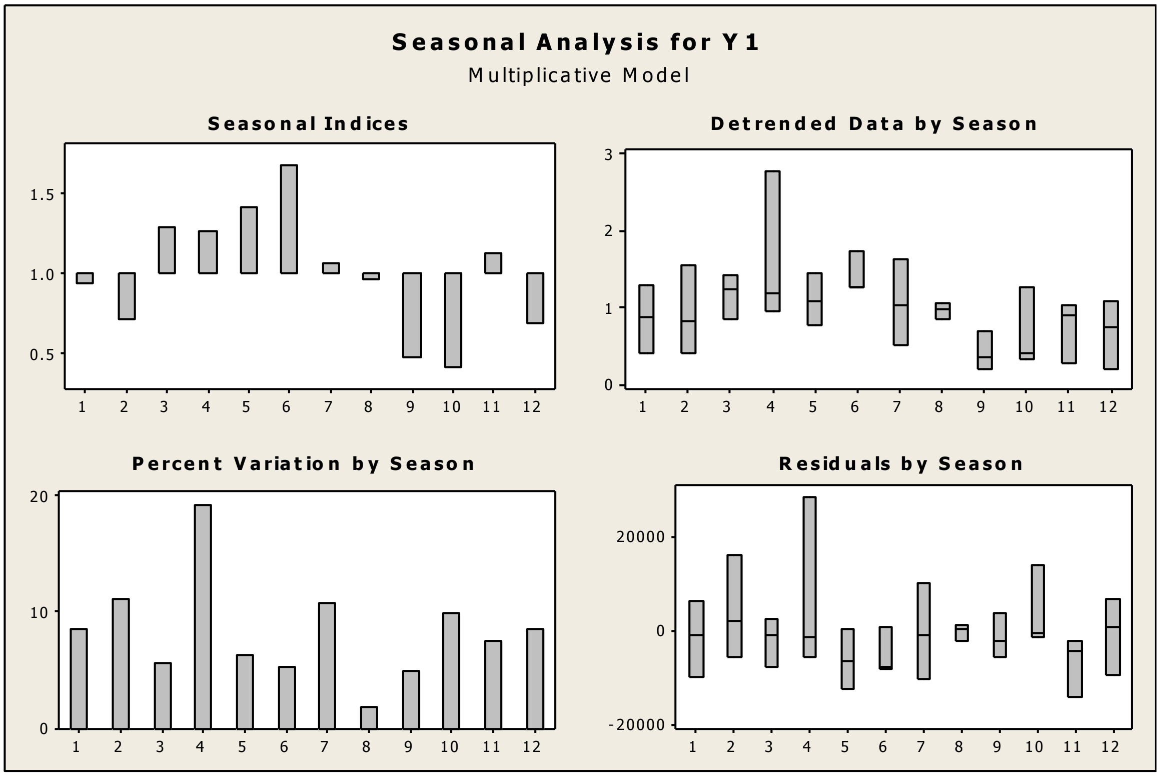

Figure 2: **Decomposition - Seasonal Analysis for Y1**

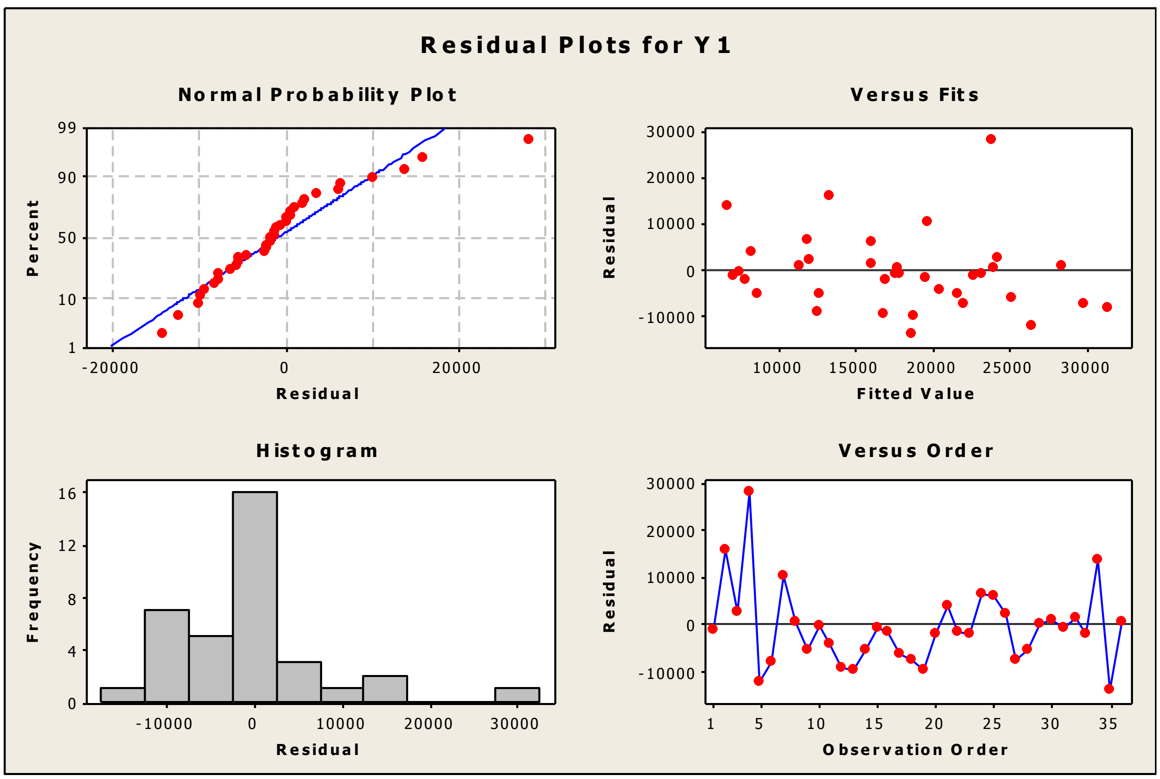

Figure 3: **Residual Plots for Y1**

IV. Double Exponential Smoothing for Y1

Data Y1
Length 36

Smoothing Constants
Alpha (level) 0.591693
Gamma (trend) 0.075950

Accuracy Measures
MAPE 78
MAD 8095
MSD 111899243

Time	Y1	Smooth	Predict	Error
May	16509	12470.2	6617.3	9891.7
Jun	29233	21618.6	10584.4	18648.6
Jul	26649	26423.7	26097.3	551.7
Aug	52012	41961.4	27396.8	24615.2
Sep	14143	26350.4	44040.7	-29897.7
Oct	23070	24709.8	27086.1	-4016.1
Nov	29873	27991.5	25265.0	4608.0
Dec	17964	22369.5	28753.8	-10789.8
Jan	3231	11158.7	22646.9	-19415.9
Feb	7028	8471.6	10563.5	-3535.5
Mar	15997	12616.4	7717.5	8279.5
Apr	3154	6861.6	12234.5	-9080.5
May	7096	6677.7	6071.6	1024.4
Jun	7267	6722.6	5933.7	1333.3
Jul	22102	15543.2	6038.5	16063.5
Aug	21117	18856.6	15581.0	5536.0
Sep	18831	18958.5	19143.2	-312.2
Oct	22155	20961.1	19231.0	2924.0
Nov	8750	13900.8	21365.1	-12615.1
Dec	14773	14350.3	13737.9	1035.1
Jan	11958	12887.3	14233.9	-2275.9
Feb	5501	8427.6	12668.6	-7167.6
Mar	17515	13583.7	7886.7	9628.3
Apr	18435	16410.0	13475.6	4959.4
May	22208	19887.5	16524.8	5683.2
Jun	14106	16617.8	20257.6	-6151.6
Jul	14485	15394.1	16711.4	-2226.4
