Industrial Engineering and Innovation Management (2023)
Clausius Scientific Press, Canada

DOI: 10.23977/ieim.2023.061011
ISSN 2522-6924 Vol. 6 Num. 10

Optimizing Inventory Allocation for Fast Moving Consumer Goods: A Stochastic Model Approach

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Keywords: Inventory Control, Deterministic Model, Stochastic Model, Optimization, FMCG-Fast Moving Consumer Goods

Abstract: In the fast-paced and competitive landscape of fast-moving consumer goods (FMCG) industries, effective inventory allocation plays a pivotal role in ensuring optimal supply chain performance. Traditional deterministic inventory models often fail to account for the inherent uncertainties and fluctuations in consumer demand and lead times, leading to suboptimal allocation decisions. To address this challenge, a stochastic model has emerged as a powerful approach that considers demand and lead time as probabilistic variables. Through a comprehensive case study of a leading FMCG manufacturer, the effectiveness of the stochastic model is demonstrated in achieving improved inventory allocation decisions. The results indicate that embracing the stochastic model empowers FMCG companies to make informed and data-driven decisions when allocating inventory resources. By embracing uncertainty and variability, businesses can develop more robust inventory allocation strategies that align with real-world demand patterns and lead times. As supply chains continue to face dynamic challenges, the stochastic model represents a valuable tool for FMCG industries seeking to optimize their inventory allocation practices and thrive in the ever-evolving consumer landscape.

1. Introduction

In the fast-moving consumer goods (FMCG) industry, where products experience rapid turnover and consumer preferences evolve quickly, effective inventory management is a critical determinant of business success. Achieving optimal inventory allocation is a complex challenge, as FMCG companies must continuously balance the need to meet dynamic customer demands while minimizing holding costs and stockouts. Traditional deterministic inventory models often fall short in addressing the inherent uncertainties and fluctuations in demand and lead times, leading to suboptimal allocation decisions.

To address these complexities and uncertainties, the application of stochastic modeling has gained prominence as a powerful approach in FMCG inventory management. Unlike deterministic models, stochastic models consider demand and lead time as probabilistic variables, enabling businesses to make more informed and data-driven allocation decisions that embrace variability and uncertainty. This study explores the use of a stochastic model for achieving optimal inventory allocation in the FMCG industry. The model leverages historical demand and lead time data to fit probabilistic distributions, providing a moNasre realistic representation of demand variability. By considering this variability, the stochastic model enables companies to calculate safety stock levels based on desired service levels and determine reorder points that account for lead time variability. By incorporating real-world variability and uncertainty into the decision-making process, businesses can navigate the complexities of FMCG inventory management more effectively and position themselves for sustainable success in the dynamic Marketplace.

This study organized into five sections. A literature review of inventory management in stochastic environment for FMCG in section 2. Section 3 presents the mathematical model. Section 4 comprises the case study and final section includes the conclusion.

2. Literature Survey

Overall, the literature on optimal inventory allocation for fast-moving consumer goods using stochastic models highlights the significance of considering uncertainty and variability in demand and lead time. Stochastic modeling enables FMCG companies to make more informed and data-driven inventory allocation decisions, leading to improved supply chain efficiency, customer satisfaction, and competitiveness in the dynamic FMCG market. The following literature survey provides an overview of key research works related to the use of stochastic models in FMCG inventory management:

Kumar and Mishra provide a comprehensive overview of the application of inventory models in the fast-moving consumer goods (FMCG) industry [1]. The study discusses various probabilistic demand and lead time distributions used in the models and explores different optimization techniques to achieve optimal inventory allocation. Valbuena (2022) focused on demand forecasting and proposed a machine learning-based approach for stochastic demand forecasting in FMCG products, this research work [2]. Husseini et al. examined the relationships between supply chain, management and industrial clusters and proposed a two-target cascade supply model with an intrinsic correlation structure [3]. Dong et al. proposed appropriate strategies for firms' transportation optimization by considering the basic inventory control structure [4]. Kchaou-Boujelben et al. used a two-stage stochastic program and considered the ε-constrained stochastic model in the supply chain management [5]. Asharizadeh et al. investigates how FMCG companies adapted their inventory allocation strategies during the COVID-19 pandemic, using stochastic models [6]. The research analyzes the impact of supply disruptions and demand fluctuations on inventory performance. The study provides valuable insights into the resilience and responsiveness of stochastic models in navigating supply chain disruptions. Pratap et al. developed an integrated production inventory model for perishable food products that considers capacity, time intervals and capacity states [7]. They considered the synchronization structure of product distribution to warehouses and product delivery to customers. Wang et al. used heuristic algorithms to estimate uncertain customer demand by considering a two-stage location problem with time windows [8]. Govindan et al. studied the time-parameterized location routing problem in perishable food supply chain management [9]. Escalona et al. investigated the process of modeling an efficient distribution network including product availability with different inventory policies and various demand situations [10]. Zhu et al. studied customer demand in online supermarkets and developed a model that takes into account the order structure between warehouses and grocery stores in a model that achieves the minimum order splitting structure [11]. Zanjani et al. examined the adverse effects of environmental impacts on products in food supply chains and investigated three-stage inventory planning, from production to distribution, using a two-objective stochastic programming approach [12]. Asghari et al. studied customer behavior in pricing and advertising decisions in closed-loop supply chain management [13]. Nasiri et al. designed a model for inventory control decisions that takes into account supply network and pricing policies in determining economic lot size [14]. Önal et al. aimed to manage the selling prices and inventory levels of all products synchronously with shelf space and storage capacity by efficiently forecasting the product demand rate [15]. Sahling and Hahn studied the determination of efficient inventory levels for products with limited shelf life [16]. Duan and Liao analyzed the uncertain inventory management situation in supply chain management of perishable products by simulation [17].

3. Methodology

A stochastic model is a valuable tool for optimizing inventory allocation for fast-moving consumer goods (FMCG) when dealing with uncertainty and random variability in demand and supply. Unlike deterministic models, which assume fixed and known parameters, stochastic models account for the inherent uncertainty and fluctuations that are common in the FMCG industry.

One widely used stochastic model for inventory allocation is the Stochastic Inventory Control Model. This model considers probabilistic demand and lead time distributions to make decisions about how much inventory to order and when to place orders. It aims to find inventory policies that balance the trade-off between holding costs and stockout costs.

The stochastic model allows FMCG companies to make more informed decisions by considering the uncertainty in demand and lead time. It helps in setting appropriate safety stock levels to reduce the risk of stockouts while minimizing excess inventory costs. The model's flexibility also enables companies to adjust inventory allocation strategies based on changing market conditions and customer demands (in Fig.1).

Figure 1: Suggested Stochastic Inventory Control Model

While the stochastic model provides valuable insights, it is essential to ensure accurate estimation of probability distributions using sufficient historical data and to periodically update the model as new data becomes available. By utilizing the stochastic model, FMCG businesses can improve inventory allocation decisions and enhance their overall supply chain performance.

3.1 Mathematical Model

To formulate a stochastic model for optimal inventory allocation of fast-moving consumer goods (FMCG), we can use a probabilistic approach to incorporate demand and lead time uncertainties. In this model, we'll consider a single-item inventory system with stochastic demand and stochastic lead time.

The notations given in Fig.2 and using the basic assumptions of the model listed as follows:

1) Demand follows a known probability distribution (e.g., normal, Poisson).
2) Lead time follows a known probability distribution (e.g., normal, exponential).
3) The replenishment order is received instantaneously at the end of the lead time.
4) Shortages are not allowed (i.e., backorders are not permitted).
5) Lead time demand is independent and identically distributed (i.i.d).
6) Replenishment orders are placed at fixed intervals (review period).

