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Polina Butrina

Preparing cities for package demand growth: predicting neighborhood demand and
implementing truck VMT reduction strategies

Polina Butrina

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Anne Goodchild, Chair

Edward McCormack

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University of Washington

Abstract

Preparing cities for package demand growth: predicting neighborhood demand and implementing truck VMT reduction strategies

Polina Butrina

Chair of the Supervisory Committee:
Anne Goodchild, PhD
Department of Civil and Environmental Engineering

E-commerce has empowered consumers to order goods online from anywhere in the world with just a couple of clicks. This new trend has led to significant growth in the number of package deliveries related to online shopping. Seattle's freight infrastructure is challenged to accommodate this freight growth. Commercial vehicles can already be seen double parked or parked illegally on the city's streets impacting traffic flow and inconveniencing other road users. It is vital to understand how the package demand is growing in the neighborhoods and what freight trips reduction strategies can cities implement to mitigate the freight growth.

The purpose of the research is to analyze Vehicle Miles Traveled (VMT) reduction strategies in the neighborhoods with different built environment characteristics.

First, the impact of individual factors on person's decision to order goods online for home delivery is analyzed. A predictive model was built that estimates online order probability based on these factors. This model is then applied to synthetic Seattle population to produce estimated demand levels in each neighborhood.

Second, two VMT reduction strategies were modeled and analyzed: 1) decreasing number of trucks needed to deliver neighborhoods' package demand and 2) package locker implementation.

Based on packages demand and built environment characteristics, two neighborhoods were chosen for a case study. ArcGIS toolbox was developed to generate delivery stops on the route, ArcGIS Network Analyst was used to make a delivery route and calculate VMT.

It was found that VMT reduction strategies have different effects on the delivery system in two neighborhoods. Delivering neighborhoods' demand in a smaller number of trucks would save slightly more VMT in a dense urban area compared to suburban one. Moreover, since the traffic perception by different road users varies by neighborhood, VMT reduction strategies will be more critical to implement in dense urban areas. Locker implementation strategy will also be more effective in VMT reduction in a dense urban area due to high residential density.

TABLE OF CONTENTS

List of Figures	1
List of Tables	3
Chapter 1. Introduction	5
1.1 Problem Statement	7
Chapter 2. Literature review	8
2.1 Package demand forecasting	8
2.2 Urban Freight Solutions	10
Chapter 3. Methodology	15
3.1 Package Demand Forecasting	15
3.2 VMT Reduction Strategies	28
3.3 Modeling Tools	30
3.3.1 ArcGIS Toolbox for modeling delivery stops	30
3.3.2 Inputs	32
3.3.3 Output	35
3.4 Case Study: Neighborhood Choice	36
3.5 Case Study: Model Set Up	39
Chapter 4. Analysis and Results	45
4.1 Variable Number of Trucks	45
4.2 Lockers	46

4.2.1	Lockers without a walking buffer	46
4.2.2	Lockers with walking buffer	48
Chapter 5. Conclusion.....		51
Chapter 6. Discussion		53
6.1	Limitations and next steps	55
Chapter 7. References		58

LIST OF FIGURES

Figure 1.1 Density growth in metropolitan areas from 2010 to 2016. (The New York Times, 2017)	6
Figure 2.1 Effect of Spatial Attributes on Online Buying (Xinyu,2009).....	9
Figure 2.2 Street in the historic center of Stockholm on the left. Street in the historic center of the Amsterdam on the right.	10
Figure 3.1 Flow of analysis process.....	16
Figure 3.2 Percentage of people who have made a purchase for home delivery, group by age	18
Figure 3.3 Relation of income level to online ordering	19
Figure 3.4 Percentage of people who have made a purchase for home delivery, group by age	22
Figure 3.5 Percentage of people who have made a purchase for home delivery, group by employment.....	23
Figure 3.6 Percentage of people who have made a purchase for home delivery, group by income.....	24
Figure 3.7 Percentage of people who have made a purchase for home delivery, group by education	25
Figure 3.8 Percentage of people who have made a purchase for home delivery, group by Forecast Analysis Zone (FAZ) in Puget Sound Region	26
Figure 3.9 Density of the package demand for residential buildings	27
Figure 3.10 Survey results on the distance people are willing to carry a package	29
Figure 3.11 Parcels Stops Generation Toolbox’ inputs and output	31
Figure 3.12 Output Table Example.....	35
Figure 3.13 Tract 41 as a case study for a high residential density mixed-use neighborhood	37
Figure 3.14 Tract 72 as a case study for a residential neighborhood.....	38
Figure 3.15 Spatial distribution of delivery stops at Laurelhurst neighborhood constructed using randomly assigning a number of packages, predicted by a demand forecasting model (Section 3.1) to each household with equal probability.....	39

Figure 3.16 Spatial distribution of delivery stops in Belltown constructed using randomly assigning a number of packages, predicted by a demand forecasting model (Section 3.1.) to each household with equal probability.....	40
Figure 3.17 Locker Location in Belltown.....	41
Figure 3.18 Locker Location in Laurelhurst.....	42
Figure 3.19 Walking buffers around the locker in Laurelhurst	43
Figure 3.20 Walking Buffers around the locker in Belltown.....	43
Figure 4.1 Percentage of VMT savings by reducing the number of delivery trucks	46
Figure 4.2 Delivery truck VMT in Laurelhurst when modeling lockers with walking buffer scenario	49
Figure 4.3 Delivery truck VMT in Belltown when modeling lockers with walking buffer scenario	50
Figure 6.1 Picture of one of the streets in suburban neighborhood	54
Figure 6.2 Picture of one of the streets in Belltown. Carrier’s truck is double packed on the street.	55

LIST OF TABLES

Table 3.1 Data Description	17
Table 3.2 Estimate result of logistic regression model	20
Table 3.3 AIC and Sum Squared prediction error	21
Table 3.4 List of the parcels data sets that were used for delivery stops generation	33
Table 3.5 Built environment characteristics of two neighborhoods chosen for the case study	38
Table 4.1 VMT produced by variable number of trucks in Laurelhurst and Belltown	45
Table 4.2 VMT produced when modeling a locker without a walking buffer in Laurelhurst and Belltown	47
Table 4.3 VMT produced when modeling a locker with a walking buffer in Laurelhurst	48
Table 4.4 VMT produced when modeling a locker with a walking buffer in Belltown	49

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Chapter 1. INTRODUCTION

Wide internet access from any devices has accelerated e-commerce growth all over the world. Consumers are able to order anything from groceries to winter sports goods online with just a couple of clicks (or taps on the phone screen). This new trend has led to significant growth in the package delivery related to online shopping. According to U.S. Census Bureau, e-commerce sales had an increase of 16.9% in the fourth quarter 2017 compared to the fourth quarter 2016 and accounted for 9.1 % of all retail sales in the United States (The Census Bureau of the Department of Commerce, 2018).

Urbanization rates are also growing (Central Intelligence Agency, 2017). Seattle has the highest rates of urban growth in the country with 3% increase in neighborhood density (Figure 1.1). This growth results in high freight movements' influx in the city that contributes to traffic, noise, and pollution. Moreover, the city's freight infrastructure is unlikely to change much, but it is expected to accommodate the freight growth. As a result, double parked or illegally parked trucks that are blocking travel lanes, bicycle and pedestrian infrastructure can already be observed on the cities streets.

Change in average neighborhood density, 2010 to 2016.

Metropolitan areas that became more dense

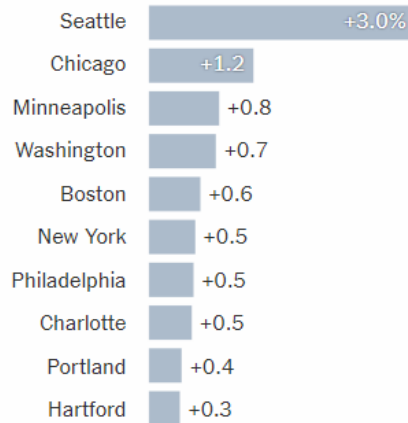


Figure 1.1 Density growth in metropolitan areas from 2010 to 2016. (The New York Times, 2017)

The last mile of the delivery includes travel from distribution center (DC) to the customer. It consists of several delivery steps including parking, loading and unloading operations, interactions with security and the final addressee, pick up goods, etc (Morris, 2009; SDOT, UW SCTL, 2018). These activities could be very complex in dense urban areas due to a convoluted process that involves multiple stakeholders and lack or aging infrastructure struggling to keep up with freight demand. The last mile in urban areas is considered to be the most inefficient part of the supply chain. (Dablanc, 2007; Kin, 2017)

Cities are working on creating sustainable communities that prioritizing bicyclists and pedestrians by removing parking on some of the streets in downtown and creating more public transit options. However, this process is likely to create more problems for freight operations. Thus, it is vital to understand where urban freight demand is concentrated and how cities can either mitigate the increased freight demand or allocate existing freight infrastructure to meet freight demand.

In recent years, cities and carriers have been testing innovative urban freight solutions. Carriers such UPS and DHL were deploying cargo bicycles across Europe and U.S. Package lockers, and

pick-up points were implemented in some cities. It is important to understand where to implement these solutions and how the different strategies can perform in the neighborhoods that have different built environment characteristics.

1.1 PROBLEM STATEMENT

In this research, following questions were investigated:

- 1) What are the characteristics of the people who are shopping online in PSRC region?
- 2) Can a model be built to forecast residential delivery demand for each neighborhood in Seattle?
- 3) Does density of the neighborhood affect the efficiency of different VMT reduction strategies measured in terms of a number of travel miles saved?

The rest of this thesis organized as follows:

Chapter 2 discusses previous research on last mile, online shoppers' characteristics, and urban freight solutions that cities are piloting. Chapter 3 discusses the Puget Sound Regional Council's household travel survey and analyzes characteristics of people who make an online order. It discusses the neighborhoods chosen for the case study. It furthermore describes the tools developed for parcel distribution modeling and two VMT reduction scenarios. Chapter 4 describes the results obtained from the proposed scenarios modeling including a variable number of trucks and lockers. Chapter 5 covers conclusion. Chapter 6 presents a discussion section where limitations and further research questions are discussed.

Chapter 2. LITERATURE REVIEW

2.1 PACKAGE DEMAND FORECASTING

The number of internet users has increased in the last decades due to significant increase in the number of smartphone use and other internet-enabled devices along with their application and services that makes internet more accessible (Al-Debei, 2015). This new trend has led to a significant growth in the package delivery related to online shopping.

With rapid changes in retail purchasing patterns, marketing agents and researchers have been studying diverse factors that may affect online shopping. Retailers, real estate developers, and urban planners are also interested in learning more about geographic distribution of online shoppers and impacts on land use development.

Researchers have studied various factors that will help predict customer buying behavior. These factors include demographic features, internet usage, product information, perception of risk, online ordering experience, website quality, etc. (Na Li, 2002)

Several studies have investigated the association between demographics and propensity for online shopping. Specifically, previous research have focused on gender, income, age and education-level difference between shoppers. (Saleh, 2015) collected data through questionnaires that study the relationship between demographics and online shopping propensity. The study found that gender had insignificant effect. On the other hand, income and education did present significant difference in the future intentions of online shopping.

(Xinyu, 2009) analyzed data from two studies on the relationships between spatial attributes and online purchases that have been conducted by (Farag, 2006) and (Weltevreden, 2008). (Anderson, 2003) suggests two hypotheses: innovation–diffusion hypothesis and an efficiency hypothesis. Innovation–diffusion hypothesis assumes that people in urban areas are more open to modern

technologies and ideas than those in remote areas because urban areas promote creative thinking and innovation. Therefore, the first hypothesis states that urban residents are more likely to purchase goods online with well-connected internet services of the urban areas. On the other hand, the efficiency hypothesis suggests that online shopping is more pervasive in groups that reside in areas with low shopping accessibility. Several past research works that tested the innovation–diffusion and efficiency hypotheses for online shopping are summarized in Figure 2.1.

