Designing A Resilient Supply Chain

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ABSTRACT

There has been a significant increase of interest in supply chain resiliency since the onset of COVID-19 as multiple supply chain disruptions have affected companies across the globe. By increasing resiliency, companies aim to increase their ability to adapt to changes occurring throughout their supply chain network. The 3PL company, Coyote Logistics sponsoring this capstone, is trying to increase their customers' supply chain resiliency through supply chain network design with a focus on transportation costs. Two Coyote customers from different industries were selected as case studies for this project, one from the retail big box industry and one from the packaging industry. An optimization model was implemented to investigate the effect of supply chain resiliency and network design on transportation costs by iterating the model over various demand and resilience threshold scenarios. The analysis across various scenarios revealed that a more resilient supply chain network only minimally increases transportation costs. For example, a 50% resilient supply chain network only resulted in a 3% increase in transportation cost for one customer. Whereas the other customer's supply chain network though equally resilient in some scenarios was not sufficient to meet certain levels of demand in others, highlighting the importance of facility capacity in resilient supply chain network design. Therefore, it is critical to understand facility capacity relative to demand locations when designing a resilient a supply chain network. For example, facilities should be spread out geographically and the facilities should be sharing the customer demand fulfillment responsibilities equally. This project underlines Coyote's work with their customers to increase their ability to respond to disruptions in the supply chain and design a more resilient network for the future. In further studies, more capacity information specific to distribution and manufacturing facilities as well as a multi-stop fulfillment strategy should be considered.

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I would like to thank my friends and family, who have supported me in every endeavor and challenge I have undertaken, without whom I would not be where I am today. Thank you for your relentless support and faith in me.

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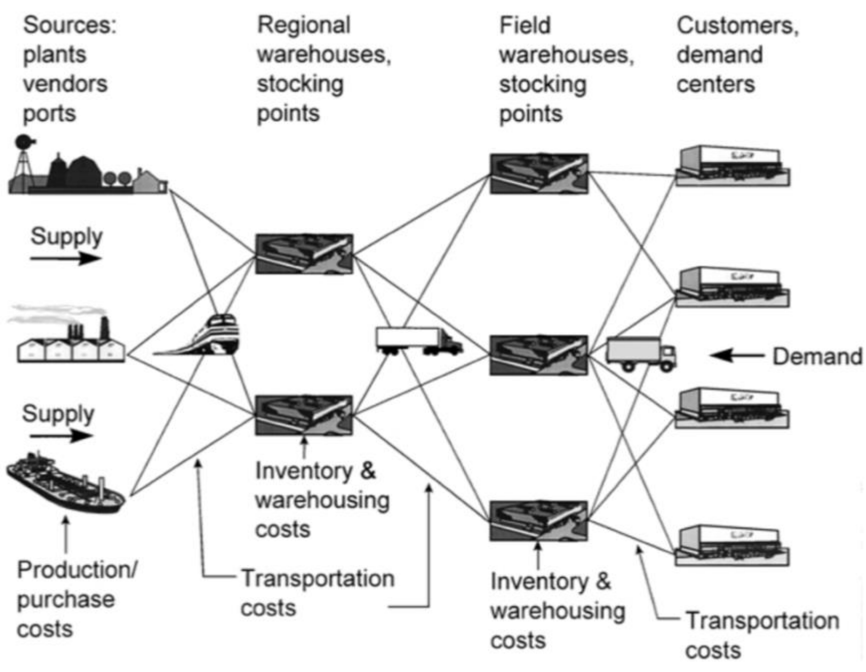
1. Introduction

1.1. Background & Motivation

Due to the COVID-19 pandemic, supply chains across the globe have experienced a multitude of disruptions. As a result, companies have moved to re-examine their supply chain networks (Shih, 2020). A supply chain network is referring to the underlying structure that supports operations and network design refers to"…configuring the nodal points on a product flow network that range from the sources of raw materials to the points of final consumption." (Ballou, 2001). An example of a theoretical supply chain network can be found in Figure 1.

Figure 1 *Representation of a Supply Chain Network*



Ballou, R. H. (2001). *Unresolved Issues in Supply Chain Network Design*.

In addition to the disruptions of COVID -19, supply chains have been growing steadily more global, and therefore, more vulnerable. The increased vulnerability of supply chains has led to a growing interest in making supply chains more resilient (Alfarsi et al., 2019). Resiliency is difficult to define as there are various definitions of resiliency found throughout the literature. A multidisciplinary approach to defining supply chain resilience was proposed by Ponomarov and Holcomb as: “The adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function” (Ponomarov & Holcomb, 2009, p. 133). Ponomarov and Holcomb went on to say that resiliency will help to lower the negative effects of disruptions in the supply chain, including an increase in cost. Therefore, it is important to consider supply chain resilience when optimizing a supply chain network for costs.

The COVID-19 pandemic has further demonstrated the importance of having a resilient supply chain network, as U.S. and European businesses reported having nearly $4 trillion in lost sales (Mitchell, 2021). To provide better service to their customers, Coyote Logistics, a U.S. third-party logistics (3PL) company, is exploring methods to increase the resiliency of a supply chain network while also minimizing costs from a transportation standpoint. As a result, Coyote has identified two target customers for this project: a “big box” retailer and a packaging manufacturer.

1.2. Research Problem

This capstone project identified the optimal supply chain design decisions for two target customers identified by Coyote Logistics. As Coyote services these customers’ outbound transportation network, this project accounted for current and projected industry trends, such as growth in demand and varying resilience thresholds. Accounting for industry trends and optimizing the supply chain network design allowed Coyote to build more resilient and cost-effective supply chains for their customers.

Customer 1: Customer 1 is a big box retailer that is expected to double their store count within the next three years. With the continued growth of e-commerce and omnichannel fulfillment strategies in the retail industry, this customer will increase the number of smaller shipments and individual packages it handles. These trends will impact Customer 1's supply chain network resilience and transportation cost.

Customer 2: Customer 2 is a packaging manufacturing company that is expected to see an increase in demand due to the growth of e-commerce fulfillment strategies deployed by its downstream customers. This will also impact Customer 2's supply chain network resilience and transportation cost.

This project identified Coyote customers' maximum network resilience measures and the related transportation cost to optimize supply chain network design. To specify, network resiliency is measured as a percentage of total routes where outbound transportation lead time is less than a predetermined threshold value. The threshold value ensures that a certain percentage of the demand will be fulfilled within a specified time window. This project treats all customer locations as equally important to the networks' resilience. Thus, a uniform measurement was used across all end-customers.

Instead of developing a high-level model that is applicable to all customers, the project focused on optimizing the network of two customers under varying conditions. This output enables Coyote to provide appropriate, realistic and customer-specific recommendations accounting for changes in demand and resilience levels. An underlying assumption of this investigation is that there is an optimal supply chain network design that the customers can implement.

As mentioned in Section 1.2. Coyote currently services both Customer 1’s and Customer 2’s outbound logistics needs. Therefore, this project is focused on optimizing the outbound section of the supply chain networks.

Based on the findings of the impact from COVID-19 on the supply chain and the revealed trends within the market, a network optimization model is used to identify the optimal supply chain network to minimize outbound transportation costs while maintaining a certain level of supply chain resiliency.

The research question to be investigated is: *What is the optimal supply chain network design, considering the location of distribution centers, production facilities and customers, which minimizes transportation costs and optimizes supply chain resiliency?*

After identifying industry trends and optimizing the network, this project provided Coyote Logistics and its customers a network optimization recommendation that will best position them to service end users in the future. Furthermore, there will be clearly defined parameters that indicate under which conditions which decision is theoretically optimal.

2. Literature Review

The following literature review will begin with a clarification of definitions and concepts around supply chain, contextualizing these concepts through a brief discussion of the general effects of the COVID-19 pandemic on supply chains. Next, the relevance of supply chain optimization and supply chain resilience will be established. Then, trends will be reviewed in context of the relevant industries and their impact on the retail and packaging manufacturing supply chains. Finally, a summary of prevalent supply chain network design modelling approaches will be presented, one of which will be implemented to answer the research question in this capstone.

