Optimizing Fleet Utilization by Adjusting Customer Delivery Appointment Times

by

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ABSTRACT

The supply of trucks and drivers is struggling to keep up with the increasing and volatile demand for ground transportation. As a result, for companies like Niagara Bottling LLC., supply chain managers are pressured to optimize their logistics networks. Niagara Bottling is projected to deliver over 1 million full truckloads of bottled beverages to customers across North America in 2020 and transportation costs are already their second highest contributor to Cost of Goods Sold (COGS). Currently, Niagara's customers have overlapping delivery window requirements which cause significant fluctuations in delivery volumes throughout the day. Niagara hypothesizes that if these delivery appointments were more evenly distributed throughout the day, the same number of loads could be delivered with fewer trucks and therefore less cost. A heuristic algorithm is created to maximize fleet utilization by modifying these delivery appointment windows so that multiple scenarios can be compared based on fleet utilization and cost savings metrics. This paper will further articulate the methodology and assumptions used to generate these scenarios and provide context to the recommendations for utilization improvement on Niagara's logistics network. Regions with high customer mix saw increases in utilization as high as 25% and decreases in cost as high as 45%. Regions with high delivery volumes saw increases of utilization as high as 13% and decreases in cost as high as 18%.

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1. INTRODUCTION

Niagara Bottling LLC., is a family owned and operated low-cost leader in the United States plastic bottling industry. Niagara owns 32 production facilities in North America where they manufacture, fill, package and distribute bottled beverages.

Niagara prioritizes exceptional value, quality, and service to their customers and they focus on selling a value item rather than building a distinct brand. The vast majority of their customer demand comes from private label products and only a small percentage is reserved for their own Niagara branded products. Because their facilities are vertically integrated to include the manufacturing and assembly of both bottles and caps, Niagara can control its production costs and quality much tighter than competitors.

In 2019, Niagara delivered over 900,000 full truckloads of their products to customers across North America using a consolidated pool of 55 carriers. Each remaining carrier has an established strategic relationship with Niagara Bottling to satisfy the high supply chain velocity of the bottling industry. Since bottling inventory turns so quickly, full truckloads traveling to Distribution Centers (DCs) are mostly stocked with the same SKU, and truckloads delivered directly to customers will carry multiple SKUs to meet the customer demands.

1.1 PROBLEM STATEMENT AND SCOPE

Facing a variety of complex operational constraints in the transportation environment, as discussed in Section 1.2 Motivation and Section 2 Literature Review sections below, Niagara's trucking fleet network is often underutilized therefore exposing the company to millions of dollars in incremental transportation cost. Niagara anticipates that the main behavior that is constraining this utilization metric is the overlapping and clustered customer delivery windows that the carriers must meet.

The goal of this capstone project is to reduce Niagara Bottling's transportation cost through optimizing trucking fleet utilization by adjusting the customer delivery time windows. If the fleet network runs more efficiently, then the same number of deliveries could be completed with fewer vehicles and therefore less cost. This project will focus on the customer facing side of logistics and planning instead of internal loading, scheduling or carrier booking. The customer constraints of delivery time windows will be investigated and analyzed to provide recommendations with quantifiable financial impact for customer/carrier logistics negotiations. The two most important metrics used for model comparison and sensitivity testing will be total transportation cost and fleet utilization.

1.2 MOTIVATION

The mission statement of Niagara Bottling is written on its website as "delivering an unbeatable combination of quality, price, and service through hard work and innovation." With such an emphasis on cost, it is very important for the company to maintain its cost competitive edge and drive for continuous improvement on cost reduction in its operations. In 2020, Niagara is projecting to ship over 1 million truckloads for the first time. If the trucking utilization rate is improved and transportation efficiency is increased, the potential cost saving could be significant even if only a few dollars are saved per delivery.

Other than the raw material cost (resin) to manufacture the bottles, transportation cost is the largest contributor to Niagara's Cost of Goods Sold (COGS). The most significant transportation cost drivers include fuel, driver wages, vehicle costs, vehicle insurance and permits. According to a business overview (Niagara Bottling, 2019), the non-fuel cost drivers account for 68% of the total transportation cost. By optimizing the fleet utilization to complete the same amount of loads with fewer trucks, the excess capacity in the network can be trimmed away and the total transportation costs will decrease.

Niagara has already invested significantly in strategic cost reduction projects in the transportation area that will also be enhanced with the addition of this utilization optimization. Niagara has intentionally built production facilities at the center of large customer demand clusters to minimize the distance each truck must travel. Niagara has also consolidated their carrier supply base to just 55 carriers and negotiated strategic contracts with each of them to guarantee certain rates and capacity. Another unique operational constraint for the bottled water industry is that each truck has a weight limitation of 80,000 lbs. and after subtracting off the weight of the driver, fuel and the truck itself, there is only ~45,000 lbs. of product that can be loaded onto the truck. Given how heavy liquids are, the standard truck will max out the allowable weight before it uses up all the physical space in the truck. For this reason, many of Niagara's loads have significant amounts of empty space because they are at maximum weight capacity. To combat this, Niagara has strategically aligned with companies to design trucks specifically for Niagara with, for example, no passenger seat, no secondary fuel tank, aluminum floors instead of wood and single wheels instead of double wheels. With all these other transportation optimization initiatives that Niagara is driving, being able to optimize the utilization of these trucks will only increase the values of these existing projects as well. As Niagara sees it, there are many ways to reduce transportation costs and eliminating waste in every aspect of the logistics network will be crucial to maintain their reputation as the low-cost leader in the industry.

1.3 RELEVANCE

The ever-growing demand for goods drives a continuous increase in transportation volume, including trucking transportation. On the other hand, the Cass Truckload Linehaul Index (a measure of changes in per-mile truckload linehaul rates) has a compound annual growth rate of 3.8% over the last 9 years (Niagara Bottling, 2019). Therefore, the efficient utilization of assets, such as trucks, becomes more and more important. Improved vehicle utilization can lead to a reduction of trucks needed to perform a certain number of jobs and more importantly a reduction in transportation cost per delivery jobs for companies like Niagara that do not own many of their own transportation assets.

Trucking operation efficiency is directly related to and affected by a variety of constraints, such as fleet size and operation mode, industry regulation on driving hours, detention time and delivery time window. A lot of work has been done studying these factors and their relationships with trucking efficiencies, mostly in the areas of electronic logging devices, detention times, driver turnover and safety rules. This capstone project puts focus on analyzing the impact on efficiency from changing the delivery time window constraint.

Since Niagara has a significant market share in the bottled water market in the US, and its customer base is supermarkets, grocery stores, convenience stores and other large retailers, the results of this study will be very meaningful and influential in terms of its applicability across different industries and the substantial cost saving potential with the massive market volume.

2. LITERATURE REVIEW

After optimizing their carrier negotiations and existing trucking equipment, Niagara Bottling is seeking to further reduce their transportation costs by alleviating customer logistics constraints. Specifically, Niagara Bottling is anticipating that the delivery windows and appointment times that their customers require them to abide by are driving significant amounts of cost. To understand the effect of such customer constraints, it is important to review existing literature to develop a foundation of the nuances of this industry and this project scope. This literature review will focus on four distinct research threads: the United States trucking industry, its operational constraints, specifics of bottling supply chains and existing optimization model creation strategies for this application. These research threads will provide insight for operational constraints or intricacies, so they can be accounted for in the simulations to provide better accuracy.

2.1 UNITED STATES TRUCKLOAD INDUSTRY

According to the Freight Analysis Framework (2015), the United States transportation industry handled over $18 trillion of product over 5 million ton-miles in 2017. The most common form of transportation was trucking, which accounted for 69% of the total value and 40% of distance traveled. The value of flows is projected to double by 2045 and distance traveled will increase by 66%.

The vicious capacity and demand cycles are also major factors in understanding the US transportation industry. Demand varies drastically throughout the year based on everything from weather and holidays to annual procurement cycles and peak harvesting seasons (Pickett, 2018). Adding to the complexity that comes with heavily cyclical demand is the potential gap in supply (truck drivers) in the industry. Since 2013, hiring requirements, including growth, churn, retirees and regulations, have increased by 36% and the shortage of truck drivers is anticipated to grow to nearly 240,000 by 2022 (J.B. Hunt Transport, Inc., 2015).

A very important aspect of analyzing any industry is understanding the financial impact it contributes to the economy. The United States boasted $796.7 billion in gross freight revenues in 2018, of which 80.3% was generated through trucking alone (Reports, Trends & Statistics, 2018). This huge market is not dominated by a few critical players. Rather, its top 10 for-hire carriers only make up 19% of the gross revenue (Top 100 For-Hire, 2017). In addition to the size and growth of the US transportation industry, studies show that transportation costs make up over 60% of a company's total logistics costs (Caplice, 2006) which creates a high incentive for companies to perfect their logistics strategies and optimize their supply chain flow. The expensive and expanding market coupled with the fragmented and dynamic nature of the

US truckload industry is what makes logistics improvement initiatives so tempting to pursue yet complex to fully understand and simulate.

2.2 OPERATIONAL CONSTRAINTS ON UNITED STATES TRUCKLOAD INDUSTRY

Niagara Bottling is specifically interested in investigating operational constraints in their current supply chain in the hopes of improving utilization and therefore reducing transportation cost. Due to United States hours of service (HOS) regulations, a driver can only be on duty for 840 minutes a day which includes a 30-minute break and a maximum of 660 minutes of driving (J.B. Hunt Transport, Inc., 2015). Calculating the difference, a perfectly utilized driver only spends 150 minutes a day on everything else. In practice, this is extremely difficult to achieve based on compounding factors that are difficult to control such as traffic, weather, fueling time, parking availability, facility navigation and maintaining paperwork. However, as shown in Figure 1, the factors that negatively impact a drivers' Hours of Service most are, arguably, more controllable (J.B. Hunt Transport, Inc., 2015). Only 10–15% of drivers say that more random variables such as traffic and weather often or always impact their HOS compliance. In contrast, 70% of drivers say that facility delays often or always affect their HOS compliance and 55% of drivers say the same for pickup/delivery requirements. There are many underlying factors that are driving these facility delays, such as delivery type. The main distinction of delivery type is the difference between drop and live loads. Drop loads are when the truck driver drops the full container or trailer at the destination without waiting for the receiving team to unload it. Live loads are when the truck driver waits for the receiving team to unload their cargo and drives away with the empty truck. On average, when compared to a drop load, a live load spends 5 times longer waiting to be unloaded, 2 times longer in detention and about one-third of the time in dwell (J.B. Hunt Transport, Inc., 2015). These statistics include a broad range of industries, products, carriers and routes so it is important to investigate further into the bottled water industry specifically to understand any limitations of these statistics.

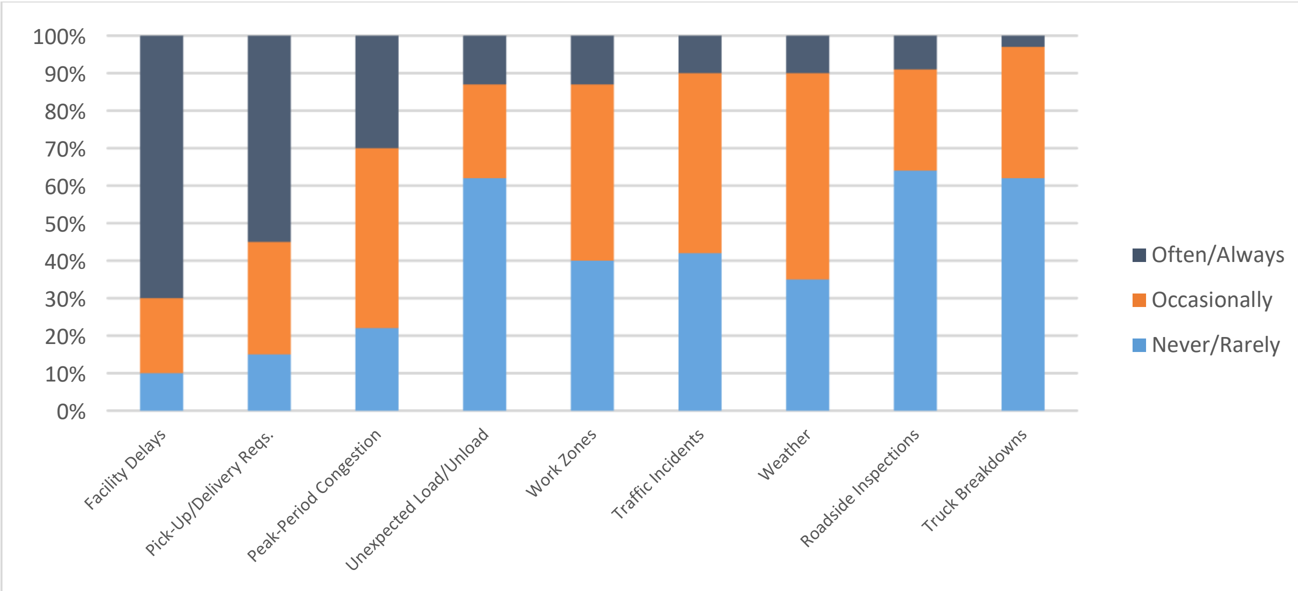


Figure 1. Motor Carrier Views on Factors Affecting Drivers' HOS Compliance (J.B. Hunt Transport, Inc., 2015)

2.3 SUPPLY CHAIN NUANCES OF BOTTLING INDUSTRY

At first glance, water in a plastic bottle might not seem like the most dynamic product category, but sales of bottled water have registered nearly continuous growth for more than three decades. Galbreth, Walker, Vincent and Hyatt (2013) describe that consumption of bottled water in the United States saw rapid increases in the 1990s and 2000s, rising from 9.8 gallons per person in 1992 to 27.6 gallons per person in 2009. Overall, consumption of bottled water grew a thousand-fold between 1984 and 2005. Between 2000 and 2009, bottled water's market share increased from 9% to 14.5%, while soft drinks fell from 30% to 24%. During the economic downturn that began in 2008, sales of nearly all beverages decreased, but bottled water sales decreased less than those of all other beverage categories.

Globally, the bottle water industry is worth $400 billion which is growing at the rate of 7% per year. Beside the raw material of plastic, transportation cost is the largest COGS driver and minimizing these costs is becoming a challenge that many bottle water manufacturers must face with such continuous industry growth. Khan, Khan, Hussain and Ashraf (2017) list several common bottled water industry supply chain problems, including labor and payload utilization, shipment routing and inventory. Khan et al. proposes some new software techniques targeting these problems, such as Routific for shipment routing and transportation cost optimization and Delivrd for inventory optimization. As bottled water belongs to fast moving consumer goods, it is considered as a "high velocity" product, which characterizes as high order frequency and high-volume shipments. The consumer need for cases of water or other bottled beverages frequently triggers consumers to visit large retailers or club stores. These huge retail players often anticipate this high volume of consumption and strategically stage full pallets of bottled beverages in the very front of the store to provide easy access for their patrons. As a result, many retailers require a very high service level to ensure that they never have stockouts of such an important product. Having frequent orders and shipments among scattered customer locations creates opportunities to optimize shipment routing and trips to minimize the transportation cost. Shippers, carriers and customer receiving locations have incentive to work together to achieve better system-wide efficiencies to be able to share the huge cost saving potential.

2.4 OPTIMIZATION MODELING AND SIMULATIONS

The increasing demand for transportation and moving goods is putting more pressure on shippers and carriers to continuously improve their operational efficiency. This requires more collaborative supply chain management practices which typically involves all parties along the supply chain. Ergun, Kuyzu and Savelsbergh (2007) describe that traditionally, shippers and carriers have respectively and independently focused on reducing their own internal operation cost by improving efficiencies. Ergun et al. also describe that more recently, they have come together focusing on improving system-wide collaboration to drive down system-wide cost and be able to share these cost savings.

Ergun, Kuyzu and Savelsbergh (2004) introduce the lane covering problem (LCP): covering a set of lanes with a set of continuous move tours with minimum cost. The problem is formulated as a covering problem on a Euclidean digraph, and it can be solved efficiently as a minimum cost circulation problem. Ergun et al. also investigate some of the LCP constraints, such as restriction on the maximum number of legs that can make up a tour and restriction on the maximum length or duration of a tour. These constraints result in highly effective and efficient optimization-based heuristics. As the majority of Niagara transportation deals with full truck-load delivery, after a delivery a truck normally needs to return to the plant for re-loading and therefore lane covering problem is not applicable for this Niagara project.

Ergun, Kuyzu and Savelsbergh (2007) develop an optimization technology that can be used to assist in configuring repeatable and dedicated continuous truckload trips. This technology is valuable to companies that send truckload shipments regularly and are looking for collaborative partners to maximize the utilization of a dedicated fleet or have better negotiation power for transportation procurement. Timing is a critical factor of the practical viability of continuous move tours. Ergun et al. develop a heuristic that very effectively and efficiently incorporates fast routines for checking time-viability of a tour with dispatch time windows considered. This optimization technology is based on the time constrained lane covering problem. This model focuses on reducing the amount of truck repositioning and involves collaboration among different shippers and carriers. The scope of this Niagara project is different by not involving other shippers, but the idea of developing an effective heuristic for a time constrained optimization transportation problem is adopted.

As compared to more collaborative shipper-carrier network, some research has focused on truckload procurement for a single shipper. Moore et al. (1991) develop a simulation and optimization tool, which in real time identifies two lanes that can be served in sequence and a set of carriers that can serve both lanes. Reynolds Metal Company has used this tool in centralized procurement and has achieved $7 million of annual savings in transportation cost. Caplice and Sheffi (2003) describe an auction run by a shipper to determine the minimum cost allocation of its lanes to carriers. It is assumed that bids from carriers on bundles of lanes consider the lane integration effect in carriers' existing network. Song and Regan develop a simple model to simulate the way in which carriers identify tours minimizing the lane covering cost. However, this model doesn't take into consideration any practical constraints, such as dispatch time windows.

