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Material Management using Selective Inventory Control and ARIMA Methodology in a Manufacturing Industry

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Abstract- In the past 10 years manufacturing industry has gone through significant changes. Competition has increased dramatically. Customer focus on product quality, product delivery time & cost of product, due to this organization should introduce a material management system to renovate and enhance both quality and productivity continuously. Inventory control is a critical aspect of successful management and today it is the major thrust area for increasing productivity. In the present work an attempt has been made to implement inventory control techniques like Combined Cost Matrix of ABC and HML analysis at Mahindra & Mahindra Swaraj Mazda Ltd. Asron, which is an automotive manufacturing company. The Bill of Materials for its T-3500 Truck has been taken and Combined Cost Matrix of ABC and HML analysis has been done on the 800 items. Sigma level of the supplied goods on the basis of quality is calculated, which comes out to be 3.47. Use of Bar Coding for fast and accurate data entry along with savings in labour cost to has been introduced. To insure the smooth manufacturing activities with minimum inventory, the accurate demand forecasting has been done using "ARIMA" methodology

Key words: *HML, ARIMA, inventory control, EOQ.*

1. INTRODUCTION

The inventory stocks consumes large portion of business investment. The inventory need to be managed well to maximize profits. Unless inventories are managed well; they are unreliable, inefficient and costly in fact many small business loss out due to poor inventory management. There are material which are used in maintenance and calibration etc. such as few, lubricant and special gauges etc.[1]&[2] Computerization of Inventory, to create data base of the stacked items in a systematic order. Many types of useful information can be pulled out by creating appropriate quarries. [3] Most remaining operation (MRO), Earliest Due Date (EDD) etc. are used for inventory control, Material Requirement Planning (MRP) and Scheduling Methods like Shortest Processing Time (SPT) [4].It has been concluded that Quality Improvement and Continuous Supplier Control were of paramount importance in Inventory Management[5]. Authors proposed an integer programming model to select vendors and determine the order quantities [6].Kasilingam & chee proposed an integer programming model to select vendors & determine the order quantities. The model consider stochastic nature of demand, quality of supplied part , cost of purchasing& transportation[7].ARIMA Models has been to Predict Next-Day Electricity Prices. Price forecasting has become increasingly relevant to producers and consumers in the new competitive electric power markets[8]. El Hag used adjusted ARIMA for the forecasting of internet traffic The self-similarity AARIMA model was suggested to give a

quick and simple way to model Internet traffic by retaining all the properties of the ARIMA models while capturing the [9]. It has been studied that Very Short- Term Load Forecasting Based on ARIMA Model and Intelligent Systems like Artificial Neural Networks techniques for load demand forecasting in distribution substations
[10].

2. METHODOLOGY

BOM for the Truck T 3500 is taken. After omitting the M standard items, 800 items were taken for ABC and HML Analysis.ABC and HML Analysis were done for 800 items. Then combined cost matrix of ABC and HML analysis was also done to overcome short comings of single criteria ABC analysis. Actual sales data were arranged to find accurate demand forecast for the product. Demand forecasting was done using ARIMA methodology and results compared with the actual sales. Data for defective components supplied in a particular period was gathered to calculate sigma level for the supplied goods. Data on the workers working for data entry purposes was gathered to calculate the benefits of the application of Bar Coding system in the Stores.