2.1. Disruptions in the Supply Chain Network from the COVID-19 Pandemic

The expansive impact of the pandemic on supply chains can be explained by the "ripple effect," which describes how one disruption within the network leads to repercussions up and down the entire supply chain (Ivanov & Das, 2020). The inherent interdependencies among the nodes throughout the supply chain network allow for the effects of disruptions to be carried from node to node (Pettit et al., 2019). The types of disruptions along the supply chain range from limited material availability, expanding lead times, to underutilized production capacities as well as changes in demand among others (Ivanov & Das, 2020). Furthermore, the "bullwhip effect" helps to explain how the magnitude of a disruption along the supply chain grows as it moves up the supply chain away from the source. Specifically, the "bullwhip effect" describes how demand volatility becomes increasingly amplified from node to node (Lee et al., 1997). The effect of COVID-19 on supply chains must be understood because of the inherent interconnectedness, which spreads and amplifies impacts from disruptions throughout the supply chain network. The specific impacts from the pandemic on the relevant retail and manufacturing industries for this capstone will be discussed in further detail in Section 2.2. and Section 2.3, respectively.

2.2. Big Box Retail Industry Trends and Characteristics

The big box retail industry experienced various impacts from COVID-19. The COVID-19 pandemic not only accelerated the e-commerce and omni-channel fulfillment strategies' present in the retail industry, but also drove significant growth in demand for furniture and appliances. In Q4 2020, e-commerce retail sales increased by 32.1% (Ward, 2021) compared to Q4 2019, whereas brick and mortar sales grew by only 6.9% (Ward, 2021). As for omni-channel commerce, analysts predict a cumulative annual growth rate (CAGR) of 14.8% between 2020 to 2027 (ReportLinker, 2021). Furthermore, in the next few years, residential furniture demand is expected to grow between 4% to 8%, doubling the historical growth rate (Stump & Mullens, 2021). These forecasts, however, may not be achievable due to the current global supply chain crisis. Additionally, firms' profits are directly impacted by the increasing costs, predominantly driven by the increase in transportation and raw material costs.

To continue the growth of omni-channel fulfillment strategies, having available inventory on site at the retail locations is required to support growth in demand, as consumers are more likely to make a purchase after being able to touch and test the furniture or appliance (ReportLinker, 2021). Increase in brick-and-mortar store openings is required to service the growth in demand, as well as to have a competitive advantage. However, discount retailers, such as Customer 1, are extremely sensitive to cost increases and service disruptions. Therefore, network optimization and creating a resilient network is critical (Sheffi, 2005) to service the current and future demand, as well as maintaining and improving profit margins.

The retail industry experienced shifts, or disruptions, in areas such as demand volumes and channels. The packaging industry also experienced disruptions, as explained in Section 2.1.

2.3. Packaging Industry Trends and Characteristics

The impact of COVID-19 on the packaging industry is illustrated below through industry studies and an examination of an example company. Increase of demand for packaging has been primarily driven by the rise in e-commerce fulfillment channels. With the accelerated shift of retail demand towards e-commerce channels as stated in Section 2.1., the packaging industry is expecting a demand increase of 5% CAGR in the next five years (Electronics Newsweekly, 2021).

For Sealed Air Corporation (SEE), an industry leader in the same market segment as this project's target company, revenue grew in Q3 2021 compared to the same quarter from the prior year by 14%, while the profit margins decreased from 32.6% in Q3 2020 to 28.7% in Q3 2021(*Sealed Air (SEE) Beats on Q3 Earnings & Sales, Raises '21 View*, 2021). Similar to the big box retail industry presented in Section 2.1., the primary driver for the cost increase are freight costs. In order to service the growth of demand in this industry and minimize freight costs it is critical to optimize the target customer's network to decrease transportation costs.

As discussed above, COVID-19 caused various disruptions which cascaded through supply chains in the retail and packaging industry. Companies are working to address these disruptions using different strategies; one of these is supply chain network design and modelling. The approaches to modelling will be discussed in Section 2.4.

2.4. Approaches to Supply Chain Network Design

The considerations of a supply chain network design are shaped by the characteristics that decision makers can influence in the supply chain. The areas that can be influenced by this capstone are the transportation routes from distribution centers (DCs) to customer locations and resilience thresholds. This capstone project considered the following factors when designing the supply chain networks: demand, transportation cost, distance, and lead time. The following sections will discuss the relevant facility location literature and modeling approaches. The project's model was based on the target customers' current supply chain network, where the origin nodes are supplier locations, and destination nodes are either retail locations or downstream customer locations. In between the two nodes are Coyote's customers' facility locations, which would either be DCs or manufacturing (MFG) locations. The objective function of the model was to minimize both the inbound and outbound transportation costs.

2.4.1. Optimization Models for Supply Chain Network Design

To optimize supply chain networks, optimization in the form of mathematical modelling is often implemented. There are various forms of mathematical modelling, such as linear programming (including mixed integer linear programs) and non-linear programming. A linear program consists of a linear objective function and constraints. The mixed-integer linear program (MILP) employs the use of binary and integer variables, where binary variables are used as an "on / off" switch (Ye, 1998), where a route or facility is turned "on" when being utilized, and turned "off" when not being utilized. Non-linear programming models do not maintain a linear relationship between the decision variables and can become more difficult to solve (Azaron et al., 2008). This capstone developed and implemented a MILP model.

2.4.2. Dealing with Uncertainty in Supply Chain Network Models

Two approaches to uncertainty in modelling supply chain network optimization problems will be reviewed in this section: the deterministic and the stochastic approach.

The deterministic approach, often regarded as the simplest approach, is the earliest and most-often employed form in optimization methods (Azaron et al., 2008), where all inputs have known values. At the heart of the facility location problem is the deterministic approach, solving for the lowest traveled distance between a known set of location nodes for one defined scenario. In 1965, Hakimi suggested one of the earlier deterministic models for this problem, *P-medium*, by weighting the distances between nodes using the relative demand and a fixed number of facilities (S. H. Owen, M.S. Daskin, 1998).

There are stochastic programming options which incorporate random variables into deterministic models to account for uncertainty (Birge & Louveaux, 2011). The stochastic model approach aims to model the nature of real-world problem-solving more accurately through probabilistic and scenario planning, which requires the probabilities of random variables (S. H. Owen, M.S. Daskin, 1998). Scenario-based stochastic programming utilizes a set of discrete scenarios and matches them with probabilities. Mulvey et al., 1995 defined a scenario planning approach that is a robust formulation identifying the near optimal solution to a problem over multiple scenarios. In practice, however, there are drawbacks to this approach. It requires a lot of data, which is not readily available in industry, such as probabilities of events and the impacts of rare occurrences. (Zokaee et al., 2017). Furthermore, the definition of scenarios can be difficult, as the researcher generally can only investigate a limited amount. Defining the relevant scenarios is a challenge in and of itself. Hodgson in 1991, proposed a similar approach by performing sensitivity analyses on the *P-Medium* problem, discovering that relative changes in demand and distance had little influence on the optimal solution (Snyder, 2005).

This capstone utilized a deterministic approach, using the data provided by the sponsoring company and discrete scenarios to investigate the effect of various conditions, in which the supply chain network may need to operate.

2.4.3. Supply Chain Resilience and Service Levels

To account for supply chain resiliency, the project incorporated a transit lead time constraint. This is because shorter lead times translate to faster responses in the supply chain network and, most crucially, a variable that the sponsor company can influence directly. Since the resilience and service level requirements are specific to each customer, this project adapted proximity metrics used in network optimization research (Farahani & Elahipanah, 2008), more specifically a lead time requirement. This was measured by a percentage of routes that are within the targeted lead time and compared against a predetermined target that was provided by the respective target companies or this project's corporate sponsor. The project measured transit days for all candidate routes, by assigning a binary variable of 1 or 0 to the route. Routes that are less than the targeted lead time will be given a 1, and those that are greater than the targeted lead time will be assigned a 0. Lastly, the sum of the lead time binary variable was used to calculate a percentage of routes that are within the targeted lead time, which had to be equal to or greater than the predetermined target percentage.

