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José Luis Machado León

Ridehail and Commercial Vehicles Access in Urban Areas: Implications for Public Infrastructure Management

José Luis Machado León

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Anne Goodchild, Chair

Don MacKenzie

Lillian Ratliff

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Abstract

Ridehail and Commercial Vehicles Access in Urban Areas: Implications for Public Infrastructure Management

José Luis Machado León

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

As urbanized populations and concentrations of activities increase, there is growing pressure in dense and constrained urban areas to unlock the potential of every public infrastructure element to address the increasing demand for public space. Specifically, there is a growing demand for space for parking operations related to the access to land use by people and goods. On one side, ridehailing services, such as those provided by Uber and Lyft, are on the rise and with them the associated passenger pick-up/drop-offs (PUDOs) operations. On the other side, freight and servicing trips require supply of adequate infrastructure to support vehicle access and load/unload activities, and final delivery/service to customers. This dissertation aims to provide insights based on real-world datasets and tests to support the management of two key public infrastructure that provides access to land uses: alleys and curb lanes. To achieve this goal, first,

this dissertation will investigate what roles alleys play in cities and inspect alleys' physical characteristics and vehicle parking operations in theses spaces. Secondly, this research will examine factors of PUDO dwell time and evaluate the impact of adding curb lane PUDO zones and geofencing ridehailing vehicles to these zones using a hazard-based duration modeling approach. Finally, this dissertation will analyze the impact of different ridehailing curb management strategies on curb lane utilization based on simulation.

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DEDICATION

to my daughter, Nicole Andrea

Chapter 1. INTRODUCTION AND RESEARCH QUESTIONS

The challenges faced by different transportation network users in dense and constrained urban areas are expected to increase as urbanized populations and concentrations of commercial activities increase (Dablanc, 2009; Nourinejad et al., 2014; Rodrigue et al., 2009; USDOT, 2015). Therefore, there is growing pressure in cities to unlock the potential of every public infrastructure element to address the increasing demand for public space.

This dissertation acknowledges this challenge and focuses on two main types of urban transportation infrastructure that provide access to land uses: alleys and the curb lanes. This PhD dissertation considers two independent research plans, one focused on alley infrastructure and commercial vehicle operations, and the second focused on curbspace parking and passenger pick-up/drop-off operations.

1.1 Alley Infrastructure and commercial vehicle operations

Freight and servicing trips require the supply of adequate infrastructure to support vehicle access, load/unload activities, and final delivery/service to customers (Dablanc, 2007). However, existing infrastructure attributes (e.g., width, height clearance, road infrastructure barriers) and the accommodation of street furniture (e.g., streetlights, bollards, benches, green infrastructure, power lines) may not meet the dimensional requirement to support the commercial and emergency operations. Additionally, potential conflicts with vulnerable transportation network users (e.g., passenger vehicles, pedestrians, and cyclists) may impact the efficiency and safety of these operations.

Despite their historical role as providing access to land uses for freight and servicing, to a large extent, alleys are overlooked as a resource in modern freight access planning. No major city in North America has a comprehensive geospatial database of its alley network. There is no literature about the current nature of commercial vehicle operations in these spaces. Without that knowledge, it is impossible to understand the capabilities of these infrastructures as part of the transportation infrastructure network, nor is it possible to conduct comprehensive urban freight planning.

Alleys can provide access to land uses and parking infrastructure for freight, service vehicles, emergency and passenger vehicles, as well as cyclists and pedestrians. This is particularly true for cities with extensive alley networks. For instance, the city of Chicago, Illinois, has approximately 1900 miles of alleys. The City of Los Angeles, California, has an estimated alley network of more than 900 miles, and Baltimore’s alley network encompasses over 600 miles (Newell et al., 2013). Moreover, the City of Vancouver has 404 miles of alleys (Ardis, 2014), City of Montreal 280 miles (Plourde-Archer, 2013), City of Toronto 194 miles, and Beijing, China,1,204 hutongs or alleys (Leinonen, 2012).

The City of Seattle, like many cities, lacks accurate, up-to-date and, detailed information on the location and features of its alleys, and the operations occurring on them. Meanwhile, the city faces both urgent- and longer-term pressures to better manage alleys as part of the larger urban freight infrastructure. With a population of 725,000 and a density of 8,350 residents per square mile, in 2018, Seattle was the sixth most congested city in the USA (Cookson, 2018; Guy, 2018). Since 2010, Seattle has grown by 18.7%, becoming the fastest growing city in the decade among the 50 largest U.S. cities (Guy, 2018). At the same time, the city is expected to grow by 120,000 additional inhabitants and 115,000 additional jobs by 2035 (OPCD, 2018). Seattle’s unprecedented growth and geographic constraints set up a significant challenge for the municipality to efficiently meet the demands for the movement of people, services, and goods. In its alleys, Seattle is fortunate to have a resource that not all cities have, providing a “back door” to the city.

This research focuses on the alley’s role as a network connector, its physical attributes and constraints, and its use by parked vehicles. Specifically, this effort aims to answer the following research questions in Chapter 2 of this dissertation:

- *Research Question 1: How do physical characteristics of alleys play a role in their function?*
- *Research Question 2: What are the characteristics of vehicle parking operations in alleys by time of day and vehicle type?*

To our knowledge, this effort has resulted in first comprehensive alley inventory in the U.S. with an accurate GIS map of the network's geospatial locations as well as measurements of physical attributes (e.g., alley length, alley width and, narrowest points). The attributes collected in this study directly impact alley operations and functionality, particularly for commercial and emergency vehicle access. Before this time, the city relied on a countywide street network database that only included alley centerlines. Evidence-based understanding of the existing parking behaviors in alleys in Seattle, was obtained through data collection of use patterns for every vehicle occupying the alley during observation periods. The data collected include vehicle type, parking duration, and, consequently, how long and at what times of day alleys were vacant.

1.2 CURBSIDE PARKING AND PASSENGER PICK-UP/DROP-OFF (PUDO) OPERATIONS

Cities are dealing with a greatly evolving transportation landscape in which technological advancements and new business models are providing alternative ways to move people and goods. One of these changes involves ridehailing services, which allow users to book rides and pay for car service through a smartphone app. For instance, cities such as Seattle, Wash., San Francisco, Calif., and New York have experienced significant increases in the numbers of ridehailing trips in recent years. Seattle observed 91,000 ridehailing trips in 2018, five times the level in 2015 (Gutman, 2018). Similarly, San Francisco's ridehailing trips in 2016 were 12 times the number of traditional yellow cab taxi trips (SFCTA, 2017), and that ratio was two times in New York (Schneider, 2020).

With the growth of ridehailing services, concerns about their potential negative impacts have increased as well. According to Erhardt et al. (2019), there are several mechanisms by which ridehailing vehicles can increase traffic congestion, including empty cruising behavior, which is vehicle miles driven without transporting passengers, and the impacts of passenger pick-up/drop-off (PUDO) vehicle maneuvers on traffic flow in areas of high demand for ridehailing services.

Curbside management is increasingly vital because of the growing popularity of ridehailing services, coupled with the strong ongoing demand for the curbside by all road users. Efficiencies in curbside management offer the possibility to minimize negative impacts (e.g., from searching for parking, double parking, or queuing) while supporting outcomes such as economic development and social equity.

A potential curb management policy solution is the designation of passenger PUDO zones for ridehailing vehicles, representing a space and set of operating guidelines to manage where, when, and how rideshare activities occur. PUDO zones and their operating guidelines can be fixed or flexible. For instance, the University of California Irvine offers 17 fixed PUDO zones to which requested ridehailing pick-ups and drop-offs on the campus are directed (Uber, 2018). Similarly, the Seattle-Tacoma International and Portland International airports have established fixed PUDO zones to which ridehailing vehicles are directed by operating agreements with ridehailing companies (Port of Portland, n.d.-b; Port of Seattle, 2019). Flexible PUDO zones can be used to respond to relatively short-term needs, such as high ridehailing activity over weekends due to nightlife (DDOT, 2019). In addition to the PUDO zone implementation examples above, multiple cities in the U.S. are considering new pilot tests or extending their current PUDO zone capacity, such as in Fort Lauderdale, Florida (City of Fort Lauderdale, 2018), Washington, D.C. (DDOT, 2019), San Francisco (Smith et al., 2019), Cincinnati, Ohio (Fehr and Peers, 2019), and Bellevue, Wash. (City of Bellevue, 2019).

PUDO zones can be coupled with virtual management strategies that are enabled by advances in technology. Geofencing is one of these strategies and consists of a virtual perimeter around a real-world geographic area that is established to direct or exclude vehicles and passengers to/from the area. Geofencing has been applied on the Seattle-Tacoma International Airport premises to document trip activity and billing (Port of Seattle, 2018). In Bellevue, this technology helps to minimize conflicts between ridehailing vehicles and bicycles by keeping ridehailing PUDO operations out of bike lanes (City of Bellevue, 2019).

All these reasons have motivated a series of studies to describe ridehailing PUDO operations in the street and make recommendations about the allocation of PUDO zones (City of Fort Lauderdale, 2018; DDOT, 2019; Fehr and Peers, 2019; Lu, 2018; Smith et al., 2019). Collectively, these studies have investigated PUDO operation metrics, including dwell times, the number of passengers picked up or dropped off, PUDO operations demand and the number of simultaneous PUDO operations, double-parking, parking occupancy, business satisfaction with PUDO zones, PUDO citations, and curb space productivity (measured as the number of PUDOs per unit length-of-curb space per unit of time). however, the effectiveness of current and emerging curb management technologies on these PUDO metrics and the inter-modal curb space competition have not yet been investigated. Therefore, there is a gap in understanding of the factors that impact these operations as an essential part of the analytical capabilities for curb management evaluation such as simulation tools.

Notably, more research into PUDO dwell time is warranted, as it is a key operational metric for the design and allocation of scarce curb infrastructure. The dwell times of ridehailing vehicles in PUDO zones dictate the maximum utilization of these spaces and, consequently, the probability of finding a space, a primary element of curb level-of-service (National Academies of Sciences, Engineering, and Medicine, 2010). Our research included in Chapter 3 and Chapter 4 of this dissertation aims to answer the following questions:

- *Research Question 3: What factors impact the dwell time of passenger car PUDO operations in the street?*
- *Research Question 4: How does curb space allocation to PUDO zone impact PUDO dwell time in the street?*
- *Research Question 5: How does geofencing of ridehailing vehicles impact PUDO dwell time in the street?*

To answer research questions 3-5 we developed the first sound parametrization of ridehailing passenger load/unload dwell times by using a hazard-based duration model approach. Naturalistic data from a previous study of PUDO operations in Seattle (Ranjbari et al., 2020) is leveraged to link dwell times essential characteristics including the locations of these operations, passenger maneuvers, operation management strategies, and nearby traffic.

Curb management relies on metrics to design, plan and assess the performance of parking infrastructure. Parking occupancy, for instance, is a conventional parking metric frequently used by local governments in performance-based parking pricing programs. Specifically in Seattle, parking rates are frequently adjusted to achieve a parking occupancy rate between 70 and 85 percent (Baruchman, 2018).

Allocating curb space for PUDO activity is not a new concept, however, due to the increased demand for ridehail in recent years and the need to efficiently manage the space, there have recently been efforts to improve the analytical capabilities for curb management and identify and enhance the understanding of relevant metrics.

The lack of curb data and metrics is a challenge that hinders research in this area. To overcome this, some authors have used interview-based research for identifying policy problems and solutions based on public and private perspectives (Diehl et al., 2021). Another series of studies attempted to model different aspects of parking and ridehailing services, but had to rely on assumptions regarding the performance of ridehailing vehicles to represent real-world operations without empirical data (Beojone & Geroliminis, 2021; Kondor et al., 2020; Su & Wang, 2019; Xu et al., 2017; Yu & Bayram, 2021).

Building upon the research on PUDO operations dwell time contained in Chapter 3 and Chapter 4 of this dissertation, our research aims to answer the following questions in Chapter 5:

- *Research Question 6: How does space allocation for PUDO operations impact traffic congestion and overall curb utilization in areas with high PUDO curb demand?*
- *Research Question 7: What is the impact of curb and ridehail management strategies, including geofencing and increasing ridehail passenger occupancy, on PUDO and other curb users' operations?*

This research aims to understand the impact of ridehail curb management strategies on traffic operations, PUDO operations and other curb users, including paid parking and commercial vehicle loading. This was achieved by using simulation models to evaluate, under varying street and curb demand profiles, the effect on curb management metrics of adding PUDO zone space, geofencing PUDO vehicles to PUDO zones, and increasing the occupancy of PUDO vehicles. In VISSIM software (version 9), the discrete event simulation was built by using the software graphical user interface. The VISSIM-COM interface with Python (version 3.8) was used to access and manipulate VISSIM objects during the simlaution dynamically. Our hazard-based duration model developed in Chapter 4 of this dissertation was used to estimate PUDO vehicle dwell times in the simulation

By responding to the proposed research questions 3-7, we derive practical implications for curb management policies by evaluating ridehail management strategies and improving the representation of passenger load/unload dwell times for future research and practice.

Chapter 2. BRINGING ALLEYS TO LIGHT: AN URBAN FREIGHT INFRASTRUCTURE VIEWPOINT

This chapter is structured as follows; a literature review section discusses the role of alleys in cities worldwide based on academic journal articles, city guidelines, manuals and city planning documents. The data collection method section describes the alley inventory and occupancy methods developed. The Seattle case study section describes the empirical findings from the approach implementation in the City of Seattle. The chapter concludes with a summary of findings and recommendations for policymakers.

2.1 LITERATURE REVIEW

2.1.1 *Concept of the Alley and Predominant Roles*

Alleys are narrow pathways between or behind buildings functioning like a **narrow street or path** with walls on both sides (Cambridge Dictionary, n.d.). Alleys are referred to by many different names in the literature. The term laneway is usually used in Canada, UK, and Australia; mews, in UK; and hutongs in China. Alleys range from the pre-car era designs when cities needed to be walkable to post-automobile alleys in North America offering access to motorized vehicles (Wolch et al., 2010).

Alleys primary role is **connectivity** rather than mobility (Bain et al., 2012), providing access to land use either for motorized mode, non-motorize modes, or both. They have different spatial infrastructure characteristics than streets. Alleys' narrow width and location between buildings give them a volumetric attribute (i.e., length, width and vertical clearance attributes) that is often missing in a multilane street (Bain et al., 2012).

For alleys with vehicle presence, often, there is only enough space for one vehicle to drive through the alley. That means that few vehicles use them, and those vehicles are traveling low speeds. In these cases, as spaces with low traffic volumes and speeds, the alley may be the perfect candidate for shared use with non-motorized modes. However, alley's physical constraints may lead to conflicts between users as the demand for these spaces and the need for access alley's adjacent land use. For instance, during the periods where large vehicles are present, alleys can become inaccessible to other users, such as pedestrians (NACTO, n.d.).

For alleys operate as **shared streets,** the usage of bollards, signs, and design features help to make clear the intended alley users (NACTO, 2013). Hutongs are examples of non-motorized shared spaces. They consist of narrow streets, single-floor or low-rise courtyard buildings, and a highly connected street grid that facilitates walking and cycling and limits motorized traffic (Zhao, 2014). Similarly, woonerfs in the Netherlands act as shared streets and can be described as cul-de-sacs with highly restricted automobile access that privileges activities such as biking and walking (Wolch et al., 2010).

In some countries such as the U.S., U.K., and Canada, alleys have been predominantly designed to have a **utilitarian, freight and emergency access function** (Ardis, 2014); providing access to the rear of large lots and space for garbage cans, utilities, and other everyday aspects of living (Ford, 2001; HPO, 2014). In early Washington D.C., the back of the lots likely had kitchens, stables, carts, wagons, and animals in addition to other dependency buildings, equipment, and storage areas (HPO, 2014). Chicago's alleys saw servants and suppliers working in middle-class areas and small manufacturing, repair shops, rear houses, and children's play space in working-class areas (Conzen, 2005).

In some cities such as Montreal and London, where great fires consumed much of their buildings, planners turned to alleys not only as service streets but as firebreaks, and new standards were established for widths, construction and building heights on alleys (Ardis, 2014). Additionally, today's fire codes regulations establish the right-of-way minimum dimensions requirements. The International Fire Code indicates that lanes shall provide emergency vehicles an "unobstructed width of not less than 20 feet and an unobstructed vertical clearance of not less than 13 feet 6 inches" (International Code Council, 2015).

More recently, some cities are turning into alleys to reach the goal of reducing environmental impact. The City of Chicago, IL, pioneered their Green Alley Program in 2006 (Chicago Department of Transportation, 2007), after which other cities such as Washington DC followed (District Department of Transportation, n.d.). These programs strategies such as the management of stormwater and the mitigation of the urban heat island effect (the increased temperatures in urban or metropolitan areas due to human activities) and the implementation of permeable asphalt (Newell et al., 2013).

Alleys have also served as **inhabited spaces**. For instance, in the late 19th century and following the Civil War, a large influx of poor urban migrants resulted in an increase of substandard alley dwellings (Wolch et al., 2010) in the United States. Some contemporary cities have recently passed zoning regulations that encourage housing density in alleys. Mainly, alley houses are a growing trend in Canadian urban centers such as Toronto (Mathieu, 2019) and Vancouver (City of Vancouver, n.d.).

Alleys can serve as **functional social spaces** that foster community cohesion by offering a safe place for active recreation, pedestrian activity, community gatherings and events. For instance, the City of Sydney's, Australia, Laneways Temporary Art Program ran between 2008 and 2013 to ¨inject new energy into the urban life and stimulate creativity and innovation in the city.¨ (City of Sydney, n.d.). In Seattle, more than 5,000 people attended alley events as part of the Alley Network Project between 2008 and 2012. Seattle's alley events and projects have included art and poetry events, lighting installations, pet adoption events, holiday caroling, and film and sport event screenings (Sadeghi K. Majid et al., 2015; Stenning & Somers, 2012).

Some alleys, often located in commercial areas, can support **commercial development** by providing space for outdoor dining, additional entrances to neighboring businesses or could become tourist destinations, increasing adjacent property values. In some locations in China and Europe, old alleys have survived urban planning makeovers to become cherished elements of contemporary cities. Beijing´s 1,204 hutongs have great historical value and have recently received renewed commercial interest from the real estate and tourism industries (González Martínez, 2016). Similarly, mews in London hosts some of the most desirable addresses in the city and have become a tourist attraction in and of themselves (Ardis, 2014).

2.1.2 *Empirical Studies of Alleys*

The following summarizes studies that have used direct observations as part of their approach to document alley characteristics and vehicle activities in cities worldwide.

Several studies have investigated alley space with a focus on surrounding buildings in China and the U.S. Two of Beijing's alleys showed in their premises building types such as lodging, educational, commercial and residential (Yao & Xin, 2018). In Washington D.C., alley dwellings have been studied at different times of the city's history. In 1896 and 1912, two investigations documented dwellings in 35 and 275 alleys, respectively. More recently, in 2011, the District of Columbia Office of Planning conducted the D.C. Historic Alley Building Survey. It was designed to identify extant alley buildings determined to be 50 years or older in over 15 historic districts (HPO, 2014). These studies share the limitation that infrastructure physical attributes and vehicle use characteristics of the alleys were not investigated.

Motivated by an evaluation of the appropriateness of alley housing in Toronto, an alley inventory was conducted that documented which alleys were public, private and are serviced by the city for snow removal or salting (City of Toronto, 2006). The study identified 2,433 alleys and their lengths, but it acknowledges that outstanding work remains to validating alley classifications and completing field confirmation of alley characteristics. The report provides estimates of alley widths, typically between 16 and 19 feet, and allowing passage for a single vehicle in one direction. The connectivity role of alleys, providing vehicular access to the rear of lots, is considered as their main function. City services in Toronto alleys include regular services generally limited to litter pick-up/cleaning during the spring, summer and fall seasons, and salting in the winter months to provide safe passable conditions after snow events. However, city-wide snow plowing operation is not feasible in alleys due to constrained operating conditions and the absence of snow storage space (City of Toronto, 2006).

In the City of Los Angeles, Wolch et al. (2010) conducted physical audits of 300 alleys and behavioral observations of activities inside alleys. Alleys were selected for audits by dividing the total population of 12,309 alleys into the city's thirty-six Community Planning Areas and applying a random stratified sampling approach. Based on the distribution of LA's alleys, most of them are in residential zones (58%) followed by commercial districts (20%), industrial zones (6%) and zones with other land uses (9%) (Wolch et al., 2010).

Wolch et al.'s physical audit instrument was the Systematic Pedestrian and Cycling Environmental Scan for Alleys, which includes 14 questions divided into three sections concerning: i) surrounding land uses ii) substrate and iii) use, conditions, and safety. Wolch et al.'s behavioral observations were conducted in 30 alleys during weekdays and weekends and consisted of 12 observation periods per alley of 5-10 minutes each. Based on this study, access by vehicles was a prominent use of LA's alleys.

Also, in Los Angeles, Seymour and Trindle (2015) quantified the different uses in one renovated and one control alley. The alleys were located one block away from each other and primarily surrounded by commercial land uses and one residential building with offices.

Focused on commercial vehicle curbside loading, Transportation for London (2017) published guidelines for facility size required for freight vehicle parking and navigation and specified strategies for reducing multimodal conflicts at the curb. Although still under development, the guide considers a street audit and provides examples of adequate baseline data that would be gathered in the audit, including the number of vehicle lanes, waiting and loading restrictions, multimodal facilities, and primary vehicle accesses for premises.

There is a growing pressure in cities to expand upon the current purpose of their alleys and better use underutilized alleys to encourage housing density, create lively spaces, pedestrian and bicycle connectors, and spaces for delivery vehicles to load and unload. As cities aim to incorporate in their plans the increase in connectivity for non-motorized modes and other functions provided by alleys, research on alleys as elements of urban structure and dynamics is warranted (Wolch et al., 2010).

By deprioritizing vehicle access, some of these initiatives can have unintended consequences for freight and emergency vehicles access if the current and future use of alleys by these vehicles is not explicitly considered. Meanwhile, there is limited coverage of freight and emergency vehicles in guidelines for multimodal streets (NYSERDA, 2019).

The literature review of empirical studies in alleys showed that some alley features had been researched including adjacent building types, number of access points, pavement type, and slope. Related to activities in alleys, previous studies documented uses by vehicles and non-motorized modes. Despite these efforts, alleys have not been the subject of any comprehensive study focused on commercial and emergency response vehicle activities, including those of freight, waste management, servicing, firefighting, and police vehicles. Thus, little is known about the physical characteristics that could preclude vehicle movements in these spaces. Additionally, the existing studies do not capture sufficient data about vehicle operations in alleys including type of vehicle and stop durations.

