Raw Material Minimum Order Quantity Optimization

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ABSTRACT

The sponsoring company, wants to review their raw material ordering policy and production plan for one of their product segments. This product faces a high degree of volatility in demand and the company currently orders one month of demand worth of products from the suppliers. The suppliers offer incremental discounts for larger quantities of raw materials ordered, and the company wants to leverage this discount better. To that end, our research focuses on how to optimize the raw material ordering policy in a way that reduces the total costs, while storing sufficient raw materials to ensure continuity of the production plan. The model we developed provides the optimal minimum order quantity (MOQ) to use while re-ordering raw materials. It also incorporates a switching rule that automatically switches the MOQ value to a higher or lower value depending on the demand forecast and determines the order quantity (OQ) of the raw material.

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1. Introduction

Inventory management is one of the most important responsibilities in an organization, as it involves reasonable amounts of capital and impacts the service level to customers. For companies with their own production lines, inventory can be categorized into different levels: raw material inventory, work in progress inventory, and finished goods inventory. While many organizations aim to reduce inventory at all three levels to reduce inventory costs, having sufficient raw material inventory to prevent production delays and stock-outs is vital. Many inventory decisions can be made based on an understanding of the relevant costs: item cost, ordering cost, holding cost and stockout cost (Schroeder, Goldstein, & Rungtusanatham, 2016).

In this project, the sponsoring company is in the fast-moving consumer goods (FMCG) industry. The project's objective is to review the raw material ordering process and production planning for one product segment and optimize the raw material ordering policy.

1.1. Problem Statement

The product in question faces high volatility in demand either due to seasonality or from unexpected order spikes. Suppliers offer different minimum order quantities (MOQs) of the raw material with different price scales, depending on the quantity ordered. Currently, the company chooses an MOQ that can cover 1 month of future demand. Due to the large degree of demand volatility, components ordered from suppliers have a lot of fluctuation in quantity. Currently, it is unclear whether the large amount of volatility in the demand is due to seasonal changes in demand or mere unexpected spikes. With the current process, the company is not able to take advantage of the discounts offered for purchasing larger quantities. This forms the basis of our research problem: how to optimize the raw material ordering policy in a way that reduces the total costs while storing sufficient raw materials to ensure continuity of the production plan.

This project develops a mathematical model to optimize raw material ordering quantity for the product that hits the "sweet spot" between costly oversupply and equally costly lack of goods. The optimal order quantity will maintain a balance between the ordering cost and the holding cost. The ordering cost reduces as the re-order quantity increases, due to the incremental discounts offered by the suppliers, while the holding cost increases with greater quantities due to the associated storage costs and opportunity cost tied up in holding the inventory. The model will provide the optimal MOQ to use while re-ordering raw materials. It will also incorporate a switching rule that automatically switches the MOQ value to a higher or lower value depending on the demand forecast and determines the order quantity (OQ) of the raw material. If we identify seasonality in the demand, then we can use the switching rule to switch between peak season and non-peak season to reduce the holding cost.

The model will also focus on optimizing inventory to avoid stock-outs and achieve the target service level of 99.3% that has been set by the company, as the basis for this study. The company will use the results of this project to provide a global model for supplier ordering and will generalize this approach across other business segments within the company.

2. Literature Review

In this section, we discuss key research done in the area of raw materials ordering, production planning and inventory management, which helped us develop a model that optimizes raw material minimum order quantity (MOQ). We begin by explaining the production planning techniques that are commonly adopted in large consumer goods companies. Since costs are the main decision driving factor, we review the various costs associated with inventory and production. These costs associated with inventory management enable us to identify the balance between reducing costs and maintaining sufficient inventory levels to avoid stock-outs. To optimize the current production methods, we look at two different types of inventory review policies – continuous review and periodic review – that are relevant in optimizing inventory management. Finally, we review two methods of computing the optimal order quantity that balances all the costs involved.

2.1. Production Planning

Material Requirements Planning (MRP) is a commonly employed technique in large manufacturing organizations to optimize production. MRP systems calculate the quantity of materials required and schedule their purchase or production.

Figure 1 illustrates the general structure of the framework for hierarchical production planning where each of the stages has its own planning parameters. Demand data is generated from the market and becomes the basis of demand forecasts. Demand forecasts are passed to two planning components: Master Production Schedule (MPS) and MRP. The MPS or the aggregated planning generates an optimal master schedule that gives the production amounts needed to fulfill the customer demand across the planning horizon. This schedule along with the customer orders comprise the next input for the next step, which is the MRP system. The MRP system calculates gross requirements based on the production schedule and derives requirements for each material in each time period or release date. The system considers all the parameters for optimization and generates the production orders. These production orders are checked for availability of raw materials in the procurement stage and then moved to production control until all the materials are available. Finally, the orders are batched to the shop floor for production (Gansterer, Almeder, & Hartl, 2014).

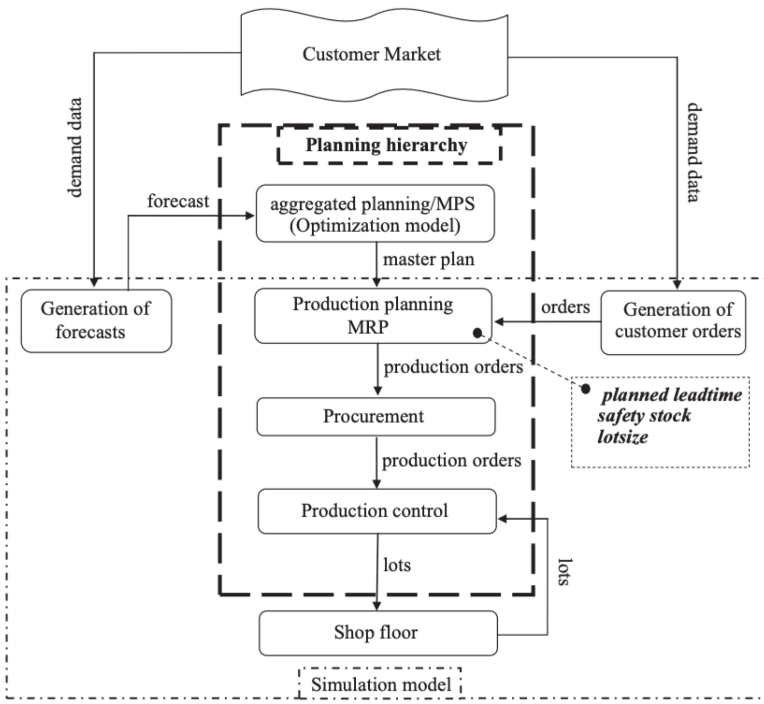

Figure 1. Framework for hierarchical production planning (Source: Gansterer, M., Almeder, C., & Hartl, R. F. (2014). Simulation-based optimization methods for setting production planning parameters)

MRP systems have a few limitations: 1) they ignore dynamic lead times and capacity constraints (Rossi, Pozzi, Pero, & Cigolini, 2017); and 2) they do not consider seasonality when calculating the economic order quantity. This can lead to infeasible production schedules and can take significant effort to adjust the plans. For these reasons, they are not the most efficient tools for determining the ordering policy for products with seasonal demand.

An extension of MRP is a distribution requirement planning (DRP) system. MRP is determined by a production schedule that is already fixed by the company, whereas, in a DRP system, the consumer demand is the driving factor. It is a complex information and control system that considers sales forecast with inventory levels to schedule how much material is needed and when it is needed. If there are multiple locations, it can also determine which location the material needs to be delivered to, in anticipation of the demand (Rizkya et al., 2018).

The main inputs for DRP systems include: 1) demand forecast; 2) current inventory level; 3) safety stock target; 4) lead time for replenishment; 5) target service level; and 6) historical inventory usage. The planning time horizon varies from daily, weekly, monthly, and quarterly, to annually, depending on the need.

According to Bookbinder & Heath (1988), one of the limitations of the DRP system is that the downstream demand determines the upstream demand, which we take into account while designing our model.

2.2. Inventory Costs

Among the most important criteria while making inventory decisions are the associated inventory costs (Schroeder, Goldstein, & Rungtusanatham, 2016) which are listed below:

- **Item cost:** This is the cost associated with buying an individual item. It is typically a cost per item that is multiplied by the quantity ordered.
- **Ordering or setup cost:** This is a one-time cost that is incurred when ordering a batch of items. It is associated with the entire order and does not depend on the order size. This includes any costs associated with transportation, receiving, expediting, etc.
- **Holding cost:** The holding cost is associated with carrying the inventory for a period of time. It is charged as a percentage of the dollar value per unit time. For example, a 20% holding cost means that it costs 20 cents to hold $1 of inventory for a year. The holding cost typically consists of cost of capital, which represents the opportunity costs of missed opportunities for other investments; cost of storage, which is the cost of space, insurance and taxes; and cost of obsolescence, deterioration, and loss, which are assigned to items that have a high risk of being obsolete, have a shelf life or can lose their value in the market.

- **Stockout cost:** This is an economic impact of stocking out and losing sales as a result. It can be a lost one-time sale or a lost customer who is unlikely to buy again.

