Modeling of Urban Freight Deliveries; Operational Performance at the Final 50 Feet

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A dissertation
submitted in partial fulfillment of the
requirements for the degree of

Doctor of Philosophy

University of Washington

2021

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Program Authorized to Offer Degree:
Civil and Environmental Engineering

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Abstract

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Operational Performance at the Final 50 Feet

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The demand for goods and services is rapidly increasing in cities, in part due to the rise in online shopping and more varied delivery options. Cities around the world are experiencing an influx of goods pickup and delivery activities. The movement of goods within urban areas can be very constraining with high levels of congestion and insufficient curb spaces. Pick-up and delivery activities, specifically those that are out of vehicle activities, encompass a significant portion of urban goods movement and inefficient operations can negatively impact the already highly congested areas and truck dwell times. This dissertation aims to provide insights and data-driven approaches to support freight plans in various cities around the globe with a focus on urban freight deliveries. To accomplish this goal, this dissertation first proposes to discover the current delivery process at the final 50 feet by creating value stream maps that summarize the flow of delivery activities and times, time variations between activities. The map will be based on the data collected from five freight-attracting buildings in downtown Seattle. Secondly, this research explores contributing factors associated with dwell time for commercial vehicles by building regression models. Dwell time, in this study, is defined as the time that delivery workers spend performing out-of-vehicle activities while their vehicle is parked. Finally, this dissertation predicts total time spent at

the final 50 feet of delivery, including dwell times and parking-related times through discrete event simulations for various “what if” delivery scenarios. Multi-objective simulation-based optimization algorithms were further used to discover the optimal numbers of parking and building resources (e.g. number of on and off-street parking capacity, number of security guards or receptionists). This aims to better understand how increased deliveries in urban cities can impact the cost distributions between city planners, building managers, and delivery workers. This will also identify the areas for improvement in terms of infrastructure and resources to better prepare for the future delivery demands based on various scenarios.

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ACKNOWLEDGMENTS

It is my pleasure to express my sincere gratitude to several individuals who were influential in the completion of my Ph.D. research.

First and foremost, I sincerely thank my advisors, mentors, and counselors, Prof. Linda Ng Boyle and Prof. Anne Goodchild for their guidance, assistance, encouragement, and warm support in every step of my doctoral program at the University of Washington. I would also thank Prof. Don MacKenzie and Prof. Anne Moudon for their outstanding insights and valuable inputs as committee members.

This work would not materialize without the financial supports of the City of Seattle and Urban Freight Lab members. I would like to recognize the important roles of Christopher Eaves and Jude Whillcher, Loren VandenBerghe, John Dodero, Travis Vaughter, Trent. J. Mcneal, Kevin Condon. Thank you for your collaborative efforts.

I am also very thankful for my colleagues. Special thanks to Klaas Fiete Krutein, Dr. Giacomo Dalla Chiara, Gabriela Giron-Valderrama, José Luis Machado León, Polina Butrina, Manali Sheth, Anna Alligood, Dr. Andisheh Ranjbari, Caleb Diehl, Katie Ward, Jennifer Ross from the Supply Chain Transportation and Logistics Center. For both technical and personal supports, I thank my colleagues from the Human Factors and Statistical Modeling Lab: Dr. Ali Ajdari, Steven Hwang, Mayuree Binjolkar, Huizhong (Edith) Guo, Jundi Liu.

Most importantly, I want to thank my parents for giving me the strength to reach for my dreams and showing me the world as a place filled with great opportunities. I could not have asked for better parents or role-models. Last but not least, I am grateful for my beloved husband for his continuous love, support, and encouragement along the path of my academic pursuits.

DEDICATION

To my beloved husband, Justin Ham,

my dear parents, Mr. Hyun Suk Kim and Mrs. Hyun Sook Choi,

and my big brother, Dong Kun Kim for their endless love and support

Chapter 1

INTRODUCTION

The demand for goods and services is rapidly increasing in cities, in part due to the rise in online shopping and more varied delivery options. Cities around the world are experiencing an influx of goods pickup and delivery activities. The additional related traffic has added pressure to already congested urban roads. Package delivery services are taking a large portion of the logistics sector [21]. Apart from long distance intercity freight movements, the final 50 feet of urban freight delivery involves various activities from loading/unloading goods to pick-up and delivery operations, serving the end customers [116]. This final 50 feet of a supply chain may be more or less than 50 feet but the term of the final 50 feet represents such activities which can be complex and costly, accounting for up to 28% of a product's total transportation cost [65].

1.1 Problem statement & Background

The focus of most urban freight research has been on vehicle mobility such as freight demand forecasting and traffic management. This has led to a lack of understanding of fundamental aspects of the urban goods movement, such as pick-up and delivery activities within the building (vertical movement) [89]. The delivery process does not end until the package is delivered to the final customer. The processing time spent outside of the vehicle (i.e. dwell time) can be much longer than the driving time, as much as 87 % of the entire urban freight delivery process [13, 16]. Analysis and documentation of the out of vehicle activities performed by various types of delivery workers are limited, and there is a sparsity of data to examine the overall system. Understanding urban freight deliveries in the final 50 feet is particularly difficult because factors influencing dwell times are often proprietary to independent private companies, and are therefore, not shared with researchers and city planners. For this reason, most traffic and parking policies overlook the complexity of urban freight delivery activities. An in-depth analysis of the driver's delivery process and performance for the final 50 feet of the delivery process plays a vital role in understanding and improving urban freight delivery.

Understanding the vertical goods movement within the building and dwell times associated with urban goods deliveries are important because they can directly influence the roadway capacity and performance. The lack of curbside space, due to excessively long stays by delivery workers, could increase urban congestion as other delivery vehicles circle the city blocks while looking for parking spaces [129]. Vertical movements can also encompass non-value added time or time that unnecessarily increases the overall delivery time with no corresponding benefit to the customers [49]. These factors can cause negative cascading impacts on road congestion, adding costs and pressures to the trucking industry, building management, and city officials.

Freight movement is changing rapidly and it is essential to understand the process flow of goods globally, regionally, and locally to develop operations and infrastructure that are ready to meet for future demands. This research focuses on the movement of goods locally and more specifically within freight-attracting buildings in downtown Seattle. There has been an increasing demand for deliveries in downtown areas, but there is limited space with which to move, both structurally and operationally. Insights gained from this research can be expended and scaled to be used in the decision making process for urban freight policies in many cities.

1.2 Study purpose & Research questions

This research aims to provide insights and approaches that are based on analysis of data to support freight plans in various cities around the globe with a focus on urban freight deliveries. To accomplish this goal, three main research questions were developed. The research questions were developed based on the need for a better understanding of the urban freight system to improve the decision making process for future urban freight policies. The results from first and second research questions will be key components to design and validate the simulation model in the third (final) chapter as shown in 1.1.

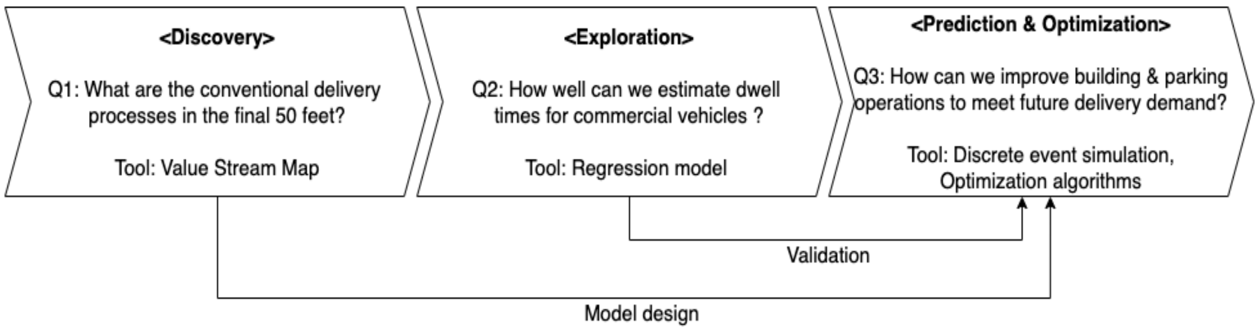


Figure 1.1: Three main research questions

1.2.1 Research question 1: What are the current delivery processes in the final 50 feet?

The focus of this research question is on the **Discovery** of the process associated with the final 50 feet of the urban freight delivery using value stream mapping. This chapter provides value stream mapping of delivery activities, delivery times, time variations between activities based on the data collected from an office building in downtown Seattle.

1.2.2 Research question 2: What factors from the final 50 feet of delivery processes influence dwell times for commercial vehicles?

The focus of this research question is on **Exploration** contributing factors associated with dwell time for commercial vehicles using statistical models. This chapter provides statistical models with explanatory variables based on the information gathered from the first research question. The models can provide insights on the magnitude of influences of each factor on dwell times, which could help the cities on developing policies and priorities that are specific to delivery characteristics.

1.2.3 Research question 3: How can we improve building & parking infrastructure to meet future delivery demands?

The focus of this research question is on **Prediction & Optimization** of the cost distribution between delivery workers, building managers, city planners with increasing numbers of deliveries in urban buildings. By controlling the number of building and parking resources, our model aims to minimize the costs for not only the managers (e.g. building managers or city planners) who plan infrastructure operations but also the users (e.g. delivery companies) who perform deliveries at the infrastructure. This chapter introduces the simulation-based multi-objective optimization (SMO) approach using various "what if" delivery scenarios. First, a discrete event simulation which is built based on the value stream map from the first research question, individual dwell times for each commercial vehicles can be estimated including long wait times in queues and processing time for different delivery scenarios. The model is then validated with the dwell time model which is a product of the second research question. Finally, multi-objective optimization algorithms are used to provide information on the optimized infrastructure resources (e.g. number of on and off street parking capacity, number of security guards or receptionists) that can be ready for the future years based on various scenarios.

1.3 Organization

The dissertation is organized as follows:

The next chapter provides a general overview of the final 50 feet of urban freight deliveries and presents the literature relevant to this dissertation work.

Chapter three describes the data collection method for five urban buildings in downtown Seattle, USA.

Chapter four introduces the lean philosophy and value stream mapping (VSM) approaches to examine the delivery process flows in an office building in downtown Seattle. These approaches are used to identify areas of improvement, which can enhance the overall quality of service and work performance.

Chapter five develops statistical models that explores factors associated with dwell time for commercial vehicles. The models provide insights on the levels of influences of each factor on dwell times, which could help the cities on developing policies and priorities that are specific to delivery characteristics.