This Niagara Bottling capstone project focuses on the impact on asset utilization from changing the delivery time window constraint and the time-constrained lane covering problem while taking into consideration the dispatch time windows on the lanes. Gronalt, Hartl and Reimann (2003) develop new saving algorithms for time constrained pickup and delivery of truckload shipments. The objective function of this model is to minimize the empty vehicle movements with several underlying assumptions. The lower bound of the objective function is first calculated with the time window constraint completely relaxed. Then several heuristic solution algorithms are introduced for result comparison. A conclusion is drawn that empty vehicle movements for covering a set of lanes increase rapidly with increased time window tightness.

The methodology literature review is summarized in Table 1. The approach in Gronalt, Hartl and Reimann's research is the most relevant to this project, as it develops a heuristic to quantify the impact on vehicle operation efficiency using dispatch/delivery time window as a critical variable constraint.

Table 1. Methodology Literature Review Summary

Authors	Year	Operational Environment	Decision Variables
Ergun, Kuyzu and Savelsbergh	2007	System-wide collaboration	Transportation Cost, time-viability
Ergun, Kuyzu and Savelsbergh	2004	Continuous move tours	Transportation Cost
Moore et al.	1991	Two lanes that can be served in sequence	Real time matching
Caplice and Sheffi	2003	Auction run, integration effect in carriers' existing network	Minimum cost allocation
Gronalt, Hartl and Reimann	2003	Delivery window as a critical constraint	Minimize the empty vehicle movements

2.5 LITERATURE REVIEW CONCLUSION

The typical variant constraints and underlying assumptions of the lane covering problem (LCP) can be leveraged to this Niagara Bottling capstone project, as the objective is to set up a model that minimizes the transportation cost covering all the lanes between Niagara plant and customers. With the clear majority of cases being full truck-load deliveries, this capstone project will consider the fact that one truck needs to return to a Niagara plant from the previous load to be re-loaded for the next delivery if time allows. Because this project specifically is interested in finding out how delivery time window changes will affect the asset (fleet) utilization, this constraint will be the focus and the model will be run with different length of delivery time window, given a set of loads within a certain time period. As the model is being established, literature regarding heuristics for the time constrained lane covering problem (TCLCP) will also be leveraged to ensure that the resulting solution is truly the optimal one. As discussed further in Section 3.1, this model will be scoped to include three different shipping locations distinctive in demographics, geography, transportation market and customer demand. The delivery time window effect will be observed and analyzed from model output for these locations. Such location specific modeling and analysis haven been the focus of previous research of lane covering problem.

3. DATA AND METHODOLOGY

One of the most crucial parts of this project is to determine a scope that is both attainable in the context of the capstone project expectations and directly applicable and representative of Niagara's logistics network. In order to understand the current state of Niagara's trucking network, two main sources of historic data were provided. First, a weekly "Scorecard" file is analyzed which contains a row of trip data for every load offered to every carrier for that week. Second, an annual "Procurement Report" is analyzed which contains details of the cost specifics on loads that were accepted by carriers. The rest of this section will discuss how each source of data was investigated, validated by Niagara and formed into meaningful assumptions to use in the optimization modeling procedure.

3.1 SCORECARD DATA CLEANING AND ANALYSIS

The largest data set provided by Niagara bottling was the weekly Scorecard data files from January 2019 - October 2019. Many cleaning operations and data filters were needed to make this data set a reliable baseline for model development:

1. **Focus on 3 Manufacturing Facilities:** Niagara specifically selected each of these regions (region A, B and C) since they were defined by different supply chain nuances, as shown in Table 2. The intention is that if the same model can work for each region individually, then it can be applied across the rest of the North America locations.

Table 2. Source Region Scoping Comparisons

Region	# Distinct Customers	Average Distance Per Route (Miles)	Average Weekly Outbound Truckloads
Region A	21	138.33	337.8
Region B	71	113.96	847.6
Region C	49	150.68	849.1

- Region A: Region A was chosen as the relatively simple network with lower volume and a smaller customer mix. Region A is dominated by two customers, customer A1 and A2, that together account for 82.3% of the demand fulfilled by the Region A facility.

- Region B: Region B was chosen as one of the most complex networks that Niagara has. Region B is responsible for more than triple the customer mix and more than double the volume of region A. Region B is characterized by a large volume of trips, but overall, the average distance of each trip is the shortest due to the densely populated area that region B is servicing.

- Region C: Region C was chosen as a balance between Region A and Region B. Region C is characterized by medium customer mix, high volume and has the longest average distances travelled per route.

2. **Use Fiscal Week (FW) 33 through FW 42 of 2019 for sampling**: Due to Niagara's rapid growth, the first filter only includes the most recent 10 weeks of operation based on the project kickoff date. Niagara was also in the process of making changes to the formatting of the Scorecard report and the reporting expectations of their carriers so the agreed upon scope included data formats that were standardized with each other.

   The main concerns with a 10-week sampling of data was the possibility of losing demand trends such as seasonality or holidays. However, when verifying the validity of the assumptions made based on this 10-week sample (August through October 2019) and assumptions that could have been made based on data earlier in the year, Niagara agreed that the more recent data was a more representative sample of the current state.

3. **Filter out rejected loads**: An advantage to the scorecard reports is that they accounted for every load offered to carriers even if the load was rejected. For this analysis, only loads that were accepted and completed will be considered.

4. **Create calculated fields**: The following fields were calculated to further characterize logistics behaviors:
   - Pickup Duration (hours):
     $(\text{SOURCE\_ACTUAL\_DEPARTURE} - \text{SOURCE\_ACTUAL\_ARRIVAL}) * 60 * 24$
   - Speed (miles per hour):
     [MILES]/([LAST_STOP_ACTUAL_ARRIVAL]-[SOURCE_ACTUAL_DEPARTURE]) *24)
   - Delivery Duration (hours):
     ([LAST_STOP_ACTUAL_DEPARTURE]-[LAST_STOP_ACTUAL_ARRIVAL])*60*24
   - One Way Travel Time (hours):
     [MILES]/Speed
   - Total Load Delivery Time (hours):

Pickup Duration + One Way Travel Time + Delivery Duration

- Driving Utilization (%): This number will be used to understand how many hours out of the maximum 11 hours per day the truck is actually driving.
  One Way Travel Time/11
- Shift Utilization (%): This number will be used to understand how many hours out of the maximum 14 hours per day the truck driver is on duty.
  Total Load Delivery Time / 14

5. **Filter outliers from calculated fields**: Niagara emphasized that much of this arrival and departure data is self-reported and the quality of it depends heavily on the carrier and the level of technology they use. To eliminate some of these reporting errors, the long tail of the resulting distribution is excluded. Specifically, any calculated pickup duration or delivery duration over 5000 hours and any calculated Speed over 100 MPH is eliminated from the analysis.

3.1.1 INITIAL OBSERVATIONS OF SCORECARD DATA

After the data cleaning, data filtering and calculated fields were approved by Niagara, many observations were made about the current state of the transportation network that were very influential to the logic when making assumptions for the optimization model. These assumptions will be summarized in Section 3.3 Final Assumptions and Calculations, so the reminder of this section will focus on the current behavior that drove these assumption decisions.

1. Each region is characterized by a few dominating customers. See Figures 2, 3 and 4 below for region A, region B and region C customer mix respectively.

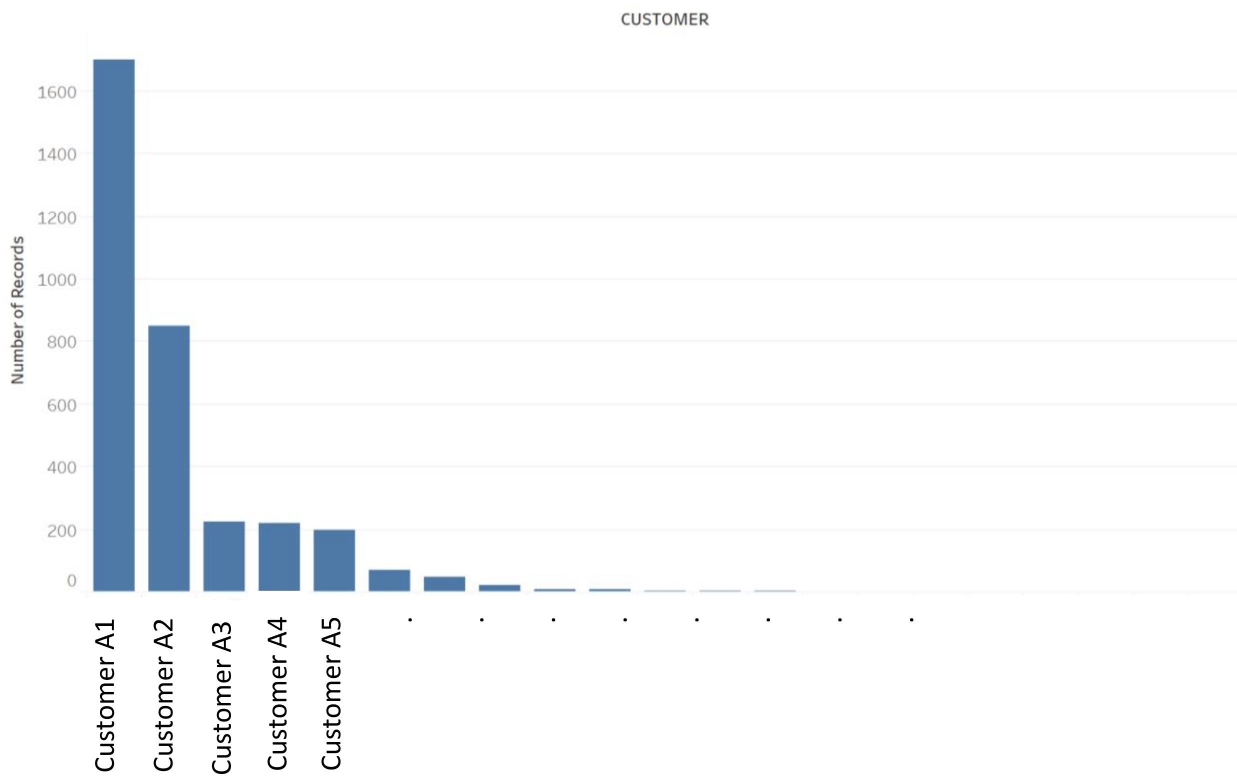


Figure 2. Region A Customer Mix

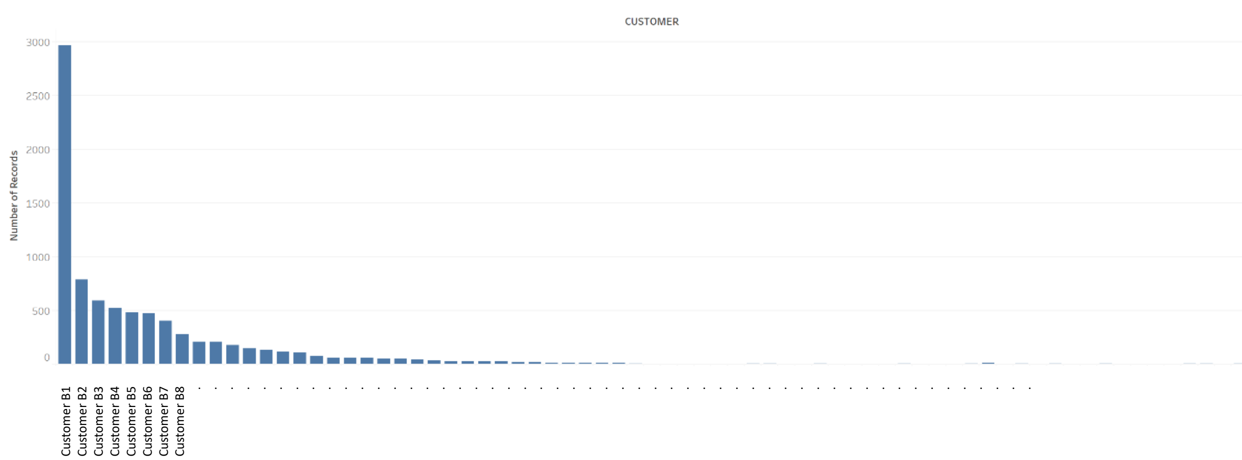


Figure 3. Region B Customer Mix

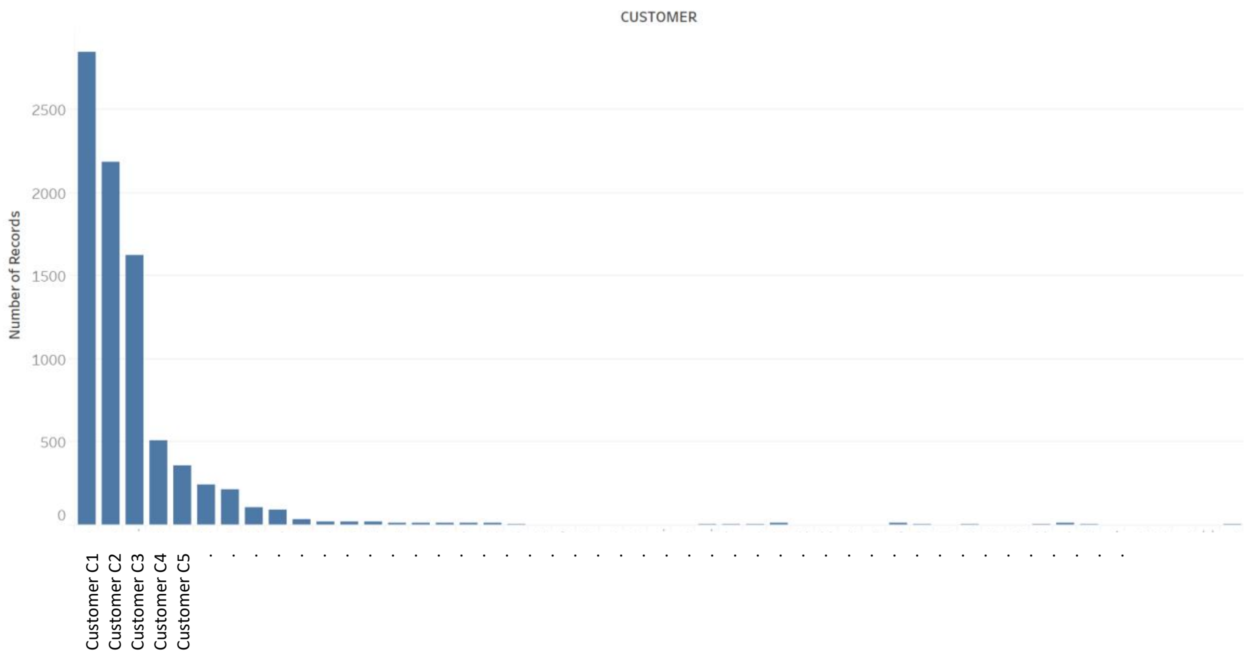


Figure 4. REGION C Customer Mix

2. As shown in Figure 5 and 6, there is a high degree of variability of pickup (loading) times and delivery (unloading) times at each Niagara facility. Trips that are pre-loaded have a much smaller average loading time when compared to live load trips. Trips that are drop shipments have a much smaller average unloading time when compared to live unload trips. However, only ~30% of loads are pre-loaded and only ~20% of loads are drop shipments.

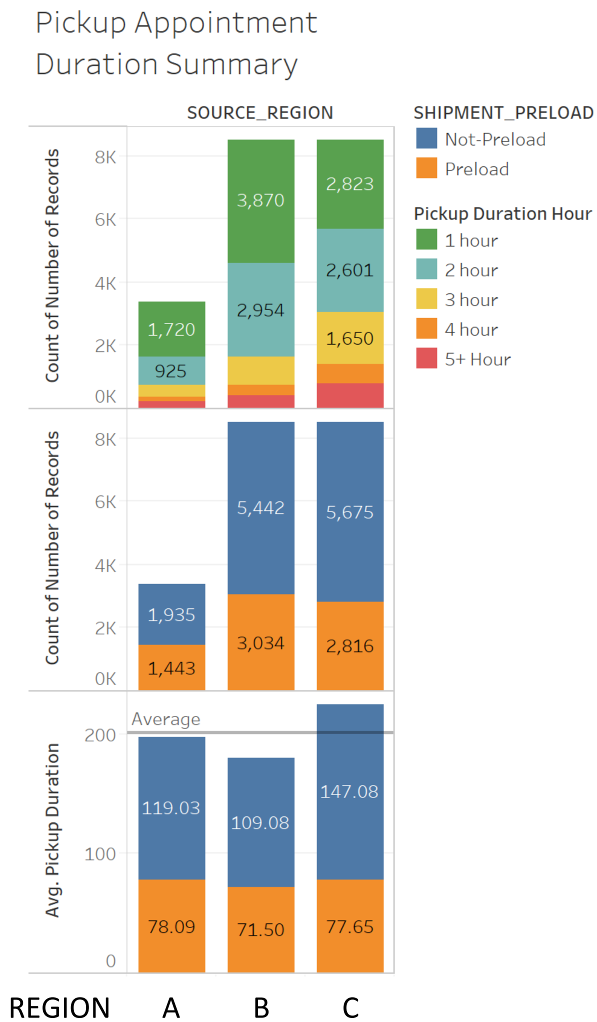


Figure 5. Pickup Duration Variability

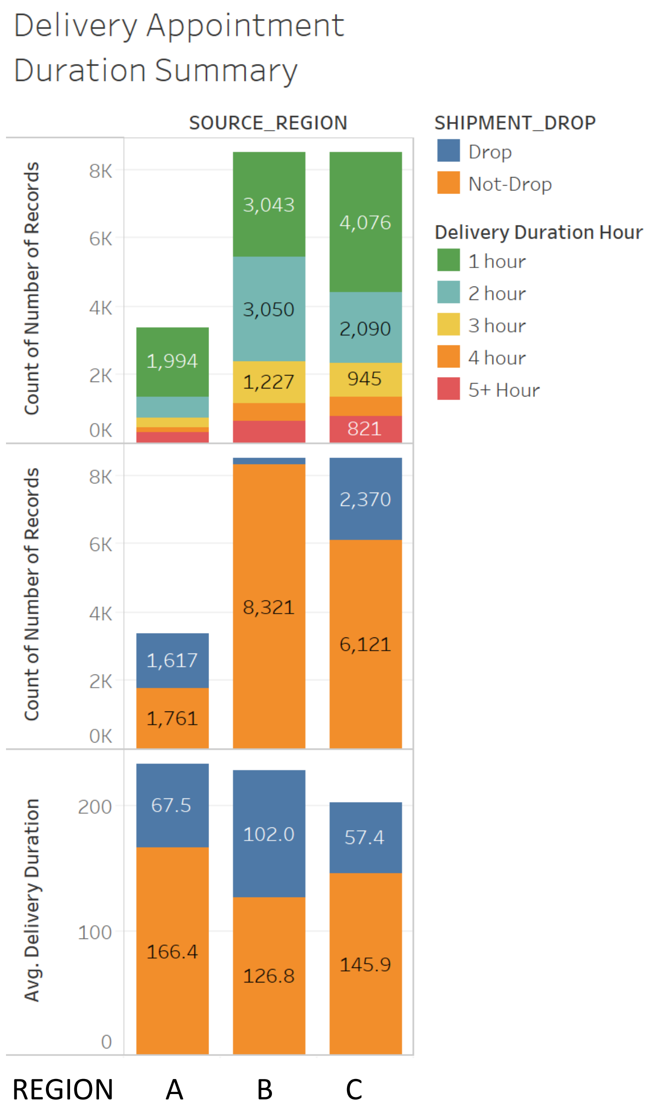


Figure 6. Delivery Duration Variability

3. As shown in Figure 7, 8 and 9, delivery appointment times are clustered in certain hours of the day which could lead to congestion. When comparing these congested times of day with delivery duration (the time it takes to unload at the customer), the expectation was that the congestion would cause longer delivery times. However, this was not the case and the opposite behavior was observed—delivery times were faster during congested hours. After further analysis, this phenomenon appeared to be partially explained by strategic drop shipments at peak times. However, there could be other factors at play here that are not captured in this Scorecard dataset such as the staffing levels of the customer unloading docks.

