Chapter 5

Development of a New Model for Seasonal Products

5.1 INTRODUCTION

Successful marketing requires capabilities such as understanding, creating, delivering, capturing and sustaining customer value. Only a select group of companies have historically stood out as master marketers. Those companies focus on the customer and are organized to respond effectively to changing customer needs. They all have well-staffed marketing departments, and their other departments accept that the customer is king.

To ensure that they select and execute the right activities, marketers give priority to strategic planning key areas such as managing a company's businesses as an investment portfolio, assessing each business's strength by considering the market's growth rate and the company's position and fit in that market, and establishing a strategy. The companies develop a game plan for achieving each business's long-run objectives.

This chapter discusses about the 2 sections. Section 5.2 discusses about the methodology involved in choosing the models for the demand forecast calculation and Section 5.3 discusses about the results and the analysis of the forecasting models used for the products.

The model developed in this work helps to determine the throughput in a supply chain and establish the minimal levels of inventory to be held in the buffers between the successive producing and consuming entities. The sales data of various products was analyzed so as to fit the best forecast method for the respective forecast horizon. In order to fit the best forecast model for each product, a new model has been developed which selects the model dynamically. A forecast accuracy measure was used to compare among different forecast methods chosen, with Mean Square Error being the better choice, since it penalizes large error more than small data, thereby capturing the information easily than the other error measures. The proposed algorithm is better, when compared to Static

Forecasting; since it takes into account the recent trend, seasonality etc., observed in the sales data. This Forecasting model is giving satisfactory results as different products were analyzed and the model is chosen based on the history of the product, thus producing optimistic forecast for the future horizons.

5.2 METHODOLOGY

The algorithms developed for demand forecasting are discussed in this section and the methodology comprises of 2 sections as given below.

5.2.1. Design of the system

5.2.2 Data Analysis and Experimentation

5.2.1 DESIGN OF THE SYSTEM

This Section explains the forecasting models selected to be incorporated in the Dynamic Forecast Model. A comprehensive algorithm and a program has been developed which analyses the data, fits the data to each selected model and find the mean square error associated with each of them.

After analyzing various time series forecasting methods, the following methods have been chosen to be used in the Dynamic Forecasting Model.

5.2.1.1 WEIGHTED MOVING AVERAGE (WMA)

The weighted moving average assigns more weight to some demand values (usually the most recent ones) than to others. In this method, equal weights are assigned to all periods in the computation of the simple moving average.

The algorithm is shown in Fig 5.1. The sales data and the forecasting horizon are fed as inputs. The weightages considered are 0.2, 0.3 and 0.5. The mean square error is calculated and the forecast for the respective period gets generated.

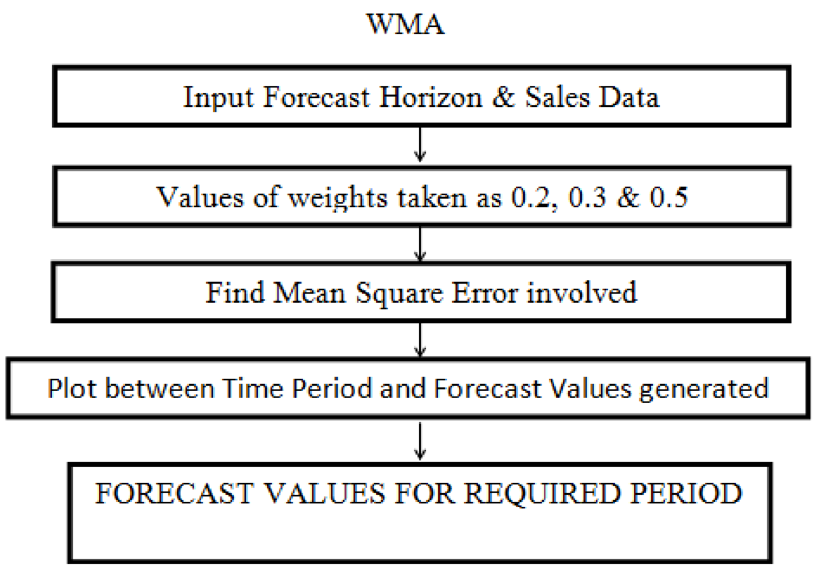


Fig. 5.1- Algorithm for Weighted Moving Average

5.2.1.2 .A. LINEAR REGRESSION

The algorithm for Linear Regression is shown in Fig 5.2.

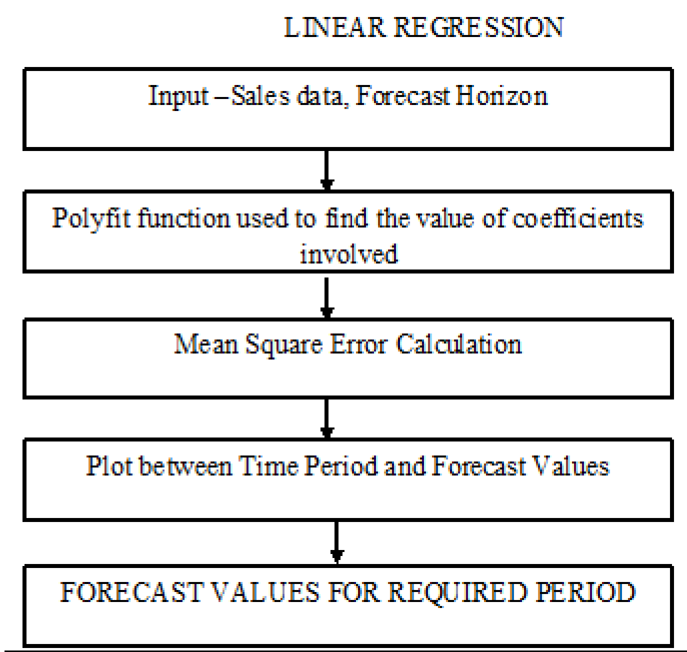


Fig. 5.2 -Algorithm for Linear Regression

The sales data and the forecasting horizon are inputs. The value of the coefficients is determined and the error is calculated. Forecast for the respective period is determined based on the least mean square error value.

5.2.1.2. B. POLYNOMIAL REGRESSION

The algorithm for the polynomial regression is shown in Fig 5.3. The respective forecast horizon and the sales data are provided as inputs. The coefficients for the order 2 are calculated and the mean square error is determined. A plot is generated between the time period and the forecast values.

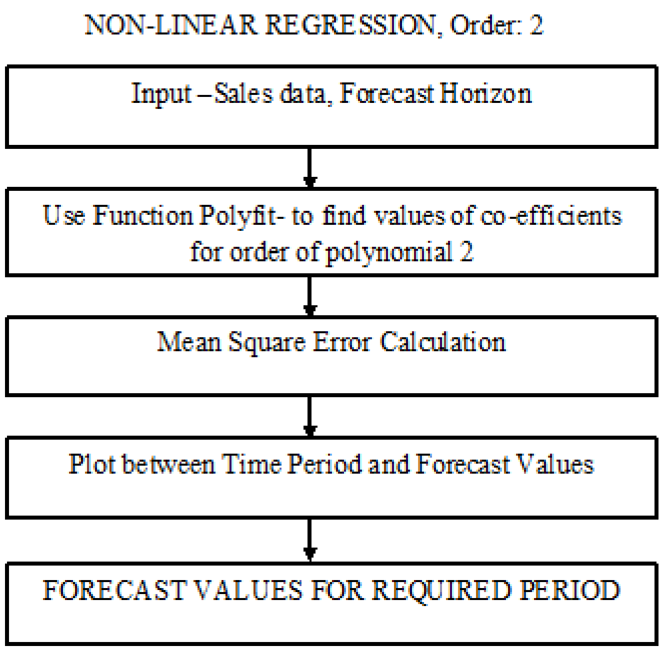


Fig. 5.3 Algorithm for Polynomial Regression, Order 2

The polynomial coefficients of order 3 are calculated for the polynomial regression and the forecast values are generated as shown in Fig 5.4