For our project, we consider the holding cost and the ordering cost which includes the item cost multiplied by the quantity ordered. There is no separate setup cost associated with placing an order and we assume that transportation or any additional cost is included in the item cost.

The annual cost of inventory is then a factor of the ordering cost and the holding cost and we want to find the optimal quantity that minimizes the total cost, as shown in Figure 2.

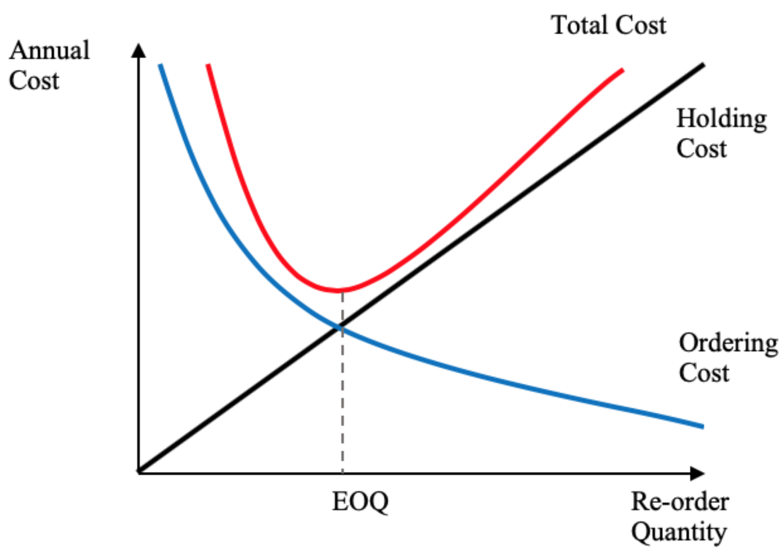

Figure 2. Plot of annual cost vs. reordering quantity

(Source: adapted from Schroeder, R. G., Goldstein, S. M., & Rungtusanatham, M. J. (2016). Operations Management in the Supply Chain: Decisions and Cases)

2.3. Inventory Review

By doing regular inventory review, organizations understand what raw materials to order and when to order them. It ensures that the organization holds the correct quantity of inventory, in the right place, at the right time. We look at two commonly adopted types of inventory review methods: continuous review and periodic review.

In a continuous review system, the inventory on hand is continuously reviewed, and replenishments are made whenever the inventory falls below a certain reorder point. Krzyzaniak (2015) specifies the calculation of the reorder point and safety stock using the base controlling parameters of service level, demand distribution and lead time. For continuous review, if the inventory position (IP) falls on, or below, the review period R, a replenishment order Q is placed to the supplier, and a fixed ordering cost is charged.

In a periodic review system, inventory is reviewed at regular intervals, and based on the level of the available inventory at the time, varying quantities are ordered. It is assumed that the IP is reviewed frequently enough so that a review period is shorter than the replenishment lead time (Wang & Xiao Xia, 2015). In a periodic review policy (T, R), T represents the review period that elapses between reviews, and R is the order-up-to level or base stock; i.e., the amount to which the stock should be raised by a replenishment order. This policy works well for a product with lumpy demand and can ensure high service levels.

Singha, Buddhakulsomsiri, & Parthanadee (2017) propose a method to find the optimal R & Q levels for both periodic and continuous review that minimizes the average total cost where R is the review period and Q is the order quantity. It considers shortage cost on a per-unit basis; however, we will ignore that in our initial model, as there is no record of loss of sales since everything that is produced is sent to the retail channels. In their research, the authors also include three types of storage space capacity constraints: 1) over-ordering is not allowed because of the limited capacity; 2) over-ordered items can be returned to the supplier because of the limited capacity; and 3) over-ordered items can be stored in additional rented space with an extra rental expense. For our model, we do not consider any space or capacity constraints and assume we have unlimited capacity.

2.4. Optimal Order Quantity

In a DRP system, once the demand forecast is obtained, the next step in the process is to determine the lot size. Equation 1 gives the formula for determining the economic order quantity (EOQ) considering the demand, order cost and storage cost (Rizkya et al., 2018). Using the below equation, optimal order quantity can be calculated:

$$Q = \sqrt{\frac{2*D*C}{h}} \qquad \text{(Eq. 1)}$$

where Q is the optimal order quantity, D is the mean demand of the material, C is the ordering cost and h is the holding cost for a period.

The EOQ formula in Equation 1 is based on the following assumptions: 1) demand is constant, known and deterministic; 2) lead time is constant and known; 3) stock-outs do not occur because demand and lead time are exactly known; 4) items are ordered in lots; and 5) item cost is constant and no discounts are given for larger purchases.

Firoozi, Tang, Ariafar, & Ariffin (2013) extend the traditional EOQ model by considering quantity discounts offered by suppliers. The typical pricing schedule offered is as represented by Equation 2.

$$P = \begin{cases} P_1 \; for \; Q_1 \le Q < Q_2 \\ P_2 \; for \; Q_2 \le Q < Q_3 \\ \vdots \\ P_n \; for \; Q_n \le Q < Q_{n+1} \end{cases} \qquad \text{(Eq. 2)}$$

In their research, the authors solved the problem using a two-stage heuristic algorithm where they used a binary variable that is equal to 1 if the order quantity falls within the "k" interval, or equals 0 otherwise.

In conducting this literature review, we thoroughly understood the various systems where inventory control plays a critical role. For our project, the basis of the model will be a DRP system that the company uses to define a schedule of raw material ordering quantity and frequency. Researching inventory review policies helped us understand what works best for this product. Optimal order quantity, by incorporating the quantity discounts, is an important step in establishing the best parameters for our model. Finally, with the understanding of all the inventory management costs, we can tie all aspects of our model together and simulate for different iterations to reduce the total cost.

2.5. Demand Seasonality

Demand seasonality refers to seasonal demand peaks during a year. Promotions, holidays or temperatures are considered as triggers of demand peaks (Cartier & Liarte, 2012). When analyzing demand seasonality, Zhong (2009) used the Analysis of Variance (ANOVA) test to characterize the known demand seasonality for manufacturing plan within a year. The ANOVA test calculates the mean of existing subgroups and compares the variances between, and within, subgroups (Angelovska, n.d.). However, ANOVA test is not applicable for this project because 1) peak and non-peak months appear in different months each year, which makes it difficult to group months into sub-groups; and 2) the two-year historical demand provided by the company for the three types of products is insufficient to identify seasonal patterns.

3. Methodology

In this chapter, we describe the development of the proposed solution. We begin by understanding the supply chain structure of the product. Then, we analyzed the historical material usage to identify any seasonal patterns and trends in raw material usage. After the data analysis stage, we implemented the logic behind the current DRP system that the company is using as the base inventory policy to optimize. Under this policy, we apply switching rules to determine order quantity and order frequency for each segment, at different time periods in a year.

3.1. Product Supply Chain

As a first step, we started by understanding the end-to-end supply chain of the product and key determining factors that would help us make a better analysis in order to recommend the best inventory policy.

The raw materials comprise all the components and the packaging material and are single-sourced. Raw material suppliers offer quantity discounts for incremental quantities of raw materials ordered. The contracts with the suppliers are usually negotiated for 2 years' time period. Once the raw materials are procured, the product is manufactured and then shipped to several distributors, in and around the region. From there, it is distributed across countries and continents to various retail channels via ocean and air shipping.

Mapping out this flow, as shown in Figure 3, has helped us understand the complexity involved in the product – uncertainty in demand, volatility in demand and promotional pressure from retail.

Because the retail stores are the customer, the sponsoring company does not have the end customer's demand at the point of sale, and instead, we are considering the production demand to be the end customer demand.

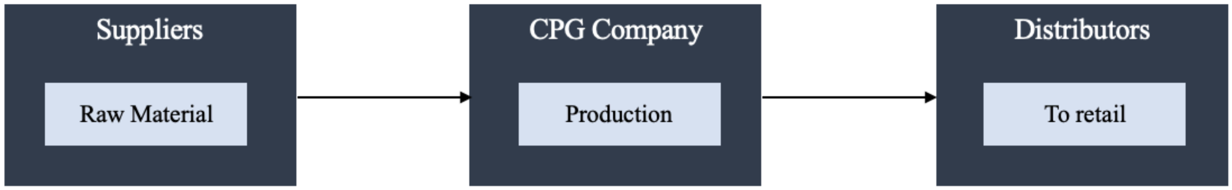

Figure 3. Product's supply chain

3.2. Data Analysis

We are implementing the mathematical model for three stock keeping units (SKU) of the product segment, with differing levels of demand: Low, Medium and High, which become three different use cases in the model. The model can then be generalized and applied to other SKUs or product segments by changing the input variables.

For the three SKUs, we received data on the past two years' actual usage of raw materials in production, and the demand forecast for the next 18 months, totaling 45 months of usage data (actuals + forecast).

The following input data sets are being used in the model:

Waterfall forecast for the upcoming 18 months: This is a weekly rolling forecast for the material usage demand per week that is continuously revised. With every new revision, the forecast for the upcoming weeks is updated. A sample of this data is illustrated in Figure 4. We can observe that in the short term, there are more changes in the forecast with the newer planning versions, whereas, in the long term, it seems to remain unchanged. Since it is a rolling forecast, we considered the most recent forecast standard, from the date of model simulation.

