E-commerce and the environment:
Finding the optimal location for in-store pick-up

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ABSTRACT

In recent years, ecommerce has been expanding at an increasing rate. Many retailers are making efforts to improve their channel integration to enhance the order fulfillments for their customers. Therefore, companies often see network optimization as a key element within the ecommerce building. At the same time, more companies are trying to make their supply chains more sustainable, and transportation evidently accounts for a large share of CO_2 emissions. Nonetheless, the trade-off between cost reduction and CO_2 emissions reduction is often difficult to determine, and even harder to see as a tool for a company to make strategic decisions.

Our research focuses on an American department store chain with the aim to select the optimal stores as pick-up spots and evaluates the environmental impact of the findings. We use more than 10 million records provided by The Company and develop a binary integer linear programming model to estimate potential savings. We perform a sensitivity analysis to analyze the impact of the customer's decisions in both economic and environmental magnitudes. Results show the significant importance of two variables: the customers' willingness to travel and pick up their packages, and the customer's willingness to avoid using a motor vehicle. Our results include savings of $77K in Massachusetts and $1,319K in California. Finally, with this analysis we provide recommendations for implementing the order-online-and-pick-up-in-store mode in a sustainable and cost-effective way, including educating the customers in using more environmentally friendly transportation modes.

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Glossary

- **Binary integer programming:** Mathematical optimization in which each variable is only binary (0 or 1) and represents a decision. (Chinneck, 2016)
- **Vehicle routing problem:** an optimization and integer programming problem seeking to deliver discrete quantities of a product to certain demand with a fleet of vehicles. (Caric, Tonci, and Hrvoje, 2008)
- **Manhattan distance:** the sum of the absolute differences of two points' Cartesian coordinates. (Hajjaji, 2016)

CHAPTER 1: INTRODUCTION

Retailers often struggle with optimizing the route design of their deliveries in a way that does not alter the service level. On one side, there is the operational efficiency per trip, which can be achieved by maximizing the number of packages in one route; and on the other side, there is the quality constraint, which is a customer-focused variable that might have a bigger impact on the company's profit than the operational efficiency itself. Within their e-commerce business, retailers are providing more delivery options to customers, from changing the time frame of delivery to offering alternative pick-up locations.

The Company is an American chain of upscale department stores, headquartered in Seattle, Washington, and operating in Canada and Puerto Rico. They began as a shoe retailer and expanded its inventory to include clothing, accessories, handbags, jewelry, cosmetics, and fragrances. In 1993, the company expanded into the e-commerce business. The Company has a fulfillment center in the East Coast, and each year millions of packages are delivered to the West Coast from this fulfillment center by national parcel carriers, such as UPS, USPS, and FedEx. The Company spends millions of dollars on transportation every year. Currently, their ecommerce network is shipping packages to various customers across the country. The Company has a physical infrastructure of about 350 stores in the network. Transportation rates are based on zones and weight. The Company looks to optimize the network by reducing the transportation cost while maintaining high service level.

In this study, we focus on the usage of current stores as a last mile solution for ecommerce delivery. To be more specific, the stores will have a special section for consolidating the packages that will work as collection points for customers.

The goal of this project is to determine the optimal locations for consolidating parcel packages in order reduce costs and evaluate the resulting carbon dioxide emissions. The goal of this project must consider maintaining or improving customer service. Therefore, the objective of this project has three dimensions:

1. Reduce costs that include transportation and handling.

2. Reduce the environmental impact measured in carbon dioxide emissions.
3. Maintain or improve customer service.

To accomplish the objective, the project will analyze potential methods such as binary integer programming and last mile vehicle routing, and then compare results to suggest a comprehensive solution that can be both optimal and feasible in the organization.

CHAPTER 2: LITERATURE REVIEW

In this project, we aim to accomplish e-commerce deliveries optimization by determining the optimal stores for customers picking up their packages, considering cost savings, environmental impact and customer service level. We conducted a review of the literature related to optimizing e-commerce networks by setting up pick-up points for consolidating packages, especially lockers, to identify appropriate methodologies and constraints. Aside from transportation cost, we took into consideration the carbon dioxide (CO_2) emissions because The Company was looking to improve its environmental footprint. We reviewed related literature to recognize the factors to be considered when calculating CO_2 emissions. We also reviewed literatures regarding customer's choice between pick-up from stores and home delivery, as it can help us better maintain or improve customer service level and more accurately calculate the cost saving and CO_2 emissions.

2.1 PARCEL LOCKER NETWORK TO IMPROVE THE LAST MILE DELIVERY

A parcel locker network, which consists of many lockers to address the last mile delivery of online retailers, is a solution to optimize the logistics network. Deutsch and Golany (2018) designed a parcel locker network to maximize total profit by confirming the optimal number, locations, and sizes of parcel lockers facilities. They expressed the problem as a 0-1 integer linear programming and showed how to transform it into an Uncapacitated Facility Location Problem (UFLP) to solve it. Their results showed that lockers can be advantageous to cities by taking advantage of consolidation opportunities and reducing the number of failed deliveries, and by offering convenience to customers. Finally, they applied this algorithm on the network of Toronto, Canada. They were able to identify 65 locations to open parcel locker service with minimum total daily cost of $3,420.

To optimize the delivery of medication from a local pharmacy to patients in Netherlands, Veenstra, Roodbergen, Coelho and Zhu (2018) used an algorithm and proposed a robust heuristic to select which lockers to open. They met the goal of minimizing routing costs by solving a problem that included 100 patients and 50 potential lockers.

These studies are very useful for determining the optimal locations for consolidating packages for customers to pick-up. However, both research projects considered only the cost saving and did not take environmental impact into account, which is a relevant aspect for the sponsor company.

2.2 IMPACT OF SELF PICK-UP ON CO_2 EMISSIONS

Considering the use of various systems to improve last-mile delivery, Carotenuto et al (2018) aimed to compare the environmental and logistics implications of parcel deliveries in the e-commerce business. They compared point-to-point and locker deliveries, stating the pros and cons of both. They evaluated the impact not only on the cost but also on the environment. CO_2 emissions would decrease by more than 21% based on the scenario of To-BE Distribution Tours (Depot-Lockers). However, this model did not include the impact of customer travel from original locations to the pick-up locations. It is important to take customer travel into consideration as it also generates large amounts of CO_2 emission.

Wygonik and Goodchild (2018) developed regression models to identify the relationship between goods movement and CO_2 emission in urban areas. According to their models, the CO_2 emission was different in different scenarios: passenger travel, local depot delivery and warehouse delivery. Road density and distance are two important factors to CO_2 emission.

Velázquez, Fransoo, Blanco and Mora (2014) developed a detailed estimation method based capable of aggregating CO_2 emission in a transportation lot-sizing model. Their model has some accuracy limitations for real emissions; however, they provide important insights for a comprehensive CO_2 emission calculation.

Different from these researches, our capstone project includes the impact from line haul, vehicle routing and customer travel, which will make our calculation more accurate.

2.3 WHAT MATTERS TO CUSTOMERS' CHOICE OF CHANNEL

It is important to understand customers' behavior so that we can maintain or improve customer service level. Alberts and Abinader (2018) analyzed the drivers of customers' choice between pick-up from the store and home delivery. According to the analysis, location, price and distance matter to customers' decision. Every dollar increase in home delivery causes a person to be 20.7% less likely to choose home delivery. The authors found that for customers who choose pick-up from the store, the time window does not matter. Moving the window to next day will not affect a customer's choice. It would be a benefit to online retailers as they can consolidate more parcel packages to make the shipment from the distribution center or warehouse to the stores more efficient without affecting customer service level.

In contrast to the research papers mentioned above, we would optimize the network by choosing the optimal stores from hundreds of candidates as pick-up points. The setup cost, operating cost and capacity are very different, compared to using lockers. Moreover, when determining the optimal locations to maximize total cost savings, we showed the impact of CO_2 emission from our solution. Finally, we analyzed the drivers of customers' decisions between pick-up from the store and home delivery so that we can better maintain the customer service level.

CHAPTER 3: METHODOLOGY

3.1. DATA MANAGEMENT

In this project, we did not generate new data on The Company's logistic network but relied on 9 months of historical data. The data sources provide parcels real delivery record from the Company's stores to the customer's households.