Chapter six investigates the impacts of increasing numbers of deliveries in urban buildings using discrete event simulations in terms of costs for delivery workers, building managers, and city planners. Multi-objective optimization algorithms are then used to provide information on the optimized infrastructure resources (e.g. number of on and off street parking capacity, number of security guards or receptionists) that can be ready for the future years based on various scenarios.

The last chapter presents the key findings from this research, highlights their contribution, and present areas for future research

Chapter 2
LITERATURE REVIEW

This chapter provides an overview of the final 50 feet of urban freight deliveries and presents the literature relevant to each research area; 2.1) **Discovering** of urban freight delivery process associated with the final 50 feet, 2.2) **Exploring** contributing factors associated with dwell time for commercial vehicles, 2.3) **Optimizing** building and parking resources to efficiently manage increasing demand for deliveries in the future.

2.1 Urban freight delivery processes associated with the final 50 feet

Numerous studies regarding the "last mile" of urban freight deliveries have been conducted while research in the final 50 feet of the delivery processes is still scarce. Although urban freight delivery may vary by the characteristics of each city, there are activities that are observed regardless of the delivery type (e.g., loading goods, checking in, maneuvering within buildings). It is therefore important to understand how operations across various urban freight deliveries can contribute to congestion and affect the overall quality of life for residents, retailers, freight carriers, and government agencies.

Allen et al. [15] conducted a comprehensive review of 162 freight studies (from the 1960s to 2008) in 18 countries. The majority of data were based on freight operations from the UK, followed by the US, the Netherlands, Germany, and Italy, indicating active efforts worldwide on improving the urban freight system. The review noted three primary purposes of these freight studies [15]:

1. to gain an understanding of urban freight operations,
2. for policy and decision-making, and
3. for use in urban freight modeling.

The review also highlights a need for a systems approach to measure inefficiencies and to provide better communication between the public and private entities for the development and implementation of freight plans and policies [110, 16]. A more quantitative approach can be achieved with our study method, which can also provide a useful tool for highlighting the impact of freight transport movements to stakeholders, either directly (receivers, shippers, and carriers) or indirectly (city authorities, and residents). Rhodes et al. also state that quantifying and addressing both horizontal and vertical "last mile" inefficiencies are important from a planning perspective[129].

Value stream mapping (VSM) is an effective tool for identifying system efficiencies and has been used in industries related to manufacturing and health care services [139, 130, 157]. The urban freight delivery process consists of many activities and parties, with few standardized processes. Using a systems approach provides insight on dwell times and failed deliveries by decomposing the delivery process. Cherrett et al. emphasized the importance of understanding freight vehicle dwell times (i.e. the times the vehicle remains stationary) because shorter dwell times could reduce traffic delays and minimize the environmental impacts of freight [38]. A more in-depth understanding of vehicle dwell time was proposed by Allen et al. [13] with 12 steps of activities performed by a goods vehicle driver when making a delivery. The first research question of this dissertation examines the final segment of the delivery process and considers the many steps associated with the delivery tasks.

One factor that impacts dwell time is the parking location. The parking options can be classified as on-street, off-street parking, and alternative options such as double parking or illegal parking [33]. The decision of where to park may be influenced by the package size and weight, and distance to the recipient's location [33]. The existence of off-street loading facilities does not necessarily mean they are always used [38]. According to Cherrett et al.'s review of the recent UK studies, the proportion of on-street and off-street parking varied by the type of location served [38]. Deliveries made in shopping centers tend to include a higher percent of off-street parking facilities while deliveries made to local shops on the street use more on-street parking [38]. Based on the parked location, the levels of conflicts with pedestrians, bicyclists, and other vehicles can be different, which may cause extra delivery time.

Understanding the total delivery time as well as the time for each delivery task is important when imposing time restrictions for parking and freight loading facilities [110, 109]. Too little time given at the loading facilities may lead to excessive enforcement using fines for parking/loading, clamps, and towing-away. These can impact delivery workers' operation significantly[13]. Too much dwell time can be an indicator of an inefficient process with fewer on-time deliveries.

Another factor that may influence dwell time is the time associated with using elevators. Pivo et al. state that drivers would worry less about the congestion if slower traffic could be offset with faster elevator service [127]. Delivery workers are required to use freight elevators in many office buildings no matter the size of the delivery. The bottleneck may occur because the number of freight elevators in the office buildings are limited to one or two [127]. Morris points out the lack of requirements regarding the number of freight elevators in commercial buildings of many American cities, including Atlanta, Boston, Chicago, Dallas, New York and Seattle [116]. Even though each building has different freight elevators, this study can provide insights on how much time associated with elevators can take up in the total delivery time for similar office buildings in other urban areas.

Failed deliveries are another central issue in the urban freight system. Failed deliveries are very costly as the driver needs to return (sometimes multiple times) before a successful delivery. A 2016 Interactive Media in Retail Group (IMGR) report in the UK showed that failed deliveries can cost up to $780 million (equivalent to $1 billion US dollars) [113]. The cost burden for failed deliveries has prompted interest in solutions that can help streamline the final segment of the delivery process.

2.2 Commercial vehicle dwell time

Commercial vehicle dwell time can be examined in terms of the challenges created by the current commercial vehicle parking systems, factors related to dwell time, and ways to improve commercial vehicle parking systems.

2.2.1 Challenges created by the current commercial vehicle parking systems

With the explosion of the e-commerce market, demands for dedicated delivery services to the end customer have increased rapidly [112]. This has resulted in high frequencies of urban freight deliveries in many cities, aggravating the fragmentation of freight flows [92]. When there are not enough legal parking spaces for commercial vehicles, delivery workers are left with options such as cruising until finding other parking spaces or double-parking in unauthorized areas. A study conducted at a busy commercial street in Istanbul with a high parking occupancy rate showed that a vehicle parked for an hour can cause 3.6 other vehicles to cruise for parking. The authors pointed out that the current calculation for congestion costs does not account for the costs of cruising for parking. The external cruising cost for parking can be estimated as approximately equal to the external congestion cost in one trip, which is a significant contributor to congestion [79]. Unauthorized parking behavior is another growing issue that is caused by a scarcity of commercial parking spaces in many cities. Parking fines in Toronto have been increased 70 percent between 2006 and 2009, with an estimated $ 2.5 million CAD paid by FedEx, United Parcel Service, and Purolator in 2009 [122]. In 2018 in NYC, where parking spaces are extremely limited, FedEx and UPS incurred $ 14.9 million and $ 33.8 million respectively in parking fines [23]. Studies have shown that the delivery vehicles pay $ 500 to $ 1000 per truck per month for parking fines in New York City [74]. Although parking fines are imposed to discourage unauthorized parking, many delivery companies allocate costs for parking fines as a part of doing businesses in urban areas [156]. In 2013, data collected at over 60 locations in Chicago showed that trucks parked illegally 28.7 percent of the time, far more than 3 percent of illegal parking rate for passenger vehicles [87]. In 2018, commercial vehicle parking observations in downtown Seattle showed that 40 percent of commercial vehicles (with delivery vehicles constituting the biggest share) parked in unauthorized locations including passenger vehicle loading zones (PLZs), the middle of the road, tow-away zones, and no-parking zones [63]. With increasing challenges created by commercial vehicle parking systems in cities, it is important to understand the factors correlated with dwell time in order to explore possible improvements to the current parking policies.

2.2.2 Factors related to commercial vehicle dwell time

Dwell time for commercial vehicles (also referred as parking duration or service time) is not determined by parking management or enforcement policy, but rather by operational constraints [82]. It is challenging to obtain detailed data and to account for variations in influencing factors. To better understand the urban freight system, researchers have gathered empirical data on dwell time. Morris (2004) conducted a time and motion study at loading docks at six commercial office buildings in the central business district of New York City [115]. Sixty percent of observed deliveries were made in the morning, and the average truck dwell time was found to be 31.5 minutes, ranging between 22 minutes and 48 minutes. Kim et al. (2018) observed an office building in the Seattle central business district that had an average truck dwell time of 20 minutes, ranging between 9 minutes and 43 minutes. The authors further broke down the total truck dwell time into time spent for entering, delivering and exiting, which represented 35 percent (7 minutes), 40 percent (8 minutes), 25 percent (5 minutes), respectively, of the average total truck dwell time [90]. Cherrett et al. (2012) collected studies in United Kingdom (UK) that studied dwell time for loading and unloading. The mean lengths of dwell time were suggested based on the types of commercial vehicles: 30 minutes for the average articulated heavy goods vehicle (HGV) delivery, 20 minutes for rigid HGV delivery, and 10 minutes for vans and cars [38].

Allen et al. (2000) identified several factors that influence dwell time, including proximity between the delivery vehicle and final customer, parked location (off-street vs. on-street), type and size of the product, the number of people performing the delivery, and a requirement to receive a signature from the recipient [13]. Schmid et al. (2018) categorized factors influencing dwell time as intrinsic and extrinsic factors. They defined intrinsic factors as delivery-specific characteristics such as weight, volume, and value of delivered goods;

the number of delivery workers; and the number of businesses served [138]. Extrinsic factors included environment-dependent characteristics such as parking capacity, accessibility of parking sites, and parking enforcement [138]. The authors addressed the difficulties of obtaining intrinsic factors and used only extrinsic factors in their delivery vehicle parking duration study.

Many factors have been shown to affect the dwell time of commercial vehicles. Zou et al. (2016) used the Cox proportional-hazard model to show that arrival time, commodity types, vehicle types, and parking location all affected the on-street parking duration of commercial vehicles in New York City [165]. Dalla Chiara and Cheah. (2017) used the log-normal regression for dwell times in the loading bays of two retail malls in Singapore. Factors that were correlated with dwell time included the percentage of vehicle capacity filled with goods prior to any pick-up/delivery, pick-up activity, the ratio of goods volume to the number of workers, time spent waiting for parking, and delivery vehicle type [44]. Schmid et al. (2018) used a parametric survival model to predict parking duration for commercial vehicles using explanatory variables such as types of vehicles, types of items delivered, legal or illegal parking, and observation locations. Different lengths of dwell times were related to different types of items delivered and types of parking. For example, illegal parking occurred for only a short period of time [138]. Based on the past literature, our study included factors that are known to be related to commercial vehicle dwell time as the explanatory variables in the analysis.

2.2.3 Efforts to improve commercial vehicle parking

Cities worldwide have applied various parking policies to improve commercial vehicle parking systems. We explored those policies that involve three major areas of the systems; parking time, spaces, and operations.

