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ENHANCING PERISHABLE SUPPLY CHAIN EFFICIENCY AND DETERMINING SUITABLE INVENTORY POLICY

Dr. T Radha Ramanan[1], Sagi Mohit Varma[2], Kanaparthi Vivek[3]

[1] Prof, School of Management Studies, National Institute of Technology Calicut, NIT Campus P.O 673 601, Kozhikode, Kerala, India

[2,3] Department of Mechanical Engineering, National Institute of Technology Calicut, NIT Campus P.O 673 601, Kozhikode, Kerala, India

Abstract: This study compares the traditional Supply Chain Economic Order Quantity (EOQ) model with a Vendor Managed Inventory (VMI) model for perishable goods in the Fast-Moving Consumer Goods (FMCG) industry. Using simulations with uniform and normal demand distributions, the research examines variables like lead time, demand unpredictability, and inventory holding costs. It aims to optimize inventory management by analyzing warehousing and transportation costs, packaging quantities, and storage expenses. By optimizing shipment schedules and setting appropriate stock levels, the goal is to reduce overall costs. The study highlights the importance of collaboration and information sharing in integrating VMI as a decision support system. Results show VMI outperforms EOQ, reducing costs by 27% for normal demand and 29.4% for uniform demand, significantly improving supply chain efficiency. This research supports the use of VMI for better inventory parameters and advances techniques in managing perishable FMCG products.

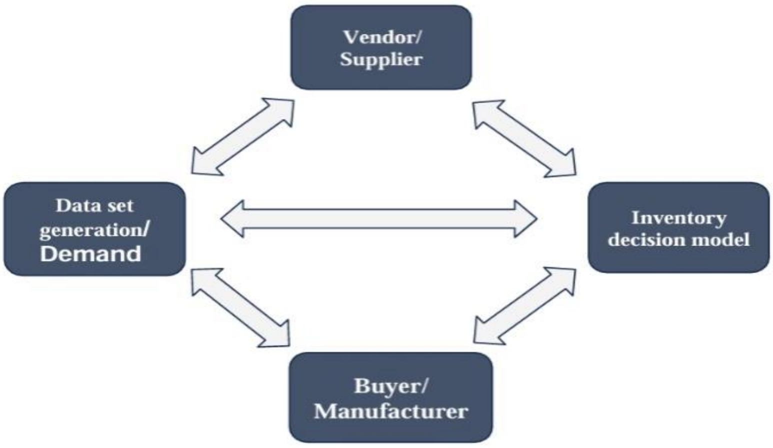
Keywords – Economic Order Quantity, Fast-Moving Consumer Goods, inventory management, Decision Support System, Vendor Managed Inventory.

I. INTRODUCTION

Effective inventory management is a vital aspect of any supply chain, as it influences overall costs and operational efficiency. Poor inventory management can lead to high inventory costs, stockouts, and dissatisfied customers. Vendor Managed Inventory (VMI) has emerged as a popular strategy, shifting the responsibility of inventory management from the customer to the supplier. In a VMI system, the supplier monitors the client's inventory levels and determines the timing and quantity of restocks, freeing the buyer to concentrate on other business areas. Many manufacturers have adopted VMI systems to enhance retail customer service levels and improve inventory turnover. These systems achieve their objectives by employing more accurate sales forecasting methods and optimizing supply chain inventory distribution. VMI allows retailers to expand the range of vendor products available at a given location, thereby boosting the profitability of the vendor's brand for both the retailer and the supplier. Without VMI, retailers managing inventory independently might not achieve the same level of efficiency. Retailers managing inventory independently are unlikely to achieve the same productivity gains as those using VMI, as vendors can offer a more responsive replenishment system based on accurate demand data. VMI, also known as vendor-managed replenishment (VMR), involves the vendor managing inventory levels for both the vendor and retailer by leveraging the retailer's sales and inventory data to prevent excess stock. This means the vendor has the authority to manage inventory at retail locations through information sharing (Yao and Dresner, 2008). Compared to traditional practices, VMI reduces inventory costs and increases overall supply chain profitability (Heydari, 2014). Many successful retailers, such as Wal-Mart and Kmart, have implemented VMI, which helps lower total inventory costs while enhancing customer service levels (Simchi-Levi et al., 2007). Additionally, a survey of 137 businesses by Dong et al. (2007) found that VMI was the most commonly used strategy for fostering a cooperative relationship between vendors and retailers. Moreover, a refinery firm, which has over 85 subsidiaries and is China's largest manufacturer and supplier of petrochemical goods, used the VMI strategy to drastically cut the system's cost (Zhao et al., 2010). Elvander et al. (2007) proposed a methodology for assessing the feasibility of constructing a VMI system. Sari (2007) then commented on the benefits of VMI deployment in various SC situations, such as varying degrees of outside supply capacity, demand uncertainty, and lead-time.

