Simulating Inventory versus Service Risk in Medical Devices

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Summary: Medical device companies struggle to balance inventory and service performance, as the products are non-interchangeable and inventory investment is expensive. To find the right level of inventory, we first used unsupervised clustering method to find demand pattern uncertainty for each product. Then, we developed a simulation-based approach to determine the required inventory to achieve a target service level guarantee. We produced a data-driven simulation model, and derived insights and recommendations to help the sponsor company in their inventory reduction effort.

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Before coming to MIT, Maria Rey graduated with a Bachelor's degree in Industrial Engineering from Tecnologico de Monterrey in Mexico. She had 2.5 years of manufacturing experience from her work in P&G and Kellogg's Mexico. Upon graduation, Maria will join General Mills as a Supply Chain Analytics Consultant in Minneapolis, MN.

KEY INSIGHTS

1. Medical devices companies struggle to balance inventory and service performance, as the products are non-interchangeable and inventory investment is expensive.
2. A key component of managing inventory is to align service metric measurement with the planning system that sets inventory level.
3. Strategic decision making is simplified by clustering material numbers with similar demand patterns.
4. Our simulation method demonstrates the implications of policy changes on different material numbers. This delivers valuable insights that aid in inventory reduction.

Introduction

Inventory management is a critical exercise for medical device companies. Given that most of the products can be life-saving, their availability directly affects hospitals' capability to perform surgery on patients. The non-interchangeable and market-specific products add to the inventory management complexity. This criticality causes MedCo, the sponsor company, to have higher inventory levels than necessary to respond to customer demand.

MedCo seeks an optimal inventory level that balances inventory excess and service risk. Their service level is inconsistent across different SKUs, causing them to have inventory excess in some SKUs and unsatisfactory service level in others.

They currently measure service success using LIFR (line-item fill rate). Although, their inventory planning system relies on classical inventory models that assume a normally distributed demand and uses a CSL metric. This causes a discrepancy in how service is measured and how the optimal inventory level is calculated.

Demand Characterization

To help us understand the underlying demand characteristics, MedCo provided access to inventory, demand, forecasting and supply data. MedCo also provided access to their current inventory management tool, known as the entitlement model, to compare our output to their current inventory target levels.

We used clustering to group similar material numbers and provide recommendations on their inventory strategy. Using a k-means algorithm and the software JMP 13.0 Pro, the resulting clusters are summarized in Figure 1.

The graph shows each cluster's mean, which allowed us to name each cluster by its predominant characteristics. Cluster 1 represents commodities. Cluster 2 is high volume products. Cluster 3 represents service risk, given the high COV and low DOS. Cluster 4 represents sparse demand, given the high COV, which translates into high DOS. Finally, cluster 5 represents high volume commodities.

After clustering, we used order transaction data to plot distributions of the average order quantity for the different SKUs. The data showed that most material numbers had a majority of small quantity orders and several sparse large quantity orders. We used the Excel add-in '@Risk', and determined that gamma distribution best fitted the data. This is mainly due to the flexibility of the distribution in both shape and scale.

Along with the order quantity distribution, we also studied the distribution of the order frequency for each material number. This analysis showed that it follows a normal distribution across all clusters.

The final distribution we studied was that of replenishment lead time. The distribution of supply lead time is assumed to be normally distributed. This is based on interviews with MedCo's analysts and on partially available data from the supply data source.

Having the distributions for order quantity, order frequency and replenishment lead time, we proceeded to build a simulation model. This model ties service performance on a per order basis using LIFR, instead of using a CSL metric.

Simulation Model

To create a connection between performance metric and input parameters, we created an as-is simulation program. This program took historical distribution of operational measures as discussed above. It simulated the stock allocation process, and calculated the performance measures for every instance. Finally, we tabulated the LIFR measure and found the 90^{th} percentile of LIFR as a 'performance guarantee'.

We applied the method to products with different gamma parameters, and recommended the new target level of inventory. For some material numbers, we found large discrepancies between current stock levels and proposed level from this model.

