Network Design in MRO Inventory for Oil & Gas Company

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ABSTRACT

To mitigate operational disruptions, oil and gas companies maintain high levels of Maintenance, Repair, and Operations (MRO) inventory. However, our sponsor company was found to have twice the non-moving inventory value compared to its competitors, prompting an interest to reduce inventory holding costs — the cost associated with the storage of inventory, such as cost of capital, annual warehouse fees, annual taxes, and annual warehouse costs. This study aims to reduce such costs by segmenting 19,153 MRO SKUs based on their demand characteristics and building a Mixed Linear Integer Programming (MILP) model to redesign the network of warehouses and plants. By eliminating the 1:1 relationship between warehouses and plants, the warehouses can serve more than one plant and the sponsor can avoid individual inventory management for each plant. Through our MILP model, we investigated different levels of consolidation though scenario analysis. In the most conservative scenario without inventory systems integration, the new network design resulted in a 12% reduction in warehouse and transportation costs and a 22% reduction in safety stock holding costs. While full inventory system and legal entities integration led to 27% savings in both.

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1. INTRODUCTION

1.1 MOTIVATION

The COVID-19 pandemic revealed to the world the impact supply chains have on organizations' ability to deliver the products and services that customers need. The disruptions in supply chains led many organization leaders to rethink the supply chains they have built over decades and to transform them to be more agile and resilient in preparation for disruptions to come. From the consumer goods industry to the automotive industry, companies have adhered to high levels of inventory to meet the demand of sales when under a stressed situation. This is similar to Maintenance, Repair and Operations (MRO) inventory, in which high inventory would mitigate the risk of disrupting operations due to missing machinery, equipment, and tools necessary to run a business.

This is the situation faced by many companies in the Oil & Gas industry, including our sponsor company. Oil & Gas is one of the largest industry sectors in the world and plays an influential role in the global economy as the world's primary fuel sources, generating an estimated $6 trillion in global revenue in 2021 ("Oil and Gas Global Market Report 2022, By Type, Drilling Type, Application", 2022). The sponsor company is one of the world's largest publicly traded international oil and gas companies ("Sponsor's 2021 Annual Report", 2022). The company provides products including energy, chemicals, lubricants, and lower-emissions technologies through their three primary business units: BU1 (focused on exploring for and developing oil and natural gas), BU2 (focused on engineering, manufacturing, and delivering products needed by consumers) and BU3 (focused on commercializing lower-emission business opportunities).

At the beginning of 2022, a study from a consulting firm revealed that our sponsor company carries two times more dollar value of non-moving MRO materials — inventory in warehouses with zero months usage over a period of 2 years or greater — than their competitors ("Supply Chain Transformation Assessment", 2021). Thus, the Supply Chain team is motivated to realize opportunities to reduce the MRO inventory holding costs — the cost associated with the storage of inventory, such as cost of capital, annual warehouse fees, annual taxes, and annual warehouse costs — for approximately 800,000 stock-keeping units (SKUs) (Sponsor Company, personal communication, 2022).

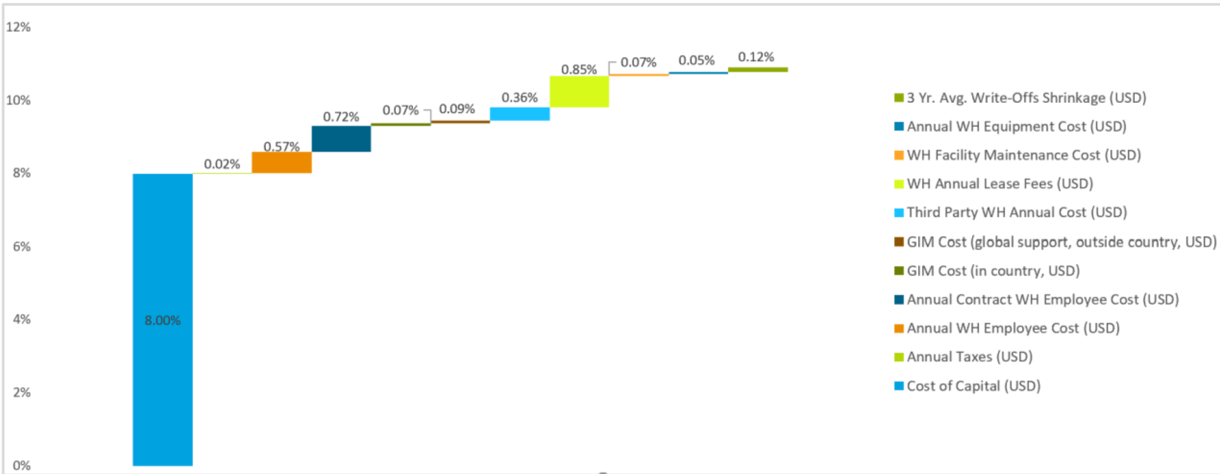
This inventory that serves all three business units — BU1, BU2, and BU3 — is held in 74 warehouses and approximately 80 refineries/plants worldwide, which typically have a 1:1 ratio (Sponsor Company, personal communication, 2022). That is, a SKU that is held in a warehouse can fulfill the requests for one and only one specific refinery/plant. Although in the past our sponsor company have implemented inventory optimization models within some sites, now they want to challenge the 1:1 network design to realize opportunities for reducing holding costs and potentially consolidating inventory through an optimized supply chain network. This presents an opportunity for our sponsor company to both bring efficiency in their inventory management and allocate capital resources to other functional areas in their company.

1.2 PROBLEM STATEMENT AND RESEARCH QUESTIONS

Our sponsor company's goal is to reduce the MRO holding cost. Today, the network for MRO inventory is designed as a 1:1 relationship between warehouses and plants. Our sponsor company wishes to have an optimized network that helps them reduce the holding cost components depicted in Figure 1, such as Cost of Capital, Warehouse (WH) Facility Maintenance Cost, Global Inventory Management (GIM) cost, etc. Through the optimized network, there is potential to consolidate and reduce the MRO inventory. However, reducing inventory could potentially negatively affect service levels — the expected probability of being able to satisfy all possible inventory requirements. Therefore, our goal of reducing inventory should not compromise the high service level targets our sponsor company has set in their systems to avoid any disruption in production and loss of profits.

Figure 1

Global Inventory Holding Cost Component Breakdown



Note. These holding costs components were calculated based on the year 2021 and communicated during the sponsor's 2021 Holding and Ordering Costs Overview Meeting in 2022. From Sponsor Company, personal communication, 2022.

In that context, the questions to be answered include:

1. Is the current network design of our sponsor company the most cost-efficient?
2. How can our sponsor company redesign their MRO inventory network to reduce their holding cost while keeping target service levels?
3. How can our sponsor optimally allocate inventory with the recommended network?

1.3 SCOPE: PROJECT GOALS AND EXPECTED OUTCOMES

The project's goal is to provide our sponsor company with a quantitative optimization model that reduces the MRO inventory holding cost, while maintaining the required target service levels. The reduction of MRO holding cost can potentially allow the company to liberate cash flows and to invest it in other business initiatives.

To assist, we hypothesize that optimizing their network of warehouses and plants would be the best course of action to assist our sponsor company's three business units. An optimized network would potentially allow the company to break the 1:1 ratio from warehouse to plant. Instead of each plant having its own inventory, we expect that through an optimized network our sponsor company would have the ability to reduce holding cost components from Figure 1, including: Cost of Capital; Annual Taxes; Annual Contract Warehouse (WH) Employee Cost; Third Party WH Annual Cost; WH Annual Lease Fees; WH Facility Maintenance Cost; and Annual WH Equipment Cost. Although the Global Inventory Management (GIM) costs and the 3 Year (Yr.) Average (Avg.) Write-off Shrinkage is not in scope of the project due to data limitations, we discuss the implications of such costs in the Discussion chapter. Lastly, the Annual WH Employee Cost is also out of scope given that the sponsor company would not reduce their workforce based on the optimized network, but rather deploy their employees in additional functional capacities.

In addition, we hypothesize that having an optimized network would potentially allow the sponsor company to consolidate inventory. Hence, through a formal method to segment MRO inventory the sponsor company would be able to define where to allocate the inventory to fulfill the internal demand, resulting in lower inventory levels.

Lastly, to ensure that the requirements of internal stakeholders are met, these hypotheses should have a regional focus (North America, Latin America, Europe, Asia) and include those SKUs that the company's Supply Chain team agrees are most important. Based on input from the sponsor, the project is focused on the 84,654 MRO SKUs stored in the state of Texas from United States within the region of North America.

In that context, the deliverables to the sponsor company include:

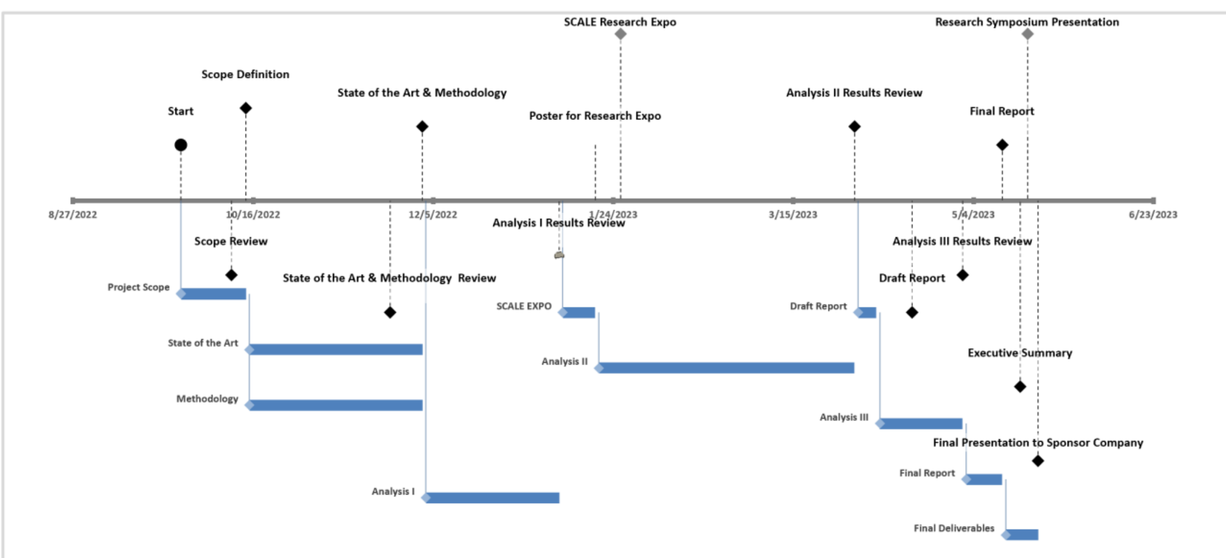
1. A network optimization model to reduce holding costs through consolidation of inventory.
2. An inventory model that segments SKUs and recommends inventory location after consolidating the sponsor's company supply chain network.

1.4 PROJECT PLAN OF WORK

To build the network optimization model and recommend where to hold the inventory in the new network to reach our sponsor's company goal — reduce holding cost — our project plan included the plan depicted in Figure 2. First, we reviewed the literature regarding the challenges in managing MRO inventory, the identification of appropriate segmentation methods, the strategies to reduce MRO inventory, and the methods to optimize supply chain networks while estimating the inventory reduction due to consolidation. Second, we identified a methodology for MRO inventory segmentation, network optimization, and inventory reduction estimation. Third, we interviewed key stakeholders from various teams and visited warehouses and plants to further understand the current state. This helped us to gather appropriate qualitative feedback and quantitative data to run our analysis that served as inputs to our model, which was validated after running a test compared to the current state (resembles the real-life). Consequently, we reviewed results from the model for further improvements. Lastly, we synthesized information and provided recommendations for implementation to our sponsor company.

Figure 2

Project Timeline



2. STATE OF THE ART

Having the right amount of MRO inventory and in the right place in the Oil & Gas industry can save companies downtime and bring productivity to their operations. Large inventory volume reduces the risk of operations downtime but increases the holding cost of a company. Long lead times for MRO response, on the other hand, may lead to an increase in operations downtime. Thus, the central problem of our capstone is how our sponsor company can reduce MRO holding costs while maintaining target service levels. In simple terms, finding the perfect balance between supply and demand would generally optimize inventory. But this is more complex, and companies face challenges to reach optimality. Thus, to address the problem, we reviewed literature in several areas. First, we examined the current management challenges of MRO inventory. Second, we reviewed the most common strategies to optimize MRO inventory across companies' supply chains. Lastly, we assessed network design optimization method while investigating methods to estimate the inventory reductions by consolidating inventory.

