# A Strategic Tool for Finding Optimal Last Mile Fleet Size & Fleet Composition, using Knapsack, Bin Packing, and Aggregate Planning

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ABSTRACT

As a result of the COVID-19 pandemic, the ecommerce share of retail has grown at an accelerated rate, increasing the number of home deliveries and delivery speed expectation from customers. Moreover, demand variability over the year and delivering a wide variety of products in terms of weight and volume has increased the last mile delivery cost for most companies. We developed this capstone project for one of the biggest retailers in Mexico, Coppel. Our work is focused on creating a strategic tool that allows our sponsor company to define the optimal fleet composition for their last mile delivery operation at each logistic facility, and to formulate an allocation strategy for their different order types. To find the optimal solution in terms of cost, we built a combination knapsack & bin packing model, with aggregate planning. To see how level of service, defined as the delivery speed, and demand variability over the time impacts cost and $CO_2$ emissions, we selected 3 different regions, which are Culiacán, Tecamac, and Monterrey. These three regions were selected, as they cover most of the characteristics of Coppel's last mile operation. Our results indicate that it is financially beneficial for Coppel to reassess their order allocation restrictions and the usage of third-party, for both full truck rentals and small parcel carriers.

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# 1. Introduction

## 1.1 Motivation

The last mile can be defined as the last part of the business-to-consumer supply chain, where the product is delivered to the consumer's home or collection point (Gevaers et al., 2009). The main objective of last mile is to deliver the products in the shortest amount of time, with the greatest profit and customer satisfaction. Last mile delivery is vital to retailers, as it is the part of the down-stream supply chain that directly connects retailers with the end consumer and is typically the most expensive segment of their supply chain (Frederick et al., 2019). According to Suguna et al. (2021), the last mile accounts for about 40% of total logistics costs globally.

Retailers have also been under immense pressure to increase capacity, speed, and flexibility, as the importance of ecommerce has become more prominent (Altenried, 2019). According to Viu-Roig and Alvarez-Palau (2020) "E-commerce has seen very high growth rates in recent years, a trend that will be accentuated by the impact of COVID-19, which has led to a further increase in Internet purchasing" (p. 13). The increase in e-commerce is up two digits in most developed nations. According to Kim (2020), "Consumer's adaptations to online shopping, which has been accelerated by the pandemic, are not likely to end or reduce after the COVID-19 passes" (214). Online shopping has turned every home into a potential delivery point for companies, which has accelerated the growth in delivery numbers (Viu-Roig & Alvarez-Palau, 2020). As a result of the increase in online purchasing, last-mile has been shouldered with the burden of delivering the larger quantity of packages. Consumers expect smarter, faster, and more reliable last mile deliveries (Suguna et al., 2021).

Last mile delivery is now an extreme site of competition between companies. A major factor in this competition is delivery speed. Delivery speed has been taken to a new level, because of same day delivery (Suguna et al., 2021). Same day delivery is rapidly growing, as it appeals most to the millennial generation who live in cities. The pandemic has heightened the importance of delivery speed, and it is now one of the most important aspects of customer satisfaction (Suguna et al., 2021). Also, because of the pandemic, same day delivery is being viewed more as a requirement, than a luxury. Companies that develop faster delivery options separate themselves from their competition, by being able to satisfy customers' needs at a quicker rate (Suguna et al., 2021). Amazon is a major driver of this competition, as they are continuously trying to speed up their delivery of products, with the goal of mitigating the largest disadvantage of purchasing online, the lag between a customer purchasing and receiving their product (Altenried, 2019).

The rise in demand for last mile delivery has also contributed to a rise of delivery vans in cities; the increase of these delivery vehicles has had a significant impact on environmental sustainability (Siragusa et al., 2020). With the increase in last mile delivery has also come an increase in consumer awareness of sustainability issues with last mile delivery. Consumers expect a decreasing carbon footprint, without sacrificing delivery speed (Gevaers et al., 2009). The rising demand for last mile delivery constitutes the need for innovation to decrease the impact on the environment (Awwad et al., 2018). There are many ways companies can migrate towards greener last mile policies (Edwards et al., 2010). A few options are electric vehicles, alternative fuels, or optimization techniques (Awwad et al., 2018).

Last mile delivery is a crucial part of retailers supply chains, because of its impact on total logistics costs, customer satisfaction, and the company's carbon footprint. With its high level of importance, having an optimal last mile fleet and order allocation strategy is ideal. The purpose of this capstone project is to formulate a model that optimizes a company's last mile fleet and provides an order allocation strategy. In the next section, we introduce this capstone's corporate partner, whom this optimization model is initially built for, provide company background, and formally describe the problem this capstone is seeking to solve.

### 1.2 Company Background & Problem Statement

Coppel is one of the biggest retailers in Mexico, selling everything from refrigerators to clothing. The company has more than 1,600 stores and over 180 cross docks and distribution centers, for its last mile operation (J. G. Ramos, personal communication, October 5, 2021). Coppel saw high growth rates of last mile deliveries for E-commerce because of the COVID-19 pandemic, like the rates discussed in Viu-Roig and Alvarez-Palau. The accelerated growth rates that Coppel experienced are the reason for this project. For example, in the year 2020, the demand for delivery of online orders climbed from 2% of all products sold to 20%, at its peak. The demand leveled off to approximately 11% of total product sold. During 2020, Coppel delivered around 11 million products with their own-fleet of 1,350 mid-sized trucks and vans, and a small participation of third-party carriers. The split between owned fleet and third-party for the last mile delivery was 70% owned fleet and 30% third-party. Coppel has two types of products, hardline and softline Hardline is items like furniture and appliances, which most require an exact delivery appointment and to be delivered in a specific truck type with two employees. Softline items are products like clothing, footwear, and toys. Softline is mainly delivered with third-party carriers, with only a small percent being delivered by Coppel's own-fleet (J. G. Ramos, personal communication, October 5, 2021).

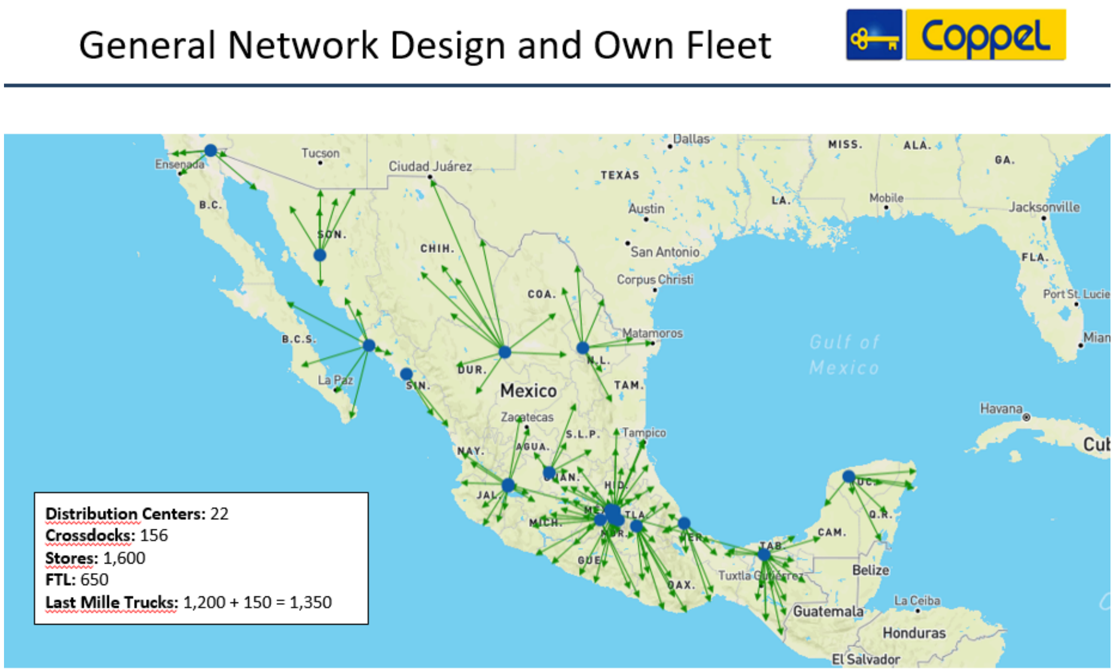
Over the course of 2020, Coppel has spent 137 million on their last mile operation (J. G. Ramos, personal communication, October 5, 2021). The number of deliveries also represents an annual estimated consumption of 6.2 million liters of fuel or 14.6 million $CO_2$ kg. When an item is delivered with Coppel's own-fleet, on average it takes about 2.6 calendar days to deliver the order to a customer, after the order is placed and confirmed. When the last mile delivery is outsourced to a third-party, the delivery time increases to 4.5 calendar days, after the order is placed and confirmed (J. G. Ramos, personal communication, October 5, 2021).

Coppel's margin was impacted by the increase in demand for last mile delivery in 2020. The cost increase was mainly driven by the shift from customers purchasing in store and leaving with the product in hand, to purchasing online and requiring delivery, because of the COVID19 pandemic (J. G. Ramos, personal communication, October 5, 2021). With the rapid increase of last mile delivery demand, Coppel expanded its last mile delivery capacity without optimizing, as it was putting customer service needs first.

Additionally in recent years, Coppel has propelled multiple initiatives forward to focus more on environmental sustainability (J. G. Ramos, personal communication, October 5, 2021). For example, the creation of the Sustainability Department to monitor KPI's, promote specific practices, and follow up on projects that have a sustainable impact. An important factor to focus on is fuel consumption, as it is the second largest $CO_2$ generator of the company and is therefore one of the main concerns to address (J. G. Ramos, personal communication, October 5, 2021). By calculating total fuel consumption, this will allow Coppel to begin to understand their $CO_2$ emissions, and provide a base for which to explore the green options discussed in Awwad et al.

**Figure 1**

*Coppel Network Design*




With the rapid growth in demand for last mile delivery, and the need to remain competitive in the market, Coppel is motivated to refine their last mile delivery approach. The main problem for Coppel, and main motivation for this capstone is twofold:

1) Optimizing the last mile delivery fleet by determining the optimal number of last mile vehicles and delivery vehicle mix
2) Understanding the best order allocation strategy for this newfound last mile delivery fleet

The optimization strategy has three main influencing pillars: financial impact, delivery speed, and sustainability. While all three pillars shape last mile delivery for Coppel, cost is the optimization focus. This capstone's goal is to create an optimization model which assists Coppel in finding the optimal delivery fleet and order allocation strategy that minimizes the total last mile cost for Coppel, while meeting the target delivery speed and $CO_2$ footprint.

Now that we have defined the motivation for this capstone and our problem, we will explore the existing literature, explain our methodology, and review our results. We do this in the following chapters: in Chapter 2, we review the relevant literature, in Chapter 3, we explain our methodology and data, and in Chapter 4 we report and discuss the results.

## 2. Literature Review

In this chapter we describe the literature related to the approach we took to achieve optimization. First we review the literature on strategic fleet composition and planning and its impact on this capstone; we then review the literature on the optimization models that influenced our methodology: multiple knapsack problem, bin packing problem, and aggregate planning.

### 2.1 Strategic Fleet Composition & Planning

An important part of a company's supply chain, which allows it to achieve its target service level and optimize costs, its fleet size and composition (Hoff et al., 2010). Balancing own-fleet and third-party operators is a problem faced by industries ranging from transportation suppliers to good owners. Regarding the fleet size, it is necessary to consider demand forecast variability, third-party rates, and transportation costs for own-fleet (Hoff et al., 2010). Last mile fleet composition is under strong pressure to reduce movement costs, which requires frequent last mile fleet adjustments (Hoff et al., 2010). Last mile transportation planning models must be able to adapt to increasing demand, high quality of service, and be flexible to the ever-changing consumer needs (Baldi et al., 2019). Strategic planning is crucial when evaluating various last mile transport options (i.e. various own-fleet trucks and third-party carriers), and allocating these resources to the right places.

The fleet composition of Coppel's last mile is not homogeneous, meaning Coppel uses a variety of sizes of trucks (J. G. Ramos, Personal Communication, October 5, 2021). As discussed in Hoff et al, Coppel's fleet is mixed as it allows it to be more optimal in terms of cost and providing a better service level. The fleet is also not homogeneous for a few business reasons as well. First, the same fleet is used to serve different purposes on the same day, such as store fulfillment and home delivery. Each fulfillment type (store or home) has its own demand and delivery time constraints. Second, Coppel offers a wide variety of products, which vary in regard to volume and delivery complexity (i.e. assembly). Third, the local topography could demand a truck with a specific motor power and tires for hilly areas or unpaved roads (J. G. Ramos, Personal Communication, October 5, 2021). Finally, few areas are restricted because of local regulations and street width, which dictate the truck size (i.e., downtown streets). Coppel must balance these with the necessary considerations discussed in Hoff et al and Baldi et al, like demand forecast variability, third-party rates, and the transport costs for their own-fleets. It is because of the importance and reasons outlined by Baldi et al and Hoff et all, that our optimization model is a strategic planning tool, instead of an everyday tactical tool. Now that we have established the importance of fleet planning, we will review the optimization model approach in Section 2.2.

### 2.2 Optimization Methodologies

Because of the growing demand for last mile, rising $CO_2$ emissions, and customers' expectations of rapid delivery, Coppel's current last mile fleet needs to be optimized. In the next section, we review three main optimization methodologies, the multiple knapsack problem, the bin packing problem, and aggregate planning. In our proposed mathematical model, we combine the three problems into a single objective function. The methodology provides an optimal solution, which reduces costs, while providing total $CO_2$ emissions, and maintaining delivery speed.

#### 2.2.1 Knapsack for the Last Mile

The knapsack problem is derived from the idea of a climber trying to maximize the space in their pack for a trip (Assi & Haraty, 2018). The climber is trying to choose the items that provide the highest value to them on their trip, but still fit within their pack. According to Assi and Haraty (2018), the knapsack problem is one the most studied combinatorial problems. A more traditional definition of the knapsack problem is maximizing profits by filling a knapsack with a set of items (n), while conforming to the weight constraint of the knapsack (Assi & Haraty, 2018).

The many different variations of the knapsack problem include Binary Knapsack, Multiple Knapsack Problem, Bounded Knapsack, Multiple Choice Knapsack, Multi-Objective Knapsack, & Multidimensional Multiple Choice Knapsack (Assi & Haraty, 2018; Bazgan et al., 2009). The Multiple Knapsack Problem is an expansion of the traditional binary knapsack with simply more knapsacks. However, for this capstone we focus on Multiple Knapsack with Assignment Restriction problem (MKARP), as Coppel has restrictions on which types of trucks orders can be packed into. According to Handoko et al. (2014), a MKARP is a variant of the Multiple Knapsack where certain items can only be assigned to specific subsets of the knapsacks. The assignment restrictions, or constraints, for this capstone is further elaborated in on Chapter 3. Like research done by Handoko et al. (2014), our model is built on the MKARP, but includes a secondary capacity constraint to incorporate the volume and time capacities of the trucks. This capstone uses integer variables, instead of hard binaries, as this allows the model to be more efficient, while achieving the same functionality. The objective for this problem is to select the trucks and truck types that minimizes the cost, while not exceeding the trucks' limits and adhering to the delivery time constraint. While a MKARP fulfills most of our models needs, there are aspects, like characterization of bins, which more resemble a Bin Packing Problem. Because of this, the next section will review Bin Packing Problems.

### 2.2.2 Bin Packing Problem

Research by Baldi et al. (2019), found that bin packing problems have been used for strategic modeling and making tactical decisions in transportation. Packing problems, which look for the optimal arrangement of items to sets of "bins", have been used in strategic planning of last mile fleets as the models allow companies to create their optimal fleet composition by moving through three main steps. The first is to select the types of trucks and third-party carriers, the second is to determine the number of each vehicle or carrier type, and lastly how to assign the parcels or orders to each truck or third-party carrier (Baldi et al., 2019). There are many similarities between Baldi et al. (2019) research and this capstone's problem. The main similarities are that Baldi et al. (2019) structured their research for a strategic approach, instead of an everyday operational model. The research also characterized their bins by capacity, cost of use, and categorized each bin by type. This capstone has the exact same. The research from Baldi et al. (2019), found that the Generalized Bin Packing Problem was efficient in finding solutions for both strategic and daily operational decisions for transportation.

In comparing the Multiple Knapsack model to the Generalized Bin Packing Problem (GBPP), we have found that there are benefits of both. Baldi et al. (2019) found that the GBPP was a strategic tool that could be used for tactical planning for the last mile fleet composition. However, the capacity constraints modeled by Assi and Haraty (2018) and Handoko et al. (2014) are vital to the construction of our model. Because of our blended needs, we chose to mix the MKARP with the GBPP, to create the base model that fits this capstone full requirements. The next section explores Aggregate Planning, as this capstone is working across multiple periods, but seeking one optimal solution for all.

### 2.2.3 Aggregate Planning

Traditionally, aggregate planning has been used to determine the optimal production, work force, and inventory levels for each period of the planning horizon (Gomes Da Silva et al., 2006). The main goal of an aggregate plan is to fulfill the known demand in the most cost-effective manner, for all time periods. In research by Rasmi and Türkay (2021), aggregate planning is described as a process that helps to determine levels of capacity, with the main goal being to balance supply and demand. Aggregate planning is best at finding strategic and tactical decisions that are 2-18 months in the future, without incorporating operational details. Aggregate planning is vital when trying to deal with fluctuating demand over the planning period (Rasmi & Türkay, 2021). It is because of these reasons stated in Rasmi & Türkay, that we have chosen to incorporate aggregate planning into the optimization model. The model determines level of capacity which balances the supply (delivery capacity), with the demand (number of orders to be delivered).

While aggregate planning models typically focus on product production, workforce planning, or scheduling, this capstone uses the ideas of aggregate planning to find the optimal fleet of trucks, as explored in research by Seong Ko et al. (2002). In Seong Ko et al. (2002), the yearly allocation of trucks is determined by taking the forecasted monthly demand, with the goal to minimize the annual operating costs. This specific research used a Vehicle Routing Problem to determine the allocation of orders to trucks and number of trucks, and then assessed the needs each period to find the optimal annual solution. This project uses aggregate planning in the same manner that Seong Ko et al. (2002) did, however this project is using a knapsack and bin packing to find the optimal order assignment. Seong Ko et al also did not allow for the purchase or sale of trucks throughout their model, while this capstone is incorporating purchasing and selling own-fleet trucks to determine the overall optimal solution.

In Chapter 2, we examined the importance of strategic fleet planning, the multiple knapsack problem, bin packing problem, and aggregate planning. The literature we reviewed helped to build our methodological approach for creating our optimization model, including assisting with construction of constraints and the objective function. The review also provided a better understanding of the why this model is needed and how it can impact Coppel in the future. Now that we have laid the foundation through the literature of our methodology, the next chapter describes our methods in detail.