II. METHODOLOGY

Fig 1: Ensemble Model



In In the proposed decision support system, an ensemble model is employed, as shown in Figure 1. This model collects coordination information and historical sales data from both buyers and suppliers to forecast demand. The dataset for this study was created using statistical distributions. Using the forecasted demand and its variations, the inventory decision model determines key inventory parameters such as total inventory costs, optimal service levels, marginal costs, and minimum and maximum stock levels. This method aims to enhance inventory management by accurately predicting demand and adjusting inventory strategies accordingly. The data generation process involves using 12 data points from an initial data taken from the demand dataset of an FMCG product. The same has been used to estimate the parameters of the distribution and then generating the new data points. The generated data is then extended up to 52 data points for each distribution refer Fig 2 and Fig 3, for uniform and normal distributions respectively. The paper incorporates 2 types of distribution namely Normal distribution and Uniform distribution for generating the subsequent dataset. The significance of both the beta distribution and the uniform distribution in terms of demand for a product lies in their ability to model and predict different demand patterns and variability.

Uniform Distribution Model:

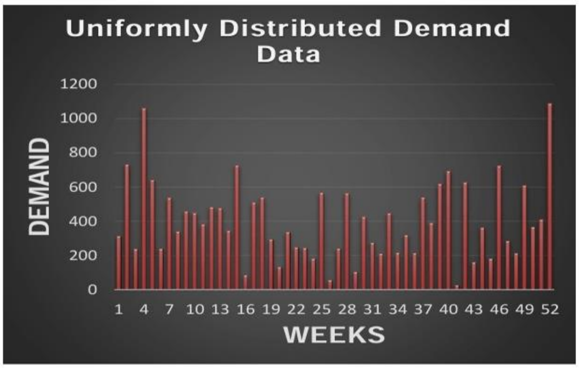


Fig 2: Generated Dataset -Uniform Distribution

$$X_t = a + (b - a) * U$$

where U is a random number between 0 and 1.

a= Lower Limit of demand, b = Upper Limit of demand

The uniform distribution assumes that demand for a commodity would be equally probable within a certain time frame. In the absence of any noticeable trend or pattern in the data, this distribution can still be used to estimate demand. The uniform distribution helps to simulate a product's demand pattern, for example, if the demand for the product is consistent over the course of the period. Businesses may make sure they have enough inventory levels throughout the period to match client demand by utilizing the uniform distribution to model demand.

Normal Distribution Model:

$$X_{t+1} = \frac{\alpha X_t}{\alpha X_t + \beta(1 - X_t)}$$

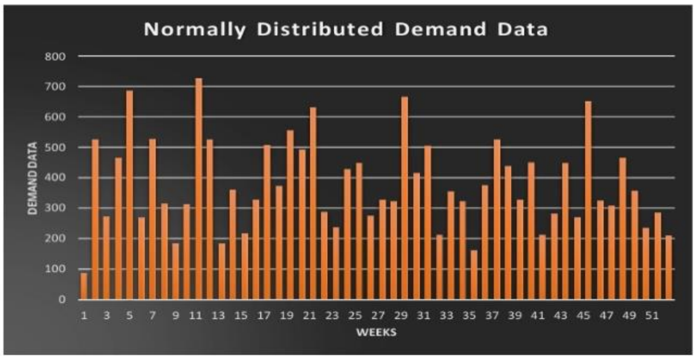


Fig 3: Generated Dataset -Normal Distribution

Where X_t is the previous generated data value and it is calculated initially by random number generation. The distribution parameters, α and β can be calculated as,