Notations:

Q	Order quantity (the number of units to order)
D	Demand distribution, representing the probability distribution of demand
P	(Selling Price): The price at which the product sold.
C	Unit cost
Co	Cost of stockouts (shortages)
Cu	(Cost of Excess Supply): The cost incurred for each unit of supply that remains unsold.
S	Selling price per unit (can vary based on the quantity ordered)
h	Holding (inventory carrying) cost per unit
T	Selling season length
SL	Desired service level (typically expressed as a percentage)
I_0	Initial Stock Level): The initial inventory or stock level at the beginning of the selling season.
P_D	Demanded product price
P_S	Selling product price
D(q)	(Demand as a Function of Order Quantity): The demand for the product, which can be a function of the order quantity q
R(q)	(Revenue as a Function of Order Quantity): The revenue generated from selling the product, which can be a function of the order quantity q.
P(q)	(Selling Price as a Function of Order Quantity): The price at which the product sold, which can be a function of the order quantity q
L(I)	(Initial Inventory): The initial inventory level at the start of the selling season
α	Service level (e.g., 95%, 99%)

z_α: Z-score corresponding to the desired service level α (from standard normal distribution)

Figure 2: Suggested Model notation list

It's important to note that the choice of probability distributions for demand and lead time will depend on the historical data and characteristics of the FMCG products being analyzed. Additionally, real-world considerations, such as minimum order quantities, production capacity, and supplier constraints, may need to be incorporated into the model to make it more practical and applicable to specific business scenarios.

3.1.1. Price Model

It can be formulated as a mathematical programming problem to determine the optimal order quantity that maximizes expected profit or expected utility while considering uncertain demand. Additionally, the model may incorporate pricing decisions. The Single-Period (Newsvendor) Model with pricing considerations:

Objective:

Expected Profit Maximization:

Maximize $E[\pi]$

Where π represents expected profit, which is calculated as:

$$C\,min(Q,D) - hmax(Q-D,0) - C_0 max(D-Q,0) \tag{1}$$

Expected Utility Maximization:

$$Maximize\ E[U(Q)] \tag{2}$$

$Maximize\ E[U(Q$ The utility function $U(Q)$ represents the decision-maker's utility as a function of the order quantity Q.

Constraints:

Demand Constraint

$$E[D] \leq Q \leq T.E[D] \tag{3}$$

Ensures that the order quantity Q is between the expected demand and the maximum possible demand within the selling season.

Service Level Constraint

$$P.Prob(D \leq Q) \geq SL \tag{4}$$

In practice, solving the Single-Period (Newsvendor) Model with pricing often involves iterating through different values of Q and S to find the combination that maximizes the objective function (expected profit or expected utility) while satisfying the constraints.

3.1.2. Revenue Model

It considers both uncertain demand and variable revenue. In this case, the objective is to balance holding costs, stockout costs, and revenue from sales.

Objective

$$E[\pi] = \sum_{d=0}^{\infty} [(R(d) - C).\min(Q.d) - h.\max(Q - d, 0)] . P_D(d) \tag{5}$$

In this objective function, we consider that the revenue R can vary depending on the order quantity q, and we use the demand distribution ($P_D(d)$) to calculate the expected profit.

Expected Profit Maximization: The objective is to maximize the expected profit:

$$E[\pi] = \int_0^Q [P(q) - C(q)] . D(q)dq - h\int_Q^{\infty} (q - Q). D(q)dq \tag{6.}$$

We integrate over the order quantity q to account for the variable pricing, cost, and demand. The first integral represents revenue, while the second integral represents holding costs.

Constraints:

Service Level Constraint: Ensure that the desired service level mets:

$$(R(d). (1 - SL) \leq h. (Q - d), \qquad for\ each\ d) \tag{7}$$

$$\int_0^Q D(q)dq \geq SL \tag{8}$$

Order Quantity Constraint: The order quantity (Q) should be non-negative: $Q \geq 0$

The objective is to determine the order quantity (Q) that maximizes the expected profit, considering both variable revenue and uncertain demand. The service level constraint ensures that the desired service level is met for each possible demand level, and the order quantity constraint ensures that the order quantity is non-negative.