2.1 CURRENT MRO CHALLENGES IN COMPANIES

Stocking the right number of MRO parts is essential, as many companies carry millions to billions of dollars' worth of spare parts (Basten & Houtum, 2014). This increase in costs and pressure on companies to reduce expenses anywhere possible has led to more attention to MRO inventory management (Bechtel & Patterson, 1997). Gilbert and Finch (1985) explain another reason why companies are giving more attention to MRO inventory. The increasing interest in receiving goods closer to when they are needed, also known as just-in-time (JIT), is leading to a decrease in work-in-progress inventory (WIP). Hence, there is less stock between workstations, making equipment maintenance and repair critical to reduce breakdowns and productivity (Gilbert & Finch, 1985).

However, companies have challenges in determining appropriate inventory levels for MRO parts, as their usage is very volatile and is hard to have an accurate forecasted demand. As Schroder (2004) stated, “managing spare [parts] is like walking a tightrope” with managers trying to find the perfect balance with overstocks on one side and stock-outs on the other. Some challenges in predicting demand and controlling stock for MRO parts are the high number of parts managed, the presence of intermittent or lumpy demand patterns, and the risk of stock obsolescence (Bacchetti, et al. 2012).

High number of parts managed: MRO parts have unique characteristics and companies hold tens to hundreds of thousands of them (our sponsor holds 800,000 SKUs) increasing the complexity of analytical tools to manage inventory (Hill, 2014). Therefore, segmenting MRO items, discussed further in our literature review, helps reduce the challenges in forecasting demand and determining optimal inventory policies (Bacchetti, et al. 2012).

Presence of intermittent or lumpy demand patterns: Boylan and Syntetos (2010) define intermittent demand as frequent observations with zero demand and sporadic non-zero demand. Intermittent demand with high volume size variability is called lumpy demand (Boylan & Syntetos, 2010). Because of this intermittent demand and volatile lead times, companies often choose to hold large buffers of inventory to mitigate the risk of production downtime (Chen et al., 2019). Hence, it is a challenge to maintain target productivity and service levels with the opposite objective of reducing inventory.

Risk of stock obsolescence: Schroder (2004) describes that some MRO parts may have not been purchased within the past three years due to their low usage rate. Therefore, lead times may not be up to date, leading managers to overestimate to avoid a stockout. This results in inventory obsolescence (Chen et al., 2019) which over time, may translate to waste and loss (Hill, 2014).

By examining these challenges, we determined to focus on investigating the methods to classify MRO parts based on their unique characteristics of demand. This would serve as input in deciding where to locate inventory in the supply chain network based on their demand characteristics. As Bacchetti, et al.

(2012) explained, the integrated view of classification, demand forecasting, and inventory management can potentially lead to effective management of spare parts.

2.2 COMMON MRO INVENTORY MANAGEMENT STRATEGIES

2.2.1 MRO INVENTORY SEGMENTATION

Clustering MRO parts into groups with similar characteristics helps companies manage inventory and reduce the complexity of working with hundreds of thousands of individual parts (Ernst & Cohen, 1990). These segments can be based on many different factors, including usage rate, holding dollar value, turnover, criticality, commodity, and more (Hill, 2014). Although increasing the number of clusters may lead to better accuracy, four clusters provide a good trade-off between accuracy and implementation viability (Chen et al., 2019).

Bechtel and Patterson (1997) segment MRO items by two major groups, consumables and spare parts, whereas Gilbert and Finch (1985) suggest an ABC analysis, which consists of prioritizing ratings of SKUs that are most important (A), intermediate importance (B), and least important (C). Similarly, Bacchetti et al. (2012) and Teunter et al. (2010) explain that most companies rarely rely on more than one criterion and often use ABC analysis for spare parts based on demand volume or dollar value. However, Gilbert and Finch (1985) describe a multiple criteria approach for ABC, in which Class A items are those with long lead time and high criticality, Class C items are those with short lead time, and all others are Class B items. This classification can easily be extended to more than three clusters (Teunter et al., 2010) and is widely used due to its practical implementation but may not be the best method to reduce cost and increase service measures for complex inventory systems (Ernst & Cohen 1990).

Boylan et al. (2008) use demand characteristics as criteria to segregate MRO inventory into four clusters: intermittent demand for those with infrequent demand observations, erratic demand for those with volatile demand size, lumpy demand for those with infrequent demand observations and variable demand size, and smooth demand for those with frequent demand and small variability. Chen et al. (2019), however, extend the classification factors to include lead time, unit price, number of plants using part, commodity group, how recently the part is used, and inventory on hand. Overall, segmenting the inventory would help to both identify the best forecasting method (Boylan et al., 2008) and pool high-value, intermittent items into a centralized site (Hill, 2014).

K-means clustering, a widely used unsupervised machine learning algorithm, has been proven to be an effective method for SKU segmentation based on demand characteristics, such as mean and variation of demand (Jain, 2010). By partitioning SKUs into distinct groups, k-means enables businesses to better understand and manage their inventory and supply chain performance (Chen & Wu, 2012). The algorithm iteratively assigns each SKU to a cluster with the nearest centroid, updating the centroids until convergence is achieved (Arthur & Vassilvitskii, 2007). This approach allows for identification of patterns and trends in SKU demand, facilitating targeted inventory management strategies and optimizing resource allocation (Syntetos et al., 2016). Further, the inclusion of both mean and variation of demand as features in the clustering process accounts for both the magnitude and volatility of demand, ensuring a more comprehensive understanding of SKU behavior (Panigrahi et al., 2018).

We approached our segmentation of MRO SKUs for our sponsor company similarly to Boylan's et al. methodology. We applyed the k-means clustering method, as we believe that demand characteristics of each cluster would help identify different inventory management strategies.

2.2.3 NETWORK DESIGN OPTIMIZATION

Companies are always seeking ways to reduce costs to improve profitability and ultimately create more value for shareholders. As costs continue to rise, companies have more pressure to reduce their costs without affecting their competitive position. Caplice (2015) suggests that network models could be used to make better decisions that impact the companies' supply chains. One of these impacts is being able to provide the required service level with lower inventory and fewer assets, such as warehouses.

Thus, a strategy that companies could pursue to reduce inventory without hurting the required service level is to create an optimized network design of their warehouses and plants. The optimization consists of the consolidation and unification of multiple regional warehouses into fewer, sometimes bigger, warehouses. In addition, the option to downsize or even close some of their warehouses is becoming more attractive to companies. This strategy enables the elimination of underutilized warehouses. In this way, network design optimization is a plausible way for a company to save costs, mainly in transportation, inventory, and warehousing. Melachrinoudis & Min (2007) states that these cost reductions are possible due to economies of scale that a network design enables; the decrease in the number of warehouses and duplicated inventory allows the company to bring down inventory holding cost and inventory shortage risk.

Chen et al. (2019) proposes that common challenges in MRO inventory with characteristics such as high variance in the demand, slow moving but high value, and irregular lead-times can be mitigated by creating a network to centralize MRO parts in fewer warehouses. Picking material from centralized warehouses also creates savings by making the handling of inventory easier and enabling lower freight transportation rates through economies of scale (Melachrinoudis & Min, 2007). Moreover, Gong and Yücesan (2012) mention that a network designed to facilitate transshipment could lead to cost reductions and better service due to an increase in flexibility and responsiveness. Transshipments are a particular network design where goods are moved from an origin node to an intermediate warehouse or distribution center and finally to the plant or node that requested the goods.

To evaluate the effectiveness of a network design to reduce inventory holding costs, the savings produced by the reduction of inventory levels must be calculated. Goentzel (2016) suggests that the savings from an initiative that reduces the inventory levels could be calculated by multiplying the dollar value of the inventory reduction by the percentage that represents the inventory holding cost. Melachrinoudis and Min (2007) provide another technique to estimate the savings in inventory reduction that results from a warehouse consolidation. The technique is called the Square Root Law, which determines the optimal amount of inventory to stock based on the amount of inventory in each location before consolidation.

In the field of inventory management, the Inventory Square Root Law has been extensively studied and applied to various supply chain scenarios. Harris (1913) initially proposed this concept, which has since been widely accepted and adopted by practitioners and academics alike (Harris, 1913). The basic premise of the Inventory Square Root Law is that the safety stock level should be adjusted in proportion to the square root of the ratio of the new and old number of warehouses. Silver et al. (1998) further explored this concept in their book, "Inventory and Production Management in Supply Chains," where they examined the applications and implications of the Inventory Square Root Law in diverse supply chain contexts.

Nonetheless, a major drawback of warehouse consolidation is that it tends to lengthen lead times, impacting negatively on customer service (Melachrinoudis and Min, 2007). To Melachrinoudis and Min (2007), the effectiveness of the supply chain relies heavily on the warehouse. Therefore, the success and failure of the supply chain operations depends on how well companies can manage a network of warehouses that enables them to satisfy customer needs with the lowest possible inventory and transportation costs. To achieve this, the literature suggests mathematical programming models.

Mathematical programming, such as Linear Programming (LP) and Mixed Integer and Linear Programming (MILP), is commonly used in supply chain (Caplice, 2015). Linear programming is an optimization technique that has variables, linear constraints, and a linear objective function to minimize or maximize. In warehouse location selection, however, MILPs are recommended given that the fractional answers resulting from LPs are not suitable (Caplice, 2015). In this sense, MILPs are formulated very similarly to LPs but are solved very differently as the variables can only be integers. Therefore, we formulated a MILP of MRO inventory for our optimization model, which is further explained in our Methodology chapter.

3. METHODOLOGY

Based on the literature that we reviewed and after several meetings with the sponsor company, we approached the main research question – how can our sponsor company redesign their MRO inventory network to reduce their holding cost while keeping target service levels? — by optimizing the supply chain network design. This would allow the sponsor company to decrease the number of warehouses in their network, reducing the warehouses' expenses, which are the components of holding cost depicted in Figure1, and reducing the inventory levels through consolidation, which would impact the cost of capital. Our methodology to optimize the supply chain network design is divided into five sections:

1. Data Collection and Analysis
2. SKU Segmentation
3. Network Optimization Model
4. Validation
5. Sensitivity and Scenario Analysis

Through these steps we developed models that closely mimic the real-world setting to deliver an accurate assessment and recommendation to the sponsor company.

3.1 DATA COLLECTION AND ANALISYS

In any research project, data collection and analysis are critical components that directly impact the quality and reliability of the study's findings. This is especially true in the field of network optimization, where data is often vast, complex, and dynamic. In this section, we discuss the methods and techniques employed to collect and analyze the data used in our network optimization study. We describe what data we collected, and how we processed and analyzed the data to derive our insights.

3.3.1 DATA COLLECTION

First, we received data listing the Texas inventory at the material-warehouse level from the sponsor company, including the stock on hand (SOH); safety stock (SS); reorder point (ROP); unit of measurement (UoM); yearly shipments from 2018 through 2022 (referred to as "goods issue" in the data and in this paper); SKUs' category families; movement frequencies, and more. The data dictionary is presented in Appendix A. Second, we received data listing the materials that are stored at third party warehouses (3PLs) and the plants to which such 3PLs serve for our sponsor company. The data dictionary is presented in Appendix B. Third, we received data about their both chemical and refinery plants, including their address, inventory system, and legal entities. The data dictionary is presented in Appendix C. Lastly, we received data regarding their warehouses, including their address, inventory system; legal entity; fixed costs; and estimated average utilization. Nonetheless, we needed to clean and manipulate the data for analysis.

3.3.2 FACILITY DATA CLEANING

Currently, the sponsor company owns six plants in Texas (two refineries and four chemical plants that serve the Product Solutions business unit), which are denoted by their plant codes in this paper (i.e., 001). Each plant has an onsite warehouse owned by the company. Each on-site warehouse, denoted by their plant code with a preceding 'W' in this paper (i.e., W001), has a fixed cost, which are yearly operating costs the sponsor company incurs, including WH Facility Maintenance Cost, Annual WH Equipment Cost, Annual Contract WH Employee Cost.