3. RESULT AND DISCUSSION

3.1 *ABC Analysis*

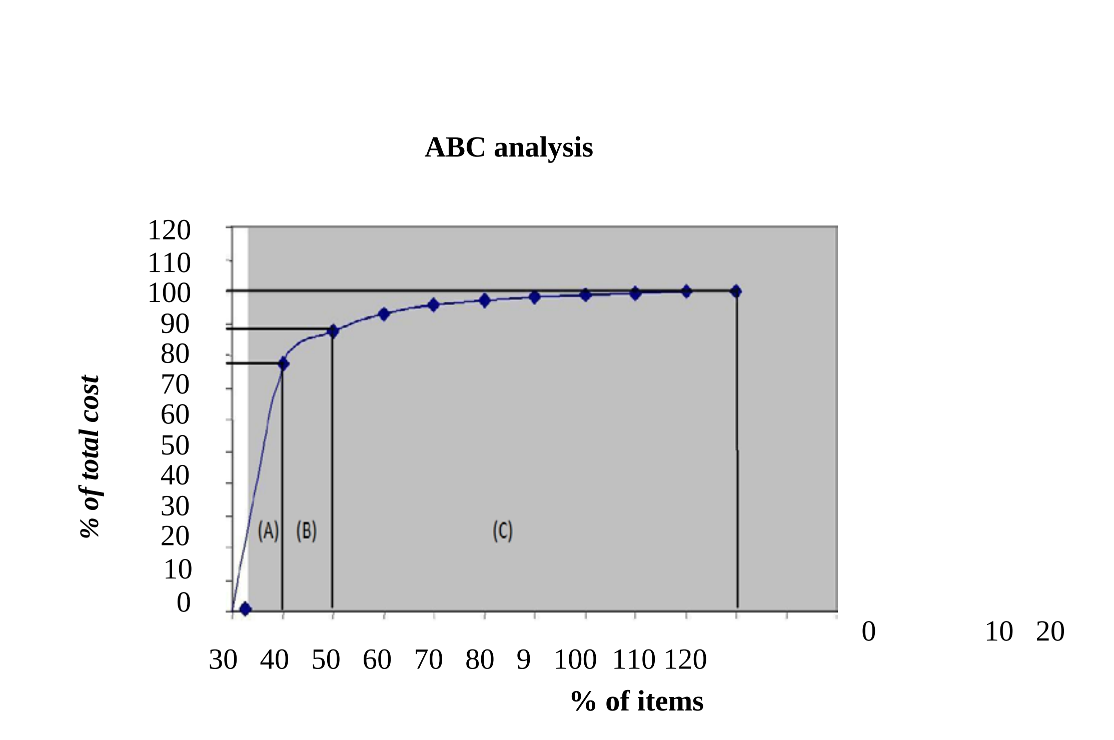

Fig.1 ABC analyses of materials.

A Class items Just 10% of the total items consume 77.83%of the total Inventory cost. B Class items , the next 10% of the total items spend 10.28% of the total Inventory cost. C Class items remaining 79% of the total items vanish about 12.43% of the total Inventory cost .A Class items wash up 77.83% of the total value of the stock. If the organization do strict control over this class of items, the problem of surplus monthly Inventory can be solved at large scale. For A class items orders should be frequent and smaller.

3.2 ***HML (High, Medium, and Low Value) Analysis****:*

ABC analysis is not helpful for the materials to less the cost of inventory, due to some high individual cost items fall in C or B class of ABC analysis. It do because the consumption of such items is low; although the items are expensive they fall in C or B class. By the rule of ABC analysis, company needs to purchase in bulk of C class items, if company did this then high inventory will be blocked. In order to eliminate such a situation we need to do HML analysis to support ABC analysis to find out expensive items. High Value Items First 10% items are high value items. These items observe

77.43% of the total inventory cost. However „A" Cla ss items of ABC Analysis with item no 10, 140, 681, 685, 688 and 1395 appear as „M" Class items in HML Analysis & item no.1396 as Low value item. Medium Value Items 10% items are medium value items. These items eat up 11.21% 0f the total cost.

However „B" Class items of ABC Analysis having no.59, 69, 90, 210, 237, 498 and 840, appear as „H" Value items in HML Analysis. Item no. 21, 202, 218, 499, 795, 1025, 1026, 1041 and1042 appear as Low value items in HML analysis.Low Value items left 80% of items consume only 11.47% of the cost. However „C" Class items of ABC Analysis such as item no 4, 328, 461, 982,1047,1048,1160 appear as

„M" Class items in HML Analysis. So company needs to keep the strict command while purchasing these items, in spite of their being „C" Class items.