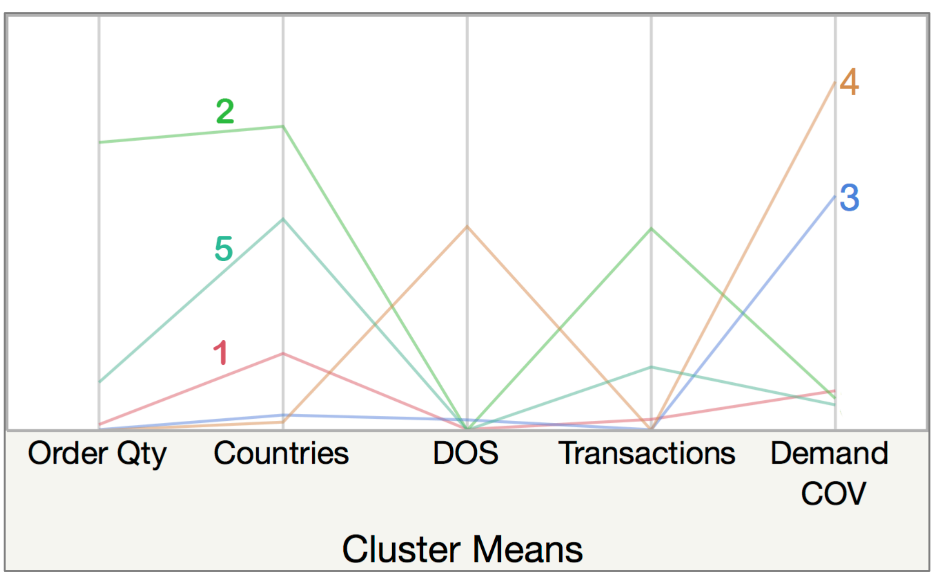

Figure 1: Cluster means comparison

As an example, by applying the simulation algorithm to an SKU, we show that MedCo needs 26,000 units of inventory to ensure that 90% of the time we reach a 98% LIFR performance. The current model recommends that MedCo maintain an IOH level of around 61,000 units. Figure 2 shows the comparison of weekly IOH level and suggested inventory levels by both the entitlement model and the simulation model.

The graph shows two lines corresponding to MedCo's entitlement model: base safety stock (base SS) and total entitlement. The former is the base inventory level calculated under the normality assumption; the latter is the base level plus and additional cushion provided by market intelligence. Our simulation output, in this sample case, is in between these two lines. This means that the inventory level should be higher than the base safety stock, but significantly lower than their total entitlement calculation.

Sensitivity and Insights

The optimal inventory level obtained with the simulation model can be higher or lower than MedCo's current output. The results and recommendations vary according to the type of material number based on the clustering we initially performed.

For fast moving materials, certain customers tend to order in large quantities from a central distribution center (DC). As a result, exceptionally large orders skew the distribution of the demand and disturb the DC's inventory level unexpectedly. Figure 3 illustrates this behavior for two different countries, using a sample material number from cluster 2.

Country A exhibits a consistent ordering pattern, having large amount of orders spread across the year. Each order is of small value. In country B, the ordering pattern is erratic. Some of the orders require tens of thousands of units. It creates a high level of uncertainty and pressure on the supplying DC.

We used the same simulation tool to identify the effects of irregular order patterns. It shows that for that part number, by cutting 50% of the demand variability from the current demand distribution, we can reduce 23% of inventory investment.

In order to achieve this goal, MedCo can identify large customers within its top selling SKU, and identify the irregular customers. If the node is an internal customer, then MedCo should build additional inventory according to their planning system.

For external customers, MedCo can negotiate with the customer to order products following an (s, S) strategy that aligns the interest of MedCo and the customer. MedCo can also engage in VMI arrangements to better forecast its inventory consumption.