Additionally, the sponsor company rents a physical warehouse, named Logistics Center (LC), that contains inventories for all six of the sponsors' Texas plants, but the inventory is decentralized in the system. This means that, for example, if a valve is stored in LC for Plant 001, that valve cannot be used by Plant 003. Hence, we computed the fixed cost of each plant at the LC by taking the proportion of stock value stored at the LC for each plant. Hence, we denote the warehouse of LC as 6 separate warehouses, denoted with LC and superseding plant code (i.e., LC-001). Lastly, the sponsor company uses 14 third party warehouses (3PLs) to store additional inventory to serve the six different plants in Texas. Such warehouses have a fixed Third Party WH Annual Cost and are denoted as 3PL1, 3PL2, 3PL3, etc.

To formulate an accurate optimization model for our study, it was necessary to ascertain the capacity of each warehouse. While the warehouse dimensions were available, information regarding the dimensions of the products housed within was not available. To address this data gap, we estimated the warehouse capacities by computing the maximum throughput of supply over the preceding five years, utilizing the available shipment records, and finally used the utilization rate to calculate the capacity at 100% utilization for each warehouse. Noteworthy is that reducing the number of warehouses would help the sponsor reduce the warehouse expenses and potentially reduce inventory. Hence, we assume that the utilization of 3PLs is 100%.

Lastly, as part of our network optimization process, it was necessary to determine the distances between each warehouse and plant in our network. This was achieved by geocoding the address of each warehouse and plant to obtain their corresponding latitude and longitude coordinates. Subsequently, we calculated the Euclidean distance between each pair of coordinates to determine the distance between the warehouse and the plant.

3.3.3 SKU DATA CLEANING

Overall, global MRO inventory represented $1.5 billion in global stock value with over 92,000 SKUs. The data contained more than 98 distinct UoM, but about 90% of the SKUs had a UoM equal to EA, which means eaches or unit. Thus, after discussing with our sponsor company, we defined not only that Texas as the geographic scope of our project but also to focus on only SKUs with units of measurements of eaches/units (EA). This leads us to analyze approximately 84,654 SKUs, totaling a stock value of approximately $227 million.

Given that we have the yearly goods issues quantity to plants of each material from 2018 to 2022, we discussed with the sponsor company to model annual demand of each plant as the maximum yearly goods issue to each plant for each material. This makes the network more robust and flexible to demand variation because the maximum historical demand represents the upper limit of what can be expected in terms of demand. Thus, designing the network to meet this level of demand can provide a buffer against demand variations and unexpected spikes in demand.

Lastly, we manipulated the data to understand where each SKU was stored, which in this paper we define it as storage location, using the listing of materials that are stored at third party warehouses (3PLs) and the storage bin column from the SKU list data set. The storage bin column indicated that the SKU was in the Logistics Center if the storage bin column started with the letter “T”, or that the SKU was stored in a 3PL if the storage bin column contained the name of the 3PL, or else was on the onsite warehouse of the plant associated with the SKU.

3.3.4 SKU ANALYSIS

Subsequently to collecting and cleaning the data, we performed descriptive analytics. The 84,465 SKUs are categorized by both their category family, which is a high-level description of the product, and their movement frequency, which is a description of the usage of the product over a time period, which are defined as:

- Fast: materials with 12 or more months usage over a period of 2 years.
- Medium: materials with 3 to 11 months usage over a period of 2 years.
- Slow: materials with less than 3 months usage over a period of 2 years.
- No-Move: materials with 0 months usage over a period of 2 years or greater.
- Deadstock: materials with 0 months usage over a period of 5 years or greater.

Figure 3 shows that 98% of the SKUs are Equipment and Materials withing the MRO inventor of our sponsor company and Figure 4 displays that 32% of the materials are Deadstock, 54% are NoMove, and only 0.3% are Fast. This suggests that our sponsor company is utilizing space and is incurring holding costs from its obsolete inventory, which are defined as Deadstock in this paper. But it also creates opportunities to optimize its inventory management processes. For instance, by reducing the Deadstock inventory, our sponsor company can increase their capacity to better serve their Fast, Medium, and even NoMove products.

Figure 3

SKU Distribution by Category Family

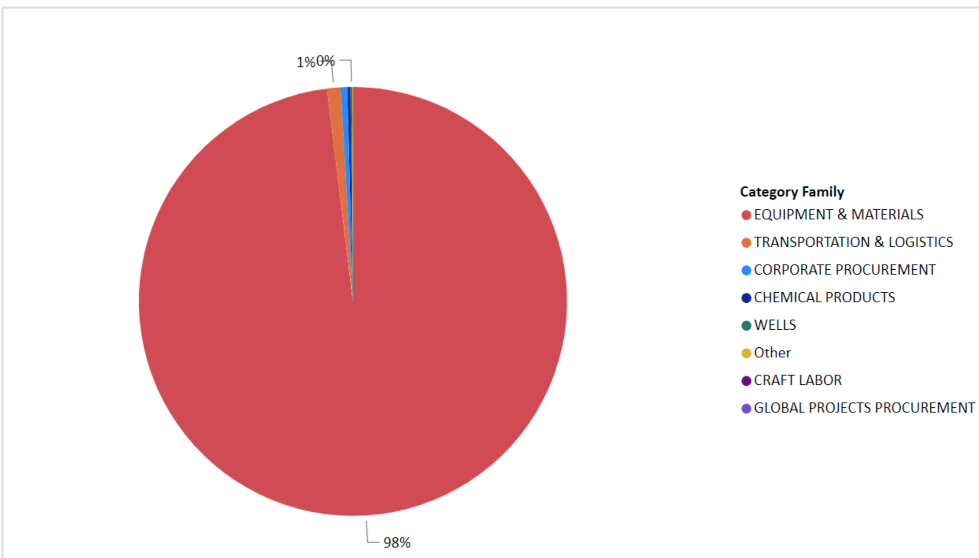
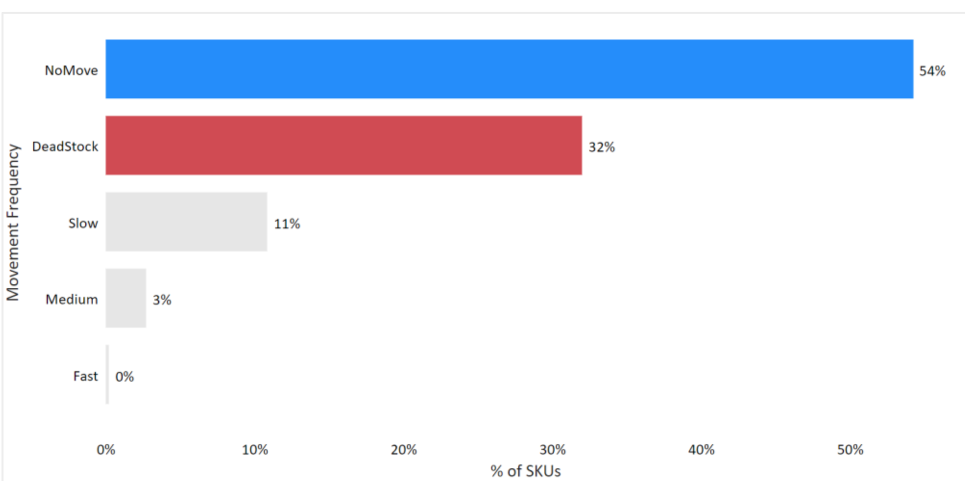


Figure 4

SKU Distribution by Movement Frequency



Indeed, Deadstock inventory represents a stock value of approximately $29 million, which is about 13% of total MRO inventory stock value (Figure 5). Moreover, Figure 6 shows that 20% of the Deadstock materials represent about 95% of Deadstock's stock salue (USD) and 35% of materials represent about 99% of its stock value (USD). Thus, besides the benefits of increasing capacity by writing off Deadstock inventory, the sponsor company has opportunities to save costs of capital and holding costs.

Figure 5

SKU Stock Value (USD) by Movement Frequency

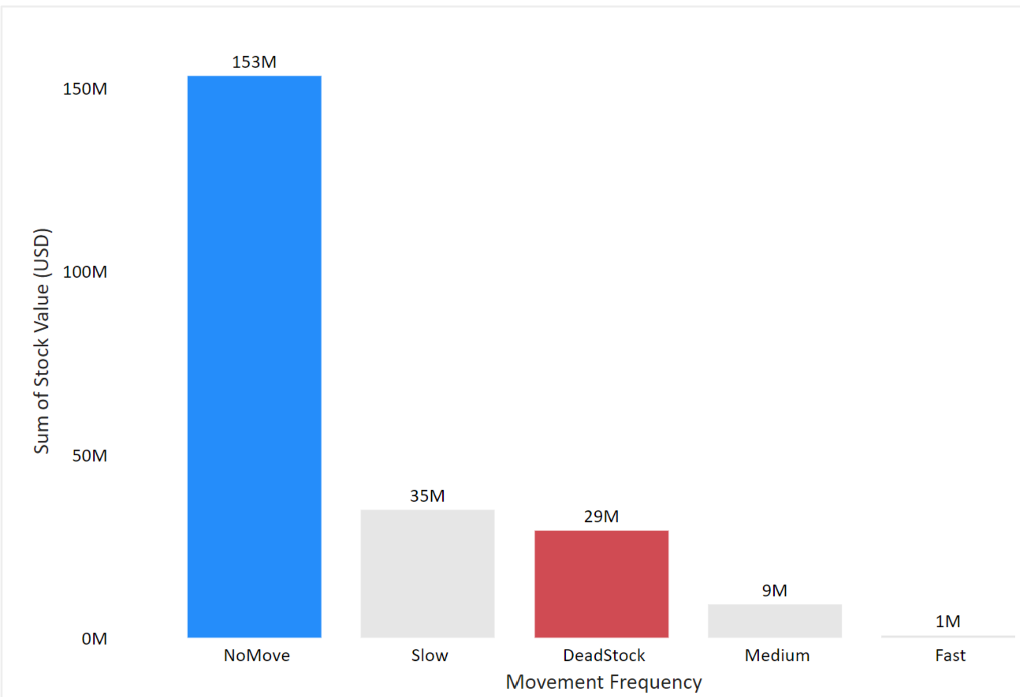
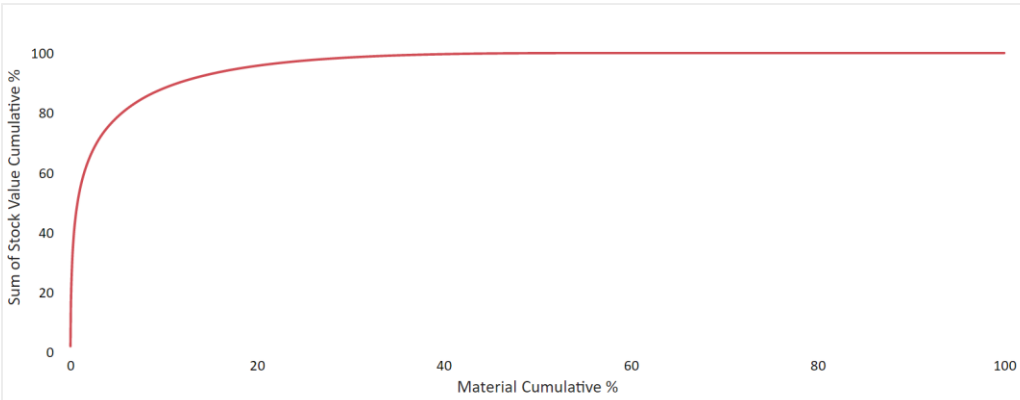


Figure 6

Deadstock SKU Percentage by Stock Value (USD)

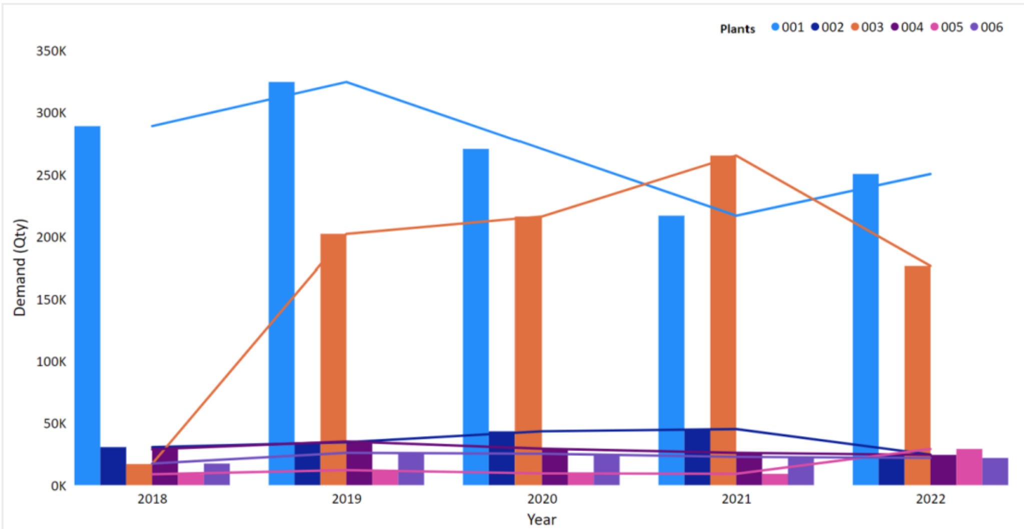


3.3.1 FACILITY ANALYSIS

Stemming from the SKU analysis, we then investigated the demand from year 2018 through 2022, during which there was an average of 19,237 goods issues (shipments) per year with a total average quantity of 546,222 units per year (demand). Figure 7 depicts that plant 001 and 003 required significantly more MRO inventory than the other 4 plants. Thus, there is the opportunity to store inventory in their respective on-site warehouses such that the products are closer to the consumption points, which in this case are the plants, bringing lower delivery times and higher service levels.