Results of HML Analysis showed „A" Class items of ABC Analysis with item no 8, 140, 681, 683, 686 and 1395 appear as „M" Class items in HML Analysis. A Class item no.1396 of ABC analysis appears as Low value item. The „C" Class items of ABC Analysis such as item no 4, 328, 461, 982, 1047, 1048, and 1160 appear as „M" Class items in HML Analysis.

This vindicates that HML Analysis erase the short comings of the ABC Analysis.

3.3 *ARIMA or Box- Jenkins Model Building Strategy using EViews 7 & JMulTic Software.*

Step –I the order of integration is tested for our monthly series on the variable, i.e. sales. Augmented Dickey Fuller statistics is applied to

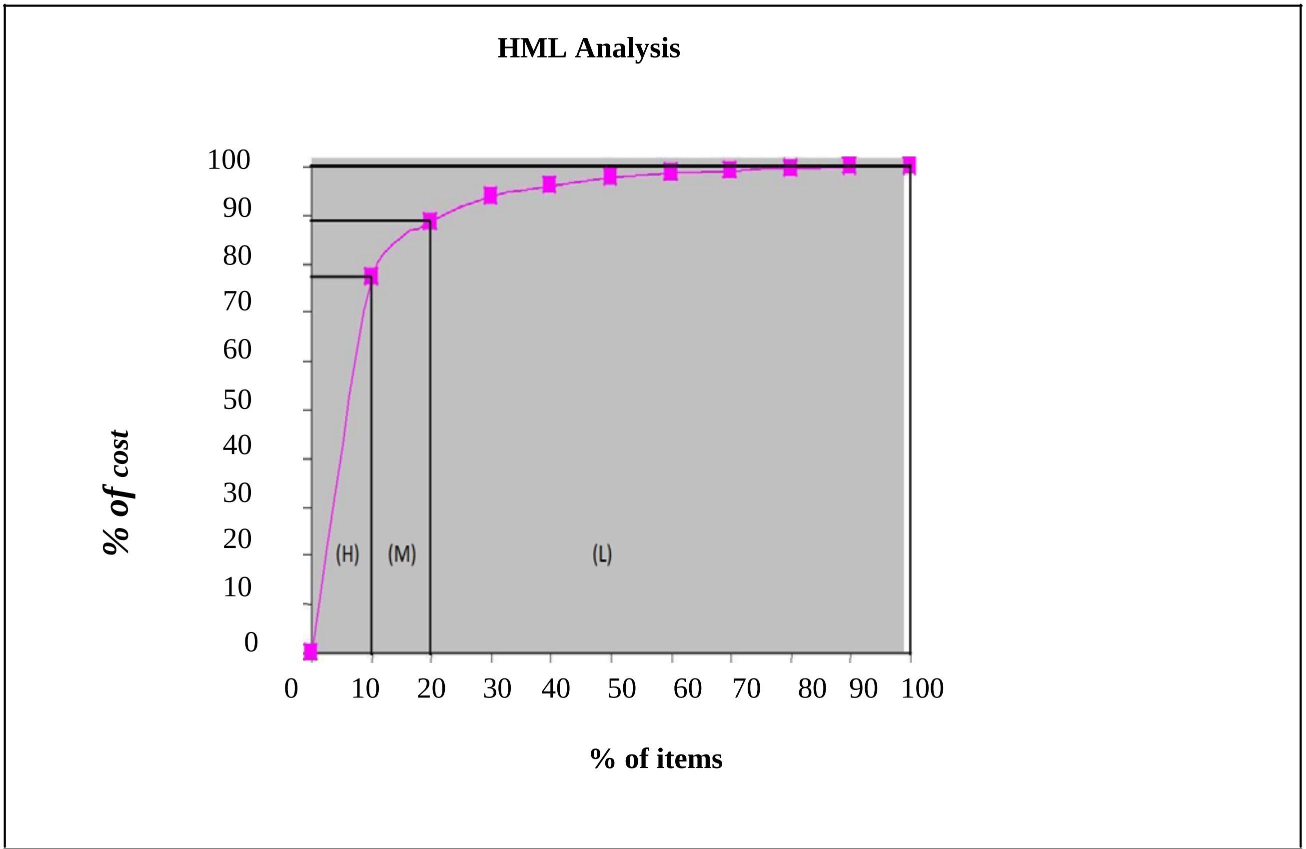

Fig.2 HML Analysis

check the stationary of the series. Initially the test has been applied upon zero order of integration, i.e. sales at levels. The observed value of test statistics is -1.423 with p value of 0.5713.Hence the observed value is statistically insignificant and thus, reveals the presence of unit root in level series. To solve the problem of unit root the series of sales is differenced at first level. Hence the following operation is applied.

$$\text{Sales} = \text{Sales}_{t} - \text{Sales}_{t-1} \text{---------} \quad (i)$$

After differencing once, as defined in model – (i) we check again the presence of unit root by applying ADF test statistics. At first difference, the observed value of ADF test statistics is 11.771 with a p value of 0.000.Hence the observed statistics is – ve and significant, Thus satisfying the condition of stationery at first order of integration. Therefore in our ARIMA process the order of integration for the variable sales would be 1.

Step – II: Involves examination of the order of Auto regression (AR) and Moving Average (MA) terms. Three different information criteria are applied to check the order of ARIMA terms. These criteria are (i) AKaike information criteria (ii) Hannan-Quinn Criteria and (iii) Schwarz criteria.

TABLE 1 Observed values of the order of AR (p) and MA (q)

