Optimizing the Logistics Network for Pipeline Inspection

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ABSTRACT

The sponsor company for this capstone has a complex logistics network due to the fact they use a service model for their products. Their products use advanced technology to service water, wastewater, oil, and gas pipelines across the world. This requires managing the movement of these products from their inventory holding locations to the customer site in both the forward and reverse directions, as well as for maintenance operations. The goal of this capstone is to assess a supply chain network and make recommendations for the sponsor company to minimize logistics costs while maintaining high service levels and high product utilization rates. We optimized the current network using the uncapacitated Facility Location Problem. This allowed us to identify the number of facilities required to serve all the North America projects and cluster the demand geographically. Based on historical data, we then used forecasting techniques to establish an inventory policy for the product families under analysis for every inventory holding location. The proposed optimized network could lead to a total mileage reduction of 20%, reducing cross-border shipments and streamlining operations.

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- Aviva Kosansky & Alessandro Scutari

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1 INTRODUCTION

1.1 Motivation

To cut costs in the supply chain, it is critical to understand the network and product demand. Having an understanding of how the network operates allows one to find inefficiencies and then optimize the network to obtain lower costs. An optimal network minimizes transportation costs and unnecessary shipments, leading not only to lower costs but also to increased service levels. An accurate demand forecast can lead to lower inventory costs and less expedited shipments, which, in turn, will lead to lower transportation costs. Lastly, accurate inventory policies will also lead to lower transportation costs, as there is less movement of parts between hubs, as a part should already be located in its optimal hub.

The sponsor company for this capstone is interested in understanding the baseline inventory needed at each of their hubs to minimize their transportation costs. In this study we focus on the North America operations for two different product families. Currently, the sponsor company has three main pain points we look to address in this project.

First, the division of the sponsor company we are working with has four main hubs in North America; two located in Canada and two in the United States. These hubs refer to inventory holding locations, and some of the hubs are also capable of tool maintenance and repairs. For the two product families we will focus on, most of the inventory is held in Canada. This is mainly due to the fact all major repairs can only be performed in the Canadian hubs. Given this, the company constantly ships tools across the border, which can be costly and cause delays when going through customs. Because shipping across the border is one of the pain points our sponsor company wants to eliminate, we do not allow cross-border shipments in our optimal solution.

Second, the company currently does not have a demand planning process, and therefore allocates tools to jobs on a first-come-first-served basis from the nearest hub to the project. This can be costly, as the nearest hub with inventory may be across the country or in another country.

Third, the lack of demand planning can lead to project delays and poor customer service. The sponsor company would like to investigate how optimizing their network and implementing an inventory policy could help eliminate these three pain points.

Given the background, this project investigates how to reduce the sponsor company's costs for tool shipments, while maintaining the appropriate inventory in their hubs. This project is modeled in two steps. First, we address the network design optimization problem to find the optimal shipment hub for each project site. Next, we focus on the inventory management of each hub to be able to effectively address the project demand and maintain high service levels. In this project we provide insights into the optimal shipment network for each project location and the baseline inventory stock for each hub to be able to manage demand.

1.2 Sponsor Company

The sponsor company for this project is a leading water technology company that develops innovative solutions and smart technologies related to the world's water, from agricultural and industrial use to drinking and wastewater. The division of the company we are focused on is the Assessment Services division. They facilitate projects with tools enabled with proprietary technology to assess and repair water pipelines. Applications cover a wide range of services related to pipeline assessment, inspections, and infrastructure monitoring. The company also provides specialized engineering services such as analytics on the pipelines. The Assessment Services division we are focusing on offers 15 different tool families. Each family contains a tool kit, which is comprised of a main part along with multiple spare parts. For the purposes of this project, we focus on the network design and inventory management of the main part of two product families.

2 LITERATURE REVIEW

This project focuses on the optimal trade-off between costs and service level for the shipment of tools from hub to project site. Additionally, we analyze the best baseline inventory policy for each hub based on the optimal network.

To tackle this problem, we focus our research on the *supply chain network design* literature. Among the wide spectrum available, we narrowed down the research to scientific papers that fit appropriately to our business case, analyzing *facility locations* and the flow of material. Moreover, given the necessity to understand which product to keep in inventory in which location, we look at the literature of best practices in *inventory management* and *forecasting techniques.*

2.1 Network Design

There are typically three levels of decisions in supply chain management (SCM) *strategic, tactical, and operational* (Melo et al., 2007). The *strategic* level addresses long-term planning decisions (e.g. 3 to 5 years) in terms of supply chain (SC) configuration; at this stage, management evaluates problems such as the number of facilities, their geographical location, the capacity, and the demand allocation (Manzini & Bindi, 2009). The *tactical* planning refers to the efforts to find the best configuration of inventory, fulfillment policies, transportation mode, and flow of material in the SC, both for the short and long term (Manzini & Bindi, 2009). Lastly, at the *operational* level, companies manage the supply chain network for the short-term scheduling, defining daily operations related to supply and vehicle routings to support customer demand (Manzini et al., 2011).

The Supply Chain Network Design (SCND) problem consists of making decisions to satisfy customer demands while minimizing the sum of strategic, tactical, and operational costs (Mohammadi Bidhandi et al., 2009) .

Supply Chain Network Design looks at the movement of products throughout their lifecycle. In this study, we focus on the *strategic* and *tactical* decisions, which have lasting effects on a company over the long and medium term, respectively. There are many different types of SCND models. Since one of our primary research objectives is to find the optimal locations for the sponsor company's hubs, we mainly focus on the *facility location problem.*

2.2 Facility Location Problem

The problem of finding the optimal set of locations to minimize transportation costs while considering other factors (such as maximizing service level) is known in literature as the *facility location problem* (FLP) (Farahani et al., 2015). Since we need to consider inventory management, we looked at a sub class of literature on facility location problems which integrate inventory management decisions. This category of literature is known as the *location-inventory problem* (LIP) (Farahani et al., 2015). According to Farahani et al. (2015), the goal of the LIP is integrating strategic supply chain design with tactical and operational inventory management decisions. A typical LIP is structured with predetermined supply location, and tries to identify the optimal number of hubs, allocate customers to each hub, and optimize the inventory service level at each hub (Farahani et al., 2015). While the LIP is a good way of assessing inventory, due to data constraints we did not use LIP.

Another subclass of facility location problem is called *fixed charge facility location problem*, in the forms of both *uncapacitated* and *capacitated* (including capacity constraints) formulations (Daskin, 2013). According to this model, *fixed costs* are used to open facilities and the *operating costs* are used in relation to the routing to serve all the customers from a certain location. Due to lack of data regarding operating costs, we did not implement this subset of the FLP.

For the solution of these optimization problems, Daskin (2013) introduces heuristic construction and exchange algorithms that can be used to find the optimal solutions as these problems are NP hard. The main algorithms used are ADD, DROP, EXCHANGE, and HYBRID.

ADD algorithm adds facilities to the solution until the algorithm fails to find a facility whose addition results in a decrease of the total costs (Appendix 1).

DROP algorithm removes facilities from the solution until the algorithm can no longer find a facility whose removal results in a decrease of total costs (Appendix 2).

SUBSTITUTION algorithm: it starts with a set of facility sites and considers every possible combination of nodes in the current solution and nodes not in the current solution. After all combinations have been evaluated, it looks for the best combination that reduces the total cost. It stops when the next combination does not result in cost savings (Appendix 3).

HYBRID: it combines the substitution, add, and drop algorithms to find an optimal solution (Figure 2).

The main performance metric of the FLP is cost-based (Farahani et al., 2014), and the primary cost components of the FLP include location, transportation from hubs to customers, and inventory of finished goods. Due to the nature of the data from the sponsor company, we use the uncapacitated FLP.

2.3 Inventory Management

As introduced in Section 2.1, network design deals with *strategic, tactical, and operational* supply chain decisions. The *tactical* level looks for the best configuration of inventory and fulfillment policies and once that has been determined, the optimal network. In our case, the inventory model for probabilistic demand is used to understand the possible approaches about what quantity should be kept in stock and where to store the products we are analyzing.

Silver et al. (2017) defines four types of control systems for inventory policy:

1. *Order-quantity (s,Q)*
2. *Order-Point: Order-up-to-Level (s,S)*
3. *Periodic Review: Order-up-to-Level (R,S)*
4. *Hybrid (R,s,S) System*

We use the *Order-Point, Order-up-to-Level (s,S)* inventory policy. Under this policy, whenever the inventory position falls to or below a reorder level s, an order is placed to raise the item's inventory position to order-up-to level S (Bijvank, 2014).

When defining an inventory policy, it is important to look at all the costs associated with holding inventory at a location. Location costs consist of the *fixed costs* (costs to establish a facility) (Farahani et al., 2015); *inventory holding costs* (the cost of carrying items in inventory); *ordering or setup costs (*fixed costs associated with replenishment); and *costs of insufficient capacity in the short run (*cost of avoiding stock-outs or the cost that is incurred when stock-outs occur) (Silver et al., 2017); in industry practice, the final three costs mentioned are referred to as safety stock, backordering, and shortage costs.

2.4 Forecasting Models and Techniques

To define accurate policies in inventory management, it is necessary to have an appropriate understanding of possible demand in future periods. Forecasting models deal with demand uncertainty, as well as informed judgements of the specific business, such as maintenance requirements, and customer needs. Common practice in the industry is to deploy time-series forecasting models, in which demand history is used to forecast the future demand (Silver et al. 2017).

According to the framework in Silver et al. (2017), time series are composed of five components: *level* (the "scale" or magnitude of the demand); *trend* (the rate growth or decline over time)*; seasonal variation* (which can be caused by natural forces or human decisions)*; cyclical movements* (repetition of patterns over the same time period)*;* and *irregular random fluctuation* (unexpected spikes or drops in demand)*.* For individual-item/short-term forecasting, these features are used to determine the best model to fit the historical data.