2.5. Summary of Research Gap

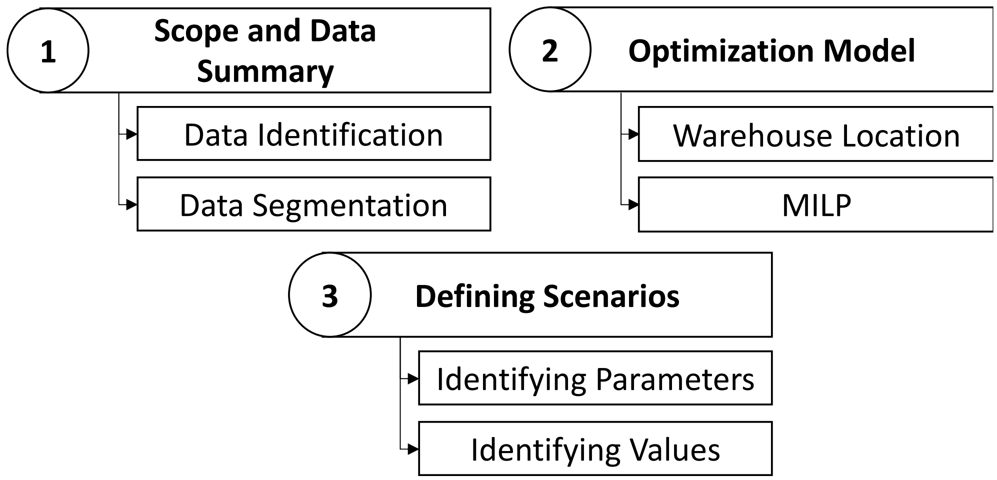
There has been an abundance of research on both the trends and the impact of COVID-19 on the retail and packaging industry, as well as optimization methods for network design purposes. However, there is no research specific the two companies' current supply chain network. By understanding the existing network optimization approaches as well as the advantages and disadvantages associated with them, the appropriate method to satisfy this project's scope as a deterministic MILP approach. The analysis of this project will take the network optimization approach for various demand scenarios, as well as exploring bounds of supply chain resilience. This approach enabled the project to assess the target companies' current network and provide recommendations for each firm under varying hypothetical conditions. From this, the project produced recommendations specific to each customer's industry and supply chain parameters. The gap in research this capstone addressed was the consideration of supply chain resilience in network optimization specific to two company's supply chain networks. The methodology behind the optimization model is described in Chapter 3.

3. Methodology

To address the research question, what is the optimal resilient supply chain network, multiple variables were incorporated into a MILP model. The variables were defined and the model built using real-world data from the sponsoring company and their customers. Furthermore, several scenarios were identified to analyze the optimal network design under varying conditions.

The methodology of this capstone followed three key steps, which are summarized in Figure 2. The first step is to review the provided industry data, identify the relevant data for the model and clean it. Second, the MILP was built and run over various scenarios, which included different levels of demand and network resilience served via distribution and production facilities. Third, the parameters of the scenarios were defined.

Figure 2 *Structure of Methodology*



3.1. Scope and Data Summary

The data for this project came from two customers selected by Coyote as use cases. Although the industries of these respective customers are inherently different, it is assumed that the methodology described in this capstone can be applied across industries. The customer data consists of inbound and outbound transportation information from a network of suppliers to distribution centers or manufacturing facilities to end-customers. The location data of suppliers, distribution centers, and customers was given by city and state. A summary of the network for Customer 1 is provided in Figure 3 and Table 1, while the summary for Customer 2 is provided in Figure 4 andTable 2.

Figure 3 *Supply Chain Network of Customer 1*

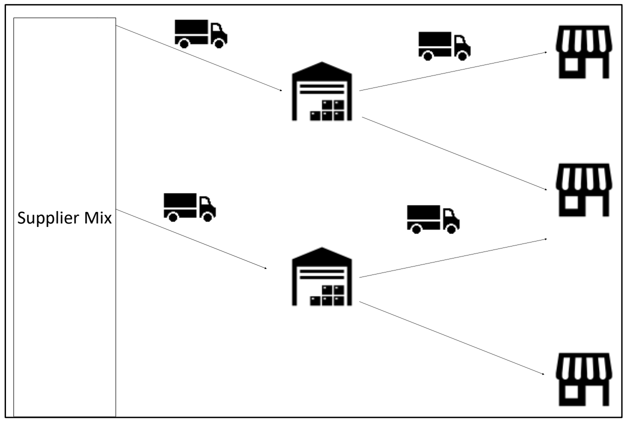


Table 1 *Supply Chain Network Summary of Customer 1*

Node Type	**Number of Nodes**
Suppliers	24
DCs	7
Retail Locations	729

Figure 4 *Supply Chain Network of Customer 2*

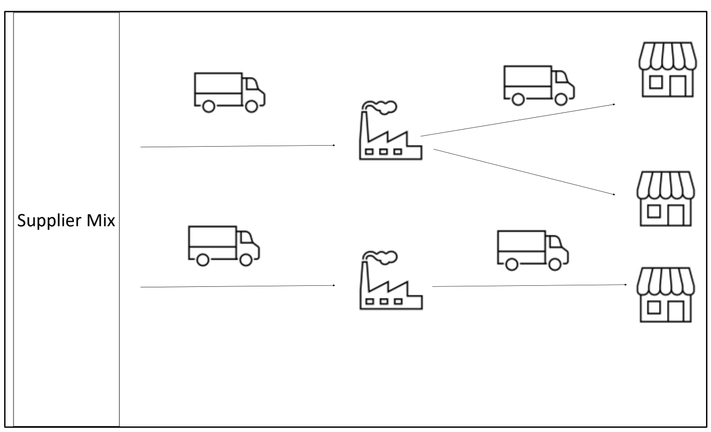
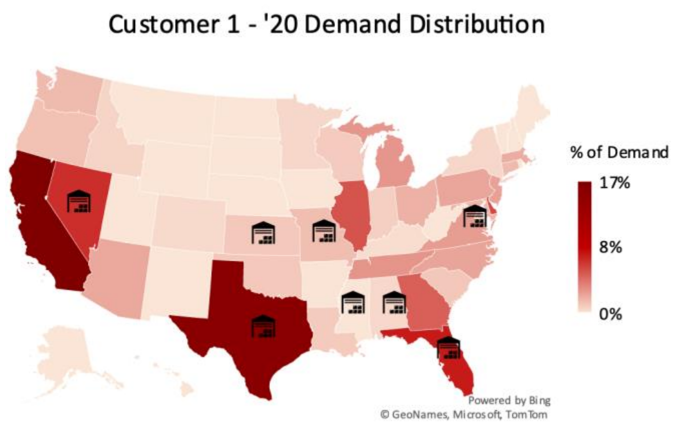


Table 2 *Supply Chain Network Summary of Customer 2*

Node Type	**Number of Nodes**
Suppliers	60
MFGs	32
Customer Locations	237

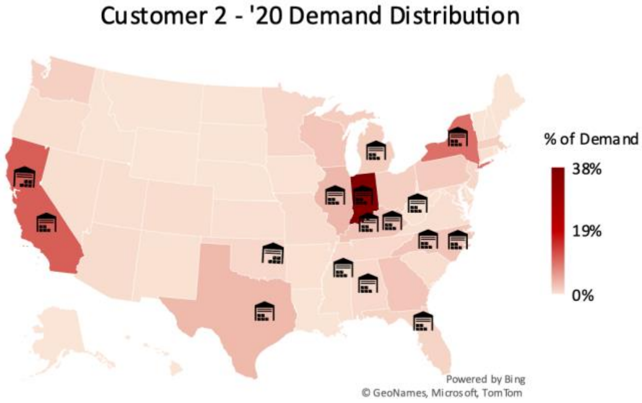
The product that flows across the network travels along the lines of transportation, which connect the nodes. The flow of goods goes from supplier nodes to distribution center nodes or from production facilities to customer nodes located at the end of the network. The portion of the network relevant to this project is in the United States. The distribution of the annual demand across the US for Customer 1 is depicted in Figure 5. The distribution of production facilities and demand for Customer 2 is depicted in Figure 6.