Aug	15997	15748.2	15387.7	609.3
Sep	24117	20708.5	15769.2	8347.8
Oct	29080	25823.6	21104.7	7975.3
Nov	16964	20889.5	26578.2	-9614.2
Dec	17281	18886.1	21212.0	-3931.0
Jan	5600	11084.3	19031.9	-13431.9
Feb	20614	16536.1	10626.6	9987.4
Mar	4374	9336.2	16527.1	-12153.1
Apr	11892	10621.8	8781.1	3110.9

Forecasts

Period	Forecast	Lower	Upper
May	10206.5	-9626	30039
Jun	9791.2	-13766	33349
Jul	9375.9	-18272	37023
Aug	8960.6	-23002	40924
Sep	8545.3	-27878	44969
Oct	8130.0	-32852	49112
Nov	7714.7	-37895	53324
Dec	7299.4	-42987	57586
Jan	6884.1	-48116	61885
Feb	6468.8	-53274	66211
Mar	6053.5	-58453	70560
Apr	5638.2	-63650	74927
May	5223.0	-68861	79307
Jun	4807.7	-74084	83699
Jul	4392.4	-79316	88100
Aug	3977.1	-84556	92510
Sep	3561.8	-89802	96926
Oct	3146.5	-95055	101348
Nov	2731.2	-100312	105774
Dec	2315.9	-105574	110206
Jan	1900.6	-110839	114640
Feb	1485.3	-116108	119078
Mar	1070.0	-121379	123519
Apr	654.7	-126653	127963
May	239.4	-131930	132409
Jun	-175.9	-137208	136856
Jul	-591.2	-142488	141306
Aug	-1006.5	-147770	145757
Sep	-1421.8	-153053	150210
Oct	-1837.1	-158338	154664
Nov	-2252.4	-163624	159119
Dec	-2667.7	-168911	163575
Jan	-3083.0	-174199	168033
Feb	-3498.3	-179488	172491
Mar	-3913.6	-184777	176950
Apr	-4328.9	-190068	181410

