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Study of Statistical GA Based Demand Forecasting Model for Automotive Batteries Manufacturing Company-Amaron

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ABSTRACT

Demand planning is an integral part of any planning process. Accurate forecasts help firms effectively plan the production process so that inventory levels in the supply chain can be optimized and supply can be matched closely with demand. Demand planning can also help the marketing department of a firm to decide upon the kind of promotional exercises required for particular product. Planning accurately leads to better distribution planning as well. Since firms can determine the exact levels of inventory to be held at each distribution center. In this paper an attempt was made to forecast the demand of Automotive Batteries. Three different methods of forecast have been used. After applying those methods, finally the mean square error was minimized and assigned the optimum weights to the forecasts by the different methods and found the resultant forecast combining all the forecasts. A suitable tool for the optimization was chosen. Here Genetic Algorithms have been chosen.

Keywords: Forecasting; Genetic Algorithm; Multiplicative Seasonality

I. INTRODUCTION

The best place to start with any time series forecasting analysis is to graph sequence plots of the time series to be forecasted. A sequence plot is a graph of the data series values, usually on the vertical axis, against time usually on the horizontal axis. The purpose of the sequence plot is to give the analyst a visual impression of the nature of the time series. After the model is specified, its performance characteristics should be verified or validated by comparison of its forecasts with historical data for the process it was designed to forecast. Several methods of time series forecasting are available such as the Moving Averages method, Linear Regression with Time, Exponential Smoothing etc. The following methods have been used in this study are Winter's Multiplicative method, Moving Average and Exponential smoothening.

Here the objective is to suggest and implement an effective method for forecasting the After Market demand of Automotive Batteries and to synchronize and achieve efficiency and effectiveness between demand and supply and create competitive edge.

II. METHODOLOGY

2.1. Winter's Multiplicative Method

This model is used when the data exhibits Multiplicative seasonality.

In this model, we assume that the time series is represented by the model

$$y_t = (R+G_t)S_t + \varepsilon_t$$

Where R is the base signal also called the permanent component

G_t is a linear trend component

S_t is a multiplicative seasonal factor

ε is the random error component

Let the length of the season be L periods.

The seasonal factors are defined so that they sum to the length of the season, i.e.

$$\sum S_t = L$$

The trend component G_t if deemed unnecessary maybe deleted from the model.

2.2.Application of the model

The multiplicative seasonal model is appropriate for a time series in which the amplitude of the seasonal pattern is proportional to the average level of the series, i.e. a time series displaying multiplicative seasonality.

2.3.Notation used

Let the current deseasonalized level of the process at the end of period T be denoted by R_T At the end of a time period t, let

R_t be the estimate of the deseasonalized level.

G_t be the estimate of the trend

S_t be the estimate of seasonal component (seasonal index)

2.4. Procedure for updating the Estimates of Model Parameters

Overall smoothing

$$R_t = \alpha(y_t/S_{t-L}) + (1-\alpha)*(R_{t-1} + G_{t-1})$$

where $0 < \alpha < 1$ is a smoothing constant.

Dividing y_t by S_{t-L}, which is the seasonal factor for period T computed one season (L periods) ago, deseasonalizes the data so that only the trend component and the prior value of the permanent component enter into the updating process for R_t .

2.5.Smoothing of the trend factor

$$G_t = \beta*(R_t - R_{t-1}) + (1-\beta)* G_{t-1}$$

where $0 < \beta < 1$ is a second smoothing constant.

The estimate of the trend component is simply the smoothed difference between two successive estimates of the deseasonalized level.

2.6.Smoothing of the seasonal index

$$S_t = \gamma*(y_t/ R_t) + (1 - \gamma)*S_{t-L}$$

where $0 < \gamma < 1$ is the third smoothing constant.

The estimate of the seasonal component is a combination of the most recently observed seasonal factor given by the demand yt divided by the deseasonalized series level estimate R_t and the previous best seasonal factor estimate for this time period. Since seasonal factors represent deviations above and below the average, the average of any L consecutive seasonal factors should always be 1. Thus, after estimating St, it is good practice to re normalize the L most recent seasonal factors such that

$$\sum S_i = q.$$

2.7.Value of forecast forecast for the next period

The forecast for the next period is given by:

$$y_t = (R_t + G_t) *S_{t-L}$$

Note that the best estimate of the seasonal factor for this time period in the season is used, which was last updated L periods ago.