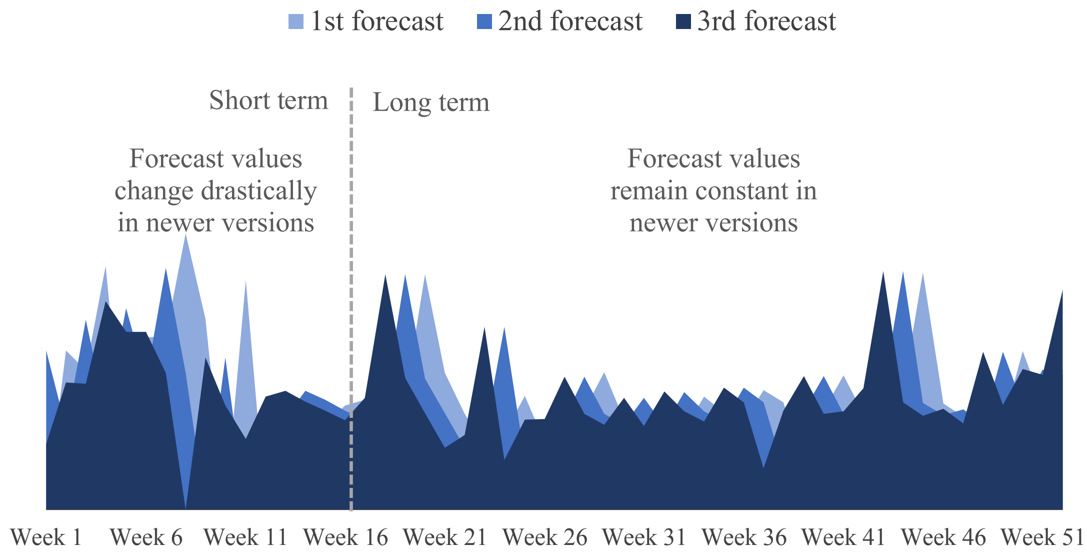

Figure 4. Waterfall forecast sample

Historical inventory trend (HIT) data: This is a data table of different inventory levels of the product, such as – available inventory, production usage, safety stock, and the dollar values for each of the SKUs. Figure 5 illustrates the actual production usage vs safety stock for the high demand product.

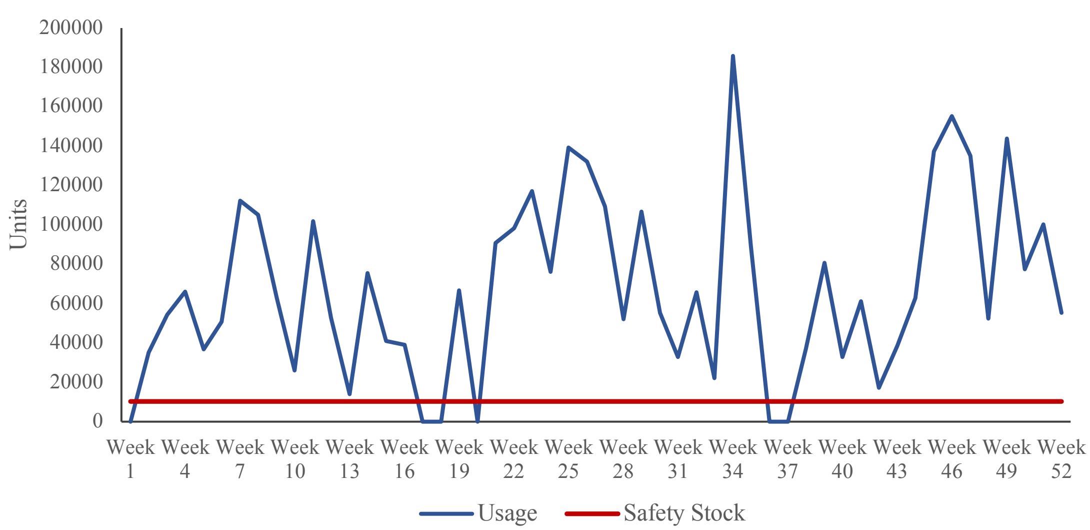

Figure 5. Historical inventory trend for the high demand product

MOQ price slab: This is the unit price ($) offered by the suppliers for the incremental quantities, as shown in Figure 6.

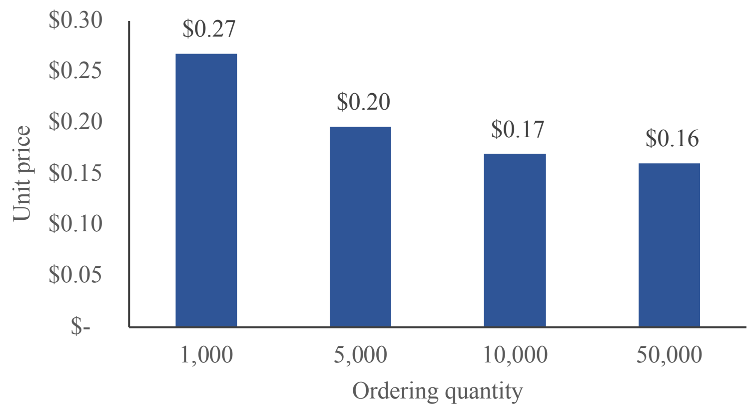

Figure 6. Quantity discounts offered by suppliers

3.2.1. Identifying Seasonality

Since the product in question faces a lot of volatility in demand, we wanted to understand if there was any inherent seasonality present, which would help us to better formulate our switching rule. By directly looking at the past 12 months' demand forecast and the upcoming 12 months' demand forecast, we could not see any inherent seasonality. Figures 7 and 8 plot the demand forecast year-over-year for the high demand and low demand forecasts. This helped us identify whether there were any repetitive peaks or valleys that would indicate seasonality from one year to the next.

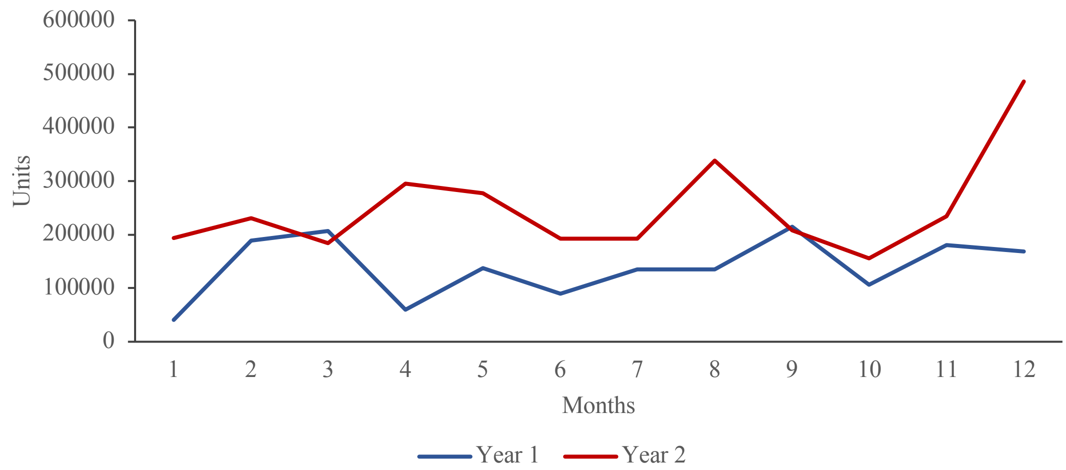

Figure 7. High demand product year-over-year

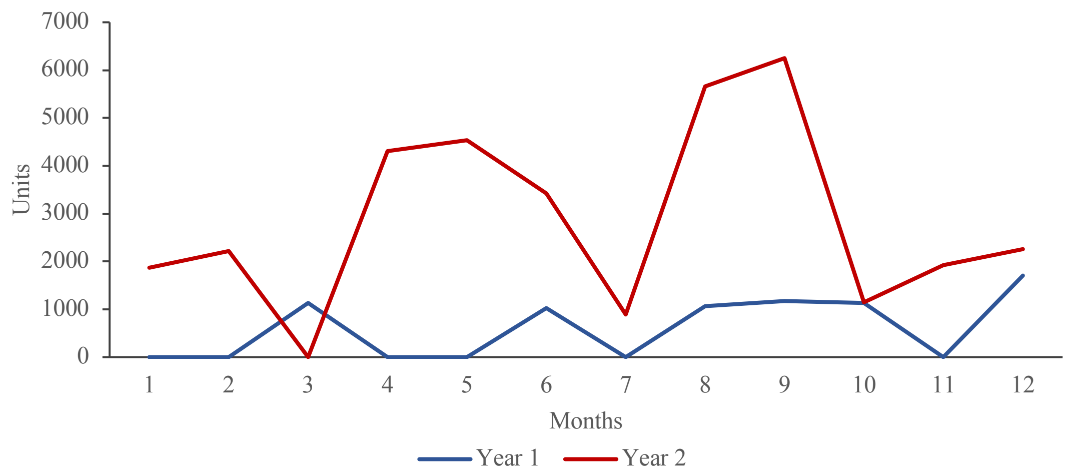

Figure 8. Low demand product year-over-year

To further verify the demand pattern within a two-year period, we first assumed that there is seasonality for monthly actual usage demand. We took the average of monthly demand for two full calendar years and calculated each month's demand as a fraction of the total annual demand, which gives us the seasonality factor. To de-seasonalize the data, we divided the monthly demand by its seasonal factor. We compared the de-seasonalized monthly demand year-over-year to check whether the annual de-seasonalized monthly demands have the same pattern which is illustrated in Section 4.1.