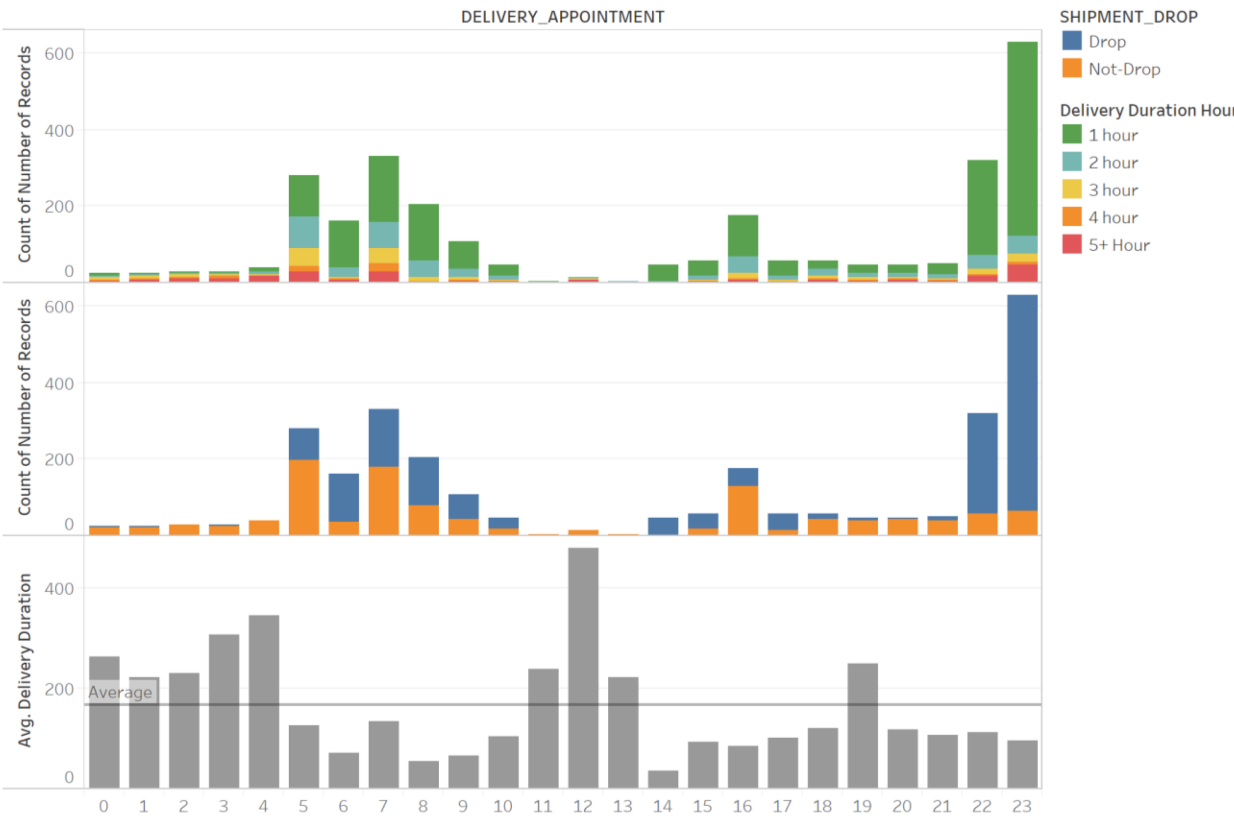


Figure 7. Region A Delivery Durations Throughout the Day

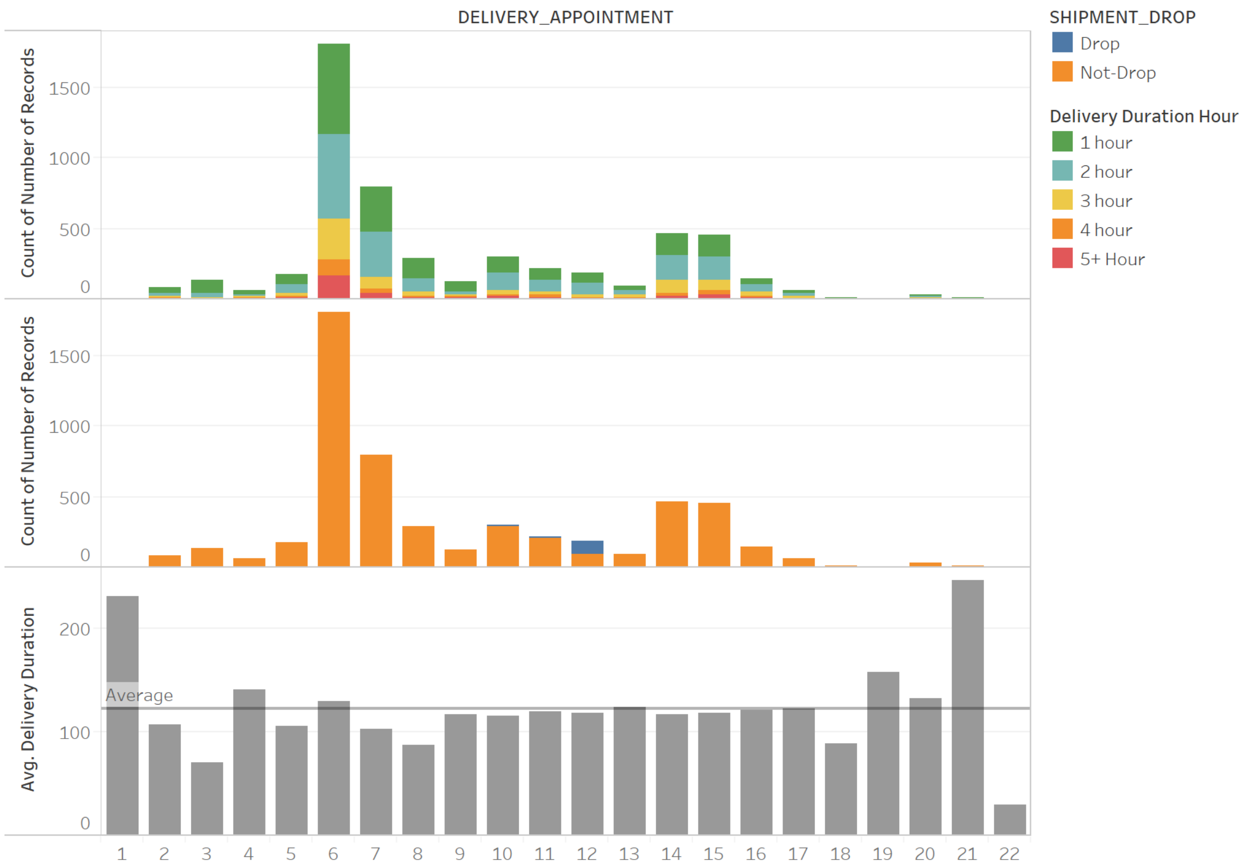


Figure 8. Region B Delivery Durations Throughout the Day

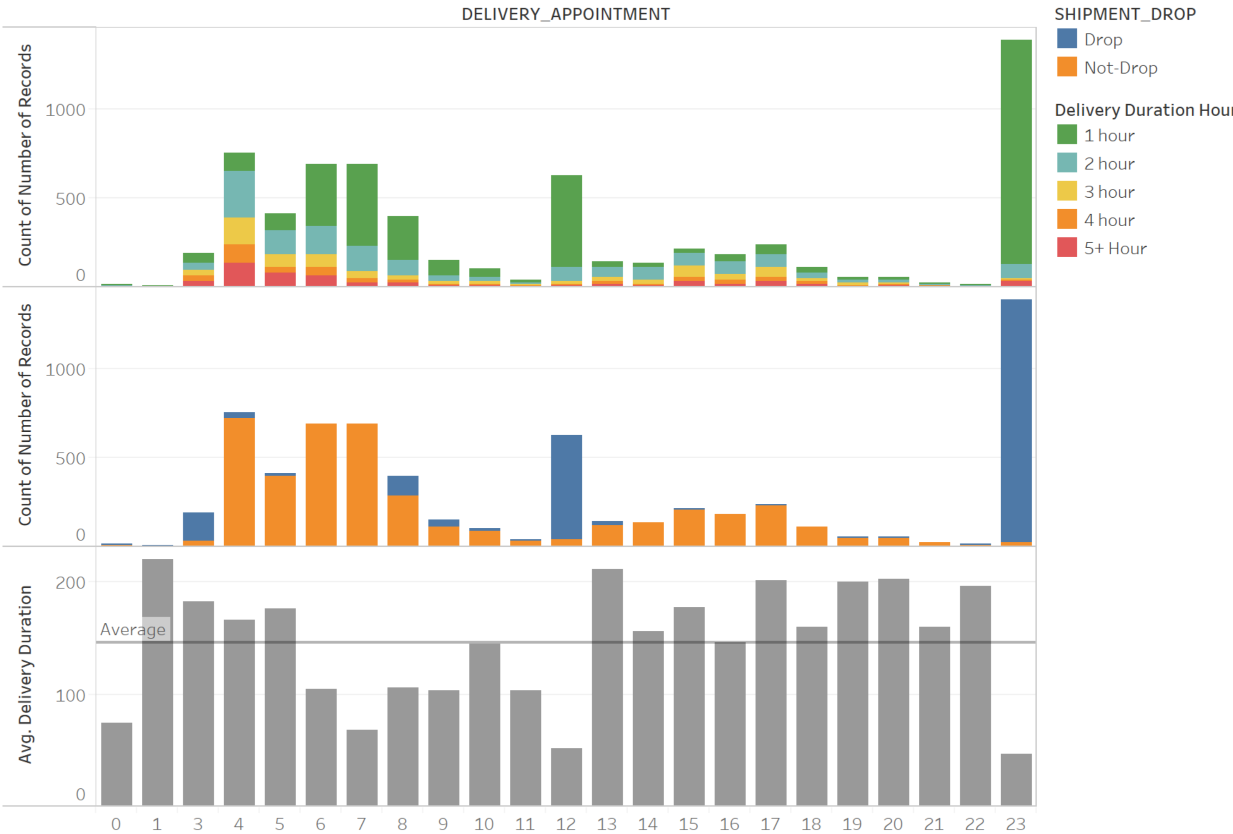


Figure 9. Region C Delivery Durations Throughout the Day

4. As shown in Figure 10, very few loads are optimized into a trip containing multiple stops. The majority of loads are full truckloads going directly to one customer and then that load is complete. There are also a relatively small number of spot shipments, which implies that Niagara is utilizing their contracts for low rates with carriers most of the time.

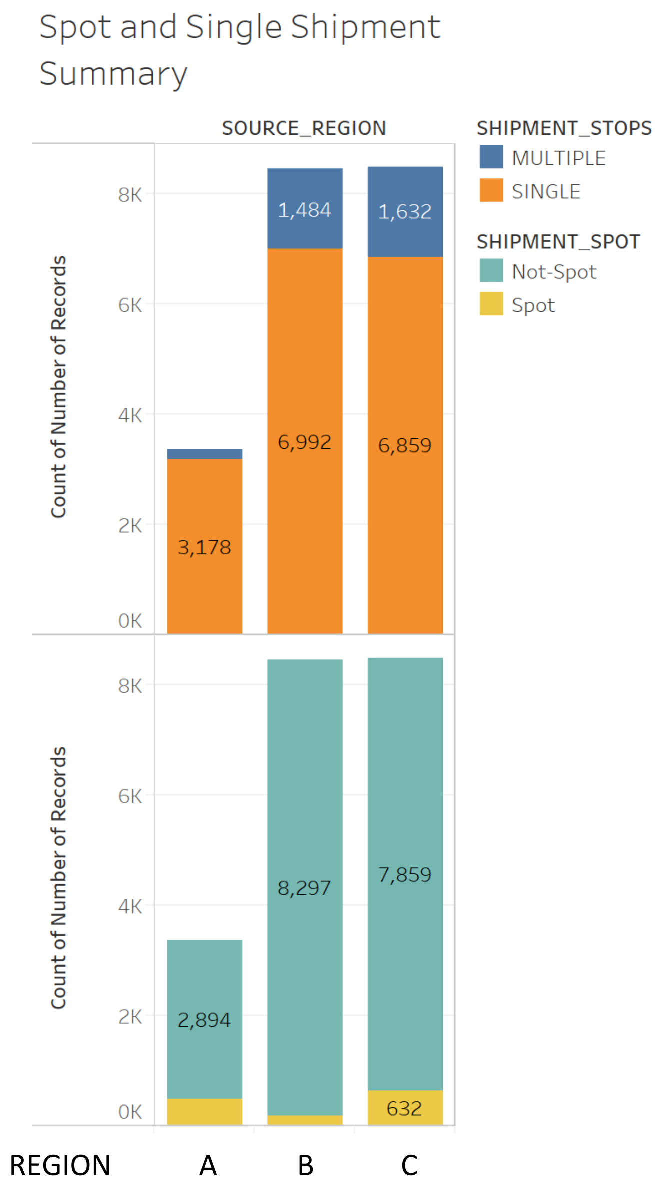


Figure 10. Spot and Single Shipment Summary

5. Average speed of the truck is very dependent on the region it is in and the length in miles of the trip. This makes sense because if a truck is travelling on densely populated urban roads versus remote rural freeways, the speed should be different. Also, if the distance is hundreds of miles, it can be assumed that most of that trip is on a highway where the speed limit is higher. If the trip is very short, say only 10–20 miles, then that truck may just be winding around slower back roads for the duration of the trip. Table 3 outlines the resulting speed assumptions.

Table 3. Average Speed Summary per Region Based on Total Mileage of Trip (mph)

Region	Speed if total trip < 25 miles	Speed if total trip 25-100 miles	Speed if total trip 100-150 miles	Speed if total trip 150+ miles
Region A	24.25	18.64	39.65	33.36
Region B	17.23	27.84	34.28	33.06
Region C	48.66	32.14	40.63	33.14

6. Carriers in different regions behave differently in terms of how long it takes them to load/unload as well as how much volume they are given. For example, in region A, 3 of the 4 highest volume carriers can deliver most of their loads to customers within 1 hour (green portion of the bar in Figure 11). However, some are only delivering the load within the hour ~30% of the time. In region B, there is no one carrier that stands out with a larger percentage of below 1-hour deliveries. Most carriers in region B are performing consistently with each other, even though their delivery durations are significantly longer than those in region A.