$$\alpha = \left(\frac{1-\mu}{\sigma^2} - \frac{1}{\mu}\right)\mu^2$$

$$\beta = \alpha\left(\frac{1}{u} - 1\right)$$

Where μ and σ^2 are the mean and variance of the data respectively.
The normal distribution is particularly effective for simulating non-uniform and skewed demand. For example, in the case of a new product launch, demand may start off slow and then rapidly increase as awareness and popularity rise. Because it has a variable form that can be changed to meet different conditions, the beta distribution can capture this sort of demand pattern.

III. INVENTORY DECISION MODEL

a) VMI MODEL

The proposed paper analyses a mathematical model formulated by Sirin (2013) in his paper titled "A Mathematical Approach to Vendor-Managed Inventory with Consignment".
From the model, it was deduced that shipment size caused a conflict of interest between supplier and buyer in terms of average warehousing and shipping cost. The aim of the inventory decision model was to reduce the average total cost which is the sum of average shipment cost and average warehousing cost by optimizing the shipment supply.
The inventory holding per shipment frequency, which depends on the minimum stock level and shipment size and is the primary factor in warehousing costs, is shown in Fig. 4.

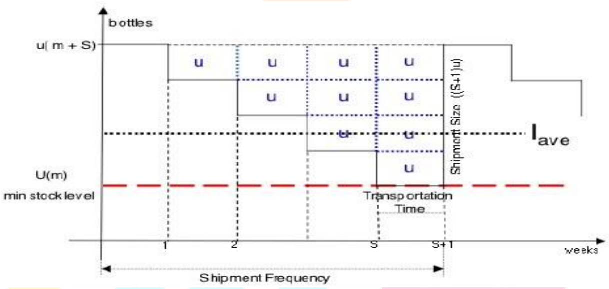


Fig 4: Inventory holding per shipment frequency (Source: "A Mathematical Approach to Vendor-Managed Inventory") with Consignment".

Following notations are used throughout the model to define the parameters as well as different costs involved,

m = minimum stock level (weeks)
M= maximum stock level (weeks)
u = weekly usage (units/week)
S = number of weeks to hit min stock level after replenishment
$S+1$ = shipment frequency (weeks)
$u(S+1)$ = shipment size (units)
k = storage cost per box ($)
b = number of units in a box (units)
FC_w = monthly fixed warehouse cost ($)
W_{ave} = average (weekly) warehousing cost per shipment frequency ($)
FC = Fixed shipping cost per shipment
VC = Variable shipping cost/shipment
SC_{ave} = Weekly average shipping cost

Buyers incur warehousing cost for storage, handling, insurance, obsolescence, and shrinkage. It has fixed and variable components, with the average cost increasing with shipment size due to increased inventory levels. Average Warehousing cost is calculated as,

$$W_{ave} = \frac{1}{2}(2um + us)\frac{k}{b} + \frac{FC_w}{4}$$

Shipping costs are included in the listed unit price of the product and belongs to the supplier. Smaller and more frequent shipments diminish the profit margin of the provider. Customs clearance, hazardous material fees, and transportation surcharges are fixed expenses, whereas delivery fees and fuel surcharges are variable prices. Bigger shipments lower the average unit shipping cost. Average Shipping costs are described as,

$$SC_{ave} = \frac{FC}{S+1} + (VC * u)$$

Average total cost per shipment frequency is defined as the sum of Average Warehousing cost and Average Shipping cost,

$$AC = W_{ave} + SC_{ave}$$

$$AC = \left[\frac{1}{2}(2um + us)\frac{k}{b} + \frac{FC_w}{4}\right] + \left[\frac{FC}{S+1} + (VC * u)\right]$$