Figure 5 *Supply Chain Network Summary of Customer 1*



Distribution Center

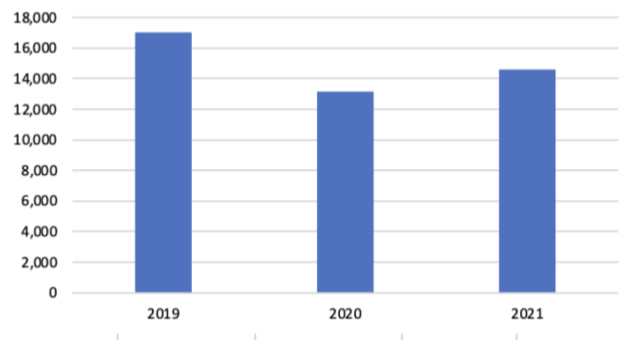
Figure 6 *Supply Chain Network Summary of Customer 2*



 Production facilities

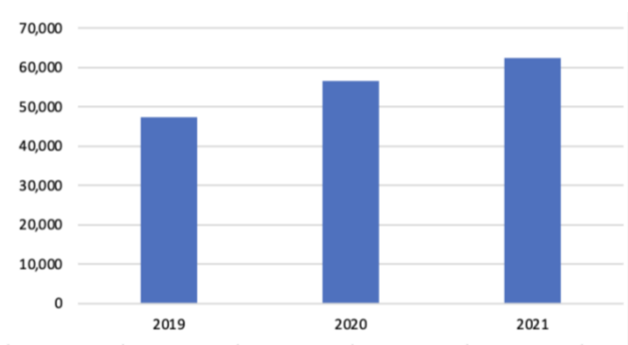
The metric used to describe the amount being transported through the supply networks of Customer 1 and 2 is pounds for weight and miles for the distance travelled. These are the standard metrics used in the United States. The demand data provided for Customer 1 spans three years, from 2019 to 2021. The individual load ID was provided along with corresponding shipment details such as weight, origin, destination, and transportation dates. The data revealed that over the three-year period demand varied for Customer 1, as seen in Figure 7. For example, demand in 2019, before the pandemic, was higher than demand during the pandemic in 2020 and 2021. However, in 2021 the demand seems to be recovering as the total increased compared to 2019 during the height of the pandemic. The similarity of demand trends in 2019 and 2020 may be a sign of consumers adjusting their behavior “back to normal” as they become more accustomed to pandemic parameters. It was decided to proceed with 2019 demand as the base demand for forecasting demand, as it is still unclear what kind of long-term effects the pandemic will have on demand in the future.

Figure 7 *Annual Demand of Customer 1*



Similar to Customer 1, Customer 2's demand data also spans three years, from 2019 to 2021. Customer 2 did not experience a demand decline as Customer 1 in 2021 but rather continued growth. However, as seen in Figure 8, Customer 2's CAGR between this period was only 2%, which is vastly different when compared to the industry forecast CAGR mentioned in Section 2.3. This slow-down in growth has been attributed to raw material supply constraints Customer 2 experienced in 2021. In addition, Customer 2's demand is heavily skewed towards a few States (Figure 5). Unfortunately, product type cannot be inferred from the demand data and an assumption was used to split the total demand across product types (see Section 4.1.).

Figure 8 *Annual Demand for Customer 2*



3.2. Optimization Model

This section will focus on the optimization model's formulation, as well as the assumptions that go into the model. The formulation for this project is a MILP that minimizes transportation costs across the supply chain. Among other assumptions detailed in Table 6 and Table 7, this project assumes all shipments over both customers are full truckload (TL). There are three inputs that make up the model's objective function: distance travelled, trucking rates, and amount transported. The distance travelled consists of two components defined below as inbound and outbound:

Inbound Transportation: inflow of materials and/or finished goods from supplier facilities to the project target customer's distribution centers or manufacturing facilities.

Outbound Transportation: outflow of finished goods from the project target customer's distribution centers or manufacturing facilities to an internal retail location or a downstream customer's distribution center and/or manufacturing facility.

The trucking rates were provided by the sponsoring company and pulled from the DAT Freight & Analytics database. Each rate is an average over 2021 monthly rates particular to a lane, with a lane being defined as a route connecting an origin and destination node. The origin node for inbound transportation lanes is the supplier and the destination is a customer's DC. For the outbound transportation lanes, the origin is a DC and the destination is an end-customer's store or facility location. The amount transported over the inbound and outbound lanes is the final component to the objective function which indicates how many trucks must travel from inbound to outbound nodes to fulfill the customer demand.

The model employs four decision variables, which are binary as well as float. Two are considered floats, one for products flowing from suppliers (i) to facilities (j) and one for products flowing from facilities (j) to customers (w). The third decision variable is binary and indicates the decision to activate a lane between facility (j) and customer location (w). The fourth decision variable is also binary and indicates the decision if a facility is open or not. Both (z_{jw}) and

γ_j are not a part of the objective function. Please see Table 3 for the variables and their respective definitions.

Table 3 *Optimization Model Decision Variables*

Variable	Definition
x_{ij}	Amount of units shipped from supplier location *i* to facility location *j*
y_{jw}	Amount of units shipped from facility location *j* to facility location *w*
z_{jw}	Binary variable, equal to 1 if facility *j* services customer location *w*
γ_j	Binary variable, equal to 1 if facility *j* is utilized

The costs, calculated by and minimized by the objective function, consist of the distance between the nodes traveled, the cost associated with that lane (between nodes) and the amount of product flow from one node to the other.

The following will introduce the optimization model's mathematical formulation. To begin, the objective function is introduced, followed by the decision variables, costs, parameters, and constraints. The sets for the model are listed below.

Sets: The sets of the model that denote the type of nodes are supplier, facility, and customer as presented in Table 4 below.

Table 4 *Optimization Model Sets*

Variable	Definition
I	Set of all supplier locations
J	Set of all facility locations
W	Set of all customer locations

The constraints of the model ensure that the objective function is satisfied within acceptable boundaries identified with the sponsoring company. The relevant constraints are listed below in lines (2) through (10) and address demand, capacity, facility utilization, and resilience among others.

$$
\begin{aligned}
&Min \quad C &&= \sum_i \sum_j d_{ij} \cdot V_{ij} \cdot x_{ij} + \sum_j \sum_w d_{jw} \cdot V_{jw} \cdot y_{jw} && && (1)\\
&s.t. && && && \\
&\sum_i x_{ij} &&= \sum_w y_{jw} && \forall j \in J && (2)\\
&\sum_w y_{jw} &&\leq K_j && \forall j \in J && (3)\\
&\sum_j y_{jw} &&\geq D_w && \forall w \in W && (4)\\
&\frac{\sum_w y_{jw}}{K_j} &&\geq P \cdot \gamma_j && \forall j \in J && (5)\\
&\sum_j \alpha_{jw} \cdot z_{jw} &&\geq r \sum_j z_{jw} && \forall w \in W && (6)\\
&M \cdot \gamma_j &&\geq \sum_w y_{jw} && \forall j \in J && (7)\\
&M \cdot z_{jw} &&\geq y_{jw} && \forall j \in J,\ \forall w \in W && (8)\\
&z_{jw} &&= \{0,1\} && \forall j \in J,\ \forall w \in W && (9)\\
&\gamma_j &&= \{0,1\} && \forall j \in J && (10)
\end{aligned}
$$

The objective function is presented in Equation (1). It is a cost function, in which the transportation costs are minimized over two parts: inbound and outbound. It is made up of the decision variables (x_{ij}) and (y_{ij}), which indicate the material flow between nodes as well as the distance and freight costs. The constraints presented in Equations (2) forces the model to ship all materials or finished goods (x) at target customer facility location (j) to be equal to all shipments received at the same facility (j) from supplier locations (i). The capacity constraints are presented in Equations (3)**.** These constraints ensure that no more is shipped out of facility (w) than the capacity of the facility allows. The demand constraints are presented in Equations (4). These constraints ensure that the amount transported to customer location (y) is greater than or equal to the demand at each customer facility (w). The facility utilization constraints are presented in Equations (5). These constraints allow the model to avoid under-utilizing any facilities (j), where the utilization minimum is based on a utilization percentage (e.g., 80%) set by the target customers. The resilience constraints are presented in Equations (6). The resilience constraints will enable the project to set parameters that ensure the shortest transit lead time in the event of a disruption in service, enabling the customers to be in the best position for service recovery. The linking constraints are presented in Equations (7) and (8). Linking constraints enable the model to tie facility decisions to routing decisions. This ensures that material shipped is only possible from facilities that are active.