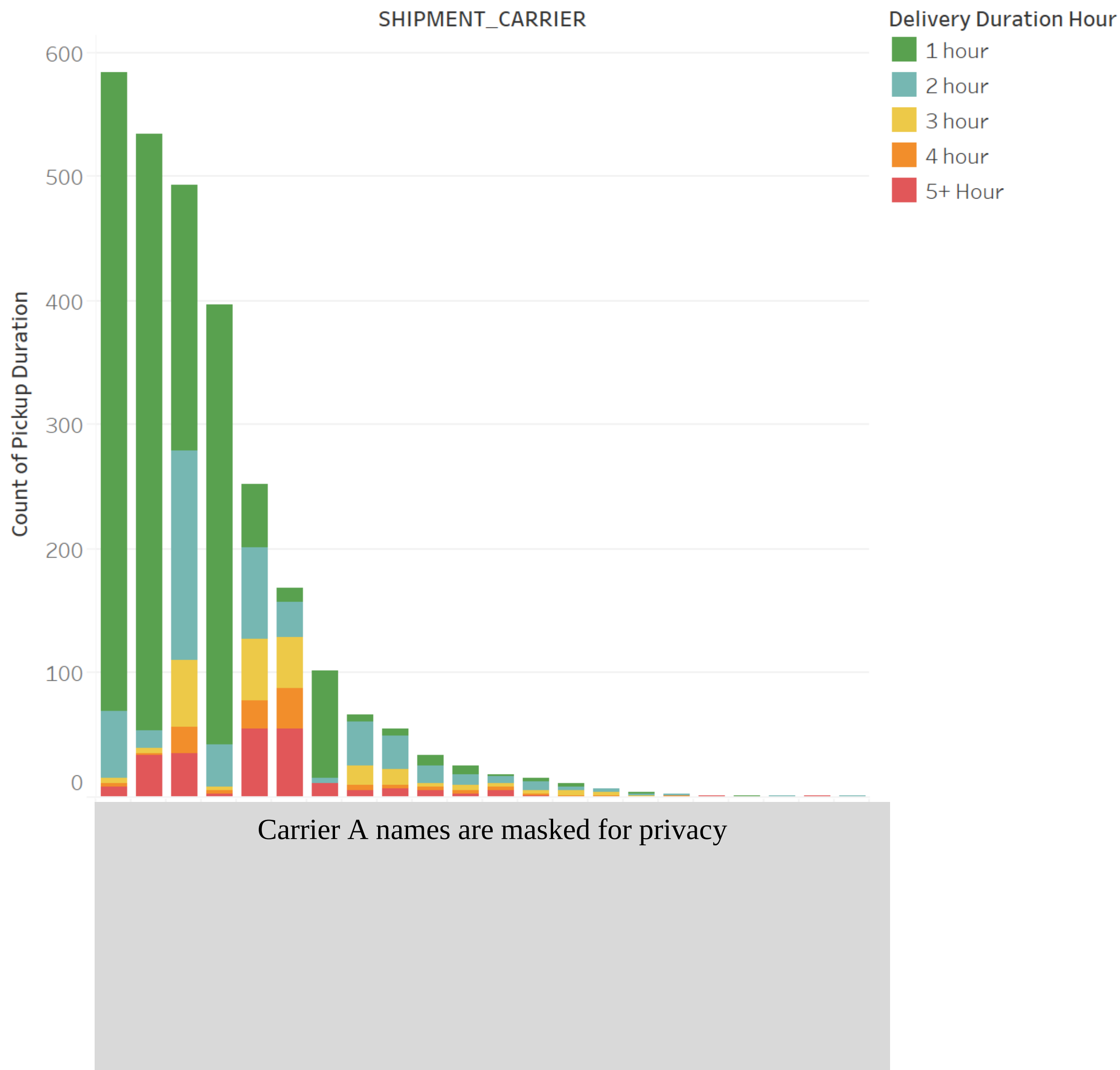


Figure 11. Region A Carrier Behaviors regarding pickup times. Only the customers that are in scope for this region (see Table 4) are included in this chart.

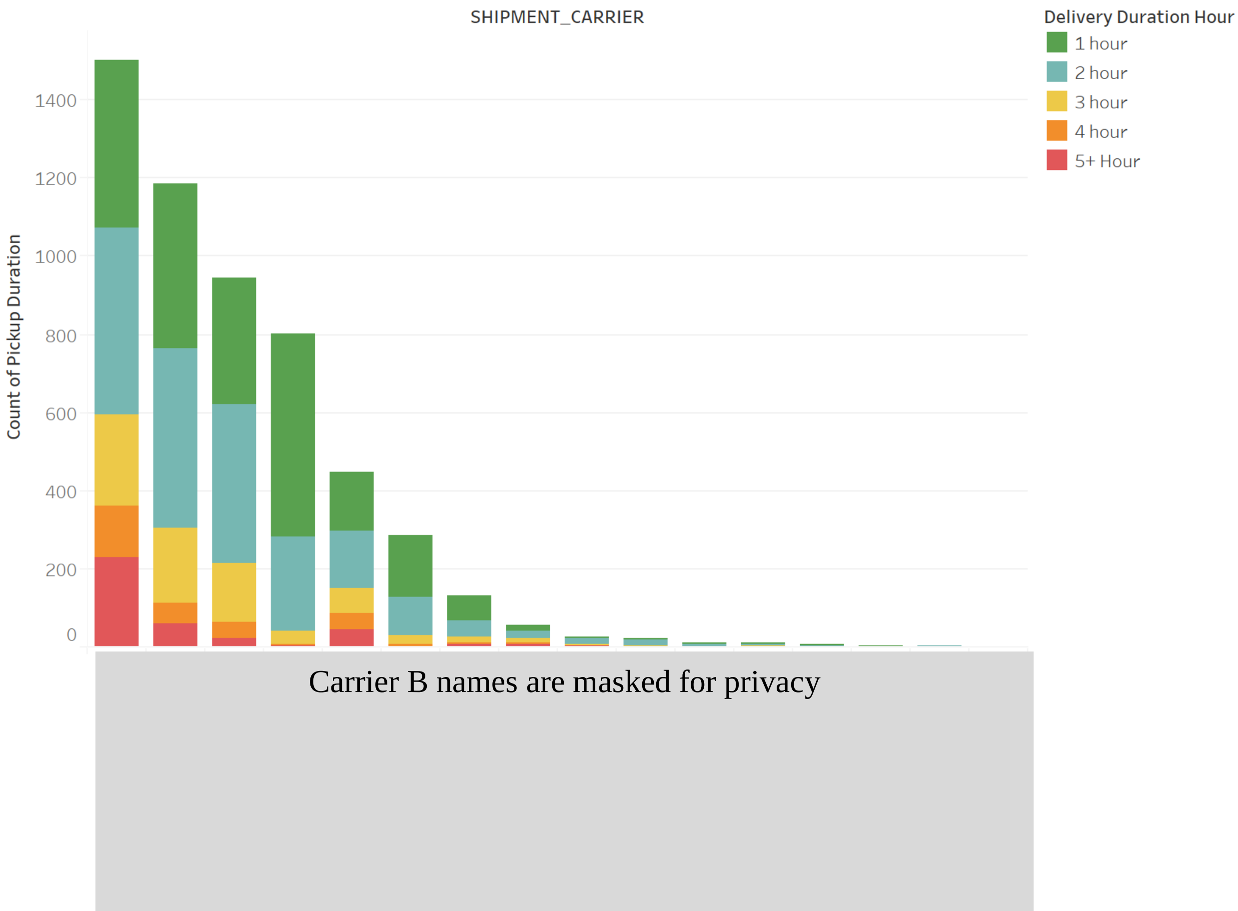


Figure 12. Region B Carrier Behaviors regarding pickup times. Only the customers that are in scope for this region (see Table 4) are included in this chart.

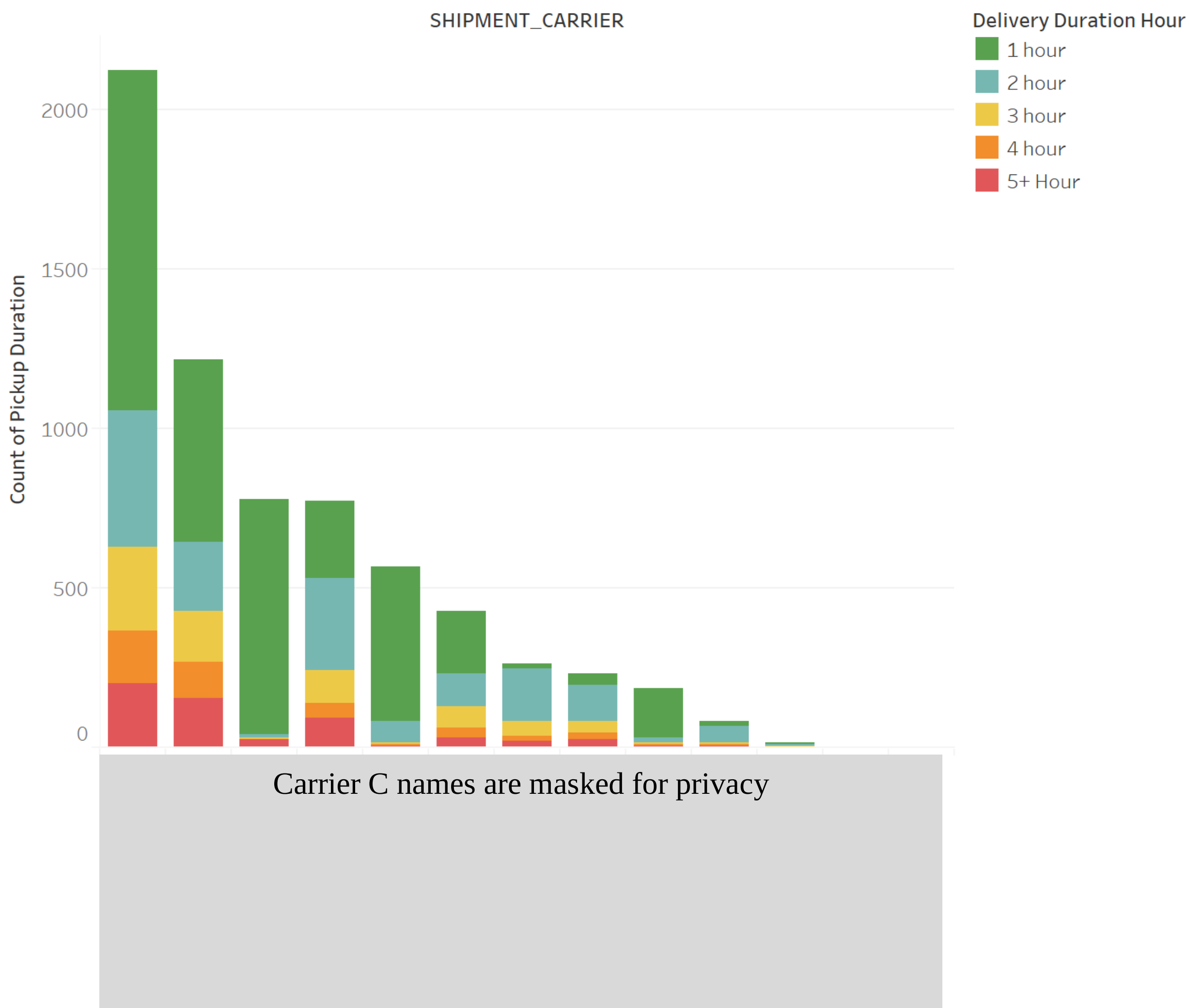


Figure 13. Region C Carrier Behaviors regarding pickup times. Only the customers that are in scope for this region (see Table 4) are included in this chart.

3.1.2 FINAL SCORECARD ASSUMPTIONS AND CALCULATIONS

After discussing the initial observations above with Niagara, the following assumptions were decided and calculated as inputs to the optimization model. Details on how these assumptions are included are found in Section 3.3 Methodology.

1. To simplify the model, only the three customers with the highest volumes in each region will be studied as outlined in Table 4. For region B, there will be six customers in scope since there is a much higher customer mix. Customer B2 is purposely excluded from region B for commercial reasons.

Table 4. Customers In Scope by Region

REGION A	REGION B	REGION C
Customer A1	Customer B1	Customer C1
Customer A2	Customer B3	Customer C2
Customer A3	Customer B4	Customer C3
	Customer B5	
	Customer B6	
	Customer B7	

2. Due to the variability in loading time when the load is preloaded versus live loaded, there will be a constant loading time assumption per region for the preload condition as well as the live load condition as outlined in Table 5.

Table 5. Loading Time Assumptions (minutes)

Region	Pre-Load	Live
A	54.7	116
B	79.94	112.6
C	67.4	142.76

3. Due to variability in unloading time when the load is drop versus not drop and variation by customer, there will be a constant unloading per customer per region for both drop shipments and live unloads. Customers that do not currently support drop shipments will have n/a in their respective column in Table 6.

Table 6. Unloading Time Assumptions (minutes)

Customer	Drop	Not-Drop
Region A		
Customer A1	78.6	196.6
Customer A2	41.7	185.2
Customer A3	n/a	124.6
Region B		
Customer B1	n/a	112
Customer B3	n/a	121.5
Customer B4	n/a	126.2
Customer B5	93.45	183.27
Customer B6	n/a	63.83
Customer B7	n/a	144.9
Region C		
Customer C1	49.54	97.16
Customer C2	60.2	284.8
Customer C3	n/a	163

4. Due to the small percentage of shipments with multiple loads, each load will be treated as a single load. In the Scorecard files for loads with multiple stops, the arrival time is only captured at the last destination of that trip. Because of this assumption, there will be additional variation in the calculation of unload times and load times.
5. Due to variability in speed based on region and total route distance, there will be a constant speed assumption by region with a step function that will apply to the total distance of the trip. The speed assumptions are outlined in Table 2.
6. Even though carriers have highly variable delivery times, there will not be a differentiator for delivery times per carrier in this model. In order to have the model make decisions based on the delivery time windows instead of the carrier performance, the decision was made to treat all carriers the same. This variation in carrier unloading times is partially captured in the customer-specific constant unloading time assumptions in Table 5.

7. Many of the Delivery Appointment Start and End times were undefined. Niagara provided baseline assumptions for each customer within each region that reflect business practices for that customer. In Table 7 below, Delivery Start Time is defined as the time of day that the customer is currently open to receive loads from Niagara. The Duration is defined as the duration of time that the customer will remain open to receive loads from Niagara.

Table 7. Delivery Window Baseline Assumptions provided by Niagara

SOURCE	CUSTOMER	Start Time	Duration (hours)
Region A	Customer A1	0:01	24
Region A	Customer A2	0:01	24
Region A	Customer A3	0:01	24
Region B	Customer B1	6:00	6
Region B	Customer B3	6:00	4
Region B	Customer B4	6:00	4
Region B	Customer B5	9:00	7
Region B	Customer B6	7:00	7
Region B	Customer B7	6:00	4
Region C	Customer C1	13:00	10.5
Region C	Customer C2	0:01	24
Region C	Customer C3	4:00	18

3.1.3 PROCUREMENT REPORT CALCULATIONS

To understand the cost benefits of this fleet utilization model, the cost structure of each load must be understood. Per Niagara's Procurement Report, there are two very important distinctions when calculating cost: fixed costs and variable costs. The fixed cost of a truck is estimated by Niagara to be \$700. Put another way, each additional truck needed to service the demand for that day will be an additional cost of \$700 regardless of other factors such as trucks route, utilization or distance traveled. The equation to calculate the variable cost per region is shown below using column titles of the Niagara Procurement Report as variable names:

$$\frac{\text{(LH+MOD)} - \text{(Tier Cost)} - \text{(FLAT\_RATE)} - \text{(Preloading Charge)} - \text{(Driver Unload)}}{\mathit{Total\ Miles}}$$

The variable costs are calculated for each customer in each region over the entire 2019 Procurement Report data set and averaged to set the cost assumptions as inputs to the model as shown in Table 8.

Table 8. Cost Assumption Calculations for each customer in each region

Customer	Variable Cost ($/mile)
Region A	
Customer A1	7.8
Customer A2	3.34
Customer A3	17.9
Region B	
Customer B1	6.1
Customer B3	4.6
Customer B4	2.9
Customer B5	4.2
Customer B6	1.9
Customer B7	4.2
Region C	
Customer C1	3
Customer C2	2.57
Customer C3	1.4

3.1.4 CONCLUSION OF PRELIMINARY DATA ANALYSIS

The preliminary analysis of the Scorecard data and Procurement Report is used to understand the current state of the Niagara bottling network. Due to observations made during this stage, this project scope has been focused on 3 regions and 12 distinct customers within those regions. Assumptions have also been made about loading time, unloading time and speed. Lastly, the Procurement Report is used to form a cost calculation structure to quantify the financial impact of the optimization model that will be used to optimize Niagara's trucking fleet utilization. The creation of this model that will be used to optimize these loads will be outlined in the next sections, 3.2 Data Preparation Coding and 3.3 Methodology.

3.2 DATA PREPARATION CODING

After understanding all the relevant fields of the Scorecard and Procurement Reports, it is important to have a standardized approach for creating inputs to the heuristic model. Due to the size of these data files and Niagara's desire for this model to be flexible and broadly applicable, Python functions are used to systematically groom the input data so that the heuristic model will have consistent inputs. All of the respective code is shown in Appendix A.

The first series of functions are focused on cleaning the data. The function *nullcheck* will delete any rows of data that are missing a value in fields that we need to use for calculations. These critical fields are in a list called 'check'.

The function *clean* will make sure that all the data types are correct for the critical fields so that the model will not error out. This is mostly defensive programming to make sure that the file is read in correctly. *Clean* also changes the Spot, Preload, and Drop fields to binary instead of categorical.

The function *filtertime* makes sure that only 24 hours of data is being considered at any given time. The model is meant to be used to improve daily utilization, so it is important that the focus remains on one day of data at a time.

Once the data is clean, the *filtervals* function adds fields for each line that populate the corresponding assumptions made in Section 3.1.3 and 3.1.4. Before calling this function, dictionaries that can be indexed for each constant assumption need to be established. A dictionary is created for customers, load times, unload times, speeds and variable costs.

The function *filtervals* performs the following steps to the data:

1. Keep only accepted loads.
2. Set the delivery window start and delivery window end to 0. This will be populated in the next function.
3. Keep only loads from the one source region specified in the input.
4. Filter out any customers that are out of scope for that source region.
5. Index into the load time and speed dictionaries for the specified source and apply the corresponding values for each load in the data frame.
6. Calculate the One Way Time field.
7. Index into the unload time and variable cost dictionaries for the specified source, initialize new rows as zero and then overwrite the zeros by iterating through the data frame and apply the corresponding values for each load in the data frame.
8. Calculate the Total Load Delivery Time, Total Cost, Driver Utilization and Shift Utilization fields.

9. Sort the values by the Delivery Window Start field and add a column called "LN" that can be used as a key to identify that specific route.

Lastly, the function *delwindows* is created to populate the default delivery window start and end times using the assumptions from Table 6.

After using this systematic approach to clean and populate the data, the optimization heuristic model described in Section 3.3 runs much smoother. This standardized approach also allows for very simple adjustments to be made to run sensitivity testing on the different scenarios that the heuristic generates. For example, many different days of data can be generated by simply changing the inputs to the *filtertime* function. Data frames can be generated easily for the different source regions by simply changing function inputs as well. Most importantly, the delivery appointment windows and the delivery appointment durations can be modified by running subsequent simple functions as outlined in Section 4.