The Company provided us with two datasets as following.

- location_dim. This dataset provides information of The Company's 683 facilities, including facility type, location and opening status. Location is the latitude and longitude information of physical facilities. Opening status is about which date physical facilities opened and closed. Each record represents information of one facility. We used this dataset was used to understand The Company's existing network and facility location, and more importantly, to determine which facilities would be the best pickup spots for customers.
- COMP_2018. This dataset provides delivery information of 10,525,878 orders mostly from January 1, 2018 to September 28, 2018. Each record represents one order delivery information, including carrier, weight, origin and destination, service group, net charge and ship date. Weight is used to evaluate truck capacity. Net charge and origin and destination were used to understand cost structure, while ship date and service group were used to understand service level. All records combined were represented the demand.

<u>location_dim Dataset</u>

We only consider physical stores as candidates for customers to pick-up their orders in this project. We create a filter to remove the data of warehouses, offices, and distribution centers. We only keep facilities type as RACK/OFF-PRICE and MAIN LINE with Open_Date<2018-9-24 and Close_Date>2018-9-24. In the end, we have 360 facilities as candidates of pick-up spots (See Figure 1).

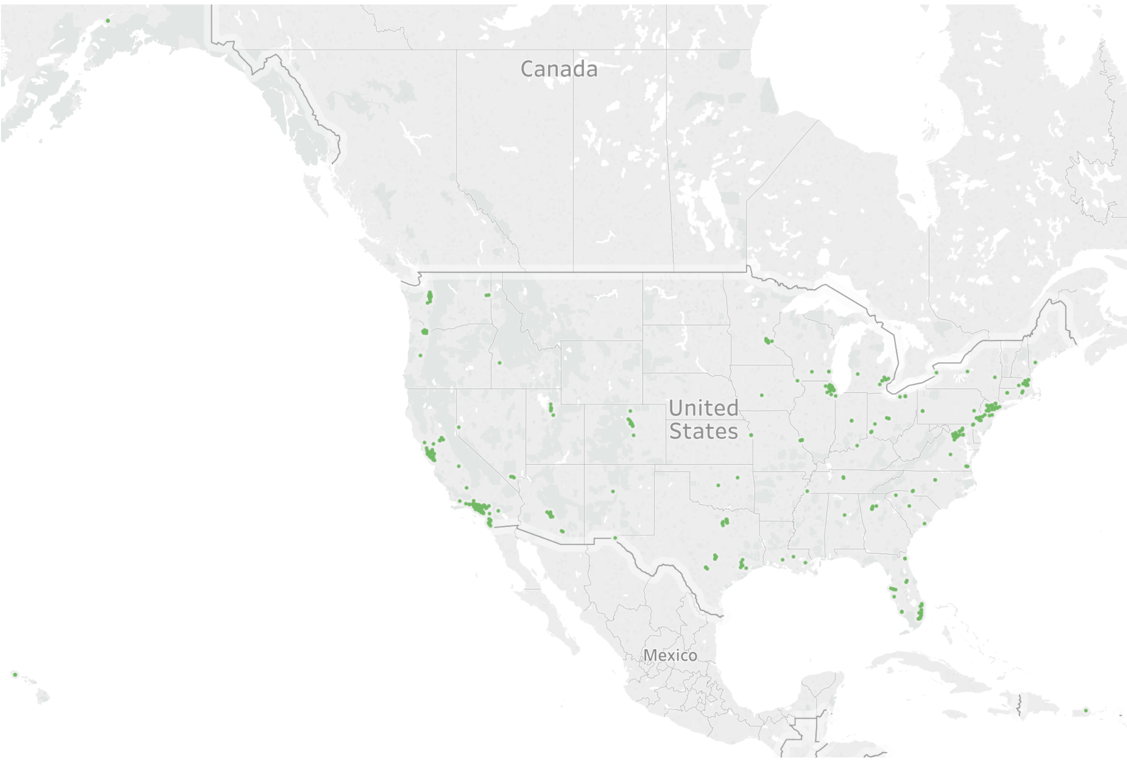

Figure 1. Candidates of pick-up spots

COMP_2018 Dataset

- In dataset of NDIR_2018, records of ship weight of more than 20 pounds or less than 0 pounds or records of net charges less than 0 are removed as records with negative numbers are bad data and packages of more than 20 pounds are unlikely to be picked up by customers in-store since the packages are too heavy. The remaining number of records is 7,561,909.
- The number of records from 2017-08-21 to 2017-12-31 and with incomplete date is only 45,219, 0.60% of the total dataset. It is more likely to be incomplete data or bad data of this period. So, we remove these records and only keep 9-month data from 2018-1-1 to 2018-9-25. The remaining number of records is 7,516,690.
- The objective of this project is to determine the best stores as pick-up spots in USA, so we remove records with invalid destination zip code such as null will be removed. The remaining number of records is 7,512,615.
- The number of records with net charge more than $36 is 16,889, which is just 0.22% of remaining dataset. These records look like outliers and bad data, so we only keep the records

with net charge no more than $36. The number of remaining records is 7,495,726 (See Figure 2).

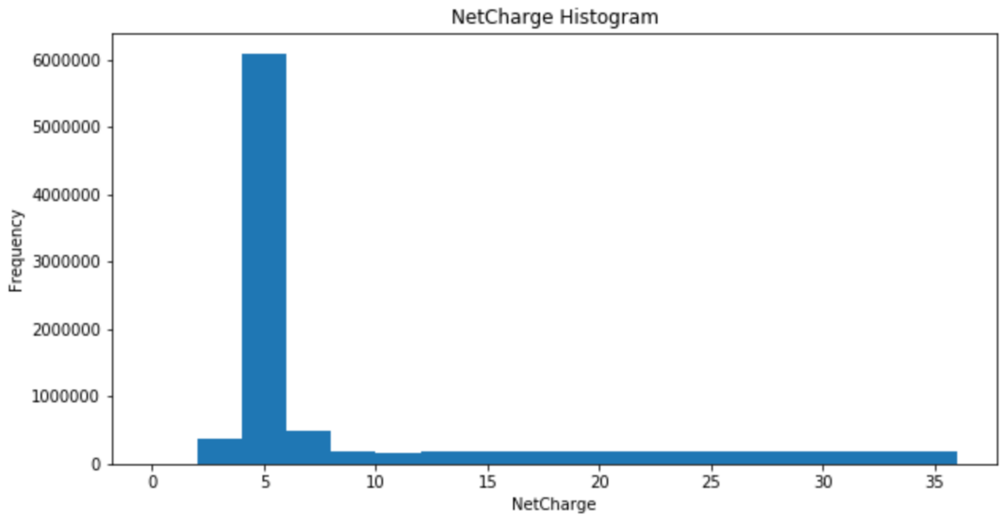

Figure 2. Histogram of Netcharge

3.2. MATHEMATICAL MODELS

As aforementioned, in this project we focus on determining which of The Company's stores are optimal consolidating locations for the customers to pick up their orders. The aim is to determine, given a certain area topography and orders' history, how many stores to enable and the capacity for each consolidating store to maximize the total resulted savings both in costs and CO_2 emissions. The emissions will consist of the summation of calculated emissions from the retailer (The Company) and the customer, considering the new situation. The costs will consist of the real transportation data from the data provided by The Company,

Furthermore, at the end of the research we perform a sensitivity analysis with the aim of analyzing the tradeoff between the environmental impact and the cost reduction impact. The idea is also to highlight which parameters are most impactful in the analysis.

3.2.1. COST REDUCTION FUNCTION

To find out the optimal solution under this methodology, we create a Binary Integer Programming function.

<u>Problem formulation</u>

Let I be the set of orders and J be the set of stores within a region. We assume that the ordering processes are independent of each other.

Let X_{ij} be a binary variable that takes the value of 1 when the order i will be picked in store j, otherwise it will be 0.

The current model is focused on maximizing savings related to the last mile transportation. However, to achieve savings, customers must be willing to accept the new scenario.

Let P represent the willingness of the demand to pick up their orders in stores for a certain range of distance in miles, it is measured in percentage and in this model, it is assumed as a fixed value.