Figure 7

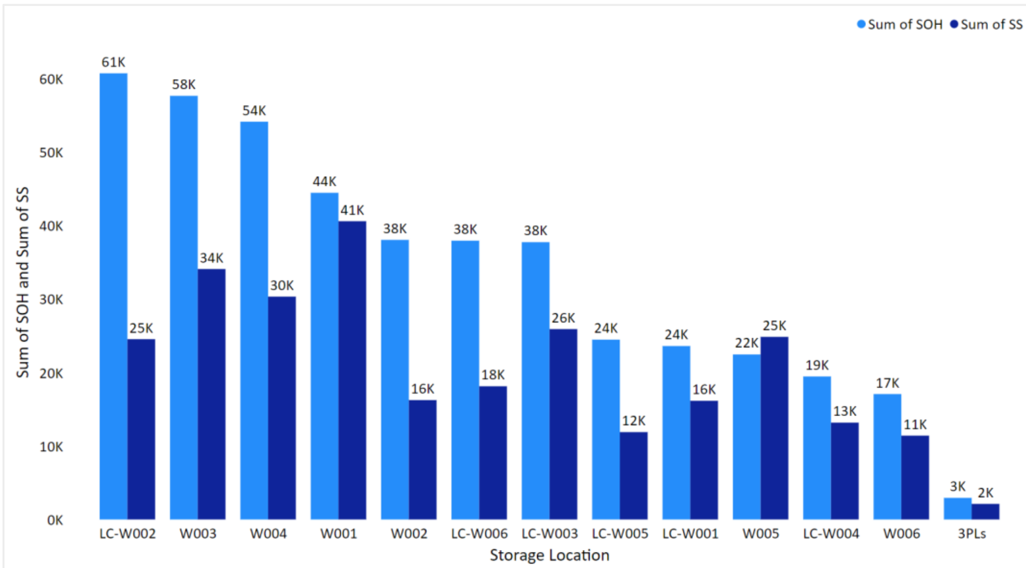
Volume Quantity and Stock Value Goods Issue Percentage by Plant



Furthermore, Figure 8 shows the aggregated stock on hand (SOH), totaling approximately 440,000 units of product and aggregated safety stock (SS), totaling approximately 269,000 units of product, by storage location. We notice that while storage location LC-002 has the highest stock on hand, W001 has the highest safety stock. This creates opportunities for our sponsor company to improve their inventory levels and consolidate inventory through an optimized network.

Figure 8

Sum of Stock on Hand (SOH) and Safety Stock (SS) by Storage Location



Stemming from this analysis, we subsequently performed SKU segmentation to simplify the supply chain network design of the 84,465 SKUs present in the stock list data.

3.2 SKU SEGMENTATION

Based on the insights of Boylan et al. (2008) and Jain (2010), we examined the SKUs segmentation for the 19,153 SKUs that had demand over the last five years (65501 SKUs had no demand over last five years). For the segmentation, we examined the mean and standard deviation by material and performed k-means machine learning algorithm to cluster materials based on their demand characteristic's similarity. The goal of k-means is to partition a set of data points into K clusters, where each data point belongs to the cluster with the nearest mean. The algorithm works by randomly initializing K cluster centroids and iteratively assigning each data point to the nearest centroid, then updating the centroids based on the mean of the points in the cluster. This process continues until the centroids no longer change or a maximum number of iterations is reached.

We used the silhouette score to evaluate the quality of clustering results. It measures how well each data point fits into its assigned cluster, compared to how well it fits into the neighboring clusters. Using K (number of clusters) from 2 through 9, we computed the silhouette score to identify the appropriate number of clusters for our data. The best silhouette score was 0.833, with two clusters (K=9). However, the silhouette score is a quantitative measure and does not provide any meaning of the clusters. Therefore, we visually represented the clusters through a scatterplot of mean and standard deviation of the materials, shown in Figure 9, and identified that four clusters (K=4) with a score of 0.828 would be best to interpret the segmentation and to perform different strategies in the supply chain.

Figure 9

Mean and Standard Deviation Scatterplot by Cluster

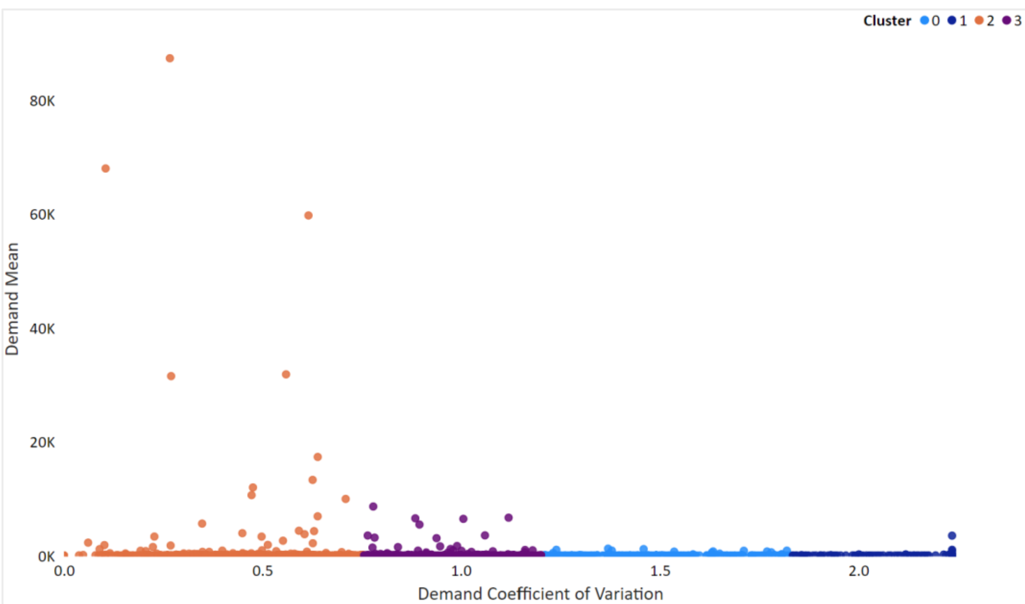


Figure 9 demonstrated that Cluster 2 has SKUs with low demand variability, Cluster 3 has low to medium demand variability, Cluster 0 has medium to high demand variability, and Cluster 1 has high demand variability. Through this segmentation, we aggregate demand by cluster and plant, shown in Figure 10, and aggregated supply capacity by cluster and storage location, shown in Figure 11, to help us simplify and scale the supply chain network design.

Figure 10

Demand by Cluster and Plant

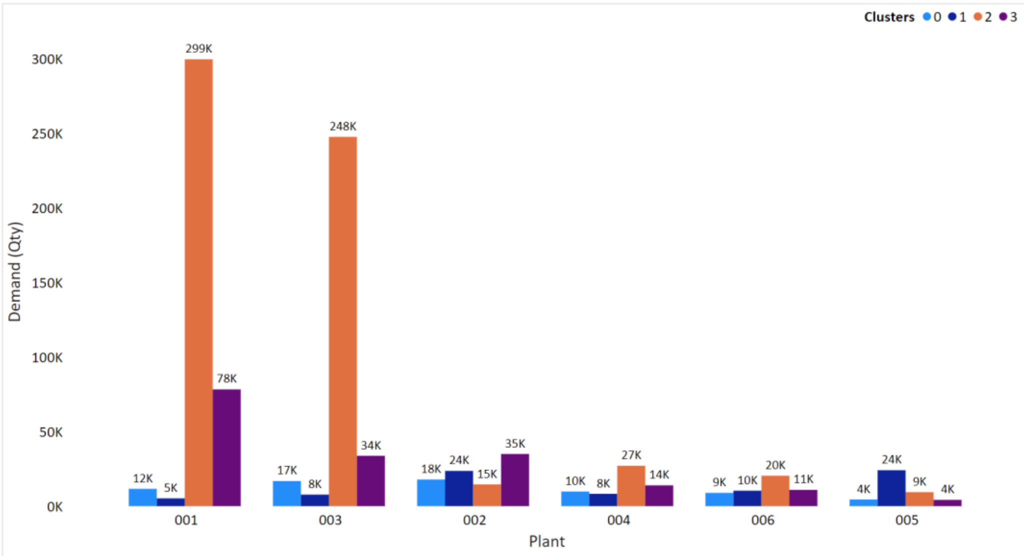
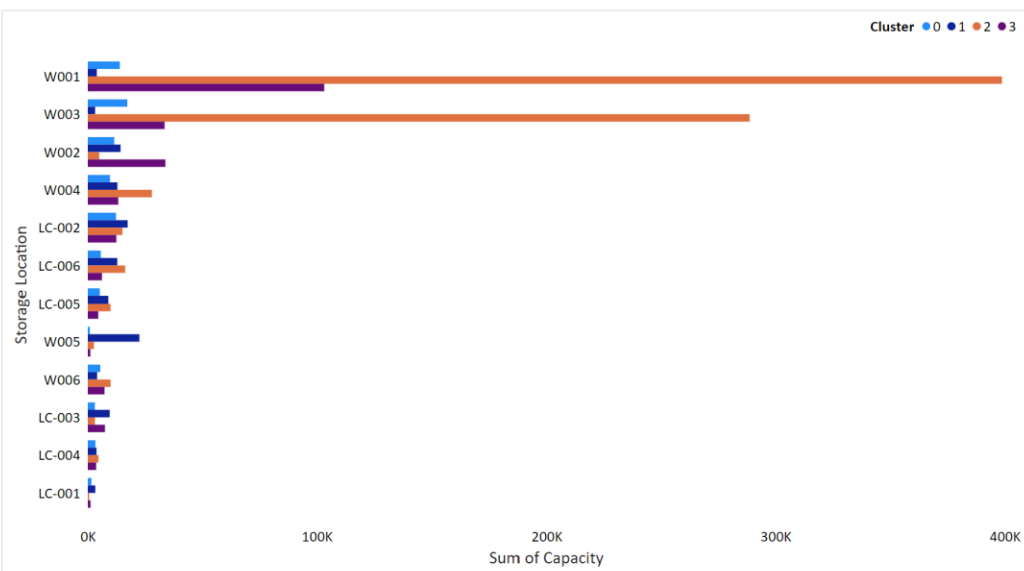


Figure 11

Supply Capacity by Cluster and Plant



3.3 Network Optimization Model

A network model consists of basically two elements: 1) nodes or vertices, which for our capstone would be the warehouses and plants that store the MRO inventory and request the parts, respectively, and 2) arcs or edges (the link between two nodes), which could be a road, for example. To optimize a network, we used a mathematical programming model, such as the MILP proposed by Caplice (2015) that considers warehouse location and the linkage between supply points (warehouses) and consumptions points (plants) to fulfill demand.