The parameters of the model include integer values as well as binary values, which are presented in Table 5.

Table 5 *Optimization Model Parameters*

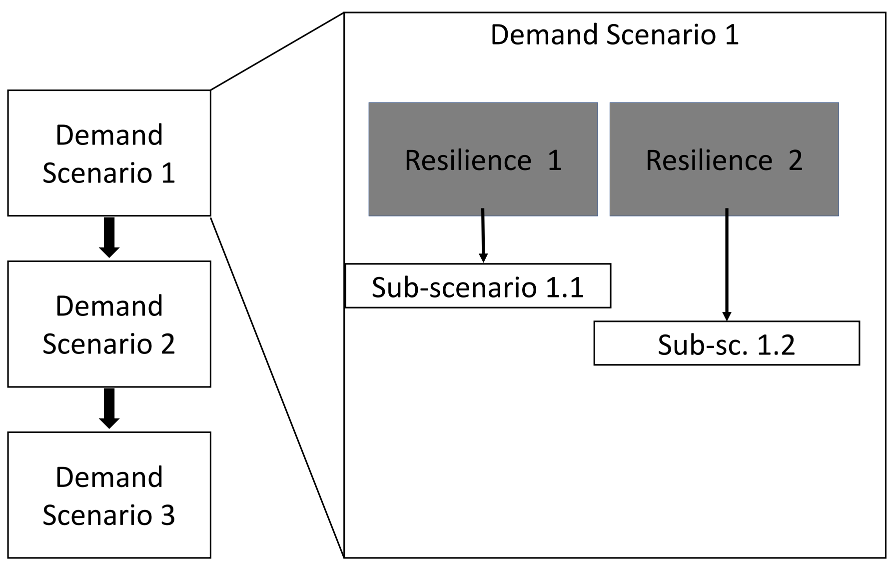
Variable	**Definition**
d_{ij}	Inbound distance travelled between node (i) and (j)
d_{jw}	Outbound distance travelled between node (j) and (w)
V_{ij}	Inbound freight rates for lanes between nodes (i) and (j)
V_{jw}	Outbound freight rates for lanes between nodes (j) and (w)
K_j	Capacity of facility (j)
D_w	Demand at customer location (w)
P	Facility utilization threshold
M	Large number for linking constraints
alpha	Binary parameter
r	Percentage threshold of resilient lanes out of active lanes in the network
R_w	Lead time of a resilient lane

The parameters of the model are populated with the customer data and the analysis specific to the information from Coyote Logistics customers are presented in Chapter 4.

4. Analysis

To investigate the parameters of the model three influencing factors are identified as key to designing a resilient supply chain network: demand, number of facilities, and network resilience. These factors are defined as parameters of the model and investigated by running the model over various scenarios and sub-scenarios to find the optimal supply chain network design. Figure 9 demonstrates the scenario approach used in this project and how the sub-scenarios are constructed. The scenarios are defined by one parameter, in this case demand, taking on one pre-defined value which remains constant over all sub-scenarios. The sub-scenarios are defined by two different resilience measures: the maximum and minimum resilience thresholds where the model is feasible. After the iterations within one (demand) scenario ran through all the sub-scenarios the process is repeated with the next demand parameter value.

Figure 9 *Summary of Analysis Scenarios*



4.1. Demand Scenarios

Meeting customer demand has become more challenging as demand has been fluctuating especially with the effects of COVID-19. Due to the demand uncertainty for both Customer 1 and Customer 2, a range of Compound Annual Growth Rates (CAGR) are used to define scenarios. CAGR is used to project growth instead of Average Annual Growth Rate (AAGR), as CAGR considers the effect of compounding and is a commonly used metric for forecasting growth rates in industry.

The three scenarios for each customer are defined in the following. A conservative, an average, and an aggressive growth rate make up the demand scenarios to cover a range of potential demand growth. As Customer 1 and Customer 2 are operating in different industries, different CAGRs for scenarios are used for each customer. Table 6 summarizes the CAGR scenarios for both customers. Based on industry research Customer 2 is projected to grow slightly faster than Customer 1.

Table 6 *Demand growth projections*

CAGR Scenario	**Customer 1**	**Customer 2**
Conservative	3%	8%
Average	4%	10%
Aggressive	5%	12%

The assumptions underpinning the demand scenarios specific to each customer are listed in Table 7 and Table 8, respectively, for Customer 1 and 2. They are based on market research and expert interviews with the sponsoring company. Table 7 covers the units of measure chosen for demand and the approach to incorporating new store openings planned for Customer 1.

Table 7 *Customer 1 Demand Assumptions*

Element	Assumption
Amount - Unit of Measure	Measured in pounds (lbs.) and assumes 35,000 lbs per TL. This applies for both inbound and outbound transportation.
Demand – New Retail Locations	Assume all new locations will be open within the first three years. This includes all locations that opened between 2020 and 2021, and planned store openings. Assume each new location's demand will become "mature" linearly in the first three years. "Mature" demand is the average demand per location in 2019. Assume 3-5% CAGR demand increase of "mature" store demand after first three years.

The assumptions for Customer 2 are listed in Table 8. and cover not only unit of measure for demand but also the product mix, which breaks down the demand to product level. According to Coyote the demand for paper and resin products are inherently different. Therefore, considering the demand on the product level is necessary.

Table 8 *Customer 2 Demand Assumptions*

Element	Assumption
Amount - Unit of Measure	Measured in cubic feet, assume maximum 3,700 cubic feet per TL.
Demand – Mix	Assume 70% - 30% resin and paper mix.

Section 4.2. covers the scenarios and assumptions specific to supply chain network resilience.

4.2. Resilience Scenarios

Resiliency is accounted for in the model, which is defined as a minimum amount of outbound routes where the transportation lead time is less than a predetermined number of trucking days (R_w). One trucking day is defined as the industry standard of 10 hours per day, based on guidance provided by Coyote. In this case, (R_w) is set as the average transit lead time for both customers in days. In terms of (r), the project has identified the maximum feasible (r) value and the lowest possible (r) value. Due to each customer having a unique facility network and different demand profiles, this project has set different resilience scenarios for each customer. See Table 9 for a summary of the available transit lead times for each customer. In this project the (R_w) threshold is set at 2.3 transportation days for Customer 1. Customer 2 (R_w) is set at the average transit days of 1.6. Although Customer 2 has a lower average transportation lead time compared to Customer 1, Customer 2 has a higher transportation lead time standard deviation, which is accounted for by taking the average of trucking days to set the parameter value (r).

Table 9 *Summary of Transit Lead Time*

Unit of Measure: Days	Customer 1	Customer 2
25th Percentile	1.2	2.0
Median	3.0	3.2
75th Percentile	1.2	5.9
Average	2.3	1.6
Standard Deviation	1.5	2.6

By considering resiliency the supply chain networks designed by the model allow Customer 1 and Customer 2 agility in responding to adverse effects impeding delivery on a lane. By design there are a minimum number of lanes that meet a lead time requirement, so if one lane is not useable another could be employed, depending how high (r) is set. As both customers prioritize improving service levels, it is critical to understand the change in transportation costs when the service level changes. The assumptions for supply chain resilience relevant to Customer 1 and Customer 2 respectively are listed in Table 10 and Table 11.

Table 10 *Customer 1 Resilience Assumptions*

Element	Assumption
Resilience – Lead Time	Assume average outbound truck travel speed of 50 miles per hour, where each truck can only travel 500 miles per day or 10 hours per day.

Table 11 *Customer 2 Resilience Assumptions*

Element	Assumption
Resilience – Lead Time	Assume average outbound truck travel speed of 50 miles per hour, where each truck can only travel 500 miles per day or 10 hours per day.

There are also general assumptions underpinning the analysis that are not specific to only demand or resiliency. These assumptions are listed in the tables below: Table 12 and Table 13 respectively for Customer 1 and Customer 2. These assumptions range from supplier location to facility capacity to truck loads for transportation.