3.3 METHODOLOGY

The goal for this capstone project is to establish a model that can help improve the transportation operation efficiency and carrier fleet utilization rates for transporting Niagara's bottle water products to customers. In other words, for a Niagara manufacturing plant for any given set of daily load delivery tasks, the model will be able to optimize the load assignment for each truck so that that truck's utilization is maximized. If every truck's utilization is maximized, all the deliveries from this Niagara plant to its customers' locations will be fulfilled with the least number of trucks and therefore will reduce the fixed transportation cost that is associated with vehicle possession. An optimization model has been developed based on the objective function of maximizing each truck's shift utilization by optimizing the load assignments.

First, all the primary model assumptions are discussed in Section 3.1. Before delivery time window constraints are introduced into the model, a baseline scenario is described that one truck can only deliver one load from the Niagara plant to one customer as the current state, and it can be used as a comparison to other scenarios with different delivery window durations and starting time. Sensitivity analysis will be an integral part of model validation to quantify the potential operational and financial benefits of proposed solutions. Business metrics, such as fleet utilization and total transportation cost, as agreed upon with the sponsor, will also be clearly calculated as model output and prioritized to enhance practicability of proposed solutions.

The model will run based on a given set of daily load delivery tasks for one pre-selected Niagara plant for a pre-selected day. The data this model uses is the transportation scorecard data provided by Niagara, which includes such useful information as plant location, carrier name, shipment mileage, shipment appointment time, destination name and address. An analysis of the transportation cost structure breaks down the total daily transportation cost to two main parts: variable cost from distance traveled by each truck and fixed cost from possessing each vehicle. In this Niagara case, almost all the shipments are full truckload, which means a truck, after delivering a previous load, will need to return to the plant and reload before executing the next delivery, if time and other constraints allow. Due to the full truckload nature of Niagara's supply chain, the truck routes and the flow volume between the plant and each delivery destination does not change. The travel cost between the plant and each destination also does not change with the assumptions that trucks take the same path between Point A and Point B and they have the same fuel cost and other driving cost for any certain load. This leaves only the fixed cost from owning the trucks to be optimized since the number of trucks needed to accomplish all the delivery jobs may vary depending on different scenarios of truck utilization.

3.3.1 SOLUTION APPROACHES

There are many important aspects to consider when scoping the objective function, the first of which is the time scope for modeling. For each day at each Niagara plant, there is a set of loads, which all need to be transported to different customers' sites at different locations. Delivery appointment and carrier truck deployment are also scheduled on a daily basis. The daily load assignment optimization will help find the load combinations that will maximize the overall truck utilization within a 24-hour period. Under the assumption that trucks to be used are not differentiated, the loads with the earliest appointment time will be assigned to a truck first. For improving the utilization for this truck, the logic is to find other loads the same truck can also deliver within the required timeframe.

From a manual calculation of the load assignment via Excel Solver, it was observed that only 3 out of a total of 206 load assignments are calculated as one truck delivering more than 2 loads. In other words, over 98% of the load assignments involve one truck delivering either 1 or 2 loads. Therefore, another assumption for this model is that load assignment only considers 2 scenarios: 1 truck with 1 load, and 1 truck with 2 loads. As referenced in Appendix B, Python codes are used to realize 3 primary functions: load assignment for 1 truck, assigned load output for 1 truck, and assignment iteration with the final result output. Figure 14 explains in pseudo-code how the algorithm works. The load assignment function looks for all possible (meaning all constraints are met) second load options for a truck that is going to deliver the earliest start time load first. It then selects the option that will maximize the total shift utilization. Once the load assignment for a truck is finished, the assigned loads will be recorded and taken out of consideration for the load assignment for the next truck, which will use the same heuristic with all the remaining loads. This process will continue until all the loads have been assigned.

```
def loadassignment():
    start with available load dataset: load
    find the earlest start time load: load0
    for i in all other loads
        if total drive time for load0 and load(i)<11 hours
        if total shift time for load0 and load(i)<14 hours
        if arrival time of load(i) after load0 delivery falls within windown(i)
        record all load(i)'s
    select the load(i) with highest total shift utilization and name it loadx
    if no loadx is found
        del load0 from dataset: load
    if loadx is found and selected
        del both load0 and loadx from load
    return updated dataset: load
```

```
def loadresult():
    start with available load dataset: load
    find the earliest start time load: load0
    for i in all other loads
        if total drive time for load0 and load(i) < 11 hours
        if total shift time for load0 and load(i) < 14 hours
        if arrival time of load(i) after load0 delivery falls within window(i)
        record all load(i)'s
    select the load(i) with highest total shift utilization and name it loadx
    if no loadx is found
        calculate load0's driving & shift utlization, transporation cost
        store output in a single-record dataset: result
    if loadx is found and selected
        calculate load0 and loadx together's drving & shift ultization, trans.cost
        store output in a single-record dataset: result
    return result
```

```
create empty dataset:df to store results
rowcount=len(load)
while rowcount>1:
    df1=loadresult(load)
    df=df.append(df1,ignore_index=True)
    load=loadassignment(load)
    rowcount=len(load)
output df
```

Figure 14. Pseudo-Code Showing the Load Assignment Algorithm

The objective for each truck's load assignment is to maximize its shift utilization of the assigned load(s), which is the ratio of its total shift working hours to regular shift length (14 hours, or 840 minutes). For a pre-selected load that is assigned to a truck as the first delivery task, the heuristic is to find all the possible other loads for which this truck can still complete delivery after finishing the first load delivery. Then only the one with the largest shift utilization will be selected as the second load task assigned. Once these selected loads are assigned to one truck, they will be removed from the load list. The same heuristic will continue to be run to find the best load assignment for the next truck, until all the remaining loads are assigned. The objective for each load assignment can be expressed in the following formula:

Load Assignment Objective: $\text{Max}((DT_1 + BH_1 + DT_2)/840)$

DT_1 is defined as the total load delivery time (consisting of loading time, unloading time and truck driving time) it takes for a truck to deliver the first load. BH_1 is defined as the total backhaul driving time for the empty truck to travel back to the Niagara plant after delivery of the first load, if time constraints permit for it to deliver a second load. DT_2 is defined as the total load delivery time for the second load.

Lastly, the model outputs include daily load assignment details for each truck, total truck count, driving and shift utilization for each truck and total transportation cost. The total truck count is the number of trucks needed to complete the deliveries for all the daily loads based on the load assignment heuristic. The total transportation cost represents the sum of transportation cost of each truck that is used for load delivery.

3.3.2 BASELINE SCENARIO

In comparison, in the scenario where one truck can deliver only one load per day from the Niagara plant to one customer, the utilization for a truck that delivers only one load is not as great as the truck that delivers more within the same daily shift period. The truck shift utilization is calculated as below for that baseline scenario:

Truck Shift Utilization= DT/840 min (14 hours)

DT is defined as the total load delivery time (consisting of loading time, unloading time and truck driving time) it takes for a truck to deliver one load.

3.3.3 TIME CONSTRAINTS

According to US Department of Transportation regulations, a commercial truck driver may drive up to a total of 11 hours during the 14-hour shift period. Therefore, two time constraints are listed below.

1. Shift length constraint: $DT_1 + BH_1 + DT_2 <= 840$ min (14 hours)
2. Driving time constraint: $DvT_1 + BH_1 + DvT_2 <= 660$ min (11 hours)

DT_1 and DT_2 are defined as the total load delivery time (consisting of loading time, unloading time and truck driving time) it takes for a truck to deliver the first load and second load. BH_1 is defined as the total backhaul driving time for the empty truck to travel back to the Niagara plant after delivery of the first load, if time constraints permit for it to deliver a second load. DvT_1 and DvT_2 are the one-way driving time respectively for the first load and second load.

The third constraint is needed to ensure the truck that has finished the first load delivery will arrive at the second load delivery location within the time window required by the customer. This means that after arriving at the first load location at its required Start Time ($StartT_1$), a truck needs to unload the cargo, drive back to the plant, load the second load, drive to the second load customer location and arrive there within the customer's specified time window (between $StartT_2$ and $EndT_2$). This constraint is listed below.

3. Delivery window constraint: $StartT_2 <= StartT_1 + UT_1 + BH_1 + LT_2 + DvT_2 <= EndT_2$

$StartT_1$ is the required start time of the first load. UT_1 is the unloading time for load 1. BH_1 is the backhaul driving time for load 1. LT_2 is the loading time for load 2. DvT_2 is the one-way driving time for load 2. $StartT_2$ and $EndT_2$ are the start time and end time for the second load delivery required by the customer.

For a pre-selected first load, if none of the remaining loads can meet all three constraints listed above, this selected load only will be assigned to one truck.

3.4 SENSITIVITY ANALYSIS

In order to evaluate the impact of adjusting customer delivery windows and delivery duration on truck utilization, a python function, called *sensitivitytesting*, is developed to perform sensitivity analysis. As shown in Appendix C, this function will be run for each customer for each day of the week. Each run will generate the optimized load scenario for each combination of delivery window start times of 00:00, 06:00, 12:00 and 18:00 and delivery window durations of 2, 4, 6, 8, 10, 12, 18 and 24 hours.

First, the *changestarttime* function is developed to read in a data frame, customer and datetime stamp and produce a data frame that changes all of the delivery start times for that customer to the datetime stamp.

Second, the *changeduration* function is developed to read in a data frame, customer and duration (in hours) and produce a data frame that changes all of the delivery end times for that customer to be exactly the 'duration' input of hours after the delivery start time.

Lastly, all of the functions mentioned so far in this paper are combined in the *sensitivitytesting* function to iterate through each scenario combination as shown in the lists named *starttimes* and *durations*. The inputted data frame is first cleaned by using the cleaning functions described in section 3.2. Then the delivery windows and durations are changed for one customer at a time. Lastly, the heuristic function as described in section 3.3.1 is run with the modified data frame and a summary table of all of the critical metrics (Number of trucks, Total Cost, Driver Utilization and Shift Utilization) of the resulting optimized load assignments are exported for analysis. Section 4 will elaborate on the results of this sensitivity analysis for each customer.

3.5 CONCLUSION

The focus of this project is to study the financial impact of adjusting customer delivery receiving windows. Using this optimization model, different truck load assignments and utilizations will be calculated based on different input parameters and will be compared to the truck utilization in the current-state baseline scenario. As the most important input parameter, different values of customer delivery window duration will be used for the sensitivity analysis in the model to study the impact on truck utilization.

4. RESULTS AND ANALYSIS

4.1 LOAD ASSIGNMENT OUTPUT

The heuristic for optimizing daily load assignment for a given day and a given manufacturing plant is realized via Python codes. An example result is shown in Table 9 below based on the load data of the region C plant on October 1, 2019. There are a total of 151 in-scope full truckloads for that day. After load assignment optimization, using only 118 trucks can complete all 151 load deliveries. Among those 118 trucks, the heuristic calculates there are 33 trucks that will deliver 2 loads. In comparison to the baseline scenario that one truck can only deliver one load, the utilization for those trucks that deliver 2 loads are significantly increased, and the transportation costs are substantially reduced.

Table 9. Load Assignment Optimization Result for 151 Loads of Region C Plant (10/1/19)

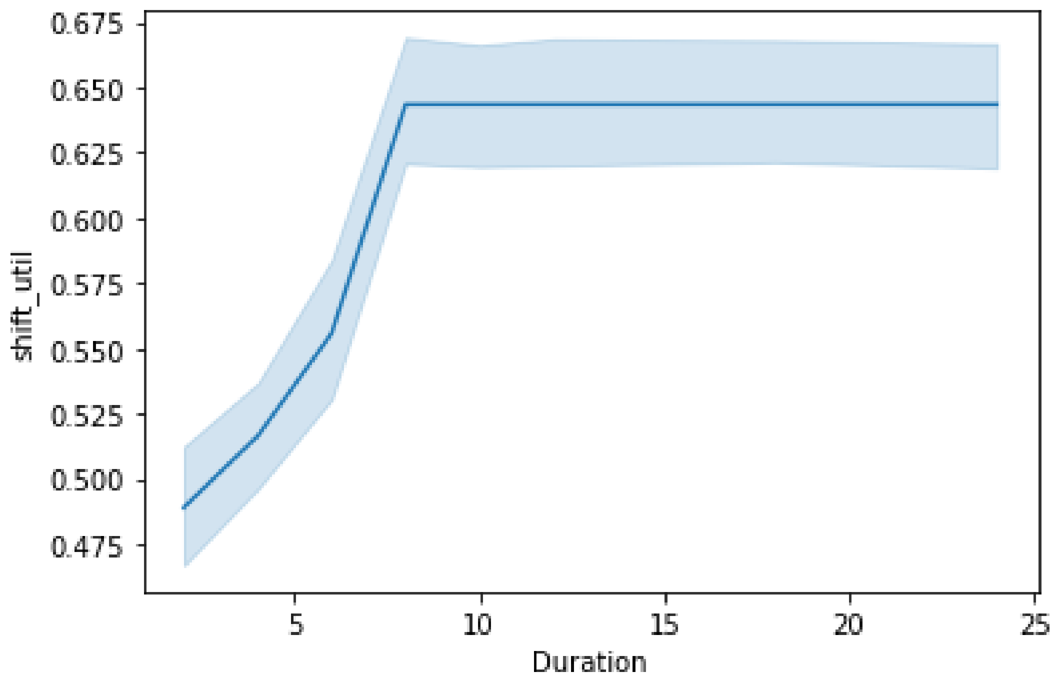
truck #	load1	load2	Transportation cost ($)	Transportation cost base ($)	driving utilization	driving utilization base	shift utilization	shift utilization base
1	0	0	759	759	52.4%	52.4%	56.3%	56.3%
2	1	70	388.5	1028	56.7%	15.2%	96.1%	66.0%
3	2	2	759	759	52.4%	52.4%	56.3%	56.3%
4	3	3	759	759	52.4%	52.4%	92.0%	92.0%
5	4	4	759	759	52.4%	52.4%	92.0%	92.0%
…	…	…	…	…	…	…	…	…
114	138	138	1275	1275	75.7%	75.7%	88.0%	88.0%
115	139	139	672	672	21.2%	21.2%	45.2%	45.2%
116	140	140	1347	1347	82.3%	82.3%	93.2%	93.2%
117	145	145	1065	1065	56.5%	56.5%	72.9%	72.9%
118	150	150	549	549	9.6%	9.6%	36.1%	36.1%

For the trucks that deliver only one load, the output lists two identical load numbers under stop1 and stop2. For the trucks that deliver two loads, the output specifies two different load numbers under stop1 and stop2. The output also displays the comparisons of total transportation cost, driving utilization and shift utilization between optimized and baseline scenarios. The results clearly show that the vehicle utilizations are increased for the trucks that deliver two loads, matching the outcome that fewer trucks can deliver the same number of loads.

4.2 DELIVERY WINDOW AND VEHICLE UTILIZATION

As described in Section 3.4, sensitivity analysis is performed for each customer for each day of the week and the impact of different scenarios with varying delivery time and delivery duration is observed.

The load delivery data for the week of June 23, 2019 is selected for three pre-determined Niagara manufacturing locations in region A, region B and region C. The average daily load volume of this selected week is found to be at a high level as compared to most of the other weeks. This can be explained that this week is the week prior to 4th of July holiday and is also in the summer month.

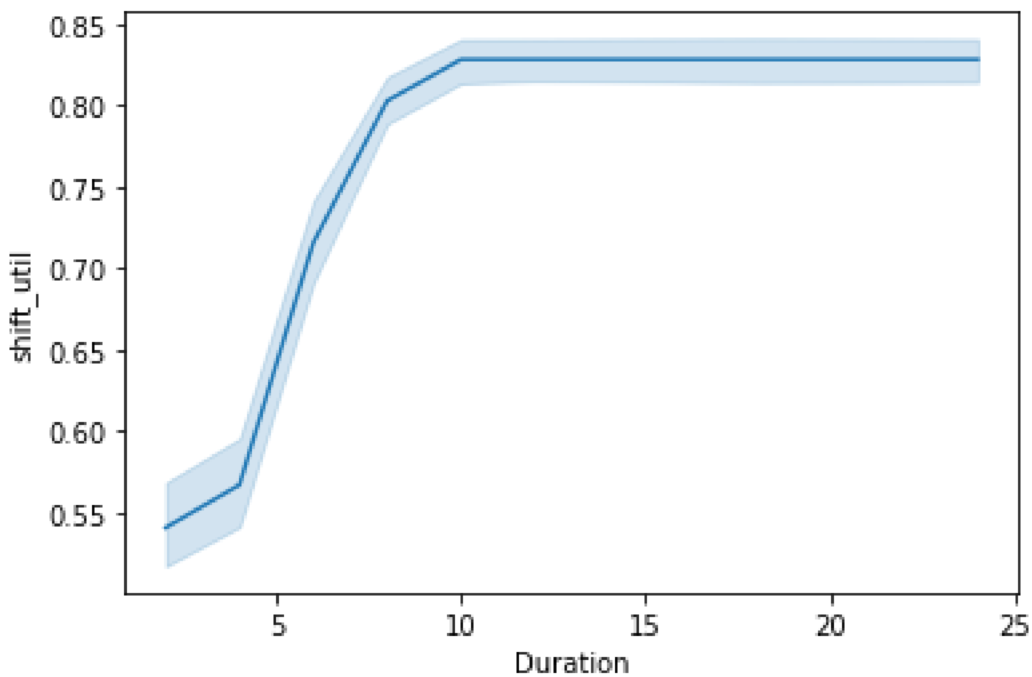


X axis: Delivery window duration (hour); **Y axis**: Average daily fleet shift utilization rate

Shaded band area: Mean +/- 2 Standard Deviation

Figure 15. Daily Truck Shift Utilization Over Customer A1 Delivery Window Duration

(Manufacturing location: Region A; Customer: A1; Date Range: 6/23/19-6/29/19)