In the Seattle case, the City's Right-of-Way Improvement Manual considers that the primary purpose of commercial alleys is to provide access for freight loading, waste collection for commercial uses, and parking (City of Seattle, n.d.-b). However, Seattle's alley advocates are working to change the idea that alleys should be solely utilitarian (Miguel, Otárola, 2015). A study about Seattle's alleys in 2010 estimated that reinvigorating alleyways could increase the amount of total public space in the city by 50% (Fialko & Hampton, 2011).

As Seattle and other cities investigate repurposing and better using underutilized alleys, an adequate assessment of physical characteristics and vehicle activities in these spaces is key to determine what is feasible in terms of street design and freight and emergency vehicle adaptation.

2.2 DATA COLLECTION METHOD

2.2.1 *Alley Inventory*

We developed data collection process to collect the locations and features of all alleys in Seattle's Greater Downtown area, which produces a replicable ground-truthed data collection method based on direct observations.

Survey Form

The developed survey captures three types of features:

1. *Connectivity to Street Network*. Constrained and congested alleys can push onto the street the queue of vehicles trying to access the alleys or force the driver to cruise for adequate space to park. Additionally, sometimes, alleys are the only access route to particular land use. The study included these characteristics:

- <u>Name of streets that the alley connects to,</u>
- <u>Whether the alley is connected to a one-way or two-way street</u>,
- <u>Whether the alley is one-way or two-way traffic</u>, and
- <u>The direction of one-way alleys.</u>

The connectivity to the street network of an alley will depend on its end-points. An **end-point** of an alley is defined as the point where an alley begins or ends. By definition, every alley has two end-points; each of them falls in one of the following categories (see Figure 2-1):

A. **Access Point**: End-point located at the block face of a city block, connecting the alley directly to the street network. This is the most common example of an end-point. Often, there will be buildings on either side of the alley's access point, but in some cases, there may be vacant lots or surface parking lots.

B. **Dead End**: End-point where an alley ends at a dead-end, such as a building or a staircase. There are three subtypes of alley dead-ends:

1. Dead end ending at a physical barrier,
2. Dead-end at a driveway, which could lead to private or public infrastructure, and
3. Dead end at an open area (private or public property), such as a public square.

C. **Intersection:** End-point where two alleys intersect inside a city block.

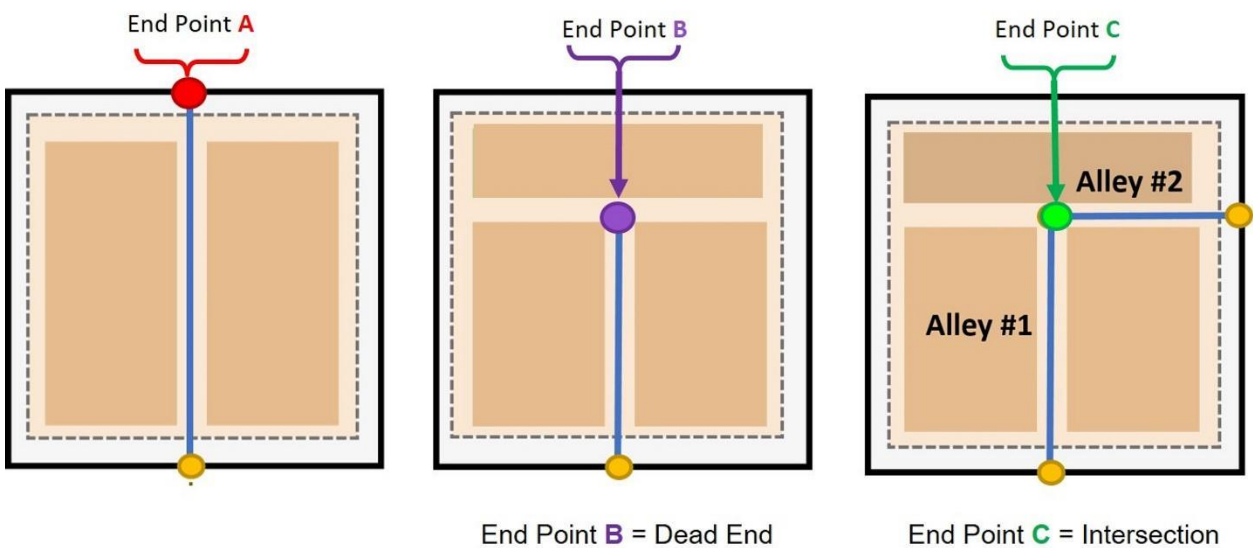


Figure 2-1. Alley end-point classification.

2. Design. The way an alley is designed has a direct impact on its functionality. The inventory examined design features at the alley end-points, alley aprons, and alley interiors.

Alley **end-point** features include width and height with measures recorded as the smallest width (i.e., effective width) and height within 30' from the alley entrance. Researchers used the 30' threshold because it captures the bumper-to-bumper length of most cargo vans and trucks conducting deliveries.

The alley **apron** is a driveway (an entranceway) that starts at the curb and continues until the start of the alley pavement. The apron edge uses a curb cut to provide vehicle access from the street. Apron width, length, and cross slope were recorded; slope can determine whether fully loaded handcarts can maneuver.

Alley's **interior** features measured included alley length (end-point to end-point), pavement surface type (e.g., concrete or asphalt), narrowest point, and fixed overhead obstructions. As most emergency vehicles are 16 feet tall or under, the researchers documented any fixed overhead obstructions under that threshold (such as trees, fire escapes, wires). We also recorded any fixed on-the-ground obstructions that protrude 1' or more into the alley, as this impacts an alley effective width.

3. Access. The features below were included to capture the infrastructure to which the alleys provide access to, and that may impact its use:

- Driveways connected to the alleys, including each driveway that grants access to a parking lot; driveways that link the alley with a nearby street; and driveways that connect the alley to private property.
- Location of buildings' main entrances.
- Private freight load/unload infrastructure.
- Passenger parking, if visible or signed.
- Restrictions on alley usage, as shown on posted signs.

It is important to note that all alley features measured in this study were chosen in consultation with the Seattle Department of Transportation (SDOT) and other City agencies, including police, fire, ambulance, and public utilities. These groups depend on alleys to provide access for commercial and emergency response vehicles to buildings.

Data Collection Mobile App and Instruments

This research included the development of a mobile data collection app that we have made publicly available online (SCTL, 2018). We implemented the survey form and data-collection process on tablets using Esri GIS software Survey123, ArcView, and ArcGIS Online. These Esri products offer a data-collection tool with features that facilitate data quality control, such as visualization and editing of the collected data. Additionally, Survey123 allows the selection of the most appropriate basemap to assist the geolocation input, which was manually collected as a

GPS coordinate reading by dropping a pin in the basemap. For this project, we selected the World Street basemap from ArcGis.com viewer that was last updated in July of 2017 (ESRI, 2017) to assist the manual input of the infrastructures' location.

For accurate measurements, data collection teams were equipped with a measuring wheel and a laser device. The first one was used to collected alley length (typically the longest measure). Every other Design feature was collected with a Laser measuring device.

Data Quality Control

Our research set up a quality control process to reduce errors from entering and propagating within the database. This helped to ensure the quality of the data before it was collected, entered, or analyzed; it also helped to monitor and maintain the data through the collection effort. We identified the types and possible sources of error specific to this type of project including:

1. **Positional error** refers to the inaccuracies of the GPS coordinate readings due to device issues (e.g., low satellite signals in urban canyons) and mistakes by humans manually collecting this data with tablets.
2. **Attribute error** is associated with the remaining non-spatial alley data collected with the survey. Some examples are incorrect data entry due to wrong measurements or data mistyped. Lack of access to the information due to obstructions or safety issues may also result in inaccurate data.
3. **Conceptual error.** The description of a real-world phenomenon or object such as an alley requires its conceptualization through identification and classification of relevant information. Concepts wrongly used can result in information misclassified and not captured information.

Table 2-1 below shows the developed project data quality-control design to address the three types of errors above. Table 2-1 illustrates the measures implemented in three stages: before data collection, during data entry, and after data entry. Three types of resources carried out quality-control procedures throughout the three stages:

1. **Supervisors**: responsible for defining and enforcing data-collection standards and methodology; training the data collectors; and monitoring and maintaining the database. They handled the data-control measures implemented before data collection and after data entry.

2. **Collectors**: responsible for data entry in-field and carrying out same-day data quality-control checks after data entry.
3. **Survey app:** the digital and online tool that helped create entry constraints, eases the digitization of the data as it is collected and ends the need for manual information digitalization. The survey app played a critical quality-control role because it was programmed to limit inaccuracies in the data-entry stage by considering the data structure rules, attributes, and relationships.

Table 2-1. Data quality control measures

	Stage 1. Before Collection		Stage 2. During data entry		Stage 3. After data entry	
	In office	In field	In field		In office	
	Supervisor(s)		Collector(s)	Survey App	Collector(s)	Supervisor(s)
Positional	- Establish physical reference of geopoints	- Deliver training session to collectors about GPS location collection with survey app	- Instructed to be always aware of their location - Keep track of surveyed alley locations with hard copies of maps	- Includes manual collection of GPS reading by dropping location pin - Includes updated base map with city blocks, building outlines, King County TNET alleys and loading bays in alleys.	- Conduct same-day check of surveyed alley locations by reviewing alley endpoints in ArcGIS Online - Check street names of alley endpoints - Check alley TNET id the alley exists in King County's TNET	- Check alleys in TNET database to identify alleys not visited (i.e. missed)
Attributes (Infrastructure features)	- Build questionaries' data entry constrains in survey app - Deliver theoretical training session to data collector	- Deliver training session on data collection with survey app and measurement devices regarding infrastructure features	- Take clear photos to aid data entries	- Includes visual and written aid for data fields	- Conduct same-day check of data collected in field using ArcGIS Online platform	- Check numeric fields for outliers - Conduct revisits to missing alley locations
Conceptual (Infrastructure concepts)	- Establish metadata and vocabulary related to the surveyed infrastructure - Deliver theoretical training to collector	- Train collectors in field on how to identify infrastructure relevant to the survey	- Write open-ended comments, take additional pictures and use "Other" categories for "undefined" cases	NA = Not applicable	NA = Not applicable	- Resolve collectors' observations - Check classification of alley endpoint types with pictures collected and basemap in

Data Collector Training

We recruited and trained 32 data collectors, who worked in teams of two to improve security conditions and enable efficient operation of the multiple data-collection instruments (e.g., laser measurement device, measuring wheel, tables). As data quality control measure, data collectors received approximately 5 hours of training in three different sessions covering the following topics:

1. *Concepts regarding the infrastructure surveyed:* This session instructed data collectors in alley concepts and the features. This session was given in a classroom-type setting, with a slide presentation that covered every feature collected in the survey.

2. *Practical aspects of data collection:* This session was done in-field, leading the collectors through the process of collecting data, such as how to use the questionnaire in the tablet and the measuring tools. Special attention was paid to teach how to take accurate measurements with the laser and wheel devices and how to divide the collection work between the data collectors effectively.

3. *Data quality control tasks:* The final session centered on how to implement the data-cleaning process. After every shift in-field, one of the data collectors in each pair cleaned the data he/she just collected.

2.2.2 *Alley Occupancy*

Occupancy data included use patterns such as how long vehicles were parked in alleys, how long and what times of day alleys were vacant, and what types of vehicles were parking in alleys. Observations were made during business days hours (i.e., Monday through Friday from 8 am to 5 pm). Using human data collectors to track alley usage allowed for the reliable capture of important details, such as windshield permit stickers and company names on vehicles.

Survey Form and Instruments

Each data collector was stationed at one of two positions in the alley. Each alley was divided in half, with each data collector covering three or four zones that met roughly in the middle of the alley. To aid with the identification of zones, detailed maps of the alleys subject of study were created. These zones allowed data collectors to quickly determine and record wherein the alley, a vehicle was parked.

Any vehicle parked in the alley for one minute or more was recorded manually in field using hard copies of data-collection sheets and maps specifically tailored to each alley and data collector’s position. The data-collection sheet was divided by zone, with space for the data collector to record:

- The start/end time a vehicle spent parked in the alley (recorded to the minute);
- The type of vehicle parked in the alley;
- If visible, the company name for commercial vehicles parked in the alley; and
- If visible, the presence of a commercial permit on a passenger vehicle parked in the alley.
- If visible, the Uber/Lyft logo on a passenger vehicle parked in the alley.

Our research designed a highly detailed commercial vehicle typology to track specific vehicle categories (see

Table 2-2). The typology covers 16 separate vehicle categories, from various types of commercial vehicles to passenger vehicles. For this research, the term commercial vehicle includes trailers, box trucks, cargo vans, cargo vans, service vehicles, waste management trucks, and construction vehicles. In the case of passenger vehicles, data collectors tracked, whenever possible, if the drivers were conducting the specific activities of goods delivery/pick-up or passenger pick-up/drop off . If relevant, collectors also tracked the presence of an Uber/Lyft logo and the company name.

Table 2-2. Types of Vehicles for Alley Occupancy Study.

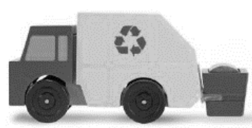
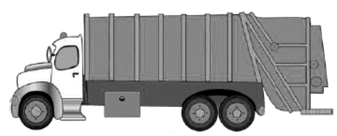
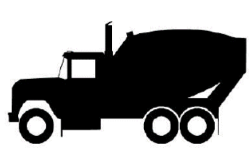
COMMERCIAL VEHICLES (CV)	
Delivery vehicles	
a.1 Trailer Truck (T)	
a.2 Single Unit Truck – Box Truck (B)	
a.3 Cargo Van (CV)	 
a.4 Cargo-bike (C)	
b. Waste Management Trucks (G)	 
c. Service Vehicles (SV) [1]	 
d. General Van (V) [2]	
e. Construction Vehicles (C)	 

Table 2-2. Types of Vehicles for Alley Occupancy Study. (continued).

II. PASSENGER VEHICLES	
Passenger Vehicle Making a Package or Food Delivery (D)[3]	
Vehicle Making a Passenger Drop-off (e.g. Uber / Lyft) (U)	
Passenger Vehicle (P)	
III. OTHER CATEGORIES	
a. Taxi (X)	
b. Motorcycle (M)	
c. Buses (B)	
d. Emergency Vehicles (E)	

[1]Service vehicles include single-unit, vans, sedans and pick-ups vehicles used for service operations.
[2]Cargo or service vans usually display a company logo. If there was not enough information visible, vehicle was marked as a general van.
[3]A personal vehicle being used to deliver packages (such as Amazon Prime Now) or food (such as Amazon Fresh).

Data Collector Training

As a data quality control measure, data collectors received approximately 3 hours of training in two different sessions:

1. *Theoretical training session.* This session was given in a classroom-type setting, with a slide presentation. It instructed data collectors on the data collection on the following aspects of the data collection effort:
   - The study parameters,
   - The typology of vehicles,
   - The data collection method,
   - Review of data collection forms and collector's position in-field.

2. *In-field training session.* This session was done in-field, leading the data collectors through the actual process of collecting data and applying the vehicle typology. Finally, data collectors did a 20-min data collection exercise and classified vehicles that parked in the alley while being supervised.

2.3 CASE STUDY OF SEATTLE

We applied the alley inventory and alley observation methods in the Greater Downtown area of Seattle. For the alley inventory, the researchers completed the data collection over three weeks in January 2018. Data collectors walked 941 city blocks to examine and collect data on the 417 Greater Downton area alleys (see Figure 2-2).

Data collectors were unable to obtain full information inside 6% of all Greater Downtown area alleys, most commonly because construction activity in or near the alley resulted in the alley being closed or fenced off. Less frequently, a truck operating in the alley did not give the data collectors enough room to record measurements safely and accurately.

Seven alleys were selected for the alley occupancy study. Some alleys provide access to off-street passenger car garages, some connect to drive-through hotel entrances, and some are used mostly for commercial purposes. Each alley as shown in Table 2-3 was chosen to represent various features (such as the number of access points for freight or passenger parking);

characteristics (pavement type, alley width, overall condition); and location (some are near—and therefore serve—office buildings, retail centers, residential buildings, or some mix of these).

Additionally, substantial development is projected adjacent to two of the observed alleys (#1 and #2). Four new residential towers will add over 2,000 apartment units and approximately 1,000 off-street parking stalls that will be accessed through alleys (SDCI, n.d.). Currently, these alleys serve several land uses including hotels, surface parking lots, residential buildings and businesses (see Table 2-3).

We deployed data collectors to observe the seven alleys and apply the granular vehicle typology introduced in Table 2-2. Six out of the seven alleys were observed for three or four days for two weeks in February and March 2018. The remaining alley was observed for one day due to security issues. The data collected provided a sample of 437 parking operations between the seven alleys.

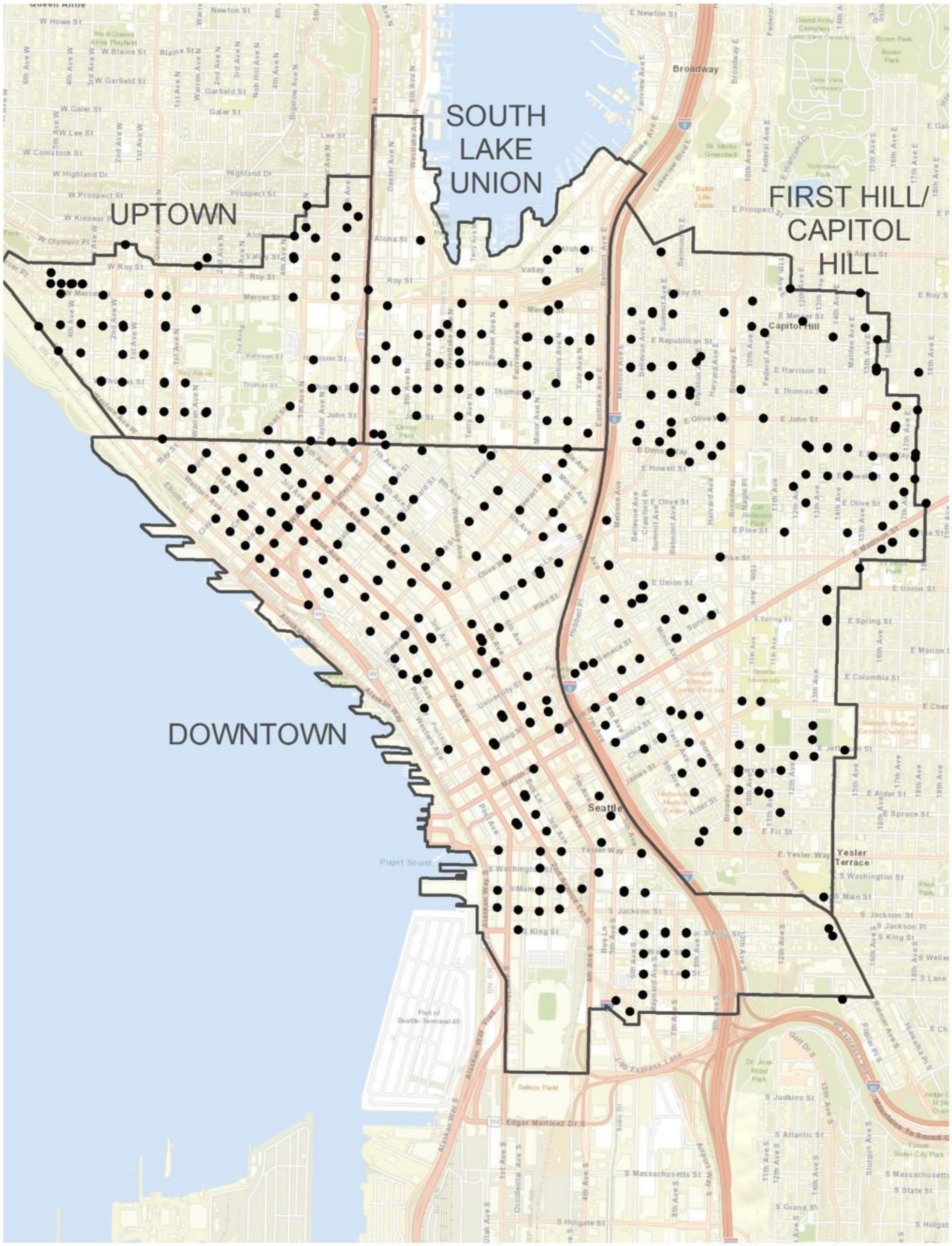


Figure 2-2 Map of the Greater Downtown Area alleys surveyed.
Dots represent the alley end-point. Note: Map scale forces dots to overlap, so not all 417 alley end-points are discernible.

Table 2-3. Alley Locations for Occupancy Study

Alley #	**Location**	**Surrounding Land Use**	**# of Days Surveyed**	**Time Frame Surveyed**	**Total Hours Surveyed**
1	From Virginia to Lenora Streets, between 4th and 5th Avenues	Two hotels; surface parking lot; one residential building; and one office building.	4	8:00 am to 5:00 pm	36
2	From Stewart to Virginia Streets, between 4th and 5th Avenues	Residential tower, commercial businesses; and surface parking lot.	3	8:00 am to 5:00 pm	27
3	From Columbia to Marion Streets, between 2nd and 3rd Avenues	Restaurants, offices and a public parking garage.	3	8:00 am to 5:00 pm	27
4	From Harrison to Thomas Streets, between Terry and Westlake Avenues	Offices and restaurants.	4	8:00 am to 5:00 pm	27
5	From Union to Pike Streets, between 1st and 2nd Avenues	A hostel, retailers, and restaurants.	1	8:00 am to 5:00 pm	9
6	From Pine to Stewart Streets, between 2nd and 3rd Avenues	Temporary construction, restaurants and retailers.	3	8:00 am to 5:00 pm	27
7	From Union to Pike Streets, between 4th and 5th Avenues	Hotel and retailers.	3	8:00 am to 5:00 pm	36

2.4 Results and Discussion

2.4.1 *Alley Infrastructure Feature Findings based on Alley Inventory*

Alley effective width: *90% of the alleys in the Greater Downtown area are just one-lane wide.* Figure 3 shows the distribution of alley widths measured as the narrowest alley end-point width. In practice, most of Greater Downtown area alleys are restricted to one lane for trucks, cargo and service vans. As box trucks are roughly 9.5 feet wide (including mirrors) and delivery vans are typically 8.8 feet wide, alleys up to 19-feet-wide provide only one lane for commercial vehicle use.

This fact is critically important to measure the load/unload capacity of the city's alleys. When a truck, car, or van parks in a one-lane alley, it blocks all other vehicles there unless they back into the alley to park, or back out of the alley to exit. Backing into street traffic and backing up into alleys are both prohibited by the Seattle Municipal code for safety reasons (City of Seattle, n.d.-a).