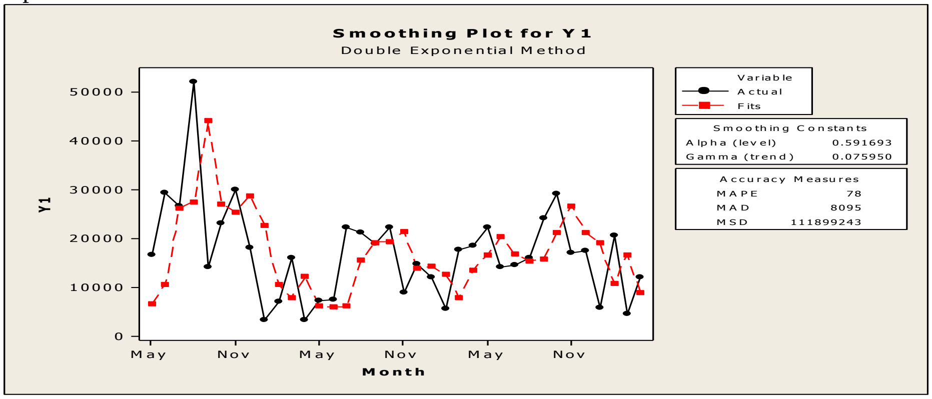

Figure 4: **Double Exponential Smoothing Plot for Y1**

4.1. Winters Method for Y1

Multiplicative Method

Data	Y1
Length	36

Smoothing Constants

Alpha (level)	0.2
Gamma (trend)	0.2
Delta (seasonal)	0.2

Accuracy Measures

MAPE	55
MAD	7454
MSD	94567481

Time	Y1	Smooth	Predict	Error
May	16509	30646.6	28675.8	-12166.8
Jun	29233	28799.9	26102.9	3130.1
Jul	26649	33519.0	30294.0	-3645.0
Aug	52012	41567.4	36828.1	15183.9
Sep	14143	25862.5	23181.9	-9038.9
Oct	23070	27813.7	23855.0	-785.0
Nov	29873	17650.7	14678.8	15194.2
Dec	17964	16035.0	13895.4	4068.6
Jan	3231	6137.9	5313.0	-2082.0
Feb	7028	7865.0	6406.2	621.8
Mar	15997	7373.3	5754.4	10242.6
Apr	3154	6983.2	5901.0	-2747.0
May	7096	6643.9	5164.0	1932.0
Jun	7267	6702.6	5008.8	2258.2
Jul	22102	6589.0	4654.0	17448.0
Aug	21117	12391.9	10509.5	10607.5
Sep	18831	7201.1	6369.8	12461.2
Oct	22155	12303.4	11841.4	10313.6
Nov	8750	11839.8	11797.6	-3047.6
Dec	14773	9297.9	9161.5	5611.5
Jan	11958	3829.9	3862.7	8095.3
Feb	5501	9591.5	10215.5	-4714.5
Mar	17515	12477.9	13063.9	4451.1
Apr	18435	9473.0	9991.6	8443.4
May	22208	16678.3	17901.1	4306.9
Jun	14106	22882.4	24583.8	-10477.8
Jul	14485	34177.2	36126.0	-21641.0
Aug	15997	40875.0	42267.4	-26270.4
Sep	24117	22787.4	22997.7	1119.3
Oct	29080	29441.5	29764.9	-684.9
Nov	16964	21569.6	21785.1	-4821.1
Dec	17281	19671.3	19692.7	-2411.7
Jan	5600	8134.5	8102.7	-2502.7
Feb	20614	9884.1	9712.6	10901.4
Mar	4374	18310.3	18717.7	-14343.7
Apr	11892	11420.9	11301.0	591.0