## 3 Data and Methodology

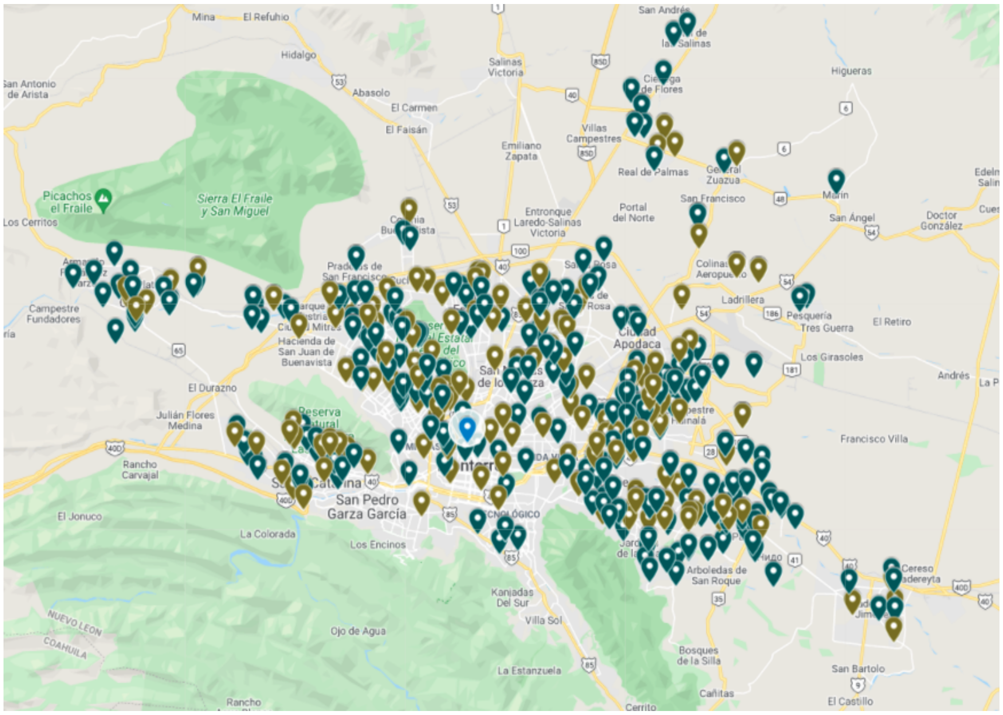
In this chapter, we first discuss the methodology we used to find the optimal fleet and allocation strategy: defining the scope, collecting, analyzing & cleaning the data, formulating the mathematical model. We then conclude by describing the model construction and parameters. Figure 2 displays the flow of this chapter.

**Figure 2.**
*Chapter 3 Flow*


### 3.1 Scope

Coppel has a large last mile network, which includes 180 distribution centers and warehouses all across México. Their own-fleet of 1,500 trucks, with the assistance of third-party carriers, delivers more than 12 million products ordered by customers per year. Coppel's last mile network is highly complex, as there are two main categories for orders, hardline and softline, which are required to be delivered in specific manners, different types of trucks, and an own-fleet assisted by various third-party carriers. Figure 3 displays an estimation of one day of orders for Coppel, which is served by one DC (blue point). The light green points are small orders, while the dark green points are large orders. This information was gathered from data Coppel provided, which we describe more in depth in section 3.2.

**Figure 3.**
*Dispersion of Coppel Last Mile Orders from Monterrey Region, per order type for one day*




Through discussions with experts at Coppel, we set the scope and determined that this project includes the choice of fleet (type of carrier, truck, and quantity) and how to optimally load each truck in terms of order type, while minimizing total costs and maintaining the target delivery speed and $CO_2$ emissions. This project does not include truck routing or facility location. We outline the important areas of this project's scope in the following sections.

### 3.1.1 Last Mile Description

In this section, we describe Coppel's last mile in detail: order types and product types, the selected regions and why, truck types, and third-party usage. We also cover the characteristics which differentiate the different types of orders, trucks, and third-party, and any restrictions each category may have.

### 3.1.2 Order Types

Coppel divides its products into two separate categories, hardline and softline. Currently, customers can order hardline and softline products within the same order. However, the hardline and softline products are then be split into two orders, one for the hardline and one for the softline, as the categories are treated independently in Coppel's last mile system.

Hardline items are items like a refrigerator, television, or a dining table. Hardline can require assembly upon delivery, is normally larger in volume, and all are delivered with Coppel's own-fleet no matter the product size. The only exception is during Coppel's peak season, which takes place in November and December, where Coppel will use an entire third-party truck to assist with deliveries. This project does include demand from the high season and allows for the incorporation of renting an entire third-party owned big truck. This model does differ from Coppel's current practices of only renting the third-party big trucks during high season and allows for the rental during any time period of the year. However, there are smaller items in hardline, like USBs or cell phone accessories, which do not require assembly, and are smaller in volume.

Softline orders are items like clothing, shoes, and small toys. These items are smaller in size and do not require any special handling or assembly by the company. Softline can be delivered with Coppel's own-fleet or a third-party carrier. Currently, 93.5% of softline orders are delivered with a third-party carrier, like DHL, FedEx and other local carriers. After discussing with the experts, we have chosen to divide orders by the size (volume), as well as hardline and softline. Table 1 displays the order types, their characteristics. The information in Table 1 was derived from discussions we had with Coppel's experts and data received from Coppel. The average kilometers per order and the average drive time are from the consolidation model, specifically for the region of Monterrey. The consolidation model is discussed more in depth in section 3.2, which describes the data. The regions of Monterrey, Culiacán, and Tecamac were selected as our pilots, however Culiacán and Tecamac's average kilometers per order and average delivery drive time are omitted from this chart to preserve company data. The next section goes into greater detail about how and why we chose these regions.

**Table 1.**
*Coppel's Order Characteristics, Nationally*

| Order Category | Volume | Avg KM per order (Monterrey only) | Own-fleet Avg Delivery + Drive Time (Monterrey Only) | Own-fleet Delivery? | Third-party Small Parcel Delivery? | Truck Size |
|---|---|---|---|---|---|---|
| Big Hardline | $M^3$ | 5.31 KM | 12.5 mins + 10 mins | Yes | No | Big |
| Medium Hardline | $M^3$ | 5.2 KM | 11 mins + 10 mins | Yes | No | Big |
| Small Hardline | $M^3$ | 5.08 KM | 5 mins + 10 mins | Yes | No | Big or Small |
| Softline (big and small) | $M^3$ | 5.08 KM | 5 mins + 10 mins | Yes | Yes | Big or Small |

### 3.1.3 Regions

For this project, region is defined as the area covered by each facility's last mile. We have focused this project on three crucial and critical regions within Coppel's last mile: Monterrey, Tecamac, and Culiacán. Each chosen region represents a greater cluster of other like regions. These regions were selected after analyzing the data Coppel provided. A more in-depth description of the data is in section 3.2.

Region 1 is Monterrey as this region has the highest number of total orders for any Coppel region, has a mid-sized population, and the distribution center currently uses and has historically used all modes of delivery transport to facilitate their last mile delivery. Region 2 is Tecamac, which is in the México City metropolitan area. This region has one of the highest demands across all order types, and the largest variety of softline products for all Coppel warehouses. Region 3 is Culiacán, which is a smaller sized region. The warehouse serves all order types and has one of the highest delivery densities for Coppel. Also, this region is the headquarters of Coppel, making it a prime location for testing. Figure 4 displays the analysis for the top 15 regions for Coppel, regarding hardline order size, for one month. This information was derived from data received from the Coppel experts. Figure 5 displays the quantity of softline orders which are ordered and fulfilled within the same region, for one month. This information was also derived from data received from the Coppel experts. We have found that regions with a mix of hardline and softline have the largest room for improvement, as these regions are typically currently using the full mix of transport vehicles (own-fleet and third-party carriers).

**Figure 4.**

*Analysis of hardline order types for top regions, for one month*

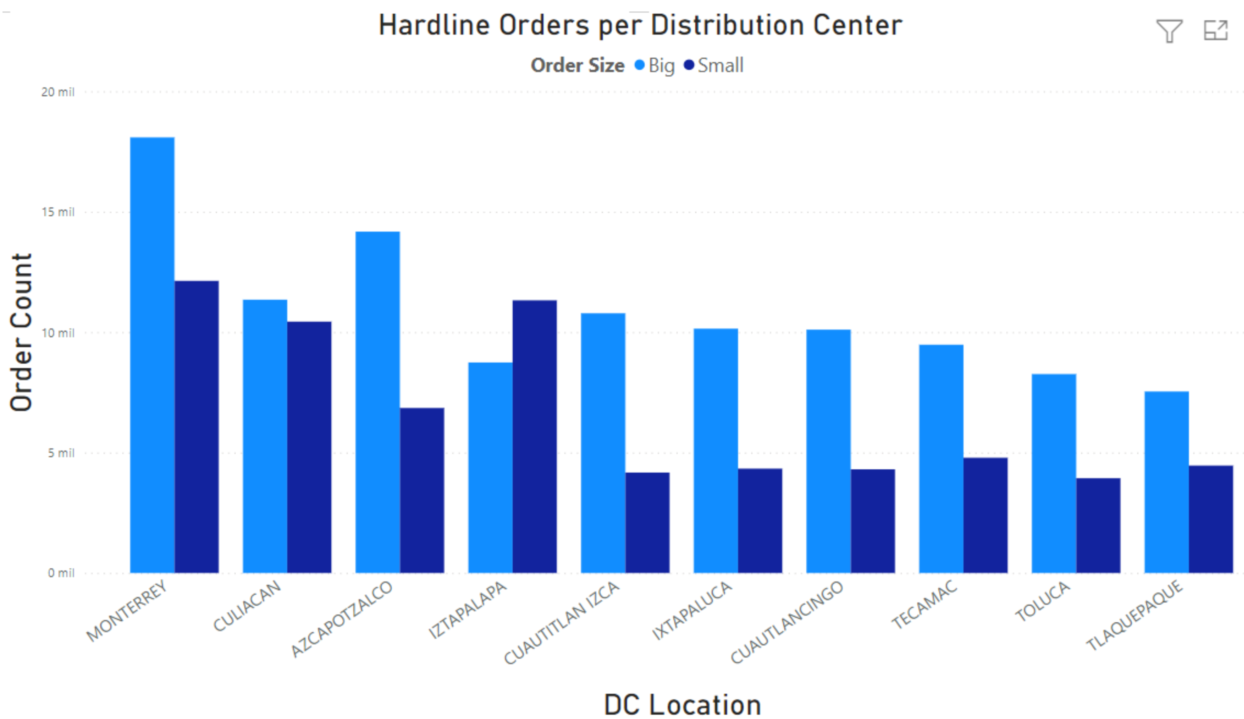
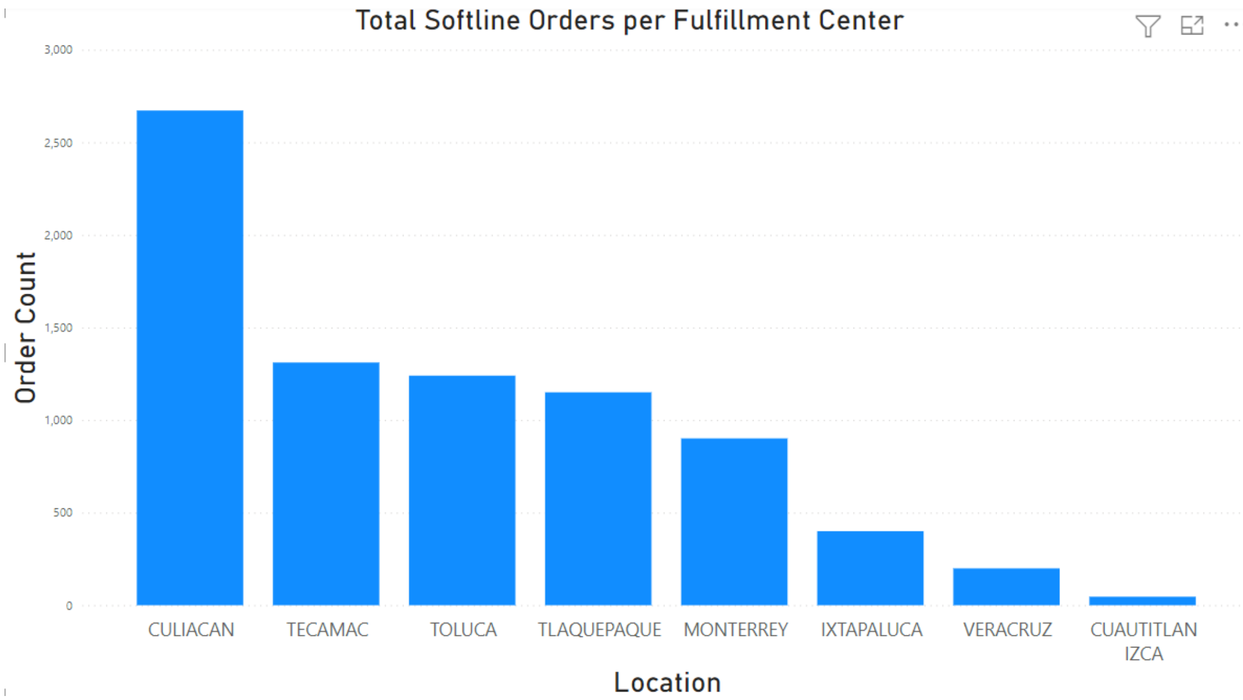


**Figure 5.**

*Analysis of softline orders, for all of Mexico, for one month*




### 3.1.4 Truck Types

Coppel has a wide range of own-fleet trucks which are used to facilitate their last mile deliveries. These trucks can be broken down into two main categories, big and small. The size of the truck is dictated by the volume of the cargo bed. A big truck has a cargo bed with a volume greater than 20 cubic meters and a small truck has a volume anything below this, typically around 6 cubic meters. Besides volume, there are also a few other differences between big and small trucks. An example is big trucks have different requirements in terms of labor. Coppel requires each large truck to have 2 employees, 1 driver and 1 person assisting with delivering the physical goods. Small trucks have 1 employee, who is both the driver and the person who delivers the orders. Appendix A is the list of kilometers per liter per truck manufacturer model type. Table 2 lists the main differences in big and small trucks for the company's own-fleet. The information in Table 2 is derived from conversations with Coppel's experts and data received from Coppel.

**Table 2.**
*Coppel Own-fleet Truck Characteristics, Nationally*

| Truck Type | Labor | Volume | Working Hours | Fuel Type |
|---|---|---|---|---|
| Big | 2 Persons | 20 $M^3$ | 6 hours | Diesel |
| Small | 1 Person | 6 $M^3$ | 8 hours | Diesel |

An important item to note is the difference in working hours between the big and small trucks. Coppel uses their big trucks to complete store fulfillment, before completing their last mile delivery on working days. Also, because big trucks are dual purpose, the minimum quantity for big trucks in the fleet composition is set by the store fulfillment frequency in that region.

### 3.1.5 Third-party Carriers

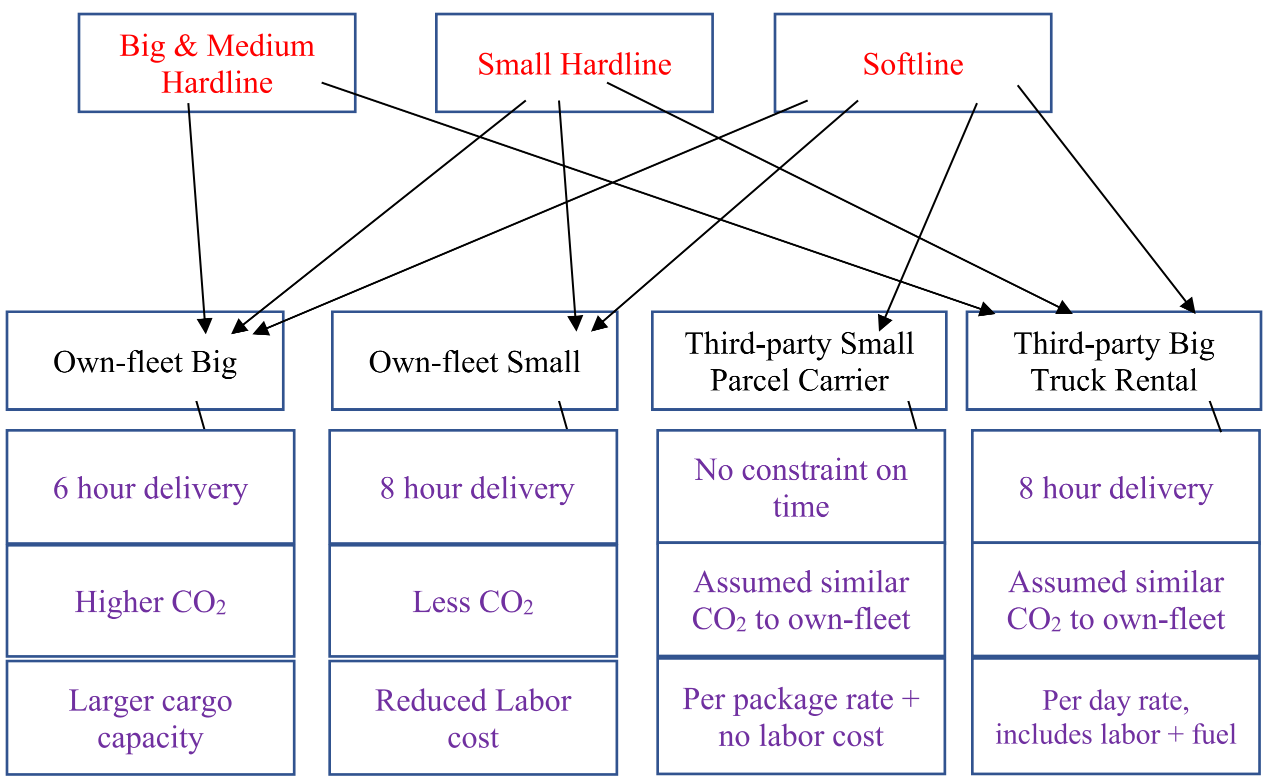
Coppel uses various third-party small parcel carriers and third-party full truck rentals to assist in their last mile deliveries. Third-party small parcel carriers deliver only softline products, and provide deliveries for Coppel all year. In the peak season, October through December, Coppel uses third-party full truck rentals to support the increase in demand. This is done so Coppel does not compromise their delivery speed. For third-party small-parcel carriers, Coppel pays a per package rate. The rate varies per package for each third-party carrier, and this rate is determined based on the package origin and destination, package volume, and weight. Because there is a variance to the per package rate, we have chosen to use the average per package rate per region for this project, as most softline products fall within the same pricing range. In terms of truck capacities and efficiency, third-party carriers use similar trucks to Coppel's own-fleet, because of this we assume the $CO_2$ emissions are the same for third-party carriers, as we do not have access to the third-party carrier truck catalog. We also assume that the full truck rentals have the same capacity constraints as a large Coppel truck. Table 3 contains the characteristics for the active third-party small parcel carriers for all regions, which we derived from conversations with the Coppel experts. The table only includes average delivery days for all third-party small parcel carriers in each region as cost is confidential information. However, it should be noted that actual third-party small parcel costs are used in the optimization model to calculate total costs for each region.

**Table 3.**
*Third-party Small Parcel Characteristics, all regions*

| Region | Avg Delivery Time (Days) |
|---|---|
| Monterrey | 3.13 |
| Culiácan | 2.26 |
| Tecamac | 2.67 |

As there are many varying characteristics of trucks, orders, and delivery methods, Figure 6 provides a visual representation and a breakdown of some of the characteristics of each delivery mode.

**Figure 6.**
*Last Mile Delivery Model Characteristics*



### 3.2 Data Collection & Cleansing

Coppel provided a wide range of data to facilitate this project. The data was from two sources. Most of the data is historical and is sourced from Coppel's software packages, like their ERP which provided the order demand information. The second source was a Coppel-owned consolidation model, which plans what orders to deliver when. The information gained from the consolidation model, delivery drive time per order type and the average kilometers driven per order type, is used as parameters for this project's model. The consolidation model was run for each region analyzed and provided the most accurate drive time and kilometers. The historical data types are constrained to own-fleet truck information, order information, and third-party information. Table 4 describes the different types of historical data we received from Coppel.