Additionally, horizontal restrictions inside the alley can reduce the alley's overall capacity. 10% of the alleys showed within-alley restrictions that reduced alley travel width by more than one foot due to overhead or on-the-ground fixed obstructions.

Based on alley width estimates in other cities, Seattle's alleys resemble those in Toronto, which are typically between 16 and 19 feet (City of Toronto, 2006). On the other hand, Seattle's alleys are slightly wider than Beijing inner city's hutongs (10-16 feet) (Zhao, 2013).

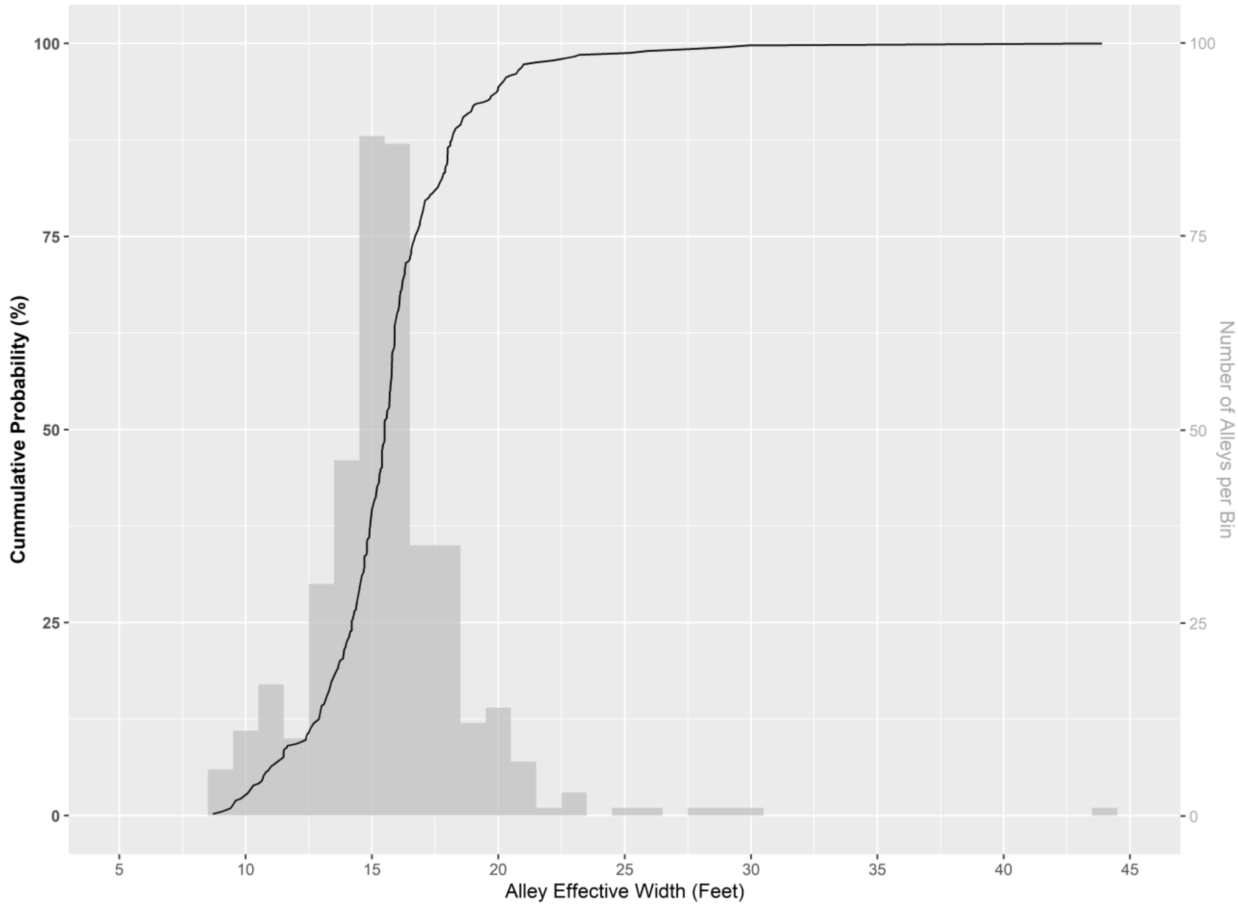


Figure 2-3. Cumulative Probability and Histogram of Alley Effective Widths in Seattle Greater Downtown Area.

Note: The figure represents 408 of 417 total alleys because nine alleys were missing alley width values.

<u>Points of access to land use:</u> *73% of Greater Downtown area alleys contain entrances to passenger parking facilities.*

Data collectors recorded all parking facility access points in each alley. Of the 417 Greater Downtown area alleys, 311 alleys (or almost 75%) contain entrances to passenger parking facilities. This within-alley passenger parking access suggests an increased frequency of vehicle entry/exit and added demands on alley use. This is important to note because these alleys cannot, therefore, be allocated solely to commercial and emergency vehicles.

The typical parking facility types found were underground garages, covered surface-level garages, and open-air surface parking lots. The covered facilities often had more than one access point in an alley, such as a separate entrance and exit. A total of 767 parking facility access points across 311 alleys were recorded.

About 33% of the alleys served at least one private freight load/unload infrastructure inside the alley. Of those, 75% also contained at least one parking facility access point. In other words, about 25% of the 417 surveyed alleys contain both freight and passenger parking facility access points. This suggests a confluence of potentially competing users in these alleys.

In some cases, albeit rarer, data collectors identified a private building entrance (for people, not vehicles) located inside an alley. Of the 417 alleys surveyed, 29 contained one private building entrance.

Local policies in Seattle consider alleys as primary means for access to the rear of homes, apartment buildings and businesses. Alleys are prioritized for delivery and servicing-vehicle access and allow expedited load/unloads up to 30 minutes. At the same time, Washington State Legislation considers that “no person shall stop, stand, or park a vehicle within an alley in such position as to block the driveway entrance to any abutting property” (Washington State Legislature, n.d.).

These policies could lead to incongruencies in commercial vehicle operations in alleys such as that parking is not allow at all. This results from the combination of two of the findings of the alley inventory, alleys are narrow and frequently show vehicle access points to land uses. Therefore, alley blockages impact vehicles parked in the alley but can also limit access to private parking facilities for passenger and freight.

<u>Infrastructure conditions:</u> *Building managers' proactive role in alley maintenance.*

Our research exposed anecdotal evidence that some building managers demonstrated a proactive role in the maintenance and managing of the alleys adjacent to their property by either:

- Enforcing rules to ensure intended use,
- Providing security cameras and/or staff,
- Placing speed bumps to slow traffic,
- Getting pavement improvements completed, and
- Placing signage to identify different usage areas and vehicle circulation rules clearly.

One example of this is shown in Figure 2-4. The recently constructed buildings on both sides of the alley are owned and managed by the same company. During the design phase of these mixed office/retail buildings, deliberate steps were taken to ensure the alley (although publicly owned) was designed to accommodate both truck deliveries to the alley's two loading bays as well as regular passenger vehicle traffic for the two parking garages accessed via the alley. Notably, the alley is signed one-way for passenger vehicles while still allowing trucks to travel in both directions. Also, the alley has a pedestrian crosswalk connecting two building entrances, a wide width, speed bumps, clear sight-lines, surveillance cameras, and frequent building security patrols.

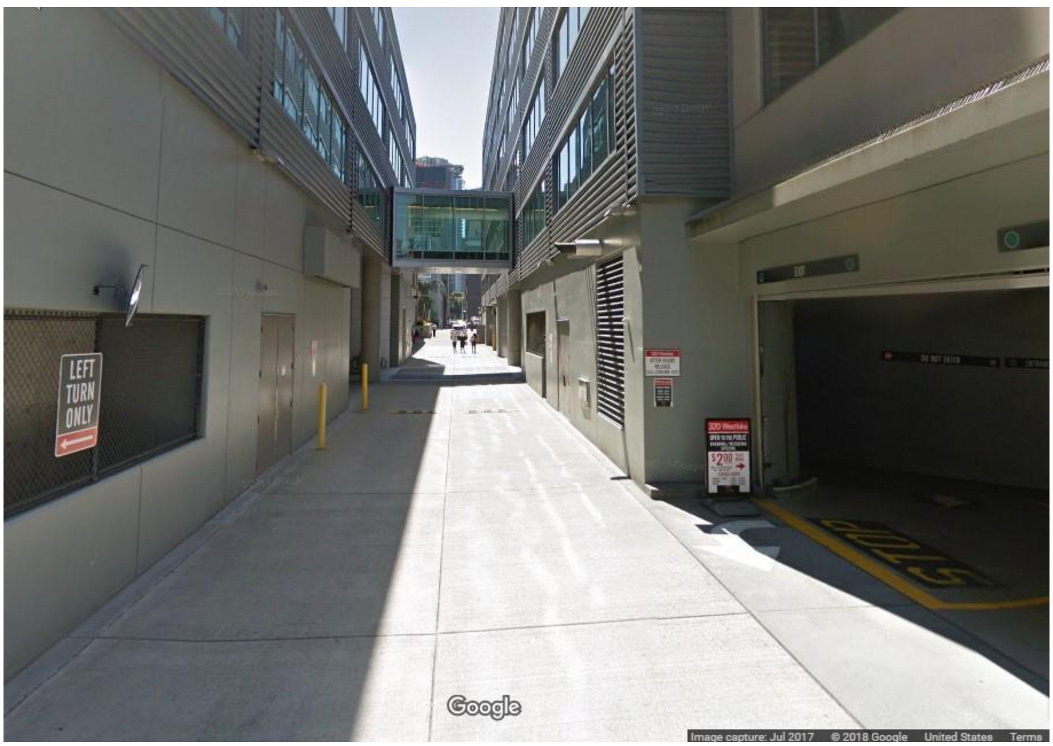


Figure 2-4. Alley in South Lake Union, Seattle, with a high level of ownership from the developer. Source: Imagery ©2018 Google.

<u>Alley Signage:</u> *Wide variety of restrictions signage found in Seattle's alleys*

22% of alleys had signage indicating some type of use restriction of the space. The types of restrictions found are listed below and it is worth noting that 5% of alleys showed one-way sings.

- One-way traffic direction

- customer and resident parking rules,
- no parking restrictions,
- load/unload parking,
- construction signs,
- garbage bin location rules,
- alley closures,
- access restrictions to non-local traffic,
- pedestrian access restrictions,
- no trespassing and littering,
- fire lane - do not block area,
- maximum vertical clearance.

Most of alleys are less than 19-feet wide but only 5% of them showed one-way signs, this could lead to unsafe situations caused by vehicles backing out of alleys. Defining entering and exiting routes for vehicles and clear signage are measures to avoid these situations.

The proportion of alleys with signage was lower in Seattle than in LA, when compared to Wolch et al. (2010)’s study, which showed that 65% of LA’s alleys had signage concerning parking, dumping, dog waste, and trespassing, It is worth noting that some of the categories of restrictions were similar in both cities, and Seattle showed additional types related to deliveries, fire lane, circulation restrictions, vertical clearance and temporary restrictions such as alley closures and construction zones.

2.4.2 *Alley Usage Findings based on Alley Occupancy Study*

<u>Observed Demand:</u> *Parking per alley is typically limited to less than three commercial vehicles.* The authors investigated the occupancy of the seven alleys by parked vehicles. Six levels of occupancy were considered ranging between 0 vehicles (vacant) and five vehicles parked at the alley at the same time. For each alley and day of data collection, the proportion of time that the alley had the different levels of occupancy was calculated. Figure 5 shows proportion of time that each alley showed different number of vehicles averaged between the days of data collection.

The occupancy study finds that all seven study alleys predominately had just one to two vehicles parked at a time. Higher occupancy levels of three or more vehicles were observed only during a small fraction of time in each of the seven alleys. The proportion of time with three or more vehicles averaged 8% between the seven alleys, and the maximum observed was 14% at the alley located at Pike & Union /1st & 2nd.

<u>Level of Vehicle Activity:</u> *Alleys are vacant about half of the time during the business day.* As shown in Figure 2-5, the seven alleys were unoccupied between 23% and 83% of the studied hours. The percentage of time that the seven alleys were empty averaged 50%.

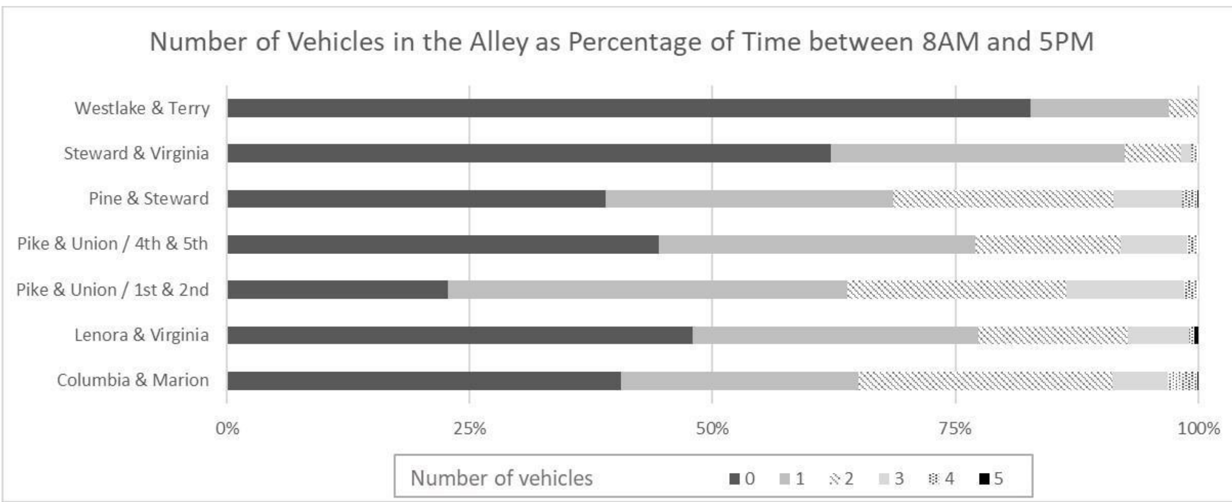


Figure 2-5. Average Occupancy Level of Alleys over the Observation Study Period.
Note: Pike & Union /1st & 2nd alley shows occupancy level of the alley between 8AM-5PM based on one day of data collection. The remaining six alleys show average occupancy level based on 3-4 days of data collection.

<u>Vehicle Dwell Time:</u> *68% of all vehicles parked in alleys were there for 15 minutes or less.* Even more, 87% of vehicles were parked in alleys for 30 minutes or less (see Table 2-4), which is the time limit considered by the Seattle Municipal Code. In general, the most frequent alley users were truck and cargo vans, at 54% of all recorded vehicles. The second-most-frequent alley users were passenger vehicles, at nearly 20%.

Since six out of the seven alleys were 17 feet wide or less, some of these parking operations could be considered as not allowed in the sense that one vehicle could block access to land uses from the alley for several minutes. Preserving alley access function may become crucial as some city blocks in downtown Seattle will accommodate new and dense growth. Policies should be in place to ensure best practices are followed for alley operations and design of access points in alleys for parking garages and loading bays in buildings.

Table 2-4. Dwell time distribution by vehicle types for all seven alleys studied

Vehicles Type	**No. of Vehicles Observed**	**15 min or less**	**15-30 min**	**30min -1hr**	**More than 1hr**	**Total share of parked vehicles**
Trucks and Cargo Vans	229	30.0%	12.6%	6.2%	3.6%	**52.4%**
Service Vehicles	31	6.0%	0.9%	-	0.2%	**7.1%**
General van	42	5.7%	2.5%	0.9%	0.5%	**9.6%**
Passenger	86	16.9%	1.8%	0.5%	0.5%	**19.7%**
Passenger making a delivery (only when logo was visible, or activity was observed)	15	2.8%	0.2%	0.2%	0.2%	**3.4%**
Garbage truck	17	3.4%	0.5%	-	-	**3.9%**
Uber/Lyft (only when logo was visible)	1	0.2%	-	-	-	**0.2%**
Others	15	1.6%	0.5%	0.7%	0.7%	**3.4%**
Unknown	1	0.2%	-	-	-	**0.2%**
Total	**437**	**66.8%**	**19.0%**	**8.5%**	**5.7%**	**100%**

2.5 CONCLUSION AND POLICY RECOMMENDATIONS

There is growing pressure in cities worldwide to find innovative ways to better manage and use scarce space. Cities increasingly recognize the potential to incorporate the increase in resources provided by functional alleys for environmental, economic and social benefits. As the literature review of this research shows that cities have try to unlock te potential of this urban infrastructure element using different approaches. Netherlands' woonerfs or alleys illustrate the implementation of shared-street schemes to improve alleys as connectors for pedestrians and bicycles. Beijing's hutongs exemplify the potential of historic alleys to become touristic attractions and enhance commercial development. Also, some Canadian cities have recently passed zoning regulations to encourage housing density in center city alleys.

As we promote connectivity for non-motorized modes in these spaces is essential to acknowledge their function of providing access for utilitarian, freight and emergency responses vehicles. Despite this important function that many alleys play, our literature review shows that alleys have not been the subject of a comprehensive study focused on physical characteristics that can preclude the movement of vehicles particularly vehicles providing these services (e.g., freight, waste management, service and fire truck). Additionally, studies related to activities in alleys do not capture sufficient data about vehicle operations including type of vehicle and stop durations. To address this gap in the understanding of alleys and help communities assess and plan alley utilization and management, our research provides with:

1. A data collection methodology to support an adequate assessment of physical attributes that directly impact alley operations and functionality, particularly for freight, waste management, and emergency vehicle access.
2. The demonstration of our alley inventory methodology in Seattle that results in the first comprehensive alley inventory in North America with an accurate GIS map of the network's geospatial locations as well as measurements of physical characteristics.
3. Evidence-based understanding of existing vehicle parking behaviors in alleys based on occupancy studies in seven alleys in the Seattle's densest area.

This research also elaborates recommendations that cites can use to better manage alley space and unlock of these infrastructures. As illustrated by Seattle's alleys, their narrow width and location between buildings with multiple access points to parking facilities and pedestrian entrances can limit vehicle operations in these spaces. Usage of these spaces by delivery vehicles such as box trucks (typically 9.5-foot wide) can lead to blockages of the entire alley for vehicles trying to access buildings in the premises or parking in the alley. To avoid unsafe situations caused by vehicles backing out of alleys, entering and exiting routes in all one-lane alleys should be defined with clearly posted operating rules.

Cities can use the information provided by a comprehensive scan of physical characteristics of urban alleys to make data driven decisions about the most cost-effective freight distribution systems for the last mile. Geospatial information of alley restricting dimensions such as effective height and width can help to decide between delivery vehicle designs that balance maneuverability, size and load capacity.

As illustrated by the occupancy study in seven alleys in Seattle’s densest area, these spaces can be vacant (without parked vehicles) a significant fraction of the time be typically used by up to two parked vehicles simultaneously. There is a potential for alleys to be used as a flexible and dynamic space that adapts to different uses and users throughout the day, including vehicle accessing land uses, space for load/unload, and nonmotorized modes such as pedestrians and bicycles.

The data quality control plans considered in this research did not include the application of validity and reliability scores, future applications of the alley inventory and observation tools could consider these scores to add to the robustness of the methodology.

This research adds evidence that alley networks are a valuable resource as both space for freight load/unload; and direct access to parking facilities and business entrances for commercial, private, and emergency response vehicles. We encourage future research to investigate how to effectively allocate alley space for load/unload, access to buildings and parking facilities and other uses.

Chapter 3. CURB MANAGEMENT STRATEGIES AND RIDEHAILING PICK-UP/DROP-OFF OPERATIONS

This chapter includes a literature review section that discusses recent advancements in the analytical capability for curb management evaluation, existing curb management metrics focused on time and ridehailing performance, and findings about PUDO dwell time from previous studies. Also, this chapter introduces the data sources that will be used in the analysis of PUDO dwell time using hazard-based models of Chapter 4 and the curb envirionment evaluation case study with simulation of Chapter 5.

3.1 LITERATURE REVIEW

3.1.1 *Curb Management Evaluation for Ridehailing Vehicles*

In recent years, researchers and practitioners have recognized the rapidly growing complexity of curb management, with emerging uses such as MoD services and high competition among all road users, and have sought new methods to address the gap in understanding and analytical capability for evaluation.

The lack of curb data and metrics is a challenge that hinders research in this area. To overcome this, some authors have used interview-based research for identifying policy problems and solutions based on public and private perspectives (Diehl et al., 2021). Another series of studies attempted to model different aspects of parking and ridehailing services relying on assumptions regarding the performance of ridehailing vehicles to represent real-world operations without empirical data. These modeling efforts investigate the provision of waiting areas to reduce empty cruising or improve passenger convenience (Beojone & Geroliminis, 2021; Kondor et al., 2020; Xu et al., 2017), the reduction of parking demand by passenger cars (Kondor et al., 2020; Su & Wang, 2019), and the flexible allocation of curb space (You Kong et al., 2020; Yu & Bayram, 2021).

Ridehial modelling efforts applied a macroscopic approach, equilibrium models, and numerical experiments to relate parking, ridehailing vehicles, and traffic congestion at an aggregated level. Kondor et al. (2020) used a different approach, based on an integrated, agent-based simulation modeling framework calibrated to represent Singapore in 2012, and investigated the relationship between on-demand vehicle fleet size, empty cruising, and the provision of different parking spaces, including waiting areas for pick-ups and spaces for on-demand vehicles not in service. Alternatively, Kong et al. (2020) introduced a framework at a road-intersection level to model competing curbside demands, including through-travel, ridehailing PUDO zones, and on-street parking.

These studies increased understanding of the potential impacts of curb management strategies and system dynamics. Xu et al. (2017) evaluated the trade-offs of reducing road capacity (and related congestion) to provide parking spaces for vacant ridehailing vehicles to reduce empty cruising. Beojone and Geroliminis (2021) also looked into the parking provision problem to mitigate empty cruising; they considered a dynamic traffic congestion model and smart parking allocation in high demand areas while relating ridehailing vehicle fleet size and customers’ willingness to share a ride.

Another aspect of ridehailing services is the potential reduction in parking demand by passenger cars and its impact on the minimum parking supply needed in urban areas. Su and Wang (2019) analyzed how parking constraints may lose their power as a travel demand management strategy as ridehailing services grow.

The modeling studies introduced above (both macroscopic and intersection-level approaches) have relied on assumptions regarding the performance of ridehailing vehicles to represent real-world operations. For instance, Yu and Bayram (2021) built macroscopic simulation and optimization models that analyzed the interaction between urban traffic congestion and flexible curb uses, including PUDO, loading/unloading of goods, and parking-only. The durations of both types of parking were assumed to follow a gamma distribution and to be shorter for PUDO than for goods loading/unloading. Similarly, Kong et al. (2020) looked into competition for curb use among vehicles traveling through the area, PUDO, and on-street parking but assumed an exponential distribution for PUDO duration. However, the reliability of those assumptions, and the analyses built upon them, were limited by the lack of real-world ridehailing vehicle loading and unloading data.