2.8.Initial values of model parameters

As a rule of thumb, a minimum of two full seasons (or 2L periods) of historical data is needed to initialize a set of seasonal factors. Suppose data from m seasons are available and let x_j , j =1, 2,…..,mL denote the average of the observations during the jth season.

2.9.Estimation of trend component

Estimate the trend component by:

$$G_0 = (y_m - y_1)/(m - 1)L$$

2.10.Estimation of deseasonalized level

Estimate the deseasonalized level by:

$$R_0 = x_1 - (L/2)*G_0$$

2.11. Estimation of seasonal components

Seasonal factors are computed for each time period t = 1, 2, · · · , L as the ratio of actual observation to the average seasonally adjusted value for that season,

$$S_{t(0)} = (S_t*L)/(\sum S_t) \quad t= 1, 2,\dots L$$

2.12. Exponential Smoothening

This is also known as simple exponential smoothing. Simple smoothing is used for short-range forecasting, usually just one month into the future. The model assumes that the data fluctuates around a reasonably stable mean (no trend or consistent pattern of growth). The specific formula for simple exponential smoothing is:

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

where F_t = smoothed average forecast for period t.

F_{t-1} = Previous period forecast

D_{t-1} = Previous Period Demand

When applied recursively to each successive observation in the series, each new smoothed value (forecast) is computed as the weighted average of the current observation and the previous smoothed observation; the previous smoothed observation was computed in turn from the previous observed value and the smoothed value

before the previous observation, and so on. Thus, in effect, each smoothed value is the weighted average of the previous observations, where the weights decrease exponentially depending on the value of parameter (α). If it is equal

to 1 (one) then the previous observations are ignored entirely; if it is equal to 0 (zero), then the current observation is ignored entirely, and the smoothed value consists entirely of the previous smoothed value (which in turn is computed from the smoothed observation before it, and so on; thus all smoothed values will be equal to the initial smoothed value S_0). In-between values will produce intermediate results.

2.13. Initial Value

The initial value of S_t plays an important role in computing all the subsequent values. Setting it to y_1 is one method of initialization. Another possibility would be to average the first four or five observations. The smaller the value of α, the more important is the selection of the initial value of S_t.

2.14.Moving Average

It is a method of forecasting which generally uses the previous values of the forecast. In this kind of time series forecast method we take the previous three periods' actual demand and take the average and this becomes the forecast for the present period.

$$\mathbf{M_t = (1/n)\ [D_{t-(n-1)}+D_{t-(n-2)}+\ldots..+ D_{t-2}+ D_{t-1}+ D_t\ ]}$$

where M_t= Moving Average for period t.

Forecast, $F_t=M_{t-1}$

III. GENETIC ALGORITHM PROCEDURE

The objective of GA is to calculate the optimum weights W= (W_1,W_2,W_3) which minimizes the mean square error in the training set to yield best forecast.

W_1 is the weight of the SES method.

W_2 is the weight of the Moving Average method

W_3 is the weight of the winter's multiplicative method.

GA ELEMENTS

Fitness function = min(MSE)

$$\text{Fitness Function MSE (Y)} = (1/12) \sum(A_n-Y_n)$$

$$Y_n = W_1Y_{1n} +W_2Y_{2n}+W_3Y_{3n}$$

Where n=1, 2…….12

Where

A_n = Actual Data

Y_n = Genetic Forecast

Y_1 = Forecast using SES'method

Y_2 = Forecast using Moving average method.

Y_3 = Forecast using Winter's Multiplicative method.

W_1 is the weight of the SES method

W_2 is the weight of the Moving Average method.

W_3 is the weight of the Winter's Multiplicative method.