3.2.2. Demand Distribution

Since we are optimizing the inventory ordering for raw materials, the demand for these materials is dependent on the final product that is produced. The requirement for these products is dependent on the requirements of the higher-level product.

In the demand distribution, if most of the observations are relatively close to the mean without much variation, then it is a good fit for a normal distribution. Otherwise, if the variation is very high with a large standard deviation, there is a chance that the demand can become negative, but we know that that is not possible in the case of real demand. If the variation is equal to the mean and the mean demand is fairly low, then it is a good fit for a Poisson distribution. Figures 9, 10 and 11 show the histogram charts for the high, medium and low demand products, respectively. We can see that the observations spread far across from the mean in each of the cases.

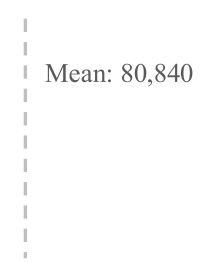

Figure 9. Demand distribution of the high demand product

Figure 10. Demand distribution of the medium demand product

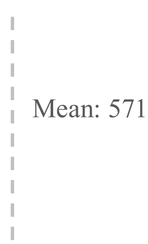

Figure 11. Demand distribution of the low demand product

Based on the presented data, we observed that the demand distribution is neither normally nor Poisson distributed but follows a random distribution.

In order to better understand the basic features and apply further calculations to historical forecast data, we conducted a descriptive statistical analysis on the 18-month weekly waterfall forecast data of the three products, which is discussed and illustrated in detail in Section 4.1.

3.3. Model Development

We initiated the model with the input data: 1) weekly demand forecast for 10 months obtained from the waterfall forecast; 2) current inventory level for each week from the HIT data; 3) safety stock target details for each SKU from the HIT data; 4) historical inventory usage obtained from the HIT data; 5) lead time for replenishment, which is a standard assumption throughout the model; and 6) target service level that was agreed upon by the executives at the company.

3.3.1. Lot Size

Typically, the lot size is determined by using the EOQ formula mentioned in Equation 1 in the Literature Review. The standard EOQ model is not applicable to our project because the real demand and product does not satisfy all the assumptions made in determining the EOQ mentioned in Section 2.4: 1) demand is not constant and deterministic and there is a lot of volatility in demand; 2) lead time is constant and known; 3) since demand is uncertain, stock-outs can occur, but we want to avoid it; 4) items are ordered in lots; and 5) unit item cost is not constant and incremental discounts are offered. Instead, we will order in incremental multiples of the MOQ. The best MOQ value will be determined as a result of the simulation by doing a sensitivity analysis, which will give us the minimum total cost and no stock-outs. In addition, the purpose of this project is to create a generalized model that can be applied to all SKUs, without any correlation among the SKUs.

3.3.2. Safety Stock

The next step is the determination of the safety stock. The HIT data gives us the current safety stock values that the company uses. In analyzing the demand pattern, we noticed that there is a lot of variation in the forecast. Table 1 shows the mean, standard deviation of demand forecast, and current safety stock that the company uses, for the 3 SKUs for a period of 52 weeks.

Table 1. Mean, standard deviation and current safety stock for 3 SKUs

SKU Type	Mean	Standard Deviation	Current Safety Stock
High Demand	63,346	44,771	10,275
Medium Demand	15,277	13,158	6,269
Low Demand	549	916	254

With such a large deviation from the mean, we observed that the safety stock used by the company was very low, therefore, we formulated a new safety stock value.

We adopted three approaches to calculating the safety stock:

Approach 1: Assume a normal distribution of the demand

We begin the safety stock calculation by assuming that the demand is normally distributed, and calculate the value using the formula below:

$$Safety\ Stock = k \times \sigma_{DL} \quad \text{(Eq. 3)}$$

where k is z-score, or the standard score, for the probability of the service level, which is 99.3% here; σ_{DL} is the value for the standard deviation of the demand over the period of the lead time.

Approach 2: Assume a Poisson distribution of the demand

By making an assumption that the demand is Poisson distributed, we can use the below formula to calculate the safety stock:

$$Safety\ Stock = k \times \sqrt{Mean}_{DL} \quad \text{(Eq. 4)}$$

This formula is similar to Equation 2, where k is the z-score, or the standard score, for the probability of the service level, which is 99.3% here; the standard deviation for a Poisson distribution is a square-root of the mean of the distribution.

Approach 3: Simulate safety stock value

Since the standard deviation of the demand is high, the normal distribution is not a good fit here, as there can be a high probability of having negative demand with such large variability. We know that the real demand is never negative and the standard deviation is very large. Similarly, in a Poisson distribution, the variance is equal to the mean, but from Table 1 above we can observe that is not the case. Thus, as an alternative, we simulated the demand for different values of safety stock to reach the optimal value.

3.3.3. DRP System

The next step is processing the data with the Distribution Requirement Planning (DRP) system. For the first iteration of the model, we used 10 months of data for the high demand SKU and then replicated it for the medium demand and low demand SKUs. Finally, with the inputs mentioned above, we designed the production plan, and then calculated the total ordering cost and holding cost. We made the following assumptions for all other costs involved in a DRP system:

1. Transportation cost is included in the per-unit ordering cost quote provided by the supplier
2. Stock-out cost is out of scope, as there is no way of calculating the cost of a lost sale.

In addition, we do not consider the capacity to be a constraint at the production facility and assume unlimited shelf life of the materials.

The raw materials have a lead time of 4 weeks; e.g., an order is placed at 12:01 a.m. on a Monday, and is received from the suppliers four weeks later at 11:59 p.m. on Sunday.

With the aforementioned constraints, we developed the model using the DRP logic with the following equations (see Table 2 for descriptions of the notation):

$$OR_t = OP_{t-4} \quad \text{(Eq. 5)}$$

$$IOH_t = IOH_{t-1} + OR_t - Usage_{t-1} \quad \text{(Eq. 6)}$$

$$PL_t = OP_{t-1} + OP_{t-2} + OP_{t-3} \quad \text{(Eq. 7)}$$

$$IP_t = IOH_t + PL_t \quad \text{(Eq. 8)}$$

$$If\ IP_t - (F_t + F_{t+1} + F_{t+2} + F_{t+3}) < SS \quad \text{(Eq. 9)}$$

$$Then, OP_t = Max\left(\left\lceil \frac{(F_t + F_{t+1} + F_{t+2} + F_{t+3}) - IP_t + SS}{MOQ} \right\rceil \times MOQ, 0\right) \quad \text{(Eq. 10)}$$

Table 2. Notation and Description for Equations 5 through 10

Notation	Description
OR	Order Received: Once the order is placed, it is received 4 weeks later
OP	Order Placed during the current week
IOH	Inventory on Hand: This is the physical inventory in the warehouse
PL	Pipeline Order: This is cumulative of all the orders placed in the past 4 weeks, but not yet received
IP	Inventory Position: Total inventory, which includes both physical inventory on hand and the pipeline order
SS	Safety Stock: Value calculated in the previous section
F	Demand forecast for the week

At every point in time, we calculate the current inventory position. Since the lead time is 4 weeks, we need to have sufficient inventory that covers 4 weeks of demand, to avoid stock-outs. If the current inventory position does not cover 4 weeks of demand and the safety stock, we place an order for the gross requirement as a multiple of the MOQ. As per Equation 5, the order is received 4 weeks after the order is placed. The current inventory on hand (IOH), or the available physical inventory shown by Equation 6, is the previous week's IOH summed up with any order received that current week, less the units used in production the previous week. The pipeline order (Equation 7) comprises any order that has been placed but for which the inventory has not yet been received, due to the lead time, and the physical inventory or the inventory position (IP) is a sum of the IOH and pipeline order as represented by Equation 8. Once these attributes are calculated, the ordering policy states that if the inventory position in 4 weeks with the current inventory level is smaller than the safety stock, then we place an order for the gross requirement, which also covers the safety stock, as a multiple of the MOQ. This is illustrated by Equations 9 and 10 and is the base ordering policy that is being followed in our model.

3.4. Model Simulation

Once the model was initialized with the above inputs and equations, we simulated the model for different values of MOQ and safety stock values. The optimal values are the ones that give us the lowest cost and achieve the target service level.

While running the simulation we considered two types of inventory costs:

Ordering cost: This is the cost associated with placing an order. This is determined by the unit cost for the MOQ of the raw material quoted by the supplier. We are assuming that any additional costs such as setup cost, transportation cost, etc., are already included in the quote.