Lag selection for AR and MA terms

Information criterion	Order of AR term	Order of MA term
AIC	3	3
H-Q	2	3
SC	2	3

Source: Author"s calculations

Table 2 Point estimates of ARIMA model used to forecast future sale

Point estimates of ARIMA Model			
Regression	Coefficient	F-Ratio	P-Value
Constant	2.313	2.699	0.392
AR1	-1.012***	0.127	0.000
AR2	-0.989***	0.120	0.000
AR3	-0.005	0.108	0.963
MA1	-0.186	0.115	0.105
MA2	-0.149**	0.075	0.048
MA3	0.640***	0.074	0.000
Note: I) *** and ** represent significant at 1% 5% levels respectively.			
Source: Authors Calculations.			

From table 1 it is evident that maximum lag of AR terms suggested by AIC criteria is 3 whereas from MA terms, all the three information criteria are providing the same order i.e. q = 3. Thus for forecasting purpose we finalize an ARIMA process of the order 3, 1, 3 i.e. ARIMA (3, 1, 3)

Step-III The third step in ARIMA based forecasting is the estimation of ARIMA model, defined above for the variable i.e. sales

In the estimated model given in the table 2 the ARIMA coefficient appearing with ** and *** are statistically significant at 5% and 1% level of significance, respectively. On the basis of this estimated model, the future values of the sales can be forecasted. Table 3 provides 40 months forecast of sales with respective confidence intervals and standard errors. Confidence intervals of forecast values signifies that the sales value of given month can fluctuate in between lower and upper bound values confidence intervals. However the estimatedforecasts have been given by the column

STEP IV: The final step in forecasting step is to check the reliability of forecasted estimate. Fig. 3 provides the reliability statistics of the forecasted values, and also of Theil"s inequality coefficient. The observed value of this coefficient is 0.25 which is statistically insignificant. Therefore it supports the inference that the observed forecast values of sales are realistic enough for policy planners.