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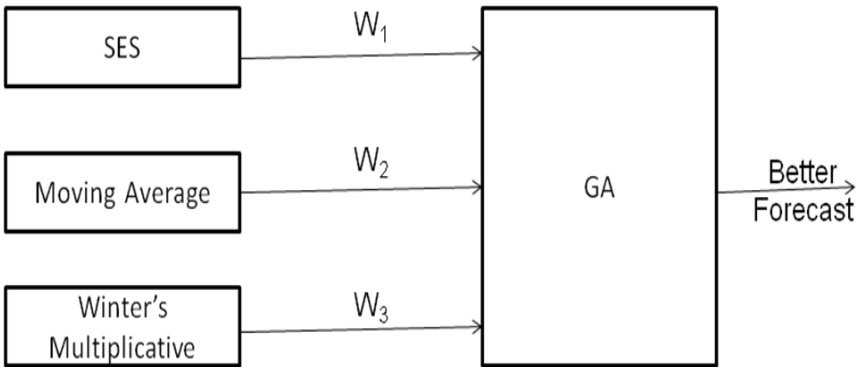

$$\sigma_j = k.Min\left\{x_j^{t-1} - a_j, b_j - x_j^{t-1}\right\}\left(1 - \frac{t}{M_g}\right)^s\left(1 + \frac{t}{M_g}\right),$$
$$j = 1, 2, \ldots, M$$

3.1. Constraints

-1 < = W < 1

∑W's =1

3.2. Evaluation

The process of evaluation the fitness function consist following steps.

1) Evaluate the objective function f(wk)
2) Convert the value of function in to fitness.for the minimization problem,the fitness is equal to the value of objective function eval(vk)=f(wk),where k=1,2,…..pop size.

Eval (v_k) = MSE (1/12) $\sum(A_n-Y_n)^2$

$Y_n = W_1Y_{1n} + W_2Y_{2n} + W_3Y_{3n}$

where n=1, 2…….12

3.3. Selection

Its target to choose which solution will remain in the new population and which solutions will be changed. It does so by executing the following steps:

1) Tournament tree selection process will be used here to pick up a pair of individuals from population.
2) After picking up pair of individuals from population, the individuals with higher fitness function will be consider for mating process through Crossover. Here the fitness function will be the best MSE.
3) Elite population will be considered in this procedure, to carry out the fit individuals for another generations.

3.4. Crossover

Crossover used here is the single point method, which randomly selects single point and exchanges the rightparts of two parents to generate offspring. The probability of crossover is set as P_c=0.25. Consequently, we expect on average 25% of chromosomes undergo crossover.

3.5. Mutation

Genetic algorithms are famous of their global search capability.the probability of mutation used here is P_m =0.2. The GA has Mutation probability, which dictates the frequency at which mutation occurs. By using a new mutation operator which called as advanced genetic algorithm, we perform the mutation for this problem which defined as follows:

Where,

K is a constant with in [0, 1]

t =generation no.

x_j^{t-1} is the jth variable to be optimized in $(t-1)^{th}$ generation

$[a_j , b_j]$ is the jth variable;s scope.

M_g is the maximum generation,

S is shape parameter.

M is the number of variables.

The Mutation of jth variable x_j is given by:

$$X_j' = x_j + \varepsilon_j$$

$$\varepsilon_j = N(0, \sigma_j)$$

Where εj is the distributed as a Gaussian random number with zero mean and σ_j standard deviation.

3.6. Algorithm

Step 1 : Start the program.

Step 2 : Estimates and Actual Values which are the input is taken through input file from home directory.

Step 3 : Population is initialized which is required for evaluating fitness.

Step 4:Start with generation number = 1.

Step 5 : Compare generations number with maximum number of generations.

If generations no.< maximum number of generations ,move to Step 7,Else move to Step 6.

Step 6 : Display the weights for the minimum MSE(mean Square Error) and yields the best forecast.

$$\sigma_j = k.Min\left\{x_j^{t-1} - a_j, b_j - x_j^{t-1}\right\}\left(1 - \frac{t}{M_g}\right)^s\left(1 + \frac{t}{M_g}\right),$$

$$j = 1.2, \ldots . M$$

Step 7 :

1) New population is created.
2) Fitness is calculated with the help of population values, actual values and estimates using Fitness function MSE (Y) = $(1/12) \sum(A_n - Y_n)^2$

$Y_n = W_1Y_{1n} + W_2Y_{2n} + W_3Y_{3n}$, n=1,2…….12

Where

A_n = Actual Data

Y_n = Genetic Forecast

Y_1 = Forecast using SES'method

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Y_2 = Forecast using Moving average method.