Table 12 *Customer 1 Network Assumptions*

Element	Assumption
Supplier Location Mix	Assume 2019 supplier location mix (by percentage) to supply future growth in demand. No business rules to adhere to.
Facilities – Location	Assume all 7 existing facilities can fulfill all product mixes.
Facilities – Capacity	Assume the annual facilities capacity is equal to the annual customer demand. Capacity will be distributed based on a percentage per facility, from 2019 actual shipments.
Transportation Mix	Assume all shipments to be in TLs.

Table 13 *Customer 2 Network Assumptions*

Element	Assumption
Supplier Location Mix	Assume 2019 supplier location mix (by percentage) to supply future growth in demand. No business rules to adhere to.
Facilities – Location	Assume all 32 total facilities (23 paper manufacturing facilities, 9 non-paper manufacturing facilities) can produce all mixes.
Facilities – Capacity	Assume maximum shipments in shipments data as the level for running the facility at 80% utilization rate.
Transportation Mix	Assume all shipments to be in TLs.

The scenarios were defined with input from the sponsoring company and literature review. However, to accommodate missing customer information for parameter values some assumptions are made about supply chain network characteristics. The analysis for this project is split into two sections focusing on demand and supply chain network resiliency scenarios. The review and analysis of the results of the model are covered in Chapter 5.

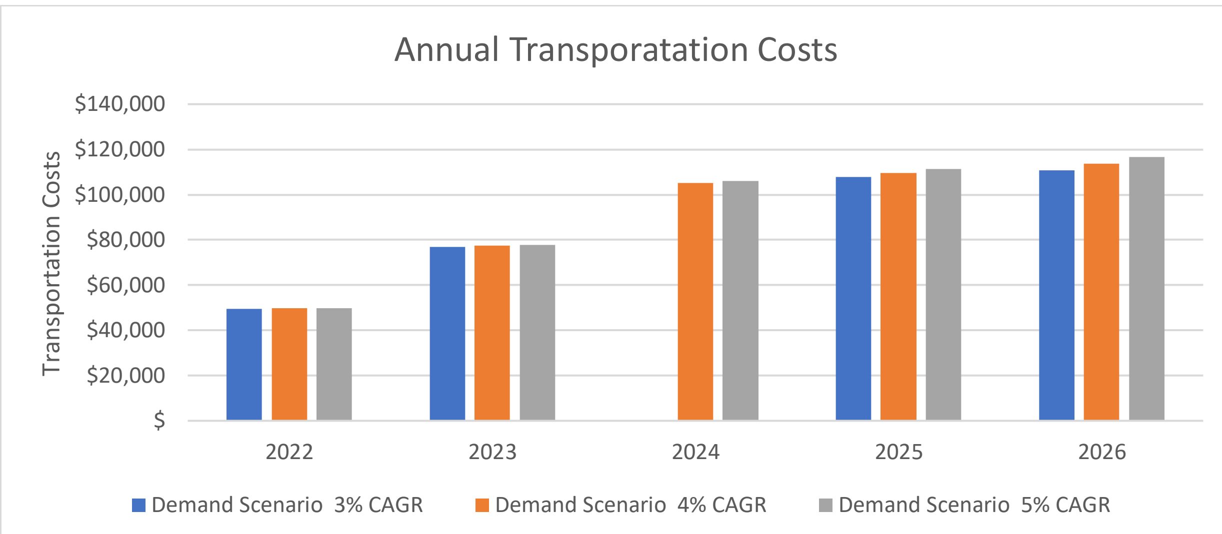
5. Results and Discussion

This capstone designs an optimization model that minimizes the transportation cost of two supply chain networks. By running the data from Customer 1 and Customer 2 through the model the optimal lanes and number of connections between supply and demand nodes are identified. The conditions that may affect the type of connections made are investigated by iterating the model through three scenarios of demand growth and two different values for network resiliency. The outcomes of these scenarios are compared and analyzed in the sections below. In the future, the customers can use this analysis as a point of reference, to react accordingly based on the demand scenario they believe to be more likely.

5.1. Change in Demand & Impact on Transportation Costs – Customer 1

The results from the model for one instance of the network resilience measure is shown in Figure 10. This indicates a general increase in demand over time and demand scenarios for one instance of the network resilience measure (r). The maximum possible (r) scenario is used as a basis for the demand scenario analysis, as the sponsoring company would want to maximize the network resilience of Customer 1. The annual transportation costs are plausible considering previous years' transportation spends, as was confirmed by the sponsoring company.

Figure 10 *Customer Transportation Costs Across Demand Scenarios for r=0.5*



In year 2024, under the given conditions for network resiliency the model was declared infeasible; therefore, no transportation costs could be calculated. This point will be further discussed in Section 5.3.

The overall growth in demand from years 2022 to 2026 results in a large increase in transportation costs within each demand scenario. Table 14 underlines this observation, displaying the percent change between demand scenarios.

Table 14 *Overall Change in Transportation Costs*

Years	3% to 4%	4% to 5%	3% to 5%
2022-2026	124%	129%	134%

However, between the demand scenarios there is minimal change. To further investigate the difference between the three demand scenarios within each year. Table 15 displays the relative cost increases when comparing the incremental increase in CAGR percentage. There is no significant difference between growing one percent from 3% to 4% and 4% to 5%. Even growing two precent from 3% to 5% results in minimal increase of transportation costs. The percent change is higher in later years when all demand nodes are fully open and the base demand has had some time to accumulate.

Table 15 *Percent Change for Each Year Across Scenarios*

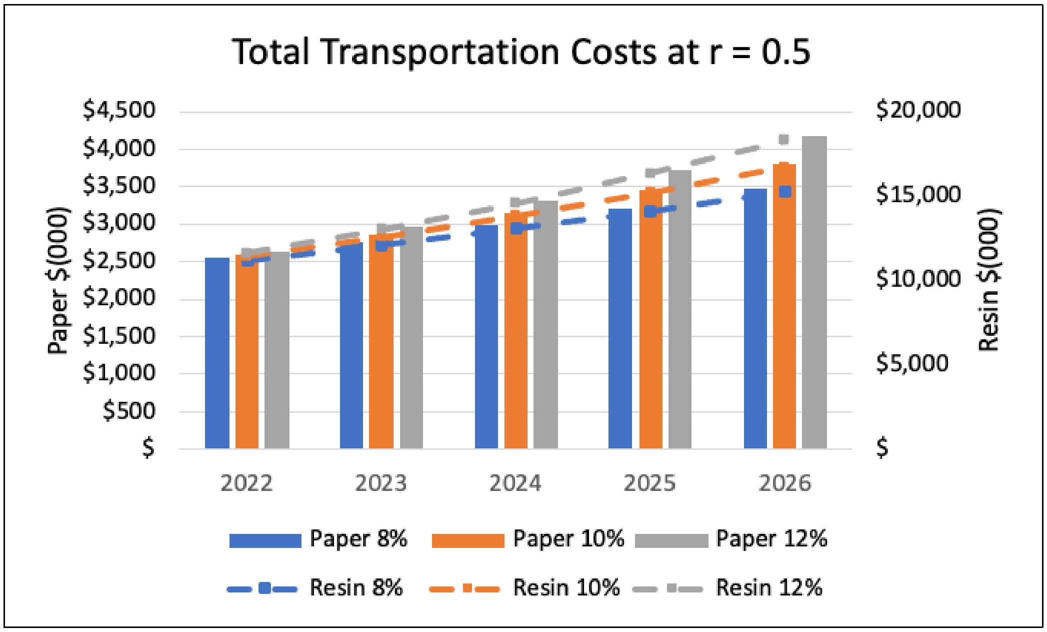
Years	3% to 4%	4% to 5%	3% to 5%
2022	0%	0%	1%
2023	1%	1%	1%
2024		1%	
2025	2%	2%	3%
2026	3%	3%	5%

Therefore, it can be assumed that the transportation costs are not very sensitive to small changes in the demand growth rate.