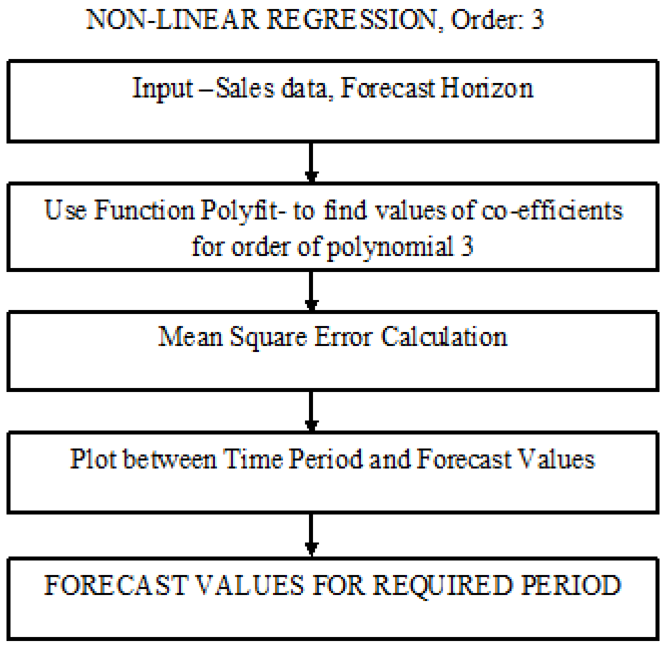


Fig. 5.4 -Algorithm for Polynomial Regression, Order 3

5.2.1.3 SIMPLE EXPONENTIAL SMOOTHING

This method keeps a running average of demand and adjusts it for each period in proportion to the difference between the latest actual demand figure and the latest value of the average. This method is appropriate when demand has no observable trend or seasonality and the algorithm is shown in Fig 5.5.

Systematic component of demand = level

The initial estimate of level, L_o, is taken to be the average of all historical data because demand has been assumed to have no observable trend or seasonality.

$L_o = \sum D_i/n$

Where D_i=Demand values

After observing the demand, D_{t+1}, the estimate of level is given as:

$L_{t+1} = \alpha D_{t+1} + (1- \alpha) L_t$

Where, α is a smoothing constant for the level, $0< \alpha<1$.

A higher value of α corresponds to a forecast that is more responsive to recent observations, whereas a lower value of α represents a more stable forecast that is less responsive to recent observations.

The forecast for all future periods is equal to the current estimate of level and is given as follows:$F_{t+1}=L_t$

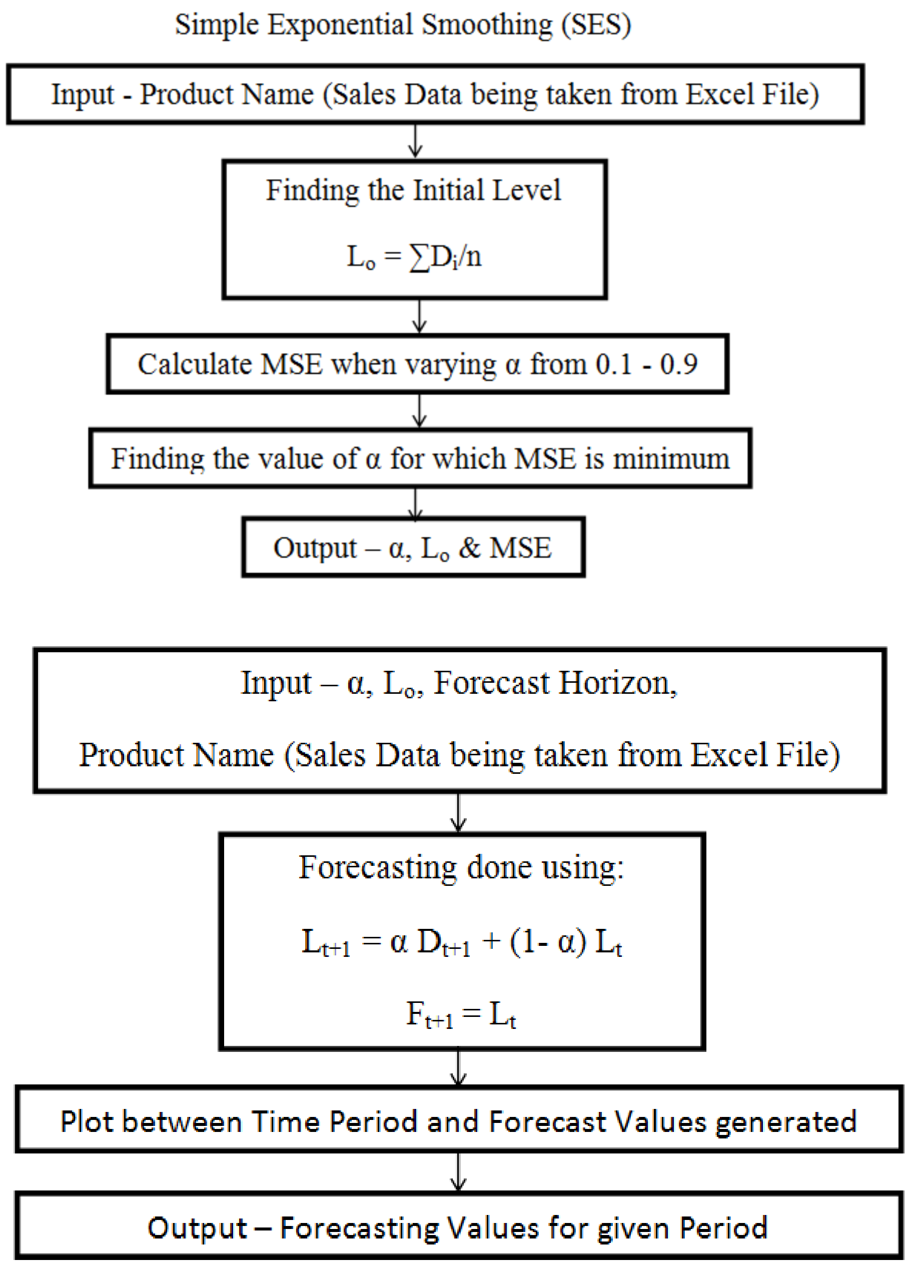


Fig. 5.5- Algorithm for Single Exponential Smoothing

5.2.1.4 ADJUSTED EXPONENTIAL SMOOTHING (HOLT'S METHOD)

This method is appropriate when the demand is assumed to have a level and a trend in the systematic component but no seasonality. This method actually projects the next period forecast by adding a trend component to the current period smoothed Forecast and the algorithm is shown in Fig 5.6.

Systematic component of demand= Level + Trend

The initial estimate of level and trend is found out by running a linear regression between demand D_t and time period t of the following form:

D_t=at+b

In this case, running a linear regression between demand and time period is appropriate because we have assumed that the demand has a trend but no seasonality. The underlying relationship between demand and time is thus linear. The constant b measures the estimate of demand at period t=0 and is an estimate of the initial level L_o. The slope a measures the rate of change in demand per period and is the initial estimate of the trend T_o.

In period t, given estimates of level L_t and trend T_t, the forecast for future periods is expressed as follows:

$F_{t+1} = F_t + T_t$

After observing the demand for period t, we revise the estimates for level and trend as follows:

$F_t = \alpha\, D_{t-1} + (1- \alpha)\, (F_{t-1} + T_{t-1})$

$T_t = \beta\, (F_t – F_{t-1}) + (1- \beta)T_{t-1}$

F_t= Smoothed average forecast for period t.

F_{t-1} = Previous period forecast.

α & β = Smoothing Constant, varies from 0 to 1 depending upon the weight given to the previous data.