Marginal cost (MC) is the change in total cost resulting from a one-unit change in quantity produced. It is expressed as the derivative of total cost (TC) with respect to quantity. In our case, MC will represent the additional cost of shipping one more week of supply.

$$TC = AC * (S+1)$$

$$MC = \frac{\partial TC}{\partial S}$$

$$MC = \frac{k}{2b}(2um + 2uS + u) + \frac{FC_w}{4} + VC * u$$

Average cost in minimum when marginal cost equals average cost. Average total cost is always affected by the marginal cost of production of next unit due to which average total cost will decline if marginal cost is less than average cost. Solving equations simultaneously will result in returning the optimal shipment frequency (S+1) and time period to reach minimum stock level after replenishment (S) leading to minimum total cost for the system,

$$S = \sqrt{\frac{2 * b * FC}{u * k}} - 1$$

Minimum stock level (m) is crucial in determining the average inventory level and inventory turn value, along with the shipment size. It acts as a buffer against possible shortages and delays in the supply chain, as well as unexpected increases in usage. For unexpected replenishment, the minimum stock level should meet the buyer's consumption throughout the supplier's manufacturing lead time and transportation time.

Maximum stock level (M) determines the flexibility of shipment frequency (S+1) and helps prevent overstocking and related costs such as expiration and holding costs. It needs to be more than or equal to the sum of the minimum stock level and the optimal number of weeks to reach the minimum stock level following replenishing (S),

$$M \geq m + S$$

b) EOQ MODEL

$$\text{EOQ} = \sqrt{\frac{2DS}{H}}$$

where:

S = Order costs (per order, generally including shipping and handling)

D = Annual Demand (quantity sold per year)

H = Holding costs (per year, per unit)

The EOQ model provides the ideal order quantity the buyer/ customer should purchase in order to reduce its total inventory costs which includes order costs, shortage cost and storage costs.

Further the comparison between the VMI and EOQ models are performed and the inventory policy which provides the least total cost is considered the better model.

IV. RESULTS AND DISCUSSION

The Weekly demand data generated from distribution model equations was used in the VMI to determine shipment frequency and quantity. Associated costs, such as warehousing and shipping, were also calculated to analyze how they varied with changes in demand. The total cost of implementing VMI was assessed, and the lowest total cost point identified. This process was applied to both uniform and normal distributions. Comparing the total costs between the two distributions, as shown in figure 5, reveals a clear correlation between cost functions and demand data. Both follow a similar pattern, indicating that total cost functions are intrinsically linked to demand data, displaying a proportional relationship.

Fig 5: Total Cost relation with replenishments for the normal and uniformly distributed demand

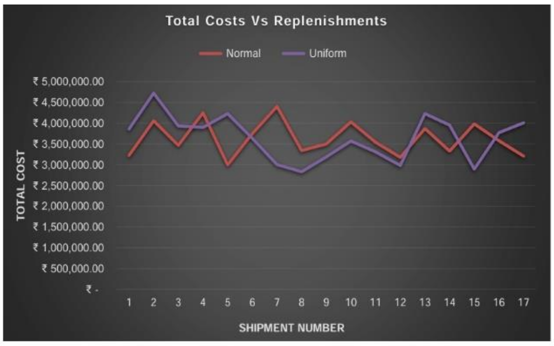
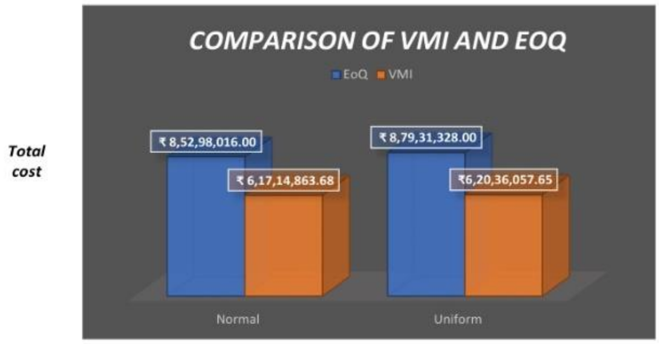