**Table 4.**
*Data Types Provided by Coppel*

| | |
|---|---|
| **Own-fleet Truck** | Current truck catalog |
| | Current maintenance costs per truck, per kilometer |
| | Store Fulfillment Frequency by big trucks |
| | Consolidation Model data - Delivery drive time and KM driven per order |
| | Current fuel consumption, including fuel type and average kilometers per liter |
| **Order Demand** | Third-party order fulfillment |
| | Order demand for own-fleet per region, including order size, type, and volume. The demand one week's worth of demand, per each quarter for a 2 year period, resulting in 8 periods of demand. |
| **Third-party** | Third-party rates, limited to origin and destination within the same region |
| | Third-party big truck rental rates, limited to origin and destination within the same region |

After receiving the historical data and consolidation model data from Coppel, it was cleaned and analyzed. We removed outliers and invalid data. We then linked the different data files where possible. Specifically for the consolidation model, this model was run three different times. After reviewing the results, an average was taken for the two parameters, delivery time per order and kilometers driven per order. In the next section, we explain our assumptions.

### 3.2.1 Assumptions

After reviewing and analyzing the data provided and the information given during our discussions with the experts, the assumptions we made to efficiently facilitate this project and formulate our mathematical problem are as follows:

- Third-party carrier trucks are like Coppel's own-fleet trucks, regarding fuel consumption.
- Delivery time for third-party carriers starts once the order is ready to be picked up.
- Third-party carriers are available every working day.
- Third-party carriers have an unknown order capacity, which are modeled as infinite.
- Third-party carriers use the same average kilometers driven per order as small hardline orders.
- The time set to physically deliver the orders from the truck (big or small) is an estimate and is not based on historical data, as Coppel does not keep record of this. The time was derived from conversations with the experts.
- Drive time between orders is based on the output from the consolidation model and is an average for both order types (big and small) together. The consolidation model was run for each region where this project's model is run.
- This model only uses truck options currently owned by Coppel.
- All own-fleet trucks are available for use each working day.
- Average kilometers per order is based on the results generated by the consolidation model.
- The average price per liter for gasoline and diesel is derived by taking an average from the fuel consumption file.
- Depreciation costs per truck are determined by the formulation that Coppel uses, which is the total investment cost divided by 6 years.
- Order demand is based on historical data provided by Coppel, for each region for a specific period.
- Additional labor is available as needed for overtime.

- All orders are available for delivery and are delivered at some point in time.

Now that we have explained the background of Coppel's last mile and scope, the next section explains our method for solving this problem.

**3.3 Mathematical Model**

To find the optimal solution in terms of cost, we build a combination knapsack & bin packing model, with aggregate planning.

**3.3.1 Mathematical Problem Formulation**

This section defines and describes the mathematical model, which is used as the base for our python model. This model incorporates aspects from a knapsack model and bin packing model. Each period is then connected with aggregate planning, to create an optimal solution for the entire 2 years, or 8 quarters. To start, we define all the notations for the mathematical problem, followed by the singular objective function. Lastly, we move through all the constraints and their definitions.

**3.3.2 Notation and Descriptions**

This section is a notational overview and their descriptions. The factors which are included for the mathematical model are listed in Table 5. Table 5 also includes the binary variables.

**Table 5.**

*Notation and Descriptions for model*

| Notation | Description | Notation | Description |
|---|---|---|---|
| $i$ | Index for $i \in I$ where T is all Trucks | $DT$ | Delivery Time per order type |
| $j$ | Index for $j \in J$ where O is all Orders | $SL$ | Cost to sell a truck |
| $e$ | Index for e $\in E$ where Q is all Quarters | $PT$ | Cost to purchase a new truck |
| $T$ | Trucks | $Q$ | Quarters |
| $O$ | Orders | OV | Volume Per order |

| | | | |
|---|---|---|---|
| $M$ | A large number | $IT$ | Initial Truck Count |
| $D$ | Total demand of all orders per Quarter | | **BINARY VARIABLES DESCRIPTION** |
| $C_{ij}$ | Cost of moving an order to the customer, ($/order), includes maintenance and fuel costs ($/per KM) | $HL$ | Equals 1 if the order is hardline and 0 otherwise |
| $W_i$ | Fixed cost of using truck (labor & depreciation for own-fleet or per day rate for the third-party full truck rentals) | $BT$ | Equals 1 if the truck is a big truck and 0 otherwise |
| $S_i$ | Volume Capacity per truck (volume/per order/per truck) | $LG$ | Equals 1 if the order is a big order and 0 otherwise |
| $B_i$ | Time Capacity per truck | $X_{ij}$ | equals 1 if order $j$ is allocated to Truck $i$ and 0 otherwise |
| $KM$ | Avg KM driven per order [derived from Coppel's Consolidation model] | $Y_i$ | equals 1 if truck i is chosen to operate and 0 otherwise per day |
| $L_i$ | Trucks bought in a period | | |
| $P_i$ | Trucks sold in a period | | |

### 3.3.3 Objective Functions

This model is a single objective model, built using a multiple knapsack, bin packing, and aggregate planning. The objective function is to minimize cost, while staying within the bounds of our defined constraints. Our objective function is modeled after Harris et al. (2014). The total costs in objective function 1 can be broken into 3 parts, variable, fixed, and acquisition costs.

The variable costs for own-fleet are defined in the model as all costs that are generated by the distance driven. Specifically, the variable costs are fuel and maintenance. For third-party carriers, the variable costs are correlated to the number of orders delivered by the carrier. The cost per order for each carrier is determined by using an average delivery cost for the region, for all third-party carriers. For own-fleet, regarding fuel, the model uses a historical estimated kilometers per liter, per truck type. Maintenance cost is calculated at a per kilometer rate, based on the total kilometers driven per each truck type.

For fixed costs there are two types. There are fixed costs for the own-fleet, which are defined as the depreciation costs of a truck and delivery labor costs. Depreciation costs are defined as the total investment divided by 6 years, and is modeled as an average per truck type, per region. Regarding labor, this fixed cost is dictated per truck type, as small trucks only need one employee while big trucks are required to have two employees. Labor costs are the same in each region. For third part fixed costs, this is defined as the per day rate to rent the entire third-party truck. Labor and fuel are included in this fixed rate.

The acquisition costs are the total costs to purchase or sell trucks which are needed to fulfill demand in each period. The cost to purchase a truck is the average estimated capital expenditure required by Coppel to purchase a new truck. The cost to sell a truck is a large number, as the model is designed to discourage selling of trucks as it is not necessarily feasible in real-time operations. The total cost for trucks sold and bought in each period is calculated by adding and subtracting trucks bought and sold in the current period from the total truck count in the previous period.

As described previously, objective (1) is the objective function which focuses on minimizing the total cost of the last mile:

$$\begin{aligned} Minimize \sum_{i \in T\ j \in O\ e \in Q} C_{ij} X_{ij} + \sum_{i \in T\ j \in O\ e \in Q} W_i * Y_i \\ + \sum_{i \in T\ e \in Q} (SL * P_i) + (PT * L_i) \end{aligned} \tag{1}$$

The next section provides an overview of the constraints.

### 3.3.4 Constraints

Like most real-world problems, there are constraints on our objective function. Our model has 9 constraints, including 2 binary constraints. Constraint (2) makes sure that all demand is fulfilled and is modeled after Harris et al (2014).

$$\sum_{i \in T} X_{ijt} \geq D_j, \qquad t \in D\ j \in O \tag{2}$$

There are two capacity constraints, and both are modeled after Harris et al (2014) and Assi and Haraty (2018). The first is constraint (3), which ensures that no truck exceeds its volume capacity.

$$\sum_{\in O} X_{ijt} * OV_j \leq S_i\, Y_i\,, \quad \forall i \in T \tag{3}$$

The second is constraint (4), ensures that no truck exceeds its time capacity. Since the truck's delivery time is the most restrictive constraint, we incorporated our service level (delivery speed) into this constraint. The total available truck delivery time is the number of delivery days set forth by Coppel.

$$\sum_{\in O} X_{ijt} * DT_j \leq B_i\, Y_i\,, \quad \forall i \in T \tag{4}$$

Two constraints restrict which types of trucks and carriers the orders can be loaded. The first is constraint (5), which requires that all big orders must be loaded onto big trucks. M is a random large number, which is used to enforce this constraint.

$$M * BT_i \geq X_{ijt}\, LG_j \quad i \in T j \in O \tag{5}$$

The second is constraint (6), which restricts all hardline orders to own-fleet trucks.

$$M * (1 - TP_i) \geq X_{ijt}\, HL_j \quad i \in T j \in O \mathrm{t} \in D \tag{6}$$

Constraint (7) ensures that all trucks purchased and sold in the current period are incorporated. This is the aggregate planning function of our model. (7)

$$\sum_{i \in T\ e \in Q} Y_{i(e)} = Y_{i(e-1)} + L_{i(e)} - P_{i(e)} \quad \forall i \in T$$

Lastly, there are two binary constraints, constraints (8), and (9). Constraint (8) equals 1 if an order (j) is allocated to a truck (i), in period (t), otherwise it is 0.

$$X_{ijt} \in \{0,1\}, \qquad i \in T,\ j \in O\ , t \in D \tag{8}$$

Constraint (9) equals 1 if truck (i) is chosen to operate, otherwise it is 0. This allows for the model to charge for the fixed costs for a truck, per day.

$$Y_{it} \in \{0,1\}, \qquad i \in T\ t \in D \tag{9}$$

Now that we have described in detail our mathematical model, the next section will discuss other model outputs and the overall construction of our model in Python.

### 3.3.5 Other Model Outputs

An important model output for Coppel is the estimate $CO_2$ emissions that are emitted by their last mile fleet operation. While this is not a constraint or objective function, it is an output of the model. The estimated $CO_2$ emissions are calculated based on the total fuel consumed. This is modeled after the United States EPA Greenhouse Gases Equivalencies Calculator (2021) formulation. The EPA's formulation is based on gallons, or the imperial system, while Coppel uses the metric unit, liters. For our adaptation, we convert liters to gallons, which 1 liter is equivalent to 0.264127 gallons. The EPA's calculator also states that 1 gallon of diesel is 10,180 grams of $CO_2$, while 1 gallon of gasoline is 8,887 grams of $CO_2$.

### 3.4 Model Construction and Parameters

Based on the formulations described in section 3.3, the optimization model was built using Python in Google Colab. The model determines the total number of own-fleet trucks needed (type and number), total number of third-party big trucks used, and the total number of orders delivered by third-party small parcel carriers, which minimizes the total overall cost over a two-year period. The model was run on the three regions discussed previously in section 3.1.3, which were Culiacán, Monterrey, and Tecamac. We ran the model for each region 6 times, as we changed the service level for each run and removed third-party big trucks as a truck option for three of the runs. The delivery speeds (service level) are 3-day delivery, 2-day delivery and 1-day delivery. We removed the third-party big trucks as a delivery option to provide Coppel an idea of the benefits and consequences of choosing to use third-party big trucks, instead of investing in their own-fleet. Although this model was built specifically for Coppel, it could be run on any last mile fleet operation that is trying to compare best options for total fleet composition. The model is designed in a simple format so that it is easy to use. In the next section we review the model parameters in depth, starting with the order parameters and concluding with the truck and third-party carrier parameters.

### 3.4.1 Order Parameters

To assign the demand to a truck type, we classified the orders based on the type and volume size of products. The order type classifications are softline, small hardline, medium hardline, and big hardline. Orders also have two main characteristics, the first of which is volume. While in real practice, orders within each category have a range of volumes, we have chosen an average volume, per order category. Each order type has a different order volume, with big hardline have the largest volume and softline orders being the smallest. The second order characteristic is the time it takes to deliver each type of order. This time was derived after discussions with Coppel's Transportation department. From our discussions, we were given the average number of orders delivered per day, per order type. We then calculated the total number of minutes in a day and divided this by the average number of orders delivered, per order type. In the next section we review the parameters that are specific to trucks and third-party carriers.

### 3.4.2 Truck & Third-Party Parameters

To calculate Coppel's fleet composition, we defined four categories of Truck Types. Two of the truck types are Coppel's own-fleet, Small and Big. The remaining two truck types are for third-party, which are Third-party Small Parcel and Third-Party Big Truck. Each of these categories has its own characteristics. The Small Trucks are specifically used for home delivery, and they require one driver per truck. These trucks can deliver small hardline and softline orders. The Big Trucks are designed to fulfill the stores and home delivery; these trucks are required to have 2 drivers per truck, and they can deliver any type of order. The Third-Party Small Parcel Trucks are exclusively used to deliver softline orders. For Third-party Small Parcel, Coppel uses a range of carriers, like DHL and small regional carriers. For Third-Party Big Trucks, Coppel uses a mix of national and regional carriers. For Coppel's own-fleet, there is one fixed cost. This fixed cost is the depreciation of the truck cost and the labor rate needed per truck type (1 employee for small trucks and 2 employees for big trucks) combined. We also included a truck purchasing cost, to account for the cost of acquiring a new truck. We used a weighted average based on the total Coppel fleet composition. This cost considers the total investment needed to acquire a new truck and adapt it to be fully operationally for Coppel, including permits. For a truck selling cost, as Coppel is not wanting to regularly sell trucks, we used a random big number to inflate the cost of selling a truck. This is to discourage the model from selling a truck.

Coppel trucks also have variable costs, which are calculated based on the kilometers driven. The kilometers driven per type of truck, is an output from Coppel's consolidation model, which Coppel's uses for order and route optimization. This parameter is an estimation of the kilometers driven for each order type in a specific region. We then used the kilometers driven to calculate the total fuel cost and maintenance cost. For fuel, the parameter is Fuel Cost per Kilometer driven is calculated based on the average kilometers per liter of fuel. Coppel tracks the fuel consumption of its fleet, so from the fuel consumption report, we derived the average kilometers per liter of fuel, per truck type. The kilometers per liter is specific to each region. The fuel cost per liter is the historic price per liter from Coppel. We then divided this cost per liter by the average kilometers per liter for each truck type, in each region. Maintenance cost is also impacted by the kilometers driven. Specifically, maintenance cost is related to the type of truck, and this model input was defined by Coppel's transportation department. The maintenance cost is an average of the total maintenance cost per kilometer driven, per truck type.

The last parameters are the third-party costs. For third-party small parcel, the cost is the average cost paid in a region to the different carriers for the delivery of softline orders. For the purpose of this project we are considering the average historical cost, and this cost is a per package rate. The cost for third-party big truck is also an average and it is a fixed cost. The cost is the total cost to rent the truck and is inclusive of all packages delivered by that vehicle.

Now that we have explained the scope, reviewed the available data, described the mathematical model, and reviewed the model construction and parameters, in the next chapter, we review our results, analysis and discussion.

## 4. Results, Analysis, and Discussion

In this chapter, we present the results, analysis, and industry impacts. This chapter begins with the results and analysis for each region. The results start with Culiacán, then Monterrery, followed by Tecamac, and finishes with all of the regions together. Our results were derived using the methodology described in detail throughout Chapter 3. We then conclude this chapter with the industry impacts of this research.

### 4.1 Culiacán Results

To examine our results for Culiacán, we review the total costs for all eight periods for each delivery speed, with and without the use of third-party full truck rentals. We also review the total fuel consumption and estimated $CO_2$ emissions, the utilization rate for Coppel's own-fleet, and review order allocation. This section concludes with a discussion of the Culiacán results.

Table 6 displays the total costs, total liters of fuel consumed, total estimated $CO_2$ emissions, and the cost per order delivered, for all versions of the model which were run, for all 8 periods. There were two versions of the model run for each of the three delivery speeds: one version allowed the use of third-party full truck rentals, indicated with TPBT in the delivery speed, and one version was run without the use of Third-Party full truck rentals. These two versions were selected to highlight the impact of using the third-party full truck rentals.

**Table 6.**

*Total Cost, Liters, $CO_2$ grams emitted, and cost per order results, Culiacán*

| Delivery Speed | Total Costs | Total Liters | Estimated $CO_2$ Emissions (grams) | Cost per order |
|---|---|---|---|---|
| 3 day delivery | $20,827,722.49 | 22,446.87 | 60,355,423.71 | $262.55 |
| 2 day delivery | $34,017,205.71 | 20,565.45 | 55,296,658.84 | $428.81 |
| 1 day delivery | $43,958,256.39 | 20,615.50 | 55,431,233.71 | $554.12 |
| 3 day TPBT delivery | $11,366,443.76 | 22,559.12 | 60,657,264.25 | $143.28 |
| 2 day TPBT delivery | $13,445,235.76 | 20,697.64 | 55,652,085.63 | $169.48 |
| 1 day TPBT delivery | $15,132,922.82 | 20,777.17 | 55,865,931.36 | $190.76 |

Figure 7 displays the cost versus $CO_2$ emissions for each of the delivery options for Culiacán. This figure allows Coppel to see the trade-offs between cost and $CO_2$ when choosing how to build their fleet.

**Figure 7.**
*Cost vs $CO_2$, Culiacán*

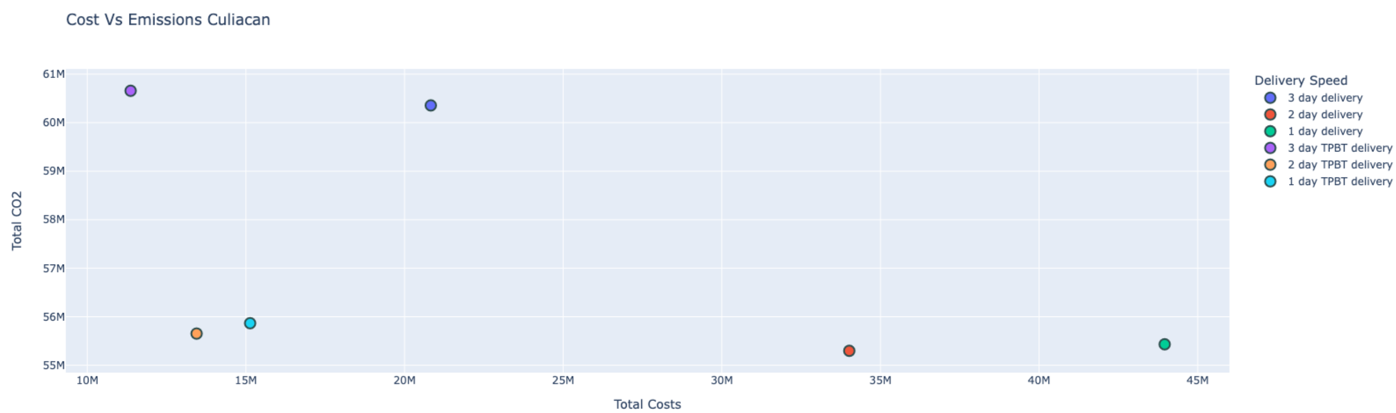



Figure 8 displays the average time utilization rate for the model run without the usage of third-party big trucks, across all periods, for the two types of trucks and different delivery speeds. The time utilization rate was calculated by taking the total delivery time available per truck type, based on the total number of trucks available and calculating the total available delivery time consumed per each order type. Figure 8 displays the average time utilization rate for all versions of the model.