Parking time

While most commercial vehicle parking limits are between 15 and 30 minutes [118], dwell times are varied based on individual delivery characteristics. Cities like Seattle and San Francisco are making efforts to measure vehicle dwell times using real-time sensor technology and to improve visibility of available parking spaces through mobile applications [34]. In some cities, commercial parking is restricted to a certain time of day. The New York City Department of Transportation (NYCDOT) is implementing delivery windows in the morning, as 65 percent of deliveries occur before 12:00 PM [122]. In Philadelphia, Pennsylvania, loading zones along the Walnut Street retail corridor require businesses to receive deliveries before 10:00 AM [162]. The American Transportation Research Institute's 2016 parking survey revealed that 61.6 percent of drivers reported that time of day affects truck parking availability [80]. Holguin-veras et al. (2011) introduced off-hour deliveries in the New York City metropolitan area. Using commercial vehicle dwell time (i.e., service time) as a performance measure, the study demonstrated that shifting 20 percent of freight traffic to night time would minimize the number of inefficient parking locations [73]. Commercial vehicle dwell time has been considered to be crucial information to provide insights into the delays associated with making deliveries [86, 38]. Jaller et al. (2013) also pointed out that parking availability during certain periods of time will depend on turnover, which will ultimately be affected by average commercial vehicle dwell time [81].

Parking spaces

Cities are making efforts to improve physical spaces for commercial vehicles by increasing and relocating commercial parking spaces. Philadelphia is reserving 80 to 100 feet as all-day loading zone in busy downtown [34]. In Washington, D.C., USA, the District Department of Transportation (DDOT) partnered with the Downtown Business Improvement District to create a 'Downtown Curb-space Management Plan' to improve commercial vehicle loading zones (CVLZs) [85]. As a part of the plan, CVLZs were relocated to the end of each block face wherever possible to make parking easier for commercial vehicles and the length of loading zones on K Street was extended from 40 feet to 100 feet to increase commercial parking capacity [85]. However, Campbell et al. (2018) found that despite the ease of parking maneuvers, locating the parking at the end of the block can increase parking time by about 4%, as the parking is farther away from the delivery locations [35]. New York City's 'Commercial Vehicle Parking Plan' recommended providing additional curbside spaces for commercial vehicles [152]. In Midtown Manhattan, where commercial activities are concentrated, CVLZs were added on the streets between 43rd and 59th and Fifth Avenue and Seventh Avenue and were later expanded to cover the additional streets between Second and Ninth avenues [152]. Spatial limitations on loading and unloading goods could potentially lengthen dwell time as delivery workers may face conflicts with other roadway users (e.g., pedestrians, bicyclists, and other vehicles). Cities' efforts to relocate and expand the lengths of CVLZs could help reduce dwell time, in addition to increase parking capacity.

Parking operations

Cities are also implementing 'Shared Spaces' or 'Flex Zones' to accommodate commercial vehicle parking. The concept of 'Flex Zones' allows the areas within the public rights-of-way to be used by different permitted users according to the time of day. In limited city spaces, flex spaces can be shared with multiple roadway users based on their activities. As a part of 'Curb Management Strategies', Washington D.C. has 28 dedicated pick-up/drop-off zones for ride-sharing cars and commercial vehicles, expected to be added more throughout the city [34]. In Barcelona, Spain, variable message signs (i.e. electronic traffic sign that shows different messages based on times) were implemented to allow 700 loading zones between 8:00 AM and 2:00 PM [126]. Despite the high capital costs required, the system gained popularity among residents, as it reduced travel time at study areas by 12 to 15 percent [126]. The city of Seattle implemented 'Flex Zones' at areas where passengers loaded and unloaded from transit and ride share services, or delivery goods were being loaded or unloaded to/from commercial vehicles. The Flex Zone functions (e.g., mobility, access for people or commerce) were categorized and prioritized on the basis of surrounding land uses (e.g., residential, commercial & mixed use, industrial) to “safely and efficiently connect and move people and goods to their destinations while creating inviting spaces within the right-of-way” [5]. In these examples, assigning shared space on the basis of the needs of different roadway users improved the management of limited curbside spaces.

The second research question of this dissertation aims to contribute to a more data-driven approach before such dynamic parking policies are implemented. By identifying explanatory variables correlated with dwell times for commercial vehicles, policy makers can better allocate parking space and time on the basis of users’ needs.

2.3 Recent trends in shopping and delivery methods and simulation/ optimization tools

In preparation for future urban freight infrastructure designs, it is important to consider changes in people’s shopping behaviors and various delivery methods, stimulated by advanced technologies. This literature review first explores recent changes in shopping experiences and delivery methods to better understand people’s expectations and recent trends in urban freight deliveries. The second part of this literature review includes investigation into simulation and optimization tools that are widely used in transportation research.

2.3.1 New shopping experiences and delivery methods

Changes in shopping experiences

Embracing new technologies, retailers are constantly making efforts to revolutionize shopping experiences for their customers. For an optimal mobile user experience, corporations are adopting technology innovations such as progressive web applications and accelerated mobile pages [141]. Voice assisted devices such as Amazon Alexa and Google Assistant are another way that shopping has been made easier. The artificial intelligence and machine learning technology in these devices allow customers to purchase goods and groceries online with improved customer services [140]. Loup Ventures expects that 75 percent of U.S. households will have smart speakers by 2025 [6], which may have a ripple effect on increasing online shopping behaviors. Retailers have recently been trying “offline to online” (also called O2O) services, which open up the store for display purposes only, allowing customers to try physical goods offline but complete buying/selling online [153]. For example, Nike’s new physical stores allow users to try exclusive products, customize products onsite and partake in fitness tests, experiences that online shopping cannot offer [78]. In another example, Nordstrom expanded its “Reserve Online and Try in Store” services to nearly 40 stores across the U.S in 2017 after a successful pilot project in the fall of 2016 [121]. With rapidly changing advancement in technologies, customers’ expectations for shopping are changing, most likely leading the demands for goods and services in urban areas to increase.

In 2020, the global coronavirus (COVID-19) pandemic made digital online shopping the top alternative to crowded brick-and-mortar stores. Because of limited public transportation, food shortages, and reduced hours at supermarkets and grocery stores during pandemic lockdowns, food shoppers were particularly impacted significantly. Despite the difficulties, developed countries such as the U.S. maintained access to food through online e-commerce platforms [36]. With a potentially lasting effect, the rate of e-commerce adoption increased during the pandemic [19]. Gatta et al (2020) studied the potential acceptability and adoption of “e-grocery” (purchase of groceries online), pointing out that changes in such shopping behavior would substantially impact how goods reach houses, as buying groceries is a recurrent activity for any household [60]. While technologies are changing people’s shopping experiences faster than ever, most cities’ infrastructure designs and policies lack rigorous data collection and scientific approaches. As our simulation and optimization models account for real-world observations in the final 50 feet of deliveries, we focus on providing data-driven tools that policy makers can use to better understand the dynamics of current and future urban freight deliveries.

Changes in delivery methods

Many logistics solutions have been suggested in the past, including last-mile consolidation, collection points/drop zones, cargo cycles, crowd shipping, drones, and delivery robots [12, 14, 29, 69]. With various types of logistic solutions, it is important to create appropriate plans and regulations to effectively manage them.

Researchers have observed urban cargo-hitching initiatives intended to assist in delivering time-sensitive parcel deliveries and have analyzed their potential performance through simulations [11]. The concept of cargo-hitching originated from the use of spare capacity transportation modes to carry freight [149, 135]. Crowd-logistics (e.g., Amazon flex, iMoveit, Zipments, Postmates, Deliv) is a type of cargo-hitching scheme [108]. Offering speedy deliveries, crowd shipping is also considered to be a new means of generating extra income or subsidizing travel costs (e.g., same-day delivery) [108]. By leveraging spare capacity in passenger transport modes, transportation network companies such as Uber and Lyft and conventional taxis (i.e., mobility-on-demand services) have been used to support grocery deliveries during the COVID-19 pandemic in 2020 [160, 72].

While there are promising benefits of cargo-hitching, occasional carriers (also called "lifestyle couriers") [108] are not professional carriers and therefore may be unfamiliar with delivery processes or get lost in a building. Although McKinnon (2016) pointed out that personal interaction between locally based carriers can alleviate the "failed delivery" problem (when no one is present to receive goods), the failed delivery problem can also be worsened when carriers are not familiar with delivery processes or building layouts, which may potentially lead to a failure to find the correct recipient [89]. According to an Interactive Media Retail Group 2018 study, the cost of failed deliveries for retailers, couriers, and consumers was estimated to be \$1.6 billion (equivalent to US \$2.1 billion) a year in the United Kingdom [131]. Inefficient operations at the final 50 feet of the delivery process can also negatively impact already highly congested areas and truck dwell times [89]. Optimized infrastructure designs developed with this study's tools can create more predictable delivery systems with optimized resource allocations for not only conventional carriers but also diverse types of innovative carriers in the future (e.g., crowdsourced, delivery robots).

There is clear evidence that people feel comfortable about using innovative delivery methods such as crowdsourcing services as alternatives to receiving goods from professional carriers. In six-week trial of crowdsourced deliveries in Finland, the majority of drivers (between the ages of 17 and 68) were younger (between the ages of 20 and 40) and were motivated to try out something new [124]. Similarly, another study found that millennial respondents (between ages 15 and 34) were more familiar with crowd-shipping, and 25- to 44-year-old respondents were more likely to have tried it [124]. Those who had already tried crowd-shipping also showed fewer worries about the absence of professional drivers. Other studies have looked at the potential benefits of crowdsourcing drivers from a social network of customers, friends, or acquaintances [48]. This idea aligns with the increasing numbers of younger shoppers. Young people who have grown up with the internet, shop online more than not. Mintel (2017) found that 55 percent of people ages 16 to 34, 42 percent of those ages 45 to 64 and 32 percent of those over 65 have used online shopping [111].

As younger people try new, innovative ways to deliver/receive goods, the use innovative delivery methods is on the rise. However, these types of deliveries can be challenging from a management perspective due to additional planning and regulations, parcel fragmentation, and potential misuse of parking spaces. While urban freight transport has evolved to meet the demand created by new shopping habits [24], analysis of building and parking designs that are appropriate for future delivery innovations has been extremely limited. This study aimed to contribute to closing this gap by creating a framework for building a simulation-based optimization tool for assessing building and parking infrastructure while minimizing freight delivery costs for both carriers and planners.

2.3.2 Simulation and simulation based multi-objective optimization tools

Simulation techniques

Simulation techniques are widely used in much operational research to assist in decision making for system analysis and improvements [151]. The simulation approach is popular not only in transportation but also in health care, production lines, and businesses. Simulation models are useful for understanding complex system flows over time. They are also useful for testing "what if" scenarios and predicting system performance before any plans have been implemented. Choosing an appropriate approach among many types of simulations is crucial.