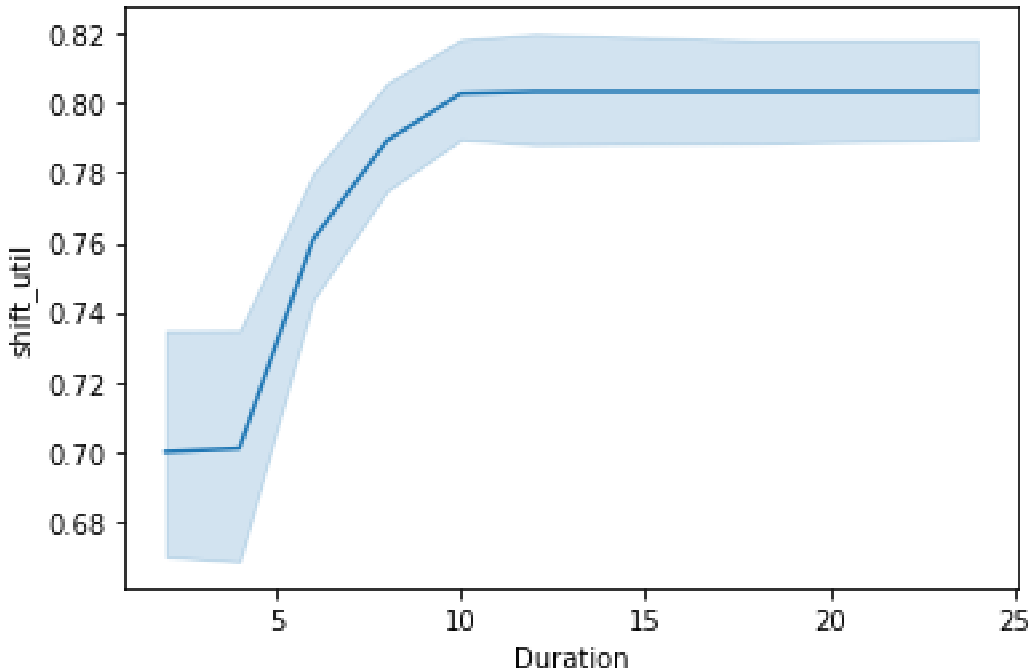


X axis: Delivery window duration (hour); **Y axis**: Average daily fleet shift utilization rate

Shaded band area: Mean +/- 2 Standard Deviation

Figure 16. Daily Truck Shift Utilization Over Customer B1 Delivery Window Duration

(Manufacturing location: Region B; Customer: B1; Date Range: 6/23/19-6/29/19)



X axis: Delivery window duration (hour); **Y axis**: Average daily fleet shift utilization rate

Shaded band area: Mean +/- 2 Standard Deviation

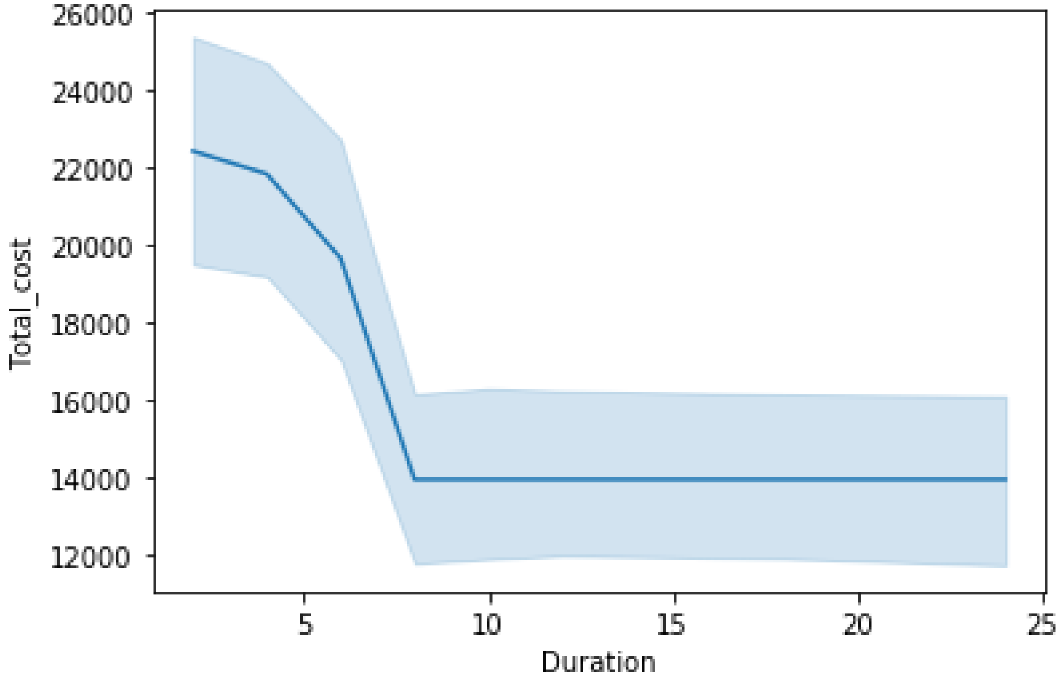
Figure 17. Daily Truck Shift Utilization Over Customer C1 Delivery Window Duration

(Manufacturing location: Region C; Customer: C1; Date Range: 6/23/19-6/29/19)

Figure 15, 16 and 17 above show that the truck shift utilization increases as delivery window duration increases between 2 hours and 10 hours, because the relaxed windows allow more trucks to be able to do a second load delivery after the first. The slopes of these curves are approximately between +1.5% to +6%/hour, which means an extra hour of delivery window duration increases the fleet utilization approximately by 1.5-6%. The utilization stops increasing after duration hits 10 hours because it is bound by the driving and working hour constraints.

4.3 DELIVERY WINDOW AND TOTAL TRANSPORTATION COST

For evaluating the impact of adjusting customer delivery window on total transportation cost, again, the load delivery data for the week of June 23, 2019 is selected for three pre-determined Niagara manufacturing locations in Region A, Region B and Region C.

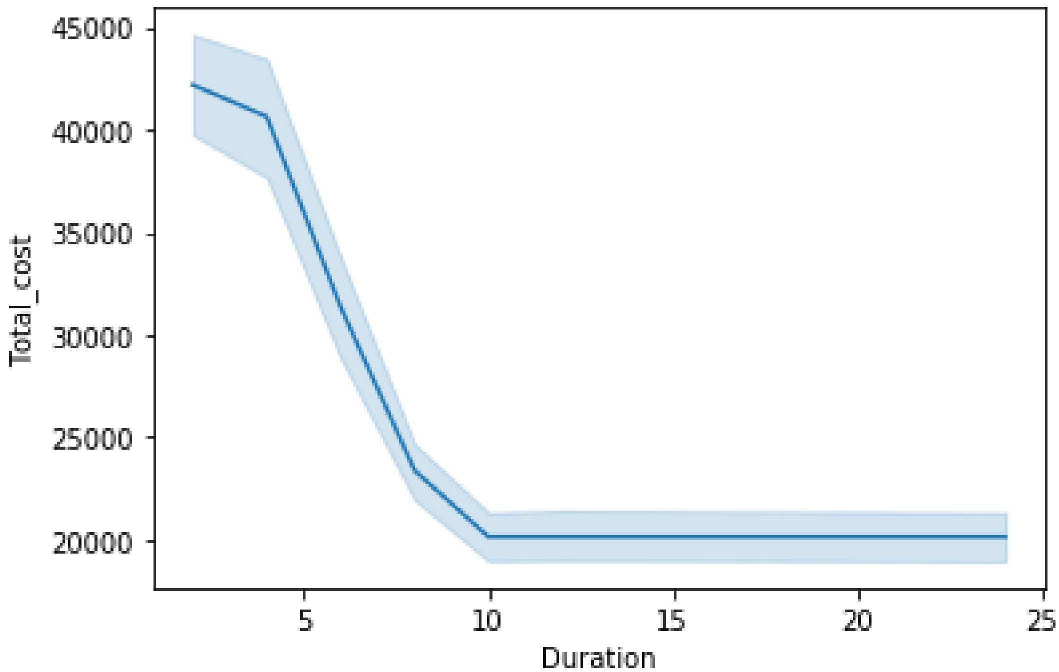


X axis: Delivery window duration (hour); **Y axis**: Average daily fleet total transportation cost ($)

Shaded band area: Mean +/- 2 Standard Deviation

Figure 18. Daily Total Transportation Cost Over Customer A1 Delivery Window Duration

(Manufacturing location: Region A; Customer: A1; Date Range: 6/23/19-6/29/19)

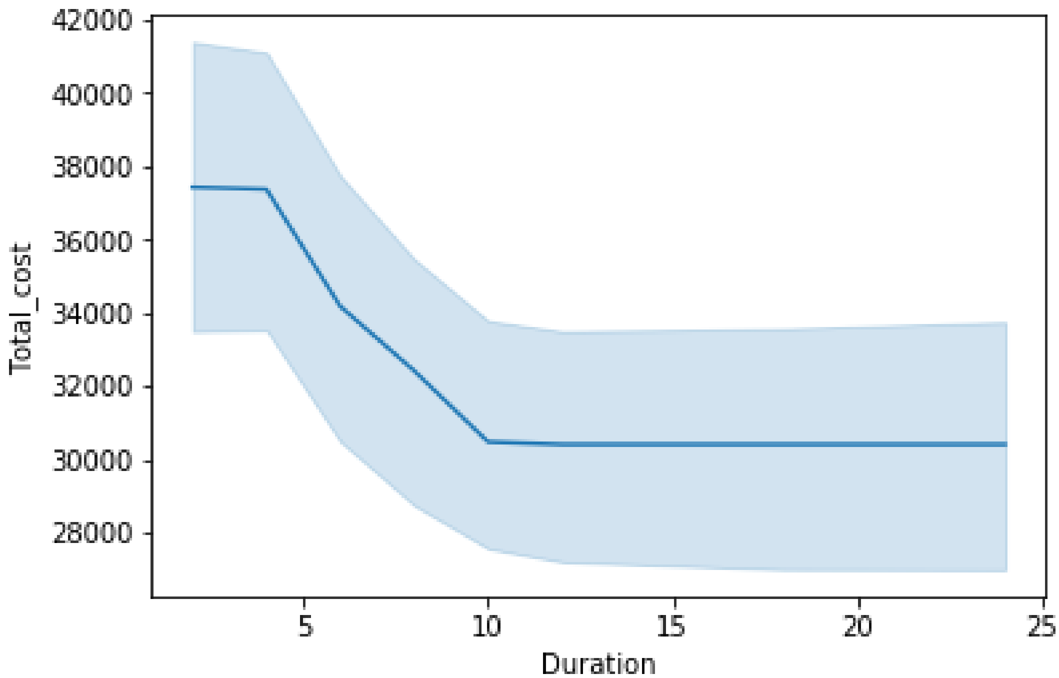


X axis: Delivery window duration (hour); **Y axis**: Average daily fleet total transportation cost ($)

Shaded band area: Mean +/- 2 Standard Deviation

Figure 19. Daily Total Transportation Cost Over Customer B1 Delivery Window Duration

(Manufacturing location: Region B; Customer: B1; Date Range: 6/23/19-6/29/19)



X axis: Delivery window duration (hour); **Y axis**: Average daily fleet total transportation cost ($)

Shaded band area: Mean +/- 2 Standard Deviation

Figure 20. Daily Total Transportation Cost Over Customer C1 Delivery Window Duration

(Manufacturing location: Region C; Customer: C1; Date Range: 6/23/19-6/29/19)

Figure 18, 19 and 20 above show that the total transportation cost decreases as delivery window duration increases between 2 hours and 10 hours, because better utilization results in fewer trucks needed and therefore results in a reduction in fixed transportation cost and total cost. The slopes of these curves are approximately between -$1,100 to -$2,800/hour, which means an extra hour of delivery window duration reduces the fleet average daily total transportation cost approximately by $1,100 to $2,800 (3% - 6.5%).The total transportation cost stops decreasing after duration hits 10 hours because it is bound by the driving and working hour constraints.

4.4 DELIVERY START TIME AND VEHICLE UTILIZATION

Based on the same set of data, the model can output truck shift utilization for different delivery start times for a specific customer. Using customer C1 for Niagara region C location as an example, with the results put onto a 3D scatter plot, it is shown that the utilization is in general higher for 00:00 delivery start time (black color dots in Figure 21) than the utilization with the other start times (purple for 06:00; orange for 12:00; yellow for 18:00). This is explainable because it is more likely for those trucks that arrive at their first delivery locations at midnight to be able to run back to the plant for their second load delivery in the morning, when most of the customers have the window open to receive deliveries.

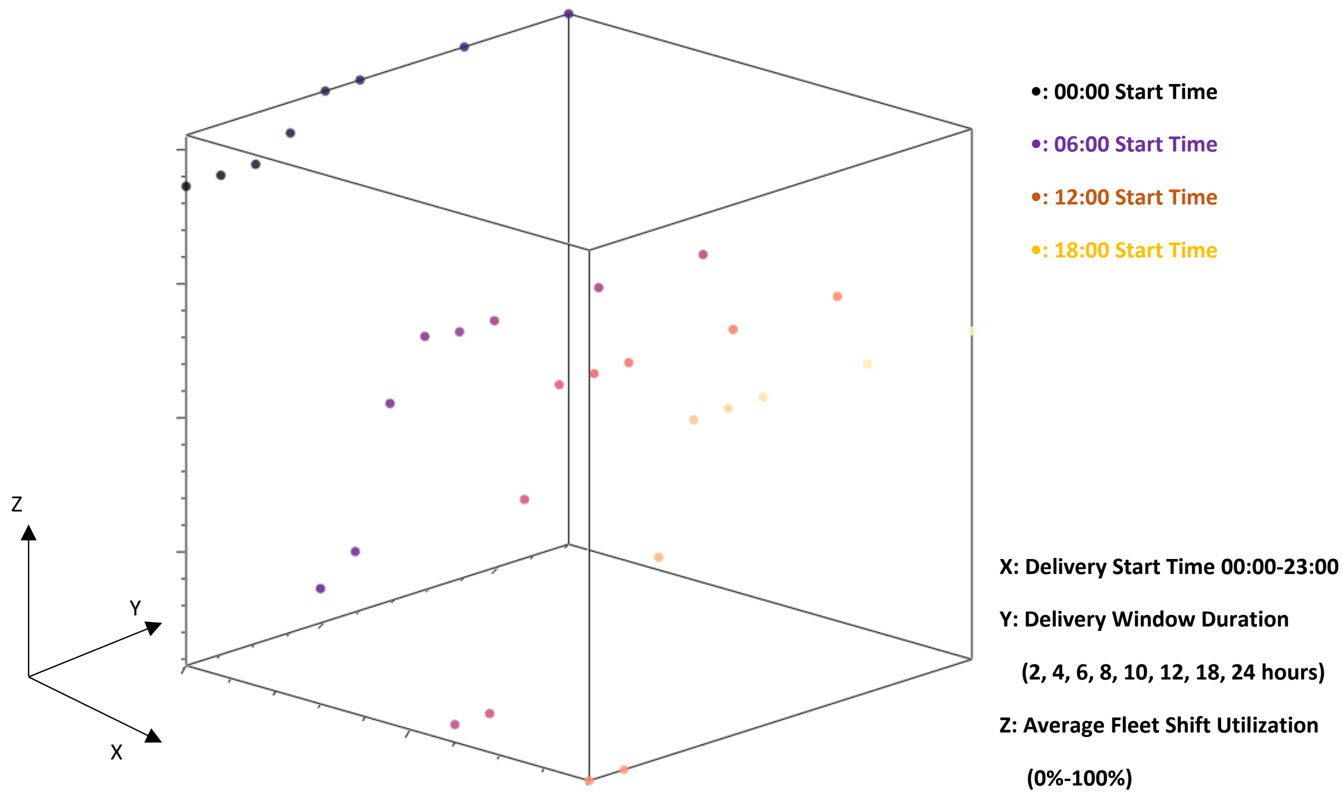


Figure 21. Truck Shift Utilization Over Customer C1's Different Delivery Start Times (3-D)

(Manufacturing location: Region C; Customer: C1; Date Range: 6/23/19)

5 DISCUSSION

As shown in Table 6, different manufacturing plants have different in-scope customers with different delivery window requirements. It is important to analyze the potential impact of adjusting customer delivery windows on a specific plant location basis. For each plant location, an evaluation has been performed, and answers and suggestions are provided to the following questions:

a. What are the suggested changes for the delivery window for each customer?
b. How much could such changes impact the fleet utilization?
c. How much could such changes impact the total transportation cost?

5.1 REGION C PLANT

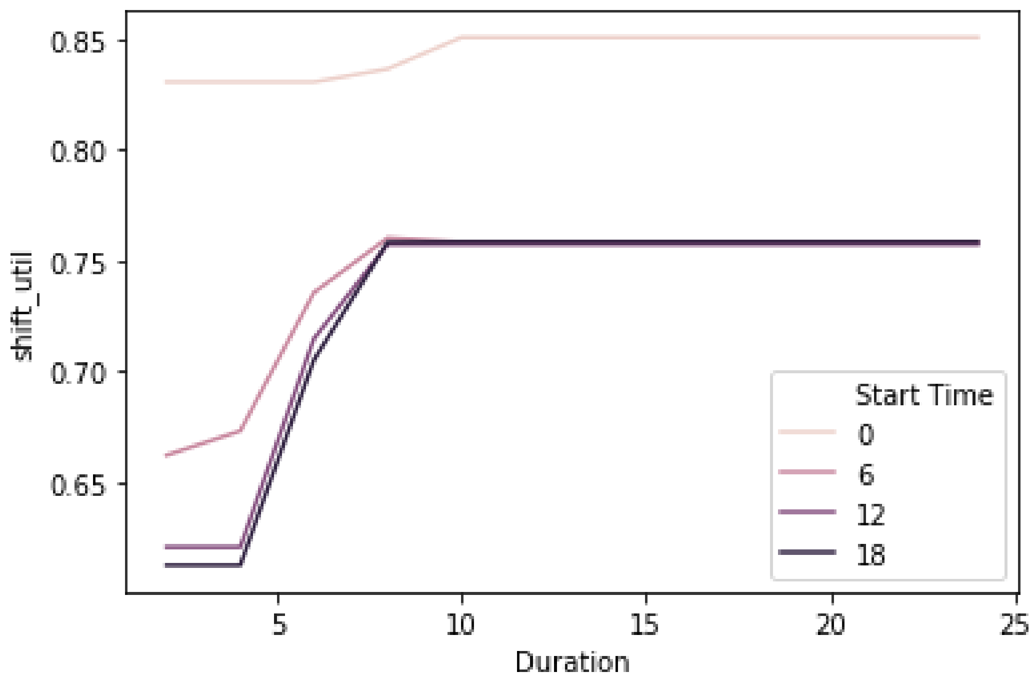
There are three in-scope customers for this project for the region C plant: C1, C2 and C3. As shown in Table 10 the delivery window duration requirements for all three customers exceed 10 hours. Based on the observation in Section 4, delivery window durations longer than 10 hours will neither further improve fleet utilization nor further reduce the total transportation cost. Therefore, extending the delivery window duration won't be effective and is not suggested.