**Figure 8.**

*Average Time utilization rate for Culiacán, per delivery speed, per truck type*

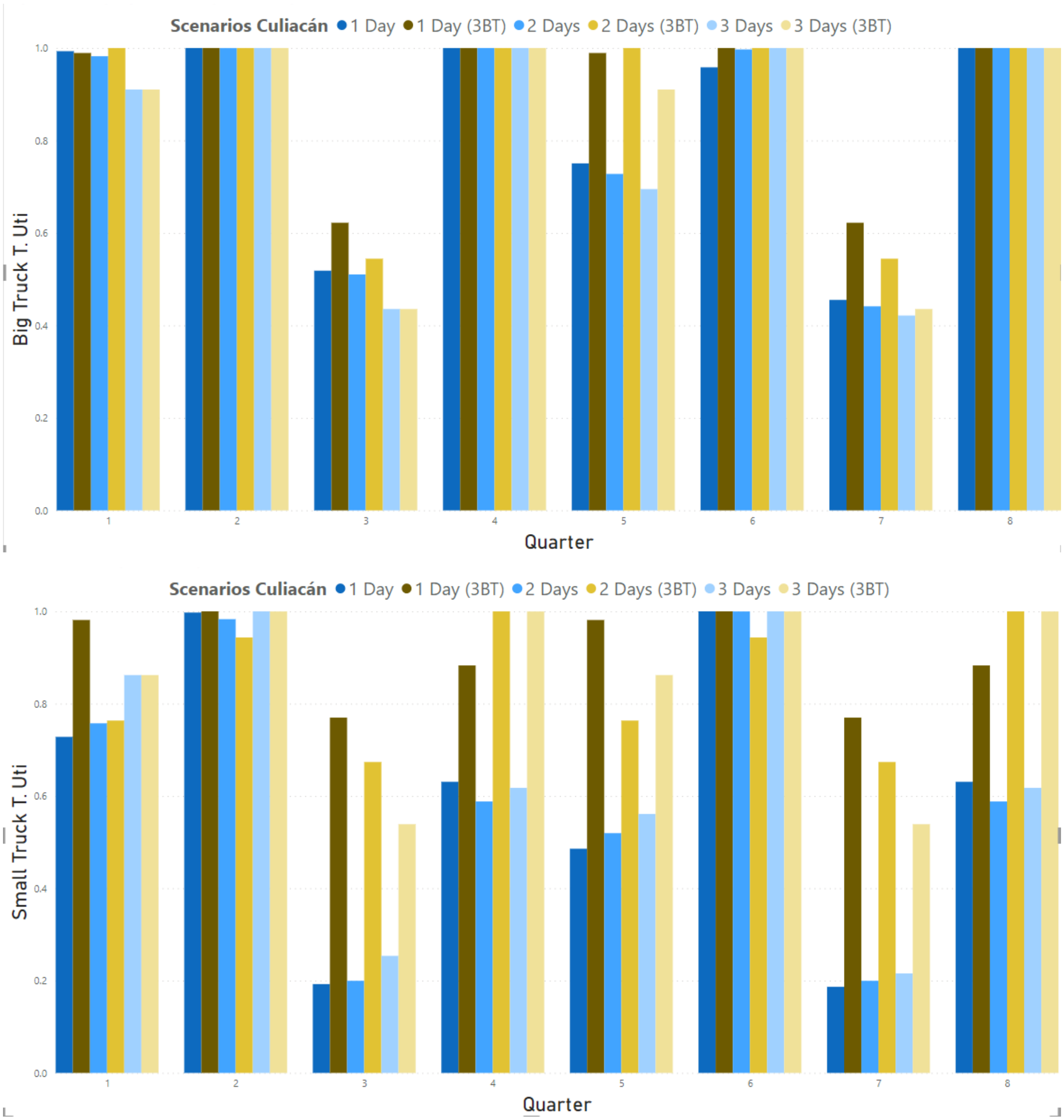



Figure 9 displays the order allocation per order type. This figure depicts what happens as the delivery speed requirement quickens.

**Figure 9.**

*Order Allocation trend, Culiacán*

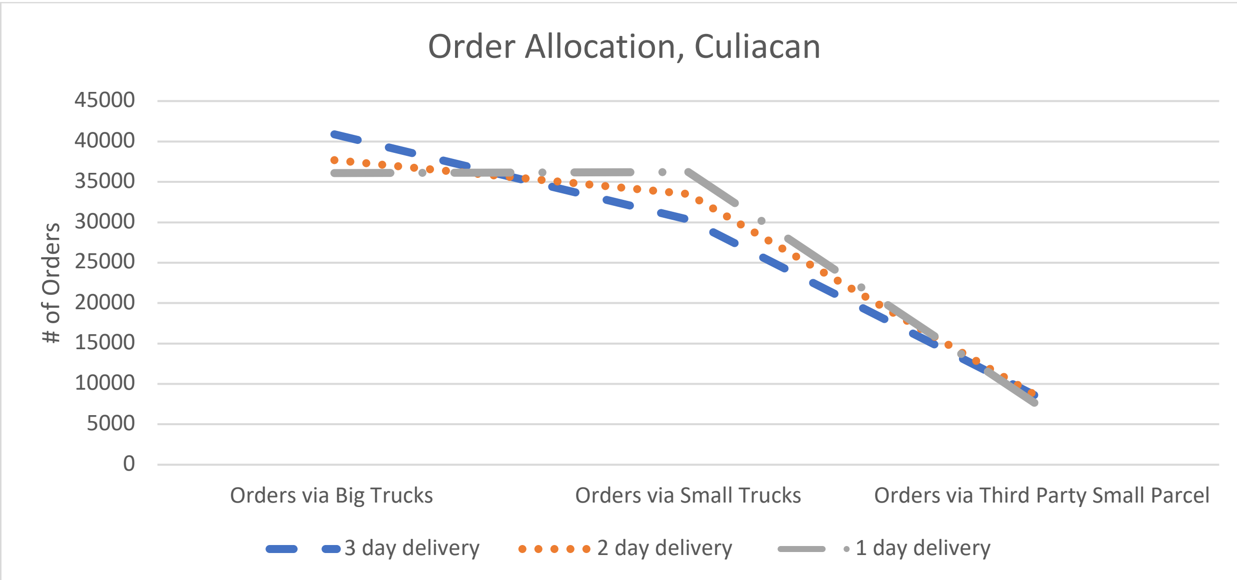



Figure 10 displays the tradeoff that occurs with order allocation, as the delivery speed requirement quickens.

**Figure 10.**

*Order Allocation trend, Culiacán, with Third-Party Big Trucks*

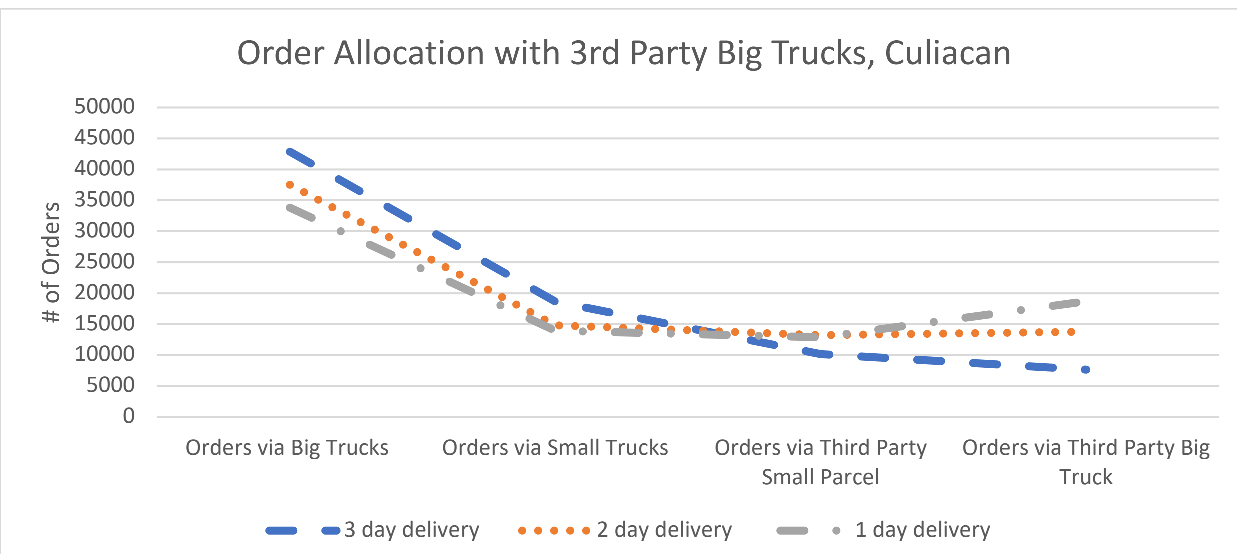



Figure 11 displays the comparison of each delivery speed, per quarter, for total number of the Coppel owned Big Trucks used. This figure was chosen to display the high variability between the delivery speeds without the use of third-party big truck rentals, and the models lack of change once third-party big trucks are introduced.

**Figure 11.**

*Coppel Big Trucks used per quarter for Culiacán*

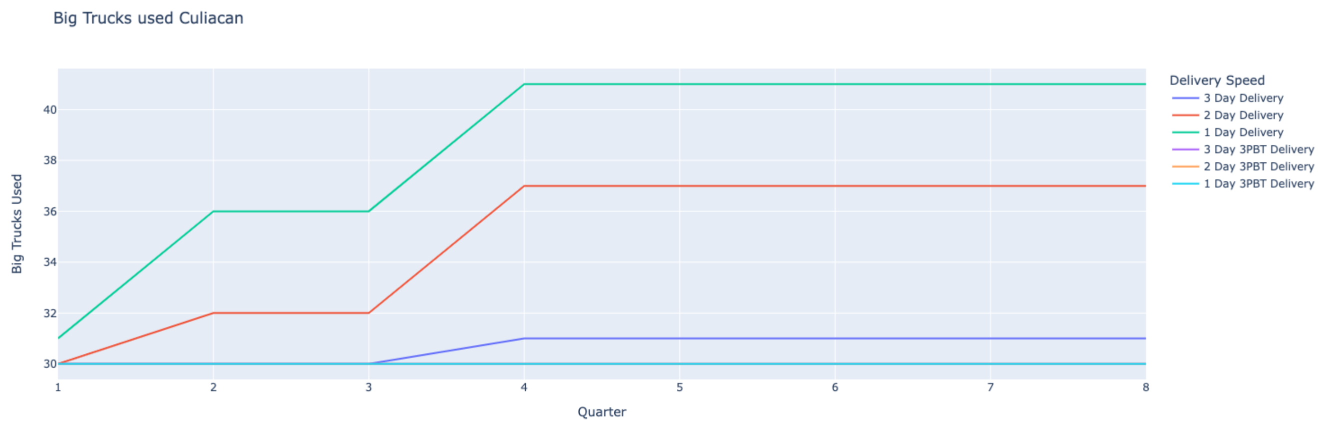
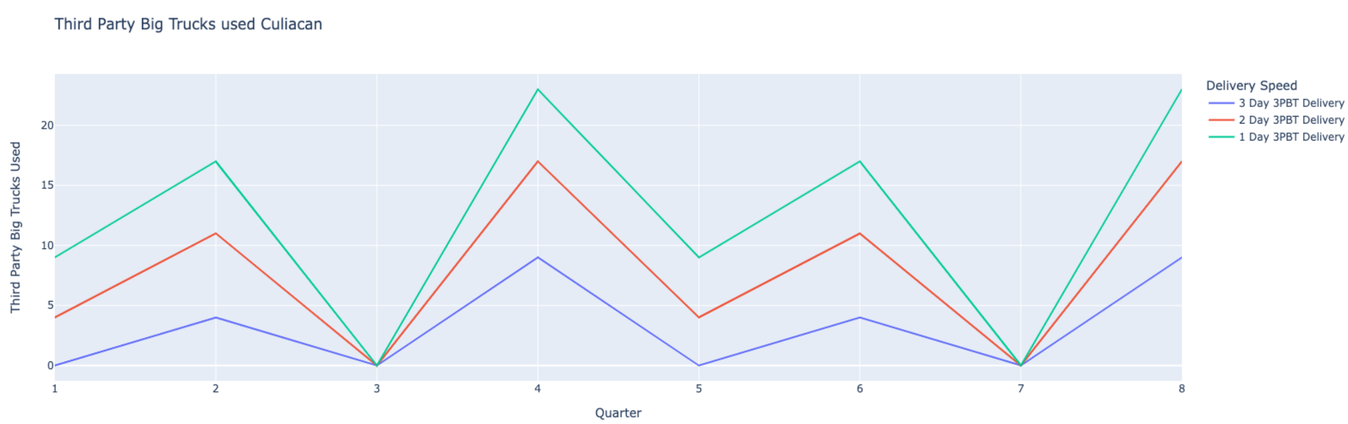



Figure 12 displays the comparison of each delivery speed, per quarter, for total number of the Third-Party Big Trucks used. This figure was chosen to display the high variability between the delivery speeds and demand for truck capacity per each quarter.

**Figure 12.**

*Third-Party Big Trucks used per quarter for Culiacán*



### 4.1.1 Culiacán Results Analysis

For Culiacán, the results were mainly what was expected for the model version where third-party big trucks are not allowed. This model behaved as expected by purchasing more own-fleet trucks as the delivery speed quickened. The purchasing of own-fleet trucks was expected because the time capacity constraints tightened, forcing the model to purchase more trucks to deliver the same quantity of demand in a shorter time frame. The model also chooses to allocate more orders to own-fleet small trucks, instead of the larger trucks. As the delivery speed increases, the model reserves the use of the own-fleet large trucks for orders that are constrained to only that delivery method. The allocation pattern of orders is indicated in Figure 9, whereas as the delivery speed increases, the orders allocated to small trucks also rises. The region of Culiacán has the highest percent of softline orders, 24% of all the three regions, so it is expected for the model to push as many softline orders to small own-fleet trucks and third-party small parcel carriers. However, when we reviewed the results where we allowed the usage of third-party big trucks, what was unexpected, but logical, is that the model maintains the current quantity of own-fleet trucks and uses the third-party big trucks to support the increases in demand during various quarters. This is visible in Figure 12, where there is high variability in the utilization of third-party big trucks. The high variability of the usage of third-party big trucks is because the model has the flexibility to use these third-party big trucks as needed and does not have to keep them once they are utilized, like the own-fleet trucks. In terms of time utilization rate of own-fleet trucks, Culiacán sees a higher time utilization rate for own-fleet trucks when third-party big trucks are rented, during the time periods where demand is lowest. The higher time utilization is because the model chooses to rent the third-party big trucks instead of purchasing more own-fleet vehicles, when the demand peaks. The higher utilization rate, however, does not correlate to lower costs. When directly comparing the same delivery time scenarios between the two models, these results indicate that for Coppel it is the most cost effective to utilize third-party big trucks as needed all year round, for the Culiacán region. The Culiacán region also continues to see the highest percent difference in cost savings of all the three regions, as the service level tightens. Currently Coppel is only utilizing the third-party full truck rental during the last quarter of the year. By allowing third-party full truck rentals to be used to supplement their own-fleet for the full year, Coppel can deliver faster, at a lower cost with similar $CO_2$ emissions. This analysis can be confirmed by referencing Table 6 and Figure 7. Appendix B contains the trucks utilized per quarter for both models, the volume utilization rate, and other results figures and tables for Culiacán.

### 4.2 Monterrey Results

Just like Culiacán, to examine our results for Monterrey, we review the total costs for all eight periods for each delivery speed, with and without the use of third-party full truck rentals. We also review the total fuel consumption and estimated $CO_2$ emissions, the utilization rate for Coppel's own-fleet, and review order allocation. This section concludes with a discussion of the Monterrey results.

Table 7 displays the high-level results for each model version and delivery speed. The table contains the total costs, liters, estimated $CO_2$ emissions, and the cost per order.

**Table 7.**

*Total Cost, Liters, $CO_2$ grams emitted, and cost per order results for Monterrey*

| Delivery Speed | Total Costs | Total Liters | Estimated $CO_2$ Emissions (grams) | Cost per order |
|---|---|---|---|---|
| 3 day delivery | $71,588,554.99 | 22,446.87 | 60,355,423.71 | $625.25 |
| 2 day delivery | $99,978,351.28 | 20,565.45 | 55,296,658.84 | $873.20 |
| 1 day delivery | $120,021,574.92 | 20,615.50 | 55,431,233.71 | $1,048.26 |
| 3 day TPBT delivery | $21,518,296.90 | 22,559.12 | 60,657,264.25 | $187.94 |
| 2 day TPBT delivery | $26,323,080.81 | 20,697.64 | 55,652,085.63 | $229.90 |
| 1 day TPBT delivery | $29,501,326.86 | 20,777.17 | 55,865,931.36 | $257.66 |

Figure 13 displays the trade-offs between cost and $CO_2$ emissions for the Monterrey region.

**Figure 13.**
*Cost vs $CO_2$, Monterrey*

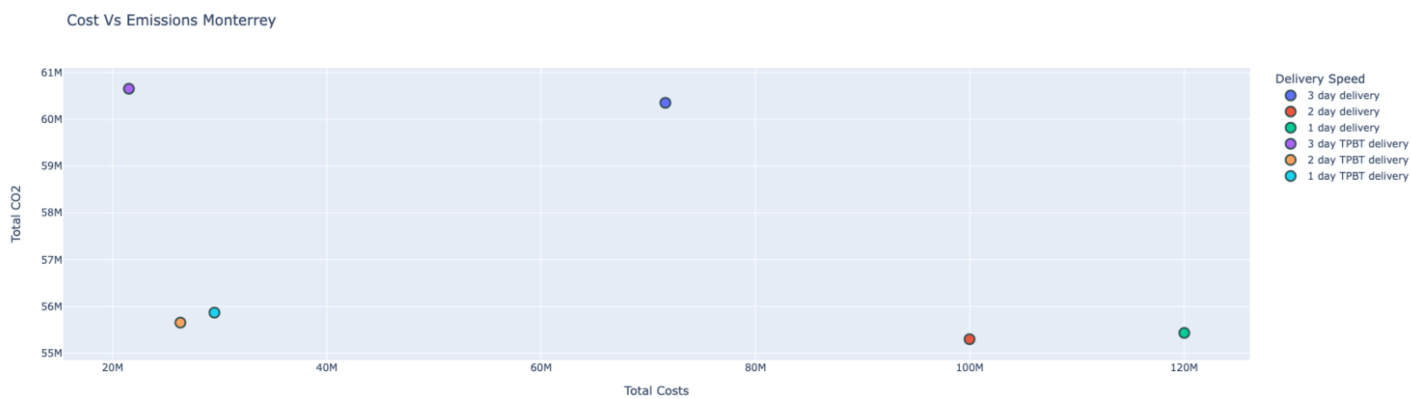
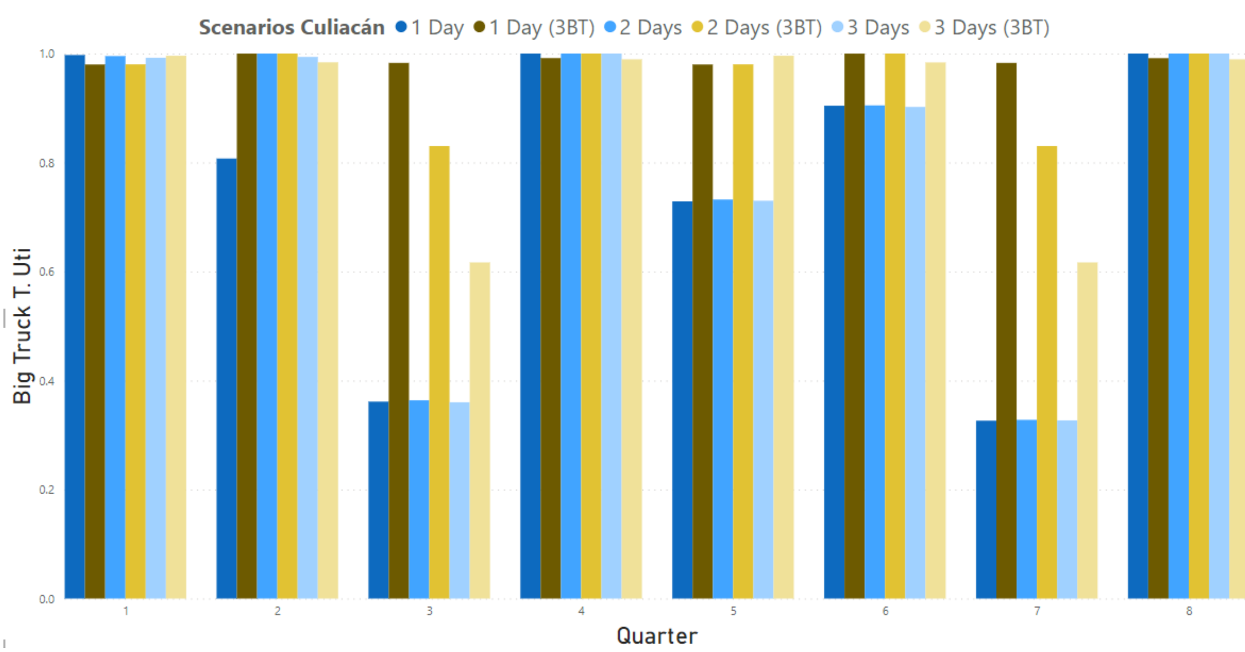



Figure 14 displays the average time utilization rate for the model run without the usage of third-party big trucks, across all periods, for the two types of trucks and different delivery speeds. This was calculated by taking the total delivery time available per truck type, based on the total number of trucks available and calculating the total available delivery time consumed per each order type. Figure 14 displays the average time utilization rate for all versions of the model.