The three key elements of a MILP model are: 1) the objective function that tries to minimize, in our case, warehouses' expenses and transportation costs, 2) the decision variables (i.e., which SKUs and in what quantities to store in each warehouse, which warehouses to keep and which ones to close, and which path each SKU needs to follow in order to fulfill an internal request), and 3) the constraints (i.e., warehouse supply capacity, plant demand fulfillment, etc.).

We designed a network optimization model to test our hypothesis that an optimized supply chain network would reduce the holding costs. We assume that all SKUs can be stored in all the warehouses, regardless of their characteristics. Our model mathematical formulation is listed on the next page of this paper (page 29). The model minimizes the fixed operating warehouse cost and transportation cost (1) subject to constraints: the supply capacity of each warehouse (2), the demand requirement of each plant (3), the minimum number of warehouses to operate (4), the maximum number of warehouses to operate (5), if you open a LC for a specific plant (i.e., LC-001), then the LC warehouse for all plants must be open (6), binary decision variable (7), and integer decision variable (8).

$$\sum_{i} FC_i Y_i + \sum_{i}\sum_{j}\sum_{k} X_{ijk} c_{ij} \tag{1}$$

$$\sum_{j}\sum_{k} X_{ijk} \leq C_i \, Y_i \, \forall i \in I \tag{2}$$

$$\sum_{i} X_{ijk} = D_{jk} \, \forall j \in J, \forall k \in K \tag{3}$$

$$\sum_{i} Y_i \geq Min \tag{4}$$

$$\sum_{i} Y_i \leq Max \tag{5}$$

$$\sum_{y \in L} Y_i \leq Z_l \, |Z|, \forall l \in L \tag{6}$$

$$Y_i \in \{0,1) \, \forall i \in I \tag{7}$$

$$Z_l \in \{0,1) \forall l \in L$$

$$X_{ijk} \in \mathbb{Z} \, \forall i \in I, \forall j \in J, \forall k \in K \tag{8}$$

Sets:

I = Set of warehouses

J = Set of plants

K = Set of MRO SKU clusters

L = set of warehouses that are part of LC

Decision Variables:

$$Y_i = \begin{cases} 0 \; if \; warehouse \; i \; is \; not \; used \\ 1 \; if \; warehouse \; i \; is \; used \end{cases}$$

$$Z_l = \begin{cases} 0 \; if \; warehouse \; l \; is \; not \; used \\ 1 \; if \; warehouse \; l \; is \; used \end{cases}$$

X_{ijk} = Demand fulfilled of SKU cluster k in plant j by warehouse i

Parameters:

FC_i = Fixed cost for warehouse I [$]

c_{ij} = Transportation cost per unit per mile to fulfill demand in plant j by warehouse I [$/unit/mile]

C_i = Supply capacity in warehouse i [units]

D_{jk} = Demand of SKU cluster k in plant j [units]

Min = Minimum number of warehouses to be used in the network [number of warehouses]

Max = Maximum number of warehouses to be used in the network [number of warehouses]

$|Z|$ = Cardinality (also referred to as length) of the set

Lastly, we leverage the Inventory Square Root Law (Silver, Pyke, & Peterson, 1998) but modified it for our study to account for different warehouse capacities. The traditional Inventory Square Root Law formula, which states that $New\ SS\ (units) = Old\ SS * \sqrt{\frac{New\ Number\ of\ WH}{Old\ Number\ of\ WH}}$, assumes that all warehouses have the same capacity. However, in many practical scenarios, warehouses can have varying capacities. To address this issue, we introduced a capacity ratio factor into the formula, which considers the total capacities of both the old and new warehouses. The modified formula is defined as $New\ SS\ (units) = Old\ SS * \sqrt{\frac{New\ Number\ of\ WH}{Old\ Number\ of\ WH} * \frac{New\ Total\ Capacity}{Old\ Total\ Capacity}}$. This approach allows for a more accurate calculation of the new safety stock by considering the differences in warehouse capacities. The results are presented in Chapter 4 and in Appendix D.

3.4 VALIDATION

To determine the validity of our model, we examined the current state (real-world environment) of the MRO supply chain network during the year 2022 and compared it with our mathematical model before optimization (referred to as the baseline model in this paper). Table 1 illustrates the expenses for both current state and baseline model for the year 2022. This helps us to determine whether our model replicates the real world.

Table 1

Current State and Baseline Model Expenses in the year 2022

Annual Expense	Current State	Baseline Model (year 2022)
Fixed Cost	$ 9,436,364	$ 9,436,364
Transportation Cost	$ 960,000	$ 959,112
Total	$ 10,396,364	$ 10,395,476

The warehouse annual fees, maintenance cost, and equipment cost are fixed costs for each warehouse. Like the capacity calculation for the LC, we use the fixed cost of the warehouse and distribute to each specific plant according to the proportion of stock value stored in the LC for each plant. The same procedure is followed for the third-party warehouse since a 3PL can hold inventory from multiple plants. The warehouse employee cost is calculated by the average salary of contract employees and multiplied by the estimated number of employees per warehouse.

Furthermore, the sponsor pays a lump sum to a third-party logistics motor carrier of $960,000 per year. For our modeling, however, we need to calculate the cost per mile per unit. Hence, with all inputs to our model, we reverse engineer such that we calculate a $0.99 cost per mile per unit that would result in a transportation cost of $960,000 to fulfill the goods issued in 2022. With this our model closely resembles the real-world environment, having a cost within 0.0038% of the current state.

3.5 SCENARIO ANALYSIS

After validating that our model is within 0.0038% of the real-world setting, we proceeded with analyzing four key scenarios that find both the optimal number of warehouses to store inventory and the optimal assignment between warehouses and plants to fulfill demand:

1. Scenario 1: Warehouses and plants maintain a 1:1 relation, as per the current state.
2. Scenario 2: Warehouses can only serve the plants that have the same legal entity and same inventory system.
3. Scenario 3: Warehouses have an integrated inventory system but can only serve plants that have the same legal entity.
4. Scenario 4: Warehouses have an integrated inventory system and can serve plants that have different legal entities.

While Scenario 1 would prescribe the most optimal network design for the sponsor company as per current state, Scenario 2 investigates the optimal network if a warehouse can serve plants with the same inventory system. Specifically, plants 004 and 005 have the same inventory system and hence not only warehouse W004 and W005 can serve plants 004 and 005, interchangeably, but also LC-004 and LC-005 can be consolidated into one LC, which is denoted as LC4. Similarly, since plants 003 and 006 have the same inventory system, not only warehouse W003 and W006 can serve plants 003 and 006, interchangeably, but also LC-003 and LC-006 can be consolidated into one LC, which is denoted as LC3 (LC1 represents LC-001, and LC2 represents LC-002. as these have different inventory systems).

Furthermore, we investigated Scenario 3 and Scenario 4, in which the sponsor company integrates its inventory systems and can transact orders and movements of MRO SKUs across multiple legal entities. Thus, in Scenario 3 the sponsor company can not only use W001, W004, and W005 to serve plants 001, 004, and 005 interchangeably but also consolidate their LC into one, which is denoted as LC1. Similarly, the sponsor company can not only use W002, W003, and W006 to serve plants 002, 003, and US1, interchangeably but also consolidate their LC into one, which is denoted as LC2. Scenario 4, on the other hand, enables the company's warehouses to serve all plants and to consolidate all 6 LCs into one LC, denoted as LC1.

Within each scenario, we perform sensitivity analysis to determine the degree of robustness of the optimal solution in response to changes in the input data, such as increasing the supply capacity of warehouses or the demand at each plant. This analysis helps to identify the critical factors that can affect the optimal solution. We also investigated if the supply throughput capacity of warehouses is increased due to the reduction of 35% of Deadstock materials currently stored in the warehouses. This allowed us to illustrate the different benefits and risks of closing warehouses and decide which option best suits our sponsor company.

4.0 RESULTS

The results chapter presents the outcomes of the four key scenarios analyzed in our study. The analysis was designed to explore the effects of different capacity levels through integration of warehouses, and consolidation of inventory, and cost structures on the optimal design of the network. The results are presented in detail below, including the key findings, trends, and recommendations that emerged from the analysis.

4.1 SCENARIO 1

Scenario 1 assesses the most optimal network design for the sponsor company as per current state, in which the warehouses and plants maintain a 1:1 relationship. The model recommends that the network should fulfill the six plants' demand with their six on-site warehouses, six LCs, and three 3PLs (3PL1, 3PL5, and 3PL10), reducing the number of facilities from 26 warehouses to 15 warehouses. Table 2 displays the costs with the optimized supply chain network compared to the baseline model. It is noteworthy that the baseline model for validation was computed only for the year of 2022; here and for all scenarios we present the baseline model based on demand which is modeled as the maximum throughput supply over the last five years, as explained in Section 3.3.3. The optimized supply chain network has about $1.4 million in savings, which is about 12% reduction in total cost, composed of 13% savings from fixed costs and 10% savings from transportation costs. However, we proceeded with evaluating the impact on the optimal solution in response to changes in the input data, such as changes in demand, throughput capacity, fixed costs, and transportation cost. This sensitivity analysis is summarized in Table 3.

Table 2

Baseline Model and Scenario 1 Optimal Model Expenses

Model	Total Cost	Fixed Cost	Transportation Cost
Baseline Model	$ 11,722,545	$ 9,436,364	$ 2,286,181
Scenario 1 Optimal Model	$ 10,280,900	$ 8,215,460	$ 2,065,400
% Savings	12%	13%	10%
Total Savings	**$ 1,441,645**	**$ 1,220,904**	**$ 220,781**

Table 3

Scenario 1 Optimization Sensitivity Analysis

Sensitivity	Number Facilities	Total Cost	Fixed Cost	Transportation Cost
Scenario 1 Optimal Model	15	$ 10,280,900	$ 8,215,460	$ 2,065,400
10 % Higher Throughput Capacity	12	$ 8,998,910	$ 7,486,500	$ 1,512,410
% Savings Compared to Optimal	-	12%	9%	27%
10 % Lower Throughput Capacity	Infeasible			
% Savings Compared to Optimal	Infeasible			
10 % Higher Demand	Infeasible			
% Savings Compared to Optimal	Infeasible			
10 % Lower Demand	12	$ 8,802,030	$ 7,486,500	$ 1,315,540
% Savings Compared to Optimal	-	14%	9%	36%
10% Higher Fixed Costs	15	$ 11,102,400	$ 9,037,010	$ 2,065,400
% Savings Compared to Optimal	-	-8%	-10%	0%
10% Lower Fixed Costs	15	$ 9,459,310	$ 7,393,920	$ 2,065,400

Sensitivity	Number Facilities	Total Cost	Fixed Cost	Transportation Cost
% Savings Compared to Optimal	-	8%	10%	0%
10% Higher Transportation Costs	15	$ 10,487,400	$ 8,215,460	$ 2,271,940
% Savings Compared to Optimal	-	-2%	0%	-10%
10% Lower Transportation Costs	15	$ 10,074,300	$ 8,215,460	$ 1,858,860
% Savings Compared to Optimal	-	2%	0%	10%

Through our sensitivity analysis, we notice that the model is robust to changes in the fixed and transportation costs. In addition, we detect that there is potential of an additional 12% savings if the throughput capacity is increased by 10% across all warehouses. Similarly, there is an additional 14% savings if the demand is decreased by 10% across all clusters and warehouses. However, the optimization model is infeasible — there is no feasible solution that satisfies all the constraints of the model while still optimizing the objective function — when the throughput capacity is decreased by 10% across all warehouses or when the demand is increased by 10% across all clusters and warehouses. The reason for infeasibility is that these changes result in higher demand than the throughput capacity can fulfill. This suggests two-fold insights: One is that the decreasing supply capacity would unable the sponsor company to fulfill the historic demand over last five years, which we know they fulfilled; hence, the estimation of supply capacity is accurate. Two is that increasing demand would unable the sponsor company to fulfill 100% of its requests, and hence the sponsor company may need to add additional capacity at 3PLs.