Table 10. Current In-Scope Customer Delivery Window Requirements (Region C)

SOURCE	CUSTOMER	Start Time	Duration (hours)
Region C	Customer C1	13:00	10.5
Region C	Customer C2	0:01	24
Region C	Customer C3	4:00	18

As revealed in Section 4.4, different delivery start times can make a significant difference to the fleet utilization and total transportation cost. Customer C1 is the largest customer to region C plant by load volume, and 10 hours is used as a model input for its delivery window duration. Figure 22 below is a 2-D display of the 3-D output of Figure 20, showing that the daily fleet shift utilization for 00:00 delivery start time (85%) is 13% higher than the utilizations with all other start times (75%). From a total transportation cost perspective and under that same 10-hour window duration, Figure 23 shows that the 00:00 delivery start time has the least total cost (about $32,000), approximately 18% less than the cost of other start times (about $39,000).

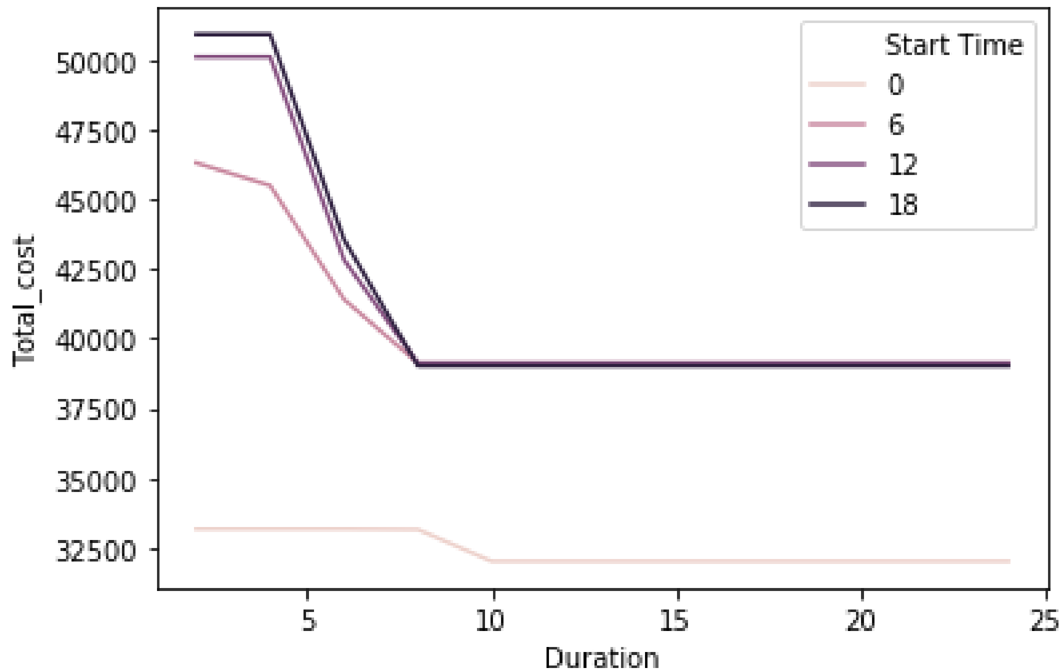
Thus, for the region C plant, the recommendation is to negotiate with customer C1 to move the delivery window start time to as close to 00:00 as possible in order to achieve significant fleet utilization improvement and transportation cost reduction. Customer C2 already have the most flexible delivery time requirement, so there is no need and room to further improve there. For customer C3, no obvious correlation is observed between utilization and delivery window or between transportation cost and delivery window, probably because its total load volume is not as significant as customer C1.



X axis: Delivery window duration (hour); **Y axis**: Daily fleet shift utilization rate

Figure 22. Truck Shift Utilization Over Customer C1's Different Delivery Start Times (2-D)

(Manufacturing location: Region C; Customer: C1; Date Range: 6/23/19)



X axis: Delivery window duration (hour); **Y axis**: Daily fleet total transportation cost ($)

Figure 23. Daily Total Transportation Cost Over Customer C1's Different Delivery Start Times

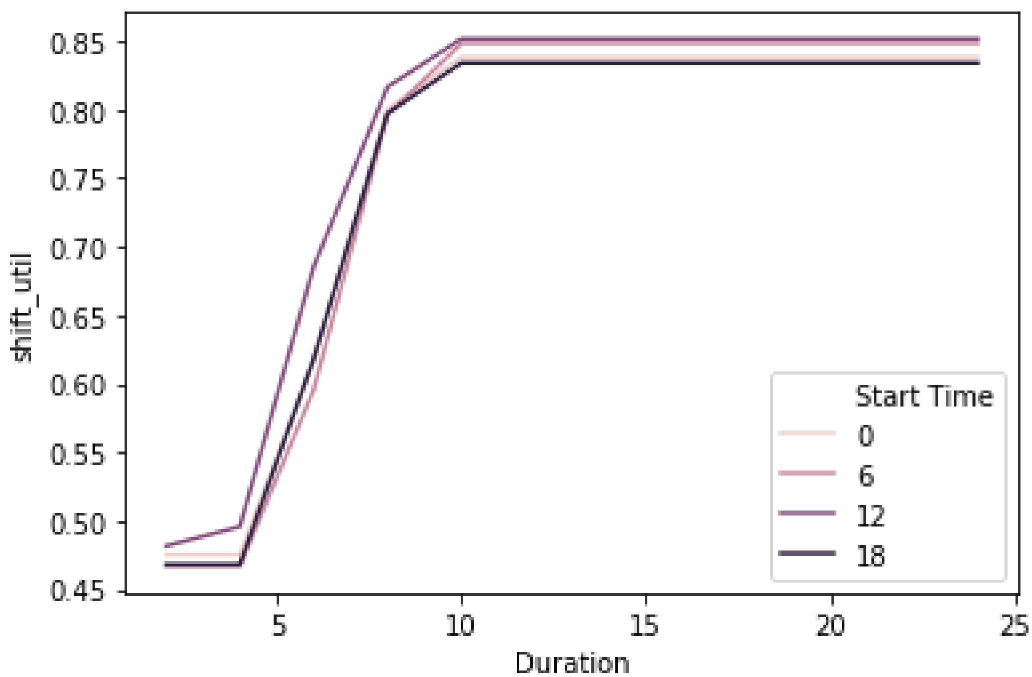
(Manufacturing location: Region C; Customer: C1; Date Range: 6/23/19)

5.2 REGION B PLANT

There are six in-scope customers for this project for the region B plant: B1, B3, B4, B5, B6 and B7. As shown in Table 11, the delivery window start time requirements for all six customers are between 6 am and 9 am, with a duration ranging 4 - 7 hours. Based on the observation in Section 4, given the same delivery start time, longer delivery window durations (no longer than 10 hours) will result in increased fleet utilization and decrease of the total transportation cost. As shown in Figure 24, if customer B1 locations increase their delivery window durations from the current 6 hours to 10 hours, the shift utilization will be increased from around 60% to around 85%. In comparison, the changes of delivery start time don't change the utilization as significantly. From total transportation cost perspective, Figure 25 shows the cost will go down from above $33,000 to below $18,000, a 45% reduction, from a 6-hour to 10-hour delivery window extension. For the other five customers, no obvious correlation is observed between utilization and delivery window or between transportation cost and delivery window, probably because their total load volume is not as significant as customer B1.

Table 11. Current In-Scope Customer Delivery Window Requirements (Region B)

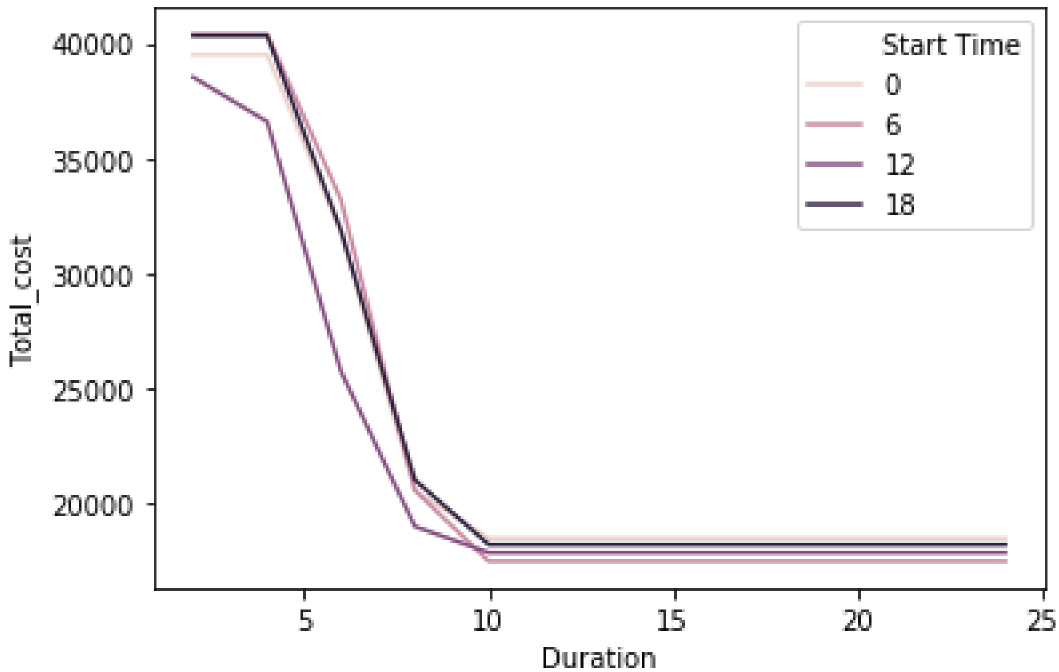
SOURCE	CUSTOMER	Start Time	Duration (hours)
Region B	Customer B1	6:00	6
Region B	Customer B3	6:00	4
Region B	Customer B4	6:00	4
Region B	Customer B5	9:00	7
Region B	Customer B6	7:00	7
Region B	Customer B7	6:00	4



X axis: Delivery window duration (hour); **Y axis**: Daily fleet shift utilization rate

Figure 24. Truck Shift Utilization Over Customer B1's Different Delivery Start Times

(Manufacturing location: Region B; Customer: B1; Date Range: 6/23/19)



X axis: Delivery window duration (hour); **Y axis**: Daily fleet total transportation cost ($)

Figure 25. Daily Total Transportation Cost Over Customer B1's Different Delivery Start Times

(Manufacturing location: Region B; Customer: B1; Date Range: 6/23/19)

5.3 REGION A PLANT

There are three in-scope customers for this project for the region A plant: A1, A2 and A3. As shown in Table 12 below, the pre-determined delivery window duration requirements for all three customers are at the most flexible and accommodating a level with 24-hour window. Therefore, no further improvement in utilization and transportation cost can be implied from running this model and no actions are suggested.

Table 12. Current In-Scope Customer Delivery Window Requirements (region A)

SOURCE	CUSTOMER	Start Time	Duration (hours)
Region A	Customer A1	0:01	24
Region A	Customer A2	0:01	24
Region A	Customer A3	0:01	24

5.4 RECOMMENDATION SUMMARY

In summary, for region C plant, the recommendation is to have customer C1 adjust its delivery window start time from 13:00 to close to midnight. The change would increase the fleet shift utilization approximately by 13% and reduce average daily total transportation cost approximately by $7,000 (18%). For region B plant, it is suggested that customer B1's locations increase their delivery window durations from the current 6 hours to 10 hours. The shift utilization would be increased from around 60% to around 85%, and the average daily transportation cost would go down approximately from above $33,000 to below $18,000, a 45% reduction. For region A plant, the recommendation is to have customer A1 stores agree to take more drop shipments.

6. CONCLUSION

Ranked after the material of making plastic bottles, transportation is the second largest cost for the Cost of Goods Sold (COGS) for Niagara Bottling, which is a low-cost leader in the United States plastic bottling industry. It is very important for the company to continuously look for opportunities to reduce its transportation cost in order to be able to maintain its competitive edge of delivering value-priced products to the customers. As an essential piece of reducing transportation cost is improving trucking utilization, this research focuses on trucking utilization impact from adjusting customer delivery receiving window.

For each pre-selected manufacturing plant location, a group of full truck loads within a 24-hour period for a few pre-determined in-scope customers have been analyzed based on a number of pre-assumed factors: distance to plant, average speed, average loading and unloading time. A heuristic is developed to assign 2 loads to as many trucks as possible, so that these trucks can increase their utilization individually and therefore improve the fleet utilization. Specific customer delivery window durations are used as one of primary constraints of the model, and different duration values are used to analyze the impacts on the fleet utilization as well as the transportation cost.

Results across all three plant locations generally show that the customer delivery window duration has a significant positive impact on the trucking utilization when the duration is longer than 2 hours and shorter than 10 hours. In that range, the longer the duration is, the higher the utilization will be. The impact levels on utilization vary with different plant locations, different customers, and different load mixes. There is little impact for delivery window duration beyond 10 hours. This means that the further utilization improvement opportunity is constrained by the daily maximum driving and shift hour regulations limit. Consequently, the improved utilization drives down the fleet transportation cost as the delivery window duration widens within 2 hours and 10 hours range. Another observation is that customers' specific delivery window start times can also have a significant impact on the utilization and transportation cost. From these insights, specific managerial recommendations for the three locations that were analyzed have been developed. The model was also used to estimate the effects of such changes in the sponsor company's transportation network.

This project's results and model analysis is consistent with the common sense that the longer the customers' delivery window durations are, the better utilization and transportation cost the fleet will achieve. However, the capability of this model is limited by its simplified and generalized presumptions on in-scope customer selections and parameter determinations. Further, the more quantifiable impacts and more accurate results will need to evaluated on a case-by-case basis with more specific and more representative inputs, such as broader customer mix, trucks delivering more than 2 loads, and speed as a function of the time of day.

Given the substantial transportation load volume of Niagara Bottling across so many manufacturing plants, it is recommended that the company take the roadmap created for this project to further analyze the financial impacts of adjusting customer delivery windows, based on different selection of plants and customers of interest. The results of such analysis can be used in negotiations with strategic customers and carriers as collaborative efforts to increase system-wide trucking utilization. Such collaborations, if successful, would reduce system-wide transportation cost and achieve system-wide cost saving, which would benefit all the parties involved.

