Decreasing Excess Inventory in Defense

By: Danaka M. Porter Advisor: Sergio Caballero Topic Area(s): Inventory, Demand Planning, Optimization

Summary: This research focused on decreasing excess inventory in both Aerospace and Defense companies as well as the Armed Forces. I created a single period model extension by using K-Means clustering to group inventory parts. Then using the cluster's attributes created a predictive demand function based on the phases of the equipment design and build. Further, I created a cost function that optimized the predicted demand quantity and provided a lowest cost optimal quantity. When tested on data from DefenseCo and the Armed Forces, the models resulted in a thirty percent decrease in excess inventory and a thirty-four percent decrease in cost respectively.



Before coming to MIT, Danaka Porter worked as a supply chain consultant at KPMG and her own business. Prior to that she graduated with a bachelor's degree in Interdisciplinary Studies from the University of British Columbia.

KEY INSIGHTS

- The equipment design is not always completed before some parts must be ordered due to their extensive lead-times. This results in both excess inventory and part shortages.
- The predictive demand function uses a probability function that determines the likelihood of change and the impact on demand and finds the optimal order quantity based on when the part is needed and when it can be ordered.
- Using the predicted demand, the cost function optimizes a quantity that is the lowest cost, while taking into account the different design phase changes.

Introduction

The inability to predict demand is a leading cause of excess inventory at DefenseCo. Equipment design is not completed prior to when parts must be ordered due to their long lead-times. This is further aggravated by a need for spare parts later on in the equipment's life. Yet another issue facing DefenseCo was the requirement to have all parts available on hand – equipment should not be sitting idle due to a lack of parts. In almost every industry it is acceptable to have stock-outs or planned backorders, or both. Typical service levels are agreed on and sit between eighty-five and ninetyeight percent depending on the industry. Defense requires nearly one hundred percent, and DefenseCo was meeting these requirements.

DefenseCo's previous ordering strategy had been to group parts by how they were ordered; via PO, competitive bidding, design and build etc., however, this strategy was not working, as an excess of inventory had built up and was costing money and space. Thus, DefenseCo was looking for a procurement strategy that would reduce the excess inventory and associated costs yet maintain the high availability of parts on hand.

Clustering and Models

The research focused on formulating an improved strategy for ordering by creating and implementing models that would allow for the same on-hand part availability yet decrease the excess inventory and associated costs. Equipped with the requirement of reducing inventory while maintaining availability, it was decided that both a demand model and adjoining cost model would need to be created. To generate these models, a different way of grouping parts was required. This research elected to use K-Means clustering as it can be unsupervised, and thus, unbiased. Part data for a class of equipment was reviewed, and the process began.

1. Clustering the data

First the data was first cleansed, standardized, and then placed into Tableau, where K-Means machine learning was used on the data. It plotted Cost vs Lead-Time and clustered the over 48,000 unique parts into five clusters. Each cluster was subsequently downloaded into Excel where statistical analysis was performed to review the clusters' attributes, which aided in the model creation. Clustering by cost and lead-time was an improved way of grouping the parts, as previously DefenseCo has grouped them by ordering strategy. The new clusters were aligned based on similar attributes, such as similar lead-time, rather than how they would be purchased.

2. Model Generation

Next a demand and cost function were created for each of the five clusters. This way specific attributes and requirements for that cluster were captured in each model. The demand function used the probability of a change to demand in each phase with the probability of increase or decrease in demand. For example, if the part was required in Phase 5, but had to be ordered in Phase 3, the probability of a demand change was multiplied by the probability of an increase in demand during that phase.

$$P(D_3|D_5) = (0.60 \times 0.1) + (0.55 \times 0.10) = 12.7\%$$

The cost function took into account the phase change, spares, decay and other key attributes to the cluster.