Within Scenario 1, we also investigated if the supply throughput capacity of each warehouse is increased due to the reduction of Deadstock inventory currently stored in each warehouse. Specifically, we calculated the sum of stock on hand from the 35% of Deadstock materials that represented about 99% of Deadstock stock value (USD), as shown previously in Figure 6. By writing-off 105,887 units of Deadstock quantity, we then added such quantity to the supply capacity to each warehouse and cluster based on their demand proportionality. We call this Scenario 1b and its results are summarized in Table 4. The results from Scenario 1b further decrease the number of warehouses from 15 warehouses (Scenario 1) to 13 warehouses. The model assesses that the network should fulfill the six plants' demand with their six on-site warehouses, six LCs, and three 1PLs (3PL1). The optimized supply chain network by adding the Deadstock quantity to the supply capacity in Scenario 1b has about $2.5 million of savings, which is about 22% reduction in total cost (10 points more than Scenario 1).

Table 4

Baseline Model and Scenario 1b Optimal Model Expenses

Model	Total Cost	Fixed Cost	Transportation Cost
Baseline Model	$ 11,722,545	$ 9,436,364	$ 2,286,181
Scenario 1b Optimal Model	$ 9,173,820	$ 7,497,050	$ 1,676,770
% Savings	22%	21%	27%
Total Savings	**$ 2,548,725**	**$ 1,939,314**	**$ 609,411**

Lastly, using the modified Inventory Square Root Law explained in Section 3.3 we calculate that Scenario 1b results in a reduction of safety stock from 137,935 units to 96,531units (30% decrease). Using a 11% holding cost (Sponsor Company, personal communication, 2022), this leads to a decrease in holding costs from $6,445,815 to $5,015,887— $1,429,928 savings (22%) in holding costs.

4.2 SCENARIO 2

Scenario 2 assesses the most optimal network design when a warehouse can serve plants with the same inventory system. The model recommends that the network should fulfill the six plants' demand with their six on-site warehouses, four consolidated LCs, and three 3PLs (3PL1, 3PL5, and 3PL10), reducing the number of facilities from 26 warehouses to 13 warehouses (2 more warehouses are reduced compared to Scenario 1). Table 5 displays the costs with the optimized supply chain network compared to the baseline model. The optimized supply chain network has about $1.5 million in savings, which is about 13% reduction in total cost, composed of 13% savings from fixed costs and 14% savings from transportation costs.

Table 5

Baseline Model and Scenario 2 Optimal Model Expenses

Model	Total Cost	Fixed Cost	Transportation Cost
Baseline Model	$ 11,722,545	$ 9,436,364	$ 2,286,181
Scenario 2 Optimal Model	$ 10,190,000	$ 8,215,460	$ 1,974,510
% Savings	13%	13%	14%
Total Savings	**$ 1,532,545**	**$ 1,220,904**	**$ 311,671**

We proceeded with evaluating the impact on the optimal solution in response to changes in the input data. This sensitivity analysis is summarized in Table 6.

Table 6

Scenario 2 Optimization Sensitivity Analysis

Sensitivity	Number Facilities	Total Cost	Fixed Cost	Transportation Cost
Scenario 2 Optimal Model	13	$ 10,190,000	$ 8,215,460	$ 1,974,510
10 % Higher Throughput Capacity	10	$ 8,946,150	$ 7,486,500	$ 1,459,650
% Savings Compared to Optimal	-	12%	9%	26%
10 % Lower Throughput Capacity	Infeasible			
% Savings Compared to Optimal	Infeasible			
10 % Higher Demand	Infeasible			
% Savings Compared to Optimal	Infeasible			
10 % Lower Demand	10	$ 8,763,020	$ 7,486,500	$ 1,276,530
% Savings Compared to Optimal	-	14%	9%	35%
10% Higher Fixed Costs	13	$ 11,011,500	$ 9,037,010	$ 1,974,510
% Savings Compared to Optimal	-	-8%	-10%	0%
10% Lower Fixed Costs	13	$ 9,368,430	$ 7,393,920	$ 1,974,510
% Savings Compared to Optimal	-	8%	10%	0%
10% Higher Transportation Costs	13	$ 10,387,400	$ 8215460	$ 2171970
% Savings Compared to Optimal	-	-2%	0%	-10%
10% Lower Transportation Costs	13	$ 9,992,530	$ 8,215,460	$ 1,777,060
% Savings Compared to Optimal	-	2%	0%	10%

Through our sensitivity analysis, we notice that the model is robust to changes in the fixed and transportation costs. In addition, we detect that there is potential for an additional 12% savings if the

throughput capacity is increased by 10% across all warehouses. Similarly, there is an additional 14% savings if the demand is decreased by 10% across all clusters and warehouses. However, the optimization model is infeasible — there is no feasible solution that satisfies all the constraints of the model while still optimizing the objective function — when the throughput capacity is decreased by 10% across all warehouses or when the demand is increased by 10% across all clusters and warehouses. The insights from infeasibility are the same as the ones discussed for Scenario 1.

Within Scenario 2, we also investigated if the supply throughput capacity of each warehouse is increased due to the reduction of Deadstock inventory currently stored in each warehouse. Similar to Scenario 1, by writing-off 105,887 units of Deadstock quantity, we then added such quantity to the supply capacity to each warehouse and cluster based on their demand proportionality. We call this Scenario 2b and its results are summarized in Table 7. The results from Scenario 2b further decrease the number of warehouses from 13 warehouses (Scenario 2) to 10 warehouses. The model assesses that the network should fulfill the six plants' demand with their six on-site warehouses and four consolidated LCs. The optimized supply chain network by adding the Deadstock quantity to the supply capacity in Scenario 2b has about $2.6 million of savings, which is about 23% reduction in total cost (10 points more than Scenario 2).

Table 7

Baseline Model and Scenario 2b Optimal Model Expenses

Model	Total Cost	Fixed Cost	Transportation Cost
Baseline Model	$ 11,722,545	$ 9,436,364	$ 2,286,181
Scenario 2b Optimal Model	$ 9,071,360	$ 7,486,500	$ 1,584,870
% Savings	23%	21%	31%
Total Savings	**$ 2,651,185**	**$ 1,949,864**	**$ 701,311**

Lastly, using the modified Inventory Square Root Law explained in Section 3.3 we calculate that Scenario 2b results in a reduction of safety stock from 137,935 units to 88,118 units (36% decrease). Using a 11% holding cost (Sponsor Company, personal communication, 2022), this leads to a decrease in holding costs from $6,445,815 to $4,928,183— $1,517,632 savings (23%) in holding costs.

4.3 SCENARIO 3

Scenario 3 assesses the most optimal network design when the sponsor company integrates its inventory systems, but warehouses can transact orders and movements of MRO SKUs to only the same legal entities. The model recommends that the network should fulfill the six plants' demand with their six on-site warehouses, two consolidated LCs, and three 3PLs (3PL1, 3PL5, and 3PL10), reducing the number of facilities from 26 warehouses to 11 warehouses (2 more warehouses are reduced compared to Scenario 2). Table 8 displays the costs with the optimized supply chain network compared to the baseline model. The optimized supply chain network has about $1.5 million in savings, which is about 13% reduction in total cost, composed of 13% savings from fixed costs and 15% savings from transportation costs.

Table 8

Baseline Model and Scenario 3 Optimal Model Expenses

Model	Total Cost	Fixed Cost	Transportation Cost
Baseline Model	$ 11,722,545	$ 9,436,364	$ 2,286,181
Scenario 3 Optimal Model	$ 10,163,200	$ 8,215,460	$ 1,947,720
% Savings	13%	13%	15%
Total Savings	**$ 1,559,345**	**$ 1,220,904**	**$ 338,461**

We proceeded with evaluating the impact on the optimal solution in response to changes in the input data. This sensitivity analysis is summarized in Table 9.

Table 9

Scenario 3 Optimization Sensitivity Analysis

Sensitivity	Number Facilities	Total Cost	Fixed Cost	Transportation Cost
Scenario 3 Optimal Model	11	$ 10,163,200	$ 8,215,460	$ 1,947,720
10 % Higher Throughput Capacity	8	$ 8,182,910	$ 7,486,500	$ 696,415
% Savings Compared to Optimal	-	19%	9%	64%
10 % Lower Throughput Capacity	Infeasible			
% Savings Compared to Optimal	Infeasible			
10 % Higher Demand	Infeasible			
% Savings Compared to Optimal	Infeasible			
10 % Lower Demand	8	$ 8,089,660	$ 7,486,500	$ 603,164
% Savings Compared to Optimal	-	20%	9%	69%
10% Higher Fixed Costs	11	$ 10,984,700	$ 9,037,010	$ 1,947,720
% Savings Compared to Optimal	-	-8%	-10%	0%
10% Lower Fixed Costs	11	$ 9,341,630	$ 7,393,920	$ 1,947,720
% Savings Compared to Optimal	-	8%	10%	0%
10% Higher Transportation Costs	11	$ 10,358,000	$ 8,215,460	$ 2,142,490
% Savings Compared to Optimal	-	-2%	0%	-10%
10% Lower Transportation Costs	11	$ 9,968,410	$ 8,215,460	$ 1,752,950
% Savings Compared to Optimal	-	2%	0%	10%

Through our sensitivity analysis, we notice that the model is robust to changes in the fixed and transportation costs. In addition, we detect that there is potential for an additional 19% savings if the

throughput capacity is increased by 10% across all warehouses. Similarly, there is an additional 20% savings if the demand is decreased by 10% across all clusters and warehouses. However, the optimization model is infeasible — there is no feasible solution that satisfies all the constraints of the model while still optimizing the objective function — when the throughput capacity is decreased by 10% across all warehouses or when the demand is increased by 10% across all clusters and warehouses. The insights from infeasibility are the same as the ones discussed for Scenario 1.

Within Scenario 3, we also investigated if the supply throughput capacity of each warehouse is increased due to the reduction of Deadstock inventory currently stored in each warehouse. Similar to Scenario 2, by writing-off 105,887 units of Deadstock quantity, we then added such quantity to the supply capacity to each warehouse and cluster based on their demand proportionality. We call this Scenario 3b and its results are summarized in Table 10. The results from Scenario 3b further decrease the number of warehouses from 11 warehouses (Scenario 3) to 8 warehouses. The model assesses that the network should fulfill the six plants' demand with their six on-site warehouses and two consolidated LCs. The optimized supply chain network by adding the Deadstock quantity to the supply capacity in Scenario 3b has about $3.0 million of savings, which is about 26% reduction in total cost (13 points more than Scenario 3).

Table 10

Baseline Model and Scenario 3b Optimal Model Expenses

Model	Total Cost	Fixed Cost	Transportation Cost
Baseline Model	$ 11,722,545	$ 9,436,364	$ 2,286,181
Scenario 3b Optimal Model	$ 8,678,470	$ 7,486,500	$ 1,191,970
% Savings	26%	21%	48%
Total Savings	**$ 304,4075**	**$ 1,949,864**	**$ 1,094,211**

Lastly, using the modified Inventory Square Root Law explained in Section 3.3 we calculate that Scenario 3b results in a reduction of safety stock from 137,935 units to 82,320 units (40% decrease). Using a 11% holding cost (Sponsor Company, personal communication, 2022), this leads to a decrease in holding costs from $6,445,815 to $4,819,255— $1,626,560 savings (25%) in holding costs.

4.4 SCENARIO 4

Scenario 4 assesses the most optimal network design when the sponsor company integrates its inventory systems and warehouses can transact orders and movements of MRO SKUs across multiple legal entities. The model recommends that the network should fulfill the six plants' demand with their six on-site warehouses, one consolidated LCs, and three 3PLs (3PL1, 3PL5, and 3PL10), reducing the number of facilities from 26 warehouses to 9 warehouses (3 more warehouses are reduced compared to Scenario 3). Table 11 displays the costs with the optimized supply chain network compared to the baseline model. The optimized supply chain network has about $2 million in savings, which is about 17% reduction in total cost, composed of 18% savings from fixed costs and 14% savings from transportation costs.

Table 11

Baseline Model and Scenario 4 Optimal Model Expenses

Model	Total Cost	Fixed Cost	Transportation Cost
Baseline Model	$ 11,722,545	$ 9,436,364	$ 2,286,181
Scenario 4 Optimal Model	$ 9,674,090	$ 7,718,840	$ 1,955,250
% Savings	17%	17%	14%
Total Savings	**$ 2,048,455**	**$ 1,717,524**	**$ 330,931**

We proceeded with evaluating the impact on the optimal solution in response to changes in the input data. This sensitivity analysis is summarized in Table 12.