Forecasts

Period	Forecast	Lower	Upper
May	15024.1	-3239.1	33287.2
Jun	16217.3	-2332.0	34766.6
Jul	23528.6	4660.3	42396.9
Aug	29826.5	10607.9	49045.1
Sep	20692.8	1094.3	40291.3
Oct	25710.1	5703.8	45716.4
Nov	17930.1	-2510.2	38370.5
Dec	17084.1	-3814.9	37983.0
Jan	6930.3	-14450.3	28310.9
Feb	10807.1	-11076.6	32690.8
Mar	12295.1	-10111.8	34702.0
Apr	10348.9	-12599.9	33297.6
May	13491.1	-10016.9	36999.2
Jun	14548.4	-9535.0	38631.9
Jul	21086.3	-3587.6	45760.3
Aug	26703.5	1425.1	51981.9
Sep	18507.1	-7388.7	44403.0
Oct	22970.3	-3555.1	49495.8
Nov	16002.3	-11164.0	43168.6
Dec	15230.6	-12587.0	43048.3
Jan	6171.6	-22307.1	34650.3
Feb	9613.0	-19535.8	38761.9
Mar	10924.0	-18903.5	40751.5
Apr	9184.0	-21330.1	39698.1
May	11958.2	-19249.9	43166.3
Jun	12879.5	-19029.5	44788.5
Jul	18644.1	-13972.2	51260.5
Aug	23580.6	-9749.2	56910.4
Sep	16321.5	-17727.4	50370.3
Oct	20230.6	-14542.7	55003.9
Nov	14074.5	-21428.2	49577.2
Dec	13377.2	-22859.6	49614.0
Jan	5412.9	-31562.5	42388.2
Feb	8419.0	-29299.0	46137.0
Mar	9552.9	-28911.7	48017.5
Apr	8019.1	-31195.8	47234.0