Y_3 = Forecast using Winter's Multiplicative method.

W_1 is the weight of the SES method

W_2 is the weight of the Moving Average method.

W_3 is the weight of the Winter's Multiplicative method.

3) Fitness for the given population is displayed.

4) Tournament Tree Selection is performed for choosing solutions which will remain in next generation.

5) Crossover using single point method is performed to generate offsprings.

6) Mutation is performed with new mutation operator defined as :

where,

K is a constant with in [0,1],

t =generation no.

x_j^{t-1} is the jth variable to be optimized in $(t-1)^{th}$ generation

$[a_j , b_j]$ is the jth variables scope.

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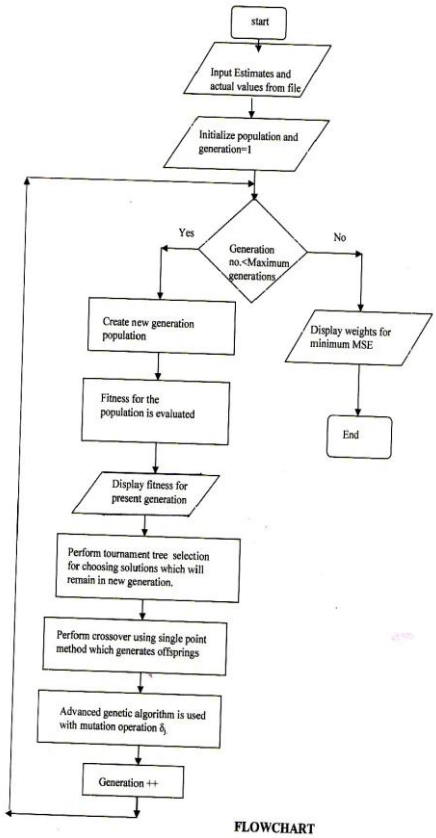
Where ε_j is the distributed as a Gaussian random number with zero mean and σ_j standard deviation.



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IV. RESULTS AND DISCUSSIONS

The methods of forecast were applied to the Hi-Life Automotive Batteries for a warehouse. Here the smoothening constants considered are α=0.2, β=0.1, γ=0.5. The Forecast values are plotted with the actual values.

Demand was Forecasted for Hi-life Batteries using Winter's Multiplicative Method for a Warehouse and a graph was plotted showing the comparision between actual and forecasted values. It was inferred that actual demand was not incommensurable with the forecasted demand due to the impact of seasonality.

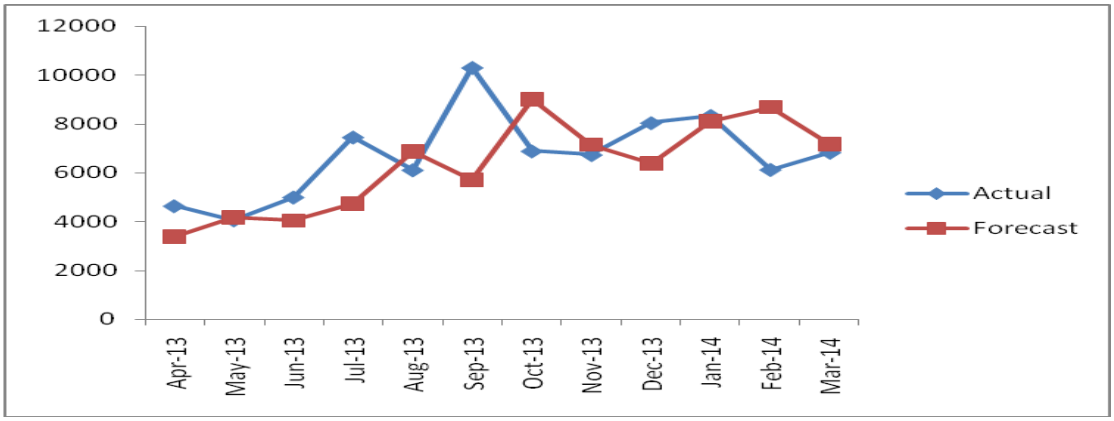

Fig 1: Comparison of Actual and Forecast using Winter's Method

Demand was Forecasted for Hi-life Batteries using Moving Average Method for a Warehouse and a graph was plotted showing the comparision between actual and forecasted values. It was inferred that actual demand was not comparable with the forecasted demand due to the effect of Previous demand.