There are several forecasting techniques used in practice and they are applied based on the characteristics of demand. The Exponential Smoothing model is used when the underlying demand is composed of level and random components (like trends and seasonality), but it can be ineffective where transactions occur on infrequent basis (Silver et al., 2017). When demands shows characteristics of "intermittency" and "erraticism" Croston's method is used (Silver et al., 2017). It considers non-zero demand size and the inter-arrival time between successive demands using exponential smoothing, with forecasts being updated only after demand occurs. (Shenstone & Hyndman, 2005). Lastly, for demand with seasonality, the Holt- Winter Exponential Smoothing Model (Silver et al., 2017), which assumes a multiplicative seasonality effect over level and trend is used.

To identify a good forecasting method, best practice is to test empirically the alternatives on the demand series to assess which one is the most accurate and choose the method with the smallest error. In the case of intermittent demand, error measures such as Mean Percent Error (MPE) and Mean Absolute Percent Error (MAPE) are not applicable as they are divided by the demand which in these cases will be zero. Alternative methods are required for intermittent demand, and two common scale-dependent measures are the Mean Squared Error (MSE) and the Root Mean Squared Error (RMSE) (Prestwich et al., 2014).The RMSE is an important metric, because it is used as a proxy for the standard deviation of the demand, which is a factor used to estimate the safety stock level.

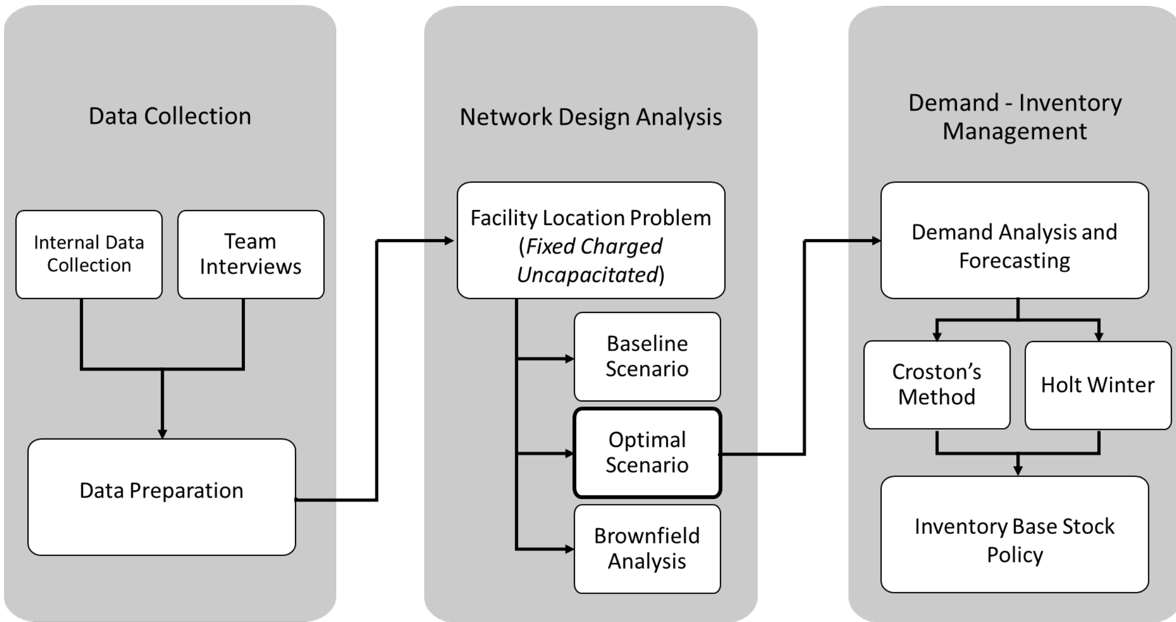
Given the complex logistics in the daily operations of the sponsor company, we will model the problem at a strategic level, integrating literature on the facility location problem. Moving from the strategic to tactical level, we use Croston's Method and Holt-Winter to forecast the demand depending on the observed trends and patterns.

3 METHODOLOGY

In this chapter we discuss the process used to analyze the current network flow, our approach to finding the optimal solution of the network flow, and the forecasting methods used. The project is developed with available shipment data dating back to mid 2020, as well as project location data for each of the two product families dating back to 2019. Each project relies on a tool kit which is made up of a main product (one pallet) plus additional spare parts. We focus our analysis on the main product of each tool kit as that is where most of the shipping costs and difficult logistics are. As shown in Figure 1 first, we collect the data, use it to recreate the current baseline; second, we propose an initial mathematical model for optimizing the network; and third, we discuss the forecasting methods used to model the demand and identify an inventory policy.

Figure 1

Workflow Diagram



3.1 Network Optimization Mathematical Formulation

Once we have defined the network in terms of flow of materials and demand for both volume and geographical distribution, the next step is to formulate the mathematical model that is the starting point of our analysis. As introduced in Section 2, the study is structured as a Facility Location Problem. Our model aims to define the optimal number of hubs and their optimal placement based on the historical demand.

We use the f*ixed charge facility location problem* to model the location and transportation costs (Daskin, 2013). Since we are not including capacity (tool availability) and demand constraints in our initial model, we use the u*ncapacitated FLP model* as a starting point.

We formulate the problem to minimize the sum of locations and transportation costs:

$\boldsymbol{Inputs}$

$f_j = fixed\ cost\ of\ locating\ at\ candidate\ site\ j \in J$

$h_i = demand\ at\ node\ i\ \in I$

$d_{ij} = distance\ from\ demand\ node\ i \in I\ to\ candidate\ location\ j \in J$

$\alpha = cost\ per\ unit\ distance$

$\boldsymbol{Decision\ Variables}$

$$X_j = \begin{cases} 1\ if\ we\ locate\ at\ candidate\ site\ j \in J \\ \qquad\qquad 0\ if\ not \end{cases}$$

$Y_{ij} = fraction\ of\ demand\ from\ node\ i$
$\qquad \in I\ that\ is\ served\ by\ a\ facility\ at\ candidate\ location\ j \in J$

Following the notation from Daskin (2013), we formulate the problem as:

$$\boldsymbol{MINIMIZE}\ \sum_{j \in J} f_j X_j + \alpha \sum_{i \in I} \sum_{j \in J} h_i d_{ij} Y_{ij} \tag{1}$$

$\boldsymbol{SUBJECT\ TO}$:

$$\sum_{j \in J} Y_{ij} = 1 \qquad \forall i \in I \tag{2}$$

$$Y_{ij} \le X_j \qquad \forall i \in I;\ j \in J \tag{3}$$

$$X_j \ \in \{0,1\} \qquad \forall\, j \in J \tag{4}$$

$$Y_{ij}\ \ge 0 \qquad \forall i \in I;\ j \in J \tag{5}$$

The objective function is the sum of the fixed facility costs and the total demand-weighted distance multiplied by the cost per unit distance per unit demand. The first constraint (Equation 2) says that each demand node $i \in I$ must be served. The second constraint (Equation 3) says that demands at node $i \in I$ cannot be assigned to a facility at candidate site $j \in J$ unless the facility at node $j \in J$ is open. The last two constraints (Equations 4 and 5) are the integrality and nonnegativity constraints, respectively. Since the facilities are uncapacitated, all demand at node $i \in I$ is assigned to the nearest open facility. Thus, the assignment variables, Y_{ij} will naturally assume integer values (Daskin, 2013).

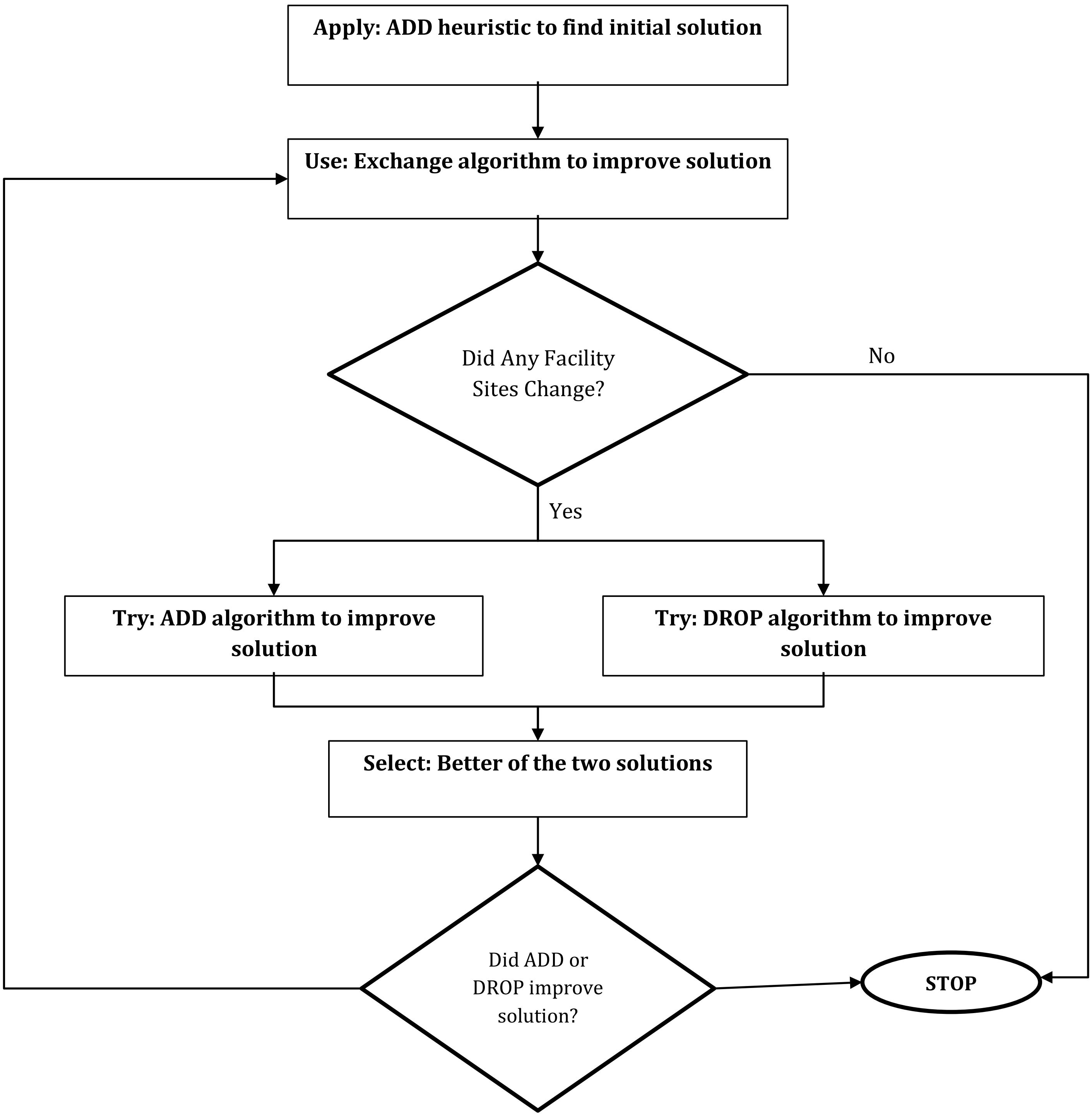
3.2 Solution Algorithms and Software Implementation

The next step after the mathematical formulation of our problem, is to collect data to assess the operations of the Sponsor Company. Then, analyze improvements to the current status using the optimal allocation of the demand to each hub.