TABLE 1 Effects of Spatial Attributes on Online Buying

Study	Sample	Method	Shopping Variable	Spatial Variable	Results	Conclusions
Farag et al. (20)	826 respondents in four municipalities in the Netherlands, 2003	Path analysis	Frequencies of online searching and online buying	Urban versus suburban	The direct effects of residential environment on online searching and online buying were insignificant.	Frequency: N
Farag et al. (16)	2,190 users collected by Multiscope, the Netherlands, 2001	Binary logit model and linear regression	Online searching adoption; online buying adoption; and frequency of online buying	Five dummy variables indicating levels of street address density; shops in 10 (20, 30) minutes by car	People living in a (very) strongly urbanized area had a higher likelihood of buying online; people with a low shop accessibility buy more often online. Spatial location affects the likelihood of online buying for different types of products differently.	Adoption: ID Frequency: E
Farag et al. (19)	360 individuals from Minnesota, U.S., 2002; 634 individuals from Utrecht, the Netherlands, 2003	Binary logit model	Online buying adoption; online buying frequency	U.S.: shops within walking distance; Dutch: travel time to shops	Shopping accessibility was positively associated with online buying adoption for the Dutch.	Frequency: N Dutch Adoption: ID American Adoption: N
Farag et al. (21)	826 respondents to a shopping survey sent to residents of four municipalities in the Netherlands, 2003	Structure equations model (SEM)	Frequencies of online searching and online buying	Shops in 10 minutes by bike; an indicator of street address density	Street address density and shopping accessibility had direct effects on online buying frequency.	Frequency: ID
Ferrell (22)	2000 San Francisco Bay Area travel survey	SEM	Teleshopping duration	Gravity-based employment accessibility	Retail employment accessibility had a positive influence on teleshopping duration.	Duration: ID
Krizek et al. (15)	About 740 adults from Seattle, Washington, Kansas City, Kansas, and Kansas City, Missouri, and Pittsburgh, Pennsylvania 2003	Chi-square and binary logit model	Online buying adoption; online buying frequency	City/suburban; distance to CBD; retail accessibility; metropolitan dummy	The observed bivariate difference in online buying within (and among) metropolitan areas resulted from confounding factors.	Frequency: N
Ren and Kwan (17)	392 Internet users in Columbus, Ohio	Binary logit model	Online buying adoption	The number (area) of shops in 6.25 (10, 12.5, 15, 20, 25) minutes by car	Shopping accessibility had a negative influence on the adoption of online buying.	Adoption: E
Weltevreden and van Rietbergen (18)	3,074 Internet users that shopped at eight city centers in the Netherlands, 2004	Multinomial logit model	The adoption of online buying	The number of shops within 5–45 minutes by car and by bike	There is no significant difference in shopping accessibility among online buyers, online searchers, and non-e-shoppers.	Adoption: N

NOTE: In the conclusions column, ID represents that findings support the innovation–diffusion hypothesis; E denotes that results favor the efficiency hypothesis; N means that no effects were found. Farag et al. (16), Krizek et al. (15), and Ren and Kwan (17) were explicitly designed to test the hypotheses.

Figure 2.1 Effect of Spatial Attributes on Online Buying (Xinyu,2009)

(Wang & Zhou, 2015) used 2009 National Household Travel Survey (NHTS) data to explore characteristics of online shoppers. The survey included the question about the frequency of purchase deliveries in a past month prior to taking the survey. Sample size was 103,198 individuals who provided valid answers. According to this research, individuals who use internet frequently, have high education levels, female, younger, healthy, self-employed, white, have higher household

income, live in a smaller household, and have children have higher delivery frequency. Housing unit density and heavy rail existence have positive correlation as well.

2.2 URBAN FREIGHT SOLUTIONS

There are many urban freight solutions that were tested and implemented in European Union and Japan. Narrow streets and sidewalks in the historical European city centers that make last-mile deliveries very challenging for the carriers. Figure 2.2 shows the historical centers in Stockholm and Amsterdam. The narrow streets and sidewalks are making loading and unloading operation very challenging for truckers. It is clear from the pictures that trucks have to either block travel lanes or block sidewalks to perform deliveries.



Figure 2.2 Street in the historic center of Stockholm on the left. Street in the historic center of the Amsterdam on the right.

There is a different picture in the U.S. with cities having more recent history and being more car-oriented. However, there are still many challenges associated with the last mile deliveries in the U.S. cities.



Figure 4. Delivery trucks parked illegally blocking either sidewalk and travel lane or bicycle lane. All pictures were taken in Seattle.

Some of the solutions that have been researched include consolidating packages either outside of the neighborhood (and distributing packages between the carriers) or inside the neighborhood.

Consolidation outside of the neighborhood

Majority of the literature covers Urban Consolidation Centers (UCC). UCC are the facilities built to be a shipment consolidation point for carriers before entering to the city. These are designed to reduce truck traffic coming into the neighborhoods, increase trucks' loading factors and improve the overall efficiency of urban deliveries (Browne et al., 2015). Previous work has shown that there are some challenges in implementation UCC including financial reasons and lack of sufficient carriers' participation (Allen et al., 2012; SUGAR, 2014; Quak, 2011). However, UCC has succeeded by providing 68% freight trips reduction in London using the London Construction Consolidation Center (SUGAR, 2014).

Consolidation inside of the neighborhood

Urban freight solutions of this type include either unattended physical delivery infrastructure (e.g., package lockers, delivery boxes, reception boxes) or commercial spaces where a customer can

pick up the delivery (e.g., click and collect package collection points, pickup points) (Allen et al., 2007).

These collection points have gained popularity in Europe. One example is the InPost package lockers network. According to a recent InPost study, implementation of the lockers decreased vehicle miles traveled from 93 miles delivering 60 packages to 43 miles delivering 600 packages (InPost, 2013). However, data for this study is not publicly available.

The pickup point networks are rapidly growing in Europe and the U. S. (Deloitte, 2015). Pickup points (PP) are retail stores (most often small businesses) that provide the option of a package pickup or drop off for the customer. One example of PP in the U. S. is UPS Access Points – these are small businesses or chain stores like 7-Eleven where UPS delivery drivers can drop off or pick up the packages for the receivers. The PPs are beneficial for retail establishments since it increases customer traffic there. The pickup points also help UPS to decrease failed first deliveries by making the customer come and pick up the shipment and decrease transportation costs by consolidating the packages at PP. Similarly, in Europe, there is a number of pickup points like ByBox in UK and France, PackStation, and Paketshop in Germany (Dablanc et al., 2015).

Most of the recent studies on lockers and PP in Europe and US are mostly qualitative. A study by (Morganti et al., 2014) explores the feasibility of PP by describing pickup point's network development in France and identifying factors that can affect PP network design. According to the interviews with companies managing PP, shippers, carriers, and retail owners hosting PP, the main difficulties in using PP were the limited capacity and competitive pricing. The interviewees noted that only light commercial vehicles are allowed to deliver to dense urban areas of some European cities because of heavy and medium truck access limitations. This limitation reduces the consolidation and increases delivery cost per package.

Studies have shown that there are some benefits to using pickup point's delivery networks. (Song et al., 2009; Edwards et al., 2010). (Song et al., 2009) compared different delivery methods including delivery to pick up points located in the post office, supermarkets, and rail stations, and truck deliveries to the customer's home with redelivery attempts accounting for the customer's trip to the carrier's depot in case of failed delivery. The study showed that traveling costs would be reduced by 58.6% in case when PP located in the postal office compared with traditional delivery. The traveling cost reduction would be smaller if PP would be located at the supermarkets. PP could reduce carrier's traveling costs from additional package delivery attempts between 4% and 9.3%. A study by (Edwards et al., 2010) showed that "the vast majority of emissions associated with traditional failed delivery arise from the personal trip to the local depot by a customer collecting a missed package." When PP were introduced to the system, they have shown significant savings in CO₂.

VMT and built environment characteristics

There are many studies on how built environment's factors influence VMT. Majority of studies have examined the relationship between people's travel behavior (and the VMT that they produce by using a household private vehicle) and built environment. Built environment characteristics have shown to be an important factor when explaining households' vehicle usage. (Diao & Jr., 2014; Hong et al., 2013; Vance & Hedel, 2007) Some of the factors that lead to lower VMT due to higher walkability, transit and bicycle use are connectivity, transit availability, density, land use diversity, street network characteristics, destination accessibility, and transit accessibility (Cervero, 2010; Frank, 2011; Moudon & Stewart, 2013; Porter et al., 2005; Ewing, 1996; Saelens, 2008).

However, there is lack of research about how built environment factors affects delivery truck VMT. Some studies mention how built environment factors like density influence the delivery vehicle choice (smaller vehicles like vans and motorbikes in denser urban areas, and medium-size trucks in suburban areas). (Dablanc, 2009)

Bronzini (Bronzini, 2008) conducted a literature review of various metropolitan planning organizations and state freight studies on the topic of the relationship between VMT, land use, and built environment. The study concluded that there is lack of research in this area. However, the literature available showed that high urban density correlates with lower truck VMT per capita.

A study by (Wygonik & Goodchild, 2016) evaluated the influence of built environment factors on VMT. Linear models were built for each of the three goods delivery models (with passenger vehicles, local depot delivery, and regional warehouse delivery). The study showed that increased road density would result in decreasing VMT. Also, reduction of the distance to a warehouse results in decreasing VMT.

Chapter 3. METHODOLOGY

The following chapter documents the methodology that was used for the analysis. The first section of the chapter shows the development of package prediction model. In the first section, 2014 and 2015 PSRC household travel surveys were analyzed. Based on the analysis, logistic model was built that was later used for the package prediction model. After, the predictions were made using Seattle's synthetic population ¹retrieved from PSRC. The second section defines two VMT reduction strategies that will be investigated. The third section covers data needed for modeling and ArcGIS script tools that were developed to generate delivery stops. The fourth section discusses the neighborhood choice for the case studies where VMT reduction strategies will be modeled. The fifth section shows model set up for the chosen neighborhood.

3.1 PACKAGE DEMAND FORECASTING

To create prediction model and to identify the critical variables that influence the probability of an individual to order online for any particular day in the Puget Sound region 2014 and 2015 Puget Sound Regional Council (PSRC) travel surveys were used. Variables considering personal, household and track level attributes have been considered, and logistic regression was used as the prediction model. Figure 3.1 shows the complete flow of analysis process.

¹ Synthetic population is a dataset that “contains a record for each household and separate records for each individual. All individual occupants are identified for any given household.” (Wheaton et. Al, 2009)

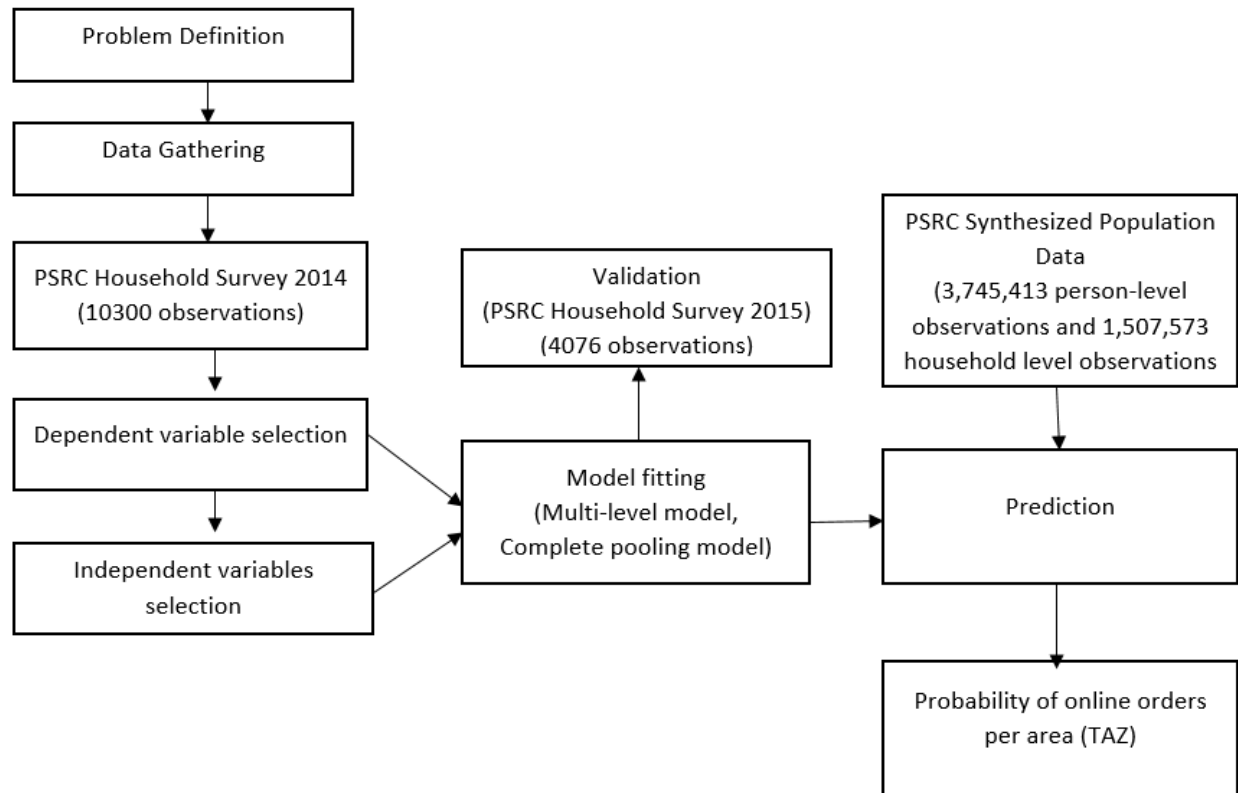


Figure 3.1 Flow of analysis process

Data

2014 PSRC household travel survey was used to investigate the characteristics of the people who shop online and to build the prediction model. 2015 PSRC household travel survey was used to validate the prediction model. It was not used in the prediction model because it has a much smaller sample size.