D_{t-1}= Previous data

T_t= Trend adjustment

Holt's Method

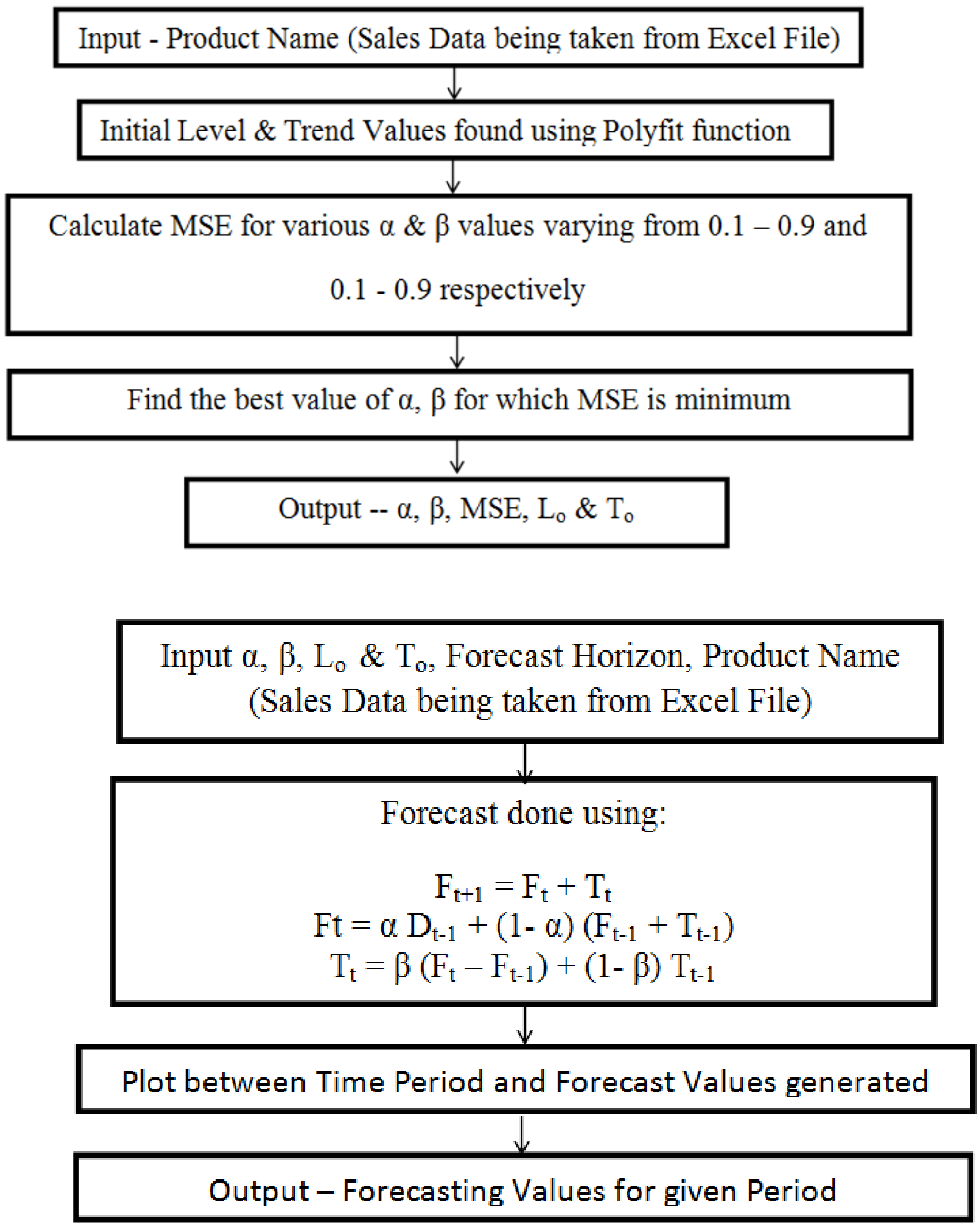


Fig. 5.6 Algorithm for Holt's method

5.2.1.5 WINTER'S METHOD

This method is used when the systematic component of demand is assumed to have a level, a trend and a seasonality factor and the algorithm is shown in Fig 5.7.

Systematic component of demand = (Level + Trend)*Seasonal factor

The periodicity of demand is assumed to be *p.* To begin with, the initial estimates of level (L_o), trend (T_o) and seasonal factors (S_1, S2, …S_p) are required. To obtain the initial estimate of level and trend, the demand data has to be deseasonalized. Deseasonalized demand represents the demand that would have been observed in the absence of seasonal fluctuations. The periodicity p is the number of periods after which the seasonal cycle repeats itself.

Once demand has been deseasonalized, it is either growing or declining at a steady rate. Thus there is a linear relationship between the deseasonalized demand D' and time t. This relationship is defined as follows:

$D_t' = L+tT$

Where, L= deseasonalized demand at period 0 or Initial Level.

T= rate of growth of deseasonalized demand or Initial Trend.

Seasonal factor, S_t, for period t is the ratio of actual demand D_t to deseasonalized demand D_t'.

$S_t = D_t/D_t'$

In period t, given estimates of level, L_t; trend, T_t; and seasonal factors S_t,…S_{t-p+1}, the forecast for the the future periods is given by the following:

$F_{t+1}= (L_t + T_t) S_{t+1}$

$F_{t+1} = (L_t + l\,T_t) S_{t+l}$

On observing Demand for period t+1 , the estimates for level, trend and seasonal factors are revised as follows.

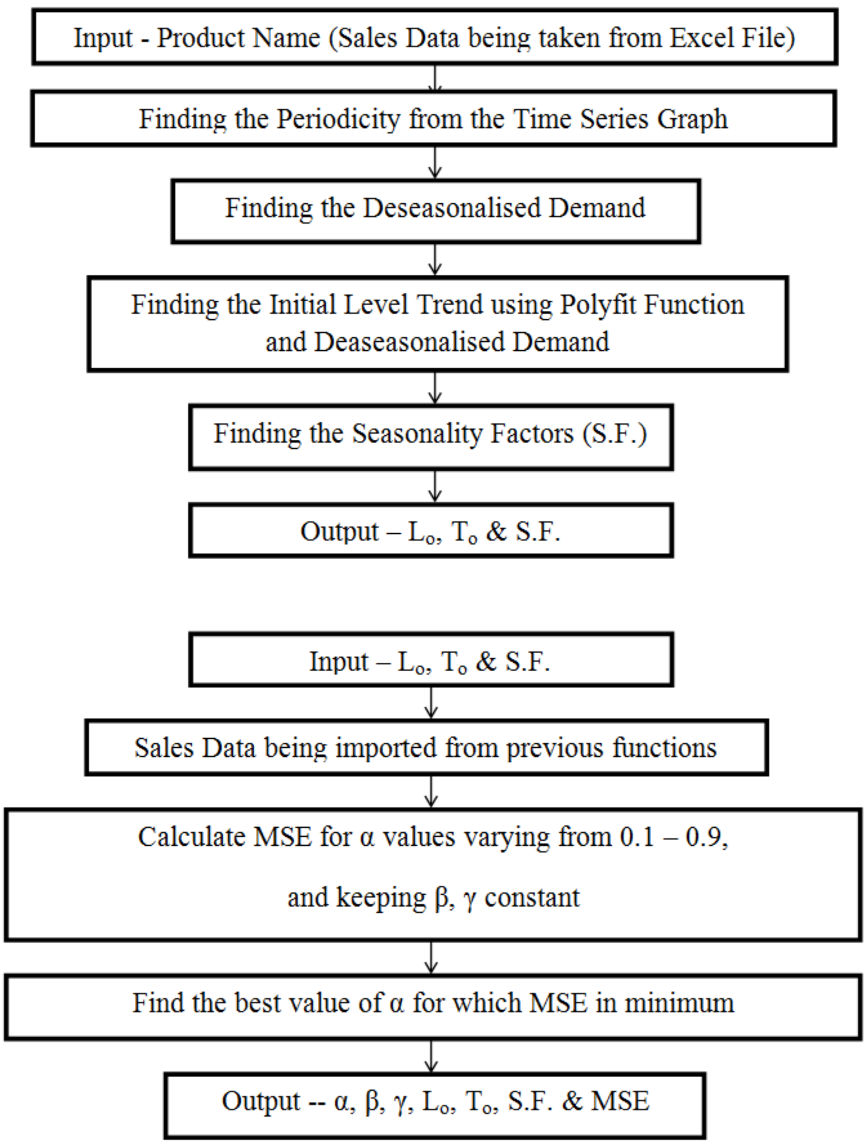
$L_{t+1} = \alpha\,(D_{t+1}/S_{t+1}) + (1-\alpha)\,(L_t + T_t)$