There are many types of computer-based simulations, such as system dynamics (SD), agent-based (AB), and discrete-event simulations (DES) [30]. Borshchev and Al (2004) stated that while SD deals mostly with continuous processes, DE and AB work mostly in discrete time (e.g., move from one event to another) [28]. This section explores various types of simulation tools and summarizes our rationale for choosing DES over other types of simulation tools for our study.

SD simulation, which was developed by electrical engineer Jay W Forrester in the 1950s, is defined as "the study of information-feedback characteristics of industrial activity to show how organizational structure, amplification, and time delays (in decisions and actions) interact to influence the success of the enterprise" [56, 57]. SD represents the real-world process as stocks (e.g., of material, knowledge, people, money), flows between those stocks, and information that determines the value of the flows. Because SD stocks do not have individuality and the SD needs to consider global structural dependencies, SD simulation is best suited for describing the system behavior as several interacting feedback loops, balancing or reinforcing them with three to four tools that are very similar to each other (e.g., piston motion) [28].

AB simulation is often called "bottom-up" modeling [136] because AB does not have global system behavior up front. Instead, behaviors at an individual level are defined first, and the complex global behavior emerges as a result of many individuals interacting with each other, living in some environment together [28]. The big advantage of using AB simulation is that models can be constructed without knowledge about global inter-dependencies [28].

DES was developed by Geoffrey Gordon, who evolved the idea for the General Purpose Simulation System and introduced IBM implementations [66]. DES models comprise entities that enter a system and travel through multiple steps before leaving the system. Each step represents a discrete timestamp (e.g., event) that alters the state of entities. Each event can be described as resources and their capacity and efficiency. In DES, entities act as a passive element of the system, and therefore, the entity will wait until its turn if the resources are pre-occupied with other entities. In this way, DES incorporates queuing in the model and is able to discover bottlenecks and measure system performance [97].

The DES model was most suitable for this study as we could simulate delivery workers (entities) traveling through a building (system), using the building and parking resources (resources). Through DES, we were interested in learning about the utilization of building and parking resources under different "what-if" scenarios. DES requires specific data for on-time distribution for each activity [96]. Fortunately, a complex delivery process and detailed activities had been documented in a discrete event flowchart with time distributions for each delivery task during a previous study conducted by Kim et al, 2018 [89]. With this previously obtained empirical data, we built our DES model with realistic complex stochastic distributions.

2.3.3 Simulation-based optimization approach in transportation research

Although DES can provide the results of specific "what-if" scenarios based on the complex and stochastic flows of delivery workers, the optimal solution is not guaranteed [151]. Therefore, an additional optimization tool was required to find the optimal solution [10] even though simulation and optimization have traditionally been considered to be different approaches in the operational research domain [54]. Numerous recent studies have used the combination of optimization and simulation tools and confirmed their effectiveness at making quick decisions about optimal system configurations and complex integrated facilities [151].

As meta-heuristic optimization can quickly identify good quality solutions, it has usually been used in combination with DES [54]. When there are multiple-objectives, simulation-based multi-objective optimization (SMO) can search for trade-offs between several conflicting objectives to find the optimal solutions [46]. Several meta-heuristic algorithms have been developed for simulation-based optimization, such as the genetic algorithm, scatter search, pychoclonal algorithm, hybrid algorithm, and nondominated sorting generic algorithm (NSGA II). Among these algorithms, NSGA II is the most commonly used algorithm for simulation-based optimization [22].

The simulation-based optimization approach has been widely used in transportation and logistics studies. Optimizing the costs of deliveries has been one popular topic. Yanchuk et al. (2020) conducted a simulation of cost optimization for package delivery with a combination of carriers for fast (same day or next day) and lazy (not the nearest day or week) deliveries [159]. Avici and Selim (2017) used SMO to develop a supply chain inventory management system by determining suppliers' flexibility and safety stock levels in terms of inventory holding costs and premium freight (i.e., expedited shipping with high costs such as airways) [22].

Transportation routing networks have been another area of popular research using simulation-based optimization. Poeting et al. (2019) and Simoni et al. (2020) simulated last-mile delivery routes to optimize them with delivery robots [128, 143]. Anderluh et al (2019) utilized SMO to select the best routes given trade-offs between the economic objective of minimizing delivery costs and the social objective of minimizing the negative impacts of delivery vehicles, such as noise and congestion [20]. Similarly but for transit, Schmaranzer et al. (2019) designed a complex urban mass rapid transit system by using SMO to minimize the cost of fleets and maximize service levels (e.g., average waiting time per passenger)[137]. Layeb et al. (2018) approached scheduling problems in stochastic multimodal freight transportation systems with a simulation-based optimization model [96].

Optimization approaches have also been applied in selecting optimal locations of facilities and managing parking systems. Jardas et al. (2020) selected an optimal location for a distribution center that would minimize delivery costs by considering the distance between a start point and the destination [84]. Wei (2020) found optimal network nodes and passages of urban underground logistics that would minimize logistic time cost, exhaust emissions, and congestion costs [155]. To determine advanced parking strategies such as dynamic pricing, Zheng and Geroliminis (2016) applied optimization to reduce congestion and lower the total travel cost of all users [164].

Although much research has used simulation-based optimization in the transportation and logistics fields, no study has utilized SMO to optimize building and parking resources, to the best of our knowledge. On the other hand, research in the fields of healthcare and production lines has a long history of using simulation-based optimization to determine resource allocations for improving system performance. For example, multiple buffer allocation studies have determined optimal buffer capacities by maximizing throughput rates while minimizing total resource capacities for production lines. Motlagh et al. (2019) produced an extensive literature review on past research that has used buffer allocation problems since 2000 [117]. Since the 1990s, the healthcare field has applied SMO to study the optimal number of expensive medical devices in an emergency (or surgical) department that can minimize the costs of medical resources while maximizing service levels for patients (e.g., minimizing waiting time) [103, 151, 52, 37]. Similarly, SMO can be applied to optimize a city's parking and building infrastructure, considering not only the city's constraints (e.g., limited parking spaces and costs) but also the costs of delivery workers and building managers. For example, if the city increases the number of on-street parking spaces simply due to increased numbers of deliveries, then the queues of deliveries will be transferred to the queues at elevators or receptionists, pushing the costs from delivery workers and building managers. Conversely, if city or building managers decrease the numbers of on– and off-street parking spaces without proper analysis, the cost may be pushed to delivery workers who use the urban infrastructure. SMO can help reveal the complex relationships among different parties and balance such ambiguity in parking and building policies.

In this study, SMO was developed to optimize building and parking resources that can minimize the costs for three parties; city planners, building management, and delivery workers.

In the previous two chapters of this research, the delivery processes in the final 50 feet and factors affecting lengthen or shorten dwell times are found with a targeted aim to discover cascading relationships between building and parking operations. In the last chapter of this research is to leverage data we found from the previous chapters and apply them to test whether the current building and transportation infrastructures are ready to meet future demands for urban freight deliveries using discrete event simulation models and optimization algorithms.

The third research question of this dissertation aims to understand cost distributions between delivery workers, city panners, and urban building managers through a discrete event simulation and optimize building and parking resources that can minimize the costs for both building managers and delivery workers through SMO. To better prepare for the rapidly increasing numbers of deliveries in urban cities, this chapter provides insights and data-driven approaches to optimize resource allocations for the parking and building infrastructures.

Chapter 3
DATA COLLECTION

Data collection occurred in five different building types in downtown Seattle, Washington, USA. We carefully selected different types of buildings to capture the full range of delivery and vehicle characteristics. The selected buildings included a residential tower, a hotel, a historical building, an office tower, and a shopping mall.

3.1 Building profiles

Table 3.1 describes key features of the observed buildings: mixed building types, number of floors, total floor area, and presence of a receptionist. In the building selection process, observing various types of freight activities at each building was important to collect sufficient data regarding explanatory variables (e.g., different types of goods, parked locations, vehicle types, etc.) to examine their effects on commercial vehicle dwell time. Therefore, the selected buildings were naturally considered to be large with the total floor area between 31k - 92k m^2. These types of buildings are often known as 'large urban freight traffic generators (LTGs)' as specific facilities housing businesses that individually or collectively produce and attract a large number of daily truck trips [83].

Prior to data collection, the researchers conducted site visits to assess each building's configuration and freight activities. This helped identify the proper placement and number of researchers for data collection (see Figure 3.1). Only the office building closed during weekends, however, we learned that relatively small numbers of freight activities are performed during weekends for other buildings based on the interviews with building managers. Therefore, the weekends were not observed in our data collection.

For each building, the data collection process occurred over five business days from Mon-

Table 3.1: Description of observed buildings

Building ID	Building types	No. of floors	Total floor area	Receptionist present	Observations (n)
A	Residential (98%)	41	89,000 m^2	Y	35
	Retail (2%)				
B	Hotel (78%)	21	38,000 m^2	Y	29
	Residential (19%)				
	Spa (2%)				
	Dining (1%)				
C	Historical Office (93%)	15	31,000 m^2	N	29
	Retail (5%)				
	Coffee shops (2%)				
D	Office (97%)	62	92,000 m^2	N	30
	Retail (2%)				
	Dining (1%)				
E	Office (76%)	25	45,000 m^2	N	34
	Shopping mall (20%)				
	Dining (4%)				
Total					157