For our problem, we implement the *HYBRID* algorithm (Figure 2), as we consider the implication of adding a hub to the network (ADD), removing a hub from the network (DROP), and reallocating the flow of equipment on the existing network to minimize the overall cost (SUBSTITUTION). The algorithm starts with an initial heuristic solution, then it iteratively adds and drops candidate locations while looking for a better solution. It also will add a new candidate location if it improves the overall objective function.

Figure 2

Hybrid Algorithm (Daskin 2013)



The next step is to formulate the optimization problem using network optimization software, run simulations, and compare the current status with the optimal solution proposed by the model. For our project, we use Llamasoft[1], a supply chain design tool that integrates optimization and scenario analysis into a user interface, to do our analysis.

The three main steps of our analysis are:

- Create the baseline scenario to model how the network is currently.
- Run the optimal baseline scenario removing all current nodes.
- Run Greenfield analysis to see the impact of adding or removing a storage facility.

The first scenario is the Baseline Scenario. There is no analysis or optimization included in the baseline scenario, it is simply a representation of the origin-destination pairs over the time period. For this we use the shipping data that went back to June 2020, which allowed us to see the origin and destination for each shipment. This is not an exhaustive list of shipments, however it does provide valuable insight into the general flow of products today.

This second scenario optimizes the current origins and destinations to find the lowest-cost pairs. By removing the flow constraints (the directional limitation of the tool movement) on the origin-destination pairs we minimize the overall cost and find the optimal origin for all the destinations assuming unlimited capacity.

The Greenfield Analysis scenario uses the optimal baseline scenario and looks at where to add an additional satellite location to continue to minimize costs. It is the process of formulating new network design strategies where there are currently no existing sites (Radanliev, 2015). Brownfield analysis refers to a specific subset of this problem where only one additional site in considered instead

[1] https://llamasoft.com/supply-chain-guru/

of an infinite amount. We used the Brownfield subset of the Greenfield analysis to suggest a new hub location for the sponsor company's network.

3.3 Demand Analysis and Forecasting

The next step is to find the monthly demand for each hub and create a demand forecast. To start, we used the results from the optimal network scenario optimization along with the original project data to allocate monthly demand to each hub. Next, we looked at the project data in a time series to understand any seasonality and trends in the data. Given these observed trends and patterns, we used either Croston's Method or Holt Winter to forecast the demand at each hub for the two products, A and B. Finally, using the forecasts we created a baseline inventory policy for each product (A and B) at each hub.

The Croston's Method is used when demand is intermittent. Specifically, we used this method when there were no trends in the data or there were many months without any projects allocated to a given hub. This method considers two components of the demand process: the time between consecutive transactions and the magnitude of single transactions (Silver et al., 2017). According to the model, the demand in period t x_t is:

$$x_t = y_t z_t \tag{6}$$

With:

$$y_t = \begin{cases} 1 \; if \; a \; transaction \; occurs \\ 0 \; otherwise \end{cases}$$

And z_t is the size of the transaction in time t.

$P\{y_t = 1\} = {}^{1}/_{n}$ is the probability that a transaction occurs, and $P\{y_t = 0\} = 1 - {}^{1}/_{n}$ the updating procedure becomes:

- If $x_t = 0$ (no demand occurs): $\hat{z}_t = \hat{z}_{t-1}$ and $\hat{n}_t = \hat{n}_{t-1}$;
- If $x_t > 0$ (demand occurs): $\hat{z}_t = \alpha x_t + (1-\alpha)\hat{z}_{t-1}$ and $\hat{n}_t = \beta n_t + (1-\beta)\hat{n}_{t-1}$

Where:

α, β are the smoothing parameters for magnitude and demand frequency, respectively;

n_t = number of periods since the last transaction;

$\hat{n}_t$ = estimated value of n at the end of period t;

$\hat{z}_t$ = estimate, at the end of period t, of the average demand size;

The final updated forecast is:

$$\hat{x}_{t,1} = \widehat{z_t}/\widehat{n_t}$$

When the demand is intermittent, the safety stock is determined using the mean square error of nonzero-sized transaction $MSE(z)$, which is updated each time a transaction occurs, and is:

$$New\ MSE(\omega) = \omega(x_t - \widehat{z_{t-1}})^2 + (1-\omega)OldMSE(z), \qquad x_t > 0 \tag{7}$$

The Holt-Winter model is used when there is significant seasonality within a product demand pattern. We applied this method for hubs where there were significant trends in the demand data with seasonality. The underlying model is:

$$x_t = (a + bt)F_t + \epsilon_t \tag{8}$$

Where:

a = the level

b = the linear trend

F_t = seasonal factor for time t

ϵ_t= independent random variables with mean 0 and constant variance σ^2.

We considered a period P = 12 months, with 1-month forecasting interval. So, looking at the underlying model, the estimates and updates of a, b and F are determined by the following procedure (Silver et al., 2017):

$$\hat{a}_t = \alpha_{HW}\left(\frac{x_t}{\hat{F}_{t-P}}\right) + (1-\alpha_{HW})\left(\hat{a}_{t-1} + \hat{b}_{t-1}\right) \tag{9}$$

$$\hat{b}_t = \beta_{HW}(\hat{a}_t - \hat{a}_{t-1}) + (1-\beta_{HW})\hat{b}_{t-1} \tag{10}$$

$$\hat{F}_t = \gamma_{HW}\left(\frac{x_t}{\hat{a}_t}\right) + (1-\gamma_{HW})\hat{F}_{t-P} \tag{11}$$

With α_{HW}, β_{HW} and γ_{HW} the smoothing factors.

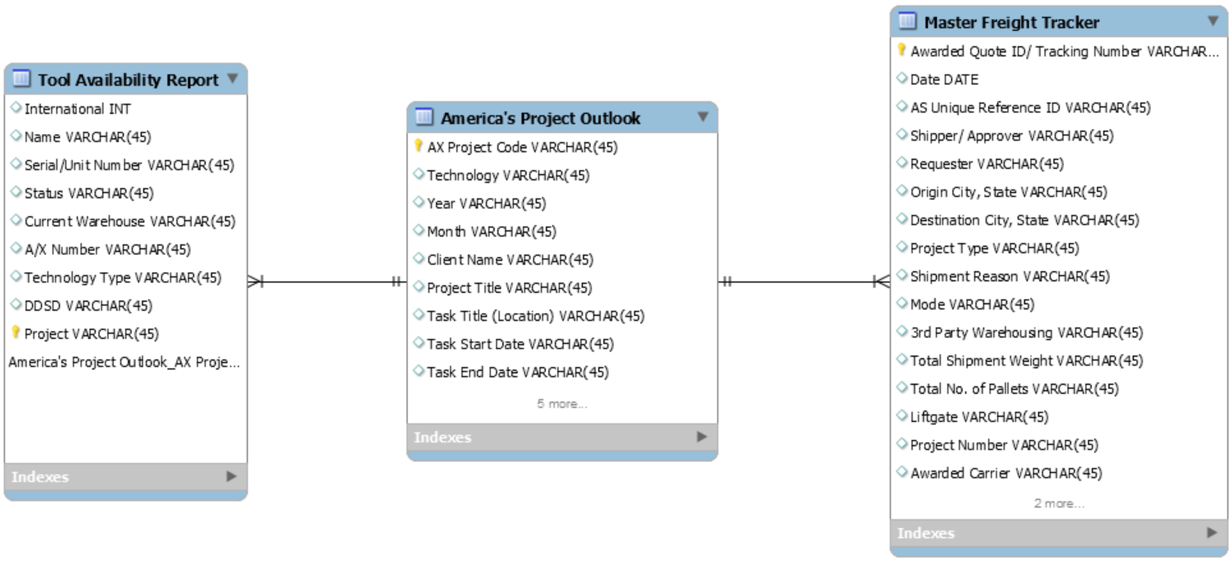
3.4 Data Collection

The sponsor company tracks their data in Excel and in a database. For this project we use three data sources. As shown in Figure 3, the America's Project Outlook table gives information about the project site locations, technology used and date of project. The Master Freight Tracker table contains the shipping data by tool, pairs of origin-destination sites and the cost of intra-hubs movements. The Tool Availability Report table maps the current availability and inventory location of each tool. The data on the project site locations goes back to January 2019 and includes information on the location of each project by tool. The shipping data goes back to June 2020 and includes information on the costs of tool shipments sent via a carrier or third-party logistics provider from origin to destination. This data does not have a 1:1 relationship with the project data, as some shipments are not tracked. These are typically for projects near hubs where the tools are driven out to the site directly from the hub. Lastly, the current availability of each tool is a snapshot of what is available on the day the data is pulled.

We use the geographical distribution of the demand from the project file to gain insights on the locations of each project. We use the shipment data for a deeper look into the movement of the equipment in the current network. The customer demand is spread out over North America, with most of the demand concentrated on the coasts and in large cities.