In these surveys, household and individuals travel patterns were collected for a 24-hour weekday period (Tuesday, Wednesday, Thursday) from a representative households sample in PSRC region including King, Kitsap, Pierce, and Snohomish counties. A sample size of the survey was 6036 households (approximately 12 100 people) in 2014 and 2442 households in 2015.

PSRC household survey consists of four different data levels that are categorized in 1) Household, 2) Person, 3) Vehicle, and 4) Trip levels. Table 3.1 Data Descriptions summarizes variables based

on those data levels. For the scope of the research, the variables from household and person-level data were considered.

Table 3.1 Data Description

Data Level	Number of variables	Example variables
Household	56	Income level Cumulative number of trips on travel day Household size Number of adults in household, etc.
Person	172	Age Gender Employment Education Purchase, etc.
Vehicle	10	Vehicle number Vehicle year Vehicle make Vehicle model, etc.
Trip	86	Trip origin information, Trip destination information, Main purpose, Main way traveled, etc.

Dependent variable

The research aims to analyze the characteristics of people who shop online and predict households who are likely to order goods online. The dependent variable “purchase” is a binary variable and obtained from person-level data.

The question in the survey was as follows: “**Adult: On travel date: Made online purchase for home delivery?**

1. Yes 2. No “.

Independent variable modification

The end goal of the analysis is to predict purchasing patterns using the PSRC synthetic population, and so only variables available in the synthetic population data were considered for the prediction model. Additionally, each predictor variable was converted to a binary 0/1 value based on the observed histograms and the domain knowledge.

The following variables were included in the model:

Age (binary variable, 1: 25-54 years old, 0:else)

The relation between age and online ordering rate is shown in the Figure 3.2 below. It identifies the high online ordering rate in age or 25 - 54 years old. So it is assumed that the people in 25-54 years old and the else, the elderly and the young have a significant difference in online ordering choice.

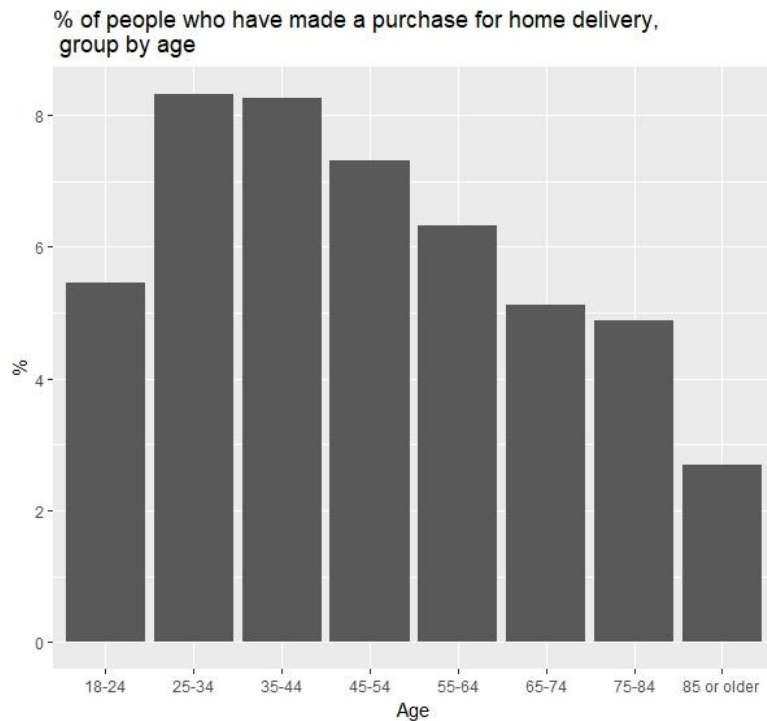


Figure 3.2 Percentage of people who have made a purchase for home delivery, group by age

Household Size (binary variable, 1: > 1 person in a household, 0: 1 person in a household)

There is a difference in the online ordering pattern between households with more than one person and one person households.

Household Income (binary variable, 1:>\$35K, 0: <\$35K)

The Figure 3.3 below shows that the online order rate increases as the household income increases. Especially, the online ordering rate significantly increases when the income is over \$35,000. So, this analysis sets the hypothesis that the household with income over \$35,000 increases the likelihood to purchase online and the binary variable with 0: less than \$35,000 and 1: more than \$35,000 is created.

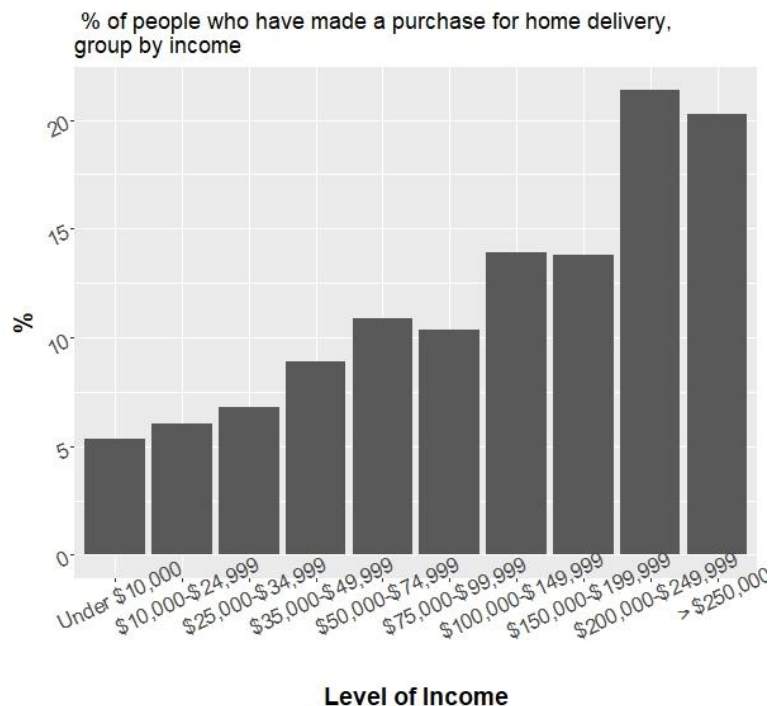


Figure 3.3 Relation of income level to online ordering

Model development

The logistic regression model was developed as a prediction model.

The estimated result of this model is shown in the Table 3.2 below. The result shows that the individual age, income, and household size are statistically significant and show the positive correlation with purchase probability. It is interpreted that the people who are 25-54 years old tend to order online. The individual in the household with a higher income than \$35,000 order online more than the people with less than \$35,000 in income. The household size shows interesting trend that bigger households have higher likelihood to order online.

Table 3.2 Estimate result of logistic regression model

Variables	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-3.03	0.11	-26.57	< 2e-16
Individual level attributes				
age (1:25-54, 0:else)	0.35	0.07	5.38	8.00E-08
Household level attributes				
income (1:≥\$35K, 0:<\$35K)	0.48	0.1	4.83	1.00E-06
household size (1:>1, 0:alone)	0.43	0.09	4.78	2.00E-06

Cross-Validation

PSRC household survey from 2015 was used to test the prediction accuracy. Results of this evaluation are shown in Table 3.3.

Table 3.3 AIC and Sum Squared prediction error

	AIC	Sum Squared prediction error
Logistic Regression	7222	0.166

Prediction - PSRC Synthetic population.

The next step was to predict an expected number of people who placed an online order for home delivery in the study area. To accomplish the goal, a detailed data about each household in PSRC region is needed. This data can be obtained from a synthetic population. Synthetic population is a dataset with the detailed socioeconomic characteristics of all households and individuals in a specific area. The synthetic population is usually used in activity-based micro-simulation models and travel demand forecasting. The synthetic population data was retrieved from PSRC.

Results

The prediction model introduced above make the individual-related probabilities based on the personal and household level characteristics. Figure 3.4, Figure 3.5, Figure 3.6, Figure 3.7, Figure 3.8 reveal some information about a characteristic of the people who tend to order online. But not all of these variables were included in the final model.

From Figure 3.4, we can see that women tend to shop more than male. The highest percentage female age group is 35-44 years old. Female group age 25-33 years old has a high percentage of online ordering as well.

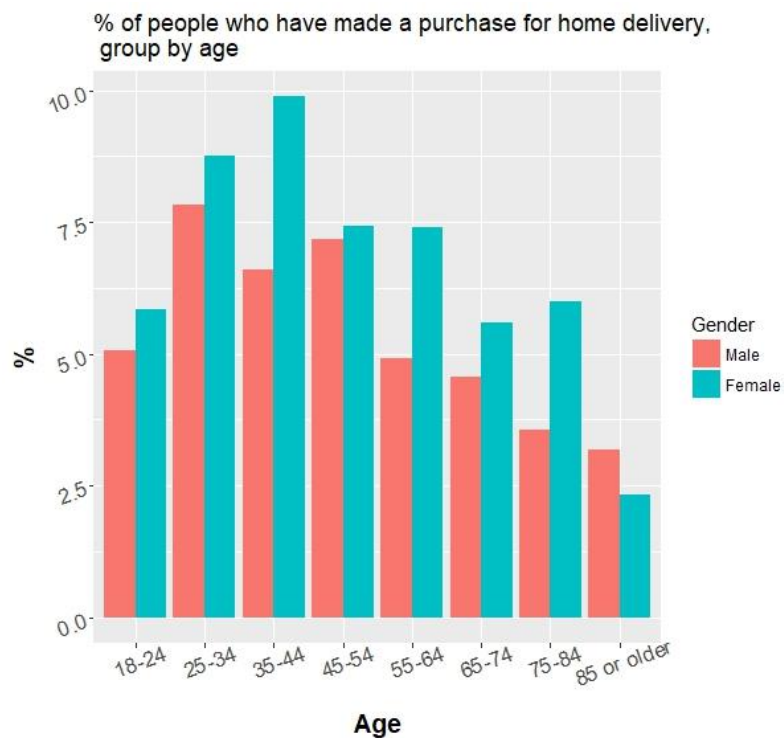


Figure 3.4 Percentage of people who have made a purchase for home delivery, group by age

Figure 3.5 has revealed a more interesting pattern. Employment groups have shown that people who are self-employed tend to shop more online.

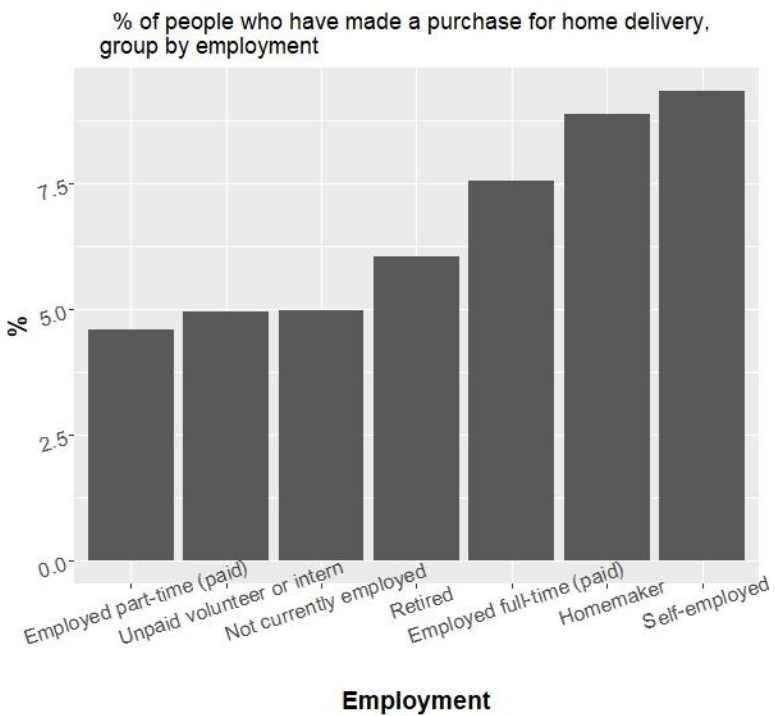


Figure 3.5 Percentage of people who have made a purchase for home delivery, group by employment

Figure 3.6 that have grouped the percentage of people who have made an online purchase for home delivery by income. The clear positive trend is visible - people who earn more - buy more.