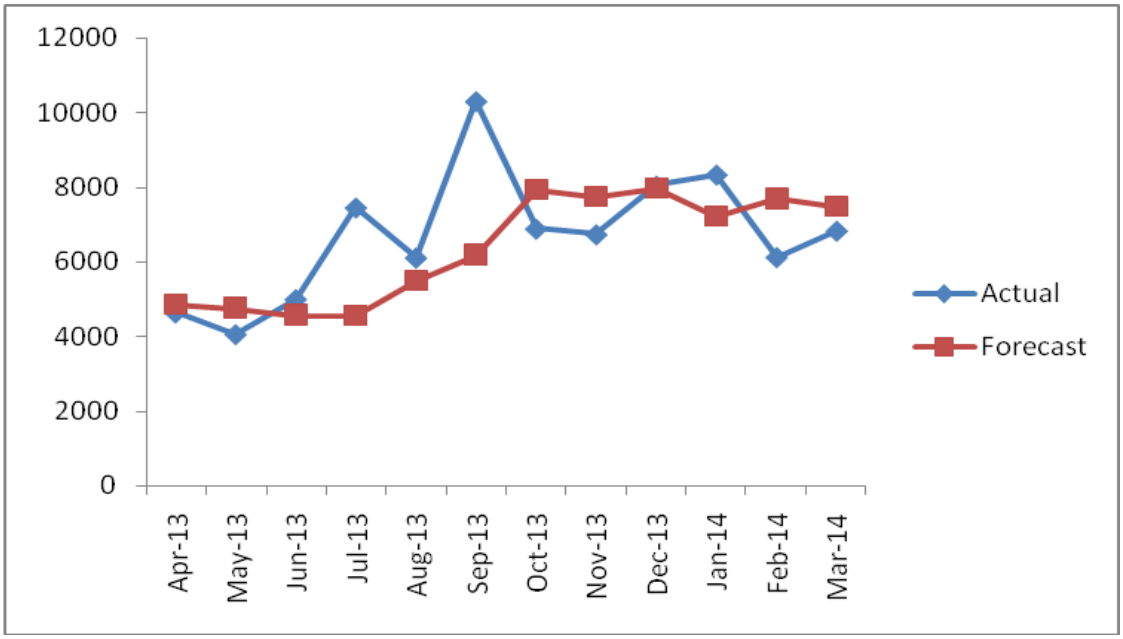

Fig 2: Comparison of Actual and Forecast using Moving Average Method

Demand was Forecasted for Hi-life Batteries by using Exponential Smoothening method for a Warehouse and a graph was plotted showing the comparision between actual and forecasted values. It was observed that actual demand of batteries is deviating from the forecasted demand due to the variation in smoothening constants.