Figure 3

Sponsor Company Data Tables



Our process uses and combines the various data points from the sponsor company to be able to create a holistic view of their demand and network with the ultimate goal to create a baseline inventory policy for each hub. Next, we discuss the results of this process.

4 RESULTS AND ANALYSIS

In this section, we present the results of the models and forecasting methods described in Section 3. We start with an overview of the network design, and then discuss the demand allocations for each hub and product, followed by the results of the forecasting method used to create each inventory policy.

4.1 Network Design

In our network design analysis, we started with modeling the current baseline for shipments of Product A and Product B. Next, we removed flow constraints from the baseline model, to find the optimal flow of products on the network. Lastly, we looked at where we could add an additional hub based on the historic project locations to minimize shipping costs.

4.1.1 Baseline Model

Our first step was to look at the current network with the data we had from June 2020 to present (Figure 4). From this we found for product A, approximately 30% of the projects involved cross border shipments, and only 10% of projects for product B involved cross-border shipments. Additionally, we found non-optimal shipments, ones from hubs that were not the closest hub to a given project. When we ran this through our model, we found an estimate of the total annual distance of this network to be 61,820 miles for Product A and 82,031 miles for Product B. It is important to note we only had data for June 2020 through March 2021; therefore, the total annual distance estimate is calculated based on the known data (75% of demand) plus a calculated percentage of the unknown shipments (25% of demand).

Figure 4

Baseline Network

4.1.2 Optimized Baseline Model

The next step we took in our analysis was to find the optimized baseline model, minimizing distance and therefore cost, for each product A and B. Based on the demand and the constraint of not sending products across borders we found the optimal origin-destination pairs for Products A and B as shown in Figure 7 and 8 respectively. The optimized baseline origin-destination pairs found are used to understand the optimal distribution of demand on each hub to calculate the inventory policy.

4.1.2.1 Product A

When we optimized the origin-destination pairs for product A, we found that the total distance saved on shipments annually was 17,303 miles. This equates to a 28% savings on the total annual mileage.

Figure 5

Optimized Solution Product A

4.1.2.2 Product B

When we optimized the origin-destination pairs for product B, we found that the total distance saved on shipments annually was 20,865 miles. This equates to a 25% savings on the total annual mileage.

Figure 6

Optimized solution Product B

4.1.3 Greenfield Analysis

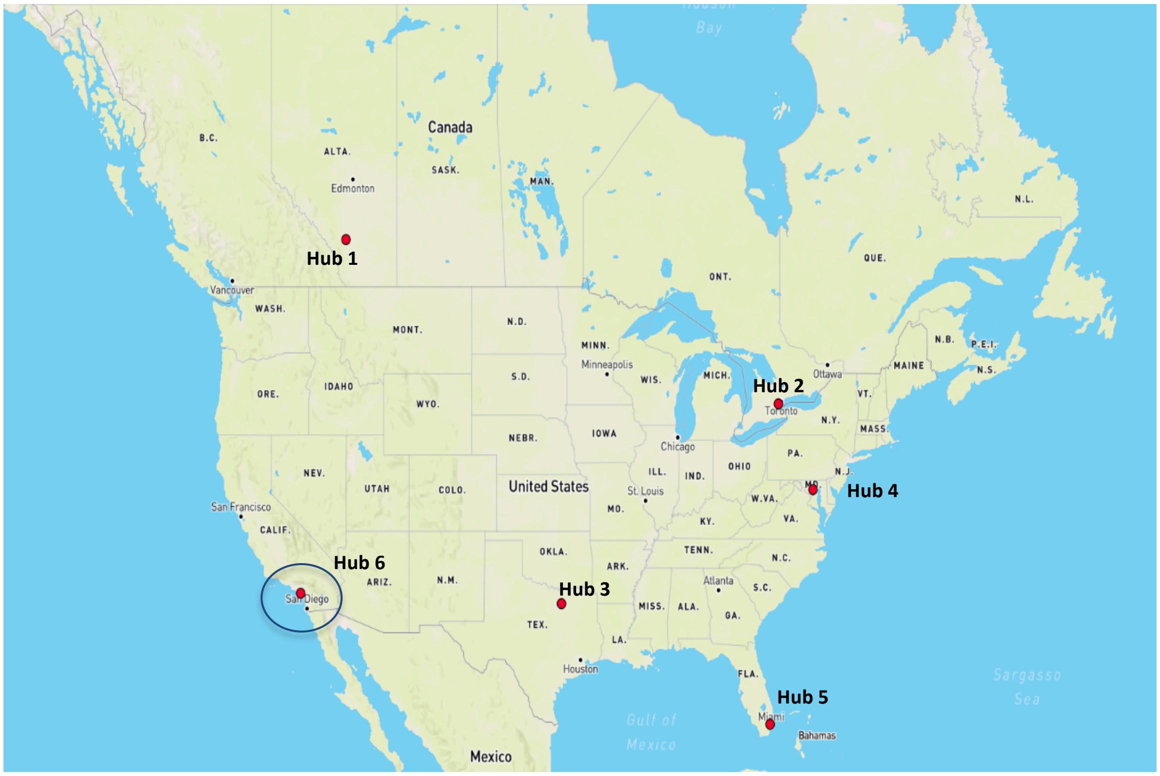
The next step in the analysis was to investigate where a hub could be added to minimize the total distance of the network and therefore the total transportation costs. We ran the Greenfield analysis on Product A and B separately, based on their demands, and compared the results. We found in both cases (Figures 9 and 10) that the optimal location for adding a hub would be in Southern California.

4.1.3.1. Product A

Based on the demand for Product A we found the best location to add a hub would be in Southern California.

Figure 7

Brownfield Site Product A

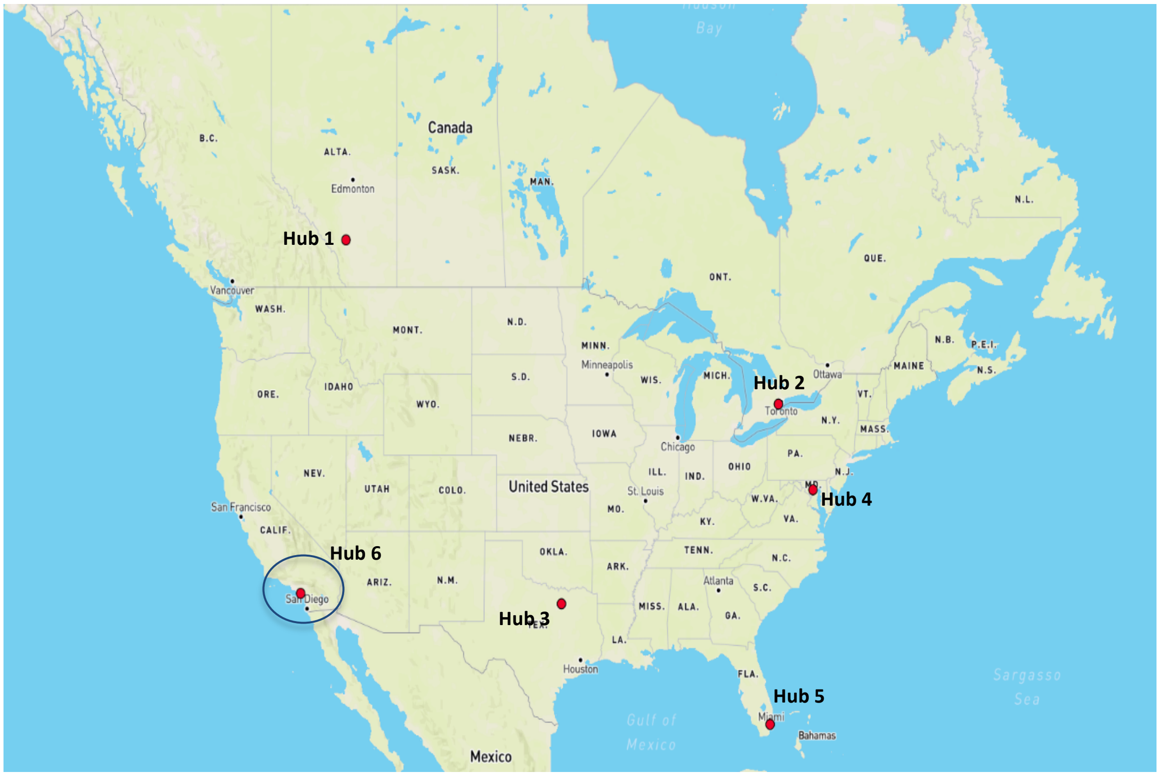


4.1.3.2 Product B

Based on the demand for Product B we found the best location to add a hub would be in Southern California.

Figure 8

Brownfield Site Product B



4.2 Demand Forecasting by Hub

Once we found the optimal network for the distribution of projects, we allocated the demand to each optimal origin hub and assessed the demand. Based on the demand distribution we looked at the forecast for each hub and product. Depending on the distribution of the demand at each hub we used different forecasting methods to determine the best inventory policy for each product and hub. Overall, we found there was seasonality in the demand, with more demand in the spring and fall months. Additionally, we found there to be more demand for projects in the US than in Canada.