Let C_i>0 be the original transportation cost of delivering order i from the company's stores, which in this model will provide the value of the savings.

Let F_j be the fixed cost of opening store j as a pick-up location. It consists of costs related to labor, infrastructure, utilities, and every related cost that resulted from the implementation. We estimate this to be 10,000 $ for the 9 months of the dataset.

Let Y_j be a binary variable, that takes the value of 1 when store j is selected to have the pick-up service, otherwise it takes the value of 0.

It is assumed that customers prefer the nearest available store. If the stores are close to the customers, customers will be more likely to use the pick-up service, and the percentage of customers who agree to travel and collect their packages decreases with the distance.

Let M be the maximum quantity of miles that the customers are willing to travel to pick up their orders.

Let D_{ij} be the distance to deliver order i from store j, in miles. In this model, it is an approximate distance, derived from a function with zip codes of customer and store as inputs.

Objective function:

$$\max \rightarrow Z = \sum_j \sum_i P * C_i * X_{ij} - \sum_j F_j * Y_j \quad (1)$$

Subject to:

$$\sum_j X_{ij} \leq 1, \forall\ i\ \in\ I, \forall\ j\ \in J \quad (2)$$

$$X_{ij} * D_{ij} \leq M, \forall\ i\ \in\ I, \forall\ j\ \in\ J \quad (3)$$

$$X_{ij} \leq Y_j, \forall\ i\ \in\ I, \forall\ j\ \in\ J \quad (4)$$

$$X_{ij}, Y_j\ = \{0,1\} \quad (5)$$

It is anticipated that each location will have different demand density, which is why the network design is not expected to be symmetric.

3.2.2. CO_2 EMISSIONS REDUCTION FUNCTION

The target will consist of maximizing the CO_2 emissions savings. The savings will result from subtracting the CO_2 emissions of the proposed scenario (buy online and pick up in store) from the current scenario (home delivery).

$$\mathrm{E}^{savings} = \mathrm{E}^{current} - \mathrm{E}^{proposed}$$

In the current scenario, the CO_2 emissions will come from the last-mile delivery trucks contracted by The Company, to deliver packages from the store to the customer's household.

In the proposed scenario, the CO_2 emissions will come from the portion of customers using private vehicles (cars) to pick up their packages in The Company's store.

Total emissions from trucks

The methodology of this project will be based on the NTM[1] Methodology, at a level of aggregation in which the following parameters are considered:

- CE = the constant emission factor of 2621 grams of CO_2 per liter of fuel
- D = distance traveled, in kilometer
- FC = fuel consumption in liters per kilometer
- LF = load factor, defined as cargo weight over the truck weight capacity

With these parameters, the NTM estimation model is contained in the following equation:

$$\mathrm{TE} = \mathrm{CE} * \mathrm{D} * [\mathrm{FC}_{empty} + \left(\mathrm{FC}_{full} - \mathrm{FC}_{empty}\right) * \mathrm{LF}]$$

The fuel consumption of the empty and full vehicle depends on the type of trailer and its capacity, according to Table 1, provided by NTM[2]. In this project, The Company's physical stores are in urban area, and the capacity of trucks used for parcel delivery are less than 7.5 tons, so we use the parameters of Type 1 of trailer for our model: $\mathrm{FC}_{empty} = 0.11$ *and* $\mathrm{FC}_{full} = 0.134$.

Table 1.Fuel consumption and maximum truck capacity.[3]

Type of trailer	W Capacity (tons)	Motorway		Rural		Urban	
		FC_{empty}	FC_{full}	FC_{empty}	FC_{full}	FC_{empty}	FC_{full}
1	≤7.5	0.122	0.137	0.107	0.126	0.11	0.134
2	14	0.165	0.201	0.152	0.197	0.171	0.228
3	26	0.204	0.273	0.199	0.284	0.244	0.352
4	28	0.201	0.294	0.205	0.318	0.255	0.402
5	40	0.226	0.36	0.23	0.396	0.288	0.504
6	50	0.246	0.445	0.251	0.495	0.317	0.634

[1] Network For Transport Measures https://www.transportmeasures.org/en/
[2] NTM Road (2008) Environmental data for international cargo transport-road transport. http://www.ntmcalc.se/index.html.
[3] Velázquez-Martínez, J. C., Fransoo, J. C., Blanco, E. E., & Mora-Vargas, J. (2014). The impact of carbon footprinting aggregation on realizing emission reduction targets. *Flexible Services and Manufacturing Journal*, *26*(1-2), 196-220.

A benefit of this formulation is that it enables us to consider the trade-off between the distance (D) and the utilization (LF) while selecting the stores that are the optimum pick-up locations. This means that when serving customers with trucks of same capacity, the location solutions are the same as those that are obtained by a traditional facility location model (facilities are located closer to the highest demand), and thus minimizing transport cost has the same result as minimizing CO_2 emission. Nonetheless, when considering trucks with different capacities or characteristics, the solution might consider selecting stores that are closer to the demand served by smaller trucks, in order to minimize the overall sum of distances (smaller transportation capacity means more required trips).

We will use a local routing equation to estimate the distance used by the trucks, in which one store distributes to many customers. In this scenario we assume that the regions are a Manhattan space with a K_{TSP} parameter of 0.97, an average factor that should depend on the topology of the region.

$$d_{TSP} = K_{TSP}\sqrt{nA}$$

In this formula n is the number of stops. A is the area of the location, which for the purposes of this research will be assumed to be a circle. To calculate the circle's area, we will use a radius of R=10 miles, which will be assumed as the maximum distance of a person to consider a pick-up location.

Accordingly, the average linehaul distance can be estimated as bellow.

$$d_{LineHaul} = \frac{R}{2}$$

To calculate the total routing distance of trucks' delivery, we will add up the estimated local routing distance and linehaul distance and then multiply by the number of trips the truck makes. The number of trips is obtained by dividing the total number of orders N by the number of stops n. Hence, the total estimated distance can be calculated as the following formula.

$$d_{TotalDistance} = \left(2 * \frac{R}{2} + K_{TSP}\sqrt{nA}\right) * \frac{(N * P)}{n}$$

Total emissions from customers' cars.

According to the EPA[4], the average passenger vehicle emits about 404 grams of CO_2 per mile. Its equivalent is 251 grams of CO_2 per kilometer. This number is an average estimation and can vary based on several parameters such as type of fuel and fuel economy. For this estimation, the vehicle utilization will be dismissed because we assume that it can be homogeneous within the US. If at any point of the research a specific analysis is required for a specific type of vehicle, more information can be found in several sources such the website of the official US government for fuel economy information (fueleconomy.gov). Furthermore, this factor will be multiplied by 2 to get the roundtrip estimation of the car's travelling.

Total emissions savings.

Figure 3 shows the comparison of the current and proposed scenario.

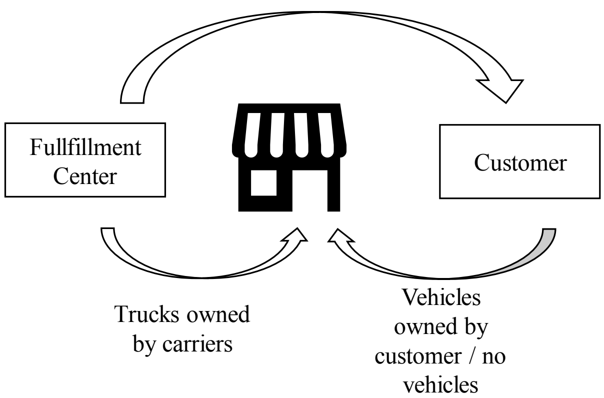

Figure 3. Current and proposed scenario

Equation 6 refers to the sustainability function to calculate total CO_2 savings.

$$Z = TE_{truck} - TE_{car} \qquad (6)$$

Where, according to the formulas explained in this section 3.2.2:

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[4] United States Environmental Protection Agency. https://www.epa.gov/greenvehicles/greenhouse-gas-emissions-typical-passenger-vehicle

$$TE_{truck} = \mathrm{CE} * d_{TotalDistance} * [\mathrm{FC}_{empty} + (\mathrm{FC}_{full} - \mathrm{FC}_{empty}) * \mathrm{LF}] \quad (7)$$

$$TE_{car} = \sum_j \sum_i 2 * P * (1 - B) * D_{ij} * X_{ij} * E_{car} \quad (8)$$

Let Z be the total emission savings in grams of CO_2.