There are a series of empirical studies or pilots that describe ridehailing PUDO operations in the street and make recommendations about the allocation of PUDO zones (City of

Fort Lauderdale, 2018; DDOT, 2019; Fehr and Peers, 2019; Lu, 2018; Smith et al., 2019). Collectively, these studies have investigated PUDO operation metrics, including dwell times, the number of passengers picked up or dropped off, PUDO operations demand and the number of simultaneous PUDO operations, double-parking, parking occupancy, business satisfaction with PUDO zones, PUDO citations, and curb space productivity (measured as the number of PUDOs per unit length-of-curb space per unit of time). however, the effectiveness of current and emerging curb management technologies on these PUDO metrics and the inter-modal curb space competition have not yet been investigated. Therefore, there is a gap in understanding of the factors that impact these operations as an essential part of the analytical capabilities for curb management evaluation such as simulation tools.

3.1.2 *Time Metrics and Ridehailing Service Performance*

Different time metrics have been considered to evaluate the performance of ridehailing vehicles in urban roadways. *Wait time* refers to the duration until a ridehailing user is picked up by a dispatched vehicle after having placed a service request. Inequitable spatial and temporal distribution of wait times may be a proxy for lack of access equity (R. Hughes & MacKenzie, 2016). *Uptake time* can be defined as the time from a pick-up vehicle's arrival at the appropriate city block to arrival at the curbside. The City of Washington D.C. evaluated an uptake time of fewer than 120 seconds on streets with certain traffic flow conditions (DDOT, 2019).

Dwell time of ridehailing vehicles or private vehicles conducting PUDOs on urban roadways is described generally as the duration of the PUDO event (Fehr and Peers, 2019; Smith et al., 2019). Lu (2018) defined dwell time more specifically as the time spent between the moment when the vehicle comes to a stop outside the flow of traffic and the moment the vehicle moves away from the stop. Alternatively, Galagedera et al. (2014) provided a definition of dwell time for PUDO operations in the context of airport curbside:

"[the] amount of time a vehicle spends parked at a curbside lane (or other passenger loading or unloading area). Typically, the dwell time is the length of time between when the driver parks (i.e., the vehicle comes to a complete stop) and when the driver first attempts to rejoin the traffic stream."

The dwell time metric is particularly relevant to curb management. Research on PUDO zone requirements at airport passenger terminals has related the capacity of these facilities to both the number of vehicles that can be accommodated while at a stop conducting PUDOs and the number of vehicles that can be accommodated traveling past the curbside zone using the adjacent through-lanes (Galagedera et al., 2014; National Academies of Sciences, Engineering, and Medicine, 2010). Dwell time is a factor of the utilization of these facilities, and consequently, it is necessary to determine whether spare capacity is available to serve additional demand and surges in demand.

Clearly defining the different processes of a PUDO operation that compose its dwell time is required to investigate the critical stochastic factors that affect PUDO zone capacity, develop a standardized service performance metric, and compare results among studies. Good examples are studies of transit vehicle dwell time related to transit capacity and design, which have been modeling this metric for decades to address transit reliability, stop design, and route scheduling, among other topics (AlHadidi & Rakha, 2019; National Academies of Sciences, 2013).

Heterogeneity in dwell time also relates to parking time limits, which can be a valuable tool for increasing turnover and reducing excess demand by diverging longer-duration users if used appropriately, or can lead to unintended consequences if not (Arnott & Rowse, 2013). PUDO zones that have been part of pilot tests to address ridehailing vehicle demand in urban roadways have also had time restrictions. Some recent examples set this limit to 1 and 5 minutes in Washington, D.C., and Fort Lauderdale, Texas, respectively (City of Fort Lauderdale, 2018; DDOT, 2019).

3.1.3 *Previous Findings on Urban PUDO Zone Ridehailing Dwell Time*

A handful of studies have investigated the dwell times of ridehailing vehicles in urban road settings based on real-world data. The ten locations considered in these studies in three different cities are summarized in Table 3-1 and represent a mix of land-use, neighborhood, and roadway characteristics, including four arterials and six local streets, of which three were one-way streets. Different time of day periods were considered among the studies, including the AM and PM peaks of the adjacent road, special events during weekdays and weekends, and periods with significant nightlife activity on weekends.

The first set of five locations was from a study in San Francisco by a consultant, which observed 586 ridehailing vehicles conducting PUDO operations during AM and PM peaks (Smith et al., 2019). PUDO operation data by multiple vehicle types, including ridehailing vehicles, buses, commercial vehicles, taxis, private vehicles, and shuttles, were obtained from video camera recordings. Another study by Lu (2018) documented 2,241 ridehailing PUDO operations in two locations of Los Angeles, Calif., during periods of nightlife activity on weekends and using a manual data collection approach.

Last, a study by a consultant collected data about ridehailing activities in three locations in Cincinnati, Ohio (Fehr and Peers, 2019). In this case, the study focused on capturing differences in PUDO operations before and after special events, including a theater show, a baseball game, and a road segment’s temporal closure to create a pedestrian area for nightlife activities. Data on 228 PUDO operations were recorded with video camaras, but the authors could not distinguish between ridehailing vehicles and private cars.

Figure 1 shows the average dwell time values of PUDO operations reported by the three studies described above, which ranged between approximately 15 and 100 seconds. Although strictly descriptive, the dwell time statistics and anecdotal evidence from those efforts indicated factors that may play a role in causing variance in dwell times. These factors can be categorized into four categories: location, passenger movements, operations management, and traffic.

- **Location:** Ideally, PUDO operations take place at the curbside in zones allocated for this use. However, drivers have been observed engaging in non-compliant behaviors, including double-parking (in-street) and serving passengers at the curbside where no stopping is allowed for picking up and dropping off passengers. These noncompliant behaviors have tended to last for shorter durations than compliant curbside operations. Dwell times at the curbside versus the street were reported for ten study locations, of which seven showed lower dwell times for vehicles stopping in the street (see Figure 3-1). Additionally, Lu (2018) reported lower dwell times for ridehailing vehicles using curbside zones reserved for transit vehicles than in PUDO zones.
- **Passenger Maneuvers:** The number of passengers in a PUDO operation will impact the total dwell time, and pick-ups and drop-offs may have different durations. For instance, for picking-up passengers, drivers are likely to wait for passengers to locate and approach the vehicle, while this step is skipped during drop-offs. Anecdotal evidence has shown

shorter dwell times before special events, such as theater shows and sport matches, when activity has been predominantly drop-offs instead of after events with a prevalence of pick-ups (Fehr and Peers, 2019). Another passenger maneuver that may drive longer dwell times is the time spent assisting passengers with luggage.

- **Operations Management:** Methods of managing the assignment of passengers and drivers based on a set of criteria, such as first-come/first-serve, and the location of the operation, such as geofencing, may impact dwell time. In May 2019, Lyft and Uber announced pilot operations at the Portland International Airport (PDX) to reduce driver and passenger wait times. The new system connects riders with their drivers more quickly by using a personal identification number (PIN). Travelers request a ridehailing, receive a one-time code, and enter the line at the pick-up location. When they reach the front of the line, they show their code to the driver and, upon validation, start the trip (Port of Portland, n.d.-a).
- **Traffic:** Congestion in the adjacent through-lane and in the PUDO zone may make drivers less likely to find a space in oncoming traffic and therefore may increase their difficulty in merging back into traffic.

3.1.4 *Summary*

PUDO dwell time is a metric required for adequate PUDO zone capacity estimation. Furthermore, understanding the heterogeneity of dwell time is necessary for correctly assessing the outcomes of curb management strategies such as parking time limits. A handful of studies have documented the dwell times of ridehailing vehicles based on real-world data. However, this critical operational metric remains largely understudied in comparison to research on transit vehicle operations, which have modeled dwell times for decades. Ongoing research efforts aim to create modeling approaches to accommodate the growing complexity of demands for curbside space and provide guidance and solutions to infrastructure managers and policy makers. However, the lack of an adequate parametrization of dwell time, and understanding of the effectiveness of current and emerging curb management technologies on curb management metrics hinders the potential of these efforts. An adequate parametrization of PUDO dwell time should consider factors of dwell time variance, including at least location, passenger maneuvers, operations management, and traffic.

Table 3-1. Summary of Empirical Studies of Ridehailing PUDOs

Location	**Observed Time Period**	**Road Characteristics**	**Adjacent Land Use**	**Sample Size (ridehailing vehicles) ***	**Reference**
Clay Street, San Francisco	PM commuter peak of a typical weekday	Multi-lane one-way street representing a downtown corridor	Offices and hotels	57	(Smith et al., 2019)
Hayes Street, San Francisco	PM commuter peak of a typical weekday	Two-lane commercial corridor with moderate pedestrian and bus activity	Commercial corridor with retail and medium-density residential	29	(Smith et al., 2019)
Polk Street, San Francisco	PM commuter peak of a typical weekday	Three-lane downtown commercial street with bike lanes and curb parking lane on both sides.	Commercial corridor with medium-density residential and close to Civic Center	78	(Smith et al., 2019)
Second Street, San Francisco	AM Peak and PM Peak commuter peaks of a typical weekday	Four-lane downtown commercial street	High-density office	58	(Smith et al., 2019)
Townsend Street, San Francisco	AM Peak and PM Peak commuter peaks of a typical weekday	Two-lane arterial road with bike lanes on both sides	Major transit center, the 4th/King Caltrain station	364	(Smith et al., 2019)
Melrose Street, Los Angeles	Nightlife during weekend nights	Four-lane arterial corridor with curb parking lane on both sides	Restaurants, bars and retail	174	(Lu, 2018)
Santa Monica Street, Los Angeles	Nightlife during weekend nights	Four-lane arterial corridor	Restaurants, bars and retail	2,067	(Lu, 2018)
Aronoff Center of the Arts, Cincinnati	Before-after special events on weekend nights	Walnut Street, a two-lane one-way street with parallel curbside parking on both sides. Streetcar runs on rail tracks in the center travel lane.	Restaurants, hotel, Aronoff Center of the Arts (theater) and governmental	57**	(Fehr and Peers, 2019)
Freedom Way, Cincinnati	Nightlife during weekend night	Three-lane, two-way road with curbside parking lanes on both sides	Restaurants, bars, park, apartment buildings	69**	(Fehr and Peers, 2019)
Great American Ball Park, Cincinnati	Before-after special events on weekday and weekend	Second Street, five-lane, one-way street with a transit-only lane for buses and streetcar. One of the travel lanes is used as taxi loading zone after games	Great American Ball Park (stadium), restaurants and bars	102**	(Fehr and Peers, 2019)

*Notes: *Ridehailing vehicles conducting PUDOs, unless otherwise noted. **Includes private and ridehailing vehicles alike conducting PUDOs*

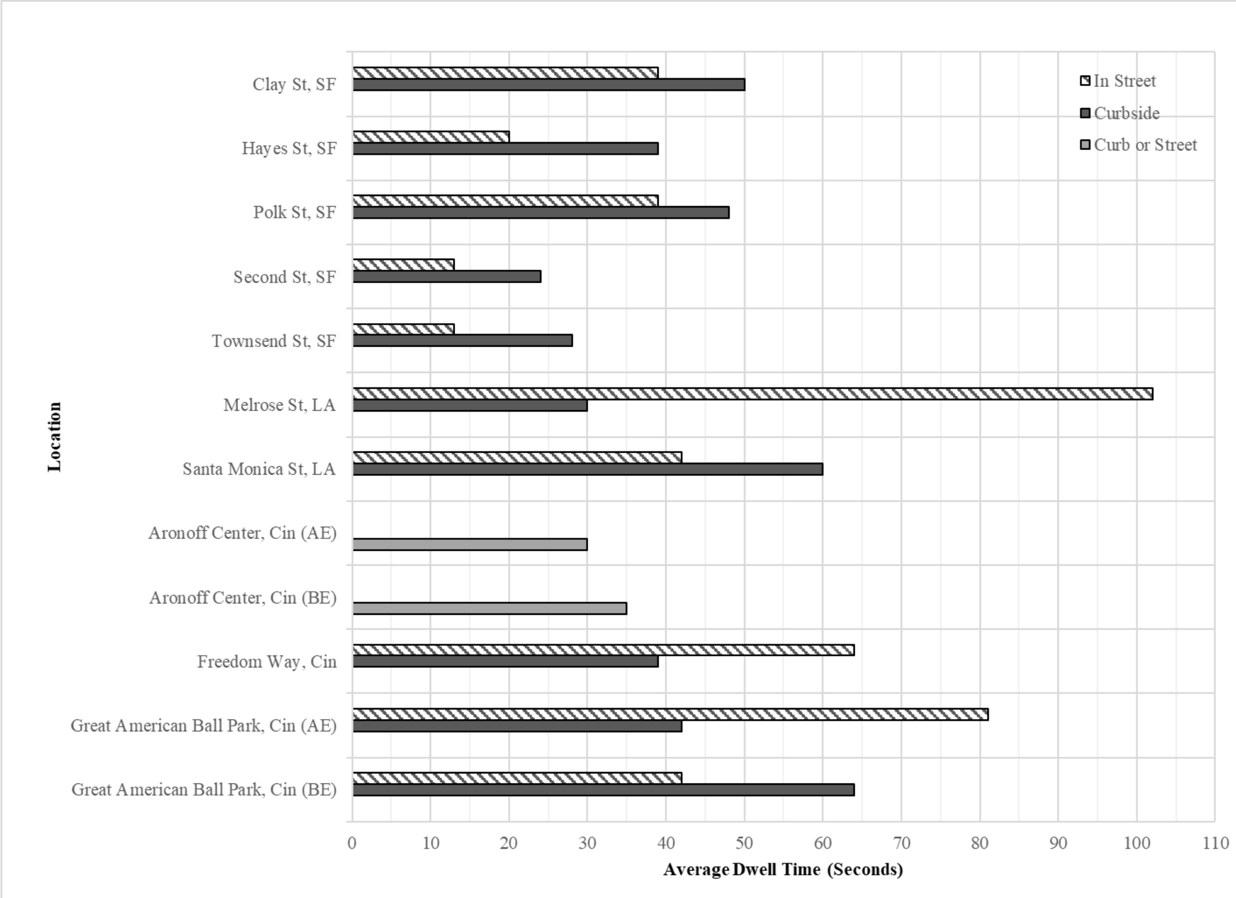


Figure 3-1 Average Dwell Time of Ridehailing PUDOS in Multiple Studies

Notes: Locations Aronoff Center, Great American Ball Park and Freedom Way show average dwell time of private and ridehailing vehicles without distinction between the two types. BE: before event. AE: After event.

3.2 DATA SOURCES

Three types of data were used in this dissertation research: vehicle stop events, off-street parking garage occupancy, and traffic volume and speed. The data sets were obtained from a previous study by Ranjbari et al. (2020) that evaluated two curb management strategies in Seattle, Wash., in an area where large numbers of workers commute using ridehailing services. The strategies were 1) a curb allocation change from paid parking to PUDO zones, and 2) a geofencing approach by ridehailing companies that directed their drivers and passengers to designated PUDO zones on a block.

3.2.1 *Study Area*

The study area included three block faces in a segment of Boren Ave N, a local two-way street with one travel lane and one on-street parking lane in each direction (see Figure 3-3). The street was in South Lake Union, a rapidly growing neighborhood adjacent to downtown Seattle, with predominantly mixed-use land including offices, retail, mixed-used commercial, and mixed-use residential (SDCI, 2017). After downtown Seattle, South Lake Union is the city's second-ranked neighborhood in order of employment density, with 2.7 jobs per 1,000 square feet.

The segment of Boren Ave N was observed during the AM and PM peak activity periods (8:00-10:00 AM and 2:00-6:00 PM, respectively), five weekdays per week during three different weeks (or study phases) between December 2018 and early January 2019. During the observation periods, the street showed an average hourly traffic volume of 155 to 370 vehicles and an average traffic speed of 12 to 14 mph. Vehicles conducting passenger pick-ups or drop-offs represented 18 to 37 percent of hourly traffic volume (Ranjbari et al., 2020).

3.2.2 *Existing Curb Space Allocation*

The studied three block faces included 1,090 linear feet of curb, out of which 530 feet were considered no parking/tow-away zones. The remaining 560 feet were allocated to different usages, which could vary during the time of day and day of the week. During the studied weekday AM and PM activity periods (8:00-10:00 AM and 2:00-6:00 PM), curb space was allocated to four main usage types, including 2-hour paid parking, PUDO zones, commercial vehicle load zones, and charter bus/shuttle bus/taxi load zones. Before any curb management strategy had been implemented as part of our research, the existing allocation of curb space in the observed block faces included the following types of usage during the AM and PM activity periods:

- 2-hour paid parking (450 feet)
- PUDO zones (20 feet)
- Commercial vehicle load zones (40 feet)
- Charter bus / Shuttle bus / taxi load zones (50 feet).

Out of the periods of high activity (and our periods of observation), several spaces for dedicated 2-hour paid parking turned into food truck zones between 10:00 AM and 2:00 PM. Figure 3-3 shows the locations of the observed block faces on Boren Ave N, and Table 3-2 describes the allocation of curb uses in each of these block faces.

3.2.3 *Study Phases and Curb Allocation Changes*

Data were collected in three different phases:

- **Phase I: Baseline**. This phase refers to the state of curb management before any strategy was implemented or changes of curb allocation were made. In the baseline, the existing allocation of curb space to PUDO zones was 20 feet.
- **Phase II: Added PUDO zones.** New PUDO signs were replaced paid parking. As a result, the curb length dedicated to PUDO zones was extended from 20 feet to approximately 270 feet, 14 times more PUDO space.
- **Phase III: Added PUDO zones + geofencing**. With the same allocation of PUDO space as in Phase II, operations by Uber and Lyft were geofenced at the existing PUDO zones. Ridehailing trip requests within a two- block distance from the PUDO zones were directed to these curb spaces.

To allow users to get accustomed to the new street conditions, data were not collected until at least one week after implementation of the curb allocation changes of phases II and III. Additionally, the street strategy changes appeared to road users as permanent changes. First, the new PUDO signs and curb paint followed the city's signage design standards, and they were identical to other PUDO signs in the city (locally called Passenger Load Zones). Second, the ridehailing mobile apps seamlessly integrated geofencing, and the trip request process looked similar to other locations with geofencing, such as the local Seattle-Tacoma airport.

Figure 3-2. Segment of Boren Ave N between Harrison St and Thomas St.

3.2.4 *Data Sets*

The data sets used included the following:

The vehicle stop event database included a total of 8,063 stop events recorded with video cameras and documented individually. The events were broken down into the following types:

- **2,827 passenger loads**: A vehicle entered the study area to stop and pick up passenger(s) different than the driver.
- **3,197 passenger unloads**: A vehicle entered the study area to stop and drop off passenger(s) different than the driver.
- **929 parking operations**: After the vehicle stopped, the driver exited the vehicle and left it parked.
- **148 un-parking operations**: The driver entered a parked vehicle and moved away.
- **962 unidentified operations**: Vehicle stop events for which there was not enough information from the video to classify them further. For instance, some cases involved a vehicle stop but neither the driver nor other passenger entered or exited the vehicle.

The aim of this study was to develop a predictive model of stop durations by passenger vehicles loading or unloading passengers. Therefore, model calibration was based on the subset of 6,024 passenger load/unload events.

The off-street parking garage occupancy database included occupancy in 5-minute intervals during the study period at three off-street parking garages managed by Amazon in the study area. The locations of the entrances and exits of the parking garages are shown in Figure 3-3.

The traffic volume and speed database included vehicle counts and average point speeds measured with two tube counters. Data were collected in 5-minute intervals during the study period. The tube counters were placed midblock on the two studied segments of Boren Ave N (see Figure 3-3Figure 3-3).

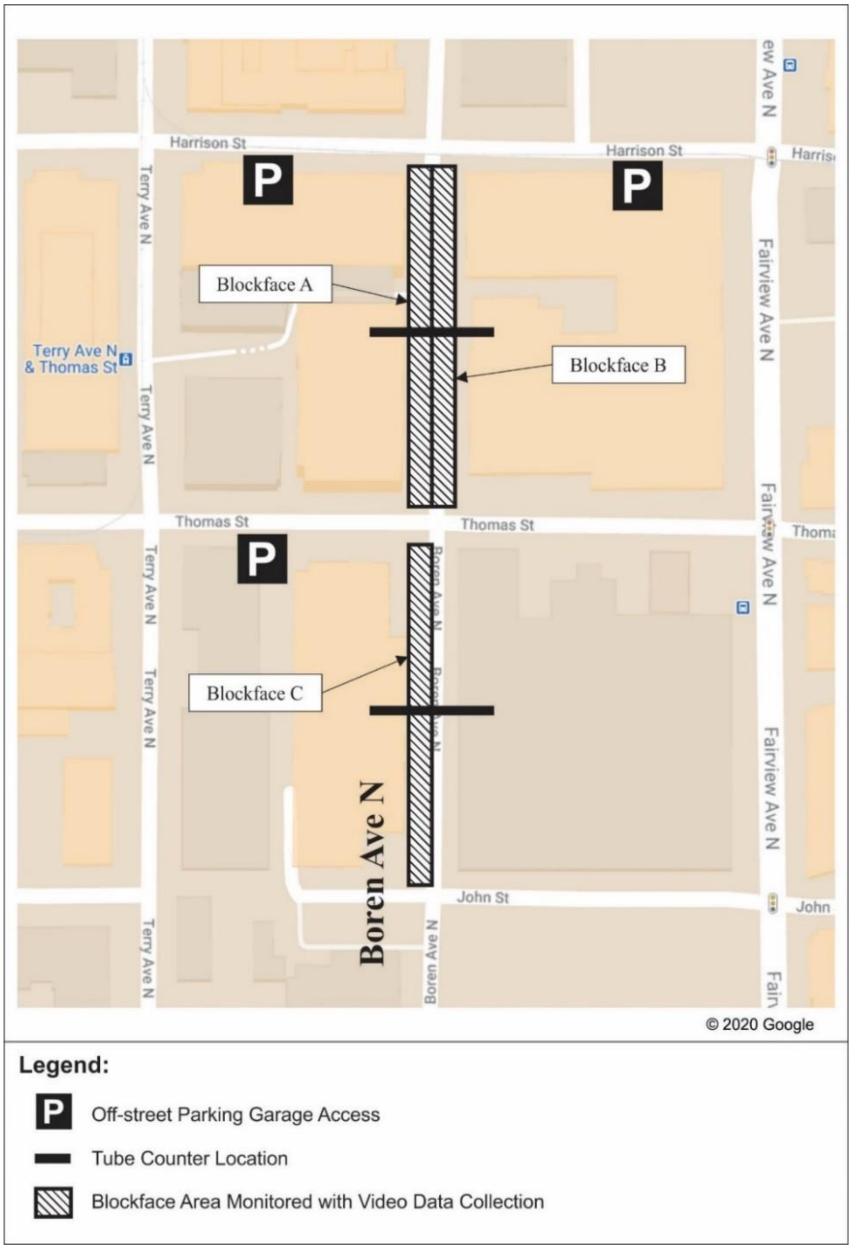


Figure 3-3 Study area and data collection details

Table 3-2 Curb space allocation per blockface during weekday AM and PM activity periods and Phase I (Baseline) of study.