3.1.3. Control Model

This model considers both uncertain supply and uncertain demand and aims to find the optimal order quantity that maximizes expected profit while taking into account these uncertainties.

Objective Function:

$$E[\pi] = \sum_s \sum_d [(P - C).\min(Q, D, s) - h.\max(Q - d, s, 0) - C_0.\max(d - Q - s, 0) - C_S.\max(d - Q, 0)] . P_D(d). P_S(s) \tag{9}$$

We consider that both supply and demand are random variables, and we sum over all possible combinations of supply and demand values. The terms represent revenue from sales, holding costs, stockout costs, and excess supply costs.

Constraints:

The service level constraint ensures that the desired service level is met based on the joint probabilities of demand and supply.

Service Level Constraint: Ensure that the desired service level is met

$$\sum_d \sum_s \min(Q, D, s). P_D(d). P_S(s) \geq SL \tag{10}$$

Order Quantity Constraint: The order quantity (Q) should be non-negative $Q \geq 0$

3.1.4. Supply and Demand Model

It finds the optimal order quantity that maximizes expected profit while considering both supply and demand uncertainties. This model helps in making inventory decisions under conditions of uncertainty in both supply and demand.

Objective:

$$E[\pi] = \sum_s \sum_d [(P - C).\min(Q, D, s) \\ - h.\max(Q - d, s, 0) - C_0.\max(d - Q - s, 0) - C_S.\max(Q - d - s, 0)].P_D(d).P_S(s) \quad (11)$$

We consider the joint probabilities of demand ($PD(d)$) and supply ($PS(s)$) to calculate the expected profit. The objective balances revenue, holding costs, stockout costs, and shortage costs.

3.1.5. Stock Model

It determines the optimal order quantity that maximizes expected profit while accounting for demand uncertainty and stockout costs.

Objective:

$$E[\pi] = \sum_d [(P - C).\min(Q, d + I) - h.\max(Q - d - l, 0) - C_0.\max(d + l - Q, 0)].P_D(d) \quad (12)$$

The demand distribution $(P_D(d))$ to calculate the expected profit. The objective balances revenue, holding costs, and stockout costs.

The objective is to maximize the expected profit $(E[\pi])$:

$$E[\pi] = \sum_d [(P - C).\min(Q, +I_0, d) - h.\max(Q + I_0 - d, 0) - C_0.\max(d - Q - I_0, 0)].P_D(d) \quad (13)$$

Constraints:

Order Quantity Constraint: The order quantity (Q) should be non-negative: $Q \geq 0$.

In this formulation, the objective is to determine the order quantity (Q) that maximizes the expected profit, considering demand uncertainty and inventory holding costs. The constraint ensures that the order quantity is non-negative.

Service Level Constraint: Ensure that the desired service level is met:

$$\sum_d \min(Q + I_0, d.P_D(d) \geq SL \quad (14)$$

3.1.6. Cost Model

This model helps determine the optimal order quantity that maximizes expected profit while accounting for uncertain demand and cost parameters.

Objective Function: The objective is to maximize the expected profit $(E[\pi])$:

$$E[\pi] = \sum_d \sum_c [(P - c).\min(Q, d) - h.\max(Q - d, 0) - C_0.\max(d - Q, 0)].P_D(d).P_C(c) \quad (15)$$

In this objective function, we consider both the probability distribution of demand $(P_D(d))$ and the probability distribution of the cost per unit $(P_C(c))$ to calculate the expected profit. The objective aims to balance revenue, holding costs, and stockout costs while considering the uncertain demand

and cost parameters.

Constraints:

Service Level Constraint: Ensure that the desired service level is met:

$$\sum_{d} \min (Q, d).P_D(d) \geq SL \tag{16}$$

Order Quantity Constraint: The order quantity (Q) should be non-negative: $Q \geq 0$

In this formulation, the objective is to determine the order quantity (Q) that maximizes the expected profit while considering both demand uncertainty and cost uncertainty. The service level constraint ensures that the desired service level is met based on the probability distribution of demand.