Let TE_{truck} be the Emissions saved from the store-to-customer trajectory by The Company's carrier.

Let TE_{car} be the Emissions created from the customer-to-store trajectory by the customer's vehicle.

Let $d_{TotalDistance}$ be the total distance saved from the store-to-customer trajectory by The Company's carrier.

Let B be Percentage of customers willing to walk, bike, or use public transportation. We will explore the sensitivity of this variable. It depends on customer's behavior (which can be clustered in regions or states).

Let D_{ij} be the distance to deliver order i from store j, in miles, the same variable mentioned in cost saving objective function.

X_{ij}: Binary variable, where 1 represents that the order i will be picked up in store j, otherwise it will be 0. This binary variable is also used in the transportation optimization model included for the first strategic objective (transportation optimization) mentioned in the introduction of this project.

CHAPTER 4: RESULTS AND DISCUSSION

After running the cost optimization model and calculating the CO_2 emissions savings that were described in the previous sections, we analyze the outputs. To get a representative sample of the total US population, we use the data from one state from the East Coast and one state from the West Coast: Massachusetts and California.

Cost optimization analysis

We performed a sensitivity analysis with different P values (the customer's willingness to pick up their orders in store). After running the cost optimization function with the restrictions described in Chapter 3, we compared the cost savings and optimal number of enabled stores. Figure 4 and Figure 5 show the impact of different P values in the cost savings and number of stores selected. The blue bars and left axis show the cost savings in dollars while the orange line and right axis show the optimal number of stores selected as pick-up locations.

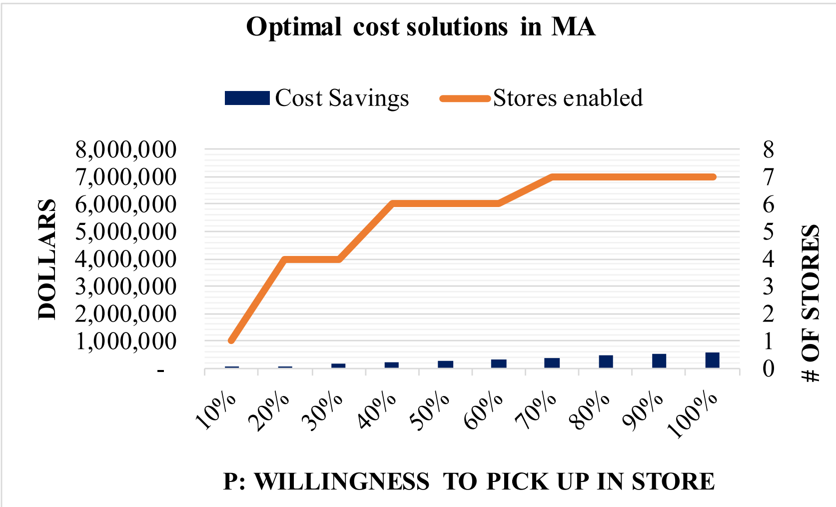

Figure 4. Optimal cost solutions in MA

Figure 4 shows that, in the state of Massachusetts and for the period of the 9-month study, The Company can save \$77K when P=20%.

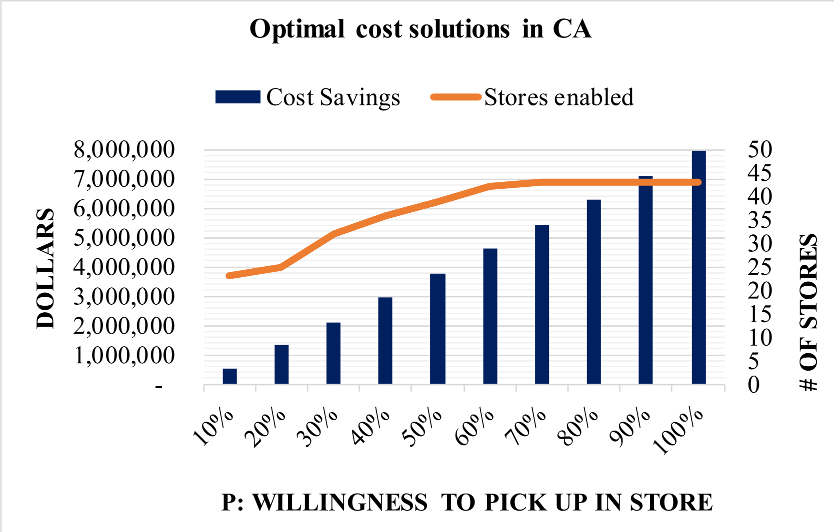

Figure 5. Optimal cost solutions in CA

Figure 5 shows that, in the state of California and for the period of the 9-month study, The Company can save $1,319K when P=20%.

Figure 6 shows the location of the stores in MA selected as pick-up spots for a P=20%. The stores selected are in the towns of Natick, Braintree, Danvers and Burlington. In the map the size of the circle is associated with the amount of cost savings in dollars.

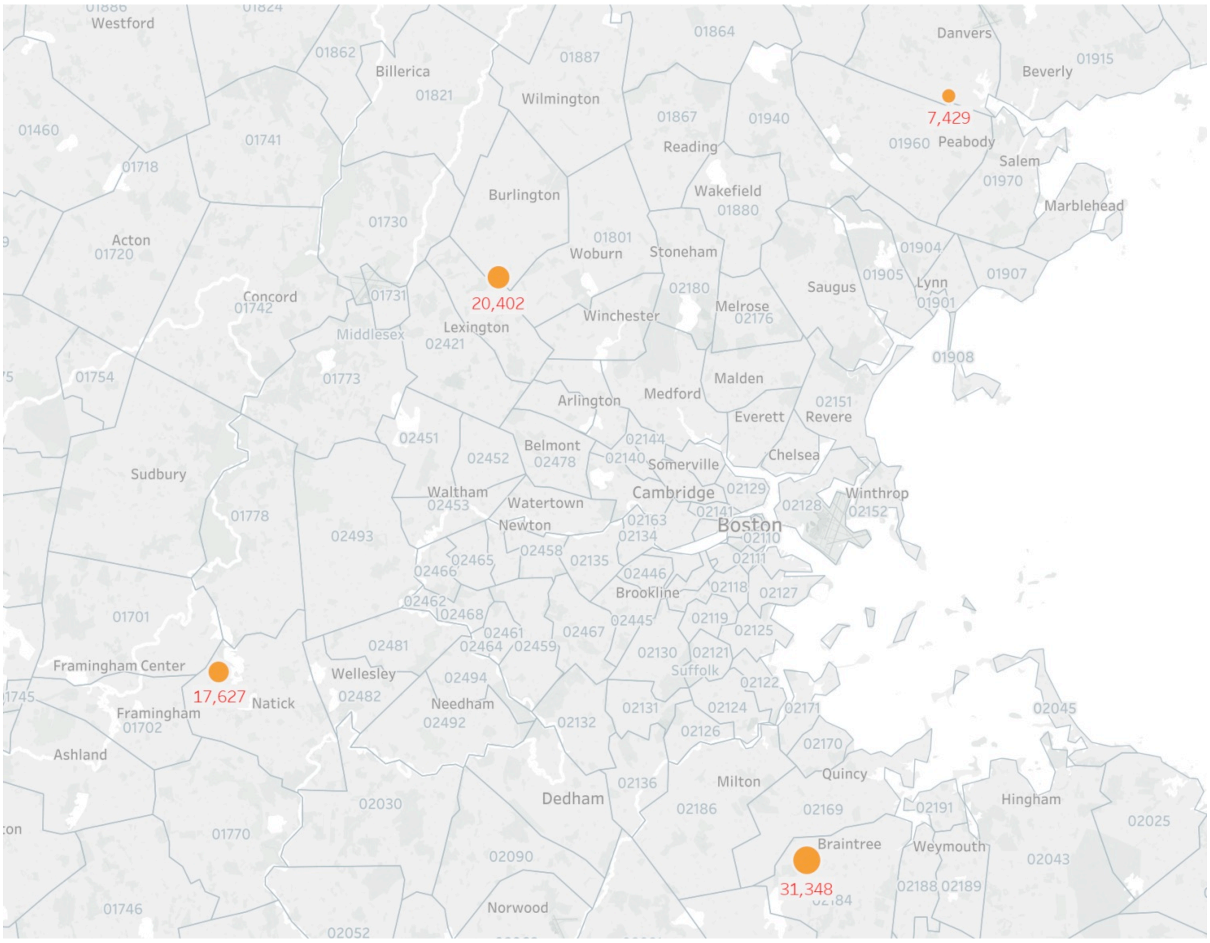

Figure 6. Selected stores in MA

Related to Figure 6, Table 2 shows the detailed cost savings per store in Massachusetts. The table shows the stores with more potential cost savings at the beginning.