Blockface*	Paid Parking (feet)	PUDO Zone (feet)	Commercial Vehicle Load Zone (feet)	Charter Bus / Shuttle Bus / Taxi Load Zones (feet)
A	200	20	0	0
B	95	0	40	0
C	155	0	0	50
Total	450	20	40	50

*Figure 3-3 represents the locations of blockfaces on Boren Ave N.

Chapter 4. HAZARD-BASED MODELING OF PUDO DWELL TIME: A NATURALISTIC ANALYSIS

This chapter describes our research on hazard-based modeling of PUDO dwell time with naturalistic data described in Chapter 3.

4.1 METHODOLOGY

The modeled phenomenon was the end of the stopping operation of a vehicle that loads or unloads passengers (i.e., the event). Therefore, the duration of the event (i.e., survival time) is defined as the time that the vehicle remains stopped. Hazard-based duration modeling deals with the statistical representation of time to event data and has methodological and conceptual advantages over the more traditional regression methods (Bhat & Pinjari, 2007).

Hazard-based models have been used extensively for several decades in biostatistics and industrial engineering to examine issues such as the effects of chronic diseases on life expectancy and the time mechanical components take to fail under various conditions. Time to event data are frequently used in transportation problems; recent examples of the application of hazard-based models to such transportation data include the investigation of the stop durations of commercial vehicles picking up and delivering urban goods (S. Hughes et al., 2019; Sharman et al., 2012), flight departure delays (Kim & Bae, 2021), drivers' braking time performance (Yadav & Velaga, 2021), the time to complete an overtake (Bella & Gulisano, 2020), the time to complete vehicle ownership transactions (Khan & Habib, 2021), and disruption durations for subway systems (Louie et al., 2017).

Hensher and Mannering (1994) and Bhat (2000) provided extensive reviews on the application of hazard-based duration models to transportation problems. Moreover, Washington et al. (2020) discussed methodological, computational, and estimation issues in transportation duration modeling.

4.1.1 *Mathematical Formulation*

Let T be a non-negative random variable representing the duration time of an individual, in this case, the stop event of a vehicle loading/unloading passengers. Following Ettema et al. (1995), we explain the most important equations of the hazard-based duration modeling framework. We will assume that T is an unconditional distribution of durations with probability density function $f(t)$ and cumulative distribution function $F(t) = \Pr\{T < t\}$, giving the probability that the event has occurred by duration t.

An essential function in hazard modeling is the survivor function $S(t)$, giving the probability that the process has survived until t:

$$S(t) = 1 - F(t) = P(T \geq t) = \int_t^{\infty} f(u)du \tag{4.1}$$

The hazard function $h(t)$ describes the probability of occurrence at t conditional on survival until t:

$$h(t) = \lim_{\Delta t \to 0} \frac{\mathrm{P}(t \leq T < t + \Delta t | T > t)}{h} = \frac{f(t)}{S(t)} \tag{4.2}$$

The cumulative hazard function $\Lambda(t)$ and survival functions are related as follows:

$$\Lambda(t) = \int_0^t h(u)du = -Log\, S(t) \tag{4.3}$$

The shape of the hazard function is determined by the distributional assumptions made for the probability density function $f(t)$. For a detailed review of possible distributions, the reader is referred to Lawless (2002). Initial tests were conducted with no explanatory variables to determine a suitable baseline function. The Weibull, normal, logistic, lognormal, and log logistic distributions were all tested, and the log logistic distribution was found to provide the best fit to the data. Test results are shown in the Results section below. The hazard, cumulative hazard, and survival functions related to the log logistic distribution are as follows (Lawless, 2002).

$$h(t) = \frac{\lambda\beta(\lambda t)^{\beta-1}}{1+(\lambda t)^{\beta}} \tag{4.4}$$

$$\Lambda(t) = \frac{\lambda\beta(\lambda t)^{\beta}}{1+(\lambda t)^{\beta}} \tag{4.5}$$

$$S(t) = \frac{1}{1+(\lambda t)^{\beta}} \tag{4.6}$$

where α > 0, β > 0 and t > 0.

4.1.2 *Effects of Covariates*

Individual cases in the sample of passenger load/unload events may show heterogeneity in duration that can be explained by factors such as the number of passengers loaded or unloaded, time of day, or whether the location occurs in the middle of the street or at the curb. Two primary types of models allow for incorporating such factors as covariates (i.e., explanatory variables): 1) proportional hazard (PH) model and 2) accelerated failure-time (AFT) models.

In the proportional hazard model, the covariates act multiplicatively on the baseline hazard (see equation *4*.4). This leads to the property of proportionality, implying that the ratio of hazards for specific sets of covariates (h_{1}/h_{2}) remains constant over time. In other words, there is no duration dependence or dynamics, and the conditional probability of the vehicle ending the stop is not related to the time elapsed since the vehicle stopped.

$$h(t|X) = h_0(t)g(X) \tag{4.7}$$

where

X = a vector of explanatory variables and

$h_o(t)$ = the baseline hazard function if all covariates X have a value of 0

$g(X)$ = nonnegative function related to covariates; for mathematical convenience, it is usually defined as $\exp(-X\alpha)$, where α is a vector of parameters.

In the proportional hazards model, changes in covariates shift the baseline hazard function up or down, resulting in individuals with hazard functions that are constant multiples of one another. However, this characteristic may be undesired for our data. For instance, an increasing number of passengers being loaded and unloaded may have a smaller effect (hazard ratio) 5 seconds into the duration of a stop than at 60 seconds.

AFT models, on the other hand, are log linear for T, $log\, T = X\alpha + \varepsilon$, and the effect of the covariates X is on time rather than on the baseline hazard. That is, covariates accelerate (or decelerate) time in the baseline hazard function, shifting the hazard distribution left or right by a constant amount. The direct physical interpretation of the effect of covariates in this model fits our data well. For instance, an increasing number of passengers being loaded/unloaded will slow the entering and exiting of vehicles and ending their operations. Similarly, stops in the travel lane may be quicker because such unauthorized and unsafe behaviors risk a parking violation ticket and potential harm. Thus, AFT models offer greater flexibility in modeling durations of alternative processes, and the hazard function can be shown to be:

$$h(t|X) = h_0(te^{-X\alpha})e^{-X\alpha} \tag{4.8}$$

4.1.3 *Parametric and Semi-Parametric Hazard Models*

Models that make distributional assumptions about the shape of the hazard function are referred to as parametric, and their primary limitation is that they may inconsistently estimate the baseline hazard if the assumed parametric form is incorrect. This limitation can be overcome by using approaches that do not require parametric hazard-distribution restrictions.

The partial likelihood approach introduced by Cox (1972) does not require the specification of the hazard function because it estimates only the covariate effects, and it does not estimate the hazard distribution itself. The application of the partial likelihood method and a PH form to accommodate the effect of covariates is referred to as the Cox PH model and has been widely used. The Cox PH model can be considered a semi-parametric hazard model because the PH form in which regressors are related to the hazard is fully parametric.

4.1.4 *Unobserved Heterogeneity*

In practice, it is rarely possible to include all relevant covariates in the model formulation. The omitted covariates may account for unobserved heterogeneity*;* individuals with the same value of observed covariates may have different distributions. The effects of not accounting for unobserved heterogeneity can include significantly misleading inferences, including a downward biased estimate of duration dependence and a bias toward zero for the effect of external covariates (Balan & Putter, 2020; Bhat & Pinjari, 2007).

The literature in demographic research uses the term *frailty* to refer to unobserved heterogeneity on lifetimes collectively. One standard way of including heterogeneity is to use an observed individual random effect that acts multiplicatively on the hazard, and the estimated variance of this random effect is an indication of the unobserved heterogeneity (Balan & Putter, 2020). In the PH specification, heterogeneity is introduced as follows:

$$h(t|X) = h_0(t)e^{-\beta' x + w} \tag{4.9}$$

where w represents unobserved heterogeneity. This formulation involves the specification of a distribution for w across individuals in the population, which can be a parametric or nonparametric specification. The AFT model cannot incorporate unobserved heterogeneity because of identification problems (Bhat & Pinjari, 2007).

4.1.5 *Log Likelihood Estimation*

We used a maximum likelihood approach to estimate model parameters. For a parametric hazard distribution in the presence of right censoring, the maximum likelihood function can be written in terms of the survival and hazard functions as follows (Rodríguez, 2007):

$$L = \prod_{i=1}^{n} Li = \prod_{i} h(t_i)^{d_i} S(t_i) \tag{4.10}$$

where d_i, is a censoring indicator, taking the value of one if vehicle *i* exits the stop duration and the value of zero otherwise.

Taking logs and using the relationship between the survival function *S(t)* and the cumulative hazard function, *Λ(t)* in the log-likelihood function for censored survival times can be demonstrated to be:

$$\log L = \sum_{i=1}^{n} \{ d_i \log h(t_i) - \Lambda(t_i) \} \tag{4.11}$$

The authors refer the reader to Bhat (2007) and Balan and Putter (2020) for a detailed discussion of the estimation and formulation of the Cox partial likelihood method and unobserved heterogeneity.

4.1.6 *Dependent Variable and Covariates*

The variables used in this study were related to the different data sets introduced above, including the vehicle stop events, off-street parking garage occupancy, and traffic volume and speed counts. All the variables used in the analysis were obtained from the data sets (see Section 3.2.4)either directly or indirectly after data processing. For instance, the three data sets were merged to relate stop events to traffic and off-street parking garage conditions. Another data transformation was required to estimate the number of vehicles stopped at the curb at any time based on their arrival time and stop duration. Last, all the covariates used in the analysis were assumed to be time-invariant in the duration of the stop events.

4.2 RESULTS

An analysis of the data showed that only 1 percent of the stops had a duration of more than 17 minutes. Right censoring was applied to the data when the parametric model was estimated because of the small number of long duration stops. Furthermore, including longer stops could reduce the quality and applicability of the estimated model.

4.2.1 *Descriptive Analysis*

Table 4-1 and Table 4-2 show all the variables used in the analysis, including a written description and descriptive statistics.

Table 4-1 Description of categorical variables

Variable	Description	Levels	Count	Percentage
Type of Event	Type of stop event; passenger loads were set as the reference level	Passenger load	2,827	46.9
		Passenger unload	3,197	53.1
Phase	Phase of research design; Phase I was set as the reference level	I	1,558	25.9
		II	1,967	32.7
		III	2,499	41.5
Location	Location of stop event; the curb was set as the reference level	Curb	3,706	61.5
		Street	2,318	38.5
Type of Vehicle	Type of vehicle; passenger vehicles were set as the reference level. Ridehailing vehicles were identified as such based on visible stickers on the vehicle and/or if the operation involved passenger(s) entering/exiting a Toyota Prius through the back door	Passenger	2,336	38.8
		Large passenger	36	0.6
		Taxi	33	0.6
		Ridehailing	3,619	60.1
Period	Time of day period; the afternoon was set as the reference level	Afternoon	3,132	52.0
		Morning	2,892	48.0
Trunk Access	Access of the vehicle trunk	No	5,567	92.4
		Yes	456	7.6
		Unknown	1	0.0

Table 4-2 Description of continuous and discrete variables

Variable	Description	Mean	Min.	Q_1	Q_2	Q_3	Max.
Dwell Time	Dependent variable; stop duration of vehicles that loaded/unloaded passengers; measured in minutes.	1.21	0.03	0.22	0.38	0.92	17.00
Number of Individuals	Number of individuals being loaded or unloaded	1.15	1.00	1.00	1.00	1.00	13.00
On-Street Parking Occupancy Rate	Number of vehicles stopped at the block face curb lane adjacent to the vehicle stop location at the start time of the stop event.	3.28	1.00	2.00	3.00	4.00	10.00
Traffic Volume	5-minute traffic volume counts on the travel lane adjacent to the vehicle stop location and nearest to its start time; measured in number of vehicles per 5 minutes.	6.93	0.00	4.00	6.00	9.00	31.00
Mean Speed	Average traffic speed measured in miles per hour on the travel lane adjacent to the vehicle stop location; average was based on 5-minute vehicle counts in speed bins from pneumatic tube counters placed midblock on the observed segments of Boren Ave N. The 5-minute interval closest to the start time of the vehicle stop event was selected.	11.88	0.00	10.17	12.12	14.00	27.50
Off-Street Parking Occupancy	5-minute average occupancy as a percentage at the three off-street parking garages in the study area.	0.60	0.16	0.46	0.60	0.73	0.98

4.2.2 *Baseline Hazard Distribution*

Under the specification of zero covariates, we tested four types of hazard distributions, namely Weibull, normal, logistic, lognormal, and log logistic, to find the best fit for PUDO dwell time data. The survival curves with different distributions are graphically shown in Figure 4-1. The estimation of these models uses maximum likelihood; therefore, we compared the log-likelihoods and AIC statistic of each model (see Table 4-3).

The log logistic distribution had the largest value of log likelihood and the smallest AIC, which indicated that it fit best to the hazard pattern. Several different model forms were also considered to assess the final model with covariates. In addition to the selected log-logistic model, we considered Weibull, log-normal, and logistic models with the complete set of covariates. The log-normal model was very similar to the log-logistic in terms of coefficients and standard errors. The log-logistic model's log-likelihood was greater than that of the log-normal, indicating the best fit. The other model forms (Weibull and logistic) showed greater standard errors and the worst fit in terms of log-likelihood. For all these reasons, we considered the log-logistic distribution to be superior for our data.

Table 4-3 Comparison of fitness of parametric distributions

	Weibull	**Normal**	**Logistic**	**Lognormal**	**Log logistic**
Log-Likelihood	-6436.39	-14123.6	-11722.6	-5140.93	**-5036.29**
AIC	12876.77	28251.18	23449.18	10285.87	**10076.57**

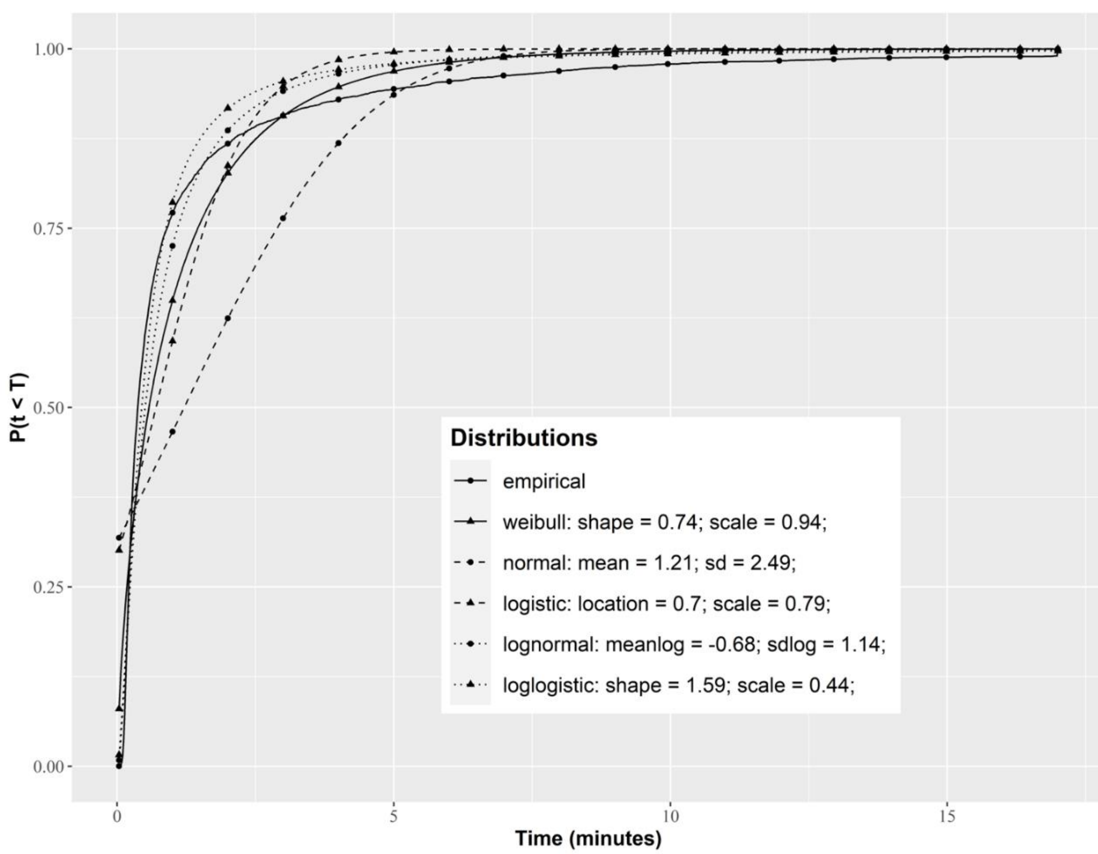


Figure 4-1 Comparison of empirical and parametric cumulative distribution functions of stop duration time

4.2.3 *Model Results*

Vehicle stop duration data were fit with different survival models, including a fixed effect AFT and Cox PH models, and a random effects Cox PH model. Stepwise model selection by AIC was used to select the appropriate variables to include in the models. The models were calibrated by using the survreg(), coxph(), coxme() and stepAIC() functions of the R-statistics software. Table 4-4 shows the models' parameters, their significance, and the models' goodness-of-fit statistics.

As described in Section 4.1.2, the AFT formulation was preferred because the direct physical interpretation of its covariate effects fit our system well, and the proportional hazard assumption might not hold in the case of passenger load/unload events. A test confirmed this by rejecting the proportional hazard assumption for the Fixed Effect Cox PH based on Schoenfeld residuals (Grambsch & Therneau, 1994) implemented in the cox.zph() function in the R-statistics software. For the Random Effects PH Cox model, gamma and gaussian frailty term distributions were considered. The gamma distribution was preferred because of better overall fit evidenced by a likelihood test (-42,275 > -42,778). The Random Effects Cox PH model showed a significantly better overall fit than the Fixed Effects Cox PH model based on a likelihood ratio test. However, this evidence in favor of the frailty model was not conclusive because nonproportionality could be confounded with unobserved heterogeneity in the univariate survival model with small clusters (Balan & Putter, 2019).

Although not directly comparable, the Fixed Effects AFT model showed better goodness-of-fit than the semi-parametric PH Cox models based on loglikelihood estimates. Unobserved heterogeneity, if significant, might lead to a marginal interpretation of the coefficient estimates, in the sense that they were averaged over all unmeasured covariates. Therefore, the estimated regression coefficients applied to an individual selected randomly from the population (Balan & Putter, 2020). For all these reasons, the Fixed Effects AFT model was considered the superior model, and it is the focus of the remaining discussion.

Because of the different model specifications, the parameter estimates had different interpretations between the AFT and PH models. For the AFT models, a positive coefficient meant that this parameter increased the stop duration. For the PH model, a positive coefficient meant that the parameter increased the hazard, reducing the stop duration.

In the AFT framework, the exponential of the estimated coefficient is called the accelerated factor (AF), which measures, for each variable, the increased survival time (stop duration) associated with an increase in the value of that variable. For example, the exponential of *Type of Event: Passenger Unload*, a negative coefficient, was 0.63; therefore, the vehicle stop duration was about 0.63 times (or equivalently 37 percent shorter) when a vehicle unloaded passengers than when loading them, keeping all the other variables at a constant.

It is worth noting that different model formulations were calibrated to assess cross-correlation between some of the covariates. We concluded that no correlation was present between *Traffic volume* and *Mean speed*. This has a logical explanation, given that Boren Ave N was a local street representing a heavily multimodal urban environment with low speed limits. The *Mean speed* variable was later excluded from the models based on stepwise model calibration. In addition, we analyzed the relationship between *On-street parking occupancy* and *Location* and concluded that the best model formulation controlled separately for both variables to avoid omitted variable bias.

The following provides a description of the remaining effects of the AFT model that were statistically significant at a 1 percent level:

- ***Number of Individuals*****:** One additional passenger being loaded or unloaded made the stop duration approximately 22 percent longer.
- ***Trunk Access*****:** If the vehicle trunk was accessed, stops lasted 84 percent longer.
- ***Traffic Volume*****:** Stop duration was 1 percent shorter with one additional vehicle traveling through the travel lane adjacent to the stop location.
- ***On-Street Parking Occupancy*****:** Stop duration was about 3 percent longer with one additional vehicle parked on-street.
- ***Location*****:** Stops were about 54 percent shorter when they occurred in the travel lane than when they happened at the curb.
- ***Period*****:** In comparison to the afternoon period, stops happening in the morning were approximately 22 percent shorter.
- ***Vehicle Type*****:** In comparison to passenger vehicles, ridehailing stops were approximately 42 percent shorter. On the other hand, stops by taxis and large passenger vehicles were 81 percent and 131 percent longer.

Last, the variables describing the effects of curb management strategies suggested different effects on PUDO dwell time:

- ***Phase II:*** **Added PUDO Zones** showed a non-statistically significant positive effect of increasing durations when new PUDO spaces were added in comparison to the Phase 1 baseline.
- ***Phase III:*** **Added PUDO Zones + geofencing** produced a statistically significant negative coefficient, indicating that stop durations were shorter during Phase 3 than in the baseline.
- **Phase – Location interaction term** showed a statistically significant positive coefficient for ***Phase III – Street,*** indicating that adding PUDO zones with geofencing may have reduced PUDO dwell times for events that occurred at the curb.