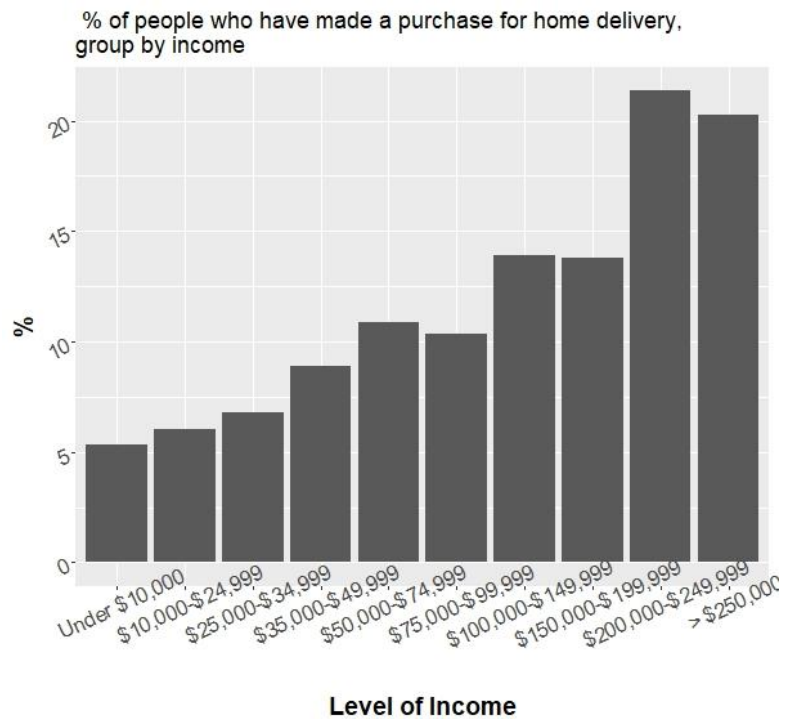


Figure 3.6 Percentage of people who have made a purchase for home delivery, group by income

Almost the same relationship we can see in Figure 3.7 that has people who order online grouped by the education level. People with higher degree tend to shop online more.

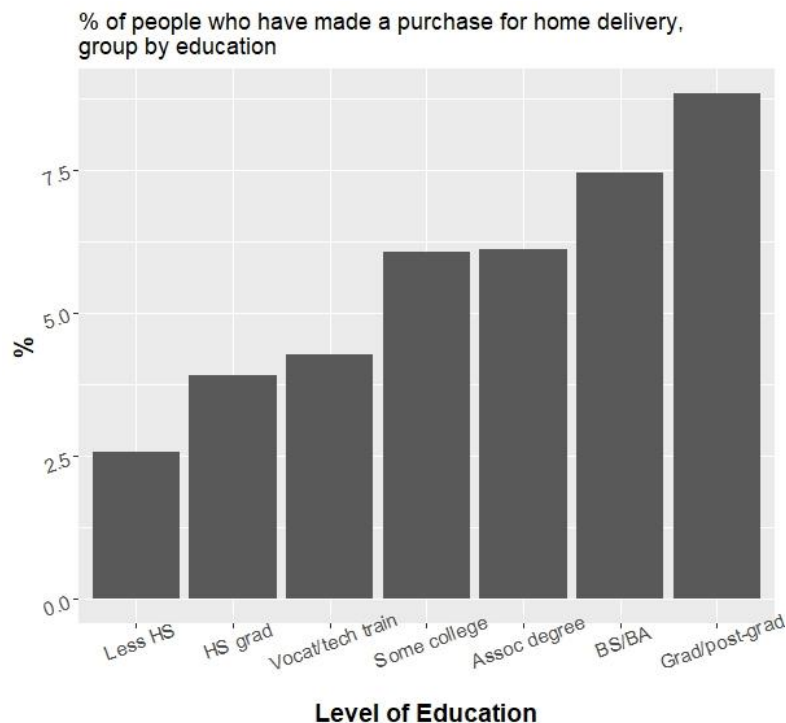


Figure 3.7 Percentage of people who have made a purchase for home delivery, group by education

To find the expected number of online orders per area, individual online shopping predictions were grouped by Transportation Analysis Zones (TAZ) and summed together to get the expected number of online orders per TAZ per day. To create maps that show the neighborhood's probabilities, the average number of online orders were regrouped by Forecast Analysis Zone (FAZ).

The final map is shown in Figure 3.8. The map suggests that people from the East side of Puget Sound including Redmond, Bellevue, Kirkland have higher percentage of orders per region. It is not surprising - a lot of people there have high income and high education level. Neighborhoods like Wallingford, Ravenna, and Ballard have high predicted rate of online orders.

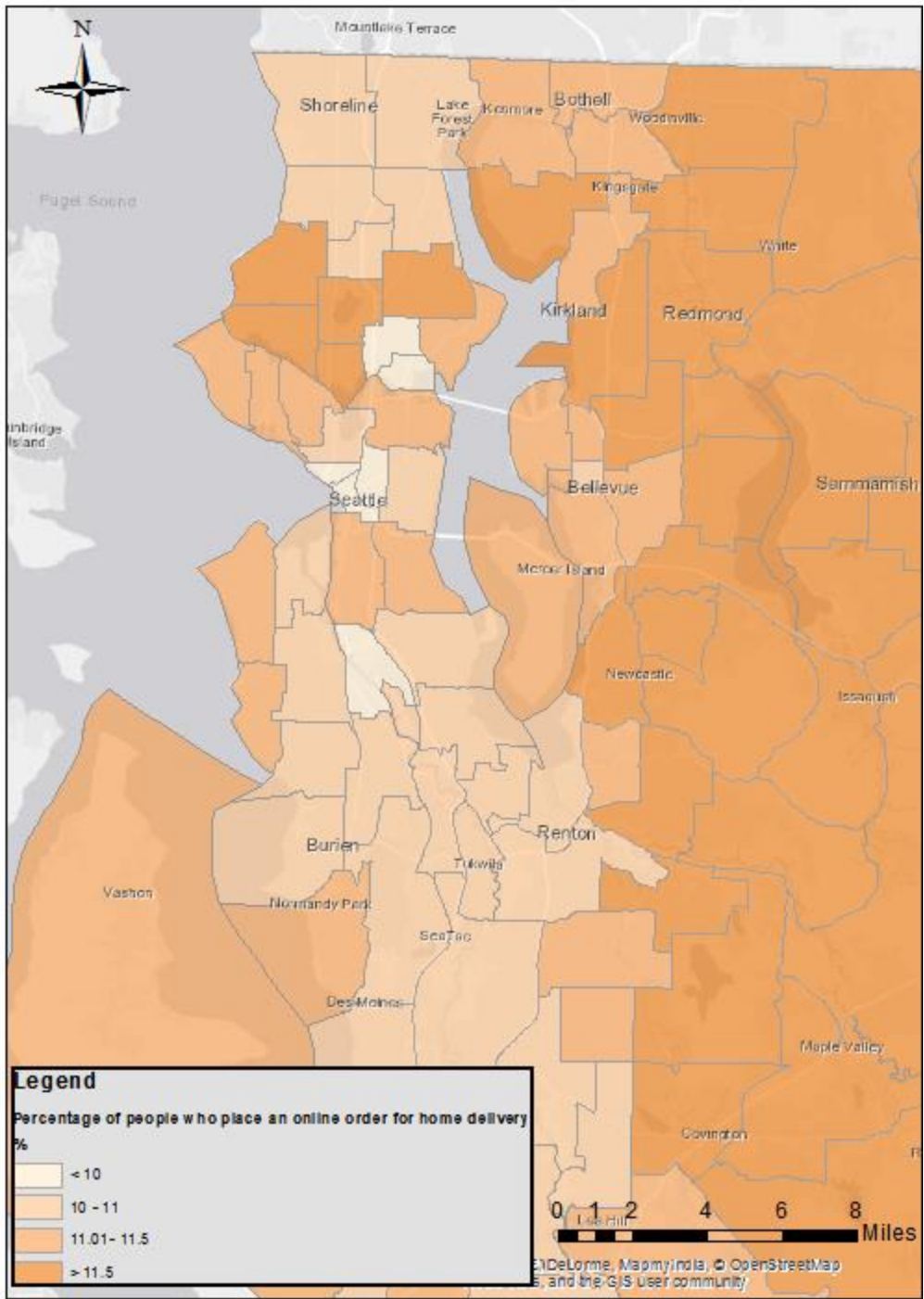


Figure 3.8 Percentage of people who have made a purchase for home delivery, group by Forecast Analysis Zone (FAZ) in Puget Sound Region

Another way to look at the data is to create the package demand density map that shows the neighborhoods that have a higher packages demand (Figure 3.9). The map shows how many

packages are coming to the neighborhoods normalized by square mile of their area. In Seattle, First Hill and Belltown has the highest density of packages coming to the neighborhood.

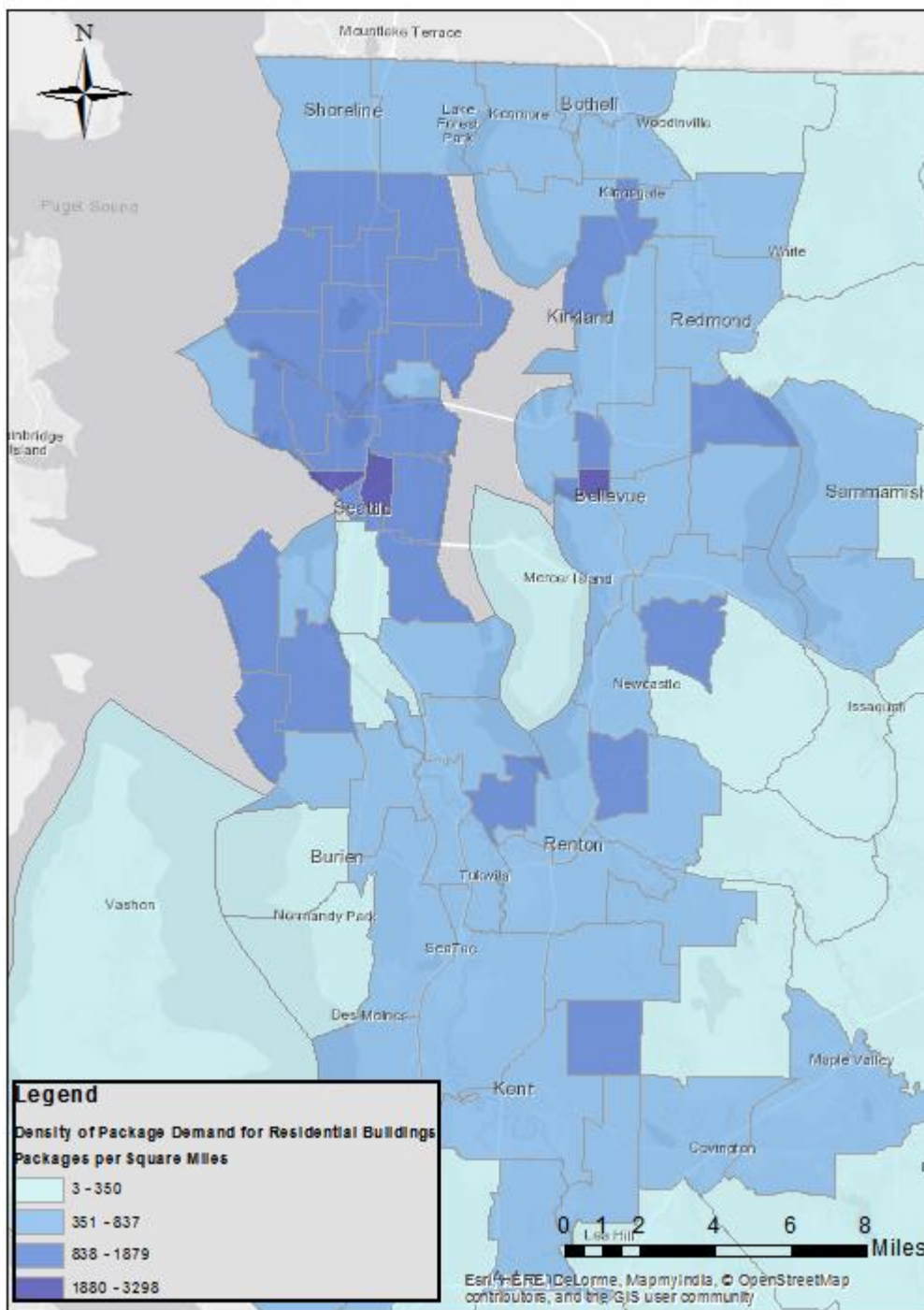


Figure 3.9 Density of the package demand for residential buildings

3.2 VMT REDUCTION STRATEGIES

We have evaluated two VMT reduction strategies:

Variable Number of Trucks

To model a fragmented delivery system where the neighborhood's package demand is delivered by multiple carriers, a range of one to nine trucks that deliver the same total amount of packages to the neighborhood was modeled. Where the system with one truck delivering all of the neighborhood's demand is an efficient scenario when the truck utilization is maximized, and it leads to lower modeled VMT. The system with nine trucks delivering the same neighborhood's demand is an inefficient scenario when the trucks are carrying only a fragment of overall delivery demand. This fragmentation is close to what happens right now when multiple carriers deliver packages to the same neighborhood using smaller trucks or underutilizing the trucks' space.

Lockers

1. Lockers without walking buffer scenario

To model the package distribution in the neighborhood with a locker, an assumption has been made that not every customer will agree to use a locker as their online order destination. To test scenarios with the different number of customers using the locker, a 3 percent to 50 percent of the total households that placed an online order were modeled to choose the locker as their preferred package destination. To choose which customers will use the locker, we have assumed that the customers that live close to the locker would be more likely to use it. A number of surveys has shown that one of the reasons customers choose to use lockers is its convenient location (Iwan, Kijewska, & Lemke, 2016).

After locker implementation to the neighborhood's parcel distribution, truck VMT decrease is expected due to a lower number of delivery stops in the neighborhood. However, since the final

leg of delivery is assigned to the customer, they can choose whether to walk, bike, or drive to the locker to retrieve the package. If the final leg is performed by a car, the overall VMT decrease could be insignificant (Wygonik & Goodchild, 2011). The current model does not take into the account the customer's final trip to get the package, and VMT produced by this trip.

2. Lockers with walking buffer scenario

In the survey conducted by Urban Freight Lab at the University of Washington, Sound Transit Link riders were asked questions regarding their online-shopping habits at the University of Washington, Capitol Hill and Westlake stations. Majority of the respondents said that they are willing to walk with a package 3 to 6 city blocks or more (Figure 3.10). To model this scenario, walking buffers were created around the lockers, and a variable proportion (from 10% to 90%) packages arriving within those buffers were rerouted to the locker.

How many blocks are you willing to carry a package?

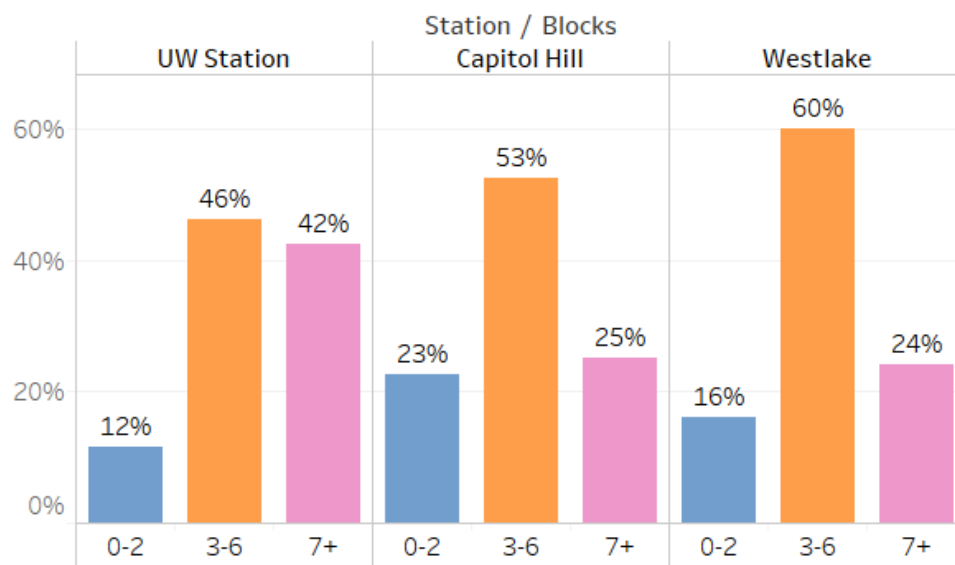


Figure 3.10 Survey results on the distance people are willing to carry a package

Assuming that the locker users that live 3 to 6 city blocks from the lockers will walk or bike to get a package, the walking buffers of 200, 300, and 400 meters were used when modeling this scenario.

3.3 MODELING TOOLS

This section discusses the data that was used to model scenarios from the previous section and ArcGIS script tools created for this project. In the beginning, ArcGIS toolbox that includes three tools for each of the VMT reduction scenarios was discussed. Then, each of ArcGIS script tools are discussed in the details. After, data used for tools' input is discussed. The majority of the section belongs to the discussion of the residential parcel data sources and creation of parcel data layer with the essential information included.

3.3.1 *ArcGIS Toolbox for modeling delivery stops*

To generate delivery stops for VMT reduction scenarios that have been mentioned in Section 3.2, ArcGIS toolbox was created for this project. The toolbox is an ArcGIS group of modeling script tools that generates number and location of stops in the delivery route. The toolbox consists of three script tools for modeling delivery stops based on one of the three modeling scenarios (discussed in Section 3.2). The script tools were developed using ArcGIS, R, and R-ArcGIS-bridge.

The chart below outlines each of the ArcGIS script tools' input and output.

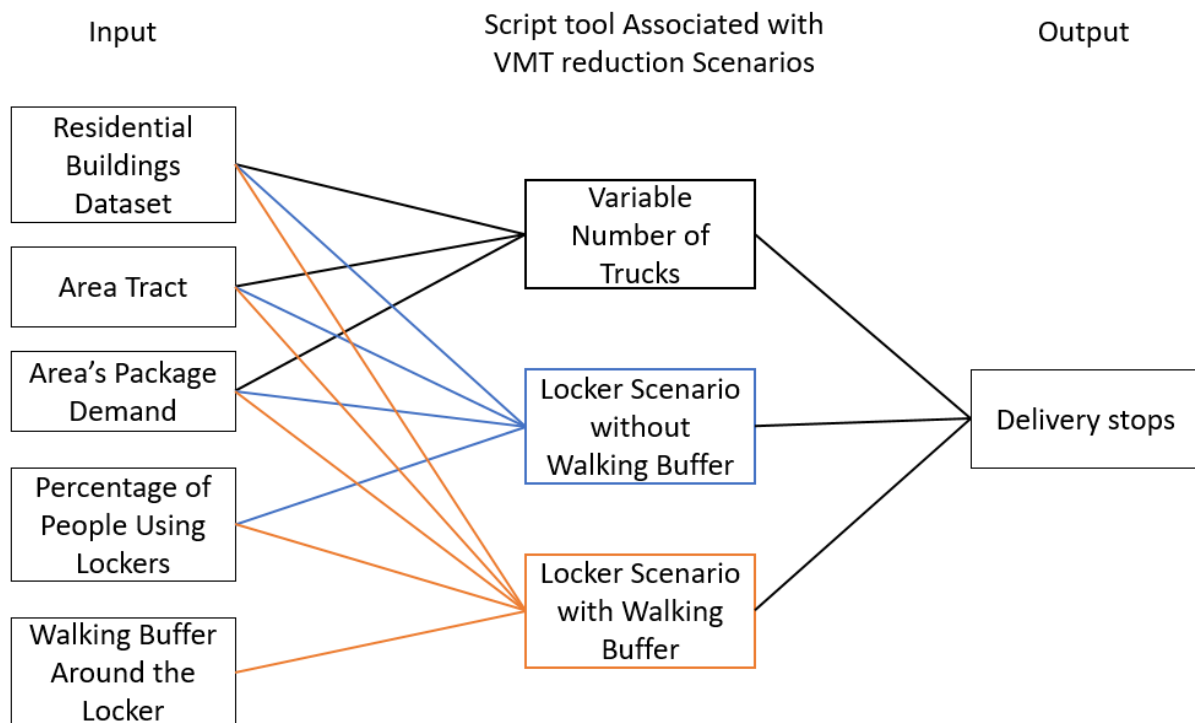


Figure 3.11 Parcels Stops Generation Toolbox' inputs and output

Each of the developed script tools will be covered below.

1. Variable number of trucks scenario

The tool takes as an input the following data: residential parcels layer (explained in Section 3.3.2.), neighborhood's census tract where the route will be analyzed, and the area's package demand to generate stops in the delivery route.

First, the tool is filtering out the residential parcels that are outside of the census tract that is given by the user. Then, out of these residential parcels, the sample equal to tract's package demand is taken. In a case of a single-family parcel, each stop will represent one delivery location. In the case of the multi-unit residential parcel, the tool makes each residential unit being equally available for selection by creating a multifamily parcels row's copies that are equal to the number of units at the multi-unit residential parcel. This way, each of the residential units in the multifamily building

is equally likely to be modeled to get a package delivery. If multiple units from the same building are selected for delivery, they are combined in a single delivery stop.

2. Locker Scenario without balking buffer

The script tool takes the same variables as in the previous tool as an input. In addition, the tool requires entering a percentage of locker users. Once completed the steps from the previous tool, it models the delivery stops that will be rerouted to the locker instead of the residential unit by removing a given percentage of closest delivery stops to the locker. Depending on the census tract chosen by the user, the tool identifies the locker location and place it into the final delivery route.

3. Locker Scenario with walking buffer

In addition to the inputs that previous tools are using, the length of walking buffer from the locker is used to choose the residential parcels within the walking buffer. The model calculates the distance from locker to the parcels, and if the parcel is outside the walking buffer, the parcel is not included. After, out of the parcels within the walking buffer, the given percentage is modeled to get a package delivery through the locker, everyone else getting the home delivery as usual.

3.3.2 *Inputs*

Residential Buildings Dataset

To generate delivery stops, six data sources were used to create a complete Residential Buildings dataset with information about number of units, number of stories, location (latitude and longitude), present use, and parcel's PIN. PIN (parcel identification number) is a unique parcel identifier that is assigned to parcels by the governmental organization (King County in the case of Seattle).

Table 3.4 List of the parcels data sets that were used for delivery stops generation

Layer Name	Source	Format
Parcels	Washington State Geospatial Data Archive (WAGDA)	.shp
Parcels for King County with Address, Property and Ownership Information	King County GIS Center	.shp
Apartment Complex	King County Assessments data	.csv
Condo Complex and Units		.csv
Residential Building		.csv
Parcels		.csv

To get the complete residential parcels data, six data sources listed in Table 3.4 were used and combined since each of the sources had incomplete information about residential units. Separate apartment complexes, condos, and residential buildings datasets are available from King County Assessment data repository. The spatial dataset was taken from Washington State Geospatial Data Archive (WAGDA).