Holding cost: This is the cost associated with storing the excess or unused inventory and the warehouse.

To determine the total cost, we first calculated a weighted average cost (WAC) per unit for the order, as shown in Equation 11. The ordering cost is obtained by multiplying the WAC by the total consumption in that simulation. Since we are simulating for different MOQ values, we needed to remove the bias in the model caused by differing ordering patterns, because each simulation can end with a different total inventory. Hence, to maintain consistency across different simulations so that we can compare the runs, we used total consumption instead of the order quantities placed, as shown in Equation 12. To determine the holding cost, we calculated a weekly average total inventory that considers both the physical inventory on hand and the pipeline inventory, and multiplied that with the WAC, as represented by Equation 13. This inventory available at the end of the week, is a function of the order placed, less the actual usage in that week. This cost is what is tied up weekly in the inventory, which cannot be used on other opportunities. The total cost is a sum of the ordering cost and holding cost.

$$WAC = \frac{unit\ price\ (\$) \times order\ placed\ per\ week}{Total\ orders\ placed} \quad \text{(Eq. 11)}$$

$$Ordering\ cost = WAC \times Total\ usage \quad \text{(Eq. 12)}$$

$$Holding\ cost = WAC \times Average\ inventory \times Holding\ charge\ (\%) \quad \text{(Eq. 13)}$$

$$Total\ cost = Ordering\ cost + Holding\ cost \quad \text{(Eq. 14)}$$

We calculated the obtained service level based on stock-out events. If the available inventory at the end of the week is below zero, it is considered a stock-out. For example, our model is simulated for 44 weeks of data. If there is a stock-out event in any one of the weeks, the achieved service level is 43/44 = 97.73%. Thus, if we want to achieve the target service level of 99.3% set by the company, we should not have any stock-outs in the period of 44 weeks in our model. Finally, we iterated the DRP model for different values of MOQ and safety stock to reach the optimal values.

While simulating, the first step was to find the optimal safety stock value. To find this, we began by using the safety stock calculated in Equation 3 and then lowered the value by 25% each time, to reach the optimal value that minimizes total cost while hitting the service level target. Once the safety stock was set, we again iterated the model with different MOQ values to reach the optimal value that minimizes cost and obtains the target service level of 99.3%.

3.5. Switching Rule

The objective of the switching rule is to switch to different values of the MOQ depending on the value of the demand. The general policy is that, if the demand forecast is very high, we want to order a higher MOQ, whereas if the demand forecast is very low, then we would switch to a lower MOQ. Since the demand for the product is highly volatile, having one large MOQ throughout can lead to overstocking and holding too much inventory at certain times of the year. With this switching rule, we can reduce the average inventory held at the production facility and reduce the overall cost.

We began by experimenting with different switching rules to obtain the optimal one. In the different experiments we conducted, the switching rule determines when to switch to a lower or higher MOQ, and also the optimal values of the MOQs that achieve the target service level and are the lowest cost.

Switching Rule 1: Current demand forecast vs. average forecast

Here we compare the forecast for the current week with the average of the rolling forecast from the waterfall data for the entire year, revised in that week. If the week's forecast is less than the average, the model will use the smaller MOQ, and if it is greater than the average, it will switch to the higher MOQ. The optimal MOQs obtained with this rule are 80,000 and 155,000. Table 3 illustrates how this switching rule is applied for a sample of five forecast values, and Figure 12 shows the ordering policy and available inventory using this switching rule.

Table 3. Switching Rule 1 for the high demand product

Forecast	Average	MOQ
59,669	80,909	80,000
57,205	82,309	80,000
101,744	83,049	155,000
112,617	81,960	155,000
67,813	73,676	80,000

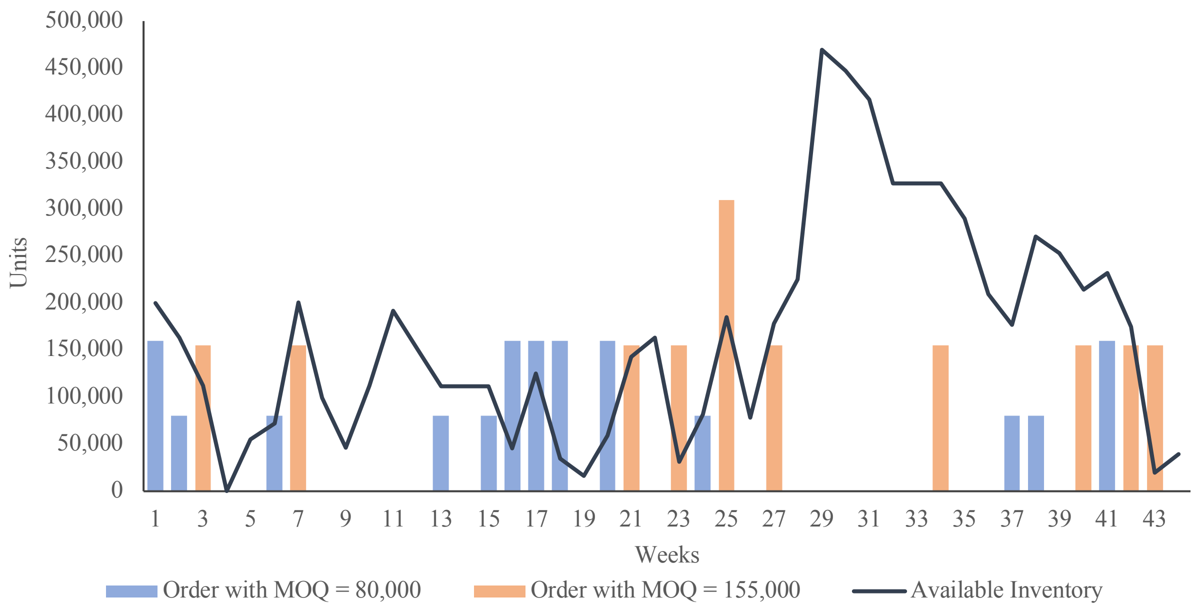

Figure 12. Switching Rule 1 for the high demand product

Switching Rule 2: Demand forecast for the 4th week vs. average forecast

Here we consider the forecast for the upcoming 4th week with the average of the rolling forecast from the waterfall data for the entire year, revised in that current week. Since the lead time is 4 weeks, we want to look at what is the demand forecast in 4 weeks.

If that week's forecast is less than the average, the model will use the smaller MOQ, and if it is greater than the average, it will switch to the higher MOQ. The optimal MOQs obtained with this rule are 100,000 and 190,000. Table 4 illustrates how this switching rule is applied for a sample of five forecast values, and Figure 13 shows the ordering policy and available inventory using this switching rule.

Table 4. Switching Rule 2 for the high demand product

Forecast 4 Wks ahead	Average	MOQ
126,502	80,909	190,000
42,527	82,309	100,000
125,498	83,049	190,000
74,060	81,960	100,000
55,068	73,676	100,000

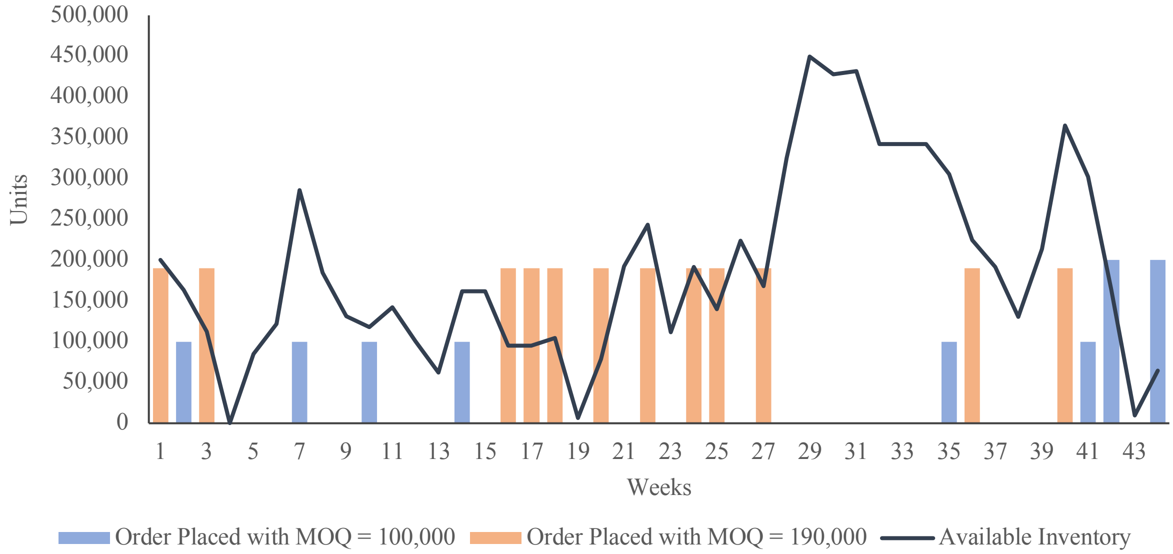

Figure 13. Switching Rule 2 for the high demand product

Switching Rule 3: Current demand forecast vs. actual usage for the previous year

Here, we compare the forecast for the current week with the average of the actual production usage for the SKU in the previous year. Since we don't have the data on the actual usage for the coming year, we use the previous year's usage, based on the assumption that the overall usage trend remains the same year over year.