$T_{t+1} = \beta\,(L_{t+1} - L_t) + (1-\beta)\,T_t$

$S_{t+p+1} = \gamma\,(D_{t+1} / L_{t+1}) + (1-\gamma)\,S_{t+1}$

Where, α is a smoothing constant for the level varying from 0.1 to 0.9; β is a smoothing constant for the trend varying from 0.1 to 0.9 and γ is a smoothing constant for the seasonal factor varying from 0.1 to 0.9.

Winter's Model



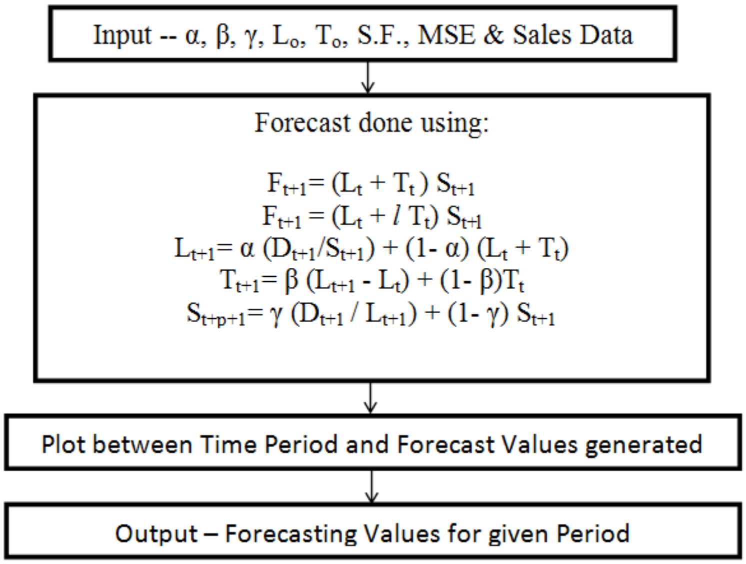


Fig. 5.7 - Algorithm for Winters method

5.2.2 DATA ANALYSIS AND EXPERIMENTATION

The sales data of many products were taken and the experimentation of products are discussed in this section.

Sales Data Analysis: The sales data of products were analyzed so as to understand the relationship, pattern, trend etc. in the past demand values.

The sales data was analyzed by using time series plot as well as scatter plot. These plots revealed the trend over time, regular seasonal behavior and other systematic features of the data. An important step in selecting an appropriate forecasting method is to consider the types of data patterns so that the methods which are most appropriate to those patterns can be utilized.

The various patterns have been observed for the different products. A horizontal pattern existed, when the data values fluctuate around a constant mean and the sales do not increase or decrease over time for these types of products.

A seasonal pattern existed, when a series is influenced by seasonal factors. A cyclical pattern existed when the data exhibited rises and falls that are not of a fixed period. The average length of a cycle is usually longer than that of seasonality and the magnitude of a cycle is usually more variable than that of seasonality. A trend pattern existed when there is a long term increase or decrease in the data.

Sales data of Products A and B are shown in tables 5.1 and 5.2 respectively. These are the coffee and Tea products whose sales volumes are considerably good.

Table 5.1- Sales data of Product A

Week	Sales	Week	Sales	Week	Sales
Week 1	15	Week 21	7.998	Week 41	6.122
Week2	10.8	Week 22	9.57	Week 42	2.52
Week3	11.25	Week 23	7.23	Week 43	5.85
Week 4	11.842	Week 24	11.032	Week 44	4.05
Week 5	23.857	Week 25	8.01	Week 45	6.0225
Week 6	9.412	Week 26	5.212	Week 46	13.59
Week 7	10.552	Week 27	3.567	Week 47	4.68
Week 8	5.04	Week 28	3.967	Week 48	3.165
Week 9	5.865	Week 29	4.95	Week 49	5.04
Week 10	19.71	Week 30	4.14	Week 50	4.68
Week 11	7.102	Week 31	4.59	Week 51	8.91
Week 12	16.47	Week 32	13.14	Week 52	5.355
Week 13	4.23	Week 33	4.86	Week 53	2.895
Week 14	6.18	Week 34	5.165	Week 54	3.42
Week 15	11.7	Week 35	5.76	Week 55	1.095
Week 16	5.902	Week 36	6.51	Week 56	10.44
Week 17	3.742	Week 37	5.49	Week 57	12.24
Week 18	5.715	Week 38	7.56	Week 58	8.82
Week 19	6.712	Week 39	4.68	Week 59	16.95
Week 20	11.002	Week 40	10.71		

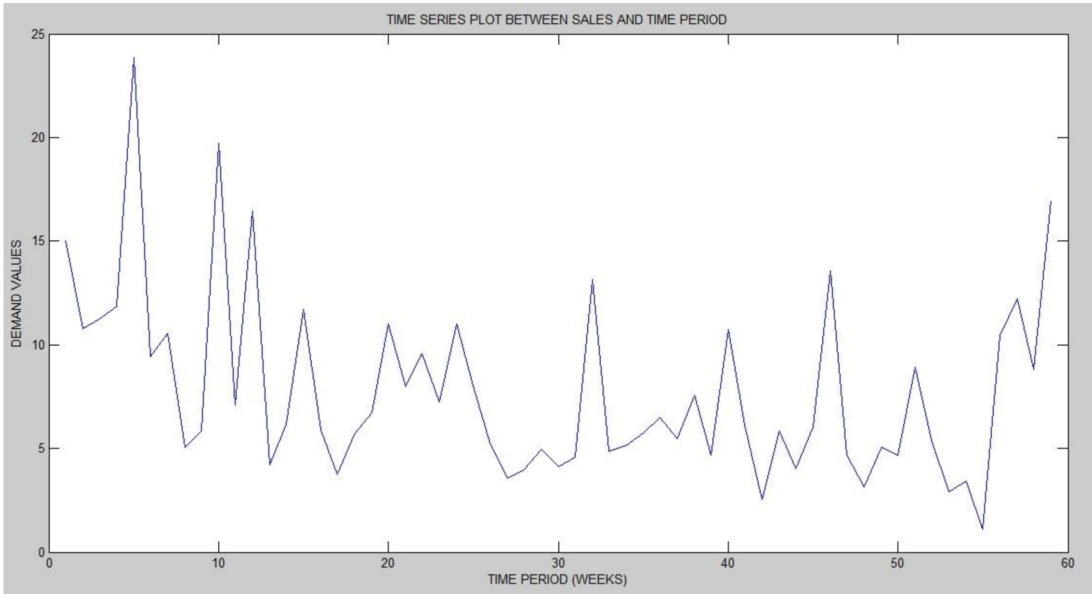


Fig.5.8- Time-Series Graph of Product A

The Time Series of product A is shown in Fig 5.8. The data reveals that the sales of the product has been fluctuating and has not remained consistent throughout the time period. Forecasting for these kinds of products becomes difficult since the forecast needs to be as close to accurate as possible to overcome the inventory and the financial losses.