The data were combined as follows:

1. The King County datasets on the residential buildings were cleaned. Missing and empty values were removed, inessential variables were removed, and variables' names were changed in the way that they would match across the datasets. After, datasets were joined together using a PIN as a unique identifier for the parcel.
2. Spatial parcel layer from WAGDA was prepared for the future merge with residential parcel dataset. The parcels with a residential present use variable were chosen. The present use variable was set equal to following values:
 - Single Family (Res Use/Zone, Townhouse Plat, Vacant(Single-family))
 - Duplex

- Apartment
- Single Family (C/I Zone)
- Triplex
- Condominium (Residential)
- 4-Plex
- Vacant (Multi-family)
- Apartment (Mixed Use)
- Condominium (Mixed Use)
- Single Family (C/I Use)
- Apartment (Subsidized)
- Fraternity/Sorority House
- Residence Hall/Dorm
- Apartment (Co-op)

3. Spatial parcels layer was merged with residential buildings dataset using parcels' PIN to get both spatial and built characteristics of the residential parcels. The parcels that were not matched either didn't have the spatial information (these entries were not included in the final dataset since we wouldn't be able to map the parcel which is essential for future delivery route) or building characteristics (the data with number of units as NA was included and treated as the building had a single unit in it).

The final dataset of the Seattle's residential buildings included 217,315 items (where each of the items represents one residential parcel) with 26 variables that consist of parcel's location and characteristics such as the number of units, number of stories, present use, PIN, etc.

Other input

The rest of the input values (Area Tract, Area’s Package Demand, Percentage of People Using Lockers, and Walking Buffer around the Locker) had to be set by the User and don’t require any data preparation.

3.3.3 Output

The tools’ output is a table where each row represents delivery stop with the residential units’ location information, present use of the parcel, number of units in the parcel, number of stories, year built, and zip code. Figure 3.12 provides an example of the output table. The example of the spatial distribution of delivery stops can be found in Section 3.5.

OBJECTID *	NAME10	PIN	PRES_USE	PRES_USE D	Lat	Lon	NbrUnits	NbrStories	YrBuilt	Elevators	Shape *
1	72	694000130	16	3	-122.343002	47.614601	98	6	2001	1	Point
2	72	656000550	16	3	-122.345001	47.615299	251	7	2008	1	Point
3	72	656000450	16	3	-122.347	47.616798	221	26	1990	1	Point
4	72	656000400	16	3	-122.348	47.617199	185	17	2011	1	Point
5	72	1991200795	11	1	-122.344002	47.620701	10	2	1925	0	Point
6	72	694000130	16	3	-122.343002	47.614601	98	6	2001	1	Point
7	72	2617360000	20	5	-122.343002	47.622501	5	1	1959	0	Point
8	72	5607950000	25	4	-122.346001	47.6175	136	7	1998	1	Point
9	72	7457200000	20	5	-122.342003	47.613499	132	26	1973	1	Point
10	72	697000025	16	3	-122.345001	47.618	371	18	1949	1	Point
11	72	2538870000	20	5	-122.341003	47.615299	31	3	1922	0	Point
...											
388	72	7457200000	20	5	-122.342003	47.613499	132	26	1973	1	Point
389	72	656000451	16	3	-122.347	47.616402	187	7	2000	1	Point
390	72	696000250	11	1	-122.345001	47.616699	320	6	1998	1	Point
391	72	696000135	11	1	-122.342003	47.6152	59	7	1925	1	Point
392	72	1991201030	16	3	-122.343002	47.618801	53	6	2008	1	Point
393	72	696000250	11	1	-122.345001	47.616699	320	6	1998	1	Point
394	72	696000250	11	1	-122.345001	47.616699	320	6	1998	1	Point
395	72	4458720000	25	4	-122.347	47.625	95	3	2006	1	Point
396	72	696000035	16	3	-122.342003	47.614899	44	6	1991	1	Point
397	72	659000740	16	3	-122.337997	47.615898	33	3	1909	1	Point
398	72	5165500000	20	5	-122.344002	47.619301	132	7	2009	1	Point
399	72	1991200600	25	4	-122.345001	47.619499	197	6	2010	1	Point
400	72	656000400	16	3	-122.348	47.617199	185	17	2011	1	Point

Figure 3.12 Output Table Example

3.4 CASE STUDY: NEIGHBORHOOD CHOICE

One of the objectives of this research is to understand how effective some of the truck VMT reduction strategies are in the neighborhoods with a range of built environment characteristics. When choosing particular neighborhoods for the comparison, following factors were considered:

1. Matching demand level for package delivery

Once the delivery demand was predicted for different neighborhoods in Seattle (See Section 3.1.), two of them with similar packages demand were chosen for the case study.

2. Varying residential density

The high residential density mixed-use neighborhood was chosen in contrast to residential neighborhood within Seattle with the majority of single-family residential parcels and lower road density. A number of studies noted that higher density is one of the factors that might reduce VMT (Boarnet & Crane, 2001; Bronzini, 2008; Brownstone, 2008; Wygonik & Goodchild, 2016). With higher density, the stops are closer to each other and truck does not have to drive much to deliver the neighborhood's demand. It would be interesting to investigate how VMT reduction strategies will affect neighborhoods with varying residential density.

3. Varying road density

Good connectivity in the neighborhood might be the other important factor that could change amount of VMT. The neighborhood with grid street network was chosen in contrast to suburban street network with curvilinear street patterns and winding streets that lengthens the truck delivery route.

Considering the factors described above, census tract 72 that is on the edge of Belltown and South Lake Union neighborhoods (referring as Belltown after) was chosen as a case of the high

residential density mixed-use neighborhood (Figure 3.13). It is one of the most densely populated neighborhoods in Seattle with 52 residential buildings and 4622 residential units.



Figure 3.13 Tract 41 as a case study for a high residential density mixed-use neighborhood

For the residential neighborhood, census tract 41 that is Laurelhurst neighborhood was chosen (Figure 3.14). This is a residential neighborhood with a majority of single-family houses with 2426 residential buildings and 3154 residential units.



Figure 3.14 Tract 72 as a case study for a residential neighborhood

Built environment characteristics are shown in Table 3.5.

Table 3.5 Built environment characteristics of two neighborhoods chosen for the case study

	Belltown (census tract 72)	Laurelhurst (census tract 41)
Land Area (sq. miles)	0.39	1.26
Total Population	5318	7789
Number of residential parcels	53	2426
Customer density (people/sq. mile)	13635.9	6181.7
Road density (miles/ sq. mile)	45.4	29.3
Intersection density (intersection/sq. mile)	433.3	167.9

3.5 CASE STUDY: MODEL SET UP

Variable number of trucks scenario

Assume that both Laurelhurst and Belltown neighborhoods have the same package demand of 400 packages. Figure 3.15 shows an example spatial residential delivery stops distribution in Laurelhurst (different runs of the model which randomly assign demand to different residential units within the neighborhood). Each of the points represents residential units that are scheduled for package delivery. These points are going to be the delivery stops on the carrier delivery route. Since the majority of the residential parcels in Laurelhurst are single-family houses, each point will represent a delivery to one unit.

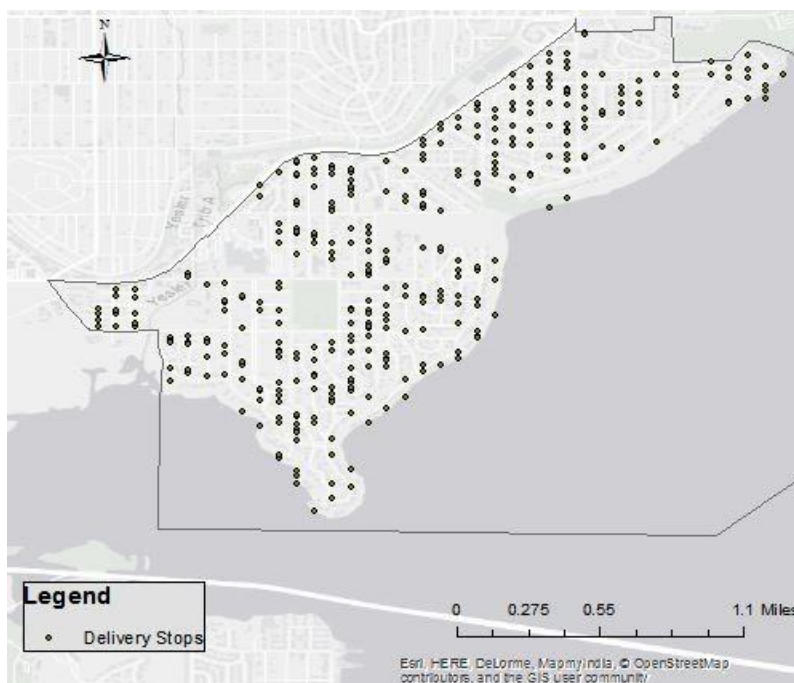


Figure 3.15 Spatial distribution of delivery stops at Laurelhurst neighborhood constructed using randomly assigning a number of packages, predicted by a demand forecasting model (Section 3.1) to each household with equal probability.

Figure 3.16 shows an example of spatial delivery stops distribution in Belltown neighborhood. Since the majority of the residential parcels there are multifamily units, the number of stops on the map is less than the package demand because some of the delivery stops will have more than one package addressee.

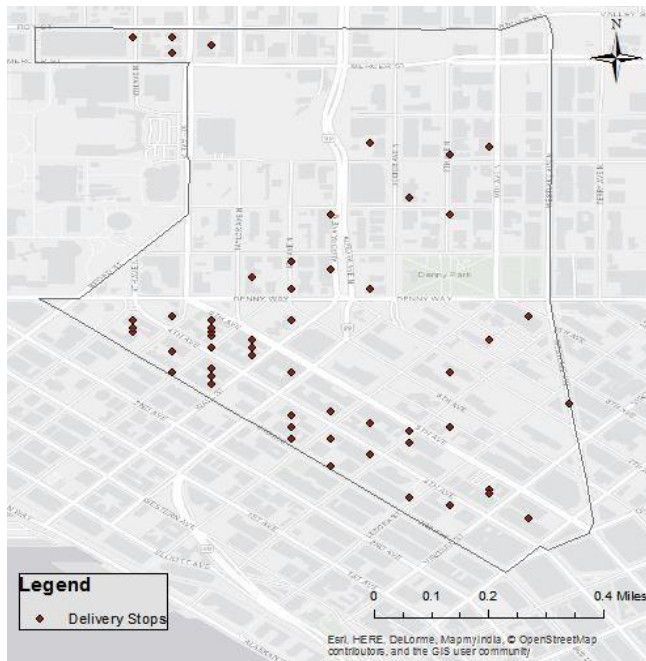


Figure 3.16 Spatial distribution of delivery stops in Belltown constructed using randomly assigning a number of packages, predicted by a demand forecasting model (Section 3.1.) to each household with equal probability.

Lockers

To model the delivery stops in the neighborhood with a locker system, one locker was placed in Laurelhurst and Belltown modeling scenarios.

- Locker location

Previous case studies and research showed that for a locker to attract customers, it should be located in the places with a high customer's density and where customers could have easy access to lockers (USPS, 2013; Iwan, Kijewska, & Lemke, 2016).

In the Belltown case, a number of delivery stops simulations were performed to identify the areas of high delivery stops density to place the locker. In Laurelhurst case, the majority of parcels are single-family residential building, and the delivery stops are spread evenly across the neighborhood. Thus, nonresidential parcel in the center of the neighborhood was chosen as the locker location in the simulation modeling.