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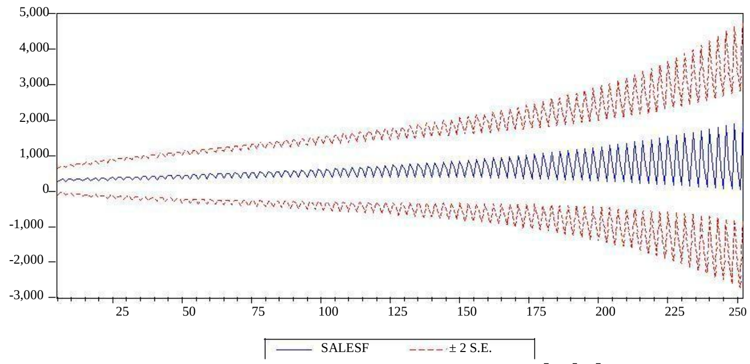

Forecast: SALESF	
Actual: SALES	
Forecast sample: 1 252	
Adjusted sample: 5 252	
Included observations: 246	
Root Mean Squared Error	323.4443
Mean Absolute Error	247.7727
Mean Abs . Percent Error	94.12736
Theil Inequality Coefficient	0.250003
Bias Proportion	0.060690
Variance Proportion	0.000057
Covariance Proportion	0.939253

Fig. 3 Reliability Statistics

3.4*The following are some of the benefits of the Bar Code data entry system.*

Fast and reliable data collection, Faster data entry: A Bar Code Scanner typically can record data five to seven times faster than a skilled typist. Better accuracy: Data entry by Bar Code System is 10,000 times accurate than the key board entry. Reduced Costs, Labor Costs: This is the most obvious benefit of Bar Code data collection. In many cases, this cost saving pays for the entire data collection system. Reduced revenue losses resulting from data collection errors: This benefit often surpasses the savings in labor costs. In most of the companies, it doesn't take many errors to amount to a great deal of lost revenue. Necessary Inventory Levels: Using Bar Codes is one of the best ways to reduce inventory levels and save on costs. Improved Management, Faster Access to Information: This benefit goes hand in hand with better decision making. With better information, one can gain opportunities and get the jump on competition.

3.4.1*Reduction in the no .of data entry workers, when Bar Coding system is used.*

When we replace the cardex system with Bar Coding system can eliminate upto great extant the labour indulge in the data entry work. Bar Coding system enters data in to the computer without taking key board On the other hand cardex system require posting of data from the card to the computer manually. Further Clubbing of activities of stores with adjoining venues is also possible. Main Store and Consumables Stores are in adjacent venues; their activities can be clubbed. Similarly Rejection Stores and Receipt Stores are also in adjoining venues; their activities too can be combined. As a rough rule we can safely reduce the strength of the data entry workers by half. One Bar Code system can replace 3 most efficient data entry workers. In all we can remove **five** data entry workers from all the stores very safely.

3.4.2 Cost-Benefit Analysis:

Costs Involved:For implementation of Bar Code system in the SML, it needs 4 sets of Barcode printer, scanner and software.

3.4.3 Benefits:

1. Saving on labour = (40,000 + 11000-1000) = Rs.50, 000 per month.
2. Swift and dependable data collection from the system.
3. Leads to eliminate of problem of wrong issuing of material.
4. It will verify the status of material in miniscule of time.
5. Instead of twelve workers seven will be sufficient.
6. The investments will be recovered in 18 months of time.

4. CONCLUSION

Category "AH" comprises of 73 items that account for 75.094% of the total cost. This group consists of items that have high usage value and high individual cost. Stringent control & frequent ordering is the appropriate technology to minimize the Inventory cost incurred on these items.

Category "CL" comprises of 632 items that account for 11.841 % of the total cost. Although consumption value of these items is very high, none the less these items are important. Quality Sigma level of the material supplied by the suppliers is 3.48. Bar Coding makes data entry very fast, accurate and reliable. Also reduces labour costs to the tune of Rs. 50,000/month. The system pays for itself in one and a half years" time. Accurate demand forecasting by ARIMA methodology is done.

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