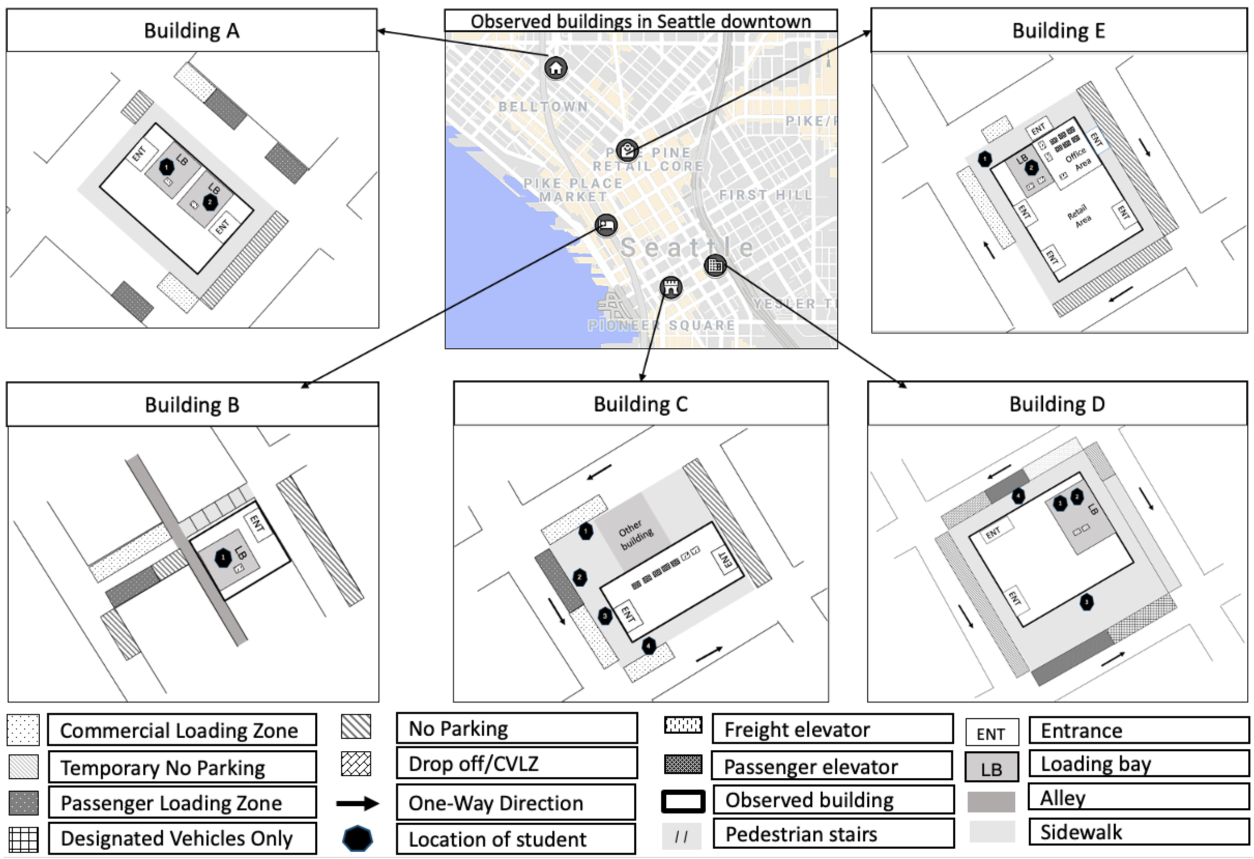


Figure 3.1: Observed buildings location and configuration

day to Friday between the hours of 6:30 AM and 3:30 PM. Data collection occurred between the months of January to March 2017. The data collection team consisted of two or four people depending on the size of the building. They were trained to observe and collect data using a customized tablet application [91]. They waited until a commercial vehicle was parked in either the loading bay or the street curbs near the building. They would then approach the delivery worker and ask permission to shadow and observe his or her delivery process. A sufficient number of deliveries were observed at each building type to estimate the impacts of key variables on dwell time.

3.2 Mobile application development

This data collection application was specifically developed to capture timestamps of each task that individual delivery workers are performing during their delivery processes [91]. The application included 5 major task categories that were broken down into colors. The major tasks that occurred within each category were then broken down into task buttons with different color codes to make it simple to follow:

- Pink: Activities involved with vehicle operation (e.g. parking, driving away, open/close cargo compartment
- Gray: Repeated activities throughout the delivery process (e.g. walking, talking, calling, organizing goods)
- Green: Loading /unloading goods
- Yellow: Activities involved waiting and taking elevator, escalator, stairs
- Navy: Activities involved delivering goods (e.g. Looking for receivers, receiver signs for goods, drop off goods, scanning goods)

To collect time-stamps the start of a task, the data collector simply presses on the task button. The application records the immediate time of tapping and calculates the duration of each task. The displayed buttons have the name of pre-identified tasks. In addition, data collectors can generate new task buttons by typing the names on the input area located at the bottom of the application if the performed action was not previously defined. The application allows a very accurate collection of various tasks and durations. The data collector also captured and recorded the frequencies of failed delivery attempts in the 'notes' section by typing the texts and numbers.

To ensure accurate data collection, the application automatically saves information that the data collector enters on the application to the web-based database in real-time. In case of low-network connection or no Wi-Fi, the information can also be stored offline on the mobile device that can then be uploaded to the web-based database when an internet connection is restored. This information can be transferred to the database at a later time by pressing the 'Export' button when there is a stable network. The list of collected data includes Name of building, Name of the data collector, Name of delivery company, Types of delivery vehicles, Types of goods being delivered, Number of delivery workers, Timestamp, Pictures, Frequencies of failed deliveries and additional notes.

The user interface of the data collection application is shown in Figure 3.2. The application was developed by using Swift programming language in iOS, an operating system used for mobile devices manufactured by Apple Inc. Different types of buildings can have slightly different delivery tasks because the delivery processes can be unique to each building depends on specific building structures and configurations. Therefore, we ensured that predefined task buttons can be easily modifiable and customizable in changing the task names and numbers of buttons for different building types.

The data collection process has three basic aspects: 1. timeliness of collecting, processing, and recording data, 2. accuracy and precision of the data collected, and 3. integration of data for efficiently supporting decision-making [55]. By using the mobile application, all three aspects could be improved from the conventional data collection methods. First, time-saving for collecting, processing and recording data could be significant. SQL database can be synchronized into a table format on a report or be shared in MS Excel format which can be used in other analyzing tools such as R or Matlab for further analysis.

Second, the accuracy and precision of the data decreased human error that occurs through the manual logging of information with pen and paper. Also, the mobile application allows a data collector to take photos which can be used for quality control of the collected data. Photos can be shared in the presentations and documentation to assist effective communication between data collectors and audiences and readers.

The collected data was later used to create a VSM, which visualizes the detailed components of the delivery process. The VSM of delivery processes in the office building can increase the visibility of the logistics process and provide a better understanding of the delivery operations in urban cities. Such information can be shared to gain information on delivery times and activities for similar office buildings in other urban areas. As many customers make purchasing choices based on the quality of services, both carriers and retailers become aware of the importance of improving the quality of delivery services for the customers. Our VSM approach can, therefore, provide vital performance metrics to make crucial decisions in various companies' policies. [95]. The ultimate goal of this approach was to ensure the applicability of VSM in the delivery operations in urban cities using our uniquely designed mobile application.

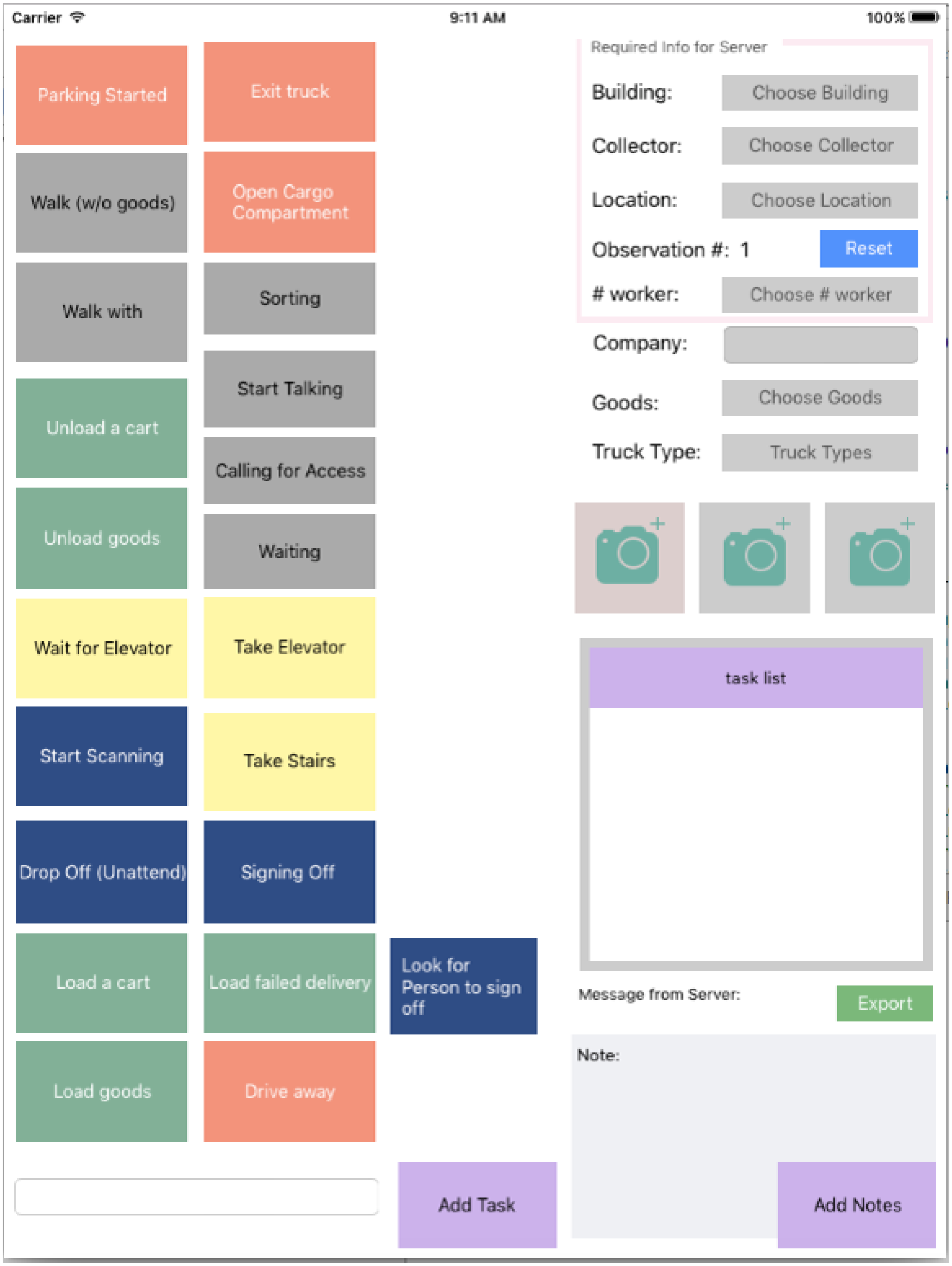


Figure 3.2: The user interface of the mobile application

3.2.1 Standardization

Prior to the start day of data collection, data collectors conducted a pilot test at the selected office building. During this pilot test, they learned how to use the application and became familiar with the application and the unique delivery operations. Also, they learned the characteristics of the building structures such as parking facilities and locations of freight elevators. Based on the pilot test results, the task buttons were created and ordered the process steps.

3.2.2 Reliability

To ensure the reliability of using the mobile application for the generation of VSM, we compared the results from the four data collectors for using the mobile application. The data collectors measured the same length of times for various delivery activities with the application by watching a pre-recorded video of delivery operations. intraclass correlation (ICC) was used to assess the reliability of data collected by the application. 98% intraclass correlation was observed for using the mobile application, indicating the mobile application method showed very low variations in collecting the same time data between the data collectors. This indicates that the mobile application can be understood clearly to different data collectors and improve the method of collecting accurate time data. Questionnaires regarding the intuitions of the mobile applications and general feedback from this test assisted shaping the final mobile application. Data collectors showed a preference for using the mobile application as compared to the pen and paper method. The main reasons included the elimination of the need for manual data entries on paper and simplicity of pressing the button to capture all the information automatically.