5.2. Change in Demand & Impact on Transportation Costs – Customer 2

The resulting demand scenarios for paper and resin are displayed in Figure 11. The y axis represents the transportation cost for the demand scenarios over time using different CAGRs as represented on the x-axis. The transportation costs grow for each scenario over time relative to demand. As 70% of demand is assumed to go to resin the scale of the transportation costs is higher compared to paper. There do not seem to be stark differences in transportation costs when comparing the yearly transportation costs between scenarios in both cases.

Figure 11 *Customer 2 Transportation Costs Across Demand Scenarios for r=0.5*



However, when comparing the transportation costs over the entire period there is a more significant change between demand scenarios.

Table 16 displays the increase in transportation costs across demand scenarios for resin and paper, respectively. Since we are considering a percentage increase the results are the same for resin and paper. Increasing demand with a CAGR of 15% as opposed to 8% results in an increase in transportation costs of 57%.

Table 16 *Overall Change in Transportation Costs*

2022-2026	8% to 12%	12% to 15%	8% to 15%
Resin	36%	46%	57%
Paper	36%	46%	57%

Breaking down the analysis year over year for each demand scenario (see Table 17) underlines the trend seen in Figure 11. The difference between demand scenarios, on a per year basis, is minimal. However, in the later years, from 2025 to 2026, the difference is larger as the demand growth compounds on itself. For example, the transportation costs for 8% versus 15% in 2026 is 20% higher, whereas, the difference was only 4% in 2022.

Table 17 *Percent Change for Each Year Across Scenarios*

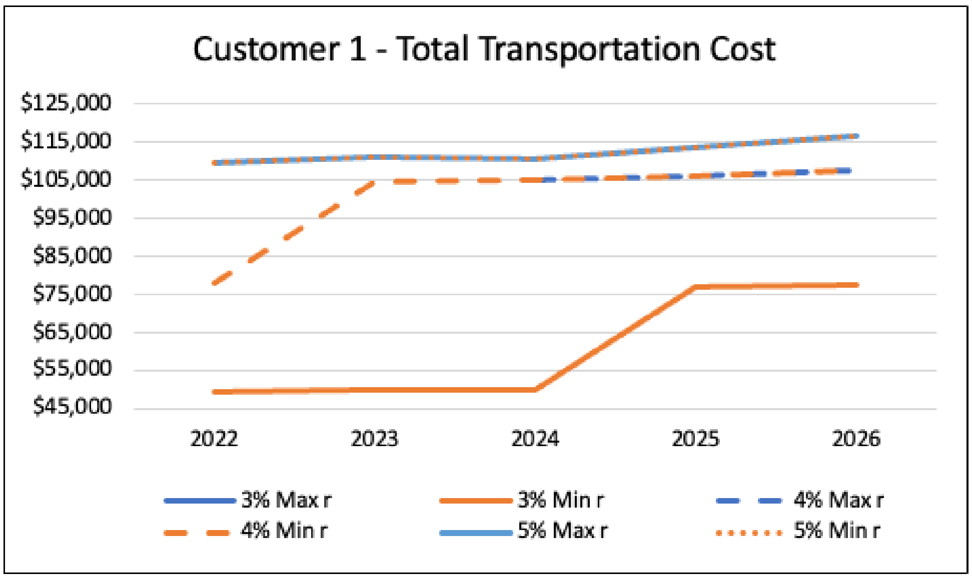
Years	8% to 12% (Resin % / Paper %)	12% to 15% (Resin % / Paper %)	8% to 15% (Resin % / Paper %)
2022	2% / 2%	2% / 2%	4% / 4%
2023	4% / 4%	4% / 4%	8% / 8%
2024	6% / 6%	6% / 6%	6% / 6%
2025	8% / 8%	7% / 7%	16% / 16%
2026	10% / 10%	9% / 9%	20% / 20%

The different demand scenarios had a varying effect on transportation costs for the two customers. Since the customer are in different industries different CAGRs were necessary to reflect realistic growth rates. The increase in transportation costs compared on a yearly basis was higher for Customer 2 versus Customer 1. This is logical since Customer 2 has a higher CAGR compared to Customer 1. The overall increase in transportation costs for the entire period was much higher for Customer 1 compared to Customer 2. This was driven by the fact that the Customer 1 demand was not only increased through CAGR but also an increase in the number of stores, or demand nodes. Section 5.3. will discuss the effect of resiliency on supply chain network transportation costs.

5.3. Change in Resiliency & Impact on Transportation Costs – Customer 1

This project used a maximum and minimum scenario for resiliency, which in Customer 1's case, was 50% and 0% respectively. Due to the lack of excess capacity and the significant increase in retail locations, there are no significant differences in transportation costs between the resilience scenarios. As shown in Figure 12, across each demand scenario, the differences in transportation costs are marginal.

Figure 12 *Customer 1 Transportation Costs, Resilience Scenario Comparisons*



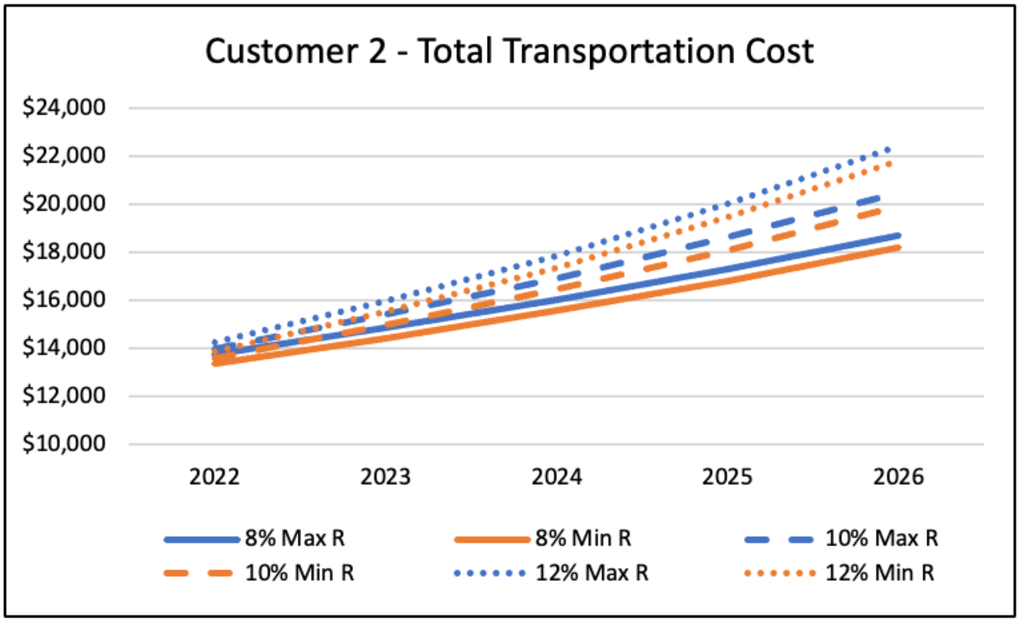
In addition, the results for 2023, at the demand scenario of CAGR 4%, is infeasible. This is primarily due to insufficient capacity to service local demand volumes, while in later years of the same demand scenario having a feasible solution. As there are no significant differences in transportation costs, it is suggested that to have a resilient network, excess capacity is required.

5.4. Change in Resiliency & Impact on Transportation Costs – Customer 2

This project used the same maximum and minimum approach as mentioned in Section 5.3., which were also 50% and 0% respectively, to measure the impact of resiliency on transportation costs for Customer 2. Unlike Customer 1, Customer 2's results yielded a 3%

higher transportation cost in the maximum resilience scenario, across all years and demand scenarios (see Figure 13).

Figure 13 *Customer 2 Transportation Costs, Resilience Scenario Comparisons*



The varying transportation costs between the two resilience scenarios indicate Customer 2's cost optimal network is slightly different from resiliency optimal network. This result suggest that Customer 2 has more potential to designing a resilient network when compared to Customer 1.

5.5. Analysis of Model Results

Customer 1 having significant risk of disruption is supported by the infeasible resilient network in the 2023, 4% CAGR scenario. Customer 2, on the other hand, does not seem to bear the same risk. After comparing the results between Customer 1 and Customer 2, this project has identified network profile is a key factor to designing a resilient network. In addition, a comparison between Customer 1 and Customer 2 showed the amount of facilities and customer locations is a key factor in designing a resilient network.