Table 5.2- Sales data of Product B

Week	Sales	Week	Sales	Week	Sales	Week	Sales
Week 1	3.936	Week 21	4.488	Week 41	5.688	Week 61	5.478
Week 2	5.994	Week 22	9.15	Week 42	5.922	Week 62	3.042
Week 3	4.464	Week 23	9.444	Week 43	6.84	Week 63	1.44
Week 4	6.336	Week 24	5.472	Week 44	4.896		
Week 5	2.322	Week 25	9.576	Week 45	4.68		
Week 6	8.64	Week 26	29.388	Week 46	12.684		
Week 7	8.43	Week 27	6.12	Week 47	13.488		
Week 8	6.786	Week 28	2.88	Week 48	4.254		
Week 9	7.392	Week 29	1.806	Week 49	5.112		
Week 10	6.12	Week 30	9.3	Week 50	3.6		
Week 11	8.97	Week 31	6.696	Week 51	4.392		
Week 12	6.954	Week 32	7.5	Week 52	4.992		
Week 13	3.96	Week 33	5.904	Week 53	4.11		
Week 14	7.704	Week 34	4.896	Week 54	7.068		
Week 15	16.302	Week 35	8.082	Week 55	6		
Week 16	12.312	Week 36	10.08	Week 56	8.64		
Week 17	23.4	Week 37	13.758	Week 57	7.92		
Week 18	11.88	Week 38	22.752	Week 58	5.904		
Week 19	3.816	Week 39	8.364	Week 59	3.606		
Week 20	7.206	Week 40	11.322	Week 60	7.278		

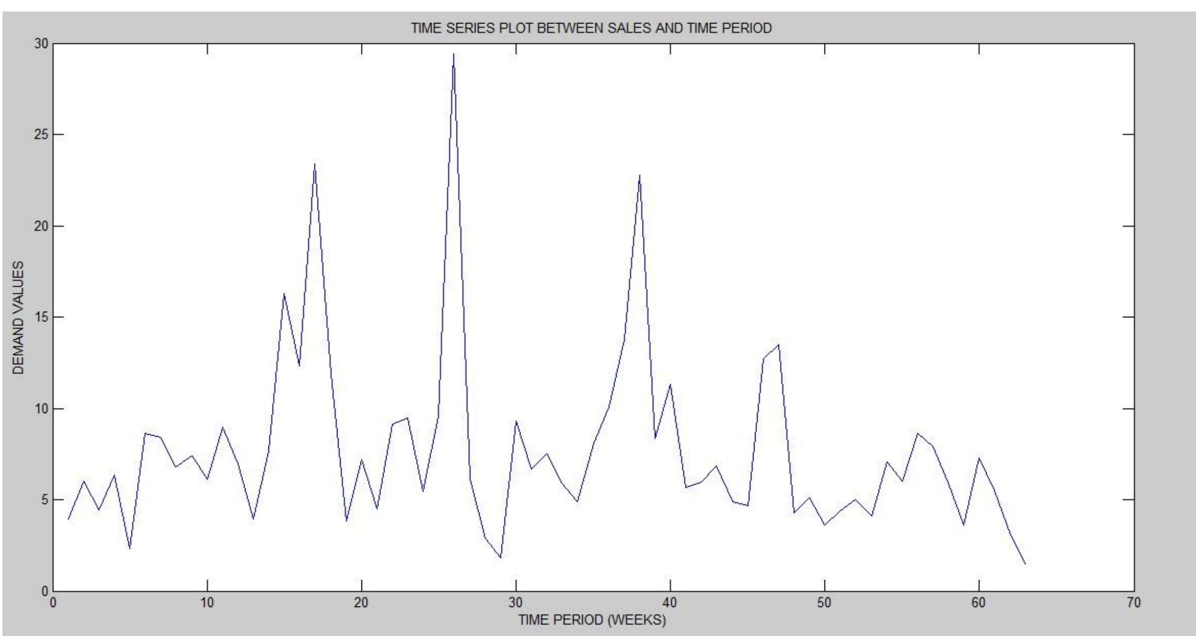


Fig. 5.9 -Time Series Graph of Product B

The time series of Product B is shown in Fig 5.9. The trend shows that there has been a peak in sales at certain point of time and has been average in the rest of the period. If the peak period has occurred due to some seasonal behavior, the normal sales trend shall be inferred.

5.3 RESULTS AND ANALYSIS OF DEMAND FORECASTING MODEL

The program for Dynamic Forecast Model was created and executed. The output of each of the products were obtained, which provides the future forecast for user specified forecast horizon, graphs containing the fit and forecast curves along with the data points, and the mean square errors of each of the five models.

The following result is achieved using the Dynamic Forecasting Model:

5.3.1 OUTPUT FOR PRODUCT A

The MSE error due to Weighted Average Method is: 21.796

The MSE error due to Linear Regression is: 17.331

The MSE error due to Polynomial Regression of order 2 is: 14.277

The MSE error due to Polynomial Regression of order 3 is: 14.200

The MSE error due to Single Exponential Smoothing is: 18.901

The MSE error due to Holts method is: 18.713

The MSE error due to Winter Method is: 18.999

The minimum MSE error is: 14.200 when using Polynomial Reg of order 3 function

The forecast for the required period using Polynomial Reg of order 3 is:

13.401

13.067

12.735

12.404

12.076

11.750

11.428

11.109

Forecast error using Modified MAPE1: 5.64

The forecast value of the Product A is shown in Fig 5.10.

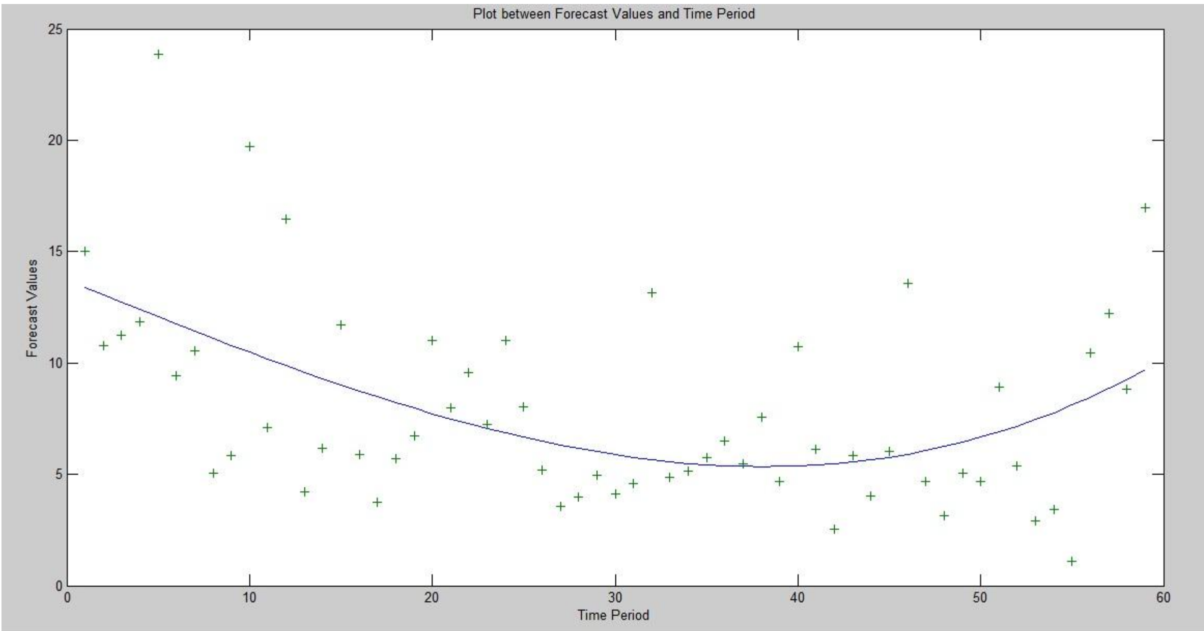


Fig. 5.10 -Forecast Values for Product A

5.3.2 OUTPUT FOR PRODUCT B

The output of the Product B is shown in Fig 5.11.