3.3 Summary

The main objective of this chapter was to develop an appropriate tool for collecting quantitative performance time measures for the final segment of delivery operations. Delivery activities inside of the buildings share similar standardized processes such as loading and unloading goods, pick-up and delivery operations, and taking freight elevators. By creating VSM with time measurements, time spent for each delivery activity could be better understood and also compared among urban buildings. Some delivery activities could be also unique to different buildings based on various delivery policies within the buildings or building conditions. In a way to observe and measure the detailed delivery activities of an office building in downtown Seattle, a mobile application was uniquely designed for data collectors to shadow individual delivery workers within the building. By using this easy-to-use mobile application, data collectors successfully captured times for each delivery task and recorded data in real-time data was used to creating a VSM which provides the overall process flow of urban deliveries. Quantifying delivery operations by using our systematic VSM approach can provide insights on the current delivery processes in the cities, which can be better accounted for the future urban policies. In carriers' point of view, VSM can provide strategies that they can learn from other delivery companies when the same actions are performed in more effective ways.

Some limitations were associated with the data collection process, as the delivery workers were aware that they were being watched by the data collectors although data collectors minimize any interactions with the delivery workers. In some cases, they rejected data collectors to follow them, resulting in potential selection bias. One approach to resolve this issue would be to use video recorders where the delivery workers may not recognize the fact that they are being monitored. Another possible approach is to position each data collector to monitor specific activities in different locations such as next to the elevator at the lobby, or at the mail room, or specific floors until the delivery workers arrive at each location, rather than following one delivery worker throughout the whole delivery process.

The goal of this research is to establish systematic methods to better understand cities' rapidly changing urban freight deliveries which will ultimately help to take a more data-driven approach to urban freight management in the future. To achieve this goal, several tools were used to analyze the collected data including 1) Value Stream Mapping, 2) statistical (regression) models, 3) a discrete event simulation and optimization in the following chapters.

Chapter 4

DELIVERY PROCESS FOR AN OFFICE BUILDING IN SEATTLE CENTRAL BUSINESS DISTRICT

Movement of goods within a central business district (CBD) can be very constraining with high levels of congestion and insufficient curb spaces. Pick-up and delivery activities encompass a significant portion of urban goods movement and inefficient operations can negatively impact the already highly congested areas and truck dwell times. Identifying and quantifying the delivery processes within the building is often difficult. This chapter introduces a systematic approach to examine freight movement, using a process flow map with quantitative delivery times measured during the final segment of the delivery process. This chapter focuses on vertical movements such as unloading/loading activities, taking freight elevators, and performing pick-up/delivery operations. This approach allows us to visualize the components of the delivery process and identify the processes that consume the most time and greatest variability. Using this method, we observed the delivery process flows of an office building in downtown Seattle, grouped into three major steps: 1. Entering, 2. Delivering, 3. Exiting. This visualization tool provides researchers and planners with a better understanding of the current practices in the urban freight system and help identify the non-value added activities and time that can unnecessarily increase the overall delivery time.

This chapter introduces the lean philosophy and value stream mapping (VSM) approaches to examine the delivery process flows in an office building in downtown Seattle. These approaches are used to identify areas of improvement, which can enhance the overall quality of service and work performance [49]. Because the freight delivery process consists of many steps, applying this new approach can help measuring the delivery time for each process accurately, especially when the delivery process needs to consider the number of carriers, types of goods, and types of delivery vehicles. With VSM approach, dwell times and failed deliveries can be better understood as it decomposes the delivery process in micro level.

We begin with the creation of a process flow map of an office building in a central business district, which provides information on each delivery task and identifies areas where bottlenecks and non-value added times could occur. This map allows one to visualize the components of the delivery process as well as those tasks that are conducted by all carriers and those that are not. Identifying the processes that consume the most non-value added time and the greatest variability will help us identify strategies to improve the overall urban freight system and be better accountable for extended truck dwell times and failed deliveries.

4.1 Office building description

The selected office building in downtown Seattle has 62 floors with approximately 5000 tenants, including gift shops, restaurants, and coffee shops. This building was referred as Building D from the data collection section in Chapter 3. Each floor has a unique floor configuration which allowed us to capture various delivery processes. Types of observed pickups and deliveries include office supplies, parcels, food items, assorted mail, recycling, and furniture.

The building is surrounded by four one-way streets (see Figure 4.1). There are seven 30-minute commercial loading zones and four mixed zones combined with 30-minute commercial loading zones and passenger drop-off zones. The loading bay has seven parking spaces with a 30-minute. The security booth at the loading bay includes a full-time security guard and is open between 6 am and 6 pm. Inside the loading bay, there are two freight elevators which require a security fob to use.

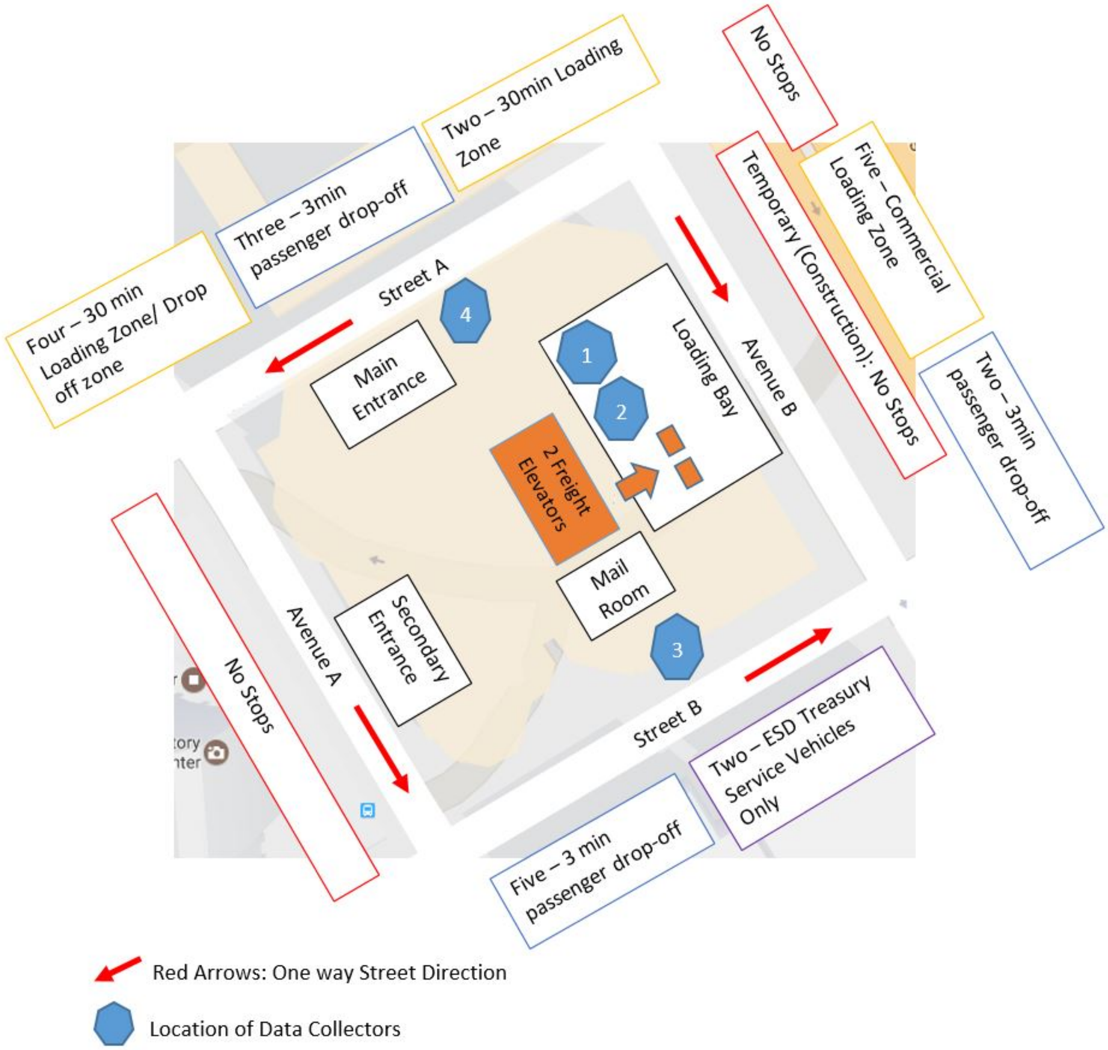


Figure 4.1: Configuration of the Observed Office Building

Delivery workers obtain a freight elevator fob from the security guard by handing in their government-issued identification card for security.

A mobile application for use in a tablet computer (Apple iPad) was developed for collecting real-time data on the delivery process. The predefined options included load/unload, waiting for/taking elevators, signing for deliveries and much more. To identify the start of a task, the data collector taps a task button. This immediately begins recording the tasks in a web-based database and can be stopped once by tapping a sub-button once the task is finished. With this approach, each delivery task is time-stamped and the duration of each task is accurately computed even when the tasks are executed concurrently. Tasks that were not predefined could also be entered manually in the application. Other information that was recorded included Whether or not a package was successfully delivered and other data collection notes.

The data collection process took place over five business days between January 31 and Feb 4, 2017, between the hours of 9:00 am and 4:00 pm. The data collection team consisted of four people, who were trained to observe and collect data using the tablet application. The data collectors would wait until they observed a truck parking in either the loading bay or the street curbs near the building. They would then approach the delivery worker and ask permission to shadow and observe his or her delivery process. Given the observational nature of the data collection and where researchers approached the worker, these deliveries were most likely not express deliveries. Data from the tablet was then used to construct the delivery process flow map that showed the detail task durations and delivery sequences.

4.2 Process flow map

The process flow map in this chapter is focused specific on Building D's the final segment of the delivery process, which is sometimes referred to as the final 50 feet [150, 51]. This segment includes out-of-vehicle activities and begins with the driver parking the vehicle and ends at the point when the driver drives away from the building. There are three major steps in this segment and they are further subdivided in subtasks:

1. Entering (e.g. parking vehicles, security check-in, unloading goods, waiting for elevators to go to the destination)

2. Delivering (e.g. taking an elevator to the destination, delivery or pick up actions, waiting for elevators to go back to truck)

3. Exiting (e.g. taking an elevator to go back to truck, loading a hand truck back to truck, security check-out)

This process flow map (see Figure 4.2) shows the delivery actions and subtasks that can be performed in parallel and those that require a sequence of events for task completion. The square boxes represent the set of actions, and the diamonds represent the decisions made along the processes. Based on the collected data, the most shared common delivery subtasks at the study location was identified. Although each delivery person can generate many paths, the common delivery subtasks provide insights for areas where more effective delivery strategies can be deployed.