Table 2. List of selected stores in MA

Store_Num	Town	TotalPackages	20% Packages	CostSaving	FixedCost
534	Braintree	36,959	7,392	$31,348	$10,000
543	Burlington	26,468	5,294	$20,402	$10,000
531	Natick	24,609	4,922	$17,627	$10,000
542	Danvers	15,634	3,127	$7,429	$10,000
			Total Savings:	$76,806	

It might be surprising that stores in the city of Boston are not selected in the optimal solution. By running the model with a maximum distance (radius) of 6 miles instead of 10 we do get one store selected in Boston; however, the cost savings are lower as less packages are picked up by customers. On the other hand, in this scenario the trucks CO_2 emission is lower because Boston is a dense city, and thus the cutoff point to achieve CO_2 savings is lower (70%). These alternative results can be found in Appendix A. By analyzing alternative scenarios, we are able to adjust to different situations that The Company might consider adequate.

Figure 7 shows the location of the stores in CA selected as pick-up spots for a P=20%. Similar to Figure 6, in this map the size of the circle is associated with the amount of cost savings in dollars.

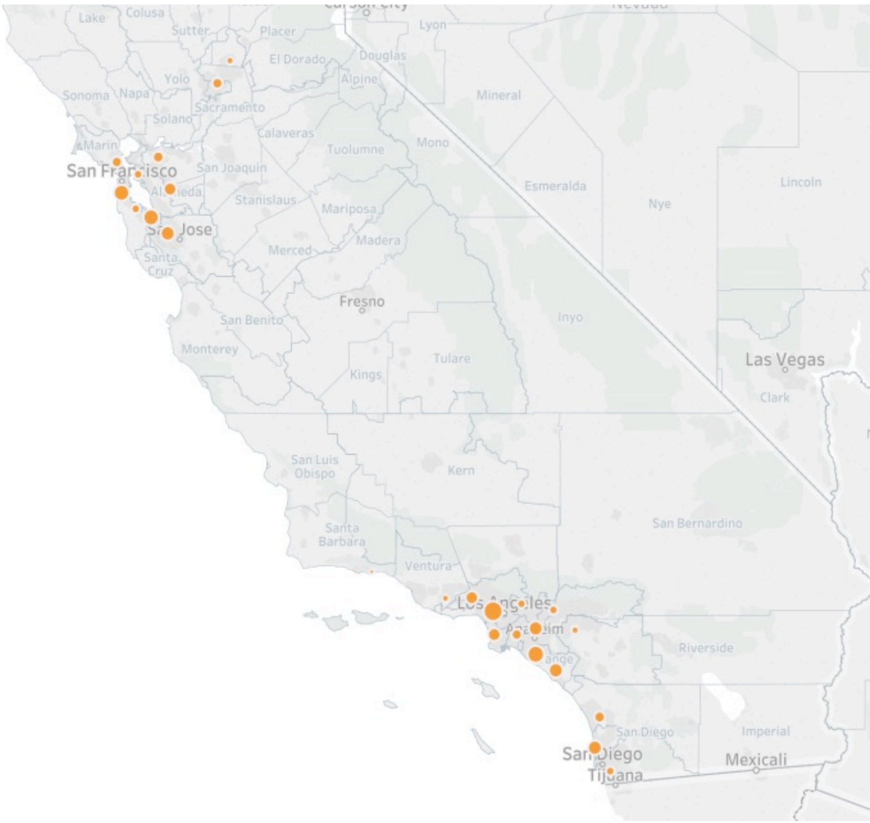

Figure 7. Selected stores in CA

The next two figures provide a closer look of the San Francisco, Los Angeles area and their nearby cities.

Figure 8 shows that within the San Francisco area and its nearby cities, the selected stores are in the counties of Santa Clara, San Mateo, Alameda, Marin, Contra Costa, Sacramento and Placer.

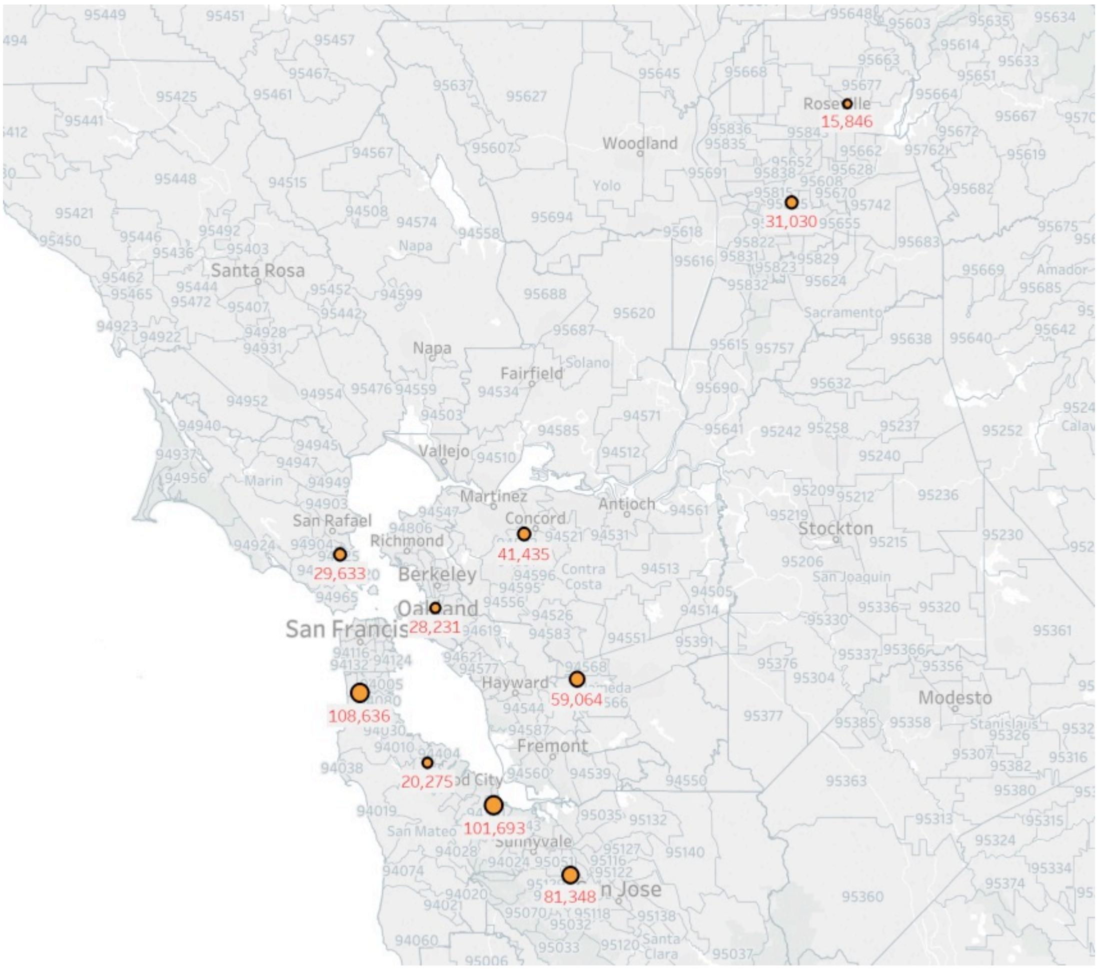

Figure 8. Selected stores in San Francisco area

Figure 9 shows that within the Los Angeles area and its nearby cities, the selected stores are in the counties of San Diego, Orange County, Los Angeles, Riverside, San Bernardino, Ventura and Santa Barbara.