The MSE error due to Weighted Average Method is: 91.717

The MSE error due to Linear Regression is: 70.652

The MSE error due to Polynomial Regression of order 2 is: 70.617

The MSE error due to Polynomial Regression of order 3 is: 61.942

The MSE error due to Single Exponential Smoothing is: 76.507

The MSE error due to Holts method is: 81.637

The MSE error due to Winter Method is: 72.199

The minimum MSE error is: 61.942 when using Polynomial Reg of order 3 function

The forecast for the required period using Polynomial Reg of order 3 is:

4.213

5.949

7.525

8.948

10.225

11.362

12.364

13.239

Forecast error using Modified MAPE1: 4.2

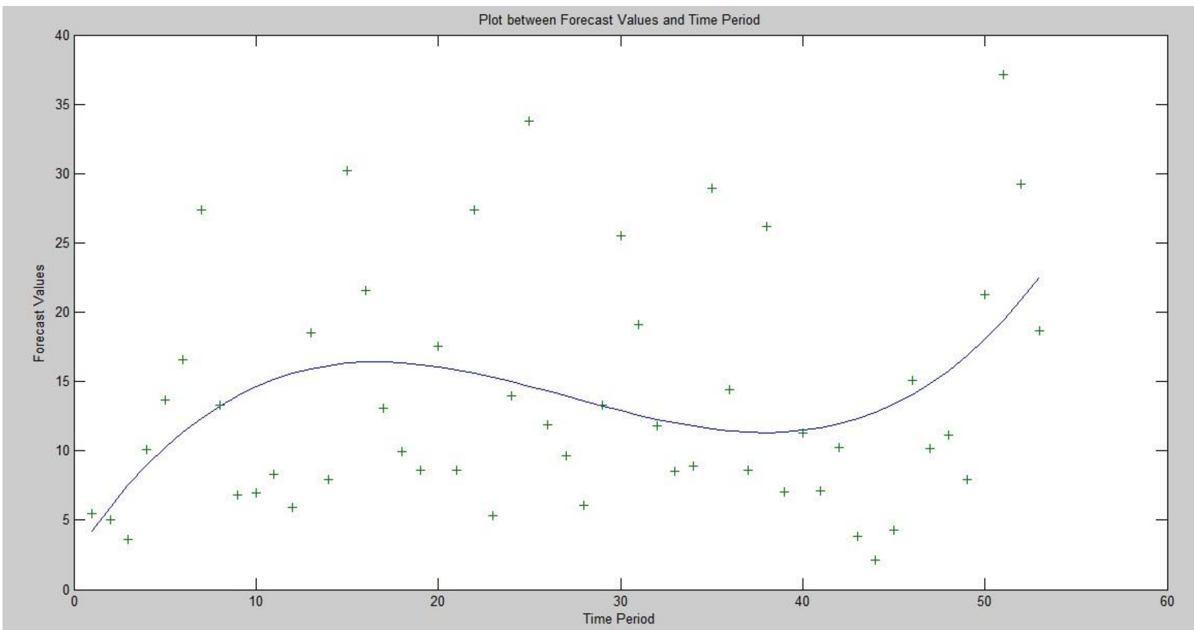


Fig. 5.11- Forecast Values for Product B

5.3.3 OUTPUT FOR PRODUCT C

The MSE error due to Weighted Average Method is: 1.544

The MSE error due to Linear Regression is: 1.032

The MSE error due to Polynomial Regression of order 2 is: 1.032

The MSE error due to Polynomial Regression of order 3 is: 1.031

The MSE error due to Single Exponential Smoothing is: 1.149

The MSE error due to Holts method is: 1.201

The MSE error due to Winter Method is: 0.993

The minimum MSE error is: 0.993 when using Winters function

The forecast for the required period using Winters method is:

2.915

2.0990

3.1684

4.7016

2.2967

2.5502

2.0236

2.8224

Forecast error using Modified MAPE1: 3.33

The forecast trend for the product is shown in Fig 5.12.

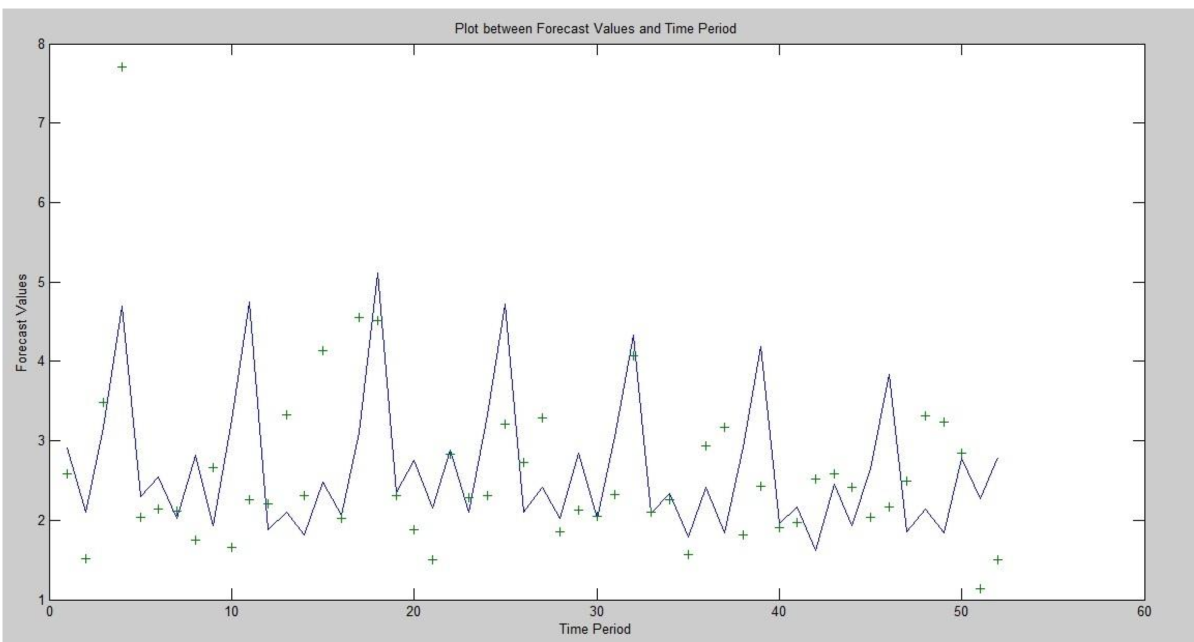


Fig. 5.12-Forecast Values for Product C

5.3.4 OUTPUT FOR PRODUCT D

The MSE error due to Weighted Average Method is: 0.663

The MSE error due to Linear Regression is: 0.568

The MSE error due to Polynomial Regression of order 2 is: 0.513

The MSE error due to Polynomial Regression of order 3 is: 0.483

The MSE error due to Single Exponential Smoothing is: 0.404

The MSE error due to Holts method is: 0.401

The MSE error due to Winter Method is: 0.411

The minimum MSE error is: 0.4012 when using Holts method

The forecast for the required period using Holts is:

1.643

1.687

1.772

1.774

1.888

1.792

1.660

1.497

Forecast error using Modified MAPE1: 4.17

The forecast values for product D is shown in Fig 5.13.