Table 4-4 Results of AFT and PH models

		Fixed Effects AFT				Fixed Effects Cox PH				Random Effects Cox PH			
Variable		**Coef.**	e^{coef}	**Std. Error**	**P-value**	**Coef.**	e^{coef}	**Std. Error**	**P-value**	**Coef.**	e^{coef}	**Std. Error**	**P-value**
Event Type (Ref: Load)	Passenger Unload	-0.460	0.631	0.042	0.001*	0.447	1.563	0.045	0.001*	0.719	2.052	0.07	0.001*
Phase (Ref: I)	II	0.077	1.080	0.043	0.071	-0.032	0.969	0.047	0.492	-0.096	0.909	0.067	0.156
	III	-0.110	0.896	0.040	0.007	0.154	1.167	0.045	0.001*	0.139	1.150	0.064	0.030
Location (Ref: Curb)	Street	-0.783	0.457	0.045	0.001*	0.975	2.652	0.052	0.001*	1.391	4.018	0.076	0.001*
Number of Individuals		0.203	1.225	0.023	0.001*	-0.191	0.826	0.029	0.001*	-0.326	0.722	0.039	0.001*
Vehicle Type (Ref:Passenger)	Large Passenger	0.836	2.308	0.209	0.001*	-0.853	0.426	0.185	0.001*	-1.272	0.28	0.284	0.001*
	Taxi	0.593	1.809	0.154	0.001*	-0.495	0.609	0.177	0.005	-0.877	0.416	0.246	0.001*
	Ridehailing	-0.543	0.581	0.024	0.001*	0.590	1.803	0.028	0.001*	0.866	2.378	0.041	0.001*
Traffic Volume		-0.010	0.99	0.003	0.001*	0.006	1.006	0.003	0.065	0.019	1.019	0.005	0.001*
On-Street Parking Occupancy		0.029	1.030	0.007	0.001*	-0.022	0.978	0.008	0.007	-0.044	0.957	0.012	0.001*
Off-Street Parking Occupancy Rate		-0.130	0.878	0.072	0.069	-0.058	0.943	0.083	0.480	0.202	1.224	0.117	0.084
Trunk Access (Ref: No)	Yes	0.608	1.836	0.042	0.001*	-0.521	0.594	0.050	0.001*	-0.906	0.404	0.068	0.001*
Period (Ref: Afternoon)	Morning	-0.250	0.779	0.044	0.001*	0.297	1.346	0.048	0.001*	0.468	1.597	0.073	0.001*
Phase*Location (Ref: Phase 1 – Street)	Phase 2 – Street	-0.061	0.941	0.060	0.310	-0.020	0.980	0.069	0.769	0.069	1.071	0.100	0.489
	Phase 3 – Street	0.175	1.191	0.057	0.002	-0.272	0.762	0.067	0.001*	-0.257	0.774	0.096	0.008
(Intercept)		0.012	1.012	0.071	0.866	-	-	-	-	-	-	-	-
Log(scale)		-0.682	0.505	0.011	0.001*	-	-	-	-	-	-	-	-
Frailty Variance		-	-	-	-	-	-	-	-	0.542	-	-	0.001*
Goodness of fit													
Log-Likelihood		-3,683	-	-	-	-45,030	-	-	-	-42,275	-	-	-
AIC		7,400	-	-	-	90,090	-	-	-	88,782	-	-	-

*: *p-value* < 0.001

4.3 DISCUSSION AND CONCLUSIONS

The growing complexity of the curb environment, driven by increasing demand for land-use access by ridehailing vehicles conducting PUDO operations and other road users, challenges the practice of curb management. Research on PUDO dwell time is warranted because of the relationship between this metric and PUDO zone capacity. This study advances the understanding of passenger car PUDO dwell time factors and facilitates reliable forecasting based on hazard-based duration models and real-world data of PUDO operations by ridehailing and other passenger vehicles.

The Log-logistic Accelerated Failure Time model was the superior formulation for describing passenger car PUDO dwell times. This contrasted with previous studies' assumptions about PUDO dwell time as an exponential or gamma distribution in models that assessed flexible curb space use at the street intersection level (You Kong et al., 2020) and macroscopic level (Yu & Bayram, 2021), respectively.

In addition, no previous models have captured the influence of explanatory factors of PUDO dwell time. Our research showed that aspects related to **passenger maneuvers**, including the number of passengers, pick-ups (as opposed to drop-offs), and the need to access the vehicle´s trunk may relate to significantly longer stop durations. These findings were expected and were in line with anecdotal evidence from previous studies (Fehr and Peers, 2019).

The **location and time of day** may also help estimate how likely PUDO operations are to take more time, with significantly longer stops in the afternoon and at the curb (as opposed to in the morning and in the travel lane, respectively). Generally, studies that have documented PUDO dwell time operations at the curb and in street have also shown longer stop durations at the curb (Fehr and Peers, 2019; Lu, 2018; Smith et al., 2019).

Traffic-related factors, including a greater number of vehicles at the adjacent curb and travel lanes, may also play a role in PUDO durations but with less practical significance.

Management factors can affect PUDO dwell times. In comparison to passenger cars, ridehailing vehicles tended to take less time, while PUDOs by taxis took longer. Additionally, the models were used to test the effects of two curb management strategies, including adding PUDO zones and later overlaying geofencing, based on before-after study conditions. Adding PUDO zones together with geofencing was found to be related to faster PUDO operations at the curb. A possible way that geofencing technology may help accelerate PUDO events is by providing information shared by driver and passenger about the stop location, which allows them to better prepare before the event.

The outcomes of this research have important implications for researchers and practitioners interested in understanding PUDO operations in the curb lane and making decisions about how to regulate those operations and integrate them into the current transportation system. Curb management policies can be improved from the current one-size-fits-all approach to a more data-driven approach that considers how significant variables can influence dwell time. The unbalanced nature of human mobility flows, such as a typical higher proportion of passenger drop-offs at a workplace in the morning commuter peak than in the evening, motivates context-specific PUDO parking time and space restrictions. Our survival dwell time model can produce PUDO dwell time estimates based on knowledge of passenger maneuvers, vehicle location (curb vs. street), time of day, nearby traffic conditions, and management factors. These estimates can be used to inform discussions and support decisions of city officials, who often struggle to define priority usages of the curb with little ground-truthed data.

In addition, this research further advances modeling efforts in curb management by providing the first parameterization of dwell time based on real-world data. Ongoing efforts to enhance analytical capabilities to model the growing complexity of the curb environment can integrate our PUDO dwell time model to estimate the needed PUDO zone capacity at a system equilibrium for a given city or blockface.

As the debate about implementing curb management strategies such as adding PUDO zones, geofencing, and pricing downtown curbside parking evolves in academic and policy circles, future research should further investigate how PUDO zone user heterogeneity drives the outcome of pricing schemes and parking time limits in these zones. Additionally, further research is warranted to assess whether different road characteristics, such as those for arterials and local streets, may explain variance in passenger vehicle PUDO dwell times.

Chapter 5. EVALUATION OF THE IMAPCT OF RIDEHAIL CURB MANAGEMENT STRATEGIES AND METRICS WITH SIMULATION

Multiple cities in the U.S. are considering curb management policies and regulations that affect ridehailing vehicles. For instance, as a curb management strategy, pilot programs are looking into the implementation of PUDO zones in Fort Lauderdale, Washington D.C., San Francisco, Boston, New York, and Seattle.

Curb management relies on performance metrics to design, plan and assess the performance of parking infrastructure. Parking occupancy, for instance, is a conventional parking metric frequently used by local governments in performance-based parking pricing programs. Specifically in Seattle, parking rates are frequently adjusted to achieve a parking occupancy rate between 70 and 85 percent (Baruchman, 2018).

This research aims to understand the impact of ridehail curb management strategies on traffic operations, PUDO operations and other curb users, including paid parking and commercial vehicle loading and the relationship between curb performance metrics.

5.1 SIMULATION DESIGN

Simulation models were developed to evaluate, under varying street and curb demand profiles, the effect on curb management metrics of adding PUDO zone space, geofencing PUDO vehicles to PUDO zones, and increasing the occupancy of PUDO vehicles.

In a previous study, Ranjbari et al. (2020) evaluated two curb management strategies in Seattle, Wash., in an area where large numbers of workers commute using ridehailing services. The strategies were 1) a curb allocation change from paid parking to PUDO zones, and 2) a geofencing approach by ridehailing companies that directed their drivers and passengers to designated PUDO zones on a block. Real-world data about ridehails from the above study in Boren Ave N were used to calibrate our simulation model of this street. The calibrated models reflect conditions observed during a typical weekday morning and afternoon commuter peak hour periods. During these periods, close to half of the traffic in the area performed passenger load/unloads. The modeled conditions correspond to Ranjbari et al. (2020)'s study phase 2, when added PUDO zones were in place and geofencing of ridehail vehicles was not implemented. In VISSIM software (version 9), the discrete event simulation was built by using the software graphical user interface. The VISSIM-COM interface with Python (version 3.8) was used to access and manipulate VISSIM objects during the simlaution dynamically.

Previously in this dissertation research (see Chapter 4), we developed the first sound parametrization of ridehailing passenger load/unload dwell times with hazard-based duration models. Our Log-logistic Accelerated Failure Time model was used to estimate the cumulative probability distribution function *F(t)* of different type of PUDO vehicles. The simulated vehicles in VISSIM followed these dwell time stochastic distributions. R-statistics software was used to calibrate the dwell time model model with the survreg() function, and the predict() function was used to estimate cumulative distribution functions.

5.1.1 *Policy Scenarios and Model Parameters*

Three policies will be evaluated with different impact on model parameters (see Table 5-1):

- **Adding PUDO zone capacity**: Increasing or reducing allocation of curb space to passenger unload/load zone type. In previous studies, this typically comes from converting other curb allocation types such as on-street parking
- **Geofencing ridehail vehicles to PUDO zones**: Directing ridehail vehicles to designated locations such as passenger unload/load zones. This strategy involves the creation of a virtual geographic boundary to make it easier for drivers and riders to locate one another.
- **Increasing the occupancy of PUDO vehicles**: To address Single Occupancy Vehicle (SOV) reduction goals, cities are considering encouraging higher vehicle occupancy rates. Ride-splitting services such as Uber Pool represent an opportunity to achieve this goal.

Table 5-1. Evaluated ridehail policy scenarios and impact on model parameters:

Policy Scenario	Impact on model parameters
PUDO Zone Capacity	Assuming a typical passenger car length of 20 feet, incremental positive variations of this curb space length per blockface will be tested
Geofencing	Based on the research on hazard-based modeling of PUDO dwell time presented in Chapter 4 of this dissertation, it is expected that geofencing would reduce dwell time in for operations happening on the curb.
Ridehail Occupancy Rate	Based on our previous research on hazard-based modeling of PUDO dwell time, it is expected that each additional ridehailing passenger would increase dwell time. Additionally, to represent an range of effectiveness of this policy on reducing PUDO vehicles, a 0% and 50% reduction of passenger load stops will be tested.

Additionally, the policy scenarios above will be evaluated under a set of different scenarios:

- **AM Commuter Peak Hour Period scenario**: considers a realistic representation of traffic conditions based on data collected in Boren Ave N. This period was characterized by a high share of passenger unloads (roughly 40% of all traffic), which is probably related to work trips with destination at the office buildings in the area.
- **PM Commuter Peak Hour Period scenario**: also based on traffic conditions on Boren Ave N, this period represents a condition of high share of stopping vehicles for loading passengers (20-30% of traffic), with some demand for unloading (2-8% of traffic). This is descriptive of a peak travel period at the workday in a mixed-use area, where employees leave the workplace and there are some incoming trips generated by restaurants and bars adding to the traffic.
- **Growing traffic volume scenarios:** to test the relationship between curb management metrics under a wide range of traffic volumes, a series of four scenarios showing traffic volume growth rates of 100%, 200%, 300% and 500% was evaluated. In these scenarios, the share of curb space demand by mode was kept constant and like conditions observed during the PM peak commuter period. Capacity of urban streets in terms of hourly volumes is driven by capacity at intersections because these streets are in grids with multiple nearby intersections. To test the theoretical impacts of curb management strategies isolated from performance of nearby intersections, this scenario assumed free flow of traffic on Boren Ave N at the adjacent intersections with two-way stop-controlled intersections.

In summary, six model parameters were selected to evaluate the impact of ridehail operations on traffic operations and other users of the road under different condtiions:

- **Number of on-street parking spaces for PUDOs:** 1, 2, 3 or 4 spaces per blockface
- **Geofencing of ridehail vehicles**: Yes or No
- **Occupancy of PUDO vehicles:** 1 or 2 passengers per vehicle
- **Reduction of PUDO traffic due to increased PUDO vehicle occupancy**: 0% or 50%.
- **Traffic volume growth on the street:** 100%, 200%, 300% or 400% growth
- **Signal control at street intersections**: all-way stop controlled or two-way stop controlled

5.1.2 *Measures of Effectiveness (MOEs)*

The following MOEs will be tracked in the VISSIM model to assess the impact of the ridehail strategies introduced above and evaluate the performance of curb stop operations:

- **Hourly throughput in travel lanes adjacent to curb parking** describes the number of vehicles successfully driving through the street during the analysis period. Provides a measure of the relative productivity of the street compared to an alternative (FHWA, 2021).
- **Hourly vehicle throughput of on-street parking spaces** is adapted from the measure above, but specific to vehicles successfully accessing curb spaces.
- **Hourly passenger throughput of on-street parking spaces** is helpful to capture that higher occupancy vehicles perform a more efficient use of the space when transporting passengers.
- **Percent of curb stops unserved/incomplete,** adapted from the throughput MoE (FHWA, 2021).
- **Occupancy of on-street parking** is the percentage of time in an hour that curb spaces are occupied by a vehicle. Describes the utilization of parking and, consequently, the probability of finding an open space.
- **Number of full curb space encounters.** Vehicles cannot park when curb spaces are full and need to wait for the next available spot where they can access.

- **Uptake time** can be defined as the time from a pick-up vehicle's arrival at the appropriate city block to arrival at the curbside. The City of Washington D.C. proposed an uptake time of fewer than 120 seconds on streets with certain traffic flow conditions (DDOT, 2019). Uptake time does not include stop dwell time at the parking space. Arrival at the city block was assumed to occur after the vehicle cleared the adjacent intersections and entered the street link in the evaluated blockface.

5.1.3 *Problem Description*

The case study area includes a 2-lane 2-way road segment of Boren Ave N in South Lake Union, Seattle, between Thomas Street and Harrison St. The study area street includes one waving-through lane for through traffic and one curb lane for parking in each direction (i.e., northbound and southbound) and an all-way-stop controlled intersection on both ends. Three main different type of road users were modeled including:

- Vehicles driving through the street and not stopping at the curb.
- Vehicles driving through the street and stopping at the curb, including:
    - PUDO vehicles: load or unload passengers. Two different types of vehicles performed these operations, including ridehails and other passenger cars.
    - PP vehicles: passenger cars that park in paid parking
    - CV vehicles: Load/unload goods by trucks

Vehicles are generated at vehicle input points in the network following a Poisson distribution and travel through the network following static travel and parking routing decisions coded in the Vissim model.

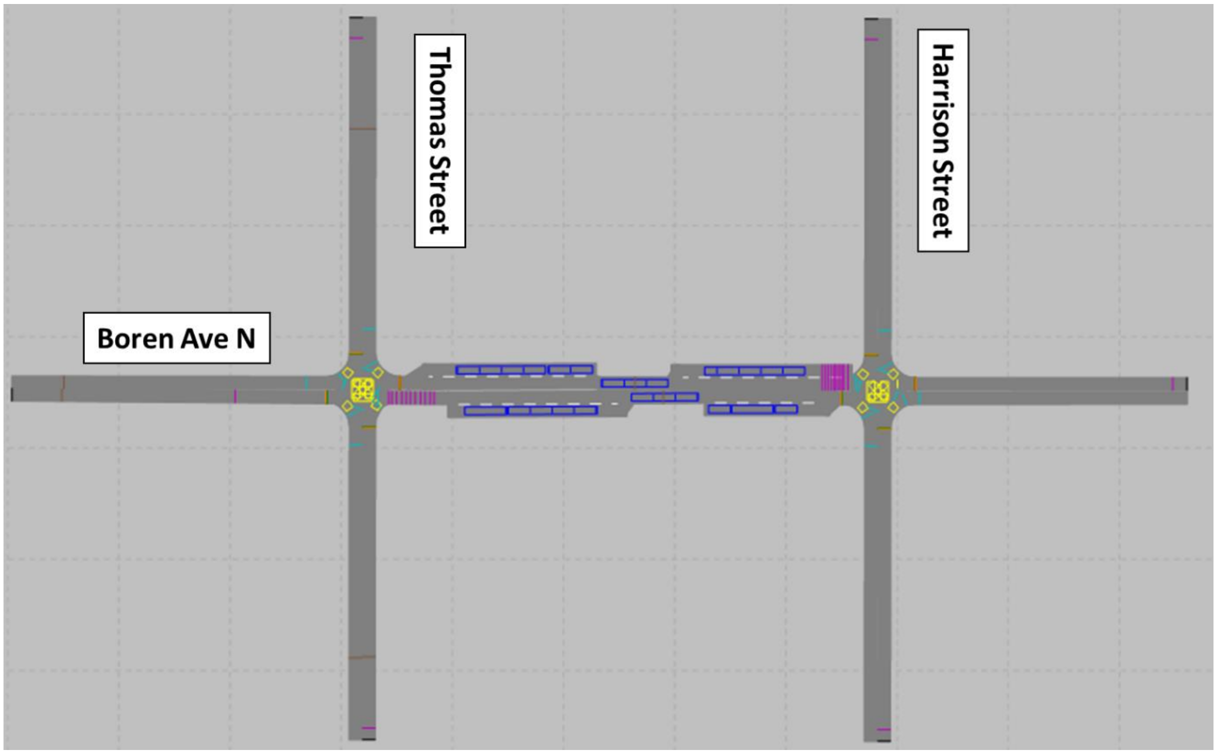


Figure 5-1. Aerial view of Vissim Model

5.1.4 *Baseline Curb Parking Supply*

Figure 5-2 shows the baseline curb space allocation modelled in Vissim. Curb use types include Passenger Unload/Load (PUDO) Zone, Paid Parking (PP) and Commercial Vehicle Load Zone (CVLZ). For calibration purposes, a zone of stops in traffic lanes on both ways of the street was coded in the model to represent the real-world behaviors observed in Boren Ave N. After the calibration step, it was assumed compliant behavior by curb users and the scenario modeling did not consider non-compliant behaviors, including stops in the travel lane and interchange uses of curb spaces (e.g. PUDO vehicles use paid parking for passenger load/unloading, trucks use PUDO for load/unload). The reasoning behind this is that curb operations should not depend on contravening existing curb access rules to minimize traffic flow impacts.

The total supply of curb parking (see Table 5-2 and Figure 5-2) is 18 spaces between blockfacces A and B, considering roughly 1 passenger car spaces for each 20 ft of curb length, and 1 truck/commercial vehicle space for each 35 ft of curb. The west blockface (A) concentrates most of the supply of paid parking spaces. The supply of PUDO spaces is balanced between both sides of the street and all the CVLZs are in the east blockface (B).

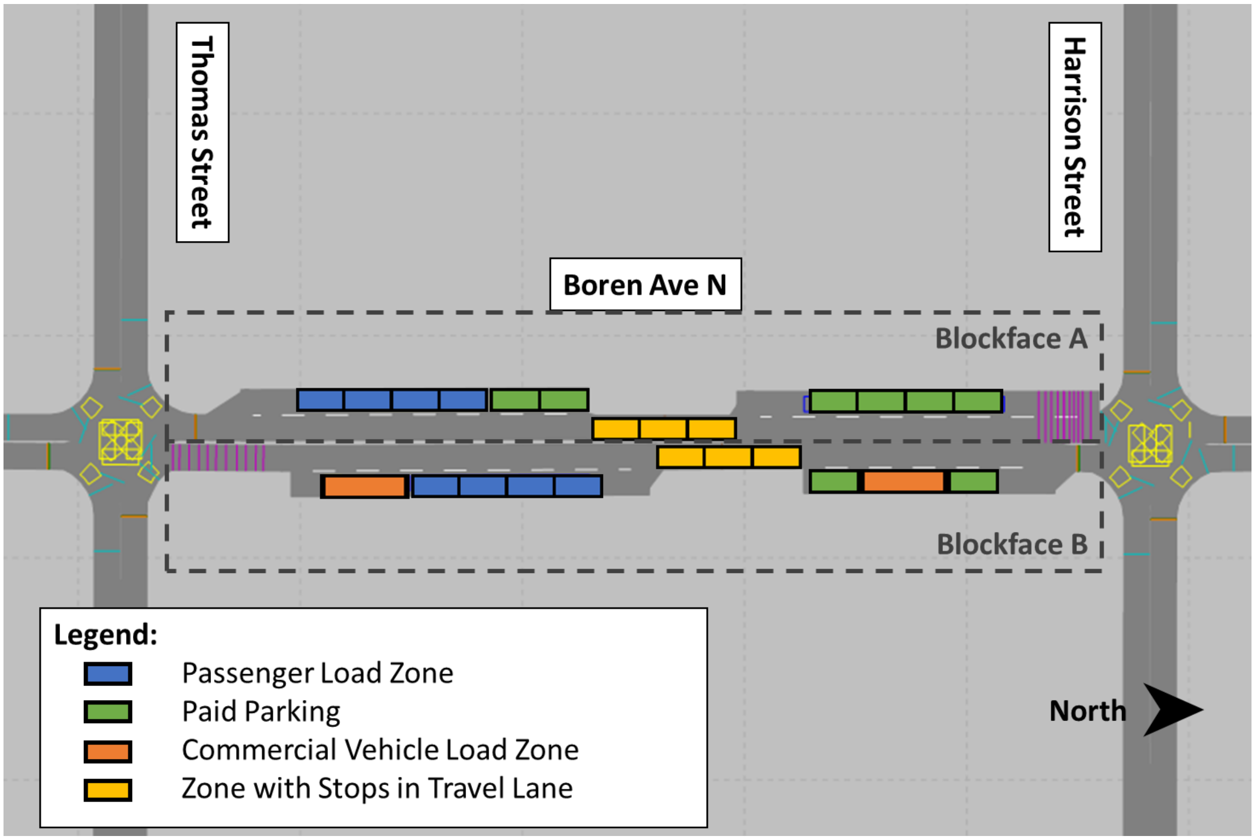


Figure 5-2. Curb space supply in simulation model

Table 5-2 Curb space allocation per blockface during weekday AM and PM activity periods and Phase I (Baseline) of study.

Blockface*	Paid Parking (Spaces)	PUDO Zone (Spaces)	Commercial Vehicle Load Zone (Spaces)	Total per Blockface
A	6	4	0	10
B	2	4	2	8
Total per Curb Use Type	8	8	2	18

*Figure 5-2 represents the locations of blockfaces and curb use types on Boren Ave N.

5.1.5 *Analysis Periods and Baseline Volume Conditions*

Two 1-hour peak periods were considered as the baseline for scenario modeling, a typical morning and afternoon peak hour commuter periods. Traffic and curb space demands for both periods were based on data collected in Boren Ave N in December, 2018. Table 5-3 summarizes the demand parameters for traffic and on the curb during both periods.