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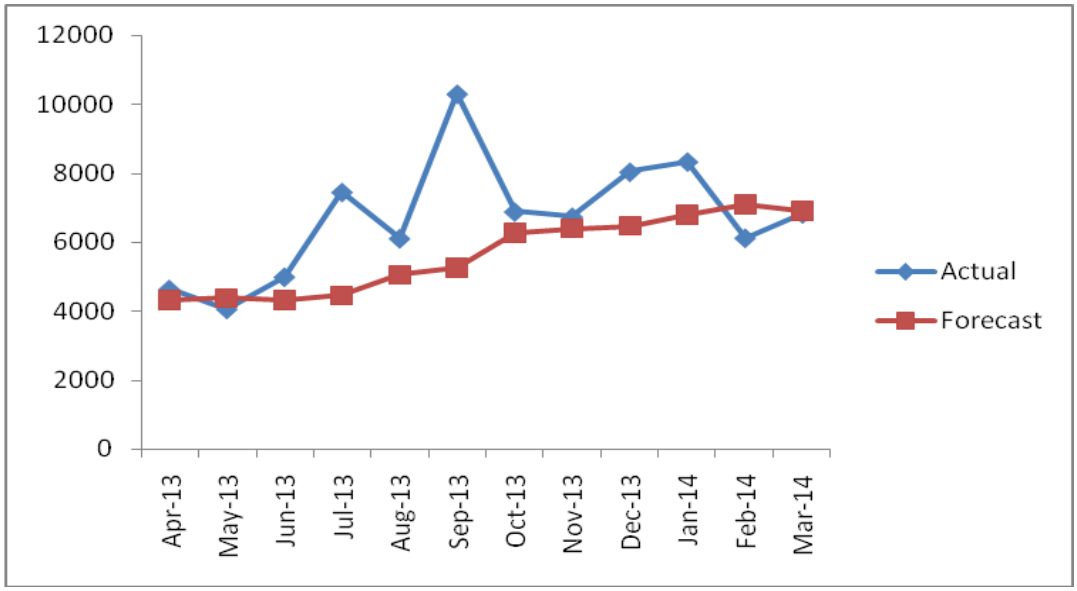

Fig 3: Comparison of Actual and Forecast using Exponential Smoothening Method

Demand was Forecasted for Hi-life Batteries by minimizing the Mean Square Error using Genetic Alogorithm for a Warehouse and a graph was plotted showing the comparision between actual and forecasted values. It was depicted that actual demand of batteries is in closure with forecasted demand using Genetic Algorithm.

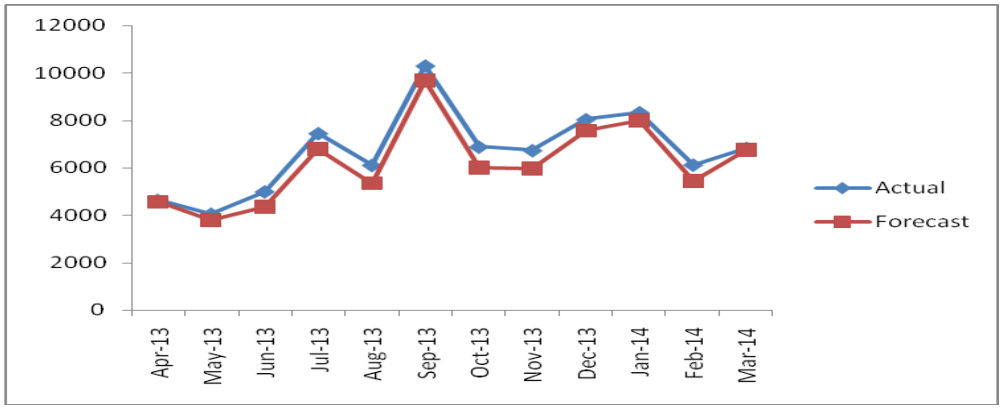

Fig.4: Comparison of Actual and Forecast using GA

V. CONCLUSIONS

After Market sector was selected for the study as company brand name influences. Subsectors in the After Market like Hi-life was considered for the study.

The analysis was carried out for the Sales data collected for the year 2013-14 and using the quantitative techniques such as Time series models for the demand forecasting. They are Winter's Multiplicative method, Moving Average technique and Exponential Smoothening. As per the study conducted, analysis was carried out in the above specified methods.

Generally winter's Method is applicable when the demand of the products varies with trend and seasonality. In the present environment, the demand of the batteries follows seasonality i.e. the batteries' demand is very high

at a particular month of the year. When winter's method is applied the forecasted values has shown the same trend as the actual values.

The reason for choosing Multiplicative method is, in plots of the series, the distinguishing characteristic between the seasonal component is that in the multiplicative case, the size of the seasonal fluctuations vary, depending on the overall level of the series.

By using Genetic Algorithms an attempt was made to minimize the Mean square error and assigned the optimum weights to all the forecast methods. The resultant forecast was calculated which was in good agreement with actual values.

For better forecasts the mean square error should be minimized using Genetic Algorithms or any other suitable method of optimization.

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