4.2.1 Hub 1 Demand and Analysis

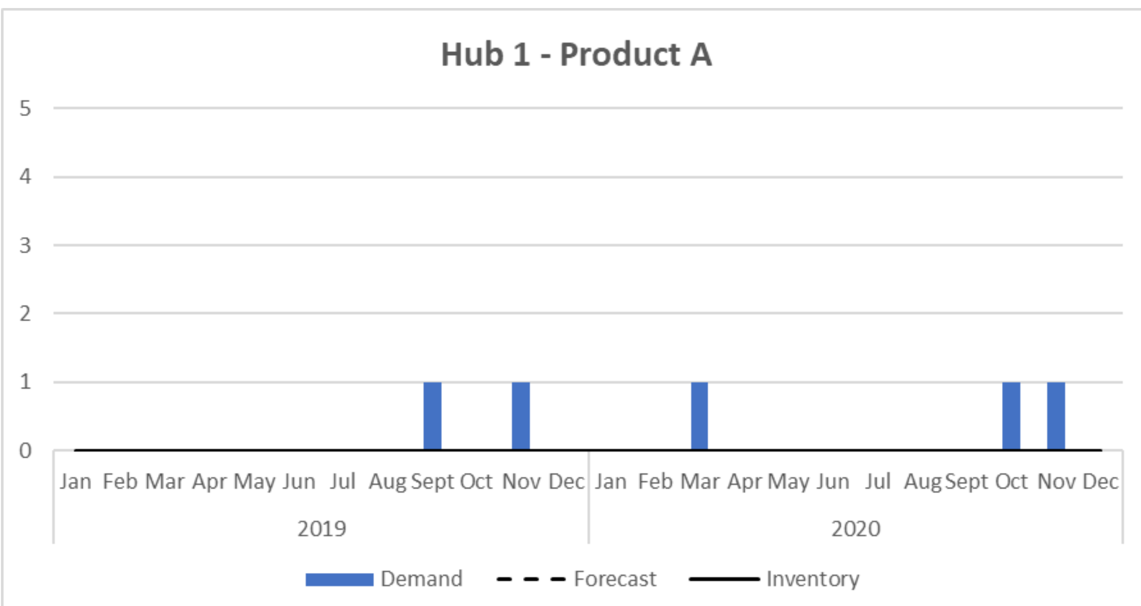
4.2.1.1 Product A

The demand for Product A at Hub 1 is very sporadic and low. Given this, we used Croston's Method to forecast demand and found that the optimal inventory policy was to not keep any inventory at Hub 1 for Product A.

As introduced in Section 2, a key quantity to establish safety stock for intermittently demanded items is the Mean Squared Error MSE(z), defined per equation (7). MSE(z) is also used as a proxy for forecast accuracy. The lower the MSE, the more accurate the forecast. Our proposed forecast produces an MSE(z) = 0.34. As shown in Figure 9, the demand is so intermittent that the model is not able to predict the demand.

Figure 9

Demand allocation Hub 1 -Product A

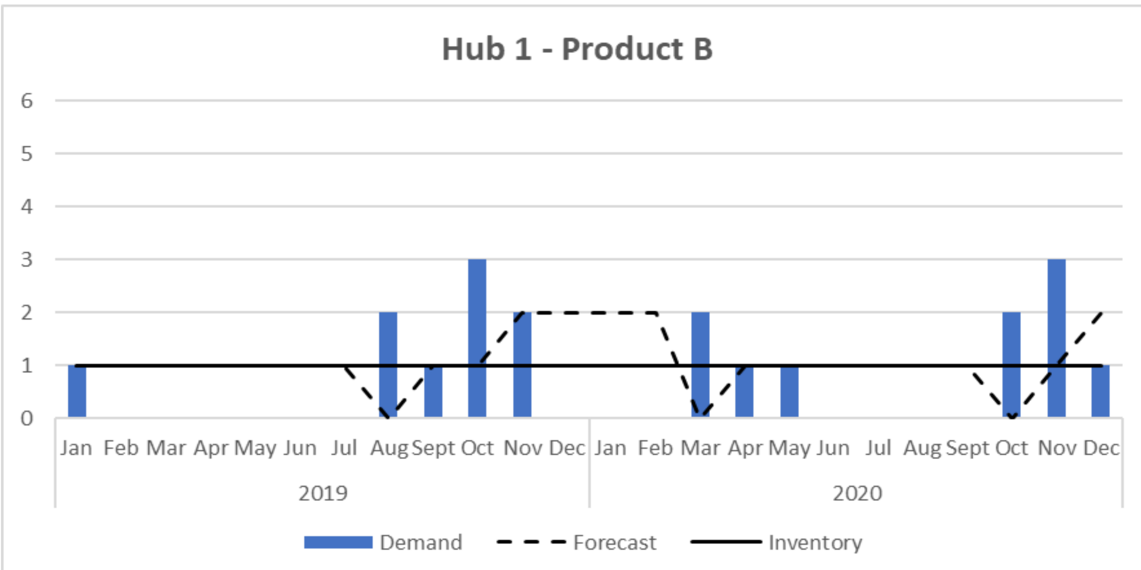


4.2.1.2 Product B

The demand for Product B at Hub 1 is a bit intermittent and low. Given this, we used Croston's Method to forecast demand and found that the optimal inventory policy was to keep one unit at Hub 1 for Product B. The proposed forecast produces an MSE(z) = 0.74.

Figure 10

Demand Allocation Hub 1 – Product B



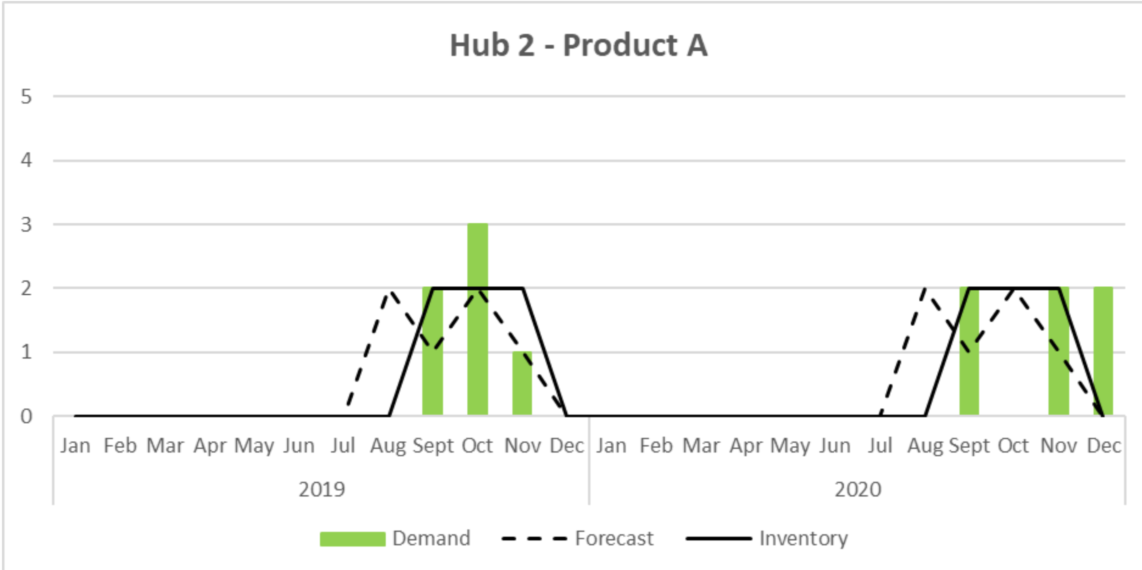
4.2.2 Hub 2 Demand and Analysis

4.2.2.1 Product A

The demand for Product A at Hub 2 shows seasonality. Given this, we used Holt-Winter to forecast demand and found that the optimal inventory policy was to keep two units of Product A at Hub 2 for September, October, and November. The proposed forecast produces an MSE = 0.83.

Figure 11

Demand allocation Hub 2 – Product A

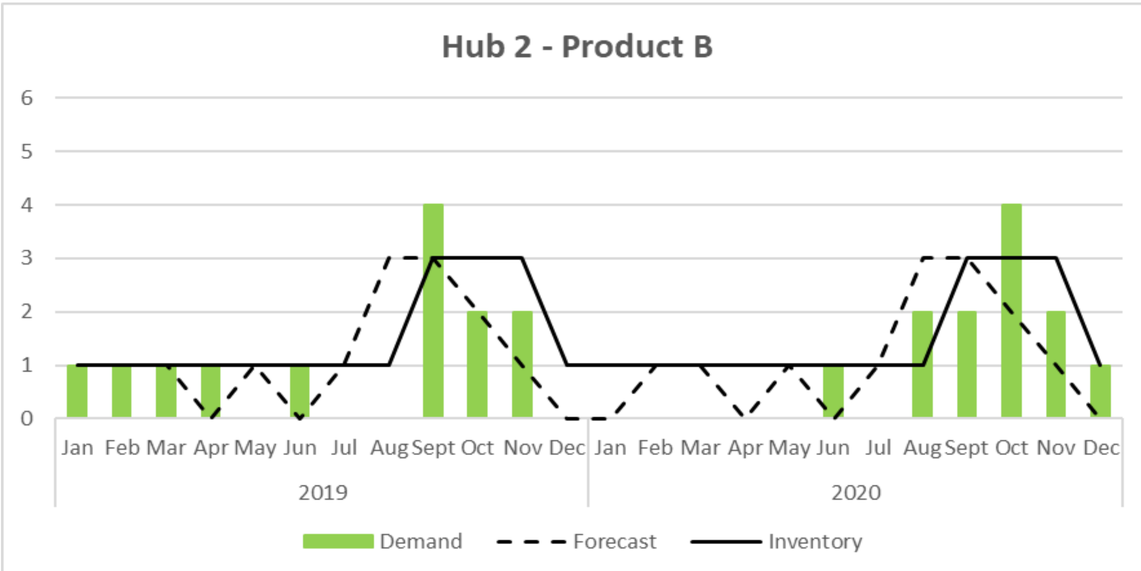


4.2.2.2 Product B

The demand for Product B at Hub 2 shows seasonality. Given this, we used Holt-Winter to forecast demand and found that the optimal inventory policy was to keep one unit of Product B at Hub 2 all year, except in September, October, and November three units should be kept in inventory. The proposed forecast produces an MSE = 1.67.