To achieve optimal inventory allocation for fast-moving consumer goods (FMCG) in the face of demand uncertainty, a stochastic inventory model can be employed. Stochastic models take into account the random variability of demand and lead times, allowing businesses to make informed decisions that consider the inherent uncertainties in the FMCG industry. The stochastic inventory model provides a robust framework for FMCG companies to make optimal inventory allocation decisions in the presence of demand uncertainty and lead time variability. By accounting for the random nature of demand and lead times, businesses can reduce the risk of stockouts, minimize holding costs, and achieve improved overall supply chain performance. Regularly updating the model based on real-world data and demand patterns ensures continuous improvement and adaptability to changing market conditions.

4. Case Study

This section describes how to use a model that takes into account uncertain demand and lead time factors and highlights how this application provides an advantage to improve the company's supply chain efficiency and customer satisfaction. It also demonstrates the potential of data-driven decisions to provide a competitive advantage in a dynamic market.

In this model, we try to maximize the profit or utility at the end of a single period by considering uncertain demand. It is used to determine the optimal ordering under product uncertainty. Balances the costs of overstock and understocking. Retailers can use this model to determine how many products they should order during the sales period. Businesses aim to determine the best order quantity in case of uncertain demand, so that businesses can maximize their profits or obtain a certain benefit. When we evaluate on a product basis, according to the nationalization status of a product in the warehouse, it is aimed to import it according to market conditions, competitor prices, seasonal effects and sell it to retail points through distributors. If the number of products is below the market demand, we aim for volume-oriented sales with lower profitability and lower discounts if the number of products is above the market demand. Discounts are also made according to competitor prices. Many variables are taken into account in order to reach these price and profitability-oriented sales figures for the most important products. Furthermore, deterministic and stochastic demands are uncertain. In the proposed model, deterministic model was calculated by taking the average of the possible maximum and minimum values (in Fig.3). The stochastic model, random values are assigned between these values [18]. (in Figure 4)

Information about the company is that there are 200 different product. The foreign orders made according to the target given at the beginning of the year, the foreign shipments, depending on the production capacity, reach our company in bulk in certain periods, not as a monthly standard. Especially for 25-30 product, extra sales campaigns aimed for profitability compared to competitors. Especially for the skus that we focus on the model, the main purpose is to maximize product sales in the summer months and in November and December to fill the retail points. In the sector, sales rates increase in these months, and in the beginning of the year and autumn periods, the market is a little more stagnant and sales are slow. Since we examine the stock status in certain quantities as deterministic and stochastic models. It is seen that our costs and sales prices change in order to be more profitable according to the stochastic model according to the variability of the stock status, and that these variables reveal a more profitable situation according to the company strategy (in Table 1 and Figure 5).

Different scenarios

S1	Increase the price when supply is low and demand is standard [Price Model↑—Supply↓ and Demand Model]
S2	Efforts to destock by lowering the price when supply is excessive and demand standardized [Price Model ↓—Supply ↑and Demand Model]
S3	Price increase as a result of increased cost of standard product availability [Price Model↑—Cost Model↑]
S4	Cost is the same in the case of standard product availability, but the product price reduced due to competitive conditions. [Price Model↓—Cost Model-]
S5	Price reduction as a result of reduced costs due to availability of standard products [Price Model↓—Cost Model↓]