If the week's forecast is less than the average, the model will use the smaller MOQ, and if it is greater than the average, it will switch to the higher MOQ. The optimal MOQs obtained with this rule are 50,000 and 90,000. Table 5 illustrates how this switching rule is applied for a sample of five forecast values, and Figure 14 shows the ordering policy and available inventory using this switching rule.

Table 5. Switching Rule 3 for the high demand product

Forecast	Average	MOQ
59,669	66,038	50,000
57,205	66,038	50,000
101,744	66,038	90,000
112,617	66,038	90,000
67,813	66,038	90,000

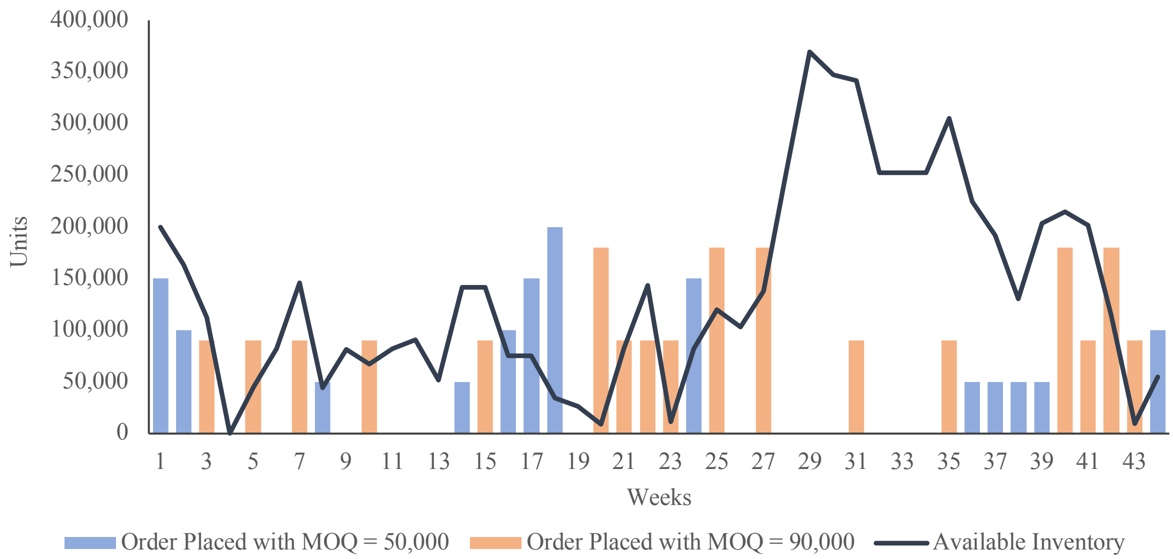

Figure 14. Switching Rule 3 for the high demand product

Switching Rule 4: Demand forecast for the 4th week vs. actual usage for the previous year

Here, we compare the forecast for the upcoming 4th week with the average of the actual production usage for the SKU in the previous year. Since we don't have the data on the actual usage for the coming year, we use the previous year's usage, based on the assumption that the overall usage trend remains the same year over year.

If that week's forecast is less than the average, the model will use the smaller MOQ, and if it is greater than the average, it will switch to the higher MOQ. The optimal MOQs obtained with this rule are 90,000 and 150,000. Table 6 illustrates how this switching rule is applied for a sample of five forecast values, and Figure 15 shows the ordering policy and available inventory using this switching rule.

Table 6. Switching Rule 4 for the high demand product

Forecast	Average	MOQ
126,502	66,038	150,000
42,527	66,038	90,000
125,498	66,038	150,000
74,060	66,038	150,000
55,068	66,038	90,000

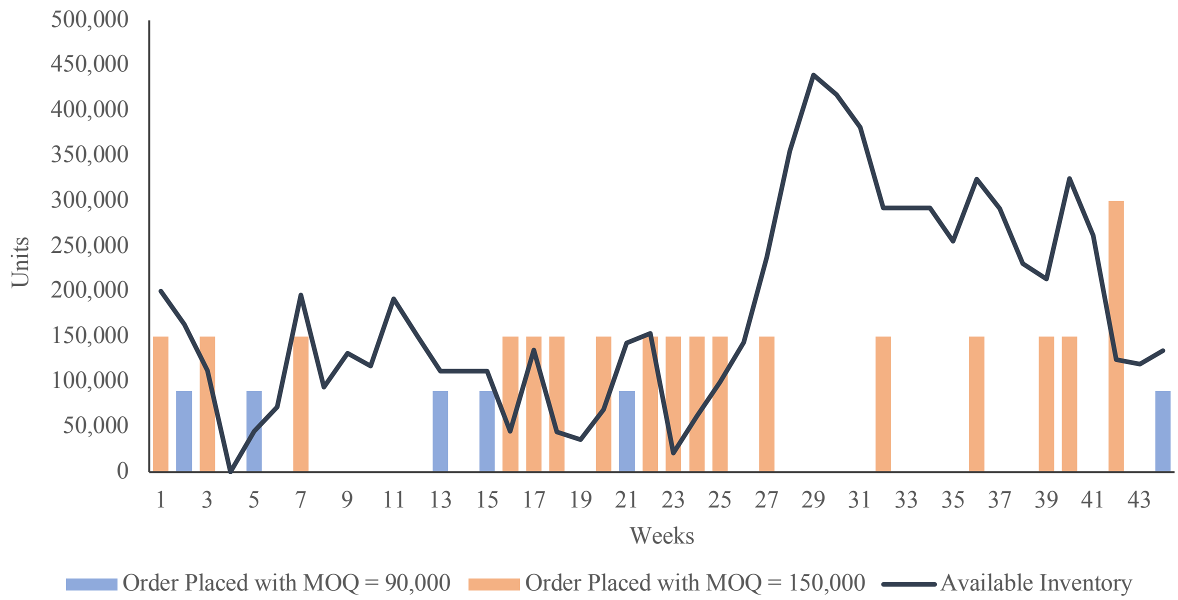

Figure 15. Switching Rule 4 for the high demand product

Switching Rule 5: Average demand forecast for the next 4 weeks vs. average forecast

Here, we compare the forecast for Week 5 to Week 8 with the average of the rolling forecast from the waterfall data for the entire year, revised in that current week. Since the lead time is 4 weeks, we are looking at the demand requirement for weeks beyond the lead time.

If the 4 weeks' average forecast is less than the average of the entire year, the model will use the smaller MOQ, and if it is greater than the average, it will switch to the higher MOQ. The optimal MOQs obtained are 55,000 and 80,000. Table 7 illustrates how this switching rule is applied for a sample of five forecast values, and Figure 16 shows the ordering policy and available inventory using this switching rule.

Table 7. Switching Rule 5 for the high demand product

Forecast	Average	MOQ
81,655	80,909	80,000
98,133	82,309	80,000
67,905	83,049	55,000
59,198	81,960	55,000
51,574	73,676	55,000

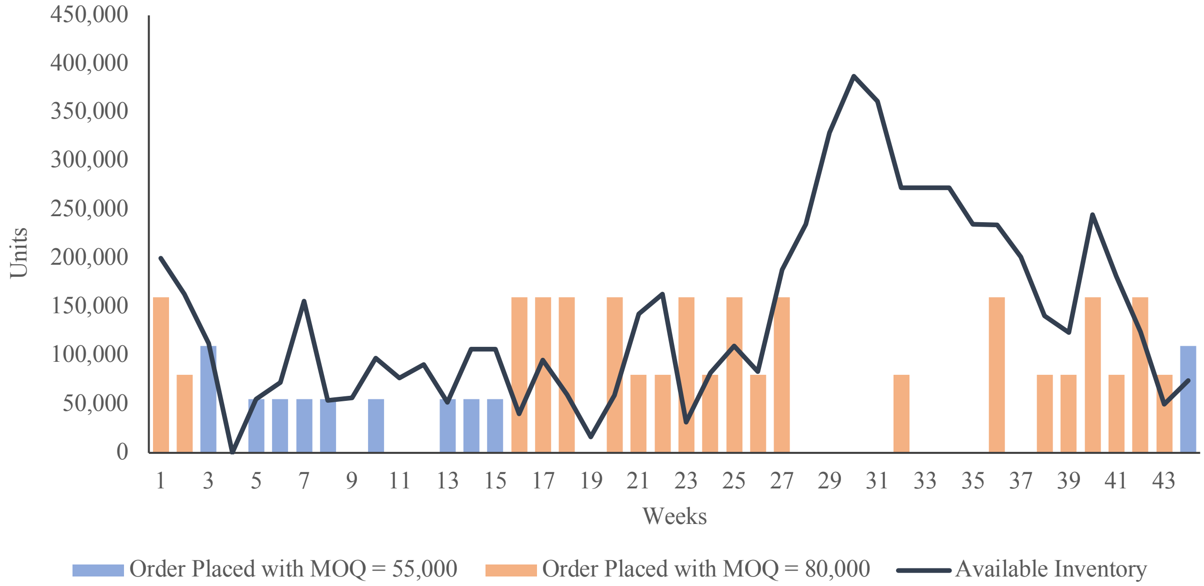

Figure 16. Switching Rule 5 for the high demand product

4. Results and Discussion

In this section, we present the results from the data analysis and quantitative analysis of the model developed in section 3. We compare the switching rules tested in Section 3.5 for all three SKUs. Then, we will present the results and our recommendation for the optimal production planning policy that the company should adopt.