Figure 12

Demand allocation Hub 2 – Product B



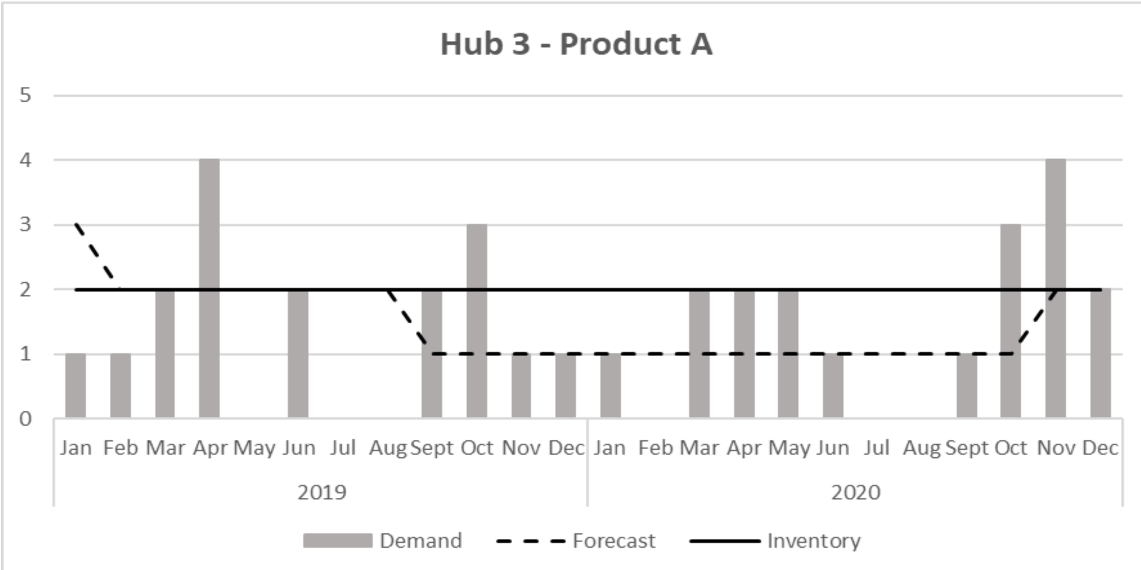
4.2.3 Hub 3 Demand and Analysis

4.2.3.1 Product A

The demand for Product A at Hub 3 is intermittent and low. Given this, we used Croston's Method to forecast demand and found that the optimal inventory policy was to keep two units of Product A at Hub 3 all year. The proposed forecast produces an MSE = 1.28

Figure 13

Demand allocation Hub 3 – Product A

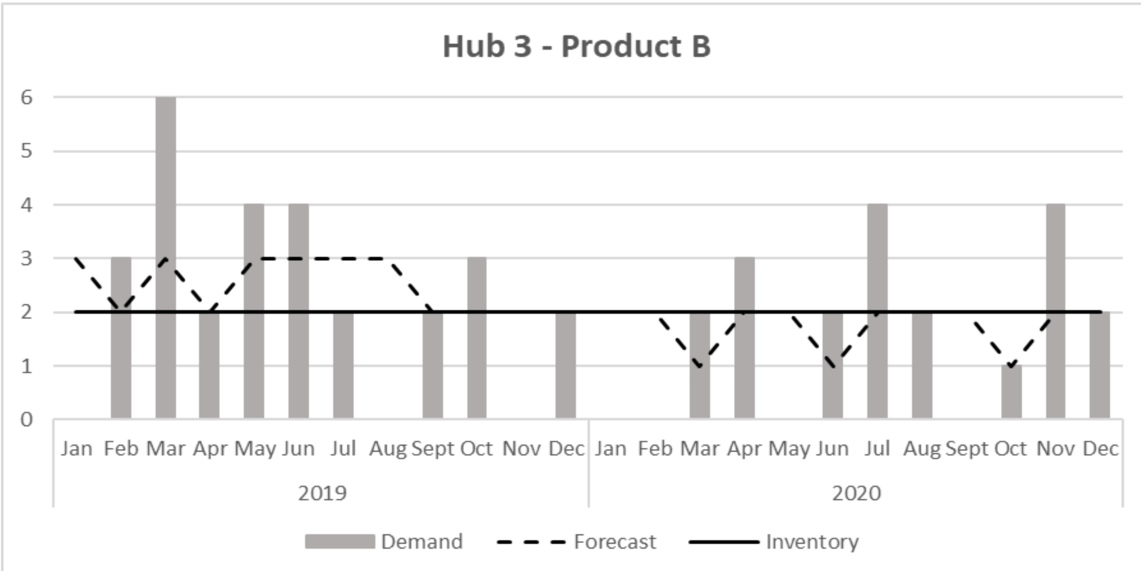


4.2.3.2 Product B

The demand for Product B at Hub 3 is intermittent and low. Given this, we used Croston's Method to forecast demand and found that the optimal inventory policy was to keep two units of Product B at Hub 3 all year. The proposed forecast produces an MSE = 1.88

Figure 14

Demand allocation Hub 3 - Product B



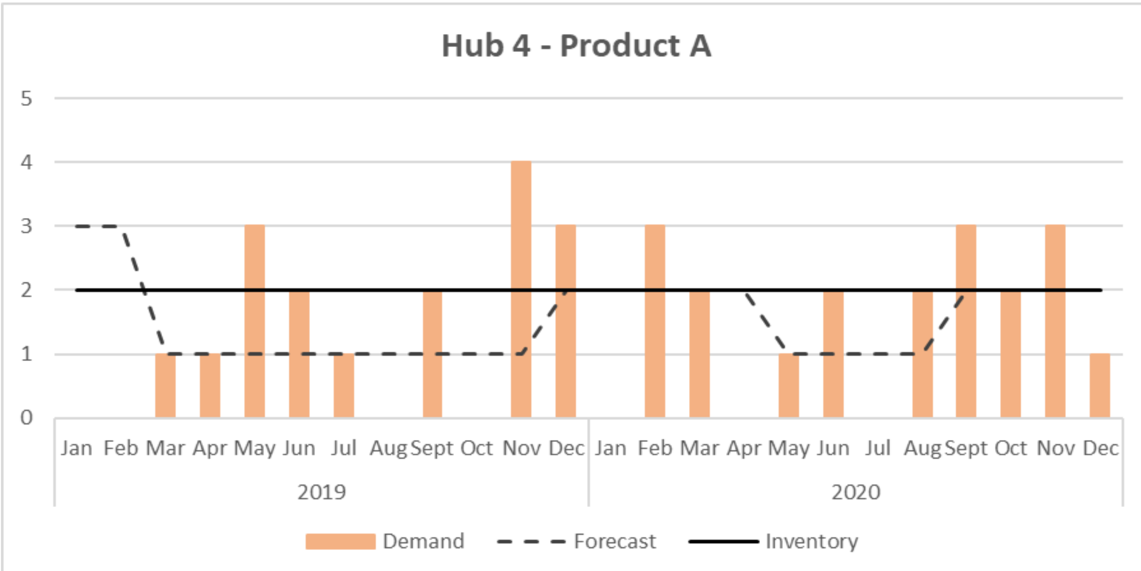
4.2.4 Hub 4 Demand and Analysis

4.2.4.1 Product A

The demand for Product A at Hub 4 is intermittent and low. Given this, we used Croston's Method to forecast demand and found that the optimal inventory policy was to keep two units of Product A at Hub 4 all year. The proposed forecast produces an MSE = 0.82

Figure 15

Demand allocation Hub 4 - Product A

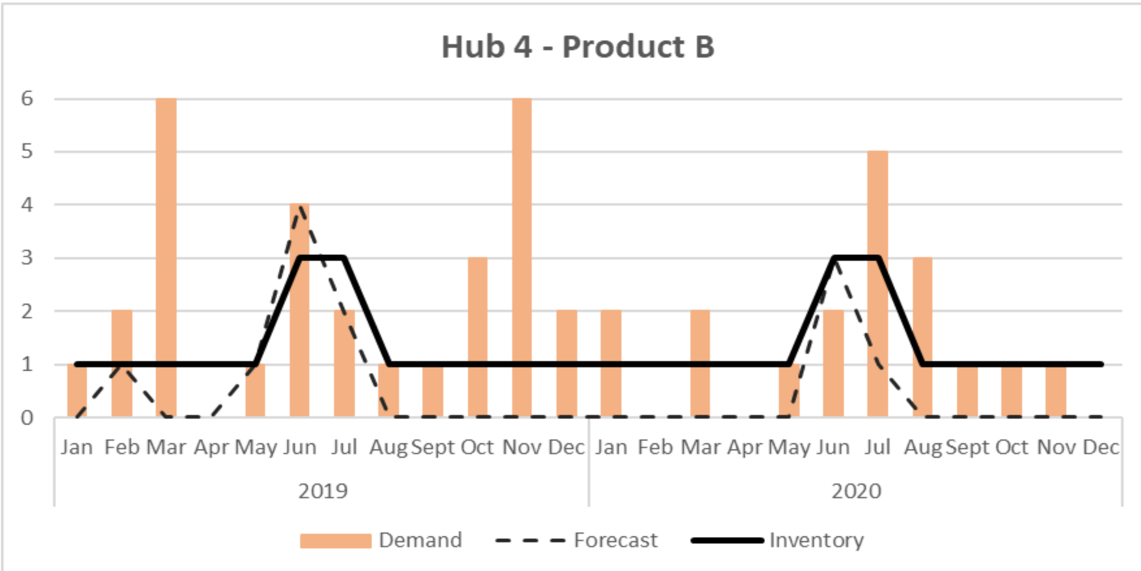


4.2.4.2 Product B

The demand for Product B at Hub 4 shows seasonality. Given this, we used Holt-Winter to forecast demand and found that the optimal inventory policy was to keep one unit of Product B at Hub 4 all year, except in June and July, when the company should keep three units in inventory. The proposed forecast produces an MSE = 5.29