Figure 3: The model’s scenario types

Scenarios	Expected Profit Maximization	Service Level
Scenario1-Deterministic	$C.\min(Q,D) - h\max(Q-D,0) - C_0\max(D-Q,0)$	$P.Prob(D \leq Q) \geq SL$
Scenario1-Stochastic	$E(C.\min(Q,D) - h\max(Q-D,0) - C_0\max(D-Q,0))$	$E(P.Prob(D \leq Q) \geq SL)$
Scenario2-Deterministic	$\sum_s \sum_d [(P-C).\min(Q,D,s) - h.\max(Q - d,s,0) - C_0.\max(d-Q-s,0) - C_S.\max(Q-d-s,0)].P_D(d).P_S(s) - C\,min(Q,D) - hmax(Q-D,0) - C_0 max(D-Q,0)$	$\sum_d \min(Q+I_0, d.P_D(d) - P.Prob(D \leq Q) \geq SL$
Scenario2-Stochastic	$E(\sum_s \sum_d [(P-C).\min(Q,D,s) - h.\max(Q - d,s,0) - C_0.\max(d-Q-s,0) - C_S.\max(Q-d-s,0)].P_D(d).P_S(s) - C\,min(Q,D) - hmax(Q-D,0) - C_0 max(D-Q,0))$	$E(\sum_d \min(Q+I_0, d.P_D(d) - P.Prob(D \leq Q) \geq SL)$
Scenario3-Deterministic	$C\,min(Q,D) - hmax(Q-D,0) - C_0 max(D-Q,0) + \sum_d \sum_c [(P-c).\min(Q,d) - h.\max(Q-d,0) - C_0.\max(d-Q,0)].P_D(d).P_C(c)$	$P.Prob(D \leq Q) + \sum_d \min(Q,d).P_D(d) \geq SL$
Scenario3-Stochastic	$E(C\,min(Q,D) - hmax(Q-D,0) - C_0 max(D-Q,0) + \sum_d \sum_c [(P-c).\min(Q,d) - h.\max(Q-d,0) - C_0.\max(d-Q,0)].P_D(d).P_C(c))$	$E(P.Prob(D \leq Q) + \sum_d \min(Q,d).P_D(d) \geq SL)$
Scenario4-Deterministic	$\sum_d \sum_c [(P-c).\min(Q,d) - h.\max(Q-d,0) - C_0.\max(d-Q,0)].P_D(d).P_C(c) - C\,min(Q,D) - hmax(Q-D,0) - C_0 max(D-Q,0)$	$\sum_d \min(Q,d).P_D(d) - P.Prob(D \leq Q) \geq SL$
Scenario4-Stochastic	$E(\sum_d \sum_c [(P-c).\min(Q,d) - h.\max(Q-d,0) - C_0.\max(d-Q,0)].P_D(d).P_C(c) - C\,min(Q,D) - hmax(Q-D,0) - C_0 max(D-Q,0))$	$E(\sum_d \min(Q,d).P_D(d) - P.Prob(D \leq Q) \geq SL)$
Scenario5-Deterministic	$-C\,min(Q,D) - hmax(Q-D,0) - C_0 max(D-Q,0) - \sum_d \sum_c [(P-c).\min(Q,d) - h.\max(Q-d,0) - C_0.\max(d-Q,0)].P_D(d).P_C(c)$	$-P.Prob(D \leq Q) - \sum_d \min(Q,d).P_D(d) \geq SL$
Scenario5-Stochastic	$E(-C\,min(Q,D) - hmax(Q-D,0) - C_0 max(D-Q,0) - \sum_d \sum_c [(P-c).\min(Q,d) - h.\max(Q-d,0) - C_0.\max(d-Q,0)].P_D(d).P_C(c))$	$E(-P.Prob(D \leq Q) - \sum_d \min(Q,d).P_D(d) \geq SL)$

Figure 4: Scenarios and used Equations

In scenarios where the cost and selling price increase at a stock level below the standard and expectation, and the number of stocks and the number of products to saturate the market are displayed, the cost decreases and the selling price decreases with more product sales, but a more profitable result is seen. In cases where these variables are acted upon, it has been determined that by offering alternatives to standard discounts or price increases, sales are made in more accurate quantities and high profits are obtained.[19]