**Figure 14.**
*Average Time utilization rate for Monterrey, per delivery speed, per truck type*



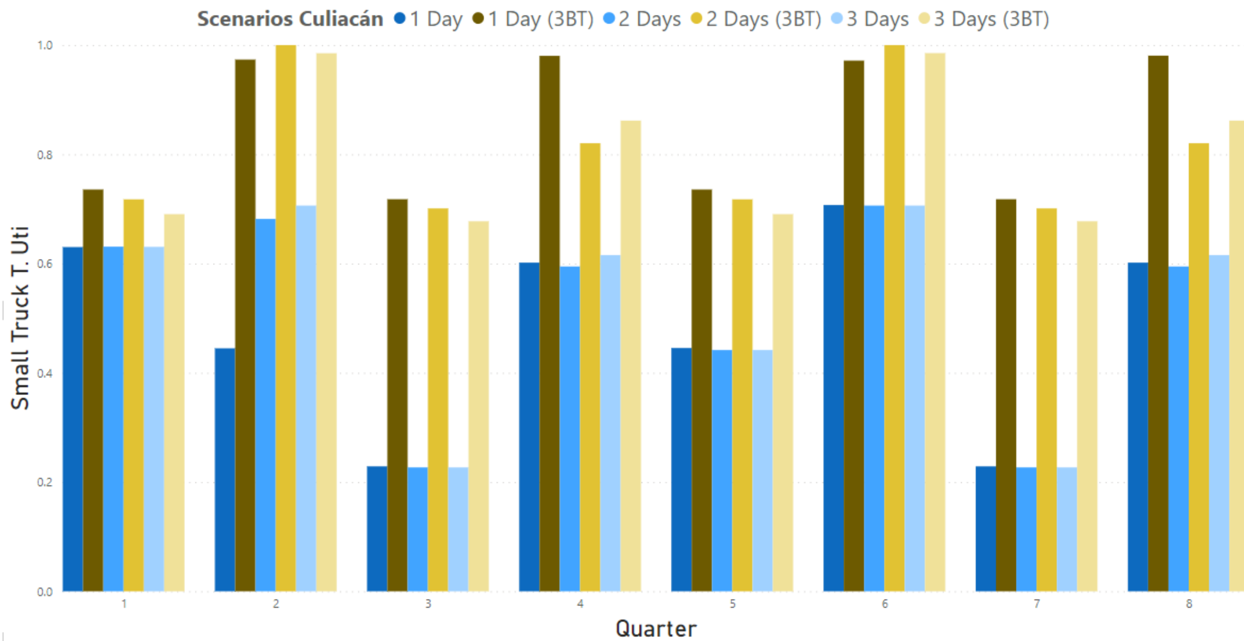



Figure 15 displays the lack of variability between increasing the delivery speed and order allocation. This figure is representative of the same information displayed in Appendix C.

**Figure 15.**
*Order allocation, Monterrey*

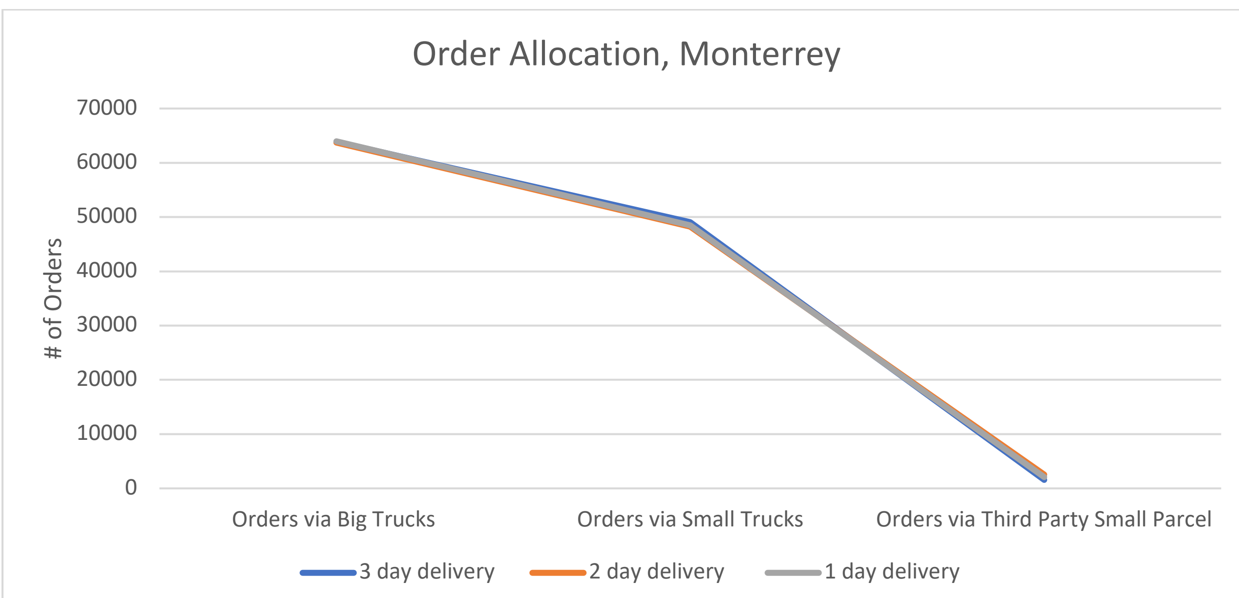



Figure 16 displays the impact on order allocation when third-party big trucks are allowed to be utilized.

**Figure 16.**

*Order allocation with Third-Party Big Trucks, Monterrey*

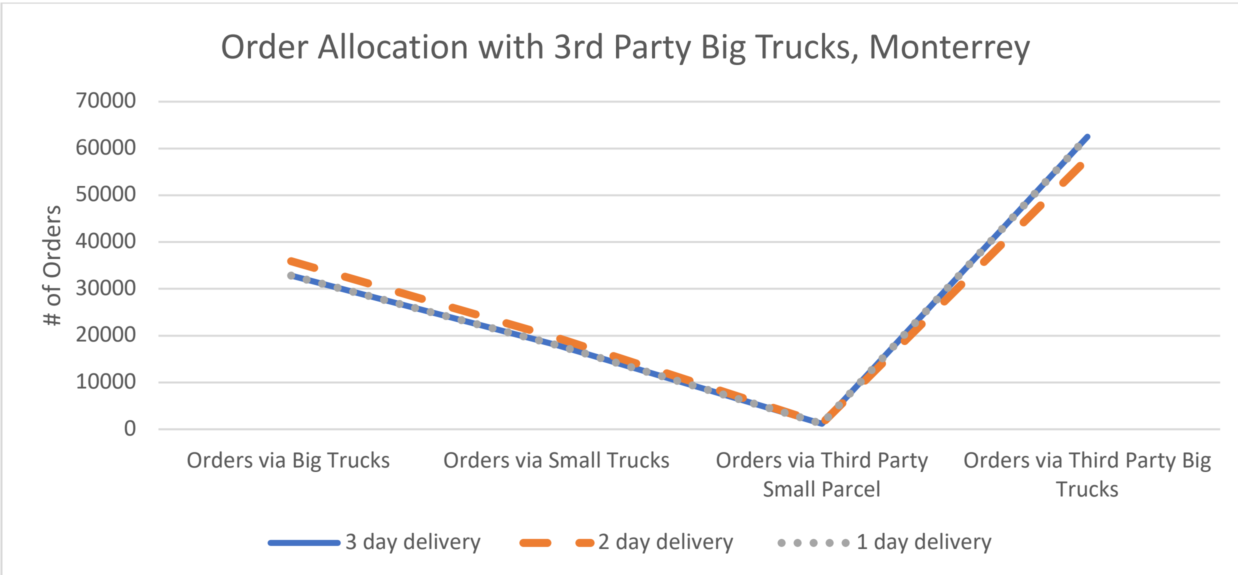



Figure 17 displays the number of big own-fleet trucks used for both versions of the model. This figure also displays how the model choose to maintain the big own-fleet trucks, once third-party big trucks are introduced.

**Figure 17.**

*Own-fleet Big Trucks Utilized, Monterrey*

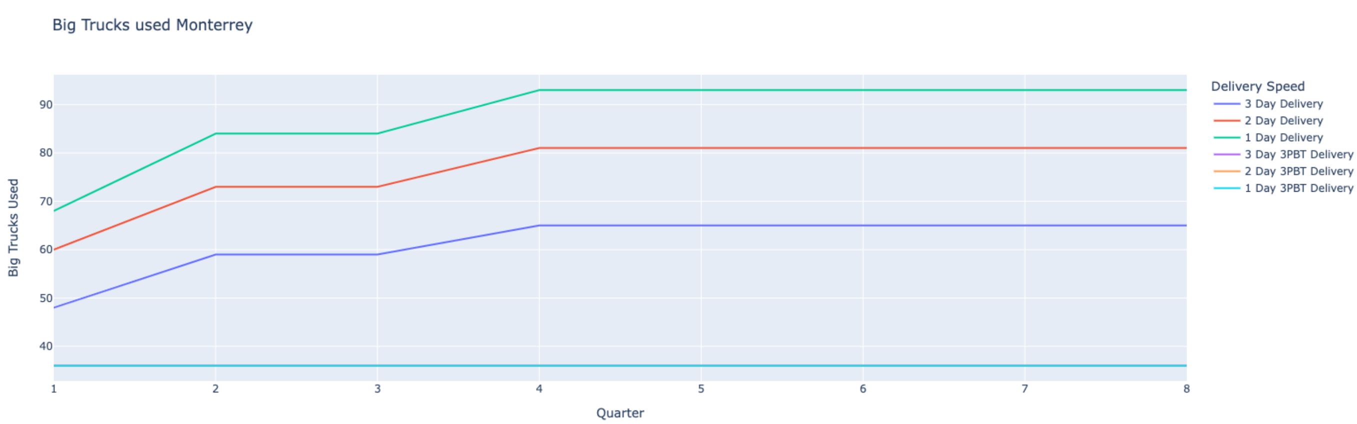
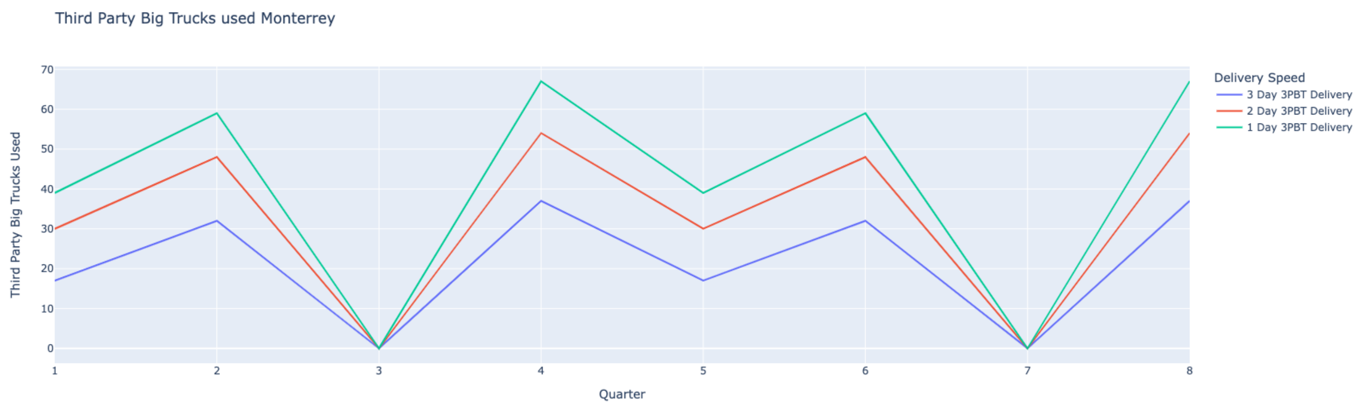



Figure 18 displays the variability of the number of third-party big trucks used. This figure shows the flexibility that the introduction of these trucks brings to Coppel's delivery options.

**Figure 18.**
*Third-Party Big Trucks Utilized, Monterrey*




### 4.2.1 Monterrey Results Analysis

The Monterrey region sees similar results as the Culiacán region. The model without the use of third-party big trucks immediately doubles the own-fleet truck count, as it is cheaper than allocating a high number of orders to the third-party small parcel carriers. However, as the delivery speed rises, the order allocation does not shift, as the results for Culiacán did. The model maintains its order allocation, as seen in Figure 15. This is because Monterrey's order demand favors hardline orders, with over 50% of the orders medium and large hardline. Because Monterrey has a greater number of hardline orders, the model is more restricted with its allocation and truck options, as the large and medium hardline orders only have one delivery vehicle option. In terms of buying more own-fleet trucks, the model for Monterrey purchases big trucks at almost the same rate for each delivery speed scenario. This purchasing rate can be seen in Figure 17. This figure also shows that the model chooses to only maintain the own-fleet trucks as soon as third-party big trucks are allowed to be used; the model does not purchase any own-fleet trucks because it is more cost effective to utilize the third-party big truck rentals. For the own-fleet time utilization rate, we see that there is a larger difference between the own-fleet truck utilization when using third-party big truck rentals, than for other regions. The utilization rate is visible in Figure 14 and is because, as previously stated, Monterrey has a higher demand of large and medium own-fleet orders. We also see that Monterrey's small Coppel trucks are under-utilized at a higher rate than the large Coppel trucks; this can also be tied back to the percent of order breakdown. When comparing cost and $CO_2$, as seen in Figure 13, Coppel can reduce their $CO_2$ emissions and lower their costs, by utilizing the third-party big trucks, with a 2 day delivery speed. The lower costs is possible because the third-party big trucks have a higher time capacity than the own-fleet big trucks, as the own-fleet big trucks must reserve some of their time capacity to delivery to Coppel's stores. Like Culiacán, in Monterrey it is more cost efficient to utilize third-party big trucks than for Coppel to increase their number of own-fleet trucks. However, unlike Culiacán, Monterrey does not see as much of a cost savings when moving from the 2-day delivery time frame to a 1-day delivery time frame, when comparing the models. Appendix C contains the trucks utilized per quarter for both models, the volume utilization rate, and other result figures and tables for Monterrey.

**4.3 Tecamac Results**

To examine our results for Tecamac, we review the total costs for all eight periods for each delivery speed, with and without the use of third-party full truck rentals. We also review the total fuel consumption and estimated $CO_2$ emissions, the utilization rate for Coppel's own-fleet, and review order allocation. This section concludes with a discussion of the Tecamac results.

Table 8 displays the high-level results for Tecamac. This table contains total costs, liters, estimated $CO_2$ emissions, and the cost per order.

**Table 8.**

*Total Cost, Liters, $CO_2$ grams emitted, and cost per order results for Tecamac*

| Delivery Speed | Total Costs | Total Liters | Estimated $CO_2$ Emissions (grams) | Cost per order |
|---|---|---|---|---|
| 3 day delivery | $65,442,760.07 | 22,446.87 | 60,355,423.71 | $784.76 |
| 2 day delivery | $88,422,189.15 | 20,565.45 | 55,296,658.84 | $1,060.32 |
| 1 day delivery | $104,631,177.71 | 20,615.50 | 55,431,233.71 | $1,254.69 |
| 3 day TPBT delivery | $15,805,041.55 | 22,559.12 | 60,657,264.25 | $189.53 |
| 2 day TPBT delivery | $18,963,043.98 | 20,697.64 | 55,652,085.63 | $227.40 |
| 1 day TPBT delivery | $21,311,959.20 | 20,777.17 | 55,865,931.36 | $255.56 |

Figure 19 displays the trade-offs between the different delivery speeds for Coppel, in terms of Cost and $CO_2$ emissions.

**Figure 19.**

*Cost vs $CO_2$ emissions, Tecamac*

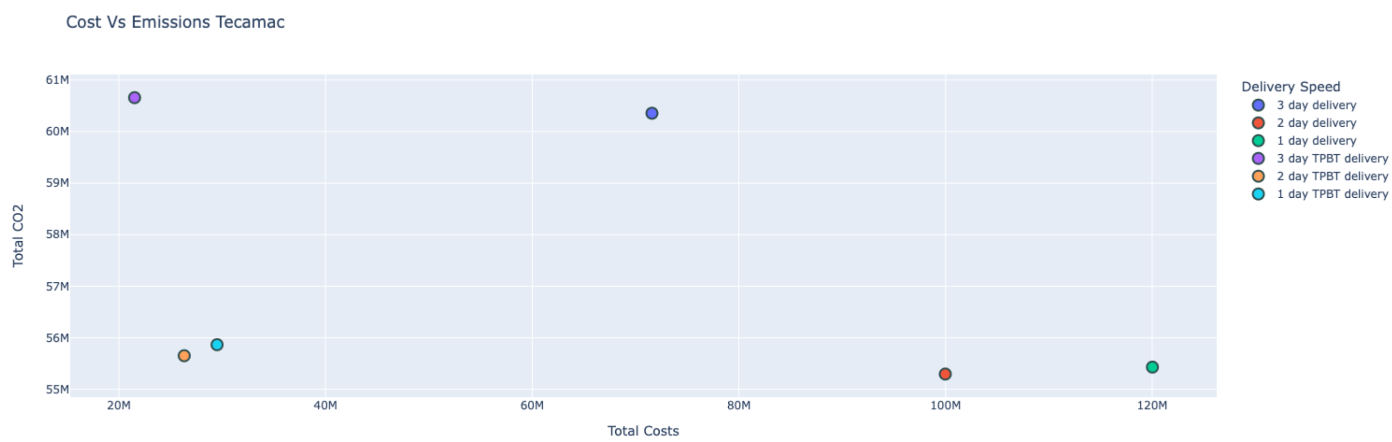



Figure 20 displays the average time utilization rate for the model run without the usage of third-party big trucks, across all periods, for the two types of trucks and different delivery speeds. The time utilization was calculated by taking the total delivery time available per truck type, based on the total number of trucks available and calculating the total available delivery time consumed per each order type. Figure 20 displays the average time utilization rate for all versions of the model.