Table 12

Scenario 4 Optimization Sensitivity Analysis

Sensitivity	Number Facilities	Total Cost	Fixed Cost	Transportation Cost
Scenario 4 Optimal Model	9	$ 9674090	$ 7718840	$ 1955250
10 % Higher Throughput Capacity	6	$ 8,055,240	$ 7,176,090	$ 879,145
% Savings Compared to Optimal	-	17%	7%	55%
10 % Lower Throughput Capacity	Infeasible			
% Savings Compared to Optimal	Infeasible			
10 % Higher Demand	Infeasible			
% Savings Compared to Optimal	Infeasible			
10 % Lower Demand	6	$ 7,945,380	$ 7,176,090	$ 769,291
% Savings Compared to Optimal	-	18%	7%	61%
10% Higher Fixed Costs	9	$ 10,446,000	$ 8,490,720	$ 1,955,250
% Savings Compared to Optimal	-	-8%	-10%	0%
10% Lower Fixed Costs	9	$ 8,902,200	$ 6,946,950	$ 1,955,250
% Savings Compared to Optimal	-	8%	10%	0%
10% Higher Transportation Costs	9	$ 9,869,610	$ 7,718,840	$ 2,150,780
% Savings Compared to Optimal	-	-2%	0%	-10%
10% Lower Transportation Costs	9	$ 9,478,560	$ 7,718,840	$ 1,759,730
% Savings Compared to Optimal	-	2%	0%	10%

Through our sensitivity analysis, we notice that the model is robust to changes in the fixed and transportation costs. In addition, we detect that there is potential for an additional 17% savings if the

throughput capacity is increased by 10% across all warehouses. Similarly, there is an additional 18% savings if the demand is decreased by 10% across all clusters and warehouses. However, the optimization model is infeasible — there is no feasible solution that satisfies all the constraints of the model while still optimizing the objective function — when the throughput capacity is decreased by 10% across all warehouses or when the demand is increased by 10% across all clusters and warehouses. The insights from infeasibility are the same as the ones discussed for Scenario 1.

Within Scenario 4, we also investigated if the supply throughput capacity of each warehouse is increased due to the reduction of Deadstock inventory currently stored in each warehouse. Similar to Scenario 3, by writing-off 105,887 units of Deadstock quantity, we then added such quantity to the supply capacity to each warehouse and cluster based on their demand proportionality. We call this Scenario 4b and its results are summarized in Table 13. The results from Scenario 3b further decrease the number of warehouses from 9 warehouses (Scenario 4) to 6 warehouses. The model assesses that the network should fulfill the six plants' demand with their five on-site warehouses and one consolidated LCs. The optimized supply chain network by adding the Deadstock quantity to the supply capacity in Scenario 4b has about $3.2 million of savings, which is about 27% reduction in total cost (10 points more than Scenario 4).

Table 13

Baseline Model and Scenario 4b Optimal Model Expenses

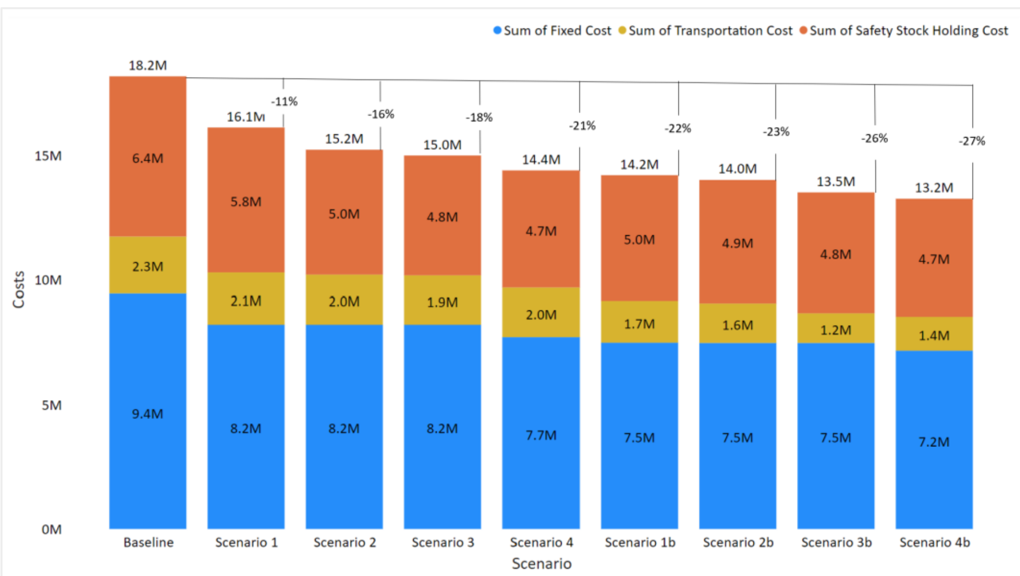
Model	Total Cost	Fixed Cost	Transportation Cost
Baseline Model	$ 11,722,545	$ 9,436,364	$ 2,286,181
Scenario 4b Optimal Model	$ 8,534,190	$ 7,176,090	$ 1,358,100
% Savings	27%	24%	41%
Total Savings	**$ 3,188,355**	**$ 2,260,274**	**$ 928,081**

Lastly, using the modified Inventory Square Root Law explained in Section 3.3 we calculate that Scenario 4b results in a reduction of safety stock from 137,935 units to 72,120 units (48% decrease). Using a 11% holding cost (Sponsor Company, personal communication, 2022), this leads to a decrease in holding costs from $6,445,815 to $ 4,708,457— $ 1,737,358 savings (27%) in holding costs.

The overall cost comparison between each scenario and the baseline is presented in Figure 12. As expected, Scenario 1 has an 11% estimated total cost reduction compared to the baseline while Scenario 4b has an 27% estimated total cost reduction compared to the baseline.

Figure 12

Total Cost Comparison Between ach Scenario and Baseline



5.0 DISCUSSION

In this chapter, we present an analysis of the optimal network design and provide recommendations on the implementation strategy. The network optimization model produced several scenarios that were evaluated based on a set of performance metrics. Based on the results, we have identified the optimal network design that balances costs, service levels, and capacity constraints. The recommendations in this chapter consider the feasibility of implementing the optimal network design, including the risks and limitations associated with the proposed strategy.

5.1 RECOMMENDATION

Analyzing the results of each scenario, we recommended that the sponsor company implements the most optimal network design in phases. Implementing the supply chain network in phases can help reduce the overall risk by breaking down the project into smaller, more manageable chunks. This approach allows teams to focus on one phase at a time, reducing the chance of errors and unexpected problems. Additionally, implementing by phases can help improve optimization by allowing organizations to focus on optimizing each phase before moving on to the next. This approach also ensures that the supply chain network is optimized to meet current needs and can adapt to changes in demand. Lastly, it allows stakeholders to see progress and provide feedback throughout the process, and helps build trust and confidence in the project team.

The first phase is to implement the prescribed model from Scenario 2 while working to increase the capacity of the warehouses by writing off the 35% of the Deadstock materials that have a total stock on hand of 105,887 units. This can potentially result in a more resilient supply chain, in which the warehouses have a supply capacity buffer, which allows them to be responsive to demand as the company moves from 26 warehouses to 13. We recommend this model for Phase 1 because the company has opportunity already to consolidate W004 and W005 LCs into one LC and W003 and W006 into another LC, as they have the same inventory system and legal entities.

The impact from implementing Phase 1 is three-fold: One, there is an estimated annual reduction of $1.5 million from warehouses fixed costs and transportation costs. Two, there is an estimated annual reduction of $1,421,152 from safety stock costs. Three, there is a one-time write-off stock value savings of $80.9 million.

The second phase is to implement the prescribed model from Scenario 2b by reducing the number of warehouses from 13 to 10. This can potentially enable the company to further decrease their warehouses' fixed costs and transportation costs by another estimated annual $1.1 million and $96,480 in safety stock holding costs.

The third phase of the supply chain network implementation involves reducing the number of warehouses from 10 to 8 in accordance with the prescribed model from Scenario 3b. This reduction can potentially be facilitated by the integration of inventory systems across all warehouses and plants. Given that the sponsor company has communicated ongoing efforts to achieve such integration, we propose a phased approach to implementation. Specifically, we recommend beginning with Phase 1 and 2, deferring Phase 3 until after the completion of the integrated system. This approach can potentially enable an iterative implementation process, with each phase providing opportunities to learn and make adjustments before moving to the next phase. In turn, this can potentially help mitigate the risks associated with directly reducing the number of warehouses from 26 to 8.

The fourth, and last, phase is to implement the prescribed model from Scenario 4b by reducing the number of warehouses from 8 to 6. This can potentially enable the company to consolidate inventory into one LC, which further decreases the safety stock by approximately 10,200 units. By the end of Phase 4, the sponsor company would have reduced a total of 65,800 units compared to the current state. This results in a total safety stock holding cost savings of $1,737,358 (27% from current state).

Figure 13 illustrates the optimal warehouses to use in the network and which warehouses to close for Phase 4, in blue and light grey, respectively. It also shows, through a link, the assignment of the corresponding inventory allocation between each warehouse and plant. The link contains a number label to identify the cluster and the supply to fulfill demand from warehouse to plant in Table 14. For example, the link (7) between W001 to plant 001 indicates that 001 is served by warehouse W001 with a supply of 11,192 units for Cluster 0; a supply of 3,752 units for Cluster 1; a supply of 299,493 for Cluster 2; and a supply of 78,240 units for Cluster 3.

Figure 13

Phase 4: Scenario 4b Optimized Supply Chain Network

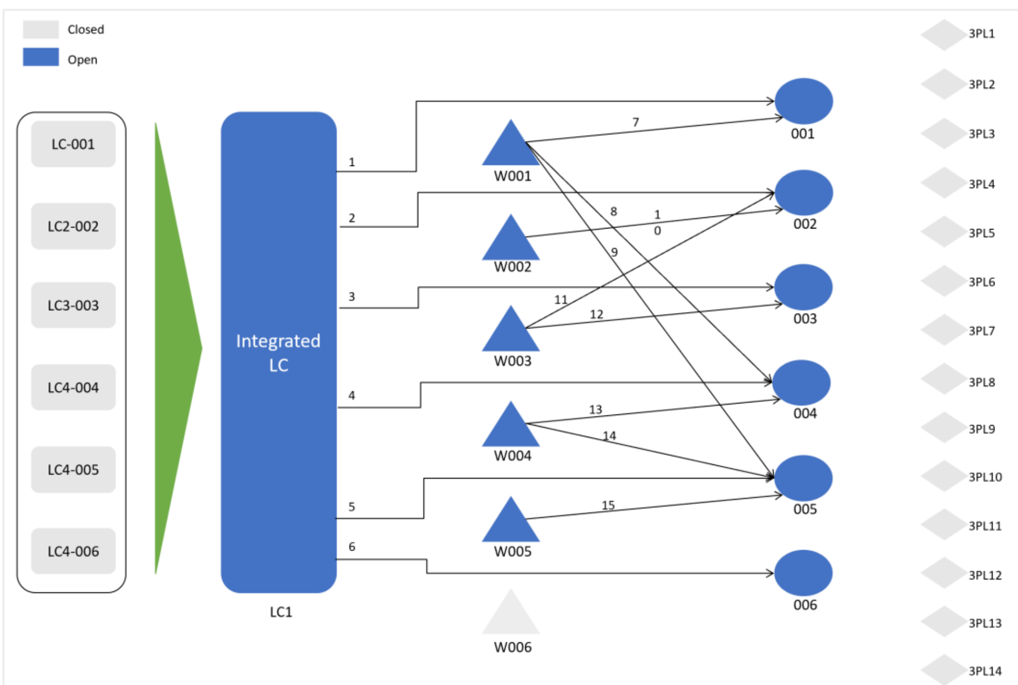


Table 14

Phase 4: Scenario 4b Optimized Supply Chain Network Inventory Allocation (units)

Label	Cluster 0	Cluster 1	Cluster 2	Cluster 3
1	416	1459		
2	7965	11456	863	6240
3	1468	4225		3502
4	1540		2492	2601
5	3499	849		1775
6	8893	10347	20389	10897
7	11192	3752	299493	78240
8			588	
9			5257	940
10	9885	12176	9774	28726
11			3953	
12	15357	3500	247504	30244
13	8250	8250	23962	11345
14		2756		
15	984	20476	4108	1492

5.2 RISKS

In today's fast-paced business environment, companies are constantly seeking ways to optimize their supply chain network to improve efficiency, reduce costs, and enhance customer service, which in our case are internal requests. One of the strategies that we observe is that our sponsor company is considering closing warehouses. However, before making any decisions, it is important to carefully evaluate the potential risks. By taking the explained factors below into account, companies can make informed decisions that can potentially help them achieve their supply chain objectives while reducing risks and costs. Noteworthy, there may be other unanticipated risks not listed in this paper that need to be thoroughly investigated.