The Morning Commuter Peak Hour Period showed approximately 100 vehicles/per hour on both directions of Boren Ave N, with 51-57% of total volume representing through traffic and the remaining demand for curb space. Passenger unloads are roughly 40% of all traffic, which is probably related to work trips with destination at the office buildings in the area. There still were some passenger loads but these made up a much smaller portion of the traffic (around 2%). Between 70-60% of all PUDO traffic were performed by ridehail vehicles, which related to transportation network companies such as Uber and Lyft, and the remaining 30-40% were performed by other passenger cars. Average vehicle occupancy of PUDO vehicles was roughly 1 passenger per vehicle. Demand for paid parking was 2-8% and there was some demand by commercial vehicles or trucks on the northbound direction (1%), typically by parcel carriers, servicing, postal or construction.

The Afternoon Commuter Peak Hour Period volumes were roughly 75-90 vehicles/per hour depending on the direction of traffic, with approximately 60-80% of total volume representing through traffic. Demands for curb stops represented the remaining 20-40% of traffic. The highest share of stopping vehicles were loading passengers (20-30%), and there was some unloading activity (2-8%). This trend in PUDO demand can be representative of the end of the workday in a mixed-use area, where employees leave the workplace and some incoming trips generated by restaurants and bars add to the traffic. More than half of PUDO vehicles were ridehails, and the share of passenger cars was higher than during the morning peak hour (38-49%). Average vehicle occupancy of PUDO vehicles was roughly 1 passenger per vehicle. Demand for paid parking was 2-5% and there was some demand by commercial vehicles or trucks on the southbound direction (2%).

Table 5-3. Traffic and Curb Use Demand per Period of Analysis and Street Direction.

Demand Parameters	Traffic Bound	A: Typical Morning Commuter Peak Hour[b]	B: Typical Afternoon Commuter Peak Hour[c]
Passenger Loading Demand (%)[a]	North	2%	31%
	South	1%	19%
Passenger Unloading Demand (%)[a]	North	38%	8%
	South	41%	2%
Split of PUDOS by ridehail/passenger car	North	58%/42%	51%/49%
	South	70%/30%	62%/38%
Occupancy of PUDO vehicles (passengers/vehicle)	North and South	1.01	1.16
Paid Parking Demand (%)[a]	North	2%	5%
	South	8%	2%
Commercial Vehicle Parking Demand (%)[a]	North	1%	2%
	South	0%	0%
Through Traffic (%)	North	57%	58%
	South	51%	77%
Total Traffic (Vehicles/hour)	North	104	74
	South	103	87

Notes:

a. *Percentage relative to total traffic.*
b. *Based on data collected at Boren Ave N, Seattle, on Wednesday December 19, 2018, from 8:30 AM to 9:30 AM.*
c. *Based on data collected at Boren Ave N, Seattle, on Wednesday December 19, 2018, from 4:30 PM to 5:30 PM.*

5.1.6 *Vehicle Dwell Time Estimation*

In survival analysis, the cumulative probability distribution function *F(t)* expresses the probability that the survival time is less than or equal to a specific time (t). The Log-logistic Accelerated Failure Time model calibrated in Chapter 4 of this dissertation was used to estimate the cumulative probability distribution function *F(t)* of different type of PUDO vehicles. These distributions were used as time distributions in VISSIM from which simulated vehicles are randomly assigned a percentile.

In this approach, the regression coefficients of the survival model apply to an individual selected randomly from the population. Estimating the cumulative distribution function for each PUDO vehicle type possible would require evaluating the coefficients for each of the possible combinations of the independent variables of the model and drawing the simulated vehicle from the correct distribution. For this reason, a fewer number of PUDO dwell time distributions were estimated fixing some of the user characteristics to an “average” PUDO vehicle. These average values were obtained based on the data collection effort on Boren Ave N and previously described in Section 3.2of this dissertation. The “average” PUDO vehicle characteristics are:

- Number of individuals (passengers) = 1
- Trunk Access = “No”
- 5-minute traffic volume on the travel lane adjacent to the vehicle stop location = 7 vehicles
- On-street parking occupancy rate at the blockface of the stop location = 3 vehicles
- Occupancy of off-street parking garages = 60%

A set of characteristics were allowed to vary between PUDO vehicle types to capture the expected impact of ridehail curb management strategies and better represent dwell times for each of following user type combinations:

- Type of vehicles: Ridehail or passenger car
- Period: Morning or afternoon
- Location of stop: street or curb
- Type of event: passenger load or unload
- Geofencing in place: Yes or No

For non-PUDO vehicles in the model, that is, passenger car parking and truck load/unload stops, the empirical cumulative distribution function of the operations observed in Boren Ave N was used.

5.1.7 *Model Validation and Simulation Parameters*

The model validation process was done according to the Washington Department of Transportation’s VISSIM protocol (WSDOT, 2014). Model validation can be broken down into two different criteria:

- **Confidence:** relates to ensure that the model results are representative of the model and not skewed towards a statistical outlier.

- **Calibration**: process to achieve adequate reliability or validity of the model by establishing suitable parameter values so that the model replicates local traffic conditions as closely as possible.

The seeding period was set to 10 minutes following WSDOT's guidelines (WSDOT, 2014). To ensure confidence of the model, that is, that the results are representative of the unknown model average, the required minimum of simulation runs was estimated using the following formula below (equation 5.1) (FHWA, 2019).

$$CI_{1-\alpha\%} = 2 * t_{\left(1-\frac{\alpha}{2}\right)N-1} \frac{S}{\sqrt{N}} \tag{5.1}$$

Where:
$CI_{1-\alpha\%}$ = $(1-\alpha)\%$ confidence interval for the true mean, where α equals the probability of the true mean not lying within the confidence interval.
$t_{\left(1-\frac{\alpha}{2}\right)N-1}$ = Student's t-statistic for the probability of a two-sided error summing to α with N-1 degrees of freedom, where N equals the number of repetitions
S = standard deviation of the model results

The number of simulation runs and error margin were selected considering computational power limitations and the similarity between alternatives. An error margin of one standard deviation at the 95% confidence level as preferred, which yields 23 simulation runs per scenario.

Calibration of the model was conducted by comparing throughput volumes, speed and number of parking operations model outputs and field data. Speed and number of parking operations were allowed to vary within 10% of the observed values. For throughput volumes, the GEH formula was used (equation 5.2) (WSDOT, 2014):

$$GEH = \sqrt{\frac{2(m-c)^2}{(m+c)}} \tag{5.2}$$

Where
GEH should be calculated to a value of 3 or lower. A value of 4 is acceptable for local roadway facilities.
m = output traffic throughput volumes from the simulation (vehicle/hour/lane)
c = traffic throughput volumes based on field data (vehicle/hour/lane)

Table 5-4 shows the calibration results. Eight data collection points in the model matched real-world screening counts and were used to track average throughput and speed among all five simulation runs. All GEH values were withing the recommended 3 or lower. Only the data collection points located on Thomas Street west of Boren Ave N - Westbound, and in Boren Ave N South of Thomas St - Northbound showed an acceptable value of 3 during the PM Commuter peak period. This volume discrepancy is probably due to the vehicle ingress/egress at Amazon's parking garages on that segment of Thomas Street, and surface lot east on the southeast corner of the Boren Ave N and Thomas St intersection which were outside the study area and not included in the model. Differences in average speed between model and field data were also within the acceptable range of 10% of the posted speed limit (WSDOT, 2014).

5.1.8 *Modeling Assumptions*

Several assumptions were made to code the simulation scenarios. These are explicitly listed below:

- Driving behaviors were assumed to follow VISSIM default values, including but not limited to driver aggressiveness, blockage time distribution of parking maneuvers and car following models.
- All vehicles stopping at the curb waited up to 60 seconds in the adjacent travel lane before they disappeared from the network. This behavior is set with VISSIM's default diffusion time parameter, which was a helpful representation of this driving behavior. Sensitivity analysis tested the impact of variations of this parameter to 180 and 300 seconds, but not significant deviations from the model scenarios and derived conclusions were found.
- After the calibration step, it was assumed compliant behavior by all curb users and the scenario modeling did not consider non-compliant behaviors, including stops in the travel lane and interchange uses of curb spaces (e.g. PUDO vehicles use paid parking for passenger load/unloading, trucks use PUDO for load/unload). The reasoning behind this is that curb operations should not depend on contravening existing curb access rules to minimize traffic flow impacts.

- Geofencing strategy does not result in volume increase due to “calling effect” at the network level for a given set of PUDO zones. This assumption is plausible in the case of a uniform distribution of PUDO zones and vehicles in an area with geofencing in place.
- Boren Ave North was assumed to not have overtaking lane. The reasoning behind this is that curb operations should not depend on creating unsafe situations for overtaking maneuvers driving onto traffic in the opposite direction.

Table 5-4. Model Calibration Results

Street Segment	Description	Field Data Volume	Field Data Avg. Speed	Model Data Volume	Model Data Avg. Speed	Difference Avg. Speed	Difference Volume	Difference % Volume	GEH
AM Commuter Peak Period									
Boren	SB: Midblock	103	11	101	10	-1	-2	-1.9%	0
Boren	NB: Midblock	104	12	108	15	3	4	3.8%	0
Thomas	WB: East of Boren Ave	190	18	184	16	-2	-6	-3.2%	0
Thomas	EB: East of Boren Ave	107	18	115	14	-4	8	7.5%	1
Thomas	WB: West of Boren Ave	221	14	194	15	1	-27	-12.2%	2
Thomas	EB: West of Boren Ave	122	16	114	17	1	-8	-6.6%	1
Boren	SB: South of Thomas St	85	12	81	14	2	-4	-4.7%	0
Boren	NB: South of Thomas St	105	15	100	14	-1	-5	-4.8%	0
Total among all street segments		1,037	-	997	-	-	-40	-3.9%	-
PM Commuter Peak Period									
Boren	SB: Midblock	100	13.5	87	14	0	-13	-13.0%	1
Boren	NB: Midblock	79	12.3	74	15	2	-5	-6.3%	1
Thomas	WB: East of Boren Ave	122	17.5	131	17	0	9	7.4%	1
Thomas	EB: East of Boren Ave	284	11.8	310	14	2	26	9.2%	2
Thomas	WB: West of Boren Ave	146	15.2	115	16	1	-31	-21.2%	3
Thomas	EB: West of Boren Ave	280	9.9	288	12	2	8	2.9%	0
Boren	SB: South of Thomas St	72	15.8	69	14	-1	-3	-4.2%	0
Boren	NB: South of Thomas St	87	14.8	61	15	0	-26	-29.9%	3
Total among all street segments		1,170	-	1,135	-	-	-35	-3.0%	-

5.2 Results and Discussion

The first thing to observe is that the marginal improvement of the adding PUDO zone strategies decreases with the number of PUDO spaces, assuming constant traffic volumes. This is represented by the impact of this strategy during the PM commuter peak hour on street throughput and the number of times a PUDO vehicle arrivals and the PUDO zone was fully occupied (see Figure 5-3 and Figure 5-4). Street productivity (in terms of street throughput) increased roughly 2% from one to two PUDO spaces per blockface, however, with additional spaces the improvement was nearly 0%. Similarly, the number of PUDO vehicle arrivals with a full PUDO zone was reduced roughly 64% by converting 1 to 2 PUDO spaces, but this improvement dropped to 31% from 2 to 3 spaces per blockface, 6% from 3 to 4. With 4 PUDO zone spaces per blockface, no occurrences of a PUDO vehicle arrival with full PUDO zones were observed. Similar results were observed during the morning peak hour period.

The AM and PM commuter peak period conditions showed that PUDO operations are well supplied with 2 or 3 PUDO spaces per blockface, as the impacts of PUDO operations on through traffic and the amount of PUDO vehicles that had to initially wait are mitigated with this PUDO capacity. These results indicate that the observed demand for the existing 4 PUDO spaces in Boren Ave N does not reach the capacity of these spaces and lead to congestion and impacts to other users. Under these conditions of “oversupply” of PUDO spaces, ridehail strategies such as geofencing may have a limited impact, as represented by the close performance of the scenario with geofencing in place compared to the baseline scenario based on street throughput and full PUDO space encounters (see Figure 5-3 and Figure 5-4).

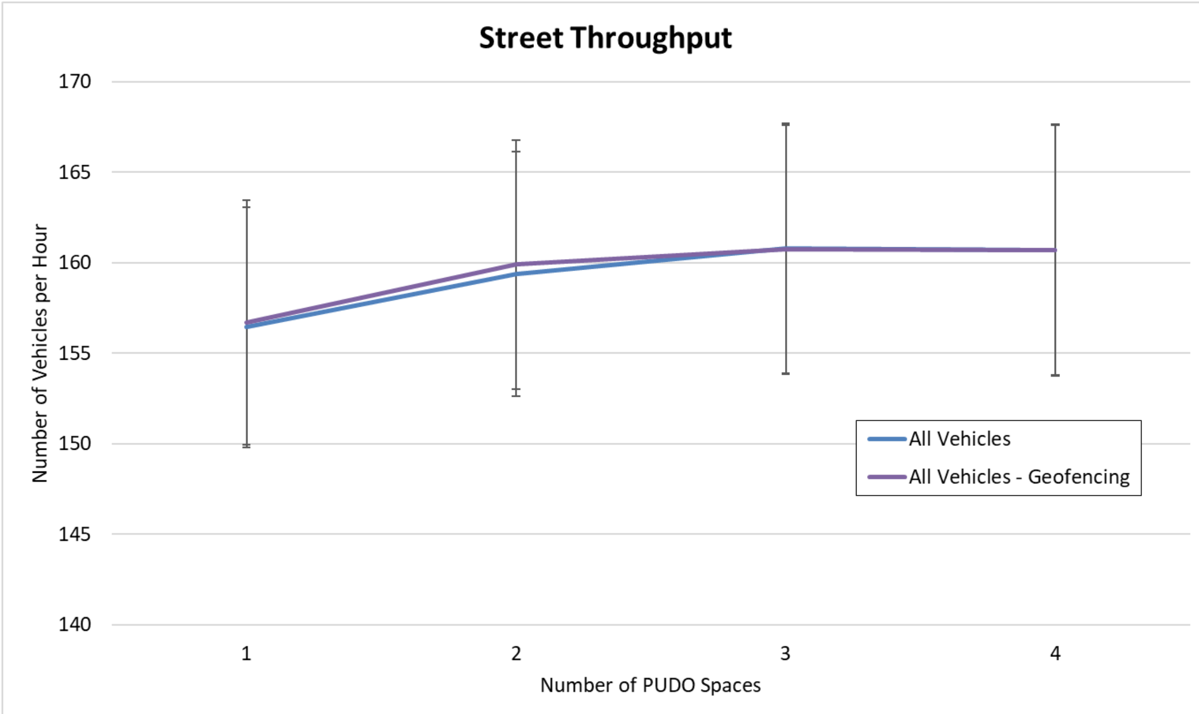


Figure 5-3. Throughput under increasing PUDO space conditions during the PM peak hour[1].

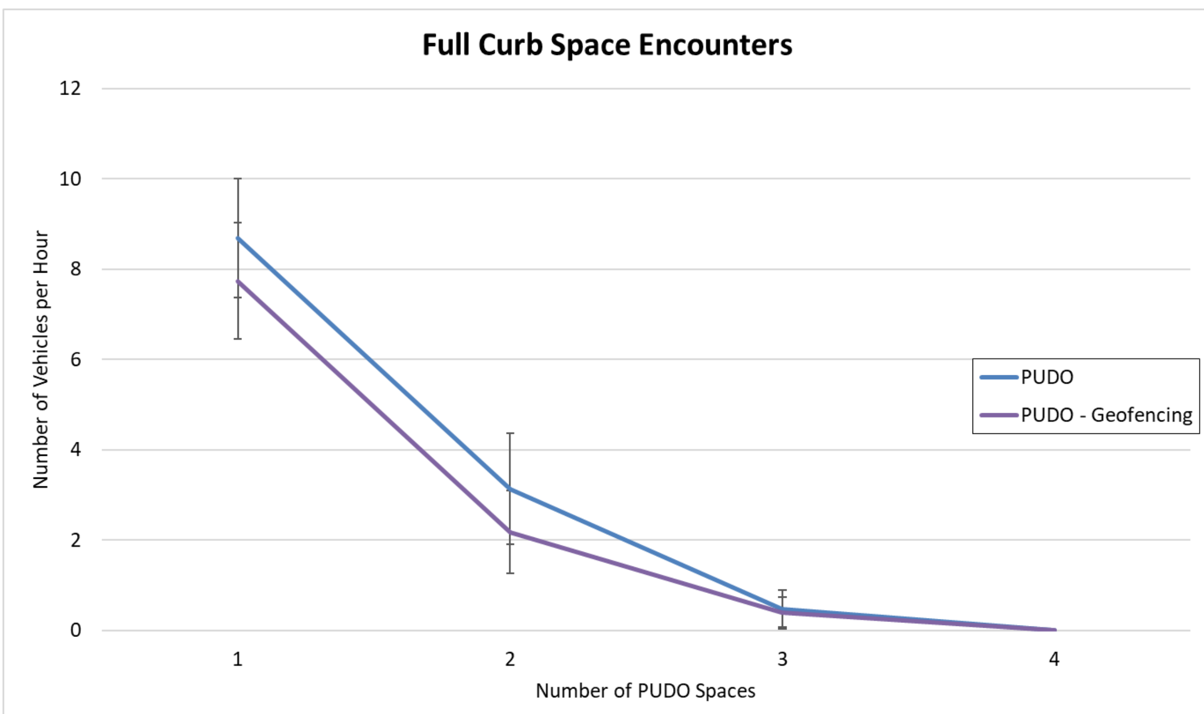


Figure 5-4. Full curb encounters by PUDO vehicles at PUDO zones under increasing PUDO space conditions during the PM peak hour[1].

[1] Geofencing: scenario with geofencing of ridehails to PUDO zone. 95% confidence interval error margin shown.

Under growing volume conditions, some relationships between curb management metrics can be identified. One of these relationships is among average PUDO space occupancy, number of full curb space encounters, number of PUDO stops uncompleted and average uptake time (see Figure 5-5, Figure 5-6 and Figure 5-7). PUDO space occupancy describes the conditions of utilization of the space, and therefore, it's related to the probability of having spaces available for incoming PUDO vehicles. Under the baseline scenario with no ridehailing strategies in place, average curb space occupancy increased with hourly volume with an average 13% increase in PUDO space occupancy for every 100% volume growth (roughly 200 more vehicles in the street). As occupancy of PUDO space increased with demand per space, so did the amount of full PUDO space encounters that grew exponentially with volume (see Figure 5-7).

All of this translated into an increase of incomplete PUDO stops and of increased delay for PUDO users. Figure 5-6 shows the ratio of unserved PUDO stops increased from roughly 0% to close to 10% for an accumulated volume growth of 400%, and final average PUDO space occupancy of roughly 70%. In the baseline conditions, average uptake time of PUDO vehicles also increased from roughly 13 sec./veh. to 38 sec./veh., a 92% increase (see Figure 5-7).

Ridehail curb management strategies showed a potential impact on the performance of PUDO spaces, and this impact was greater with increased volumes. Geofencing ridehails to PUDO spaces decreased the percentage of PUDO stops incomplete from 4-10% to 2-7% (an average decrease of 31%) for growth scenarios over 100% growth (see Figure 5-6).

The range of impact of the policy targeting an increase in PUDO vehicle occupancy is shown between the scenarios of no change in passenger loads and 50% reduction in passenger loads. If such policy is unsuccessful and vehicle efficiencies did not translate into lesser number of vehicles and curb demand, this policy could lead to higher average uptake times and unserved PUDO stops than the status quo since PUDO dwell times increase for every additional passenger load/unload (see Figure 5-6 and Figure 5-7). A logical maximum upper threshold is a 50% PUDO vehicle reduction from increased occupancy to 2 passengers per vehicles. This scenario improved curb space performance with lower uptake times and unserved PUDO stops and performed similar to the geofencing policy based on those metrics. More comprehensively, passenger throughput would be doubled under the pooling scenarios, and thus, increasing the productivity of PUDO zones overall over the geofencing scenario.

A comprehensive evaluation of ridehail strategies must not only evaluate the effect on PUDO zones and PUDO vehicles, but also on other competitive uses of the curb and road traffic. All the metrics discussed were tracked for the paid parking and commercial vehicle loading users in the simulation. In line with the PUDO mode, increased growth in volumes led to worse performance on paid parking spaces and CVLZs in terms of percentage of unserved stops and average uptake times (see Figure 5-9 and Figure 5-10). The effects of ridehail strategies on paid parking and commercial vehicle loading uses is not conclusive, due to the greater variations observed in the metrics. This variation could be driven by the smaller sample size (due to smaller share of the paid parking and commercial vehicle loading demands). Performance of paid parking and CVLZ spaces could also be driven by the balance (or unbalance) between demand and supply at these spaces, thus, leading to an effect of geofencing and the resulting nearby better conditions on the curb to be only marginal (see Figure 5-9and Figure 5-10).