Table 4.1 summarizes the time duration of each subtask, in the same order shown in Figure 4.2. The ratio of standard deviation (sd) to the mean is used to identify processes that have the greatest variation. Those ratios greater than one (highlighted) are areas that may warrant further examination.

4.2.1 Entering

Data collection began as soon as a truck parks at any of the designated on-street or off-street (loading bay) commercial loading zones. Drivers can enter the building through the loading bay or the main entrance on Street A or secondary entrance on Avenue A (see Figure 1).

In this study, 90 % of the drivers (28 out of 31) parked in the loading bay to unload goods. Large volumes of office supplies could be a big contributor to this result. The mean duration for the "parking at loading bay" process (40 seconds) was slightly longer than for "parking at the street curb" (33 seconds). In tight spaces such as loading bay, the drivers' maneuvering ability was limited, and several forward and backward maneuvers were necessary, as expected [157]. During parking activities, conflicts may also occur with pedestrians, bicyclists, and other passing-by vehicles.

Depending on the location of the parked vehicle, the driver would leave the cargo compartment open or closed. In most cases, drivers at the loading bay would leave the door open because the security guard was always present. Drivers who parked on-street tended to keep the cargo compartment closed when they left the truck for delivery. Two types of cargo compartment doors were observed: rolling and swing doors. Some heavy duty trucks had a lift that goes up and down at the back of their cargo compartment to assist the driver with entering and exiting the cargo compartment. When parking, the drivers had to allow extra space if they had swing doors or the lift. Some drivers had to lock the door after closing the cargo compartment. The wait time for the lift or locking the cargo compartment can add to the total truck dwell time.

Once a delivery worker exited the truck, he or she would walk to either the security booth to check in or the cargo compartment of the truck to unload. Several office buildings in downtown Seattle have their own unique security check-in processes. At this office building, the delivery workers were required to check-in with a security guard to obtain a freight elevator fob by exchanging their government-issued identification cards. The duration of the check-in process could vary depending on the familiarity of the drivers with the security guard. If the driver made regular deliveries to the building and was familiar with the security guard, the check-in process would be fairly quick. However, the delivery person may also take additional time to converse with the security guard. Depending on the time of day, a bottleneck could occur if multiple delivery workers arrived at the same time for check-in.

Drivers would often carry goods by hand for small and light deliveries, and a hand truck or dolly for large and heavy deliveries. The most common method to unload goods was by hand, but in the case of heavy deliveries, special equipment such as a forklift or pallet jack was used.

Doors of the cargo compartment can be located either at the back or side of the truck. Of the drivers observed, 76% carried goods on dollies or hand trucks and 24% hand-carried goods. In Figure 4.2 and Table 4.1, hand trucks or dollies are represented as ‘cart’. For pickups, the drivers skipped unloading activities and walked to the elevator directly after the security check-in.

The loading bay was located inside the building’s parking facilities where two freight elevators were accessible next to the loading dock. However, the passenger elevators were located further away from the loading dock but very close to the lobby, next to the main entrance. Therefore, the delivery workers who entered the building through the main or secondary entrances were more likely to use passenger elevators. Although the speed of the passenger elevators was approximately 2 times faster than the freight elevators, the passenger elevators had a higher volume of frequent riders. This is reflected in the mean wait time (52 seconds) for the passenger elevators.

The mean wait time for the freight elevators to go from the loading bay to upper-level floors was 31 seconds, but the range in wait time was quite large (from 3 to 193 seconds) This is much greater than the wait time for the freight elevator from destination back to the loading bay. This is not surprising as the delivery person at the loading bay may have to wait a long time for the elevator if it is at the top most floors.

4.2.2 Delivering

Having a unique floor configuration and delivery policy for each office made it challenging for the delivery workers who visited the building for the first time. Some offices required the delivery workers to use an inter-phone to enter the office suites, some were open to the public, and some had a receptionist who received and signed for goods on behalf of other office workers. If the office did not have a receptionist, the delivery worker had to find an individual receiver to deliver the goods.

Once the delivery workers arrive on the floor of their destination, they performed either delivery or pickup activities. The mean time spent for pick up (37 seconds) was much quicker than the mean time spent on delivering goods (57 seconds) which often involve unloading activities. The high volume of goods could lead to a longer time for unloading goods when the delivery workers are required to unload goods one by one by hand. On the other hand, sometimes the high volume of goods can be unloaded in bulk, resulting a short unloading time.

Three percent of the observed deliveries failed (or were not delivered). Each company has different policies on failed deliveries: most delivery workers look for an alternate person to sign for goods. Some delivery workers can drop off goods on the receiver's desks without obtaining a signature from anyone. Some companies allowed the delivery workers to leave the site after sending a picture(s) of the dropped off goods and locations to the clients remotely. Company policies can also vary by the types of goods. Better communication between the delivery workers and the receivers could help reduce the failed first delivery. A simple notification system could also allow both the delivery workers and the receivers to share information such as estimated arrival time or the wayfinding instructions. When the receivers are notified before the delivery arrivals, the chance of failed deliveries may be reduced. When the delivery workers are well informed about the building layouts, chances of being lost in the building could be decreased as well.

As expected, the average time for walking with goods (44 seconds) or goods on the cart (40 seconds) was longer than the average time for those walking without any goods (38 seconds) or with an empty cart (39 seconds). For multiple deliveries, the drivers would repeat delivery and pick up activities within the building.

The mean wait time for the freight elevator to go back to the loading bay was 63 seconds. To avoid wait time for the elevator, some delivery workers would hold the freight elevator open by blocking the elevator door until he or she comes back after completing deliveries. These delays can compound and create a continuous delay of deliveries for other drivers who are waiting for the freight elevator to other floors. Lastly, freight elevators were used by individuals that did not have any goods or freight. These individuals chose not to use the passenger elevators for their convenience which added additional and unnecessary stops. In general, elevator bottlenecks have a significant impact on office buildings with many floors.

4.2.3 Exiting

The mean time in the freight elevator to go back to the loading bay was 148 seconds. Once the driver returns to the loading bay or main lobby after completing deliveries or pickups, he or she can either walk to the security booth or go back to the truck. In this study, 76% of the drivers walked from the elevator to the security booth first. At the security booth, the drivers return the elevator fob to the security guard where they would get their identification card back.

During the peak delivery hours (10:00 am to noon), the security guard experienced a difficulty in accommodating all drivers and a queue began to form. In these situations, a securely automated check-in and check-out kiosk could be set up to help expedite the process. The building had the pre-screening program where some delivery workers can obtain the freight elevator fob in advance and use it without the check-in process.

The mean time for loading the empty cart or placing picked-up goods in the cargo compartment was 36 seconds with low variations (SD=9). Closing cargo compartment was also fairly quick with a mean time of 17 seconds. Once the drivers enter the vehicle, some of the drivers wait inside the truck to complete their paperwork, with or without the engine on. Some drivers can avoid paperwork by using a digital device that helps provide real-time paperless communication between the field and office workers.

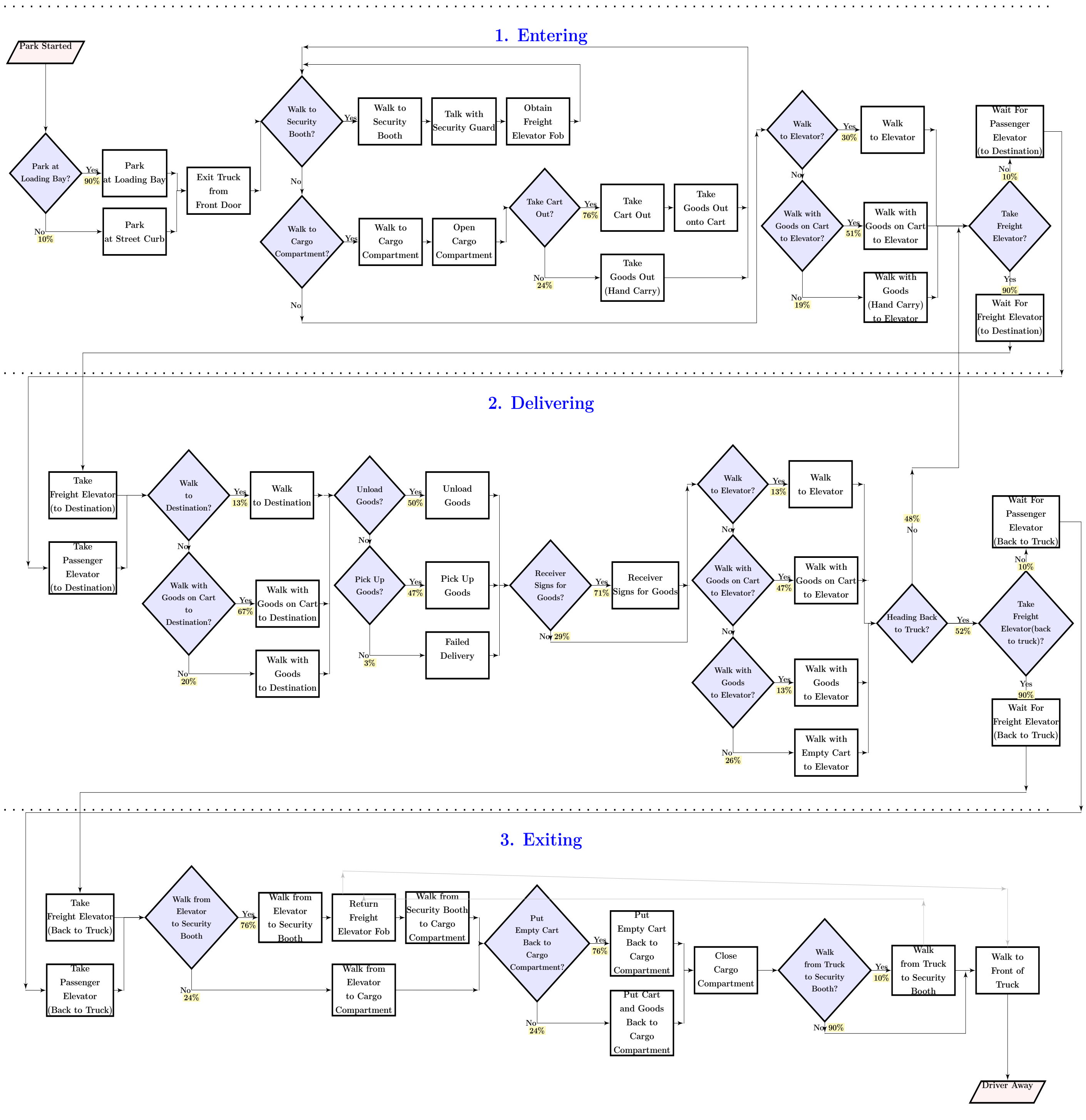


Figure 4.2: Delivery Process Flow Map (n = 31)