**Figure 20.**

*Average Time utilization rate for Tecamac, per delivery speed, per truck type*

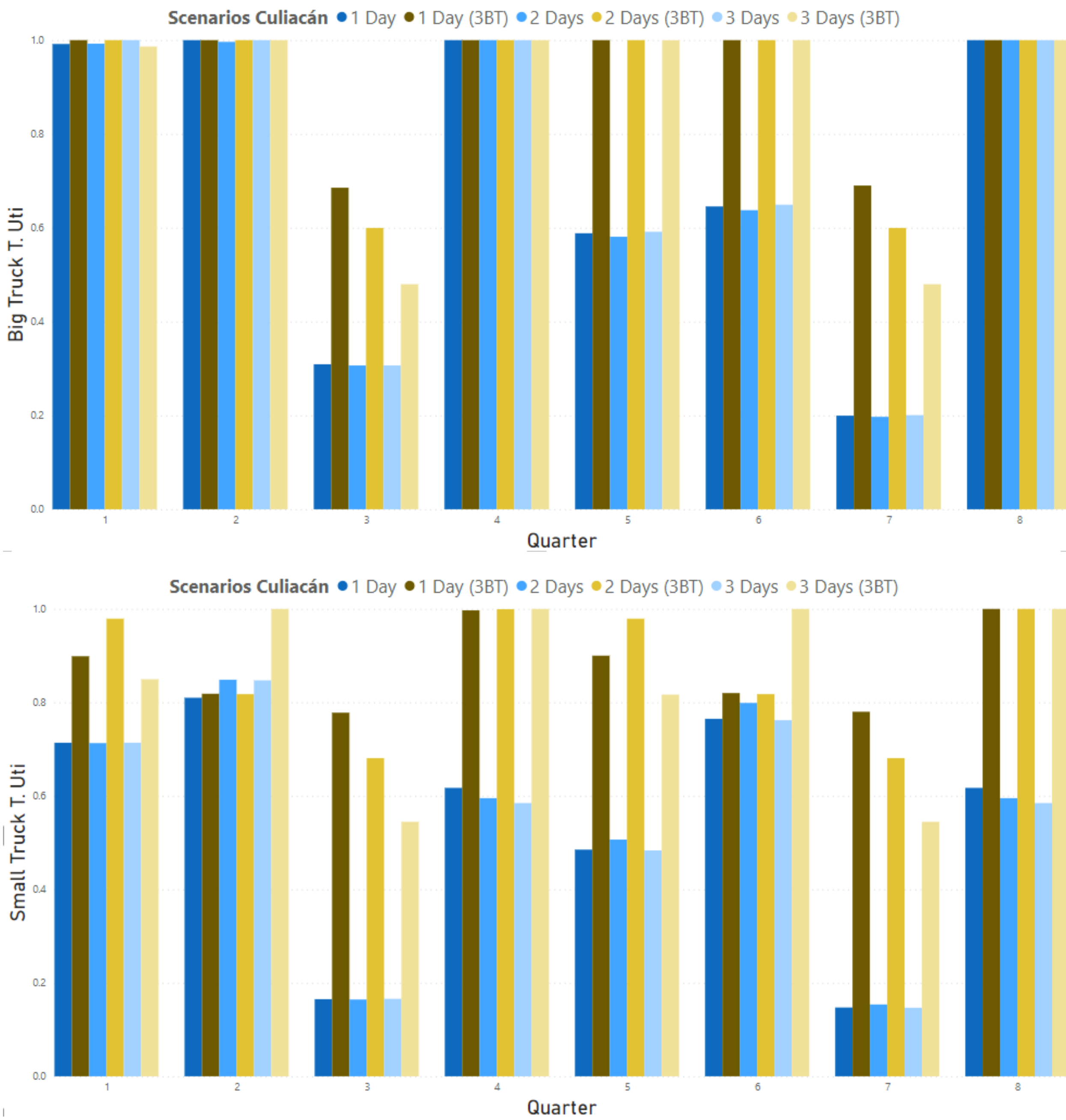



Figure 21 displays the order allocation for delivery type, for the model version without third-party big trucks.

**Figure 21.**
*Order allocation, Tecamac*

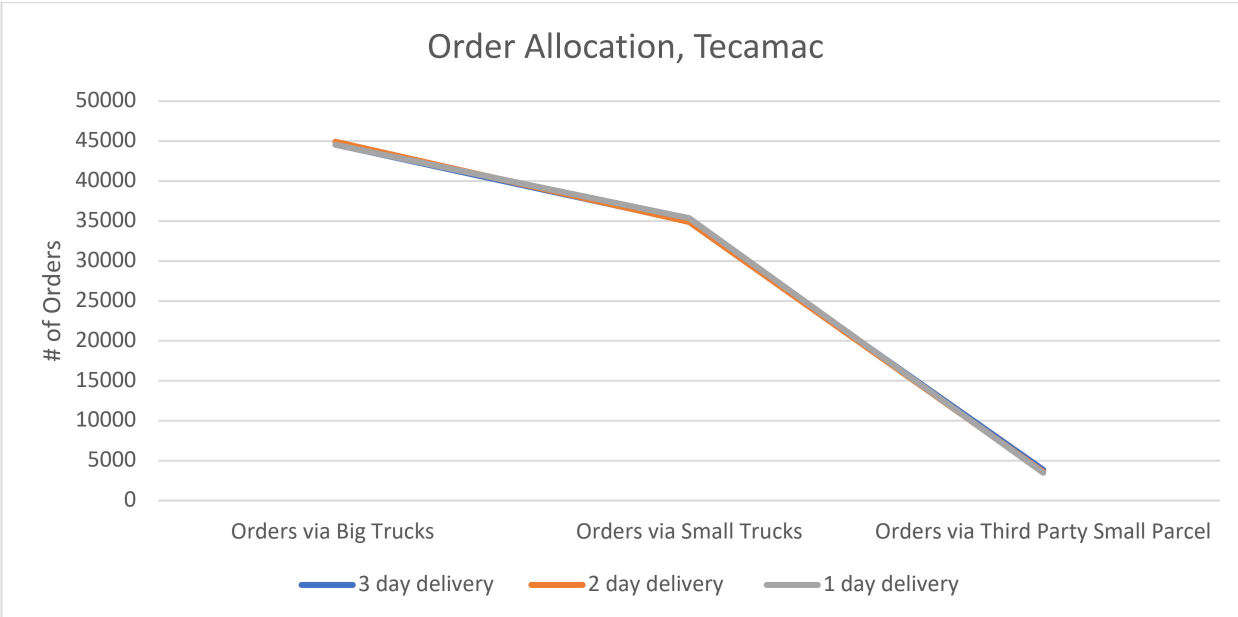



Figure 22 displays the order allocation, per delivery type, for the model with third-party big trucks.

**Figure 22.**
*Order allocation with third-party big trucks, Tecamac*

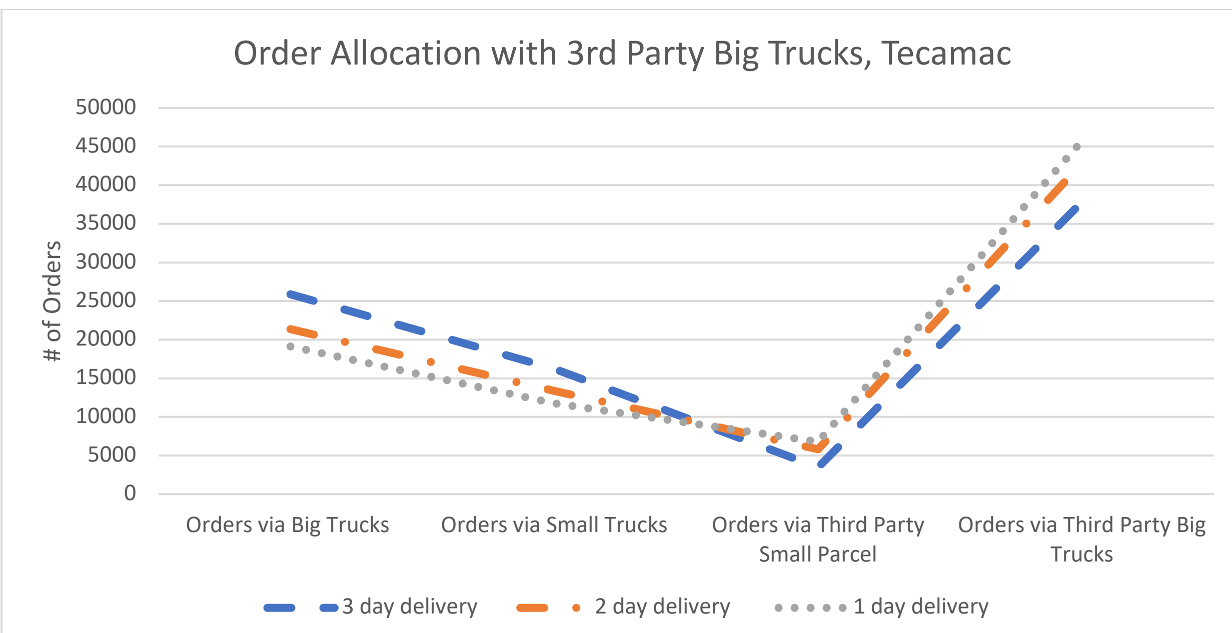


Figure 23 displays the number big own-fleet trucks purchased for both model types and delivery speeds.

**Figure 23.**

*Own-Fleet Big Trucks Utilized, Tecamac*

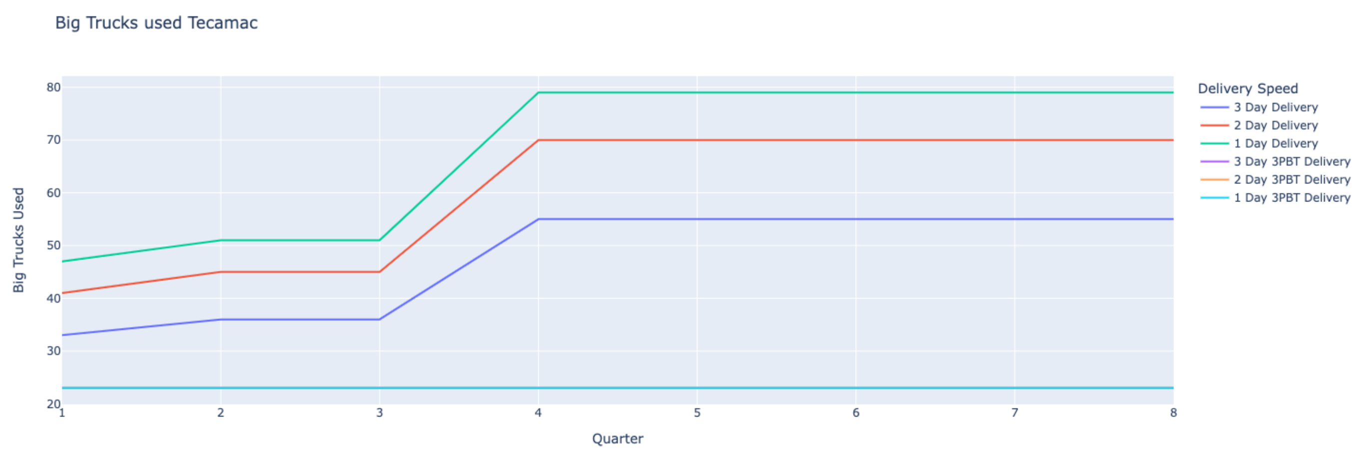
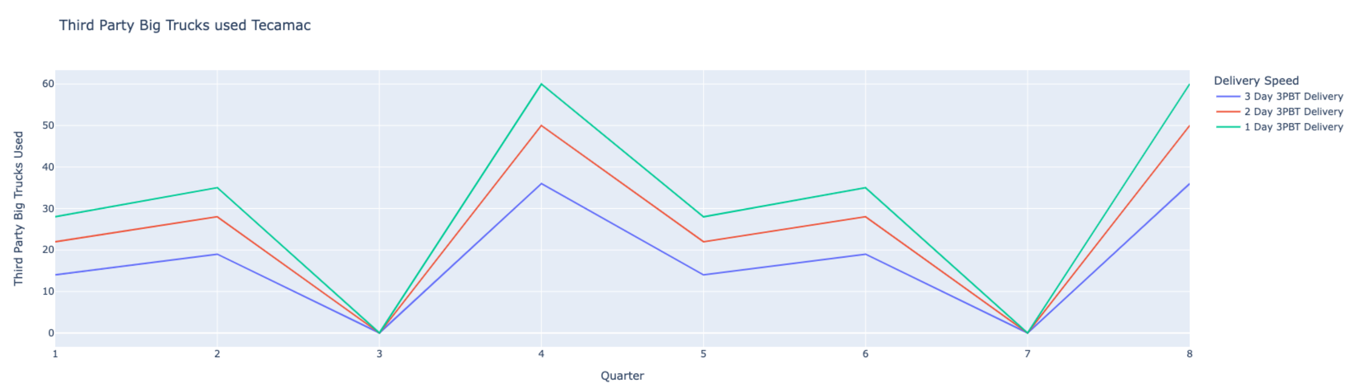



Figure 24 displays the number of third-party big trucks utilized for the Tecamac region. This figure shows the flexibility that the introduction of these trucks brings to Coppel's delivery options.

**Figure 24.**

*Third-Party Big Trucks Utilized, Tecamac*




### 4.3.1 Tecamac Results Analysis

Tecamac is like Culiacán and Monterrey in terms of its results. For the Tecamac region, the main difference is in order allocation, once third-party big trucks are introduced. The introduction of third-party big trucks provides the model relief, as more than 50% of Tecamac's orders are constrained to only big truck deliveries because they are big and medium hardline orders. As the delivery speed rises, the model chooses to push more than half of the total orders to the third-party full trucks, instead of purchasing new own-fleet trucks. The high allocation of orders to the third-party full trucks is because these third-party trucks are cheaper overall and have the option to be used only as needed. For the model version where third-party trucks are not an option, small own-fleet trucks are initially purchased at a higher rate than big trucks. Smaller trucks are purchased at a higher rate because Tecamac starts with the lowest quantity of small own-fleet trucks. However, as the delivery speed rises and the demand grows over the course of the time periods, the model chooses to favor the purchasing of big own-fleet trucks. Big trucks are favored because the big own-fleet trucks can deliver all order types. The utilization rate for own-fleet trucks in Tecamac is the lowest of the three regions, when not considering third-party big trucks. This low utilization rate is because Tecamac has the highest variance in total demand between time periods, for all regions. Once the usage of third-party big trucks is allowed, the own-fleet truck utilization rate for time starts to match the other two regions. The time utilization rate is visible in Figure 20. The utilization rate of own-fleet trucks is better for the model version with third-party full trucks are used, because the model is not forced to buy own-fleet trucks solely for the peak periods, and instead can choose to rent the third-party big trucks as needed. Like the other regions, it is significantly financially beneficial for Coppel to use the third-party big truck rentals all year round. Appendix D contains the trucks utilized per quarter for both models, the volume utilization rate, and other result figures and tables for Tecamac.

### 4.4 All Regions Analysis

Comparing all three regions and assessing the results together very clearly reveals a common theme. It is financially beneficial in all three regions for Coppel to start utilizing the third-party big trucks all year round. While each region has a different split of demand for each of the order types, each region greatly benefits from the usage of third-party big trucks. Each region benefits because these trucks do not have any allocation restrictions, like the third-party small parcel or own-fleet small trucks. By adding in a second delivery option, which has no allocation restrictions, Coppel brings more flexibility and resilience to their last mile delivery, while reducing their costs. When Coppel does not utilize the third-party big truck rentals all year round, the model is forced to purchase trucks, even when the trucks may not be fully utilized in the following quarter. This means Coppel will have time periods throughout the year where a large portion of their own-fleet capacity is underutilized. Since this model is a strategic tool, it can be assumed that in practice, Coppel would potentially not purchase these underutilized own-fleet trucks and instead choose to compromise their delivery speed instead.

Another insight we derived from running the two versions of the model is that Coppel would benefit substantially from relaxing or removing the strict order allocation constraints. At present, Coppel requires all hardline order to be delivered with their own-fleet. It is only during their high season that Coppel utilizes another delivery option for these order types. By including a new unrestricted delivery option, Coppel would see significant cost savings in every region. We suggest relaxing the order allocation constraints in Coppel's order management system to only restrict assembly required items to be delivered by own-fleet.

As we reviewed our results for all the three regions, we also noticed that the utilization of third-party small parcel carriers drastically differs from Coppel's current practice. As stated in Chapter 3, Coppel currently allocates 93.5% of softline orders to third-party small parcel carriers. The highest rate of allocation that the model reaches for third-party small parcel, is 69% of the total softline orders for the Culiacán region, with 2-day delivery with third-party big trucks allowed. The lowest allocation for third-party small parcel is 15% for the Monterrey region. The low allocation rate for third-party small parcel is because the Monterrey region has a large portion of big and medium hardline items, so the model is using the softline orders to better utilize the bigger trucks rented or purchased to accommodate the necessary hardline deliveries. After analyzing these results, we recommend that Coppel adjust their allocation rates for third-party small parcel carriers, and adjust this allocation per each region. The current allocation rate of 93.5% is not financially advantageous for them.

Now that we have reviewed the results for each region and analyzed them, in the next section, we review the industry impacts of this research.

### 4.5 Industry Impacts

This optimization model provides companies a strategic planning tool for assessing their fleet options, while incorporating various product types and constraints. While this tool was built for last mile delivery, it could be used to assess fleet options for store delivery or distribution center delivery with a few changes. With the ability to be expanded and built upon easily, this tool will allow companies to build resilience into their last mile fleet while minimizing costs, as the user can incorporate multiple delivery options. It also provides the ability to directly compare fleet choices, like different styles of trucks and third-party carriers.

## 5. Conclusion

After a surge in demand due to the COVID-19 pandemic, Coppel was seeking a financially optimal last mile delivery fleet, in terms of truck type and quantity, through the creation of strategic fleet planning tool. This capstone answered two main questions:

- What does the most financially advantageous last mile delivery fleet look like, in terms of number and types of trucks?
- What is the best order allocation for this newfound last mile delivery fleet?

By interviewing key stakeholders, analyzing quantitative data, and conducting a literature review to select the appropriate methodology, we constructed a strategic fleet planning and order allocation tool for companies who are planning their last mile delivery fleet. The tool we created to find the optimal solution is a combination knapsack & bin packing model, with the incorporation aggregate planning. The tool provides an estimated total cost for a 2-year period, estimated $CO_2$ emissions, number of trucks needed per type, and the order allocation per each delivery option. For Coppel, our main insights revolved around the usage of third-party carriers and order allocations. For each region, it was apparent that it is financially beneficial for Coppel to utilize third-party big trucks all year round, instead of just the high season. Using the third-party big trucks allows Coppel more flexibility and resilience in their last mile delivery as well. Our results also indicated that Coppel is potentially over-allocating orders to the third-party small parcel carriers. By reducing these allocations, Coppel can better utilize their own-fleet, while reducing costs and increasing delivery speed. Lastly, an easing or reduction in the order allocation constraints would greatly benefit Coppel, as the current strict allocation constraints drive their costs up and force a need for more big trucks, which are the most expensive.