4.1. Demand Seasonality

After conducting the seasonality analysis for the high, medium and low demand SKUs, we did not find any similarities in the annual demand patterns. Figure 17 illustrates the de-seasonalized demand for the high demand product for two years and Figure 18 shows the seasonality factors for the same product over the two years – Factor 1 for 2017 and Factor 2 for 2018. We can see that the demand trend is different, with the peaks occurring in different months and large variations in the seasonality factor. We concluded that there is no seasonality in demand for these two product categories and that the order spikes could be due to any promotional events at the discretion of the retailer, or any other factor out of the scope of this project.

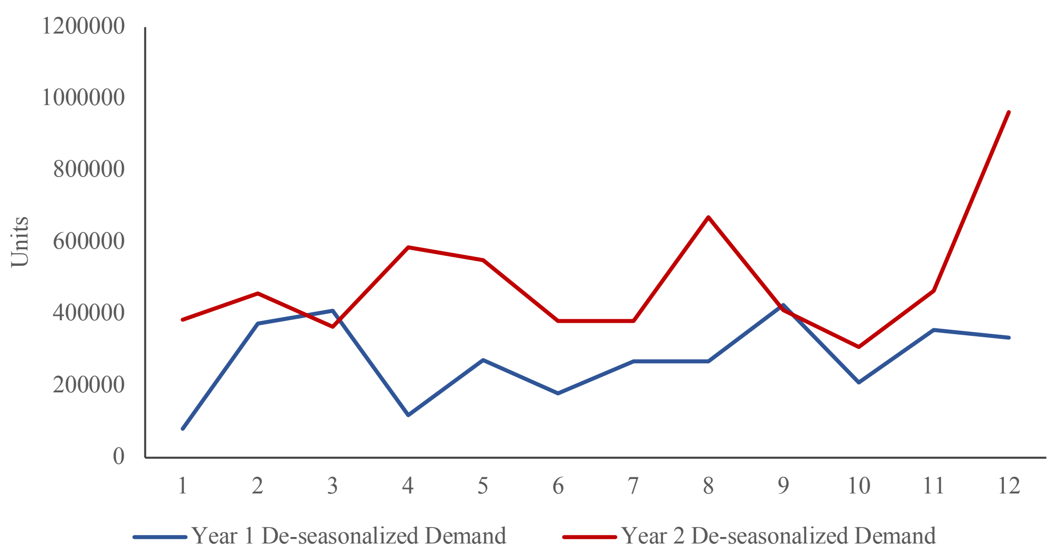

Figure 17. Demand for the high demand SKU

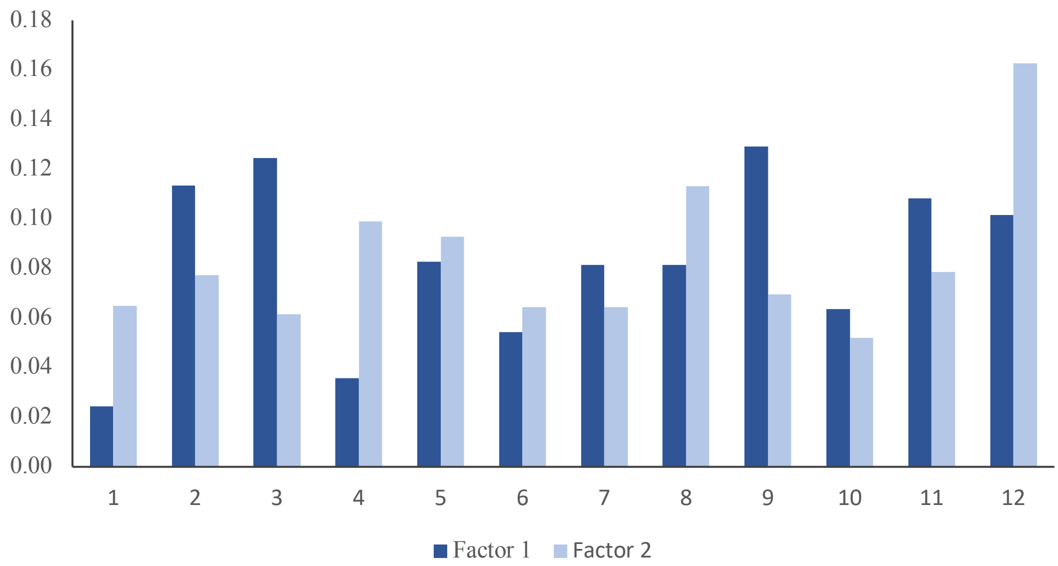

Figure 18. Seasonality factors YoY for the high demand product

4.2. Demand Distribution

Table 8 illustrates the results from the descriptive statistical analysis done on the demand forecast for the three product SKUs to identify the distribution. Chemingui & Lallouna, (2013) mention that normally distributed data should have a skewness less than 3 and kurtosis within -2 and 2. The forecast data sets for all three products don't meet the criteria. Moreover, Poisson distribution requires that the expectation of the data (mean of the data) be equal to its variance (Frank, 1967), which all three datasets don't meet. So, we concluded that the data is neither normally distributed nor Poisson distributed and follows a random distribution.

Table 8. Descriptive statistical analysis

Demand-level	Kurtosis	Skewness	Expectation	Variance
High	8.59	2.09	63962	2142651454
Medium	9.19	1.93	13085	122147163
Low	16.41	3.15	643	1100229

4.3. Forecast Error

In analyzing the data, we noticed observed that there is a high degree of forecast error in the demand forecast. The company forecasts the demand for the upcoming 18 months and then continues to review and update it in subsequent versions, as shown in Figure 4 in Section 3.2. We believe this high rate of forecast error adds bias to our model, which cannot be avoided. Figure 19 plots the forecast vs. the actual production usage of the inventory for the high demand product. Table 9 shows the mean absolute percent error (MAPE) for each of the products.

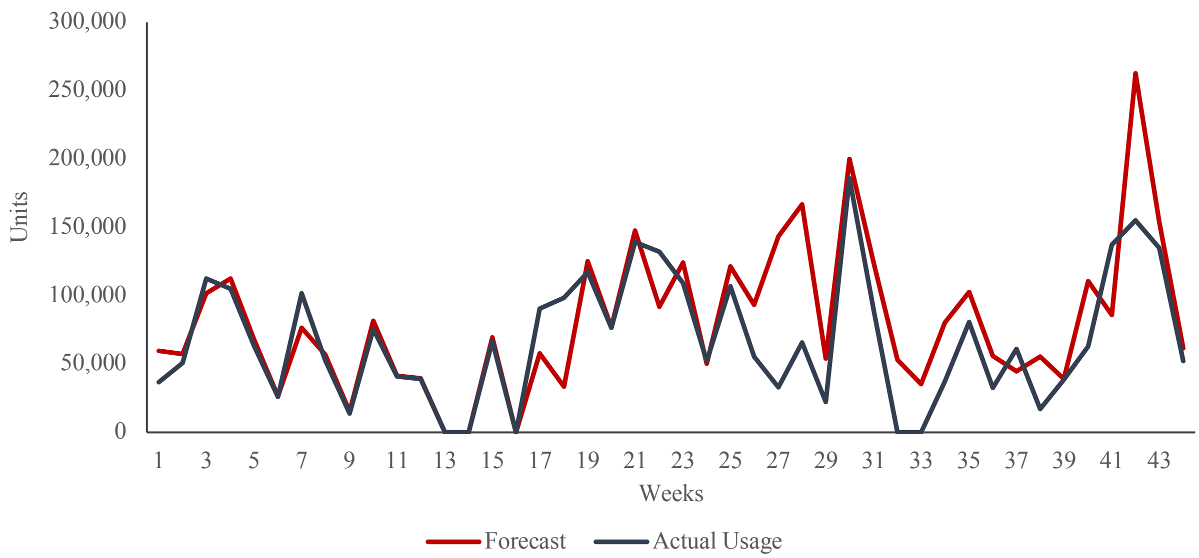

Figure 19. Forecast vs. actual usage for the high demand product

Table 9. MAPE (%) for the three products

Demand-level	MAPE (%)
High	44%
Medium	26%
Low	40%

4.4. Model development

When we calculated the safety stock using the formula in Equations 3 and 4, we observed that it was too high. Since the demand is not normally distributed or Poisson distributed, a smaller value would work well for the model. As illustrated in Figure 20, we do not need such a high safety stock, and lower costs can be achieved by using smaller levels of safety stock. A caveat is that the forecast is not 100% accurate and, in the datasets, we considered there is a high degree of forecast error. While higher safety stock can safeguard against that uncertainty, the company can also deal with this uncertainty by being more resilient.