Table 1: Analysis Results

DETERMINISTIC(D) - STOCHASTIC(S) MODEL

Inputs	RO-D	RO-S	R1-D	R1-S	R2-D	R2-S	R3-D	R3-S	R4-D	R4-S	R5-D	R5-S
Leads per Month (L)(1000)	18	20,92474896	12	11,76199585	27	31,60564016	18	14,4348862	18	16,0723433	18	15,6298625
Cost Per Lead (C)	$8,40	$9,20	$8,40	$7,26	$8,40	$7,08	$9,50	$8,44	$7,80	$7,32	$8,40	$8,78
Conversion Rate (R)	0,1%	0,10%	0,1%	0,10%	0,1%	0,10%	0,1%	0,10%	0,1%	0,10%	0,1%	0,10%
Profit per Sale (P)	$14,30	$15,56	$18,30	$17,61	$13,50	$13,99	$14,30	$12,73	$14,30	$15,39	$13,80	$14,28
Overhead per Month (H)	$3,00	$3,00	$3,00	$3,00	$3,00	$3,00	$3,00	$3,00	$3,00	$3,00	$3,00	$3,00
Outputs												
Monthly Income:	257382	$325.649,32	219588	$207.149,16	364473	$442.198,15	257382	$183.785,78	257382	$257.067,78	248382	$223.123,62
Monthly Expenses:	151203	$192.504,45	100803	$85.425,27	226803	$223.652,33	171003	$121.895,60	140403	$122.228,41	151203	$137.252,99
Projected Monthly Profit:	106179	$133.144,86	118785	$121.723,90	137670	$218.545,83	86379	$61.890,17	116979	$134.839,37	97179	$85.870,64

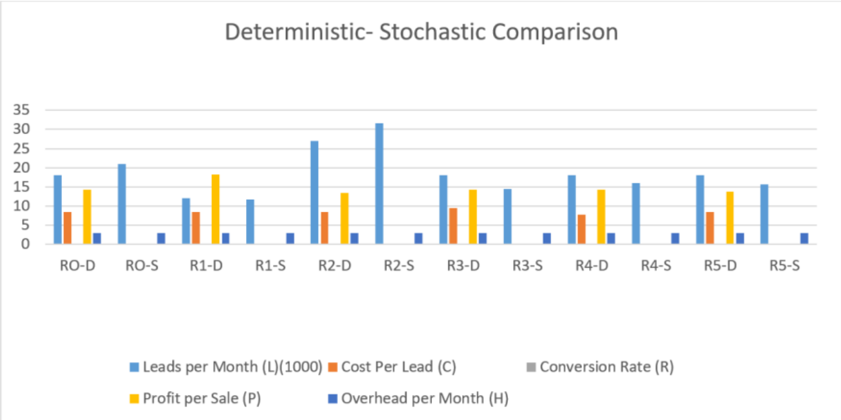

Figure 5: Deterministic and Stochastic comparison with scenarios

5. Conclusion

The application of a stochastic model approach to optimize inventory allocation in the Fast-Moving Consumer Goods (FMCG) industry has proven to be a powerful and effective strategy. The results obtained from this approach highlight the significance of considering demand uncertainties and probabilistic forecasting to achieve a delicate balance between demand and supply. By embracing the stochastic model approach, the company enhanced its ability to manage seasonal and promotional demand effectively. The model's ability to accommodate real-time data facilitated agile and data-driven decision-making, making the company more responsive to changes in the market. As a result, service levels improved, leading to heightened customer satisfaction and loyalty. The successful implementation of the stochastic model approach provided the FMCG company with a competitive advantage in the market. The ability to optimize inventory allocation efficiently and effectively contributed to improved market share, brand reputation, and financial performance. As the FMCG industry continues to evolve, the stochastic model approach remains a valuable tool for businesses seeking to optimize their inventory allocation strategies. By continuously refining the model with real-time data and embracing advanced analytics, FMCG companies can maintain their competitive edge in the face of dynamic market conditions.

In conclusion, the application of a stochastic model approach for optimizing inventory allocation in the FMCG industry demonstrates its effectiveness in achieving balanced demand and supply. The results underscore the importance of data-driven decision-making, supply chain resilience, and customer-centric strategies to thrive in the fast-paced and competitive FMCG market. Embracing the stochastic model approach empowers businesses to meet consumer demands efficiently, reduce costs, and secure a strategic position in the evolving consumer landscape.

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