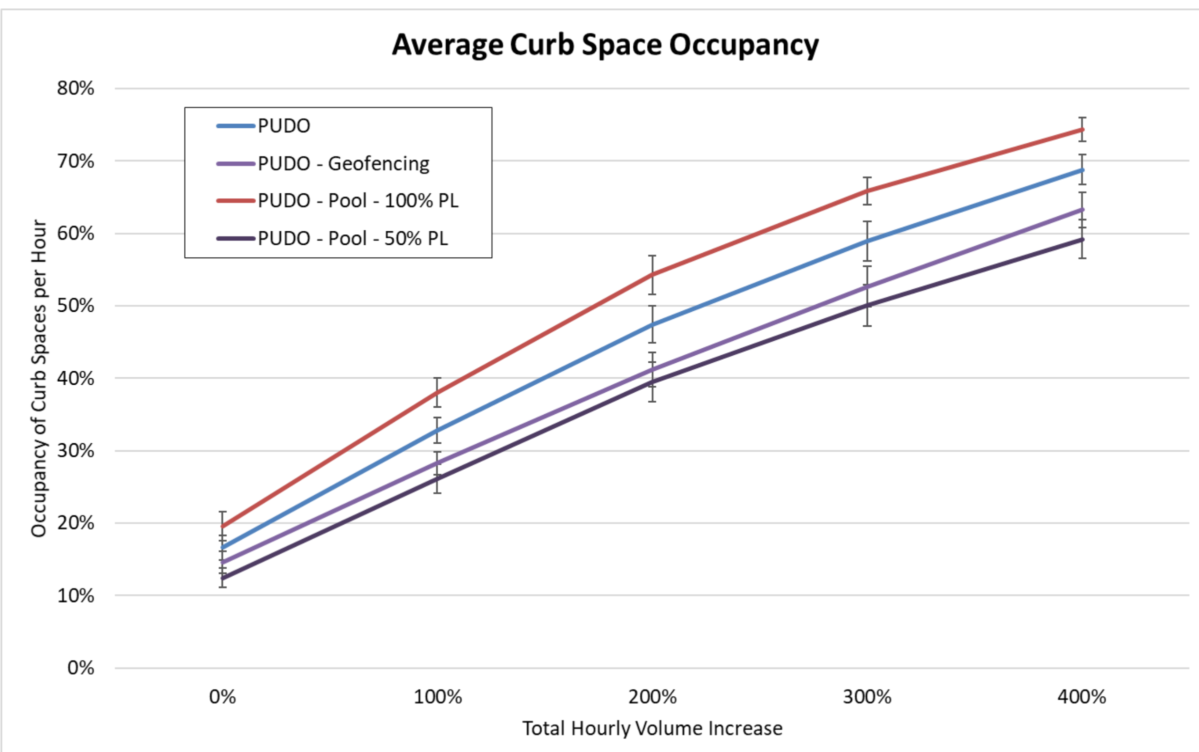


Figure 5-5. Curb space occupancy of PUDO spaces under increasing volume conditions[2]

[2] *Geofencing: scenario with geofencing of ridehaisl to PUDO zones. Pool – 100% PL and 50% PL: scenarios with occupancy of 2 passengers/PUDO vehicle and 0% and 50% passenger load reduction, respectively. 95% confidence interval error margins shown.*

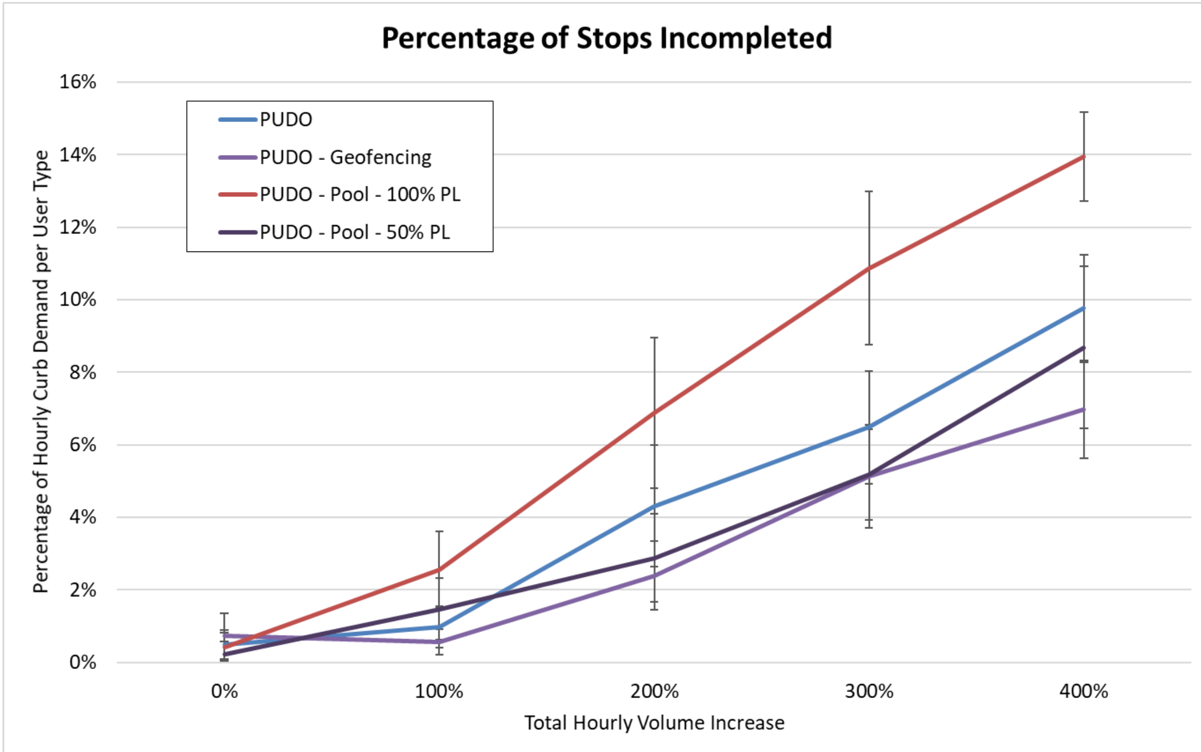


Figure 5-6. Percentage of PUDO stops incomplete under increasing volume conditions. [2]

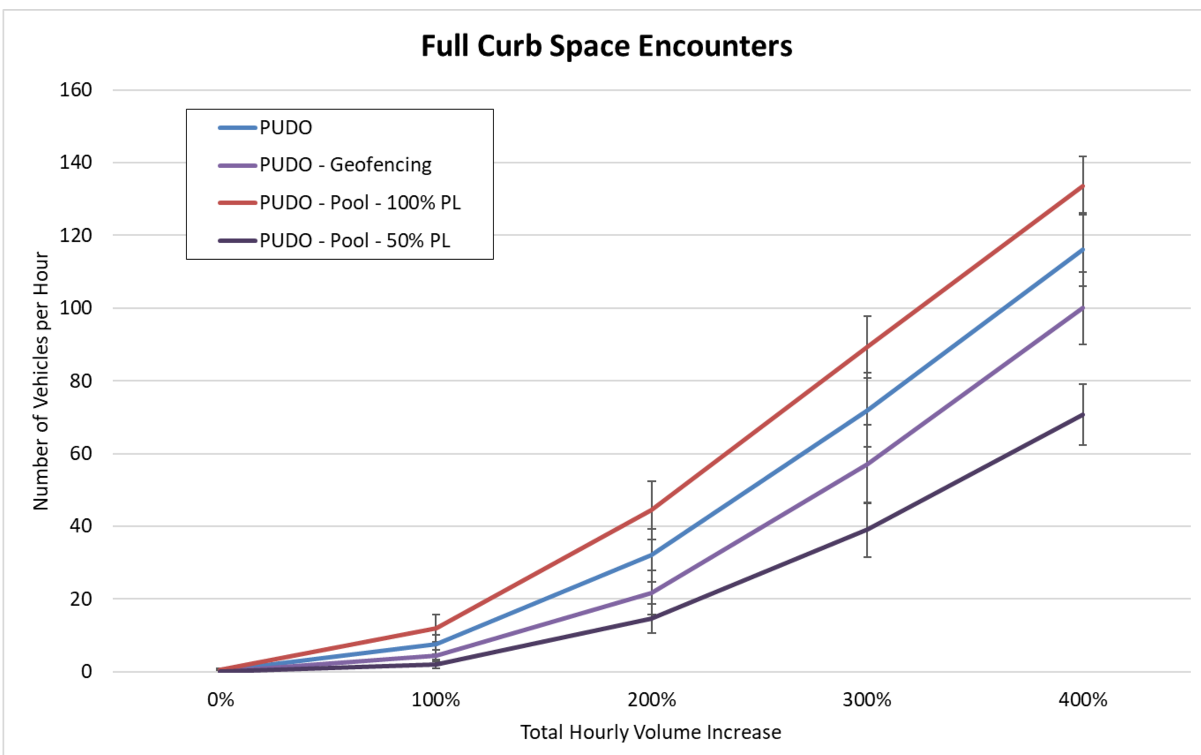


Figure 5-7. Full curb encounters by PUDO vehicles at PUDO zones under increasing volume conditions[2].

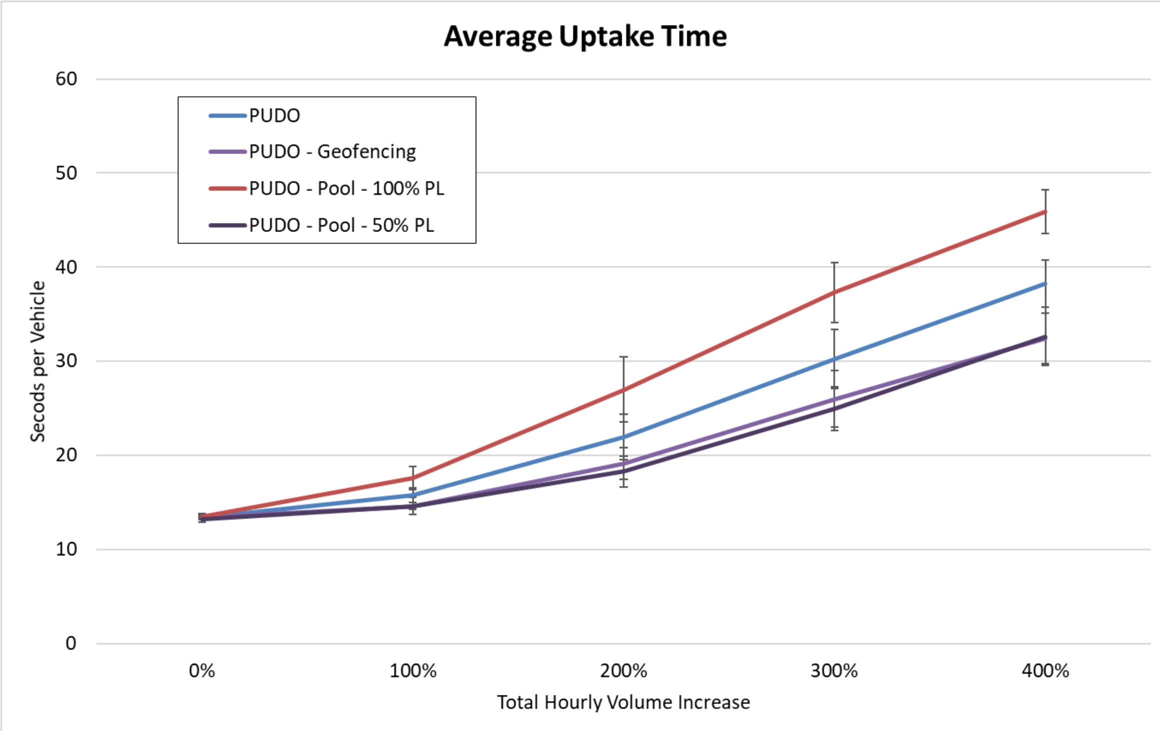


Figure 5-8. Average Uptake Time of PUDO vehicles under increasing volume conditions.

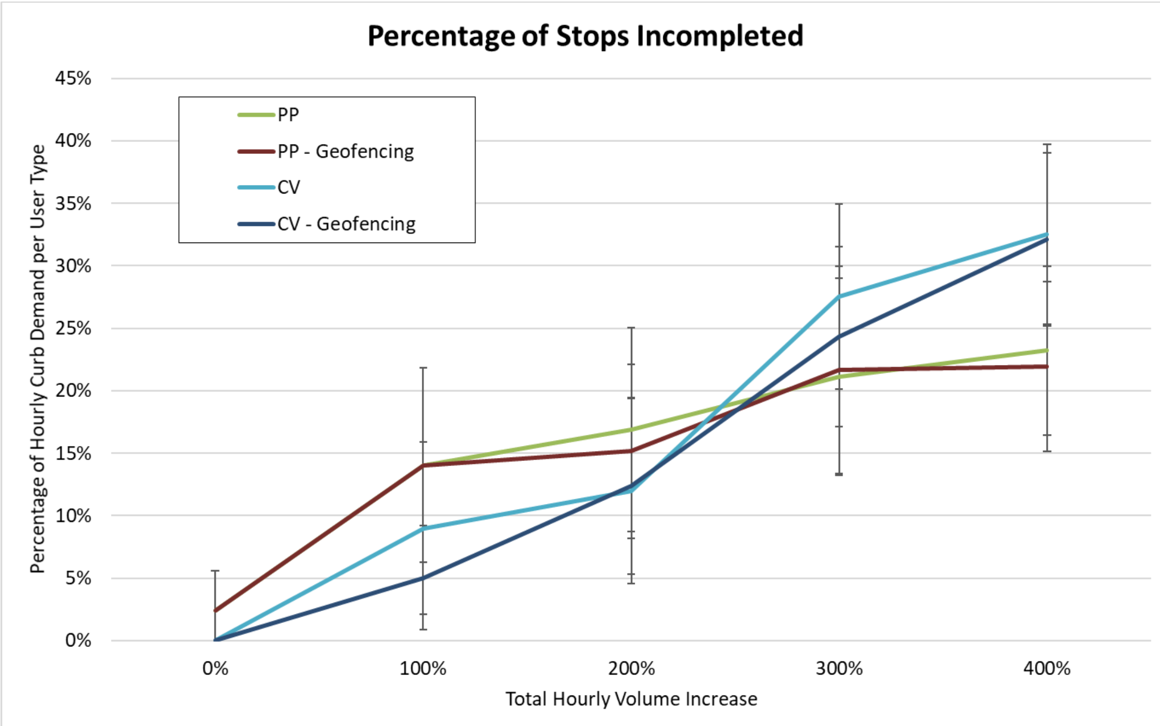


Figure 5-9. Ratio of PP and CV vehicles stops uncomplete under increasing volume conditions[3].

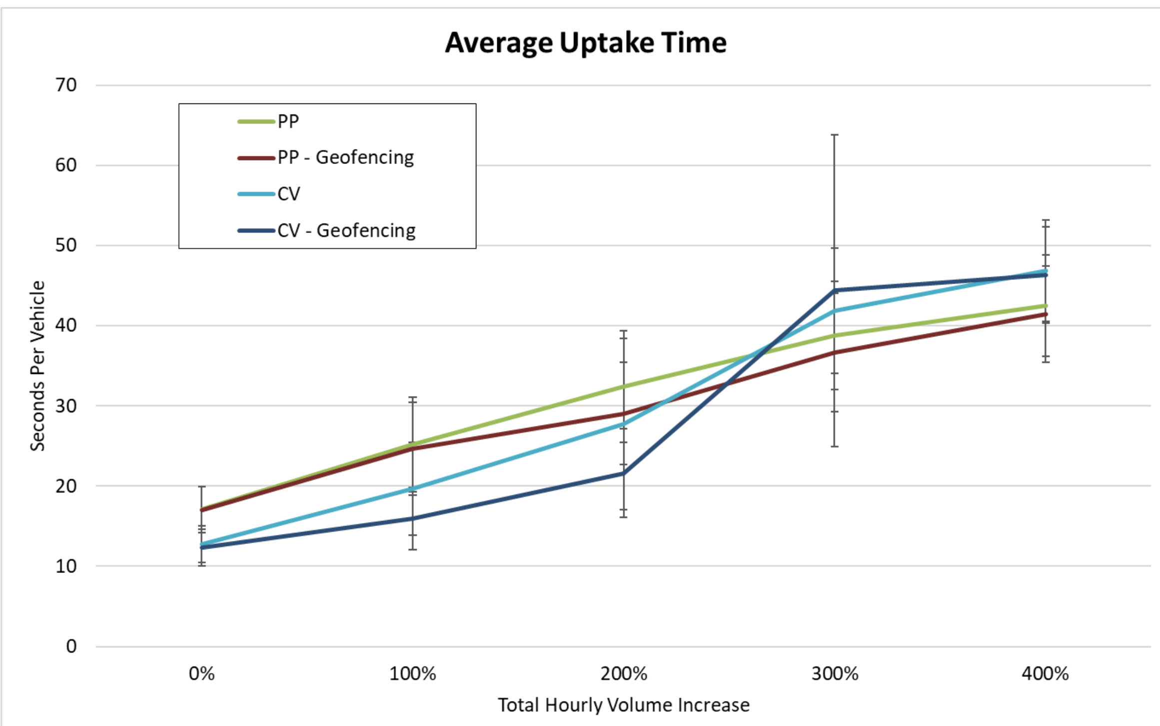


Figure 5-10. Average Uptake Time of PP and CV vehicles under increasing volume conditions[3]

[3] Geofencing: scenario with geofencing of ridehail vehicles to PUDO spaces. PP: passenger cars using paid parking; CV: commercial vehicles using CVLZs. 95% confidence interval error margins.

5.3 CONCLUSIONS

In recent years, researchers and practitioners have recognized the rapidly growing complexity of curb management, with emerging uses such as MoD services and high competition among all road users, and have sought new methods to address the gap in understanding and analytical capability for evaluation.

The lack of curb data and metrics is a challenge that hinders research in this area. To overcome this, some authors have used exploratory interview-based research for identifying policy problems and solutions based on public and private perspectives (Diehl et al., 2021). Another series of studies attempted to model different aspects of parking and ridehailing services, but had to rely on assumptions regarding the performance of ridehailing vehicles to represent real-world operations without empirical data (Beojone & Geroliminis, 2021; Kondor et al., 2020; Su & Wang, 2019; Xu et al., 2017; Yu & Bayram, 2021).

Recent pilot studies investigate ridehailing PUDO operations in the street and make recommendations about the allocation of PUDO zones (City of Fort Lauderdale, 2018; DDOT, 2019; Fehr and Peers, 2019; Lu, 2018; Smith et al., 2019). Collectively, these studies have proposed PUDO operation metrics, however, the effectiveness of current and emerging curb management technologies on these PUDO metrics and the inter-modal curb space competition have not yet been investigated.

Our research addresses these gaps by modeling and evaluating the impact of ridehail curb management strategies on traffic operations, PUDO operations and other curb users, including paid parking and commercial vehicle loading. This was achieved by evaluating under varying street and curb demand profiles, the effect of adding PUDO zone space, geofencing PUDO vehicles to PUDO zones, and increasing the occupancy of PUDO vehicles. This builds on our previous dissertation research in Chapter 4 developing the first sound parametrization of ridehailing passenger load/unload dwell times, leveraging naturalistic data to link dwell times essential characteristics including the locations of these operations, passenger maneuvers and operation management strategies.

An evaluation of AM and PM commuter peak conditions in the modelled street showed how the complexity in PUDO operations relates to curb management metrics. Periods of higher share of passenger loadings observed in the PM period drive higher PUDO space occupancy levels and number of unserved vehicles due to the longer dwell times. The strategy of adding PUDO zones showed a decreasing marginal effect on PUDO operations. Under conditions of oversupply for PUDO operations observed during the AM and PM commuter peak periods, these vehicles may have a limited impact on traffic operations, other PUDO users and other users of the curb based on the metrics evaluated, even if PUDO vehicles represent a high share of the street volumes.

The strategy of geofencing PUDO vehicles to the corresponding zones has the potential to shorten PUDO dwell times. This operational change can translate into an improvement of productivity at the curb for other PUDO vehicles. Paid parking, and commercial vehicle loading uses of the curb can also be affected by improvement of adjacent conditions from the geofencing strategy, however, this result is inconclusive due to the small sample and large variability of paid parking and commercial vehicle users in the observed conditions. The range of impact of enhancing pooling with two passengers per PUDO vehicle was tested, and showed that performance improvements focused on vehicle movements can be similar to geofencing in the case of a 50% passenger load reduction, however, overall productivity in terms of passenger throughput at the PUDO zone is much greater due to the higher vehicle occupancy.

This research constitutes the first step in understanding the impact of curb management strategies on metrics focused on PUDO vehicles and among multi-modal competition in curb environments, which is essential for efficiently manage this public asset balancing all the curb competitive needs.

Chapter 6. CONCLUSIONS

There is growing pressure in cities worldwide to find innovative ways to better manage and use scarce space. Cities with alley networks increasingly recognize the potential to incorporate the increase in resources provided by functional alleys for environmental, economic and social benefits. Also, local governments seek new tools to evaluate the impacts of curb management strategies that prioritize different users' needs, and help to understand the growing complexity of these environments.

The lack of data hinders research in these areas. On one side, despite alley's historical role providing access to land uses for freight and servicing, these infrastructures have not been studied as a resource in modern freight access planning. Also, a series of studies on curb management have used exploratory interview-based research for identifying policy problems and solutions based on public and private perspectives (Diehl et al., 2021). Another series of studies attempted to model different aspects of on-street parking and ridehailing services, but had to rely on assumptions regarding the performance of ridehailing vehicles to represent real-world operations without empirical data (Beojone & Geroliminis, 2021; Kondor et al., 2020; Su & Wang, 2019; Xu et al., 2017; Yu & Bayram, 2021).

Naturalistic data from a previous study of PUDO operations in Seattle (Ranjbari et al., 2020) is leveraged using a hazard-based duration modeling approach to link dwell times essential characteristics, including the locations of these operations, passenger maneuvers, operation management strategies, and nearby traffic. Also, our research develops the first comprehensive alley inventory in the U.S. with an accurate GIS map of the network's geospatial locations as well as measurements of physical attributes (e.g., alley length, alley width and, narrowest points).

Researchers and practitioners can use the Seattle case studies conducted in this dissertation as a measurable, in-depth investigation of curb and alley environments that suggest possible outcomes of vehicle operations in these spaces with practical implications for curb and alley management policies. Most importantly, our research provides frameworks for evaluation and analysis of the complexity of these infrastructures in dense urban areas.

Our alley data collection methodology supports an adequate assessment of physical attributes that directly impact alley operations and functionality, particularly for freight, waste management, and emergency vehicle access. Cities can use the information provided by a comprehensive scan of physical characteristics of urban alleys to make data driven decisions about the most cost-effective freight distribution systems for the last mile. Geospatial information of alley restricting dimensions such as effective height and width can help to decide between delivery vehicle designs that balance maneuverability, size and load capacity.

Our research on PUDO dwell times with hazard-based models showed the heterogeneity of this curb metric in relation to location, passenger maneuvers, operations management, and traffic. Building upon this knowledge contribution, our simulation models tested the possible impact of ridehail strategies, including geofencing, adding PUDO zones and increasing ridehails passenger occupancy, on curb utilization and the relationships between performance metrics such as average space occupancy, ratio of incomplete stops and average uptake time for different users.

With all the variations on curb configurations, curb demand volumes, transportation users in a city environment, our research represents a steppingstone necessary to provide a comprehensive view and understanding to support policies/strategies that efficiently manage this public asset balancing all the curb and alley competitive needs.

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VITA

José Luis Machado León has eight years of experience in transportation analysis projects focusing on last-mile/commercial vehicle operations, freight transportation systems, curb management for people and goods, and analysis of quality of public transit quality from the customer perspective. José leverages his data-driven research and analytics background to develop creative, data-driven solutions for transportation challenges. José graduated with a Bachelor of Science in Civil Engineering from the University of Granada, Spain, in 2013. In 2015, he moved to Seattle to pursue graduate studies in transportation engineering. José graduated with a Master of Science in Civil Engineering -Transportation Track from the University of Washington in 2018. During most of his graduate school years at the University of Washington (UW), José served as a research assistant at the Supply Chain Transportation and Logistics Center. As a key researcher on the collaboration: The Final 50 Feet of Urban Freight Deliveries, between the UW and the Seattle Department of Transportation, José created and applied a toolkit for city professional to collect data related to urban freight delivery that informed the City´s new policies on alley and loading bay infrastructure. José has over two years of experience as a transportation engineer working in consulting. He has led transportation analysis for environmental impact statements of mass transit infrastructure projects and strategic planning for critical infrastructure, including maritime facilities.

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