Figure 16

Demand allocation Hub 4 - Product B



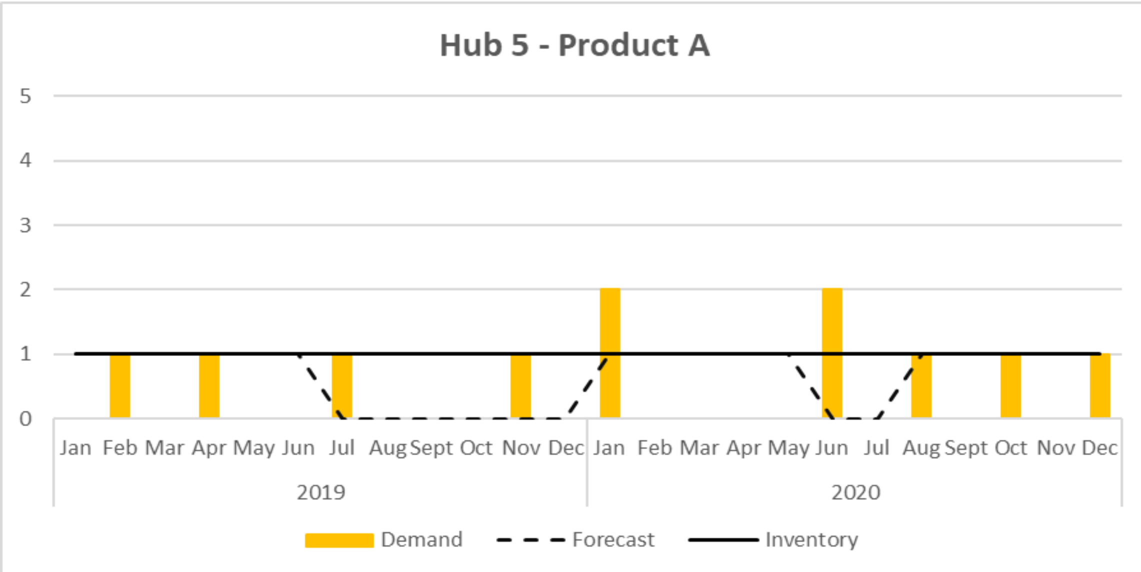
4.2.5 Hub 5 Demand and Analysis

4.2.5.1 Product A

The demand for Product A at Hub 5 is intermittent and low. Given this, we used Croston's Method to forecast demand and found that the optimal inventory policy was to keep one unit of Product A at Hub 5 all year. The proposed forecast produces an MSE = 0.28

Figure 17

Demand allocation Hub 5 - Product A



4.2.5.2 Product B

The demand for Product B at Hub 5 is inconsistent and low. Given this, we used Croston's Method to forecast demand and found that the optimal inventory policy was to keep one unit of Product B at Hub 5 all year. The proposed forecast produces an MSE = 0.23

Figure 18

Demand allocation Hub 5 - Product B

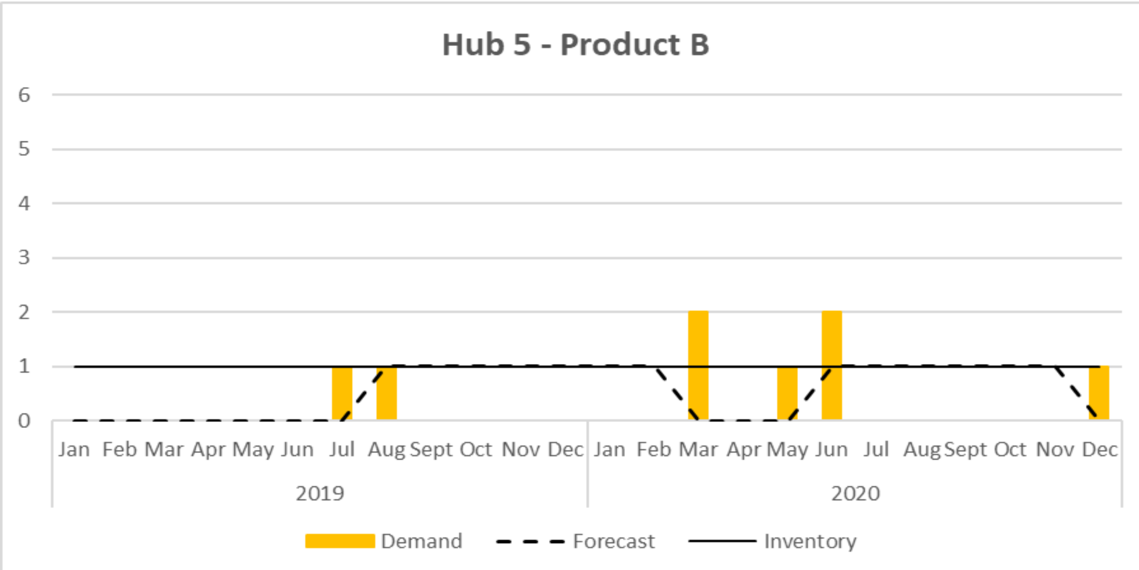


Figure 19

Summary table with comparison of MSE and RMSE for the two proposed forecasting methods

		Product A		Product B	
		MSE	RMSE	MSE	RMSE
Hub 1	Croston	0.3422	0.5850	0.7417	0.8612
	Holt-Winter	0.2917	0.5401	1.4583	1.2076
Hub 2	Croston	0.5191	0.7205	0.7976	0.8931
	Holt-Winter	1.1667	1.0801	1.1667	1.0801
Hub 3	Croston	1.2849	1.1335	1.8772	1.3701
	Holt-Winter	0.9583	0.9789	7.0833	2.6615
Hub 4	Croston	0.8179	0.9044	3.6987	1.9232
	Holt-Winter	4.2500	2.0616	5.2917	2.3004
Hub 5	Croston	0.2841	0.5330	0.2340	0.4837
	Holt-Winter	1.0417	1.0206	0.6667	0.8165

5 DISCUSSION

5.1 Managerial Insights

Based on our findings we have four main recommendations for the sponsor company. These recommendations are to collect more standardized data, establish an inventory policy, increase maintenance capabilities in US hubs, and create an inventory holding hub in Southern California. The first and main recommendation, to collect more standardized data, is of the utmost importance. From our analysis we found that moving to an asset-based inventory strategy can lead to an optimal network, providing a 20% reduction in total distance traveled and cost across the company's operations, however it was difficult to pinpoint the exact amount of improvement available given the current data. In the new configuration, the demand of every region is served by dedicated hubs and establishing an inventory policy and maintenance operations will reduce intra-hubs movements and inventory inefficiencies. By collecting more data, standardizing it, and creating a central source of truth for the data, it allows the sponsor company more visibility into their own network and operations as well as the ability to start to create accurate forecasts and demand planning.

Our next recommendation is for the sponsor company to establish an inventory policy. As discussed in Section 4, we have proposed a baseline inventory policy for Product A and B, broken down by hub. While the baseline inventory policy is not an exact monthly forecast, it sets the foundation for being able to seamlessly integrate a forecast and demand plan in the future.

Our third main takeaway for the sponsor company is that they should bring in maintenance expertise to their US hubs. Currently they are able to do minor repairs in the US hubs, but they have to send the tools to a Canadian hub for any major repairs. This results in unnecessary cross-border shipments, and subsequently, tools being held in inventory in Canada. As shown in section 4.2.2, our inventory policy suggests there is very low demand at Hub 2 and except for the seasonal surge in the fall, no inventory of product A and only one unit of Product B should be kept at this hub. This is in contrast to today, when almost all units not on a project may be stored at this hub at any given time. Adding in maintenance capabilities at US hubs and allowing this shift of inventory holding to those hubs can reduce approximately 50 cross boarder shipments annually for both Products A and B.

Finally, as our greenfield analysis showed in section 4.1.3, the recommended location to add a hub for both product A and B is in Southern California. Given that the sponsor company already has a satellite location in southern California, our recommendation would be to look into adding storage capabilities and creating a baseline inventory policy for this location.

In addition to the recommendations for the sponsor company, we believe there is room for improvement within the research. Future research and analysis could provide a more accurate network optimization if it took into consideration the fixed and variable costs at each hub along with the capacity limitations at each hub. Based on our conversations with the sponsor company, our inventory policy did not exceed capacity at each hub. As the size of their operations continue to scale up, this is important to consider. Finally, we believe there are various machine learning algorithms that could be implemented to increase the accuracy of the demand forecast and in turn increase the accuracy of the inventory strategies.

With the available data, we collected information to map the network, understand the logistics operations, and analyze the historical demand for 2019 and 2020. That said, we see that the sponsor company could benefit from a more robust data collection and data structure to track, assess, and improve their operations. Good demand planning will allow the company to deploy vehicle routing solutions to minimize shipping costs between different projects and optimize shipping modes.

Another enhancement would come from tracking the mileage estimate and number of deployments each tool is allotted between maintenance operations. This allows the sponsor company to allocate tools to projects with higher precision and minimize the maintenance costs and shipments associated with each tool. In conclusion, data collection is the key to identify the metrics to effectively assess the operations, standardize processes and identify improvement areas.

5.2 Limitations

5.2.1 Network Design

The model we developed looked at minimizing the overall distance and therefore, costs of each shipment. In our baseline model we only looked at a subset of the shipments since June 2020. In that subset we saw many cross-border (Canada-US and vice versa) shipments and many shipments between hubs. From our conversations with the sponsor company there are a few observations we can make about this network.

First, we were only able to observe a small number of shipments within their existing network. This is due primarily to two factors; the lack of historical data available, and the only shipments of tools recorded are those that are shipped through third-party logistics partners. Any movement of tools internally, by people driving equipment to and from sites is not included.

Second, the inefficacy of the network observed is due to the company's lack of planning and minimal forecasting. Their operations today are reactive, as they ship products from wherever they are available to get it to the destination as quickly as possible. This lack of visibility into upcoming projects and products needed has constrained our analysis.

In our optimized baseline scenario, we use the project data from January 2019. While we did not have the origin location each product was sent from for each of these projects, we were able to have a fuller view of the sponsor company's network. Given that in this scenario we look to optimize the network, we use all the project destination locations and the five main hubs to allocate each destination to the optimal origin hub. We use five hubs here to represent the current capabilities of the sponsor company. While they have an additional ten satellite locations across the US and Canada, we chose to not consider those locations due to capacity constraints and lack of maintenance capabilities. Additionally, it is important to note that this data included nine months of 2020 where activities were inevitably affected by COVID-19.

Another challenge in our analysis is related to the maintenance capability of the hubs. Even though most of the demand in North America is allocated in the US, the sponsor company relies on the hubs in Canada for all major maintenance operations. This system creates many intra-hub shipments that are inefficient from a logistics standpoint and it moves each tool further away from project locations. Given the sponsor company's initiative to eliminate cross border shipments, we modeled the network with the constraint of no cross-border shipments between Canada and the US.