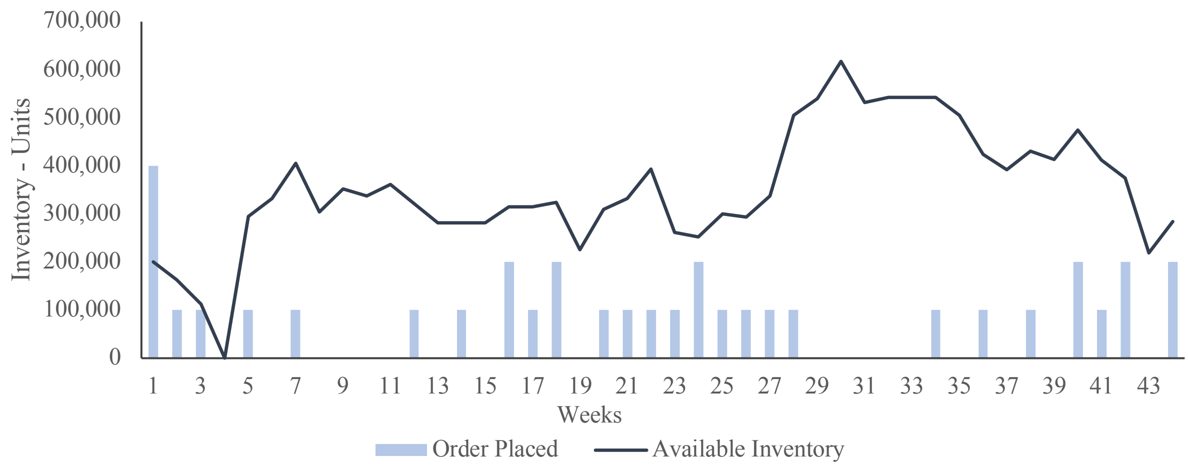

Figure 20. Inventory level for the high demand SKU with high safety stock

We iterated the model with differing values of MOQ and safety stock to obtain the values that give us the lowest cost and achieve the target service level of 99.3%. We started with a safety stock of 262,702 units for the high demand product, which is the value obtained from Equation 3, and iterated for lower values of safety stock. Once we obtained an appropriate value of safety stock, we simulated with differing values of MOQ. Table 10 illustrates the simulation results for the high demand SKU. We can observe that smaller MOQs have greater ordering cost, but lower holding cost, whereas larger MOQs have lower ordering cost due to the discount offered. A good balance between the costs and the service level is obtained when safety stock = 26,270 and MOQ = 100,000.

Table 10. Model simulation for differing values of safety stock & MOQ

Safety Stock	MOQ	Stock-Out Events	Ordering Cost	Holding Cost	Total Cost
262,702	10,000	0	$ 479,111	$ 5,916	$ 485,028
262,702	50,000	0	$ 476,942	$ 6,110	$ 483,051
131,351	50,000	0	$ 476,942	$ 4,691	$ 481,632
52,540	10,000	2	$ 479,253	$ 3,598	$ 482,851
52,540	50,000	1	$ 476,942	$ 3,757	$ 480,699
52,540	100,000	0	$ 476,942	$ 4,051	$ 480,993
26,270	10,000	4	$ 479,275	$ 3,311	$ 482,586
26,270	50,000	2	$ 476,942	$ 3,578	$ 480,520
26,270	100,000	0	$ 476,942	$ 3,821	$ 480,763
26,270	150,000	2	$ 476,942	$ 4,192	$ 481,134
26,270	200,000	0	$ 476,942	$ 4,256	$ 481,198

By repeating this process for all three products, we obtained the ordering policies with one MOQ throughout the run, which became the basis for the switching rule. The results of these simulations are represented in Table 11.

Table 11. Base ordering policies for the three products

Product	Safety Stock	MOQ 1	Stock-Out Events	Ordering Cost	Holding Cost	Total Cost
High	26,270	100000	0	$476,942	$3,821	$480,763
Medium	37,628	50,000	0	$100,818	$1,243	$102,061
Low	500	11,000	0	$5,046	$101	$5,147

4.5. Switching Rule

In simulating the five switching rules mentioned in Section 3.5, and comparing them against the base model without a switching we get the following results as shown in Tables 12, 13 and 14.

Table 12. Switching rule simulation for the high demand SKU

Switching Rule	Safety Stock	MOQ 1	MOQ 2	Stock-Out Events	Ordering Cost	Holding Cost	Total Cost
No Switching	52,540	100000	100000	0	$476,942	$4,051	$480,993
Switching Rule 1	52,540	80000	155000	0	$476,942	$4,223	$481,165
Switching Rule 2	52540	100000	190000	0	$476,942	$4,437	$481,379
Switching Rule 3	52540	50000	90000	0	$476,942	$3,862	$480,804
Switching Rule 4	52540	90000	150000	0	$476,942	$4,322	$481,264
Switching Rule 5	52540	53000	85000	0	$476,942	$3,876	$480,818

Table 13. Switching rule simulation for the medium demand SKU

Switching Rule	Safety Stock	MOQ 1	MOQ 2	Stock-Out Events	Ordering Cost	Holding Cost	Total Cost
No Switching	37,628	50,000	50,000	0	$100,818	$1,243	$102,061
Switching Rule 1	37,629	10,000	50,000	0	$102,176	$1,252	$103,427
Switching Rule 2	37,629	20,000	50,000	0	$101,327	$1,254	$102,581
Switching Rule 3	37,629	25,000	50,000	0	$102,685	$1,207	$103,892
Switching Rule 4	37,629	20,000	50,000	0	$101,327	$1,254	$102,581
Switching Rule 5	37,629	30,000	50,000	0	$101,821	$1,222	$103,043

Table 14. Switching rule simulation for the low demand SKU

Switching Rule	Safety Stock	MOQ 1	MOQ 2	Stock-Out Events	Ordering Cost	Holding Cost	Total Cost
No Switching	500	11,000	11,000	0	$5,046	$101	$5,147
Switching Rule 1	500	6,000	20,000	0	$5,230	$134	$5,363
Switching Rule 2	500	1,000	15,000	0	$5,046	$112	$5,157
Switching Rule 3	500	6,000	15,000	0	$5,178	$138	$5,316
Switching Rule 4	500	1,000	13,000	0	$5,046	$111	$5,156
Switching Rule 5	500	1,000	15,000	0	$5,046	$112	$5,157

From the costs illustrated in Tables 12, 13 and 14 we can see that the total cost for the switching rule is not significantly lower than the base model without any switching.

5. Conclusion

This research project began with the goal of optimizing the raw material ordering policy for the company by incorporating switching rules to minimize the total costs and simultaneously avoid stock-outs. When we began developing the model using MOQ and inventory levels, we believed that using a switching rule would be beneficial to the company. However, the results of our research did not support our hypothesis. Throughout our research, we gained some great insights about the data, product, and the company.

First, we concluded that there is no seasonality in the demand for the three products, and the volatility is due to promotions by the retailer or other unexpected spikes. In analyzing the forecast data, we noticed a high degree of forecast error for all three SKUs. We believe that the forecast inaccuracy added a certain amount of bias to our model as illustrated in Table 9 in Section 4.3 However, reducing this inaccuracy is out of scope for this project, but we recommend that it could be an avenue for the company to explore, in the future.

Second, we noticed that our model has a large amount of bias because every simulation ends differently with a different ending inventory level. This can potentially change the final result of the optimal MOQ and safety stock to use for the product. To compensate for this and remove the bias from the model, we use the total consumption of raw material while calculating the costs. This way, we were able to establish a standard method of comparing the different runs of the simulation based on the cost.

We expected the relationship between the holding cost, ordering cost and the total cost to follow the trend illustrated in Figure 2 in Section 2.2. While the trend remains the same, where ordering cost reduces with larger MOQ but holding cost increases, we noticed that holding cost holds much less weight in the total cost equation. Hence, in this project, the ordering cost is the determining factor. As shown in Tables 12, 13 and 14, the holding cost is between 0.8% and 2% of the total costs for the three products and does not represent much weight in determining the total cost. We noticed that, by changing the MOQ values and safety stock values, the total costs do not change drastically. The reduction in cost is typically less than 1%, as can be seen in Table 10 in Section 4.4.

Third, in analyzing the results obtained from the various model simulations and comparing the costs between the base model without MOQ switching and models with the different switching rule applied, we conclude that a switching rule is not necessarily a lower cost option. This discrepancy could be due to the various biases introduced in the model from the forecasting error, or due to the high volatility of the demand. In addition, we would also like to point out that our sample size is very small comprising only 3 SKUs, as against thousands of SKUs and products in the CPG company.

The sponsoring company can nevertheless use this model to optimize their ordering policy, with or without switching, to obtain reduced cost. Currently, the company computes varying values of MOQs and revises it every month. This proved to be a costly method of ordering the raw material, as they were not leveraging the discounts. The model generated through this project can serve as a tool that defines the MOQ to be ordered automatically.

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