Implementation Costs: Closing warehouses may require significant investment in IT systems, processes, and equipment to ensure that the remaining warehouses can handle the increased demand. This can result in higher implementation costs and longer lead times.

Inventory Management Challenges: When warehouses are closed, it can be more difficult to manage inventory levels and ensure that the right parts and equipment are in the right place at the right time. This can lead to excess inventory in some locations and shortages in others.

Supplier Management Challenges: Closing warehouses may require a reevaluation of suppliers and can impact existing contracts and relationships. This can result in increased lead times, higher costs, and reduced service levels if suppliers are not able to meet the new demand patterns.

Inventory Characteristics Challenges: Our model assumed all SKUs can be stored in all warehouses presented as options in our supply chain network. However, there is risk that a particular SKU can only be stored in one specific warehouse, such as at a 3PL location, due to its heavy and bulky characteristics.

5.2 LIMITATIONS

The first limitation in our model is that we calculated demand as the maximum historic demand over the last five years for each plant-material combination. The reasoning is two-fold: One is that considering the maximum historic demand would result in a prescribed model that is very risk-averse and maintains high service levels, which were requirements from the sponsor company. Two is that the data received was aggregated at the yearly level, and thus it was hard to identify a demand distribution by material. However, this limitation may lead to a suboptimal network when considering the variability of demand. Therefore, we suggest a future study that incorporates demand variability as a scenario in the objective function from our mathematical formulation (equation 1 in Section 3.3) that considers the probability of the demand scenario.

The second limitation in our model is that we calculated capacity as the maximum throughput over the last five years and divided it by the average utilization rate of each warehouse. Although we received the warehouse dimensions, we did not have the material dimensions. Thus, we could not compute the space capacity for each warehouse. This limitation may lead to overestimation or underestimation of capacity in certain warehouses, which can affect the optimal design of the supply chain network. In addition, the assumption of a constant utilization rate may not accurately reflect the variability in demand and utilization patterns over time. This may lead to suboptimal capacity allocation decisions, which can negatively impact the overall performance of the network. Future research could explore alternative methods for calculating warehouse capacity that consider more detailed information on material dimensions and demand variability and consider dynamic adjustments in capacity allocation over time. This would enable a more accurate representation of the supply chain network's capacity and improve the quality of the optimization results.

The third limitation in our model is that we did not have supplier inbound data, such as distances, transportation cost, and lead times. The lack of inbound cost data can lead to inaccurate cost estimates for the transportation of MRO inventory. This can have an impact on the overall cost of the system and may result in suboptimal decisions being made. Future research could explore methods for obtaining and integrating supplier inbound data into the supply chain network optimization model, which would enable more accurate cost estimates and lead time calculations and facilitate the identification of more optimal transportation routes and modes.

The fourth limitation in our model is that it did not have inventory management as part of the optimization. The reasoning was that it was out of scope for our project since our sponsor company is already working on establishing an inventory management system from a software company. Nonetheless, it is noteworthy that without considering inventory policies, our mathematical model may result in suboptimal inventory levels, which can lead to stockouts or excess inventory. The problem of determining the optimal inventory levels and order quantities for each facility is critical in ensuring that the overall system operates efficiently; without considering inventory policies, the facility location problem may not provide accurate results. Future research could explore the integration of inventory management policies into the supply chain network optimization model to improve the overall performance of the system. This could involve the development of mathematical models that consider inventory holding costs, order costs, and demand variability, among other factors, to determine the optimal inventory levels and order quantities for each facility.

6.0 CONCLUSION

In oil and gas companies, operational disruptions can result in not only millions of dollars in losses but also negative environmental consequences. To mitigate these risks, companies tend to maintain high levels of Maintenance, Repair, and Operations (MRO) inventory. A 2022 study by a consulting firm revealed that our sponsor company was underperforming in inventory management compared to its competitors, prompting the company to explore ways to reduce MRO inventory holding costs. We sought potential solutions by identifying which components of holding costs can potentially be reduced by implementing an optimization model to redesign the network of plants and warehouses. We hypothesized that an optimized network would allow the sponsor company to break the 1:1 warehouse-to-plant relationship and avoid individual inventory management for each plant. We expected that an optimized network can lead to a reduction in holding costs and potentially enable the company to consolidate its inventory. In that context, we investigated three research questions:

1. Is the current network design of our sponsor company the most cost-efficient?
2. How can our sponsor company redesign their MRO inventory network to reduce holding costs while maintaining target service levels?
3. How can our sponsor optimally allocate inventory within the recommended network?

To address the research questions, we executed a four-step methodology: One, we conducted comprehensive data cleaning and analysis, including plant demand and warehouse throughput to accurately model the current network design. Two, we segmented 19,153 SKUs into four clusters using k-means machine learning algorithm based on their demand characteristics. Three, we formulated and built a network optimization model that links the warehouses to plants by minimizing fixed and transportation costs and allocates the SKU clusters. Fourth and last, we estimated the safety stock reduction by reducing the number of warehouses and consolidating inventory.

For our optimization model, we formulated a Mixed Integer Linear Programming (MILP), with the objective of minimizing inventory holding costs components, including lease fees, maintenance fees, equipment fees, third-party fees, and contract labor costs, as well as the transportation costs of shipping one unit from a specific warehouse to a specific plant. The model generated three primary recommendations: which warehouses to retain and which to close; which specific warehouses should serve specific plants; and how much inventory by cluster should be allocated in each warehouse to fulfill the plants' demand. Constraints considered included throughput capacity, plant demand, existing lease agreement of the Logistics Center (LC), and other constraints such as binary and integer constraints.

We evaluated four main scenarios, each complemented with a sub-scenario that wrote off deadstock to increase warehouse throughput capacity. The key findings that allowed us to answer the research questions were as follows:

1. The current network design has opportunity for improvement. Even in the most conservative scenario maintaining a 1:1 relationship, the model suggests reducing the number of warehouses from 26 to 15, resulting in approximately $1.4 million in savings (a 12% reduction in total cost). Moreover, increasing warehouse throughput capacity by writing off deadstock further improves savings in warehouse expenses and transportation costs.
2. Integrating inventory systems and legal entities results in higher savings compared to a decentralized network. For example, a 1:1 optimal solution yields 12% savings in total cost, whereas a fully integrated system and legal entities increases savings to 17%. Writing off deadstock further boosts savings to 27%.
3. Reducing the number of warehouses has a positive impact on inventory needs, with safety stock decreasing in all scenarios. In the most conservative scenario, the required safety stock is reduced by 30%, resulting in 22% savings in holding costs. In the most ambitious yet realistic scenario, the required safety stock is reduced by 48%, yielding 27% savings in holding costs.

We conclude that the current network design is not optimal and that integrating inventory systems and legal entities can potentially enable the sponsor company to save on warehouse expenses, transportation costs, and inventory holding costs associated with safety stock. We recommend implementing the optimal network in phases, progressing from Scenario 1 to 4b (described in Sections 4.1 through 4.4), to reduce the risk of implementation failure due to complexity or uncertainty. Each subsequent phase can build upon the previous one.

Future research or projects on this topic could include incorporating demand variability into the objective function of a mathematical formulation to consider the probability of the demand scenario and avoid a suboptimal network. Another project we recommend is to explore alternative methods for calculating warehouse capacity based on detailed information on material dimensions. This would enable a more accurate representation of the supply chain network's capacity and improve the quality of the optimization results. Additionally, research could be conducted on obtaining and integrating supplier inbound data into supply chain optimization models to improve cost estimates and transportation route planning. Finally, integrating inventory components into the model could provide more accurate estimates of safety stock savings.

Through this study we described the importance of segmenting the vast MRO inventory that they hold based on their demand characteristics and design a supply chain network to consolidate such inventory. We believe these findings are relevant not only to our sponsor company or other Oil & Gas companies, but also to other utilities including power and pipelines. We encourage researchers or professionals who review our analysis to view our study and MILP model not just as a way to lower costs, but also as a decision support tool to facilitate future enhancements in processes.

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APPENDICES

Appendix A

Table A1

Data Dictionary for Stock List Data

Column	Description
Plant	Refinery or chemical plant code
Material	MRO SKU number
Bin/Batch	Indicates that the SKU is in the Logistics Center if it starts with the letter “T”, or that the SKU is stored in a 3PL if the it contains the name of the 3PL, or else is stored in the onsite warehouse of the plant associated with the SKU.
Movement Frequency	Description of the usage of the product over a time period
Category Family	High-level description of the product
Creation Date	The date when the material was created in inventory system
UoM	Material quantity unit of measurement
Planned Delivery Time	Lead time between order placement and receipt of order at warehouse
Safety Stock	amount of inventory that a company holds in excess of its normal inventory needs
SOH	Stock on hand at time of report
Stock Value (USD)	The dollar value of SOH
Year1 GI Qty	Year 2018 shipment quantity
Year2 GI Qty	Year 2019 shipment quantity
Year3 GI Qty	Year 2020 shipment quantity
Year4 GI Qty	Year 2021 shipment quantity

Column	Description
Year5 GI Qty	Year 2022 shipment quantity

Appendix B

Table B1

Data Dictionary for Off-site Data

Column	Description
Plant	Refinery or chemical plant code
Material	MRO SKU number
Storage Bin	Third party warehouse where the material is stored to fulfill demand of Plant

Appendix C

Table C1

Data Dictionary for Site Location Data

Column	Description
Location	Warehouse or plant code
Site	Site's name
Type	Refinery or chemical plant
Legal Entity	Site's legal entity code
System	Site's Inventory system
Location	Site's City and state
Address	Site's address

Appendix D

Table D1

Safety Stock (Units) Estimation

Scenarios		Old Safety Stock	New Safety Stock	% Decrease
Scenario 1	All	137,935	104,738	24.1%
	Cluster 0	20,709	15,730	24.0%
	Cluster 1	49,897	37,781	24.3%
	Cluster 2	39,127	29,720	24.0%
	Cluster 3	28,202	21,421	24.0%
Scenario 1b	All	137,935	96,531	30.0%
	Cluster 0	20,709	14,498	30.0%
	Cluster 1	49,897	34,764	30.3%
	Cluster 2	39,127	27,398	30.0%
	Cluster 3	28,202	19,742	30.0%
Scenario 2	All	137,935	101,487	26.4%
	Cluster 0	20,709	14,643	29.3%
	Cluster 1	49,897	35,172	29.5%
	Cluster 2	39,127	27,667	29.3%
	Cluster 3	28,202	19,942	29.3%
Scenario 2b	All	137,935	88,118	36.1%
	Cluster 0	20,709	13,234	36.1%
	Cluster 1	49,897	31,734	36.4%
	Cluster 2	39,127	25,010	36.1%
	Cluster 3	28,202	18,022	36.1%
Scenario 3	All	137,935	97,505	29.3%
	Cluster 0	20,709	14,643	29.3%
	Cluster 1	49,897	35,172	29.5%
	Cluster 2	39,127	27,667	29.3%
	Cluster 3	28,202	19,942	29.3%
Scenario 3b	All	137,935	82,320	40.3%
	Cluster 0	20,709	12,363	40.3%
	Cluster 1	49,897	29,646	40.6%
	Cluster 2	39,127	23,364	40.3%
	Cluster 3	28,202	16,836	40.3%
Scenario 4	All	137,935	90,262	34.6%
	Cluster 0	20,709	13,554	34.6%
	Cluster 1	49,897	32,550	34.8%
	Cluster 2	39,127	25,615	34.5%
	Cluster 3	28,202	18,457	34.6%
Scenario 4b	All	137,935	72,120	47.7%

Scenarios		Old Safety Stock	New Safety Stock	% Decrease
	Cluster 0	20,709	10,601	48.8%
	Cluster 1	49,897	25,784	48.3%
	Cluster 2	39,127	20,572	47.4%
	Cluster 3	28,202	14,667	48.0%