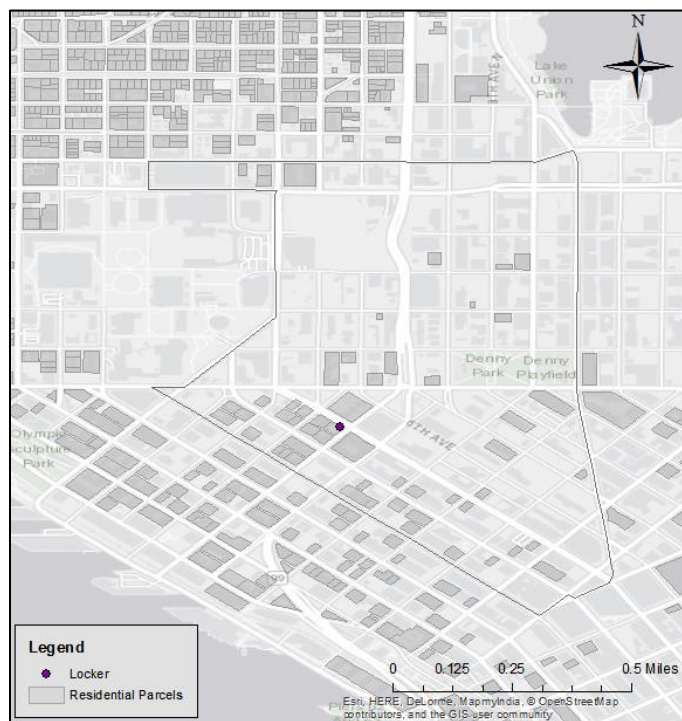


Figure 3.17 Locker Location in Belltown

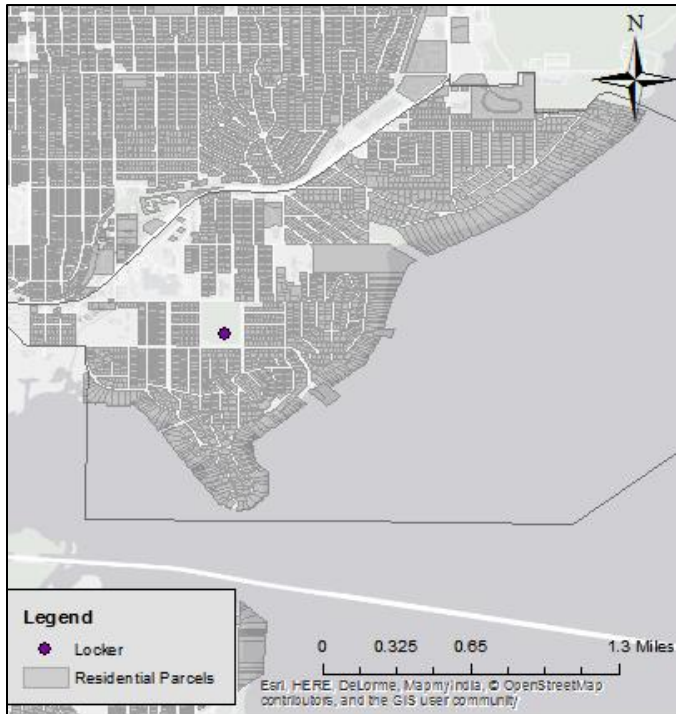


Figure 3.18 Locker Location in Laurelhurst

Scenario with walking buffers around lockers

Assuming that the locker users that live 3 to 6 city blocks from the lockers will walk or bike to get a package, the walking buffers of 200, 300, and 400 meters were used.

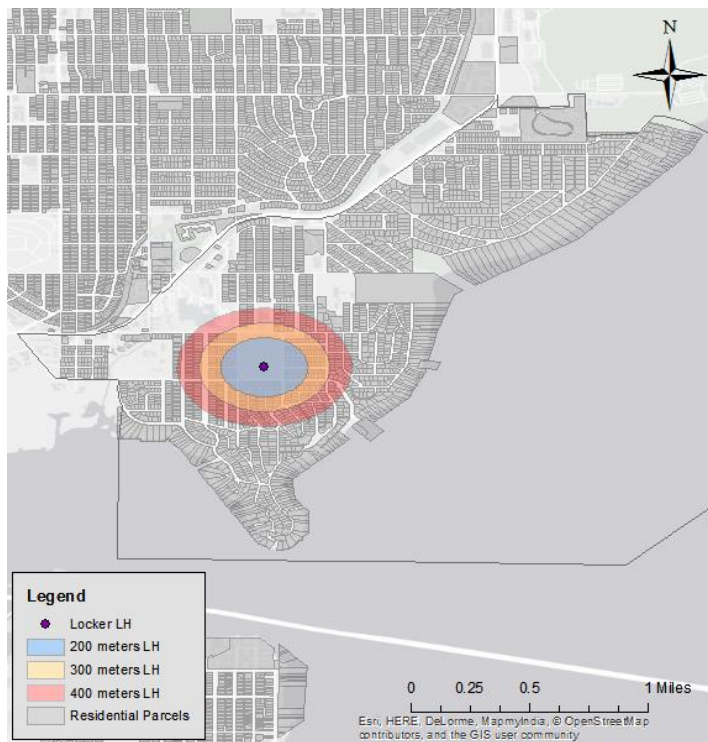


Figure 3.19 Walking buffers around the locker in Laurelhurst

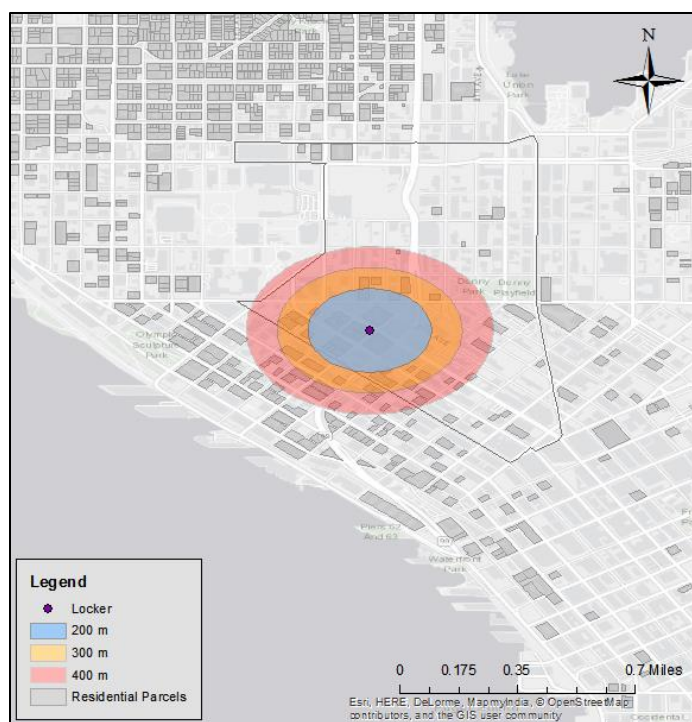


Figure 3.20 Walking Buffers around the locker in Belltown

Modeling

Each of the ArcGIS script tools mentioned in Section 3.3.1. generates a plausible delivery stops distribution under each scenario. This distribution is then used by the ArcGIS Network Analyst² tool to calculate total route length. Resulting VMT is obtained by running this model process three times and averaging the results, to account for the randomness in the delivery stops allocation.

² Additional Information about ArcGIS Network Analyst can be found here:
<http://www.esri.com/software/arcgis/extensions/networkanalyst>

Chapter 4. ANALYSIS AND RESULTS

The following section describes the results obtained from the proposed scenarios modeling including a variable number of trucks and lockers. The delivery trucks' VMT is calculated within the neighborhood only (doesn't include travel to and from DC).

4.1 VARIABLE NUMBER OF TRUCKS

The modeling showed that amount of VMT produced by the delivery truck is greater in Laurelhurst than in Belltown even though the number of packages delivered was the same in both neighborhoods. Customer density can explain the difference in VMT – Belltown is a denser neighborhood with high rise residential towers, and Laurelhurst is less dense with mostly single-family houses.

Table 4.1 VMT produced by variable number of trucks in Laurelhurst and Belltown

Number of trucks delivering packages		1	2	3	4	5	6	7	8	9
VMT (miles)	Laurelhurst	25.6	40.8	48.6	63.47	67.83	81.2	85.17	96.53	99.60
	Belltown	12.5	24.3	36	45.2	53.83	60.6	73.5	81.6	88.2

However, when reducing the number of delivery trucks from 9 to 1 trucks, VMT savings are greater in Belltown than in Laurelhurst. The VMT savings in Belltown are 75.7 miles, and in Laurelhurst are 74 miles. It can be explained by the spatial parcel distribution within the neighborhood. By delivering a smaller number of parcels by each truck in Laurelhurst, delivery stops are mostly unique to each delivery route which leads to smaller VMT savings since the delivery truck has to move to each of the delivery stops. Whereas a some delivery trucks will make repetitive stops in Belltown because there is a bigger number of packages delivered in one delivery stop.

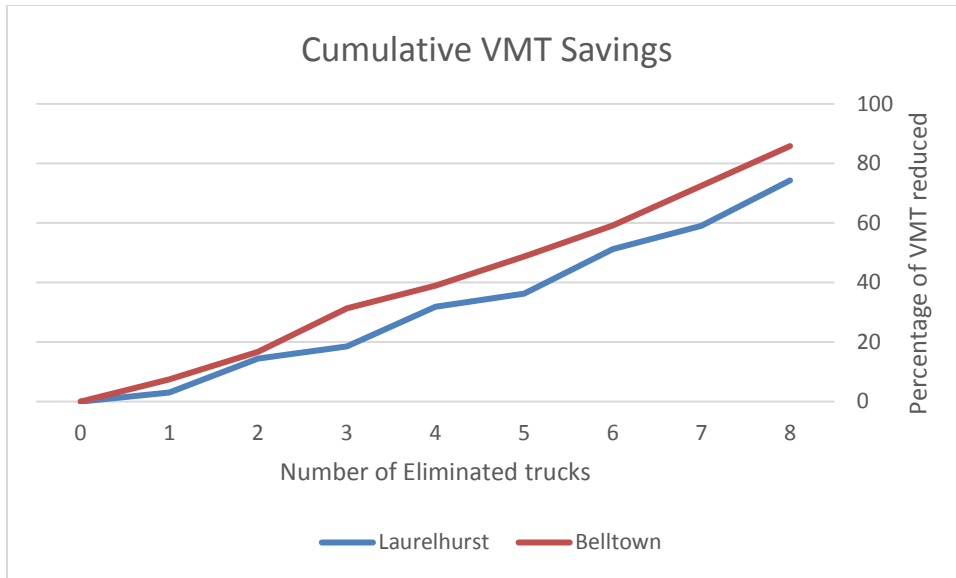


Figure 4.1 Percentage of VMT savings by reducing the number of delivery trucks

Figure 4.1 shows that cumulative VMT savings by reducing a number of trucks delivering packages from 9 trucks are slightly bigger in Belltown than in Laurelhurst. Moreover, the traffic perception by different road users can be different in dense urban areas due to increased traffic volumes, lack of parking. Overall results of decreasing a number of trucks coming into the neighborhood can be more critical in Belltown.

4.2 LOCKERS

4.2.1 *Lockers without a walking buffer*

The results of the first scenario with locker implementation without walking buffer are shown on Table 4.2.

Table 4.2 VMT produced when modeling a locker without a walking buffer in Laurelhurst and Belltown

Percentage of customers receiving their package at the locker		0	3	5	10	15	20	25	30	35	40	45	50
# of customers		0	12	20	40	60	80	100	120	140	160	180	200
VMT (miles)	Laurelhurst	25.5	26.8	26.1	24.1	23.8	23.8	22.8	21.8	20.5	20.5	18.5	17.1
	Belltown	11.4	11.4	11.4	11.4	10.4	10.7	10.4	9.4	9.1	9.1	9.1	9.4

Modeling results show that the total delivery truck VMT is decreasing with the implementation of the locker to both of the neighborhoods. The maximum VMT baseline for this scenario is the route with packages being delivered to every household. In the modeling, it refers to the route with no customers using a locker. Delivery truck VMT is 43.7 miles and 17 miles in Laurelhurst and Belltown accordingly. The least VMT scenario is when everyone in the neighborhoods is using the locker.

In the dense mixed-use neighborhood (Belltown), VMT does not change when small number of customers (0 to 40 customers) are using the locker due to the multiple delivery stops being located within one residential building. However, when more than 60 customers choose locker over home delivery, delivery vehicle's VMT starts to gradually decrease down to 9.4 miles traveled when 200 customers would use a locker.

In the residential neighborhood (Laurelhurst), there is a gradual delivery truck VMT decrease when changing the number of customers that receive the packages in the locker from 25.5 miles traveled when no customers are using the locker to 17.1 miles traveled when 200 customers are using the locker. The gradual VMT change is due to evenly distributed single-family units, and

delivery stops in the neighborhood. The decrease in the number of stops on the route will result in the decreased VMT.

4.2.2 *Lockers with walking buffer*

In this scenario, the households located within walking distance from the locker were targeted as potential locker users. The households located outside of the walking shed will receive home deliveries. The results of the modeling are shown on Table 4.3 and Table 4.4.