Fig 6: Total Cost comparisons for EOQ and VMI for normal and uniformly distributed data



Based on a comprehensive analysis of the total cost incurred by both the Vendor Managed Inventory (VMI) model and the Economic Order Quantity (EOQ) model, it can be ascertained that the former is a more suitable option for achieving cost reduction. This conclusion is drawn from a detailed examination of the relationship between the two models, as visually represented in Figure 6.The overall cost of inventory management consists of the costs associated with warehousing and shipping. The Economic Order Quantity (EOQ) model was assessed using two types of data: normal distributed and uniformly distributed. The total cost values obtained were Rs. ₹8,52,98,016.00 and Rs.8,79,31,328.00 respectively. Conversely, the Vendor Managed Inventory (VMI) model provides distinct reports for warehousing and shipping expenses. The normal distributed data incurred a warehousing cost of Rs. 14,24,612.292 and a shipping cost of Rs. 6,02,90,251.39, resulting in a total cost of Rs. 6,17,14,863.68. Similarly, for uniformly distributed data, the warehousing cost was Rs. 14,29,828.306 and the shipping cost was Rs. 6,06,06,229.34, resulting in a total cost of Rs.6,20,36,057.65. Both cases clearly demonstrate that the transportation cost comprises approximately 97.6% of the whole cost, whereas the warehousing cost constitutes a negligible proportion of the overall cost. The cost of inventory management is substantially reduced under the Vendor Managed Inventory (VMI) model compared to the Economic Order Quantity (EOQ) approach. The VMI model is characterized by its high efficiency and streamlined nature, since it empowers the vendor to assume responsibility for monitoring and maintaining the inventory levels of the customer. As a consequence, the probability of experiencing stockouts or having excessive inventory is diminished, hence mitigating the need for costly urgent orders or storage costs. Therefore, the VMI model is a more cost-effective approach for managing inventory.

V. CONCLUSION

After conducting a comprehensive comparison between the Vendor Managed Inventory (VMI) model and the Economic Order Quantity (EOQ) model, it is clear that implementing the VMI strategy offers a more beneficial alternative for minimising total costs. The choice is based on a thorough cost comparison analysis, which shows that the VMI approach regularly results in lower total costs compared to the EOQ model. By adopting a Vendor Managed Inventory (VMI) system, the supplier assumes the responsibility of monitoring inventory levels and restocking goods, hence reducing the potential hazards of excessive inventory and stock shortages. As a result, the costs associated with holding and organising expenses are decreased, resulting in a more efficient and economical operation. Therefore, it is highly advisable for firms to thoroughly examine implementing a Vendor Managed Inventory (VMI) method in order to enhance the efficiency and cost-effectiveness of their supply chain. Furthermore, this Decision Support System (DSS) model shows potential for wider use across a range of Fast-Moving Consumer Goods (FMCG) products, as long as the necessary demand data is accessible. The adaptability and diversity of this technology enable firms to extract important insights and recommendations specifically designed for optimising inventory management procedures.

VI. REFERENCE

[1] Nazar Sohail, Tariq Hussain Sheikh, “A Study of Inventory Management Case Study”, Journal of Advanced Research in Dynamical & Control Systems, Vol. 10, 10-Special Issue, 2018, pp. 1176- 1190.
[2] Chaudhry, H. and Hodge, G., 2016. Vendor-managed inventory systems in the apparel industry. Information Systems for the Fashion and Apparel Industry, pp.221-234.
[3] Achabal, D.D., McIntyre, S.H., Smith, S.A. and Kalyanam, K., 2000. A decision support system for vendor managed inventory. Journal of retailing, 76(4), pp.430-454.
[4] Madhu Babu Cherukuri, Tamoghna Ghosh, “Control Spare Parts Inventory Obsolescence by Predictive Modelling”, IEEE Smart Data, 2016, pp. 865-869. Madhu Babu Cherukuri, Tamoghna Ghosh, “Control Spare Parts Inventory Obsolescence by Predictive Modelling”, IEEE Smart Data, 2016, pp. 865-869.