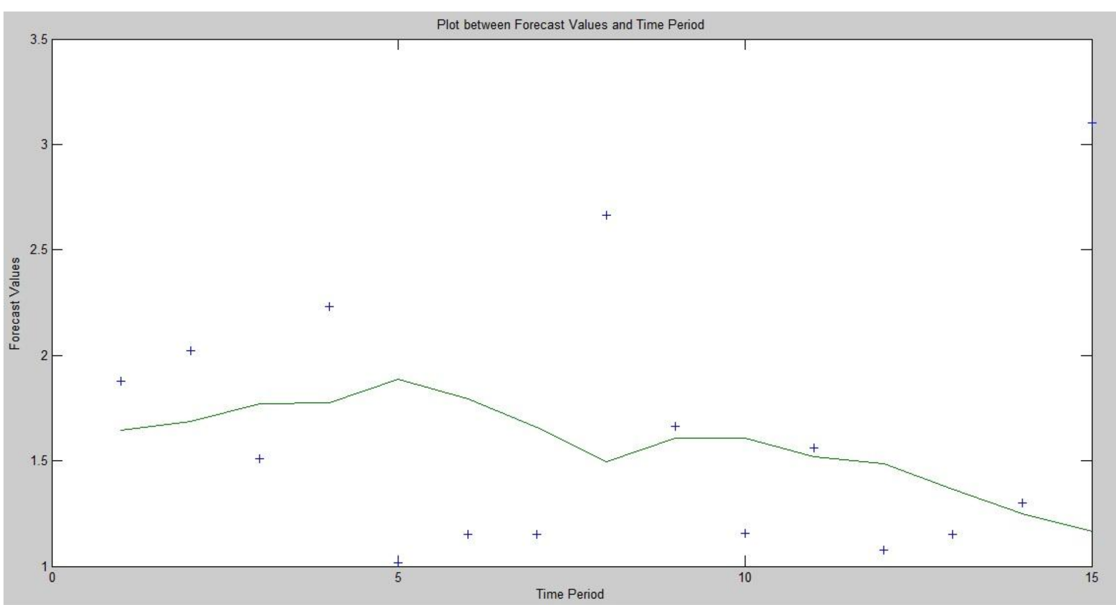


Fig. 5.13- Forecast Values for Product D

5.3.5 OUTPUT FOR PRODUCT E

The MSE error due to Weighted Average Method is: 37.632

The MSE error due to Linear Regression is: 21.237

The MSE error due to Polynomial Regression of order 2 is: 20.960

The MSE error due to Polynomial Regression of order 3 is: 20.860

The MSE error due to Single Exponential Smoothing is: 23.551

The MSE error due to Holts method is: 23.861

The MSE error due to Winter Method is: 16.132

The minimum MSE error is: 16.132 when using Winters function and the forecast values are shown in Fig 5.14

The forecast for the required period using Winters method is:

5.156

8.094

2.370

6.027

2.476

3.163

3.687

6.785

Forecast error using Modified MAPE1: 5.38

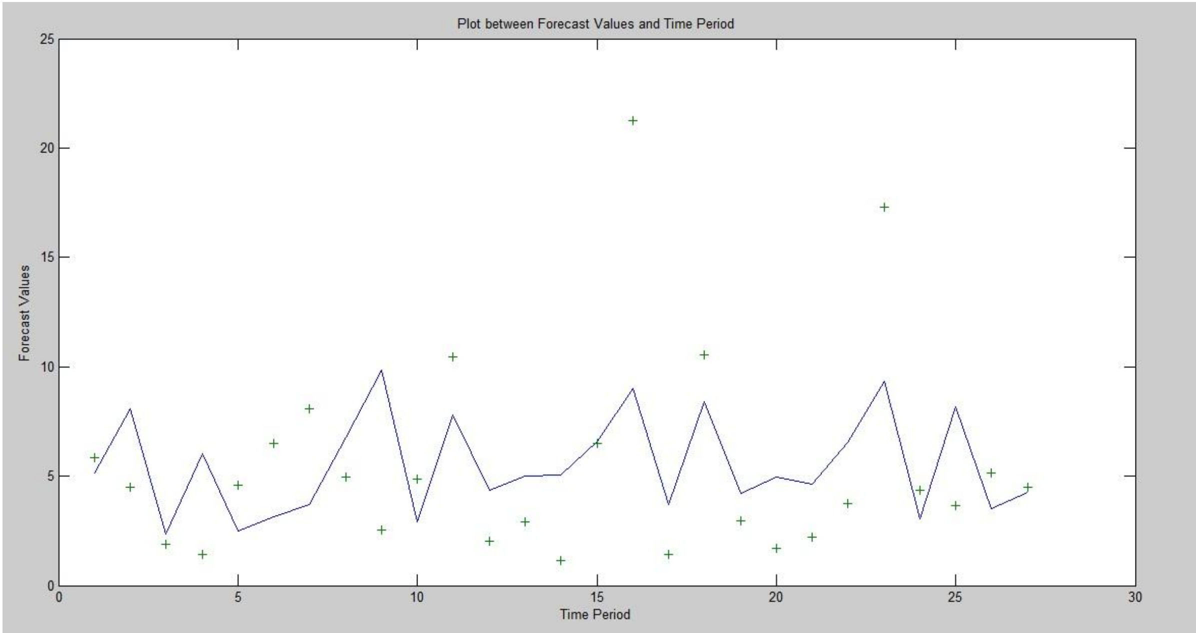


Fig. 5.14- Forecast Values for Product E

<u>5.3.6 OUTPUT FOR PRODUCT G</u>

The MSE error due to Weighted Average Method is: 40.105

The MSE error due to Linear Regression is: 31.449

The MSE error due to Polynomial Regression of order 2 is: 28.576

The MSE error due to Polynomial Regression of order 3 is: 27.769

The MSE error due to Single Exponential Smoothing is: 33.826

The MSE error due to Holts method is: 35.677

The MSE error due to Winter Method is: 37.413

The minimum MSE error is: 27.769 when using Polynomial Reg of order 3 function

The forecast for the required period using Polynomial Reg of order 3 is:

12.288

12.405

12.438

12.398

12.293

12.132

11.923

11.675

Forecast error using Modified MAPE1: 4.03

The output of the Product G is shown in Fig 5.15

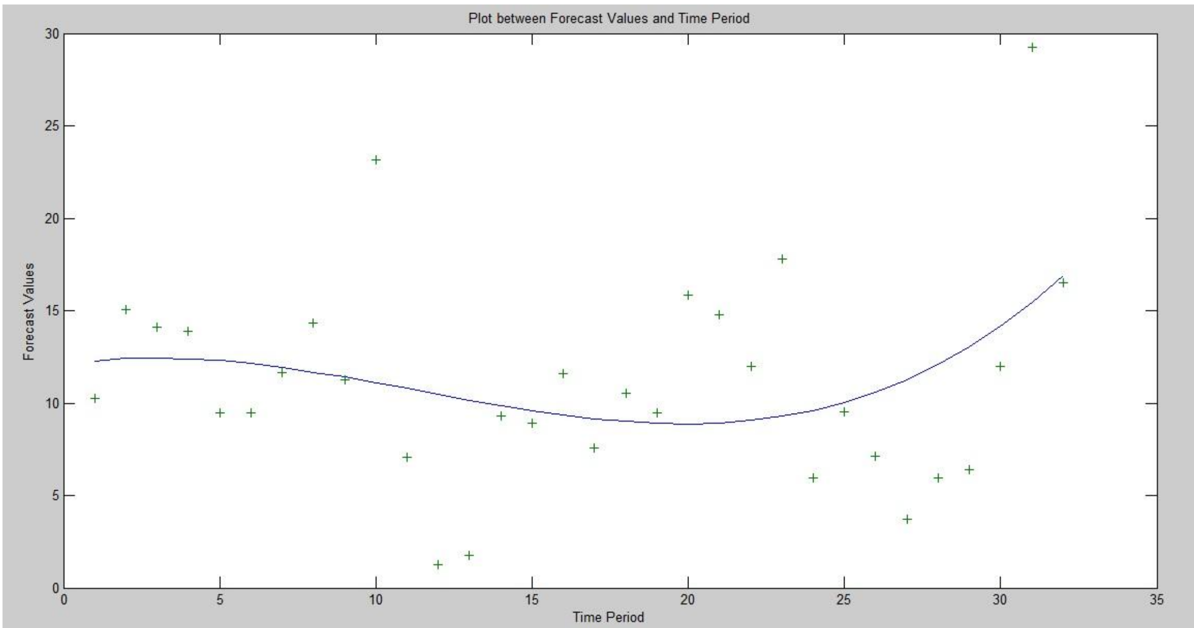


Fig. 5.15-Plot between Forecast Values & Time Period for Product G

5.3.7 OUTPUT OF PRODUCT H

The MSE error due to Weighted Average Method is: 1.5549e+003

The MSE error due to Linear Regression is: 1.0671e+003

The MSE error due to Polynomial Regression of order 2 is: 1.0549e+003

The MSE error due to Polynomial Regression of order 3 is: 981.8843

The MSE error due to Single Exponential Smoothing is: 1.1732e+003

The MSE error due to Holts method is: 1.2236e+003

The MSE error due to Winter Method is: 1.2989e+003

The minimum MSE error is: 981.8843 when using Polynomial Reg of order 3 function

The forecast for the required period using Polynomial Reg of order 3 is:

51.294

46.160

42.143

39.160

37.126

35.959

35.576

35.892

Forecast error using Modified MAPE1: 3.26

The behavior of product H is shown in Fig 5.16

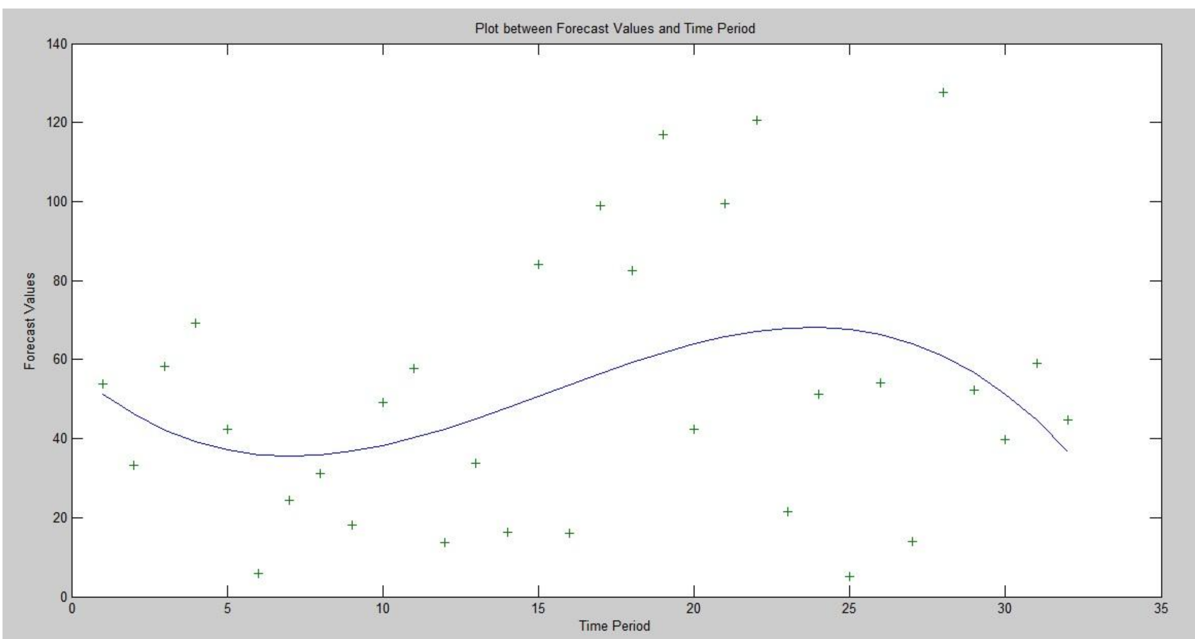


Fig. 5.16-Forecast Values for Product H

5.3.8 OUTPUT FOR PRODUCT I

The MSE error due to Weighted Average Method is: 6.0159e+004

The MSE error due to Linear Regression is: 4.7591e+004

The MSE error due to Polynomial Regression of order 2 is: 4.7396e+004

The MSE error due to Polynomial Regression of order 3 is: 4.3413e+004

The MSE error due to Single Exponential Smoothing is: 5.2080e+004

The MSE error due to Holts method is: 5.9171e+004

The MSE error due to Winter Method is: 4.2548e+004

The minimum MSE error is: 4.2548e+004 when using Winters function

The forecast for the required period using Winters method is:

437.306

569.035

697.268

624.790

394.323

805.611

310.717

414.474

Forecast error using Modified MAPE1: 1.26

The behavior of the product I in the future horizon is predicted in Fig 5.17

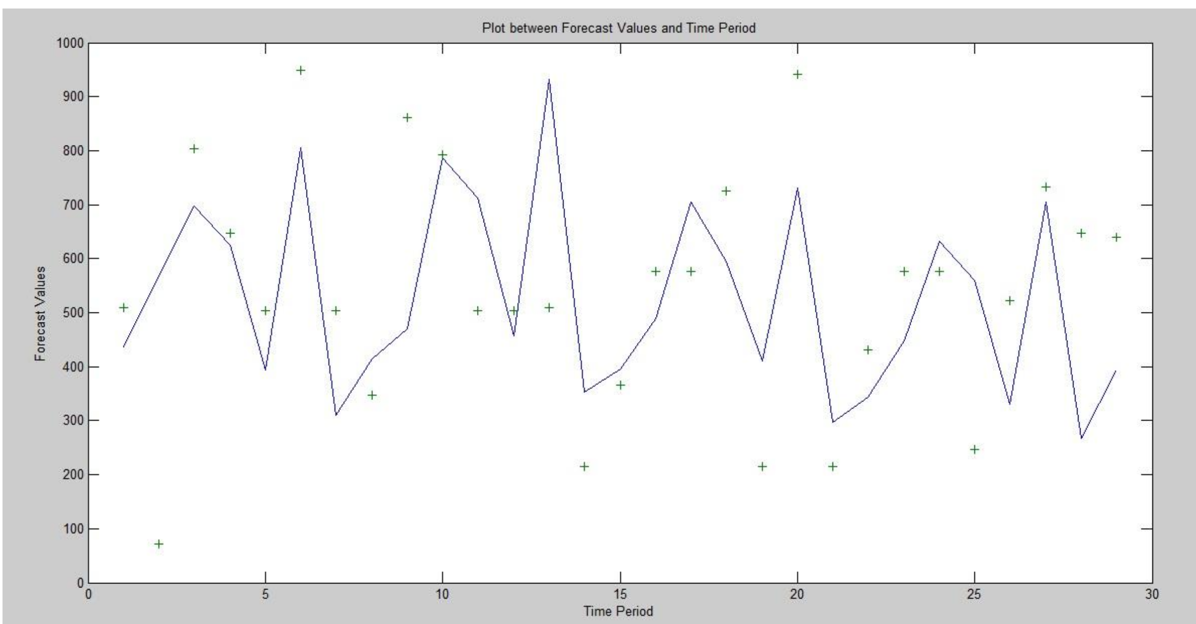


Fig. 5.17-Forecast Values for Product I

Forecasts for the FMCG products were done by selecting different models for each product based on the historical sales data by Dynamic Selection. The program allows the user to enter the product name and the forecast horizon.

The forecast value of the respective product has been determined and the forecast values and the graphs for the same have been shown in Figures 5.10 -5.17. It has been found that Polynomial regression of order 3 and Winter's method is the one that captures the past sales data better than other methods for the analyzed products. No linear trend is observed in any of the data, hence making the linear regression much lesser used forecasting method. Polynomial Regression is able to absorb variations in the data more effectively as compared to Weighted Moving Average and Single Exponential Smoothing Method. Also, Holt's method is used when there is not much seasonality observed in the sales data and any seasonality is observed, then winter's method becomes the automatic choice.