Companies whose last mile delivery entails a wide variety of products in terms of volume, delivery time, and handling, would benefit from this strategic planning tool which helps to plan and define the optimal fleet size and composition for their last mile operation. By setting different service level parameters and demand forecast, this tool allows Coppel, and companies alike, to increase resilience in its operation. It also provides insights for which types of trucks are needed and where they are needed, allowing for re-allocation and better optimization of their current fleet. Coppel, and other similar companies, can also gain the ability to enter negotiations with third-party carriers with data driven allocation numbers, which will potentially help to secure the lowest delivery cost possible. Lastly, these companies can now simulate the impact of an increase or decrease in demand on the utilization of their fleet.

**5.1 Limitations**

While our model incorporated all necessary costs and constraints to find the optimal solution for Coppel, it has some limitations:

1. The $CO_2$ calculation does not incorporate the weight of the trucks or the gradients of the roads. This limits the validity of the $CO_2$ emissions estimation, and the emissions amount should only be reviewed for high level, not exact accuracy.
2. This model is intended to assist with high level planning decisions, not the types and number of trucks needed for the day-to-day last mile deliveries. This is because this model is intended as a strategic planning tool, not a tactical one. If time was a non-issue, this model could be expanded to become a tactical tool in theory.
3. The total costs which resulted from the model was only for 8 weeks out of the year. While it does provide an accurate strategic picture of number of trucks needed and what types, the model would need to be expanded to find the total cost per each year or quarter (periods).
4. The model uses averages for each region for multiple inputs like, average kilometers driven, delivery time, third-party costs, and average maintenance costs. This is because the scope needed to be narrowed, resulting in a decrease of the number of binary variables. To derive a more exact cost, the types of trucks and orders would need to be

expanded. This would drastically increase the run time of the model, however it can be done.

5. This model does not incorporate the delivery time taken when delivering with a third-party, nor does the third-party cost increase when delivery speed increases. If this project had more time, more accurately incorporating delivery speed, would be an expansion that would need to be incorporated to provide a fuller picture of the total impact of third-party carriers.
6. The demand used in the model runs is the peak demand for each quarter. If time was a non-issue, incorporating a variety of demand would create a more accurate picture of truck types needed. Coppel would be able to assess the different truck needs for their average demand, high demand or low demand weeks.
7. This model does not include the known overtime hours or costs that Coppel pays during their high season. The model is currently forced to purchase extra trucks or use more third-party carriers, which results in excess trucks being purchased. In future uses, this extra time and cost could be included.
8. The fuel range of the trucks is not included in this model. In future versions, this could be an added capacity constraint, if the trucks needed to be limited by their fuel tank range.

While there are limitations to this model, we stand by the results as an impactful strategic tool for Coppel and other companies trying to define their last mile fleet. In the next section, we discuss the future recommendations.

**5.2 Future Recommendations**

As we investigate the future use of this model, there are recommendations we believe would improve the flexibility, usability, and accuracy of the results for the model. In this section we will describe the future recommendations and their benefits. The recommendations are to reduce the order allocation constraints, to use varied demand and more time periods, to incorporate alternate-fuel trucks, and to incorporate the real cost of third-party carriers and their delivery speed.

Reducing the order allocation constraints will bring more flexibility to the model and reduce overall costs. The results discussed in Chapter 4 demonstrate that allowing more delivery options for each order type is financially advantageous for Coppel. In the future, if Coppel could allow for more relaxed or completely remove the delivery constraints, their fleet would truly be optimized at a strategic level.

The next recommendation is to use more varied demand and more time periods. For this capstone, we used the peak demand for each quarter and only used 8 sections of time. The results then produced a fleet catered to Coppel's highest demands, meaning the fleet would be under-utilized for large parts of the year where the demand is not at its peak. By using a more varied demand and more time periods, the results would product a fleet that is more highly utilized for larger parts of the year and would have a slower build when acquiring more trucks, instead of steep peaks.

Another recommendation for this model is to incorporate electric vehicles or vehicles with alternative fuel options. The model could be easily adapted to incorporate new truck types, including third-party carriers who offer these options. The benefits of including alternative fuel vehicles are that it provides Coppel the opportunity to assess the financial and emissions impact of these choices. Understanding the impacts of alternative fuel is important as consumer interests are pushing for more green delivery options.

The last recommendation for future models is incorporating third-party small parcel delivery speed and the real cost of all third-party carriers. The model currently uses the average for costs, as we chose to focus on producing a model that is easily expandable. In future models, incorporating each third-party carrier utilized in each region with their true costs, would provide a more realistic cost figure. The tool could also be used to negotiate third-party rates, as Coppel could provide estimated number of deliveries allocated to each carrier at specified rates. For delivery speed, a new speed constraint could be incorporated instead of using the capacity of the own-fleet trucks to replicate a delivery speed constraint. Incorporating a true delivery speed constraint by assigning delivery speed to each delivery option, especially third-party, would provide Coppel more insight on how to maintain competitiveness with speed.

The model that was constructed for this capstone sets the foundation on which Coppel can create a strategic tool for their last mile fleet. Our future recommendations for this model would allow this tool to be utilized in third-party negotiations, verifying resiliency in the last mile fleet, allocating Coppel owned trucks to different regions, and assessing green delivery options.

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## Appendix A. Python Model Code

```
#Define the data
x = {} # orders of type j transported by trucks of type i at period t
y = {} # number of trucks of type i at period t
buy = {} #number of trucks of type i we buy before period t
sell = {} #number of trucks of type i we sell before period t
for t in range(number_quarters):
  for i in range(num_trucks_types):
    y[t,i] = solver.IntVar(0, infinity, '') # Number of trucks of type i at period t
    buy[t,i] = solver.IntVar(0, infinity, '') # Number of trucks of type i we buy before period t
    sell[t,i] = solver.IntVar(0, infinity, '') # Number of trucks of type i we sell before period t
    for j in range(num_orders_types):
      x[t,i,j] = solver.IntVar(0, infinity, '') # Units of orders of type j transported by trucks of type i : dim = 3 x 4
```

```
# CONSTRAINTS

for t in range(number_quarters):
  # Supply limited by capacity
  for i in range(num_trucks_types):
    solver.Add(solver.Sum([x[t,i,j] * volume[j] for j in range(num_orders_types)]) <= capacity[i]*y[t,i])
    # number of orders by truck type i x volume per order <= capacity per truck x number of trucks
    solver.Add(solver.Sum([x[t,i,j]*DT[j] for j in range(num_orders_types)]) <= TimeAvailable[i]*y[t,i])
    # number of orders by truck type i x minutes per order <= time available per truck x number of trucks

  # All orders allocated to a truck
  for j in range(num_orders_types):
      solver.Add(solver.Sum([x[t,i,j] for i in range(num_trucks_types)]) >= demand[t][j])
      # for each order type, number of orders allocated > delivery demand

  # Limits the trucks to be used for types of orders
  for i in range(num_trucks_types):
    for j in range(num_orders_types):
      solver.Add(x[t,i,j] * LO[j] <= M * BT[i]) # Large orders must be delivered in large trucks
      solver.Add(x[t,i,j] * HL[j] <= M * (1-TP[i])) # hardline orders can't be delivered in 3rd party

# Truck continuinty along period
for i in range(num_trucks_types):
  solver.Add(y[0,i] == initial_trucks[i] + buy[0,i] - sell[0,i]) # period 0
  for t in range(1,number_quarters):
    solver.Add(y[t,i] == y[t-1,i] + buy[t,i] - sell[t,i])
```

```
#Define the objective
objective_terms = []
for t in range(number_quarters):
  for i in range(num_trucks_types):
    objective_terms.append(daily_cost_truck[i] * y[t,i]) # Fixed cost
    objective_terms.append(cost_buy[i] * buy[t,i]) # cost to buy
    objective_terms.append(cost_sell[i] * sell[t,i]) # cost to sell
    for j in range(num_orders_types):
      #objective_terms.append(costs_order[i][j] * x[t,i,j]) # Variable cost
      objective_terms.append(((Km_Driven[i][j] * x[t,i,j])*MaintCost_PerKM[i]) +
                             (Third_Party_Cost[i][j] * x[t,i,j]) + ((Km_Driven[i][j] * x[t,i,j])*Truck_Fuel_Cost[i]))
```

```
# Solve
solver.Minimize(solver.Sum(objective_terms))
status = solver.Solve()

Truck_Types
Order_Types
Quarters
# Output results
rows = Order_Types.copy()
columns = Truck_Types.copy()
Order_allocation = pd.DataFrame(columns=columns, index=rows, data=0.0)
columns = Truck_Types.copy()
rows2 = Quarters.copy()
Fleet_plan = pd.DataFrame(columns=columns, index = rows2)

# Output results
print('Total cost = $', solver.Objective().Value(), '\n')
Total_Cost = solver.Objective().Value()

for t in range(number_quarters):
  for i in range(num_trucks_types):
    Fleet_plan.at[Quarters[t],Truck_Types[i]] = y[t,i].solution_value()
    Fleet_plan.at[Quarters[t],Truck_Types[2]] = 0


for t in range(number_quarters):
  for i in range(num_trucks_types):
    for j in range(num_orders_types):
      if t == 7:
        Order_allocation.at[Order_Types[j], Truck_Types[i]] = x[t-7,i,j].solution_value() +
        x[t-6,i,j].solution_value() + x[t-5,i,j].solution_value() + x[t-4,i,j].solution_value()
        + x[t-3,i,j].solution_value() + x[t-2,i,j].solution_value() + x[t-1,i,j].solution_value() + x[t,i,j].solution_value()
```

**Appendix B. Extra Culiacán Results Figures and Tables**

This table displays truck types and number used for each of the periods, for the model version run without the usage of Third-Party Big Trucks. It can be broken into 3 parts, as each section of the table represents a different delivery speed.

*Types and number of trucks needed for Culiacán, per each delivery speed*

| 3 Day Delivery | | |
|---|---|---|
| **Quarter** | **Big Trucks Used** | **Small Trucks Used** |
| 1 | 30 | 8 |
| 2 | 30 | 17 |
| 3 | 30 | 17 |

| | | |
|---|---|---|
| 4 | 31 | 20 |
| 5 | 31 | 20 |
| 6 | 31 | 20 |
| 7 | 31 | 20 |
| 8 | 31 | 20 |
| **2 Day Delivery** | | |
| **Quarter** | **Big Trucks Used** | **Small Trucks Used** |
| 1 | 30 | 16 |
| 2 | 32 | 27 |
| 3 | 32 | 27 |
| 4 | 37 | 27 |
| 5 | 37 | 27 |
| 6 | 37 | 27 |
| 7 | 37 | 27 |
| 8 | 37 | 27 |
| **1 Day Delivery** | | |
| **Quarter** | **Big Trucks Used** | **Small Trucks Used** |
| 1 | 31 | 22 |
| 2 | 36 | 32 |
| 3 | 36 | 32 |
| 4 | 41 | 33 |
| 5 | 41 | 33 |
| 6 | 41 | 33 |
| 7 | 41 | 33 |

| | | |
|---|---|---|
| 8 | 41 | 33 |

This table displays the number of trucks used for all type and all quarters, for the model version with Third-Party Big Trucks. It is broken down into the same sections as the table above.

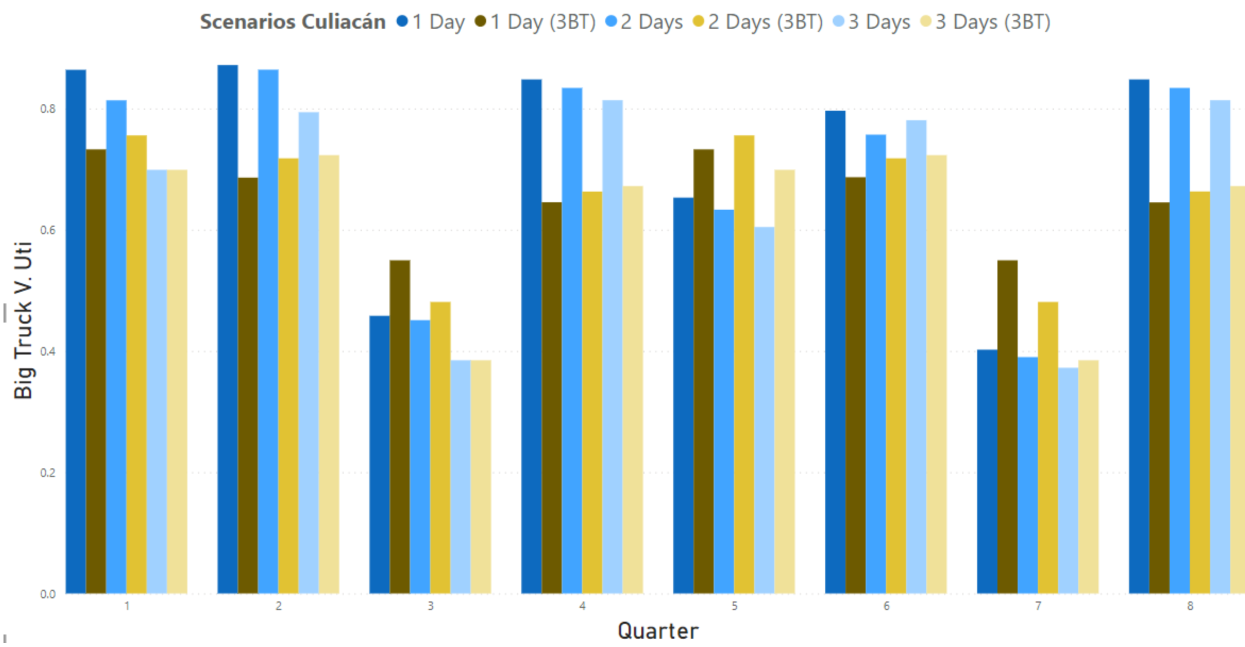
*Types and number of trucks needed for Culiacán, per each delivery speed, with Third-Party Big Trucks*

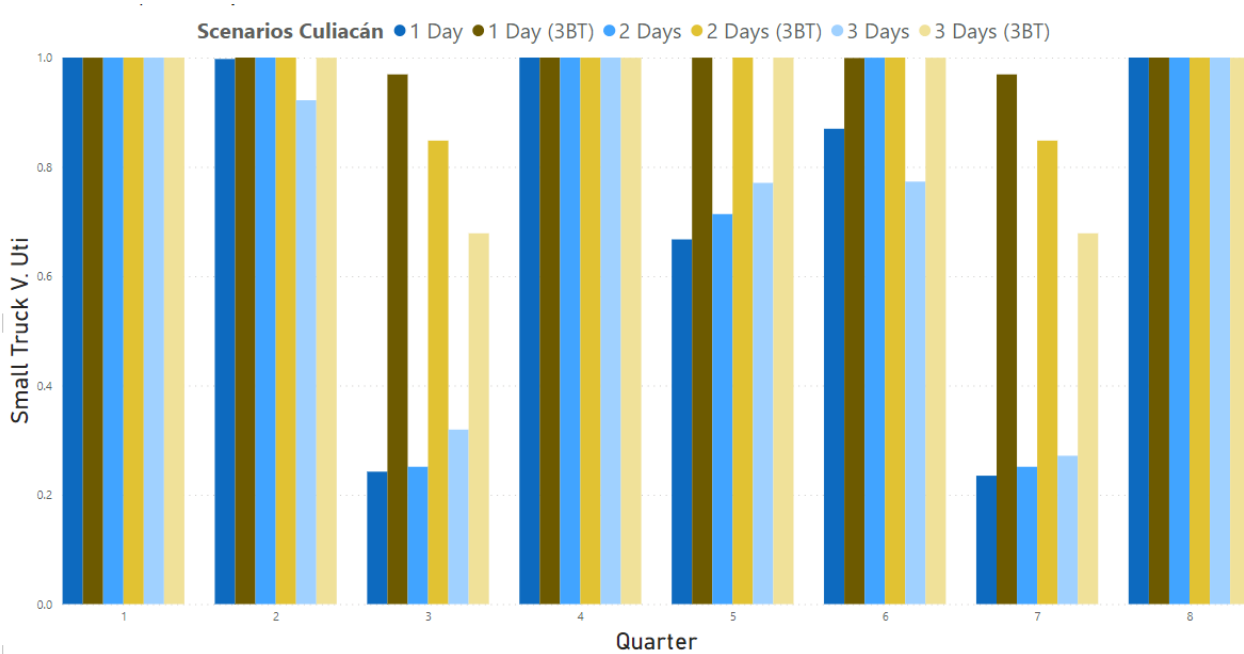
| **3 Day Delivery** | | | |
|---|---|---|---|
| **Quarter** | **Big Trucks Used** | **Small Trucks Used** | **Third-Party Big Trucks Used** |
| 1 | 30 | 8 | 0 |
| 2 | 30 | 8 | 4 |
| 3 | 30 | 8 | 0 |
| 4 | 30 | 8 | 9 |
| 5 | 30 | 8 | 0 |
| 6 | 30 | 8 | 4 |
| 7 | 30 | 8 | 0 |
| 8 | 30 | 8 | 9 |
| **2 Day Delivery** | | | |
| **Quarter** | **Big Trucks Used** | **Small Trucks Used** | **Third-Party Big Trucks Used** |
| 1 | 30 | 8 | 4 |
| 2 | 30 | 8 | 11 |
| 3 | 30 | 8 | 0 |
| 4 | 30 | 8 | 17 |
| 5 | 30 | 8 | 4 |
| 6 | 30 | 8 | 11 |

| | | | |
|---|---|---|---|
| 7 | 30 | 8 | 0 |
| 8 | 30 | 8 | 17 |
| **1 Day Delivery** | | | |
| **Quarter** | **Big Trucks Used** | **Small Trucks Used** | **Third-Party Big Trucks Used** |
| 1 | 30 | 8 | 9 |
| 2 | 30 | 8 | 17 |
| 3 | 30 | 8 | 0 |
| 4 | 30 | 8 | 23 |
| 5 | 30 | 8 | 9 |
| 6 | 30 | 8 | 17 |
| 7 | 30 | 8 | 0 |
| 8 | 30 | 8 | 23 |

This Figure displays the average utilization rate for volume. It displays the utilization rate for all versions of the model. These rates were derived in the same manner as the time utilization rate.

*Average Volume utilization rate for Culiacán, per delivery speed, per truck type*




This table displays the order allocation for all periods, for each delivery speed, for the model version without the use of third-party big trucks.

*Order allocation, per delivery speed, Culiacán*

| Delivery Speed | Orders via Big Trucks | Orders via Small Trucks | Orders via Third-party Small Parcel |
|---|---|---|---|
| 3 day delivery | 40886 | 30322 | 8122 |

| | | | |
|---|---|---|---|
| 2 day delivery | 37691 | 33521 | 8118 |
| 1 day delivery | 36089 | 36217 | 7024 |

This table displays the number of orders allocated to each truck type, per delivery speed. This data is from the model run where Third-Party Big Trucks were allowed to be utilized.

*Order allocation, per delivery speed with Third-Party big trucks Culiacán*

| Delivery Speed | Orders via Big Trucks | Orders via Small Trucks | Orders via Third-party Small Parcel | Orders via Third-party Big Truck |
|---|---|---|---|---|
| 3 day delivery | 42864 | 18652 | 10168 | 7646 |
| 2 day delivery | 37525 | 14834 | 13220 | 13751 |
| 1 day delivery | 33816 | 13954 | 12876 | 18684 |

**Appendix C. Extra Monterrey Results figures and Tables**

This table displays the own-fleet truck usage for each delivery speed. This is for the model version without Third-Party Big Trucks.