Laurelhurst

Table 4.3 VMT produced when modeling a locker with a walking buffer in Laurelhurst

% of users	Walking Buffer, meters		
	200	300	400
0	25.47	26.47	25.13
10	25.13	25.80	25.80
20	25.13	25.80	25.80
30	24.80	25.80	24.47
40	26.13	25.47	23.80
50	25.80	26.13	23.13
60	25.13	25.47	23.47
70	25.80	24.80	23.80
80	25.80	23.13	23.80
90	25.80	23.47	23.80

When targeting households within walking distance from a locker in Laurelhurst, there are mixed results regarding VMT decrease. When targeting household located within 200 meters from the locker, there is no VMT decline. When targeting households located within 300 meters VMT increase is more noticeable from 26.47 miles traveled when zero customers use the locker to 23.47 miles traveled when 90% of the customers use the locker to receive the packages. When targeting households within 400 meters, VMT decrease is steeper than in the case with 300 meters buffer,

but the amount of VMT is almost the same when 90% of customers are using a locker. Since the walking buffers covers

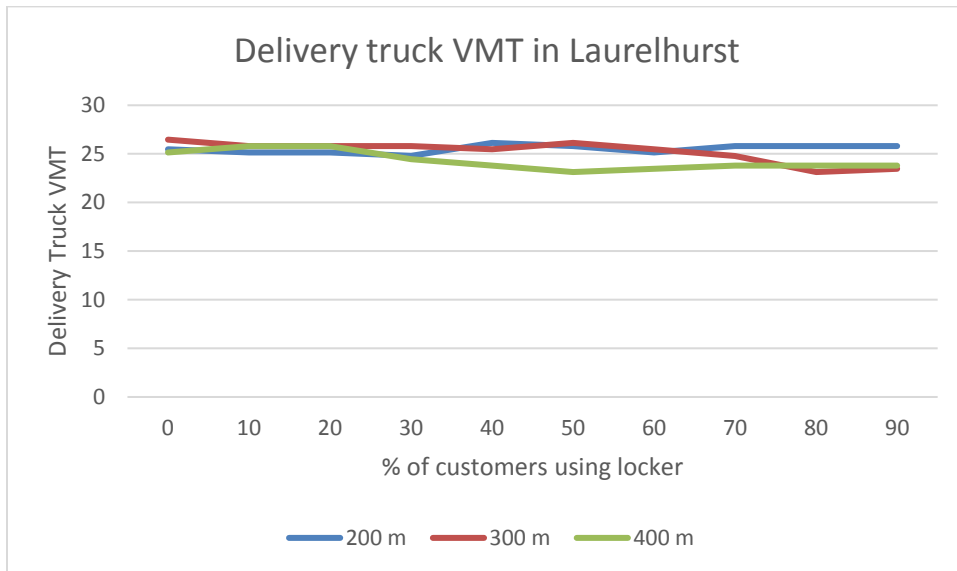


Figure 4.2 Delivery truck VMT in Laurelhurst when modeling lockers with walking buffer scenario

Belltown

Table 4.4 VMT produced when modeling a locker with a walking buffer in Belltown

% of users	Walking Buffer, meters		
	200 m	300 m	400 m
0	11.40	11.40	11.40
10	11.40	11.40	11.40
20	11.40	11.40	11.40
30	11.40	11.40	10.40
40	11.40	11.40	10.40
50	11.40	11.40	10.40
60	11.40	11.40	10.40
70	11.40	11.40	9.40
80	11.40	11.07	8.73
90	11.40	10.40	8.40

When targeting households within walking distance from the locker in the dense mixed-use area (Belltown), the VMT change is more apparent. In the case when households within 200 meters are using locker, there is no change in delivery truck VMT. In case of walking distance of 300 meters, there is no change in delivery truck VMT. In case of walking distance of 300 meters, the VMT starts to decrease when 70 percent of users are using the locker. In case of walking distance of 400 meters, VMT starts decreasing to 10.4 miles traveled when 30 % of the customers are using locker and to 8.4 miles traveled when 90% of the customers are using the locker.

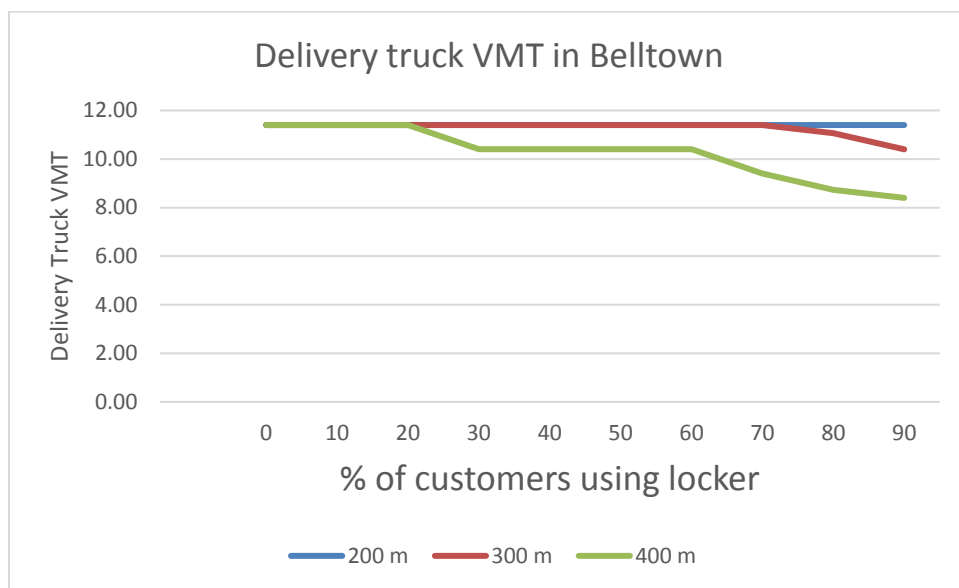


Figure 4.3 Delivery truck VMT in Belltown when modeling lockers with walking buffer scenario

Chapter 5. CONCLUSION

This research aimed to analyze the online shoppers' characteristics in PSRC region, predict package generation by neighborhoods and model VMT reduction scenarios including a variable number of trucks delivering neighborhood's demand and locker implementation.

First, we have analyzed socio-economic factors leading people in PSRC region to make an order online. We have found that young, educated and people who have high income tend to order more online. We have then build a predictive model of package demand in each neighborhood using PSRC Survey data coupled with PSRC synthetic population.

Second, we have analyzed the impact of several scenarios on truck VMT incurred while satisfied this demand. Specifically, we have modeled a variable number of trucks delivering the same demand and a locker implementation scenario. Modeling has shown that in residential area VMT reduction would be from 99.6 miles traveled by nine trucks to 25.6 miles traveled by one truck delivering the neighborhoods package demand. In denser mixed-use area route with nine trucks delivering neighborhoods, demand will be 88.2 miles, and route with one truck will be 12.5 miles. The VMT reduction of 75% in residential area and 86% in the dense mixed-use area were observed. This reduction is due to having multiple packages per delivery stop in the urban area, compared to just one package per delivery stop in the suburban area. In case of delivery truck route elimination, remaining trucks need to visit more locations in the suburban areas, while in the urban area they are likely to visit the same delivery stops (large multi-family apartment buildings).

Package consolidation in the neighborhood is another VMT reduction strategy. Rerouting packages to points in the neighborhood where customers have to pick them up leads to reduced number of delivery stops and route length. This research has shown that implementation usage of the locker can lead to VMT reduction from 25.4 miles (truck delivers packages to every address)

to 17.1 (50% of the packages rerouted to the locker) miles traveled in a suburban area and from 11.4 to 9.4 miles traveled in the dense urban area. However, the final leg performed by the customer to retrieve the packages was not accounted in the model.

An alternative scenario was modeled, where only people living within a walking buffer around the locker are assumed to get deliveries there. Immediately, the difference between dense mixed-use and residential neighborhoods is apparent: 400 meters walking buffer covers only 23% of parcels in residential and 73% of parcels covered in dense mixed-use neighborhoods. In the case of the dense mixed-use neighborhood, VMT reduced by 26% for the 400-meter walking buffer.

Chapter 6. DISCUSSION

E-commerce is continuing to grow (U.S. Census Bureau, 2018) generating many packages to be delivered to customers and returned from them. Customers' expectations are also increasing with expectations of getting the shipments immediately and having convenient options to return the goods they do not like. However, difficulties in delivering packages in the cities associated with lack of insufficient freight infrastructure and traffic congestion are leading to inefficiencies in the delivery process. Missed or delayed deliveries are negatively impacting customer satisfaction rates. At the same time, cities are struggling to keep up and are expected to deliver clean and congestion-free streets to residents. Therefore, it is important to understand where the package deliveries "hot spots" are located and what strategies can be employed to decrease a number of trucks coming into the neighborhoods.

VMT savings in dense urban areas are especially critical because of higher levels concentration of transportation activities and road users including bicyclists, pedestrians, buses, etc.

Figure 6.1 shows an example of the residential neighborhood in Seattle (Laurelhurst). The majority of the parking is unrestricted on-street parking with some exceptions along NE 45th Street and NE 41st Street. There is a low amount of vehicles on the streets and low levels of pedestrian and bicycle activities in the neighborhood. Delivery trucks will not have any obstacles to find parking. The outcomes of blocking travel lanes or crosswalks will not be critical because of the lack of any activities in the neighborhood. The consequences of adding or subtracting truck trips will not be noticed by the people who live in the neighborhood.



Figure 6.1 Picture of one of the streets in suburban neighborhood

In comparison, Figure 6.2 is an example of dense mixed-use neighborhood (Belltown). Belltown contains more congested streets with many transportation-related activities including buses running to and through the neighborhood, freight activities, higher number of bicyclists and pedestrians. Belltown has a commercial core that attracts more people for jobs with cultural activities. Majority of the parking is paid parking that is highly occupied during delivery hours. Adding or subtracting delivery parking trips to the neighborhood would be noticeable for the residents and other road users.



Figure 6.2 Picture of one of the streets in Belltown. Carrier's truck is double packed on the street.

New Seattle housing policies focus on affordability, allowing developers build higher and denser residential buildings in place of single-family houses. These policies will inevitably attract younger people to the neighborhoods, significantly increasing the demand for online order deliveries (this research has shown that younger people have higher propensity for online orders). Coping with this increased demand will be a major challenge for Seattle's urban freight infrastructure and more research in the different delivery trip mitigation strategies is clearly needed.

6.1 LIMITATIONS AND NEXT STEPS

This research provides useful insight regarding the characteristics of the people who shop online and measures VMT reduction strategies. However, the number of limitations remain:

- **There are other important metrics besides VMT**

When choosing the evaluation criteria, VMT was chosen as the universal measurement of the system. VMT measures the route performance of the truck. However, it is important to consider customer satisfaction and time spent within the building delivering packages.

- **Cost is not included in calculations**

Different scenarios might have different costs associated with them, either by making longer trips for some delivery trucks or paying for installation and maintenance of lockers. These costs were not modeled in this work.

While some VMT reductions were observed, it does not mean that carriers will be willing to implement one of the scenarios modeled. One of the main objectives for carriers is to increase the profits and satisfy the customer. The modeling does not take into account the price of implementing the solutions. It is also hard to shift customer's behavior towards more sustainable delivery options like consolidated pick-up lockers.

- **Limited data available for modeling**

Modeling and analysis were based on PSRC survey from 2014 and 2015. While covering over 10 thousand people, this survey still does not provide enough data to build reliable models of package demand. Survey design also limited use of the data as participants were not asked how many packages have they ordered, but rather provided just a binary yes/no response. Furthermore, reliance on PSRC synthetic population limits the set of attributes used for modeling.

- **Walking buffers around the lockers were modeled using Euclidean distance from the lockers**

The model does not account for the geographical features like steep hills.

Potential future directions include:

- Modeling failed first delivery and dwelling time

Every time the delivery fails the carrier has to take packages back to the DC and attempt to make a delivery on the next day. This not only creates additional truck trips to the neighborhoods but also leaves customers unsatisfied. Lockers (or any consolidation points in the neighborhood) could address failed first deliveries since the customer does not have to be present at the locker during the delivery. Failed delivery attempts can automatically be rerouted to the consolidation point (in China, a very dense package locker network is used to address failed first deliveries).

Dwelling time is another important metric that measures the efficiency of delivery operations. Dwelling time starts from the time delivery truck parked to the time it left the parking space. Factors such as getting access to the building or deciding where to leave the package affect dwelling time and information gathering strategies can be used to improve it.

- Modeling other VMT reduction scenarios

Some of the package delivery companies exploring alternatives to residential deliveries like delivery to a customer's car trunk, drone deliveries, cargo bicycle deliveries. Modeling unique characteristics of some of the alternatives would be useful to gain better understanding of full range of VMT mitigation strategies.

Chapter 7. REFERENCES

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