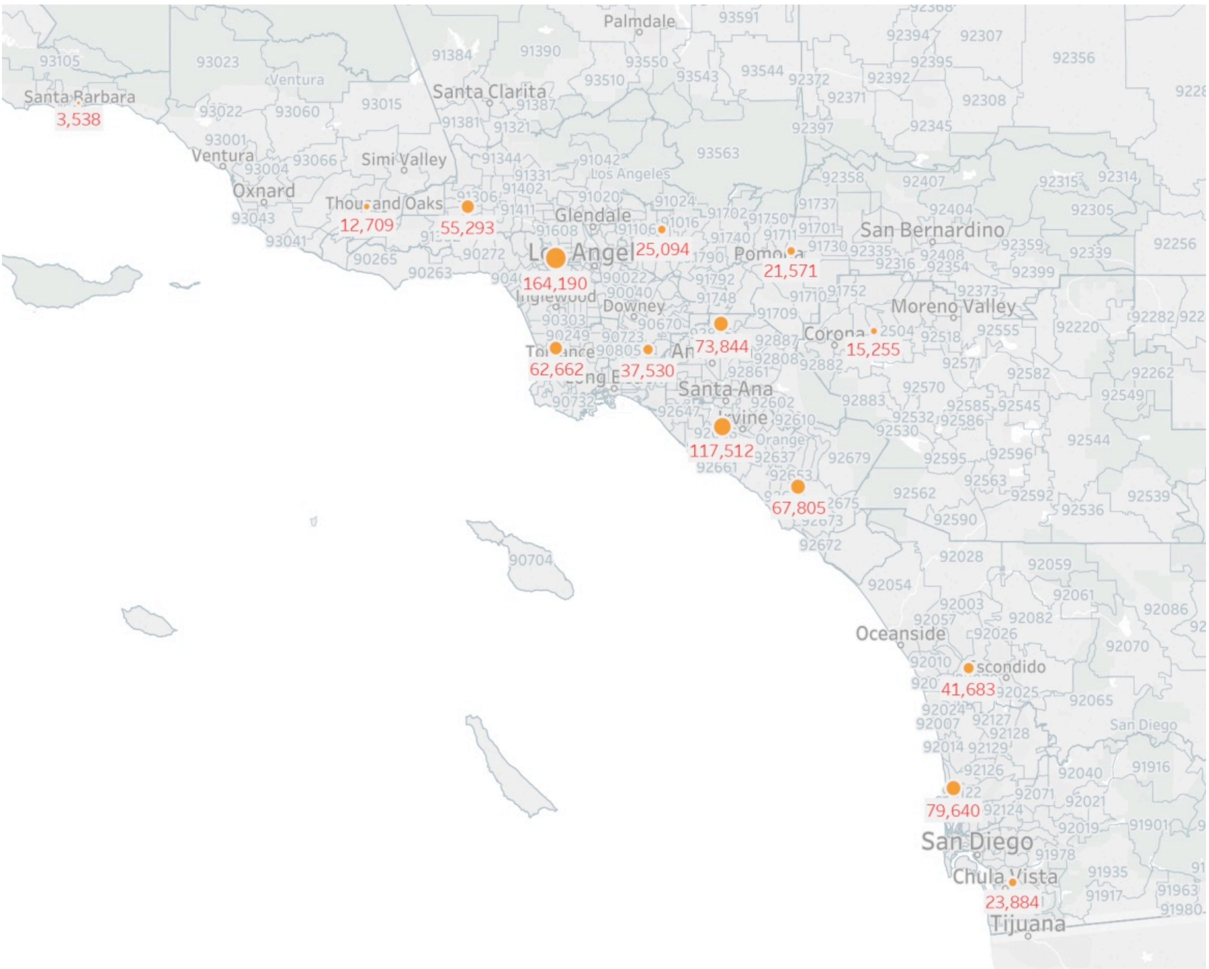

Figure 9. Selected stores in Los Angeles area

Table 3 shows the detailed cost savings per store in California. The table shows the stores with more potential cost savings at the top.

Table 3. List of selected stores in CA

Store_Num	County	#Packages	20% #Packages	CostSaving	Fixed Cost
349	Los Angeles County	158,700	31,740	$164,190	$10,000
320	Orange County	115,253	23,051	$117,512	$10,000
428	San Mateo County	110,516	22,103	$108,636	$10,000
472	San Mateo County	92,754	18,551	$101,693	$10,000
425	Santa Clara County	85,259	17,052	$81,348	$10,000
166	San Diego County	75,907	15,181	$79,640	$10,000
321	Orange County	77,340	15,468	$73,844	$10,000
326	Orange County	71,489	14,298	$67,805	$10,000
370	Los Angeles County	67,135	13,427	$62,662	$10,000
430	Alameda County	63,522	12,704	$59,064	$10,000
341	Los Angeles County	57,642	11,528	$55,293	$10,000
383	San Diego County	47,107	9,421	$41,683	$10,000
479	Contra Costa County	46,738	9,348	$41,435	$10,000
322	Los Angeles County	44,666	8,933	$37,530	$10,000
433	Sacramento County	38,053	7,611	$31,030	$10,000
423	Marin County	35,745	7,149	$29,633	$10,000
435	Alameda County	35,461	7,092	$28,231	$10,000
345	Los Angeles County	33,142	6,628	$25,094	$10,000
363	San Diego County	31,421	6,284	$23,884	$10,000
323	San Bernardino County	29,562	5,912	$21,571	$10,000
420	San Mateo County	27,761	5,552	$20,275	$10,000
434	Placer County	23,956	4,791	$15,846	$10,000
325	Riverside County	23,666	4,733	$15,255	$10,000
348	Ventura County	21,057	4,211	$12,709	$10,000
344	Santa Barbara County	12,570	2,514	$3,538	$10,000
			Total Savings:	$1,319,403	

Environmental Analysis

After developing our emissions estimation tools described in Chapter 3, we compare the trucks' CO_2 emissions and the cars' CO_2 emission. However, the difference in environmental impact also depends on two important variables:

1. The percentage of customers who would be willing to walk, bike or use public transportation. In this project this variable is encapsulated in the B parameter.
2. The number of packages that each truck delivers per trip. This number will determine the overall number of trips for the trucks.

The effect of these two variables mentioned above is reflected in Figures 10 and 11. These figures show the effect in CO_2 emission that the number of packages per truck-route has and compare it with the car emissions. These last will directly depend on the customers' willingness to walk, bike or take public transportation (our B parameter).