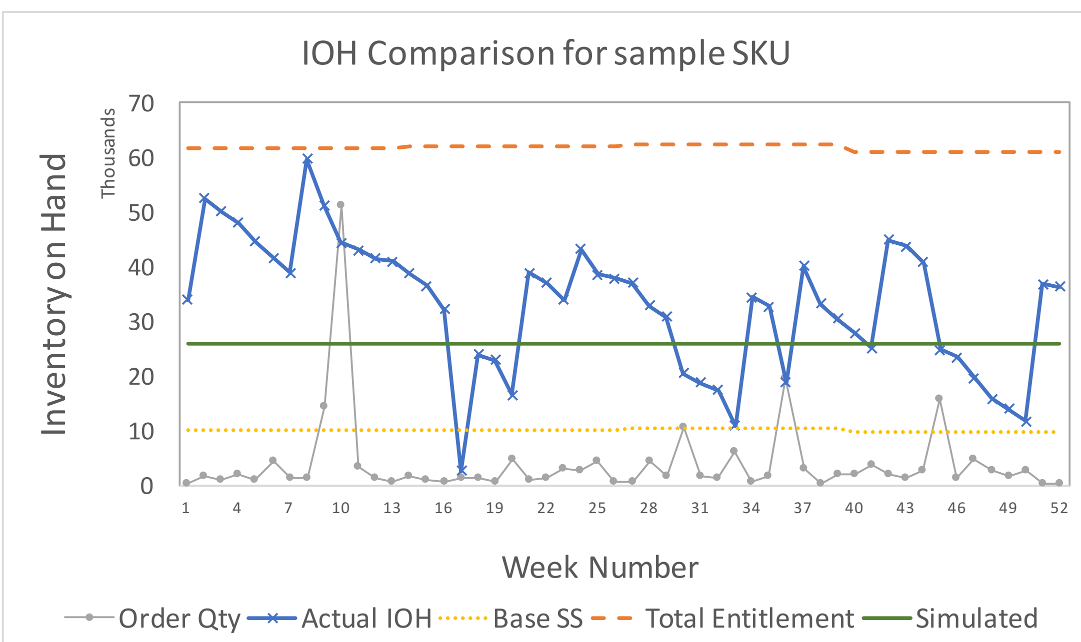

Figure 2: Inventory level comparison

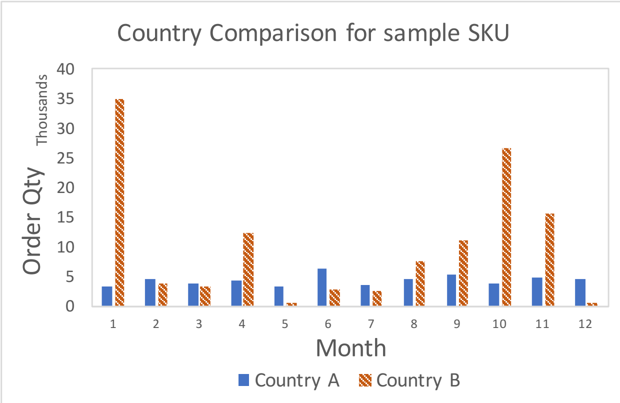

Figure 3: Demand pattern comparison by country

Another important factor to consider is replenishment lead-time. MedCo's replenishment lead-time comprises of a short transit lead time plus 'unavailable-to-schedule' lead time. The latter refers to situations where manufacturing sites cannot fulfill the request to produce the demanded parts.

In the simulation tool, we found that an unexpected increase in lead-time due to supply disruption can push LIFR to unacceptable levels. For many types of material, doubling the lead-time will triple the optimal inventory target level (hence, inventory investment). MedCo would need to ensure adequate stock globally based on past year consumption history. They can achieve this by utilizing spare capacity in the manufacturing locations and stock them globally to hedge unexpected demands.

MedCo also possesses opportunities to further optimize its supply network. The clustering techniques reveal the fact that there are sub-types of inventory that only supply a particular region or customer group. Stocking those parts in central DC in Europe is not financially and logistically optimal. We propose to have them directly shipped from manufacturing sites, instead of going through regional DC.

Finally, we found that placing advance orders is positively correlated with order fulfillment success rate. We would recommend MedCo's sales team to enter orders sooner so that any shortages will be flagged into the planning system, hence ensuring adequate supply from upstream.

Conclusion

Our simulation model helps MedCo identify a practical inventory level given service risk tolerance, without imposing idealistic assumptions on demand or supply pattern. We recommend that MedCo implements it and adapts it to other product lines that present similar issues.

Furthermore, we have used clustering techniques to find commonalities across various products. These clustered patterns drive us to think about strategic decisions in supply chain design (e.g. order size, early data entry, network design changes). By applying the insights to the right cluster of materials, we arrive at recommendations that can ultimately help MedCo both manage products profitably and service customers in need.

We believe the same methodology can be easily reapplied to other industries, especially when there is a large amount of raw data. Clustering techniques help to break down large datasets to find patterns and gain detailed insights. The simulation tool is very versatile and can accommodate various assumptions and transaction rules. It can intuitively show the impact of policy changes in realistic scenarios.