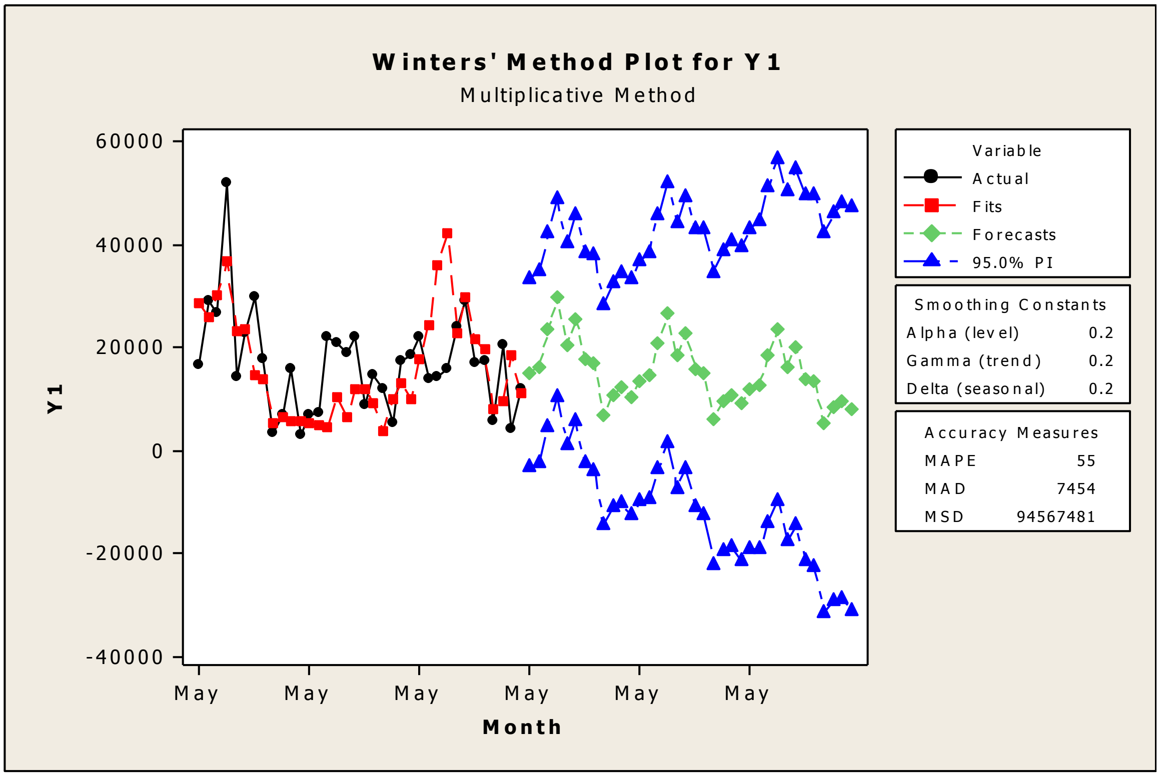

Figure 5: **Winters Method Plot for Y1**

Table 3: Forecasting Results of Y1 Production Output

Year	Month	Monthly Forecast	Trend Analysis	Weighted Moving Average	Double Exponential Smoothing	Winters Model
2014	Jan	**37**	12560.5	13997.6	10206.5	15024.1
	Feb	**38**	12321.9	8554.12	9791.2	16217.3
	Mar	**39**	12083.3	11856.1	9375.9	23528.6
	April	**40**	11844.7	11936.26	8960.6	29826.5
	May	**41**	11606.1	10221.14	8545.3	20692.8
	June	**42**	11367.5	11553.16	8130.0	25710.1
	July	**43**	11128.9	11345.1	7714.7	17930.1
	Aug	**44**	10890.3	10845.54	7299.4	17084.1
	Sept	**45**	10651.7	11349.22	6884.1	6930.3
	Oct	**46**	10413.1	11196.06	6468.8	10807.1
	Nov	**47**	10174.5	11066.75	6053.5	12295.1
	Dec	**48**	9935.9	11246.77	5638.2	10348.9
2015	Jan	**49**	9697.3	11167.41	5223.0	13491.1
	Feb	**50**	9458.7	11140.89	4807.7	14548.4
	Mar	**51**	9220.1	11201.79	4392.4	21086.3
	April	**52**	8981.5	11166.33	3977.1	26703.5
	May	**53**	8742.9	11164.24	3561.8	18507.1
	June	**54**	8504.3	11183.64	3146.5	22970.3
	July	**55**	8365.7	11169.17	2731.2	16002.3
	Aug	**56**	8027.2	11171.05	2315.9	15230.6
	Sept	**57**	7788.6	11176.78	1900.6	6171.6
	Oct	**58**	7550.0	11171.25	1485.3	9613.0
	Nov	**59**	7311.4	11172.81	1070.0	10924.0
	Dec	**60**	7072.8	11174.33	654.7	9184.0
2016	Jan	**61**	6834.2	11172.33	239.4	11958.2

Feb	**62**	6595.6	11173.17	-175.9	12879.5
Mar	**63**	6357.0	11173.5	-591.2	18644.1
April	**64**	6118.4	11172.82	-1006.5	23580.6
May	**65**	5879.8	11173.2	-4328.9	16321.5
June	**66**	5641.2	11173.23	-1837.1	20230.6
July	**67**	5402.6	11173.01	-2252.4	14074.5
Aug	**68**	5164.0	11173.17	-2667.7	13377.2
Sept	**69**	4925.4	11173.16	-3083.0	5412.9
Oct	**70**	4686.8	11173.09	-3498.3	8419.0
Nov	**71**	4448.2	11173.15	-3913.6	9552.9
Dec	**72**	4209.6	11173.13	-4328.9	8019.1

V. Discussion of Results

The discussion of results was based on the results found from the analysis, the tables and the charts developed: Forecasting models were applied using different forecasting methods to predict the future production output of their products in monthly production output.

- For Y1 Product in table 3, the monthly results using the weighted moving average model showed that the product is to be produced for 13997.6 units. Trend analysis model showed that the product is to be produced for 12560.5 units. Double exponential smoothing model showed that the product is to be produced for 10206.5 units. Winter model showed that the product is to be produced for 15024.1 units.
- These methods were applied for the product for monthly yield of the product type investigated. It was also observed that these different methods produce similar results.
- From the tables above, the results show the product types investigated and their results using different methods and models.
- Weighted moving average model were used, and the assigned weight takes care of the unknown variables that can affect the model. This showed that the model is highly rated among all.
- The tables above reveal that the models produced good results for the product types investigated.
- Time series decomposition analysis of the product shows the highest seasonal influence for Y1 product on the months of June with seasonal indexes of 1.7. From the results, the downward movement of the trend showed a continuous decrease in their future production output on the product Y1, therefore the company were advice to review their plans or strategies and the managerial decisions or stop the production of the products to avoid loss.
- It was observed that the detailed summary of the time series analysis were developed. The time series decomposition analyses were also used to show the seasonal and trend variations in the data.

VI. Conclusion

Forecasting models for predicting monthly product requirements were developed for the case study. The models were tested and analyzed using historical data collected from the company. The analysis of the models revealed the future production output of the company for the next five years of production. From the result analysis, there were different forecasting methods and there models were applied that showed the results of the future production outputs on the products. These future production outputs were observed in the five products. Time series decomposition techniques were used to study the seasonality and trend analyses in the historical data. The application of the forecasting methods and its techniques will help the production manager to understand the trend and how the future will be. It will help the production manager to understand the future and the need to develop plans or strategies on how to tackle the future production output so as to minimize cost and maximize profit. The plans developed will help the production manager in production planning and control on the product types investigated.

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