5.2.2 Inventory Policy

Our analysis at the network level led us to our conclusions on the best inventory policy for each product, A and B. Currently, the sponsor company does not do any demand forecasting, and consequently has no inventory policy. Using the historical data, we developed a forecasting model, to use as the starting point for the inventory policy. The lack of tracking of inventory expenses is a limitation to the proposed inventory validation.

For the scope of the project, we assessed the North American footprint, however the sponsor company operates worldwide, and tools are shipped out to Europe and Asia from hubs in the US and Canada. We did not consider this demand when optimizing the network and inventory for each hub. This is important to note because while they are not in scope for this project, they may impact inventory availability.

Lastly, the proposed inventory policy requires tools be held in regional hubs to cover regional demand. While this strategy will lower logistics costs, it may require capital investments in additional assets, to guarantee that each hub has the optimal inventory. For our analysis we assumed unlimited assets for each product when creating the inventory policy. Our results concluded that for the North America demand there is no need for increased assets, however, this may be needed when considering the global footprint.

6 CONCLUSION

This capstone addressed three pain points, eliminating cross-border shipments, creating an inventory policy, and improving product availability for two different product families for our sponsoring company. We assessed the current transportation network for each product family, found the optimal network, and finally created an inventory policy by product and hub location.

Our primary finding shows that optimizing the network and creating a baseline inventory policy can reduce inefficient shipments by 20%. Additionally, the proposed optimized network can lead to a 20% total mileage reduction of shipments, by reducing cross-border shipments and streamlining the operations. Increasing maintenance capabilities in all the North America hubs could lead to even larger mileage reductions of up to 50%. The analysis shows the benefit of shifting to an asset-based inventory. With increased data collection, the sponsor company can expand on this initial analysis to create a demand forecast for each product family.

An accurate demand forecast can lead to lower inventory costs, fewer expedited shipments, and fewer days in transit for each tool. All of this leads to lower transportation costs, as there is less movement of products between hubs. In addition to lower transportation costs, there will be an increase in customer service levels, as there will be increased visibility into the pipeline and products will be in inventory closer to each customer.

Understanding the flow of products is critical to identifying improvements in a network and understanding the supply chain network is imperative to facilitating operational changes. This project used in insights found from mapping the flow of products on the sponsor company’s network to give insights and highlight where there is room for improvement. From these insights, we recommended strategies for the sponsor company to implement in their supply chain to help reduce the overall milage traveled by 30%.

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APPENDIX

Figure 20

ADD Algorithm (Daskin 2013)

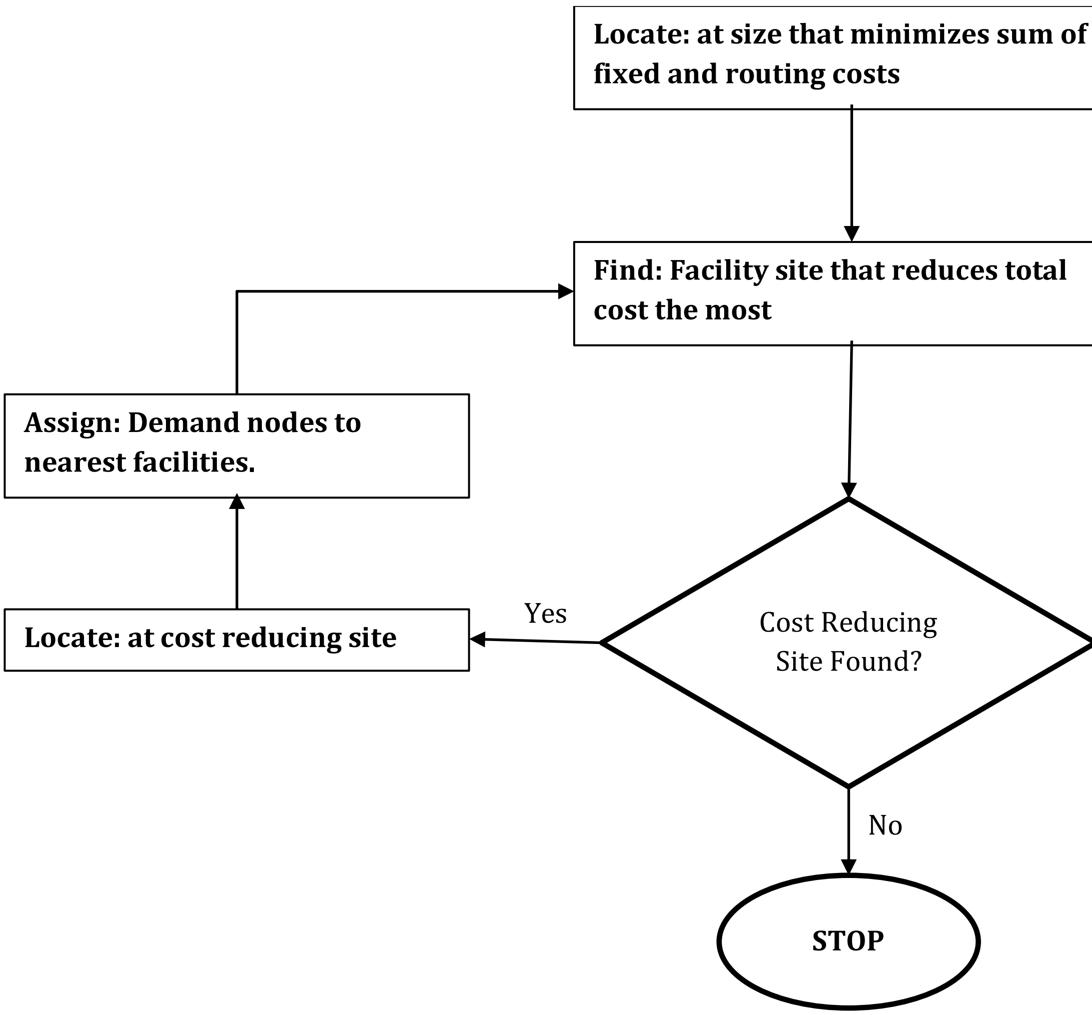

Figure 21

DROP Algorithm (Daskin 2013)

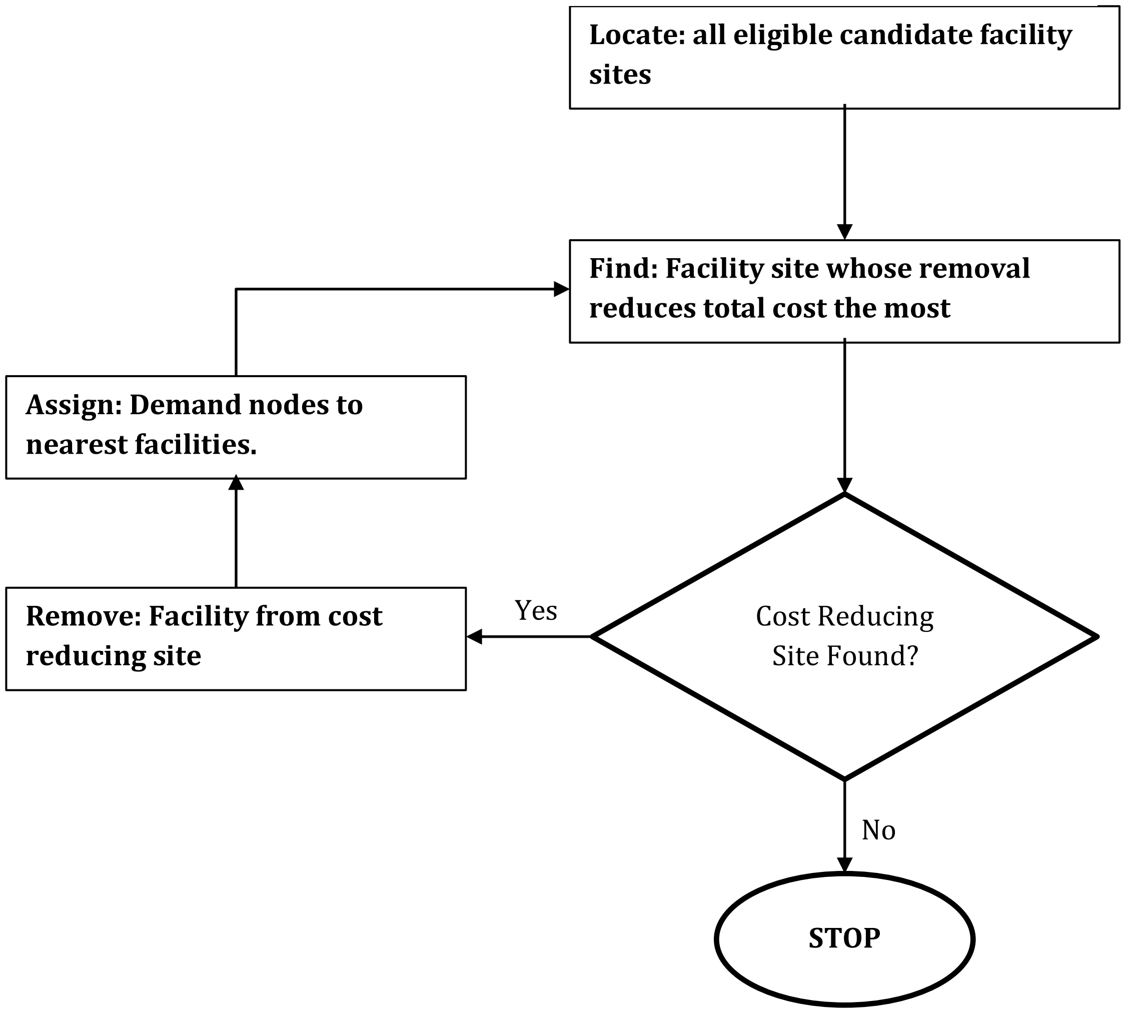

Figure 22

SUBSTITUTION Algorithm (Daskin 2013)