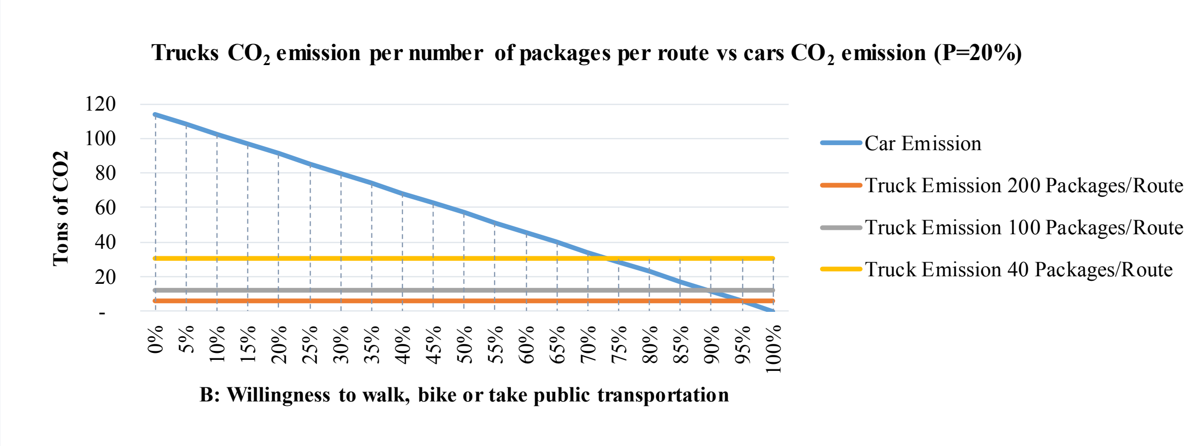

Figure 10. Trucks CO_2 emission vs. cars CO_2 emission in MA when P=20%

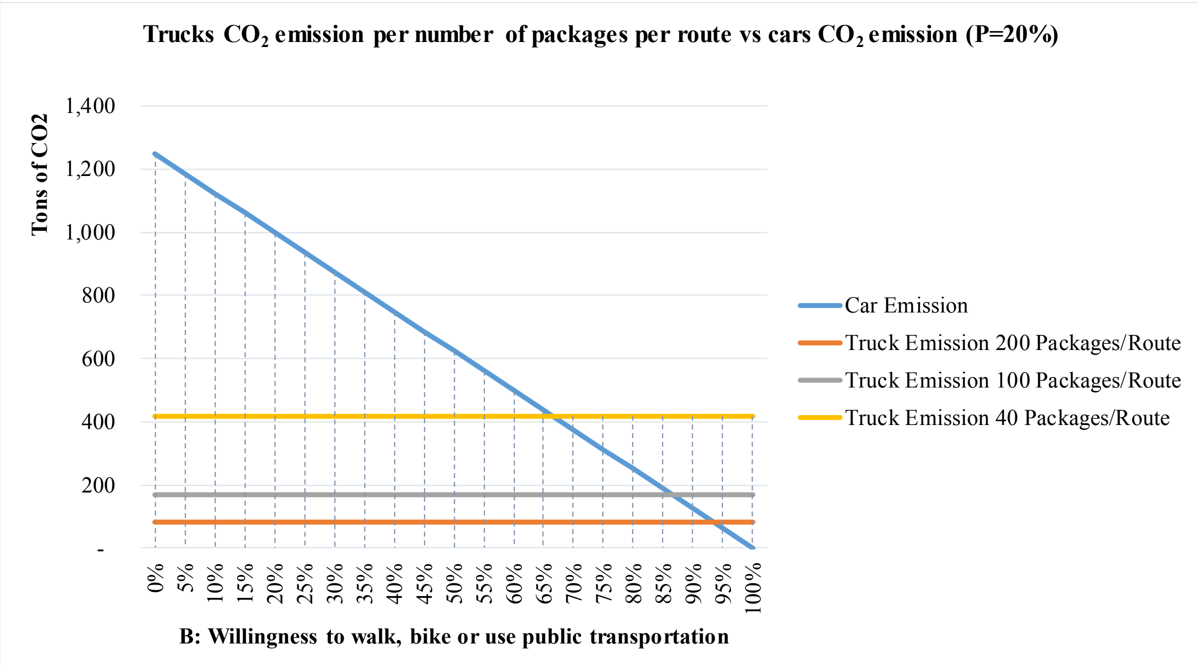

Figure 11. Trucks CO_2 emission vs. cars CO_2 emission in CA when P=20%

Figure 10 shows that, in Massachusetts, when the truck's number of packages per route equals 40, the CO_2 emission is 30 tons, whereas when the number increases to 100 and 200, the emission decreases to 12 and 6 tons, respectively. Figure 11 shows that, in California, when the truck's number of packages per route equals 40, the CO_2 emission is 419 tons, whereas when the number increases to 100 and 200, the emission decreases to 168 and 84 tons, respectively. In both cases, the cars' CO_2 emission will depend on B and will reach a trade-off point with each package-per-route truck scenario.

The results from both states can be surprising not only because B needs to reach high levels to achieve CO_2 emission savings, but also because the parcel carriers' decisions about route design have a high degree of influence. Determining the number of packages that each of these parcel trucks delivers will directly impact the trucks' CO_2 emission.

Additionally, Table 4 shows that California requires lower minimum B values to achieve CO_2 savings when compared to Massachusetts. One of the reasons for this is the difference in population density in both states. On the other hand, the difference can be compensated for if we analyze the differences in accessibility and infrastructure that both states have when it comes to walking, biking and taking public transportation.

Table 4. Comparison of B for MA and CA

	Minimum B required to have CO_2 savings	
	MA	CA
200 Packages/Route	95%	94%
100 Packages/Route	90%	86%
40 Packages/Route	74%	66%

Limitations of our models

While we believe that the methodology we developed in this project is accurate in analyzing the cost and environmental implication of setting stores as pick-up locations, we also acknowledge that there are limitations to our approach.

First, our model does not consider the possibility that the customers would be willing to consolidate their trip to the stores with other necessities. For example, there might be a situation in which the customer needs to run an errand and at the same time uses this trip to also pick up his or her order in

The Company's store. This could be estimated as an efficiency factor within the total CO_2 emissions of cars.

Second, our model does not consider any unsuccessful deliveries that the truck delivery might have. Unsuccessful deliveries usually mean higher CO_2 emission due to the inefficiency in the transportation process.

Third, there is an especially important activity in the last mile delivery within the e-commerce business and that is packaging. The amount of packaging increases in the last mile delivery and it involves several sub-processes that generate CO_2 emission.

Fourth, our model does not consider the possibility that an item would be unavailable at a store. If this scenario happened, it would directly impact the customers' willingness to travel to a further store to pick up an order.

Lastly, in our model the distances were calculated by using each locations' ZIP code, whereas using the detailed addresses would provide more precise calculations. We were not able to use customers' addresses due to privacy policies within The Company.

CHAPTER 5: CONCLUSION

In this study, we focus on analyzing the best store candidates for a pick-up-in-store channel. Our analysis has two aspects: cost optimization and environmental impact. We develop a mathematical model in which the objective function aims to maximize the cost savings, while another function measures the CO_2 emissions savings. Moreover, we endeavor to shed light on the sensitivity of the outcome to 3 parameters: the customers' willingness to pick up the order in store (P), the customers' willingness to avoid using their motor vehicle (B), and the carriers' route design in terms of packages per trip.

The Company provided us the data of a 9-month period (from January 2018 to September 2018). According to our analysis, if we consider a P value of 20%, The Company can save $77K in Massachusetts and $1,319K in California. By taking these results into account, we suggest that The Company should focus on encouraging the pick-up-in-store alternative in denser (in terms of customers, not population) locations like California, as Table 3 suggests. The Company has 25 stores to be enabled as pick-up spots in California, while Table 2 suggests only 4 stores in Massachusetts.

In addition to these results, we argue that, regardless of what the P value is, the amount of CO_2 emissions that the pick-up-in-store option can save depends on the customers' willingness to avoid using motor vehicles, which, as a minimum, must stay within the ranges from 74% to 95% in Massachusetts and from 66% to 94% in California.

In the future, this willingness can be estimated by studying the consumers' behavior, urban infrastructure, public transportation system and accessibility to alternative transportation modes such as bikes, in each region of the country. We recommend to The Company to perform this study as a foundation base to create a program to incentivize and educate its customers in using more environmentally friendly transportation modes. A good way to do so could be by providing incentives in the ecommerce platforms. We have seen companies like Amazon doing similar work by providing faster deliveries if the customers opt to pick up their orders in a pick-up location such as lockers or the company's facilities.

The number of packages per route in the last mile delivery plays an important role in measuring the environmental impact. By increasing the number of packages of each truck trip, the last mile home delivery becomes more environmentally friendly, meaning that the pick-up-in-store option would have more CO_2 emission than the home delivery option. We recommend that The Company shares the results of our study with its carriers in order to develop a cohesive and integral environmental plan.

Lastly, we believe that this sensitivity analysis will serve as a tool for The Company to make strategic decisions that will align with its environmental objectives. Our models' robustness will allow The Company to expand the analysis to every state of the country and to change accordingly some of the important parameters we encountered and presented in this project.