Customer 1's higher risk of disruption is primarily due to the different network profiles. In terms of network profile, Customer 1 is almost doubling their retail locations, while keeping the same amount of DCs, meaning that, on average, each DC services 104 retail locations by 2026. Meanwhile, Customer 1 is maintaining the same amount of facilities and customer locations, where each facility services 7 customer locations by 2026 on average. Both customers' facilities are also located in different cities. This difference in network profile suggests that the more spread out the facilities, as well as the lower amount of customer locations a facility services on average, enables the opportunity to design a more resilient network.

In terms of transportation costs, the results of this project suggests that having a resilient network does not result in a significant increase in costs, as Customer 1 had a less than 1% transportation cost increase, while Customer 2 had a 3% transportation cost increase. This suggests that for both customers, designing a cost optimal and resilient network is feasible, but understanding each facility's capacity and customer location's demand is critical.

6. Conclusion & Future Work

Due to the COVID-19 pandemic and the resulting supply chain disruptions, organizations are placing a greater emphasis on resiliency. It has become critical that organizations that are expecting high demand growth, such as Customer 1 and Customer 2, design a resilient network to support the growth in demand.

This project utilized a MILP model to design a resilient and optimal cost network, that primarily focuses on the outbound transportation of Customer 1 and Customer 2. Unlike traditional MILP optimization models, the model developed in this project also quantified resilience and was made adaptable across all of Coyote's customers. In addition, customer specific demand and resilience scenarios were utilized to design a resilient network as well as quantify the change in transportation costs of the network.

The results indicated that to design a resilient and cost effective network, organizations should aim to have DCs and manufacturing facilities located in different cities, relative to customer locations, as well as to balance the number of facilities with the number of customer locations. The results also indicate that having a resilient network will not increase transportation costs substantially, as both customers' transportation costs did not increase significantly when having a resilient network.

Lastly, various improvements can be considered in future projects that are similar, where more demand and capacity inputs will enable the project to recommend whether to combine facilities, or when and where to open new facilities. In addition, future projects can also improve upon the MILP model utilized in this project, by incorporating multi-stop fulfillment methods to allow for a more realistic model.

For future projects and analysis, there are three main avenues that can expand and improve upon the scope of this project. This would include further input demand, capacity, and multi-stop fulfillment strategies.

For Customer 1, due to the new store demand assumptions listed in Section 3.2., demand is unrealistically expected to increase by +100% within the first three years of the model's start date. With further input towards planned new store opening dates and expected demand per new store, this project will likely result in different optimized transit cost figures, fulfillment strategy recommendations, and network design recommendations.

For Customer 2, assumptions were also made in Section 4.1. As certain customer locations are likely to be only a resin or paper customer, the model the model will also provide different costs figure and fulfillment strategy recommendations.

Receiving further input from both customers regarding capacity will improve the model considerably. Further input will enable the project to provide recommendations on whether to combine existing facilities or where and when to open new facilities. More capacity data will also allow future projects to provide more realistic resilience measurements. These two potential outcomes enable Customer 1 and Customer 2 to make strategic decisions to support their significant growth in demand and to design a more resilient network.

Lastly, as the scope of this project utilizes a single stop MILP model, where it is assumed that each truck only services one customer location. However, it is unrealistic that each retail or customer location would be serviced by a single stop fulfillment method. A single stop fulfillment strategy was assumed for this project due to lack of detailed per retail or customer location demand data. In addition, per retail or customer location capacity data will be required to allow for multi-stop fulfillment network optimization. Multi-stop fulfillment will result in a lower total transportation cost, and will also most likely improve the network's resiliency, due to the shorter transit lead times between retail or customer locations. Therefore, it is recommended to include multi-stop network optimization methods for future similar projects.

References

Alfarsi, F., Lemke, F., & Yang, Y. (2019). The Importance of Supply Chain Resilience: An Empirical Investigation. *Procedia Manufacturing*, *39*, 1525–1529. https://doi.org/10.1016/j.promfg.2020.01.295

Azaron, A., Brown, K. N., Tarim, S. A., & Modarres, M. (2008). A multi-objective stochastic programming approach for supply chain design considering risk. *International Journal of Production Economics*, *116*(1), 129–138. https://doi.org/10.1016/j.ijpe.2008.08.002

Ballou, R. H. (2001). Unresolved Issues in Supply Chain Network Design. *Information Systems Frontiers*, *3*, 417–426. https://doi.org/10.1023/A:1012872704057

Birge, J. R., & Louveaux, F. (2011). *Introduction to Stochastic Programming*. Springer Science & Business Media.

Farahani, R. Z., & Elahipanah, M. (2008). A genetic algorithm to optimize the total cost and service level for just-in-time distribution in a supply chain. *International Journal of Production Economics*, *111*(2), 229–243. https://doi.org/10.1016/j.ijpe.2006.11.028

Ivanov, D., & Das, A. (2020). Coronavirus (COVID-19/SARS-CoV-2) and supply chain resilience: A research note. *International Journal of Integrated Supply Management*, *13*(1), 90. https://doi.org/10.1504/IJISM.2020.107780

Lee, H. L., Padmanabhan, V., & Whang, S. (1997). The Bullwhip Effect in Supply Chains. *SLOAN MANAGEMENT REVIEW*, *38*(3), 12.

Mitchell, S. (2021, May 19). *Supply chain disruptions may have caused up to $4 trillion in lost revenues | Reuters Events | Supply Chain & Logistics Business Intelligence*. https://www.reutersevents.com/supplychain/supply-chain/supply-chain-disruptions-may-have-caused-4-trillion-lost-revenues

Pettit, T. J., Croxton, K. L., & Fiksel, J. (2019). The Evolution of Resilience in Supply Chain Management: A Retrospective on Ensuring Supply Chain Resilience. *Journal of Business Logistics*, *40*(1), 56–65. https://doi.org/10.1111/jbl.12202

Ponomarov, S. Y., & Holcomb, M. C. (2009). Understanding the concept of supply chain resilience. *The International Journal of Logistics Management*, *20*(1), 124–143. https://doi.org/10.1108/09574090910954873

ReportLinker. (2021, July 19). *Global Retail Omni-Channel Commerce Platform Market to Reach US$14.5 Billion by the Year 2027*. GlobeNewswire News Room. https://www.globenewswire.com/news-release/2021/07/19/2264644/0/en/Global-Retail-Omni-Channel-Commerce-Platform-Market-to-Reach-US-14-5-Billion-by-the-Year-2027.html

Research and Markets; High Pressure Protective Packaging Film Market - Global Growth, Trends, and Forecasts 2021-2026: Major Players are Sealed Air, Pregis, Barton Jones Packaging, Abco Kovex and Supreme Industries - ResearchAndMarkets.com. (2021, May 18). *Electronics Newsweekly*, 217.

Sealed Air (SEE) Beats on Q3 Earnings & Sales, Raises '21 View. (2021). Zacks. https://www.yahoo.com/now/sealed-air-see-beats-q3-130501552.html

Sheffi, Y., & Rice, J. (2005). A Supply Chain View of the Resilient Enterprise. *MIT Sloan Management Review*, *47*(1), 41–48.

Stump, B. S., & Mullens, S. S. (2021). 2021: State of the Furniture Industry. *Home Furnishings Business*, *16*(5), 22–23.

Ward, S. (2021, March 24). How Do Brick and Mortar Stores Compare with Online Retail Sites? *The Balance Small Business*. https://www.thebalancesmb.com/compare-brick-and-mortar-stores-vs-online-retail-sites-4571050

Ye, Y. (1998). A review of: "Introduction to Linear Optimization", 608 pages, ISBN 1-886529-19-1, $69.00 (hardback). *IIE Transactions*, *30*(9), 855–855. https://doi.org/10.1080/07408179808966531

Zokaee, S., Jabbarzadeh, A., Fahimnia, B., & Sadjadi, S. J. (2017). Robust supply chain network design: An optimization model with real world application. *Annals of Operations Research*, *257*(1–2), 15–44. https://doi.org/10.1007/s10479-014-1756-6