*Types and number of trucks needed for Monterrey, per each delivery speed*

| 3 Day Delivery | | |
|---|---|---|
| Quarter | Big Trucks Used | Small Trucks Used |
| 1 | 48 | 25 |
| 2 | 59 | 36 |
| 3 | 59 | 36 |
| 4 | 65 | 36 |
| 5 | 65 | 36 |

| | | |
|---|---|---|
| 6 | 65 | 36 |
| 7 | 65 | 36 |
| 8 | 65 | 36 |
| **2 Day Delivery** | | |
| **Quarter** | **Big Trucks Used** | **Small Trucks Used** |
| 1 | 60 | 31 |
| 2 | 73 | 45 |
| 3 | 73 | 45 |
| 4 | 81 | 45 |
| 5 | 81 | 45 |
| 6 | 81 | 45 |
| 7 | 81 | 45 |
| 8 | 81 | 45 |
| **1 Day Delivery** | | |
| **Quarter** | **Big Trucks Used** | **Small Trucks Used** |
| 1 | 68 | 36 |
| 2 | 84 | 51 |
| 3 | 84 | 51 |
| 4 | 93 | 51 |
| 5 | 93 | 51 |
| 6 | 93 | 51 |
| 7 | 93 | 51 |
| 8 | 93 | 51 |

This table displays the number of trucks used for each quarter, for the model version where third-party big trucks were allowed.

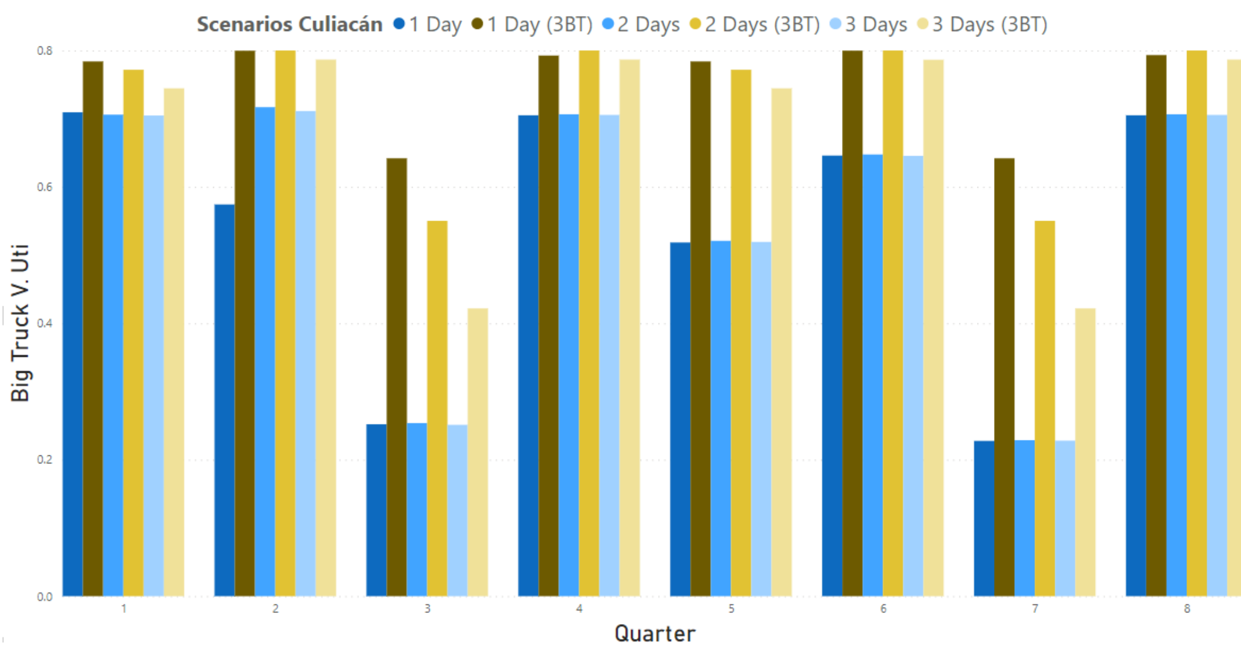
*Types and number of trucks needed for Monterrey, per each delivery speed, with Third-party Big Trucks*

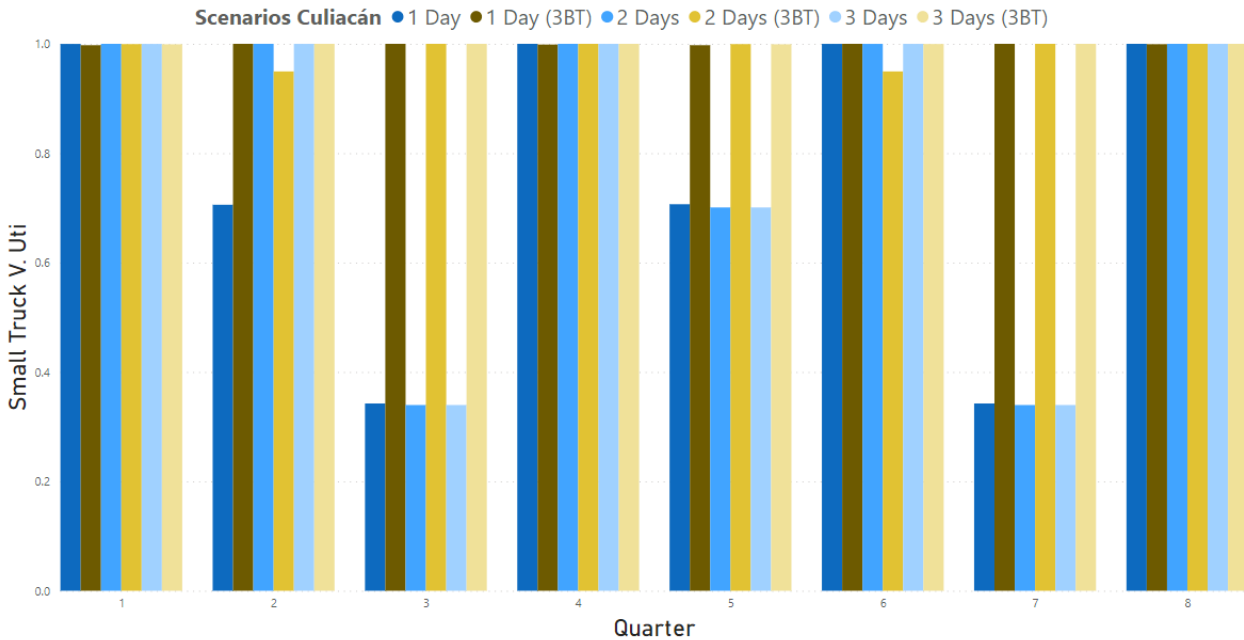
| 3 Day Delivery | | | |
|---|---|---|---|
| **Quarter** | **Big Trucks Used** | **Small Trucks Used** | **Third-Party Big Trucks Used** |
| 1 | 36 | 11 | 17 |
| 2 | 36 | 11 | 32 |
| 3 | 36 | 11 | 0 |
| 4 | 36 | 11 | 37 |
| 5 | 36 | 11 | 17 |
| 6 | 36 | 11 | 32 |
| 7 | 36 | 11 | 0 |
| 8 | 36 | 11 | 37 |
| **2 Day Delivery** | | | |
| **Quarter** | **Big Trucks Used** | **Small Trucks Used** | **Third-Party Big Trucks Used** |
| 1 | 36 | 11 | 30 |
| 2 | 36 | 11 | 48 |
| 3 | 36 | 11 | 0 |
| 4 | 36 | 11 | 54 |
| 5 | 36 | 11 | 30 |
| 6 | 36 | 11 | 48 |
| 7 | 36 | 11 | 0 |
| 8 | 36 | 11 | 54 |

| 1 Day Delivery | | | |
|---|---|---|---|
| Quarter | Big Trucks Used | Small Trucks Used | Third-Party Big Trucks Used |
| 1 | 36 | 11 | 39 |
| 2 | 36 | 11 | 59 |
| 3 | 36 | 11 | 0 |
| 4 | 36 | 11 | 67 |
| 5 | 36 | 11 | 39 |
| 6 | 36 | 11 | 59 |
| 7 | 36 | 11 | 0 |
| 8 | 36 | 11 | 67 |

This Figure displays the average utilization rate for volume. It displays the utilization rate for all versions of the model. These rates were derived in the same manner as the time utilization rate.

*Average Volume utilization rate for Monterrey, per delivery speed, per truck type*






This table displays the order allocation per delivery type, per delivery speed. This table does not include the use of third-party big trucks.

*Order allocation, per delivery type per delivery speed, Monterrey*

| Delivery Speed | Orders via Big Trucks | Orders via Small Trucks | Orders via Third-party Small Parcel |
|---|---|---|---|
| 3 day delivery | 63847 | 49083 | 1566 |
| 2 day delivery | 63721 | 48228 | 2547 |
| 1 day delivery | 63959 | 48453 | 2084 |

This table displays order allocation per delivery type and delivery speed. However, this table is for the model version which allowed the use of Third-Party Big Trucks.

*Order allocation, per delivery type per delivery speed, Monterrey*

| Delivery Speed | Orders via Big Trucks | Orders via Small Trucks | Orders via Third-party Small Parcel | Orders via Third-party Big Trucks |
|---|---|---|---|---|
| 3 day delivery | 32825 | 17986 | 1173 | 62512 |
| 2 day delivery | 35924 | 19544 | 1214 | 57814 |
| 1 day delivery | 32825 | 17986 | 1173 | 62512 |

**Appendix D. Extra Tecamac Results Figures and Tables**

This table displays the own-fleet truck usage for each delivery speed. This is for the model version without Third-Party Big Trucks.

*Types and number of trucks needed for Tecamac, per each delivery speed*

| 3 Day Delivery | | |
|---|---|---|
| **Quarter** | **Big Trucks Used** | **Small Trucks Used** |
| 1 | 33 | 17 |
| 2 | 36 | 23 |
| 3 | 36 | 23 |
| 4 | 55 | 26 |
| 5 | 55 | 26 |
| 6 | 55 | 26 |
| 7 | 55 | 26 |
| 8 | 55 | 26 |
| **2 Day Delivery** | | |
| **Quarter** | **Big Trucks Used** | **Small Trucks Used** |
| 1 | 41 | 22 |
| 2 | 45 | 29 |
| 3 | 45 | 29 |
| 4 | 70 | 31 |
| 5 | 70 | 31 |
| 6 | 70 | 31 |

| | | |
|---|---|---|
| 7 | 70 | 31 |
| 8 | 70 | 31 |
| **1 Day Delivery** | | |
| **Quarter** | **Big Trucks Used** | **Small Trucks Used** |
| 1 | 47 | 25 |
| 2 | 51 | 33 |
| 3 | 51 | 33 |
| 4 | 79 | 37 |
| 5 | 79 | 37 |
| 6 | 79 | 37 |
| 7 | 79 | 37 |
| 8 | 79 | 37 |

This table displays the own-fleet truck usage for each delivery speed. This is for the model version with Third-Party Big Trucks.

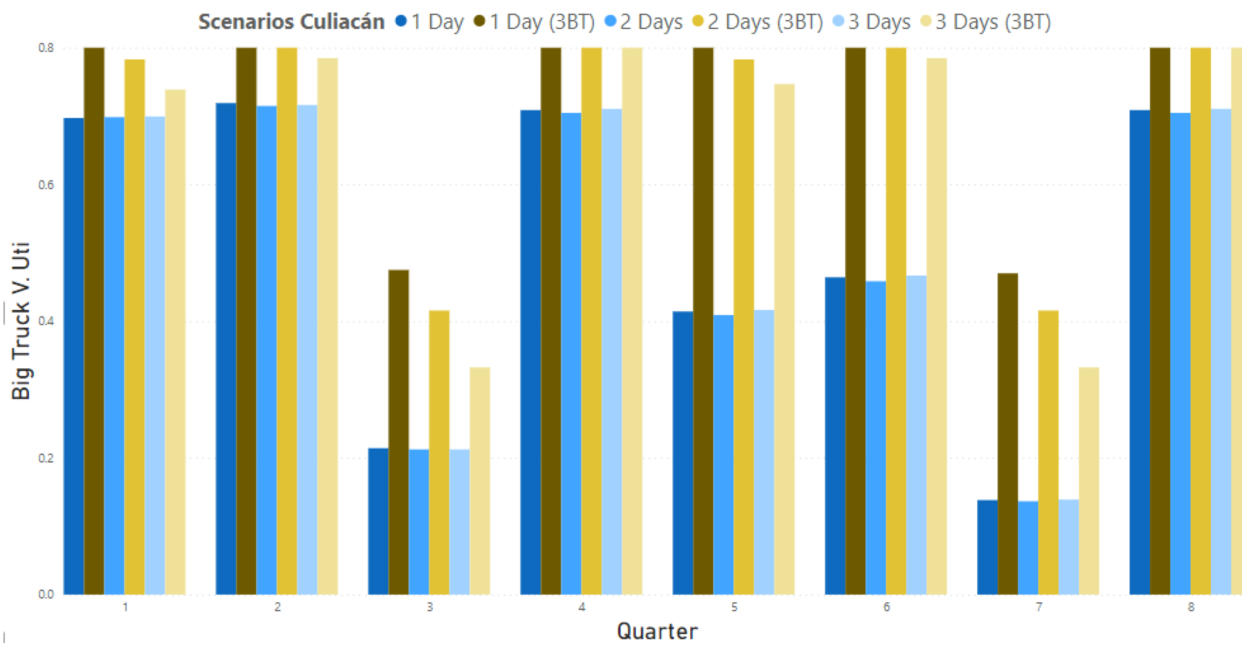
*Types and number of trucks needed for Culiacán, per each delivery speed, with third-party big trucks*

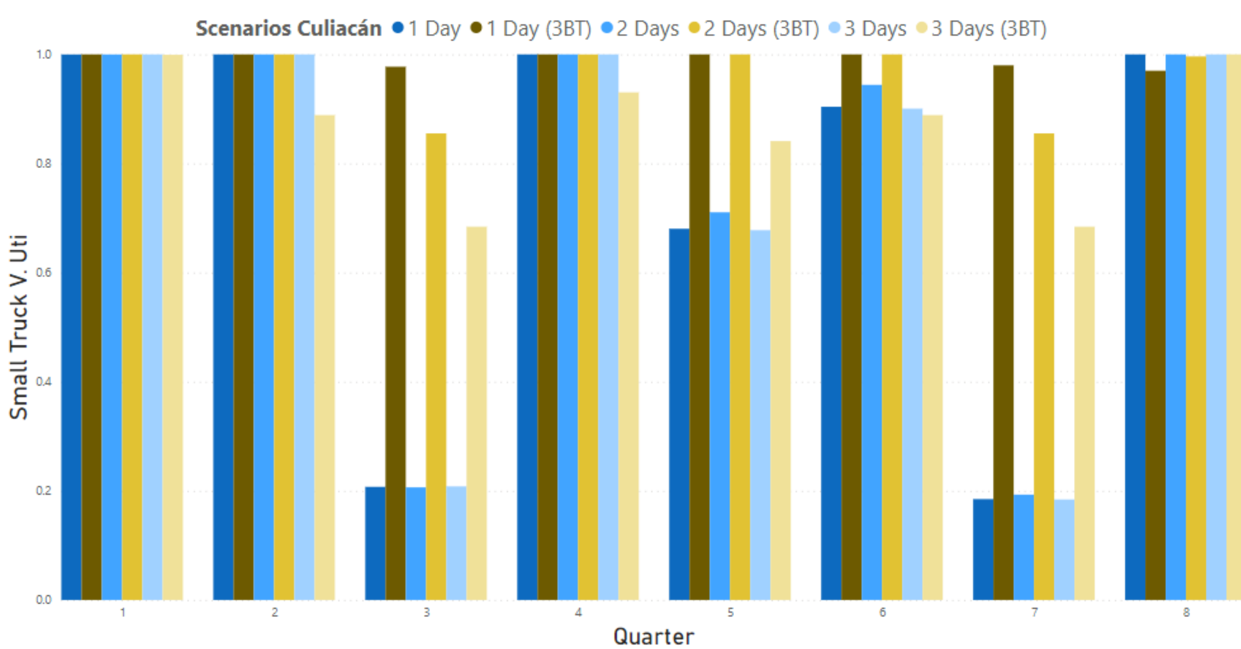
| **3 Day Delivery** | | | |
|---|---|---|---|
| **Quarter** | **Big Trucks Used** | **Small Trucks Used** | **Third-Party Big Trucks Used** |
| 1 | 23 | 7 | 14 |
| 2 | 23 | 7 | 19 |
| 3 | 23 | 7 | 0 |
| 4 | 23 | 7 | 36 |

| | | | |
|---|---|---|---|
| 5 | 23 | 7 | 14 |
| 6 | 23 | 7 | 19 |
| 7 | 23 | 7 | 0 |
| 8 | 23 | 7 | 36 |
| **2 Day Delivery** | | | |
| **Quarter** | **Big Trucks Used** | **Small Trucks Used** | **Third-Party Big Trucks Used** |
| 1 | 23 | 7 | 22 |
| 2 | 23 | 7 | 28 |
| 3 | 23 | 7 | 0 |
| 4 | 23 | 7 | 50 |
| 5 | 23 | 7 | 22 |
| 6 | 23 | 7 | 28 |
| 7 | 23 | 7 | 0 |
| 8 | 23 | 7 | 50 |
| **1 Day Delivery** | | | |
| **Quarter** | **Big Trucks Used** | **Small Trucks Used** | **Third-Party Big Trucks Used** |
| 1 | 23 | 7 | 28 |
| 2 | 23 | 7 | 35 |
| 3 | 23 | 7 | 0 |
| 4 | 23 | 7 | 60 |
| 5 | 23 | 7 | 28 |
| 6 | 23 | 7 | 35 |
| 7 | 23 | 7 | 0 |
| 8 | 23 | 7 | 60 |

This Figure displays the average utilization rate for volume. It displays the utilization rate for all versions of the model. These rates were derived in the same manner as the time utilization rate.

*Average Volume utilization rate for Tecamac, per delivery speed, per truck type*




This table displays the order allocation, per delivery type for Tecamac This table is for the model version that does not include the option to use Third-party Big Trucks.

*Order allocation, per delivery type per delivery speed, Tecamac*

| Delivery Speed | Orders via Big Trucks | Orders via Small Trucks | Orders via Third-party Small Parcel |
|---|---|---|---|
| 3 day delivery | 44557 | 34973 | 3862 |
| 2 day delivery | 44924 | 34884 | 3584 |
| 1 day delivery | 44541 | 35370 | 3481 |

This table displays the order allocation, per delivery type for the model version where third-party big trucks are an option.

*Order allocation, per delivery type per delivery speed, with Third-party Big Trucks, Tecamac*

| Delivery Speed | Orders via Big Trucks | Orders via Small Trucks | Orders via Third-party Small Parcel | Orders via Third-party Big Trucks |
|---|---|---|---|---|
| 3 day delivery | 25871 | 16213 | 3478 | 37830 |
| 2 day delivery | 21366 | 13353 | 5811 | 42862 |
| 1 day delivery | 19122 | 11739 | 6789 | 45742 |