Total Cost

$$= \begin{cases} c_i D_i + \delta (D_i - S_i)^2 - (1 + \pi_p) c_i D_i + c_i \varphi; \ \pi_p > 1, \ D_i \ge S_i \\ c_i D_i + c_i h (T_{EP} - T_U) (S_i - D_i); \ T_{EP} > T_U, \ S_i > D_i \end{cases}$$

The demand function was used to calculate the quantity demanded in a certain phase; this quantity was then placed into the cost function. The cost function was optimized in Excel using Solver and an optimal quantity that had the lowest cost was found. Figure 1 shows the same cost function for the same part, using different design phases.



Figure 1. The cost function for the same part with different phases.

Solver in Excel was used as it is a common and easy extension, and it will work without an internet connection. This was important as in certain situations specifically in defense, internet access might not always be permitted. Therefore, this model had to work without internet access, and be simple enough to be used in the field or by any person who was not an analyst or specialist.

3. Sensitivity Analysis

A sensitivity analysis was completed on the models and in clusters two and three it was found that the holding cost had a large impact on the optimized supply quantity. However, there was almost no impact on cluster four or five with respect to the holding cost.

The phase change had the largest impact on cluster four and five, as the larger the phase change was the larger the difference between the new demand model's output, and the optimized supply output. DefenseCo spent over seventy-eight percent of its total spend in clusters two and three, and therefore as the holding cost has the largest impact on these clusters, DefenseCo can manage and adjust the holding cost as necessary.

Results

Each model was tested on DefenseCo's data. The results in Table 1 below highlight a sample of the findings.

Part	Original demand	New Demand	Old Demand	Optimized Supply	Actual Need
G	3,864	4,142	7,728	4,143	3,909
н	924	975	1,036	1,023	932
I	1,071	1,253	2,142	1,253	1,156
J	566	852	849	701	657

Table 1 A sample comparison of the original order amount compared to the new demand model, and the optimized supply quantity. With the new models, DefenseCo would be able to better forecast their demand quantity, which would reduce over ordering, and, in turn, reduce excess inventory. Figure 2 shows the cost savings in green when the new models are used.



Figure 2 A sample of parts comparing the previous total cost of the order in blue, with the new demand and cost model in red, and the savings (in green) from using the new models.

There were a few instances when the new model would generate an inventory that would result in a short, although this was less than two percent of the time. In over ninety percent of the instances, the new model generated an inventory quantity of less than the original ordered quantity, which resulted in the above cost savings, while maintaining the part on hand requirement.

Furthermore, a generic demand and cost functions were also generated. These were tested on Armed Forces data and provided similar results; approximately a thirty-one percent decrease in excess inventory and approximately a thirty-five percent decrease in costs.

An advantage to the model having separate demand and cost functions is that the demand function can be used alone as a forecasting tool, or with the cost function as an optimizing, low-cost strategy. Furthermore, the functions are simple, and can be used in Excel with Solver.

New Strategy and Other Applications

These models allowed for a new procurement strategy to be created, one which allowed for a single order of parts to take place. Parts would be ordered according to the cluster they fit into; cost fell between X and Y, with a lead-time between A and B. Next the part would be matched with the phase it was required in, and the lead-time would be calculated to see when it would need to be ordered. Last, the models would be used and the optimal ordering quantity would be found. This quantity would be ordered when the lead-time was met.

This sole order would contain the entire demand requirement for a specific part based on the phase it was needed in, and the phase it could be ordered in. This allowed for better timing of order placement so that parts did not sit around in the warehouse for very long. It also allowed for large order quantities which can create the potential for discounts, thus saving money.

The models created are not specific to defense, and in fact, could be used for humanitarian relief projects. Humanitarian aid faces similar issues to defense, in that inventory must be available on hand when it is needed. Demand must be predicted well in advance before the emergency has begun. Most notable is that humanitarian relief like defense, does not focus on profit, but instead on being able to react to the situation.

Conclusion

While these models did not eliminate excess inventory entirely, they reduced it substantially, while maintaining the on-hand availability requirement. In situations such as Defense or Humanitarian Relief, the conditions are too volatile and can change without notice. For this reason, a model that would completely eliminate excess would also likely have inventory shorts. Therefore, this model serves its purpose of decreasing excess, maintaining required inventory levels, and allows the company to be able to react to the situation around them.