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APPENDICES

A. Alternative solution for Massachusetts (Maximum distance = 6miles)

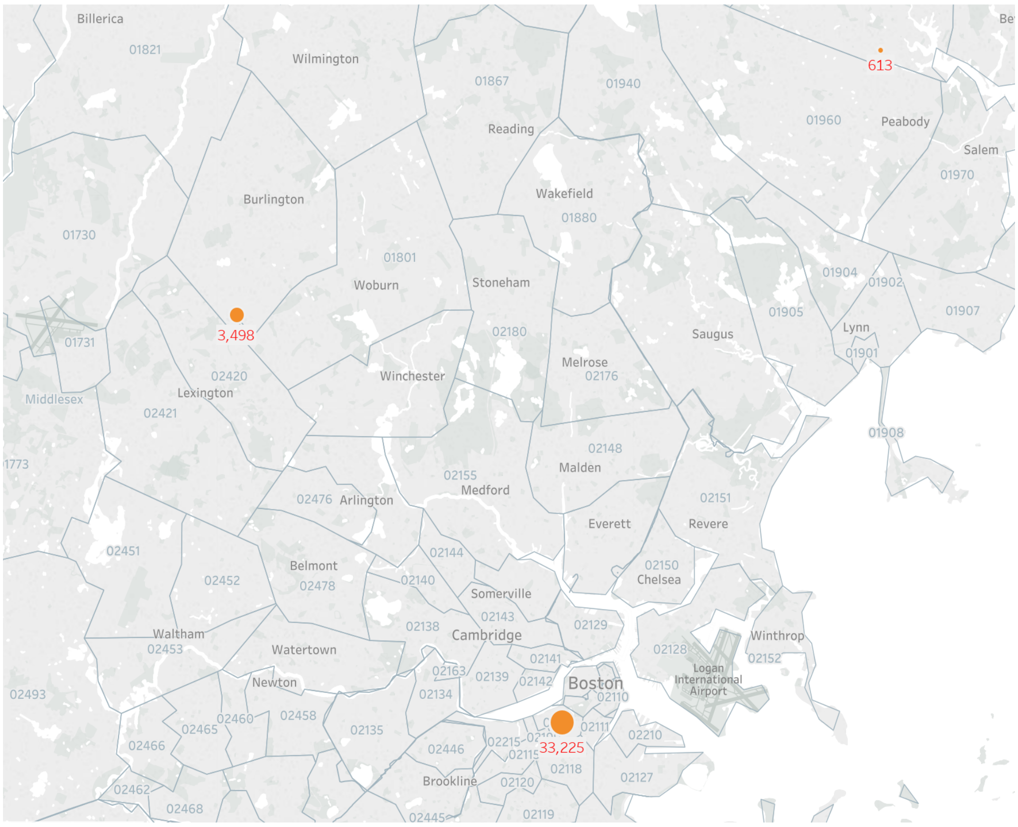

Figure A-1. Selected stores in MA

Table A-1. List of selected stores in MA

Store_Num	TotalPackages	20%Packages	CostSaving	FixedCost
547	38,656	7,731	$33,225	$10,000
543	11,429	2,286	$3,498	$10,000
542	9,545	1,909	$613	$10,000
			$37,337	

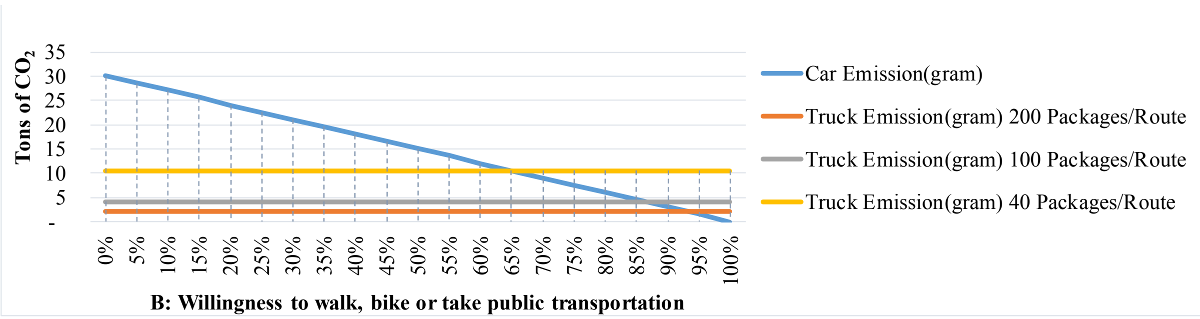

Figure A-2. Trucks CO_2 emission vs cars CO_2 emission in MA when P=20%

B. Python code

```
#Setup parameters
Pcnt=0.2
Max_Miles=10
M=10000000
#Setup variables
prob=pulp.LpProblem("Optimal Pickup Store",pulp.LpMaximize)
Dmd=pulp.LpVariable.dicts("Demand",[(i,j) for i in COMP.index for j in
StoreLoc.index],cat='Binary')
Store=pulp.LpVariable.dicts("Store Status",[j for j in StoreLoc.index],cat='Binary')

#Define objective function of maximizing cost saving
prob+=pulp.lpSum((Dmd[(i,j)]*Pcnt*COMP.loc[i,'NetChgs'])
for j in StoreLoc.index for i in COMP.index)-pulp.lpSum(StoreLoc.loc[j,'Set_Up Cost']*Store[j]
for j in StoreLoc.index)
#Set up constraints
for i in COMP.index:
    prob+=pulp.lpSum(Dmd[(i,j)] for j in StoreLoc.index)<=1
for j in StoreLoc.index:
for i in COMP.index:
prob+=Dmd[(i,j)]*Disct((COMP.loc[i,'lat'],COMP.loc[i,'lon']),(StoreLoc.loc[j,'Latitude'],
StoreLoc.loc[j,'Longitude']))<=Max_Miles
for j in StoreLoc.index:
    prob+=pulp.lpSum(Dmd[(i,j)] for i in COMP.index)<=Store[j]*M
#Solver the problem
prob.solve()

#Saved the selected order and location to open pick-up services and the amount of cost saving
#respectively
SelectedOrder=[]
SelectedLocation=[]
temp=0
Pickup=[]
save={}
tempsave=0
for j in StoreLoc.index:
tempsave=0
    for i in COMP.index:
                if Dmd[(i,j)].value()==1:
                        SelectedOrder.append(i)
                        SelectedLocation.append(j)
                        temp=temp+COMP.loc[i,'Number of Orders']
                        tempsave+=COMP.loc[i,'NetChgs']*Pcnt
    save[str(j)]=tempsave
     if Store[j].value()==1:
                Pickup.append((j,temp))
SelectedOrder=set(SelectedOrder)
SelectedLocation=set(SelectedLocation)

#Setup parameters
TEcar=404
FCempty=0.177
FCfull=0.216
Capacity_Truck=8796
```

```
Pcnt_Walk=0
A=3.1415926*(Max_Miles**2)
Ktsp=0.97
N={}
WGT={}
Disct_Truck={}
TN=0
TWGT=0
TmpN=0
TmpW=0
TEtruck=0

SelectedOrder=[]
SelectedLocation=[]
for j in StoreLoc.index:
for i in COMP.index:
                    if Dmd[(i,j)].value()==1:
                            SelectedOrder.append(i)
                            SelectedLocation.append(j)
                            TmpN+=COMP.loc[i,'Number of Orders']*Pcnt
                             TmpW+=COMP.loc[i,'Ship_Weight']*Pcnt
   N[str(j)]=TmpN
   TmpN=0
   WGT[str(j)]=TmpW
   TmpW=0
   Disct_Truck[str(j)]=(Ktsp*((40*A)**(0.5))+Max_Miles)*(N[str(j)]/100)
#Define function to calculate carbon dioxide emission of truck
def Truck_CO2_Emission():
   TEtruck=0
   for j in StoreLoc.index:
     if Store[j].value()==1:
                    TEtruck+=2621*Disct_Truck[str(j)]*(FCempty+(FCfull-FCempty)*0.3)
return TEtruck

#Define function to calculate carbon dioxide emission of car
def Car_CO2_Emission():
   TE_car=0
   Car_Disct=0
   for j in StoreLoc.index:
     for i in COMP.index:
            if Dmd[(i,j)].value()==1:
Car_Disct+=2*Pcnt*(1-Pcnt_Walk)*COMP.loc[i,'Number of
Orders']*Disct((COMP.loc[i,'lat'],COMP.loc[i,'lon']),
(StoreLoc.loc[j,'Latitude'],StoreLoc.loc[j,'Longitude']))
   TE_car=Car_Disct*TEcar
   return TE_car
```