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APPENDICES

APPENDIX A: Data Cleaning Python Code Explanations as referenced in Section 3.2

```
#Function to delete rows with Null values in critical columns (listed in list "check")
def nullcheck (df):
    check=['SOURCE', 'CUSTOMER', 'SHIPMENT_SPOT', 'SHIPMENT_DROP','SHIPMENT_PRELOAD', 'MILES', 'DELIVERY_APPOINTMENT']
    for i in range(len(df.columns)):
        if df.columns[i] in check:
            no=df[df.columns[i]].notna()
            df=df[no]
    return df

#Function to clean data (consistent data types, binary spot, preload and drop)
def clean(df):
    df['SOURCE'] = df['SOURCE'].astype(str)
    df['CUSTOMER'] = df['CUSTOMER'].astype(str)
    df['MILES'] = df['MILES'].astype(int)
    df['SPOT'] = df['SHIPMENT_SPOT'].apply(lambda x: 1 if x == 'Spot' else 0)
    df['PRELOAD'] = df['SHIPMENT_PRELOAD'].apply(lambda x: 1 if x == 'Preload' else 0)
    df['DROP'] = df['SHIPMENT_DROP'].apply(lambda x: 1 if x == 'Drop' else 0)
    df=df.drop(['SHIPMENT_DROP', 'SHIPMENT_PRELOAD', 'SHIPMENT_SPOT'], axis=1)
    return df

#Function to filter only datapoints within 1 day of the inputted time
def filtertime(df, year, month, day):
    now=datetime(year, month, day, 0, 0, 0)
    df['withinday'] = df['DELIVERY_APPOINTMENT'].apply(lambda x: 0 if (x-now).days >= 1 else (0 if (x-now).days < 0 else 1))
    df = df[df['withinday']==1]
    df=df.drop(['withinday'], axis = 1)
    return df
```

```
#creating dictionaries with constant assumption values to index into the df
filtersource=['Niagara Region A','Niagara Region B', 'Niagara Region C']
filtercust = {}
filtercust['Niagara Region A'] = ['Custoer A1', 'Customer A2', 'Custoer A3']
filtercust['Niagara Region C'] = ['Customer C1', 'Customer C2', 'Customer C3']
filtercust['Niagara Region B'] = ['Customer B1', 'Customer B3', 'Customer B4', 'Customer B5', 'Customer B6', 'Cusotmer B

loadtime={}
loadtime['Niagara Region A'] = [54.7, 116]
loadtime['Niagara Region C'] = [67.4, 142.76]
loadtime['Niagara Region B'] = [79.94, 112.6]

speed={}
speed['Niagara Region A'] = [24.25, 18.64, 39.65, 33.36]
speed['Niagara Region C'] = [48.66, 32.14, 40.63, 33.14]
speed['Niagara Region B'] = [17.23, 27.84, 34.28, 33.06]

unloadtimeRA={}
unloadtimeRA['Cusotmer A1'] = [78.6, 196.6]
unloadtimeRA['Cusotmer A3'] = [1, 124.6]
unloadtimeRA['Customer A2'] = [41.7, 185.2]

unloadtimeRC={}
unloadtimeRC['Cusotmer C1'] = [49.54, 97.16]
unloadtimeRC['Customer C3'] = [1, 163]
unloadtimeRC['Customer C2'] = [60.2, 284.8]

unloadtimeRB={}
unloadtimeRB['Customer B1'] = [1, 112]
unloadtimeRB['Customer B3'] = [93.45, 183.27]
unloadtimeRB['Customer B4'] = [1, 121.5]
unloadtimeRB['Customer B5'] = [1, 126.2]
unloadtimeRB['Customer B6'] = [1, 144.9]
unloadtimeRB['Customer B7'] = [1, 63.83]

unloadtime={}
unloadtime['Niagara Region A'] = unloadtimeRA
unloadtime['Niagara Region C'] = unloadtimeRC
unloadtime['Niagara Region B'] = unloadtimeRB
```

```
varRA={}
varRA['Customer A1'] = [0, 7.8]
varRA['Customer A3'] = [0, 17.9]
varRA['Customer A2'] = [0, 3.34]

varRC={}
varRC['Customer C1'] = [0, 3]
varRC['Customer C3'] = [0 ,1.4]
varRC['Customer C2'] = [0, 2.57]

varRB={}
varRB['Customer B1'] = [0, 6.1]
varRB['Customer B3'] = [0, 4.2]
varRB['Customer B4'] = [0, 4.6]
varRB['Cusotmer B5'] = [0, 2.9]
varRB['Cusotmer B6'] = [0, 4.2]
varRB['Customer B7'] = [0, 1.9]

var={}
var['Niagara Louisville'] = varRA
var['Niagara San Antonio'] = varRC
var['Niagara Philly'] = varRB
```

```
#Function to add rows for assumptions
    #Filter by Acceptance Code
    #Filter by source
    #Filter by customers in that source
    #Loadtime dictionary is Preload then live
    #Speed dictionary is less than 25miles, less than 100 miles, less than 150 miles, greater than 150 miles
    #Unload dictionary is drop then not drop
    #fix and var are costs associated with spot then not spot
    #Unload dictionary is drop then not drop
    #fix and var are costs associated with spot then not spot
    #calculate total cost per route
    #calculate driver and shift utilization
    #sort final df by LOADDELTIME
    #add a column to number routes
def filtervals(df, source):
    df=df[df['ACCEPTANCE_CODE']=='A']
    df=df[df['SOURCE']==source]
    df=df[df['CUSTOMER'].isin(filtercust[source])]
    lt=loadtime[source]
    sp=speed[source]
    df['LOADTIME'] = df['PRELOAD'].apply(lambda x: lt[0] if x == 1 else lt[1])
    df['SPEED'] = df['MILES'].apply(lambda x: sp[0] if x < 25
                                else (sp[1] if x<100
                                      else(sp[2] if x<150
                                           else sp[3])))
    df['ONEWAY'] = df.apply(lambda x: x['MILES']/x['SPEED']*60, axis=1)
    df=df.reset_index(drop=True)
    ults=unloadtime[source]
    fixs=fix[source]
    varss=var[source]
    df['FIXEDCOST']=700
    df['UNLOADTIME']=0
    df['VARCOST']=0
    for i in range(len(filtercust[source])):
        ultc=ults[filtercust[source][i]]
        fixc=fixs[filtercust[source][i]]
        varc=varss[filtercust[source][i]]
        for j in range(len(df['UNLOADTIME'])):
            if df['DROP'][j] == 1 and df['CUSTOMER'][j] == filtercust[source][i]:
                df['UNLOADTIME'][j]= ultc[0]
            elif df['DROP'][j] == 0 and df['CUSTOMER'][j] == filtercust[source][i]:
                df['UNLOADTIME'][j]= ultc[1]
            else:
                x=0
            if df['SPOT'][j]==1 and df['CUSTOMER'][j] == filtercust[source][i]:
                #df['FIXEDCOST'][j]= fixc[0]
                df['VARCOST'][j]= varc[0]
            elif df['SPOT'][j]==0 and df['CUSTOMER'][j]== filtercust[source][i]:
                #df['FIXEDCOST'][j]= fixc[1]
                df['VARCOST'][j]= varc[1]
            else:
                x=0
    df['LOADDELTIME']=df.apply(lambda x: x['LOADTIME']+x['UNLOADTIME']+x['ONEWAY'], axis=1)
    df['TOTALCOST']=df.apply(lambda x: (x['VARCOST']*x['MILES'])+x['FIXEDCOST'], axis=1)
    df['dr_util_init']=df.apply(lambda x: x['ONEWAY']/(11*60), axis=1)
    df['shift_util_init']=df.apply(lambda x: x['LOADDELTIME']/(14*60), axis=1)
    return df
```

```python
def delwindows(df, year, month, day):
    for index, row in df.iterrows():
        if df['CUSTOMER'][index]=='Customer C1':
            df['DELIVERY_WINDOW_START'][index]=datetime(year, month, day, 13, 0, 0)
            df['DELIVERY_WINDOW_END'][index] = datetime(year, month, day, 23, 0, 0)
        elif df['CUSTOMER'][index]=='Customer B4':
            df['DELIVERY_WINDOW_START'][index]=datetime(year, month, day, 6, 0, 0)
            df['DELIVERY_WINDOW_END'][index] = datetime(year, month, day, 10, 0, 0)
        elif df['CUSTOMER'][index]=='Customer B7':
            df['DELIVERY_WINDOW_START'][index]=datetime(year, month, day, 6, 0, 0)
            df['DELIVERY_WINDOW_END'][index] = datetime(year, month, day, 10, 0, 0)
        elif df['CUSTOMER'][index]=='Customer B5':
            df['DELIVERY_WINDOW_START'][index]=datetime(year, month, day, 7, 0, 0)
            df['DELIVERY_WINDOW_END'][index] = datetime(year, month, day, 14, 0, 0)
        elif df['CUSTOMER'][index]=='Customer B3':
            df['DELIVERY_WINDOW_START'][index]=datetime(year, month, day, 6, 0, 0)
            df['DELIVERY_WINDOW_END'][index] = datetime(year, month, day, 10, 0, 0)
        elif df['CUSTOMER'][index]=='Customer B1':
            df['DELIVERY_WINDOW_START'][index]=datetime(year, month, day, 6, 0, 0)
            df['DELIVERY_WINDOW_END'][index] = datetime(year, month, day, 12, 0, 0)
        elif df['CUSTOMER'][index]=='Cusotmer A1':
            if df['SOURCE'][index]=='Niagara Region B':
                df['DELIVERY_WINDOW_START'][index]=datetime(year, month, day, 9, 0, 0)
                df['DELIVERY_WINDOW_END'][index] = datetime(year, month, day, 16, 0, 0)
            else:
                df['DELIVERY_WINDOW_START'][index]=datetime(year, month, day, 0, 0, 0)
                df['DELIVERY_WINDOW_END'][index] = datetime(year, month, day+1, 0, 0, 0)
        elif df['CUSTOMER'][index]=='Customer C3':
            if df['SOURCE'][index]=='Niagara Region C':
                df['DELIVERY_WINDOW_START'][index]=datetime(year, month, day, 4, 0, 0)
                df['DELIVERY_WINDOW_END'][index] = datetime(year, month, day, 22, 0, 0)
            else:
                df['DELIVERY_WINDOW_START'][index]=datetime(year, month, day, 0, 0, 0)
                df['DELIVERY_WINDOW_END'][index] = datetime(year, month, day+1, 0, 0, 0)
        else:
            df['DELIVERY_WINDOW_START'][index]=datetime(year, month, day, 0, 0, 0)
            df['DELIVERY_WINDOW_END'][index] = datetime(year, month, day+1, 0, 0, 0)
        df=df.sort_values(by='DELIVERY_WINDOW_START', ascending=True)
        df['LN']= np.arange(len(df))
        df=df.reset_index(drop=True)
    return df
```

APPENDIX B: Load Assignment Heuristic Code and Result Output Code as referenced in Section 3.3.1

```
]:  #Function to output results of load assignment, utlization and cost
def load_opti_output(load):
    #Function to assign a selection of loads to one truck based on all un-assigned loads
    def loadassignment(df):
        df2=df
        df2['LN'] = df2['LN'].astype(int)
        LT=df2['LOADTIME'].iloc[0]
        UT=df2['UNLOADTIME'].iloc[0]
        TT=df2['LOADDELTIME'].iloc[0]
        DT=df2['ONEWAY'].iloc[0]
        LN=df2['LN'].iloc[0]
        TT_1=TT
        DT_1=DT
        LN1=LN
        df3=pd.DataFrame(columns=['LN','shift_util_init'])
        for i in range(1,len(df2)-1):
            T=UT+DT+df2['LOADTIME'][i]+df2['ONEWAY'][i]
            if (TT+DT+df2['LOADDELTIME'][i]<=840)&(2*DT+df2['ONEWAY'][i]<=660)&
            ((df2['DELIVERY_WINDOW_START'].iloc[0]+timedelta(minutes = T))>=df2['DELIVERY_WINDOW_START'].iloc[i])&
            ((df2['DELIVERY_WINDOW_START'].iloc[0]+timedelta(minutes = T))<=df2['DELIVERY_WINDOW_END'].iloc[i]):
                TT_1=TT+DT+df2['LOADDELTIME'][i]
                DT_1=2*DT+df2['ONEWAY'][i]
                LN1=df2['LN'][i]
                SU1=df2['shift_util_init'][i]
                result={'LN':LN1,'shift_util_init':SU1}
                df3=df3.append(result,ignore_index=True)

        df3['LN'] = df3['LN'].astype(int)
        if len(df3)==0:
            df=df.drop(df.index[0])
            df=df.reset_index(drop=True)
        else:
            #df3_sorted=df3.groupby(['LN'], as_index=False)['shift_util_init'].max()
            df3_sorted=df3.sort_values(['shift_util_init'], ascending=[True])
            N=df3_sorted['LN'].iloc[-1]
            #df=df.drop(df.index[N])
            df=df[df['LN']!= N]
            df=df.drop(df.index[0])
            df=df.reset_index(drop=True)
        return df

    #Function to output the selection of loads for the truck that gets assigned
    def loadresult(df):
        df2=df
        df2['LN'] = df2['LN'].astype(int)
        LT=df2['LOADTIME'].iloc[0]
        UT=df2['UNLOADTIME'].iloc[0]
        TT=df2['LOADDELTIME'].iloc[0]
        DT=df2['ONEWAY'].iloc[0]
        LN=df2['LN'].iloc[0]
        TC_B=df2['TOTALCOST'].iloc[0]
        FC_B=df2['FIXEDCOST'].iloc[0]
        VC_B=df2['VARCOST'].iloc[0]
        DU_B=df2['dr_util_init'].iloc[0]
        SU_B=df2['shift_util_init'].iloc[0]
        TT_1=TT
        DT_1=DT
        LN1=LN
        df3=pd.DataFrame(columns=['LN','T3','T4','total_cost_Base','FIXEDCOST','VARCOST',
                                  'dr_util_init','shift_util_init'])
```

```
    for i in range(1,len(df2)-1):
        T=UT+DT+df2['LOADTIME'][i]+df['ONEWAY'][i]
        if (TT+DT+df2['LOADDELTIME'][i]<=840)&(2*DT+df2['ONEWAY'][i]<=660)&((df2['DELIVERY_WINDOW_START'].iloc[0]
        +timedelta(minutes = T))>=df2['DELIVERY_WINDOW_START'].iloc[i])&((df2['DELIVERY_WINDOW_START'].iloc[0]
        +timedelta(minutes = T))<=df2['DELIVERY_WINDOW_END'].iloc[i]):
            TT_1=TT+DT+df2['LOADDELTIME'][i]
            DT_1=2*DT+df2['ONEWAY'][i]
            LN1=df2['LN'][i]
            SU1=df2['shift_util_init'][i]
            T3_1=df2['ONEWAY'][i]
            T4_1=df2['LOADDELTIME'][i]
            TC_B1=df2['TOTALCOST'][i]
            FC_B1=df2['FIXEDCOST'][i]
            VC_B1=df2['VARCOST'][i]
            DU_B1=df2['dr_util_init'][i]
            SU_B1=df2['shift_util_init'][i]
            result={'LN':LN1,'T3':T3_1,'T4':T4_1,'total_cost_Base':TC_B1,'FIXEDCOST':FC_B1,'VARCOST':VC_B1,
                    'dr_util_init':DU_B1,'shift_util_init':TT_1/840}
            df3=df3.append(result,ignore_index=True)

    df3['LN'] = df3['LN'].astype(int)
    if len(df3)==0:
        result={'stop1':LN,'stop2':LN,'total_cost':TC_B,'total_cost_Base':TC_B,'dr_util':DT/660,
                'dr_util_init':DU_B,'shift_util':TT/840,'shift_util_init':SU_B}

    else:
        #df3_sorted=df3.groupby(['LN'], as_index=False)['shift_util_init'].max()
        df3_sorted=df3.sort_values(['shift_util_init'], ascending=[True])
        N=df3_sorted['LN'].iloc[-1]
        TTN=TT+DT+df3_sorted['T4'].iloc[-1]
        DTN=2*DT+df3_sorted['T3'].iloc[-1]
        TC_BN=TC_B+df3_sorted['total_cost_Base'].iloc[-1]
        TCN=VC_B+df3_sorted['VARCOST'].iloc[-1]+(FC_B+df3_sorted['FIXEDCOST'].iloc[-1])/2
        DU_BN=(DU_B+df3_sorted['dr_util_init'].iloc[-1])/2
        SU_BN=(SU_B+df3_sorted['shift_util_init'].iloc[-1])/2
        #LNN=df['LN'][N]
        #SUN=df['shift_util_init'][N]
        result={'stop1':LN,'stop2':N,'total_cost':TCN,'total_cost_Base':TC_BN,'dr_util':DTN/660,
                'dr_util_init':DU_BN,'shift_util':TTN/840,'shift_util_init':SU_BN}
    return result

load1=load
rowcount=len(load1)
df=pd.DataFrame(columns=['stop1','stop2','total_cost','total_cost_Base','dr_util','dr_util_init',
                         'shift_util','shift_util_init'])
i=0
while rowcount>1:
    df1=loadresult(load1)
    df=df.append(df1,ignore_index=True)
    load1=loadassignment(load1)
    rowcount=len(load1)
    i=i+1
TT=load1['LOADDELTIME'].iloc[-1]
DT=load1['ONEWAY'].iloc[-1]
LN=load1['LN'].iloc[-1]
TC=load1['TOTALCOST'].iloc[-1]
DU_B=load1['dr_util_init'].iloc[-1]
SU_B=load1['shift_util_init'].iloc[-1]
last_load={'stop1':LN,'stop2':LN,'total_cost':TC,'total_cost_Base':TC,'dr_util':DT/660,
           'dr_util_init':DU_B,'shift_util':TT/840,'shift_util_init':SU_B}
df=df.append(last_load,ignore_index=True)
return df
```

APPENDIX C: Sensitivity Analysis python code as referenced in Section 3.4

The function *allops* with inputs *df, source, year, month and day* runs all the subfunctions as shown in Appendix A.

The function *load_opti_output* with input *df* runs all functions described in Appendix B.

```
def changestarttime(df, customer, year, month, day, hour, minute, second):
        from datetime import datetime, timedelta
        for index, row in df.iterrows():
            if df['CUSTOMER'][index]==customer:
                window=df['DELIVERY_WINDOW_END'][index]-df['DELIVERY_WINDOW_START'][index]
                df['DELIVERY_WINDOW_START'][index]= datetime(year, month, day, hour, minute, second)
                df['DELIVERY_WINDOW_END'][index] = df['DELIVERY_WINDOW_START'][index] + window
        df['DELIVERY_WINDOW_START'] =pd.to_datetime(df.DELIVERY_WINDOW_START)
        df.sort_values(by=['DELIVERY_WINDOW_START'],inplace=True, ascending=True)
        df['LN']= np.arange(len(df))
        df=df.reset_index(drop=True)
        return df

def changeduration(df, customer, duration):
        from datetime import datetime, timedelta
        for index, row in df.iterrows():
            if df['CUSTOMER'][index]==customer:
                df['DELIVERY_WINDOW_END'][index] = df['DELIVERY_WINDOW_START'][index] + timedelta(hours=duration)
        return df
```

```
def sensitivitytesting(data,customer,region,month,dates):
    starttimes=[0,6,12,18]
    durations=[2,4,6,8,10,12,18,24]
    final=pd.DataFrame(columns=['Region','Customer','Date','Start Time','Duration', 'Num_Trucks', 'Num_Trucks_base', 'Total_c
    for i in range(len(dates)):
        df1=allops(data,region,2019,month,dates[i])
        for j in range(len(starttimes)):
            df2=changestarttime(df1, customer, 2019, month, dates[i], starttimes[j], 0, 0)
            for k in range(len(durations)):
                df3=changeduration(df2, customer, durations[k])
                result=load_opti_output(df3)
                add={'Region': region,
                     'Customer':customer,
                     'Date': dates[i],
                     'Start Time':starttimes[j],
                     'Duration':durations[k],
                     'Num_Trucks':len(result),
                     'Num_Trucks_base':max(max(result['stop1']), max(result['stop2'])),
                     'Total_cost':result['total_cost'].sum(axis=0),
                     'Total_cost_base':result['total_cost_Base'].sum(axis=0),
                     'dr_util': result['dr_util'].mean(axis=0),
                     'dr_util_base':result['dr_util_init'].mean(axis=0),
                     'shift_util':result['shift_util'].mean(axis=0),
                     'shift_util_base':result['shift_util_init'].mean(axis=0)}
                final=final.append(add,ignore_index=True)
    return final
```

The following is an example of how the scenarios were generated for each day of the week from 2019 Scorecard Week 26 for Customer *B1* in region *B*. This was done individually for all of the in-scope customers.

```
data = pd.read_excel('Scorecard WK1926.xlsx')
```

```
customer='Customer B1'
region='Niagara Region B'
month=6
dates=[23,24,25,26,27,28,29]
final=sensitivitytesting(data,customer,region,month,dates)
```

...