Table 4.1: Duration (in seconds) of tasks within the Delivery Process Flow for Common Paths (n = 31)

Tasks	Subtasks	mean	sd	$\frac{sd}{mean}$	min	max	mode
1. Entering	a. Parking ended at loading bay	40	40	1.01	9	165	12
	b. Parking ended at street curb	33	30	0.89	12	67	12
	c. Exit truck from front door	14	18	1.28	3	90	3
	d. Walk from truck to security booth	27	21	0.75	4	102	8
	e. Talking with security guard	83	83	1	5	242	5
	f. Obtain freight elevator fob	34	21	0.63	2	77	12
	g. Walk to cargo compartment - Entry	17	16	0.93	2	67	2
	h. Open cargo compartment	20	20	1.03	3	75	7
	i. Take cart out	27	30	1.14	1	124	1
	j. Take goods out and place on cart	54	56	1.04	3	202	12
	k. Take goods out	51	23	0.45	26	84	26
	l. Walk to elevator	54	24	0.45	26	105	44
	m. Walk with goods on cart from truck to elevator	44	28	0.64	9	129	29
	n. Walk with goods from truck to elevator	51	29	0.57	17	105	29
	o. Wait for freight elevator (to destination)	31	49	**1.56**	3	193	10
	p. Wait for passenger elevator (to destination)	52	22	0.42	32	76	32
2. Delivering	a. Took freight elevator (to destination)	75	93	1.23	4	486	35
	b. Took passenger elevator (to destination)	67	50	0.76	36	126	36
	c. Walk from elevator to destination	55	19	0.35	36	81	36
	d. Walk with goods from elevator to destination	87	65	0.74	26	196	26
	e. Walk with goods on cart from elevator to destination	49	50	1.03	10	200	10
	f. Unload goods	57	59	1.04	11	221	21
	g. Pick up	37	11	0.31	23	58	35
	h. Receiver signs for goods	55	77	1.41	3	404	11
	i. Walk from destination to elevator	38	16	0.43	25	64	25
	j. Walk with goods on cart from destination to elevator	40	50	1.23	3	193	10
	k. Walk with goods from destination to elevator	44	14	0.32	25	56	56
	l. Walk with empty cart from destination to elevator	39	52	1.34	2	180	2
	m. Wait for freight elevator (back to truck)	63	35	0.55	20	124	59
	n. Wait for passenger elevator (back to truck)	NA	NA	NA	NA	NA	NA
3. Exiting	a. Took freight elevator (back to truck)	148	155	1.05	2	635	36
	b. Took passenger elevator (back to truck)	78	36	0.47	54	120	54
	c. Walk from elevator to security booth	27	29	1.07	3	97	18
	d. Return freight elevator Fob	44	38	0.84	5	156	6
	e. Walk from security booth to cargo compartment	34	23	0.67	9	70	9
	f. Walk from elevator to cargo compartment	30	19	0.64	9	60	9
	g. Put empty cart back into cargo compartment	42	26	0.62	5	98	33
	h. Put goods and empty cart back into cargo compartment	36	9	0.24	28	47	28
	i. Close cargo compartment–Exit	17	16	0.97	5	54	5
	j. Walk from truck to security booth–Exit	6	5	0.76	2	11	2
	k. Walk to front of truck	22	40	**1.8**	4	210	8
	l. Enter truck from front door	28	32	1.13	1	124	7

Note: highlights indicate sd/mean>1, and bold indicate sd/mean > 1.5

4.3 Delivery time and activity decomposition

All delivery workers made at least one delivery to the building, with 26% (8 delivery workers out of 31 workers) making more than one delivery. For those who visited more than one floor, the maximum number of visits are denoted in Figure 4.3 as 'D2' for visits to two different locations within the building, 'D3' for three floors, and so forth with a maximum of 'D7' for seven deliveries observed.

4.3.1 Total Delivery Time

The data collection application allowed us to collect data on dwell time for the three main delivery steps, the subtasks, as well as total delivery time. Figure 4.4 summarizes the delivery time measured for each delivery truck. The multiple deliveries are denoted with the same notations shown in Figure 4.3. The mean total delivery time was 20 minutes. This is reasonable since the parking time limit at the studied location was 30 minutes. The minimum and maximum of total delivery times were 9 minutes and 43 minutes respectively. The range of total delivery times is comparable to a previous study by Cherrett et al. which indicated 9 and 8 minutes as the shortest mean van dwell times according to 2001, and 2008 Winchester surveys [38].

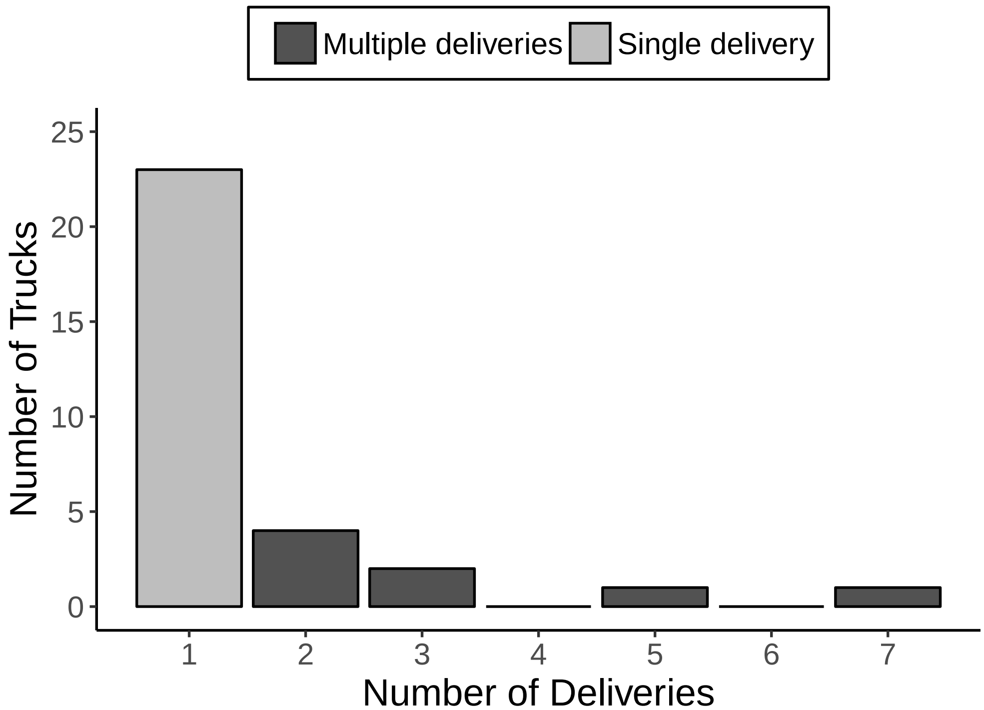


Figure 4.3: Number of Deliveries per Truck

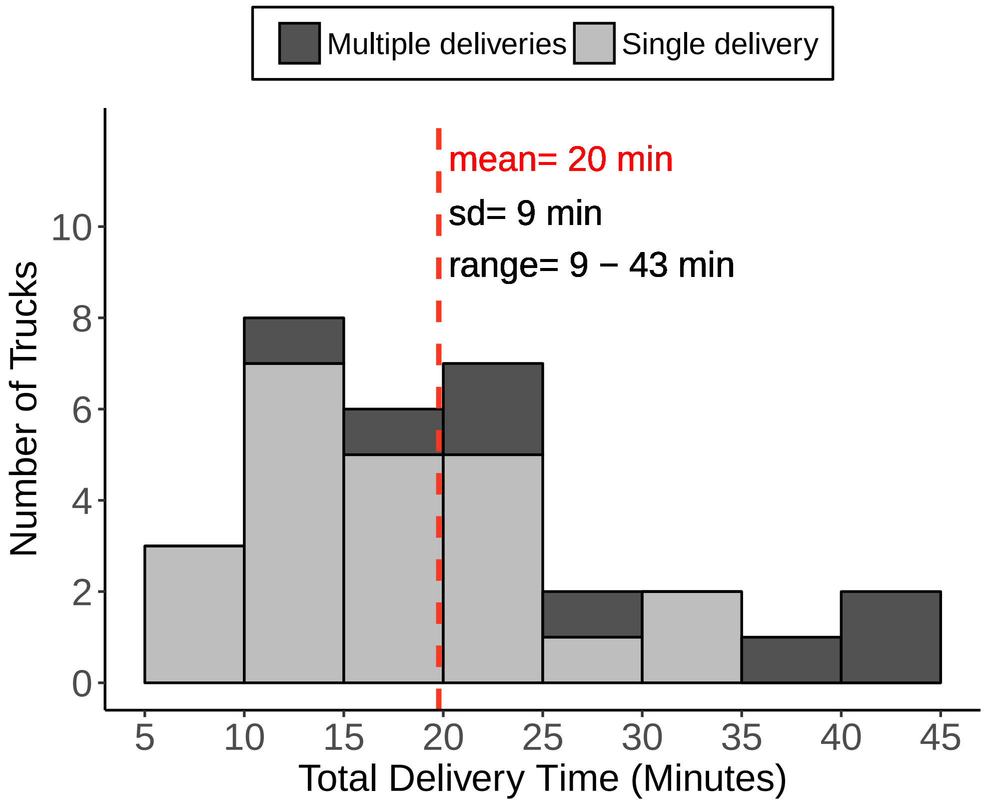


Figure 4.4: Distribution of Total Delivery Time (n = 31)

As shown in Figure 4.5, the times for each of the three delivery steps are 7, 8, and 5 minutes, respectively. The percent of total delivery times for each zone are 35% for entering, 40 % for delivering and 25% for exiting. Unloading and organizing goods prior to deliveries encompass a great deal of the time in the delivery process. The highest variation is shown in the delivering step at the final destination. Differences in delivery workers' experience and familiarity with the building, and the level of interaction with the receptionist are some of the contributors to these variations.

4.3.2 Variation in Delivery Time

The subtasks in Table 4.1 are visualized in Figure 4.6, which shows the distribution of delivery time based on the ratio of the standard deviation and the mean (sd/mean). The

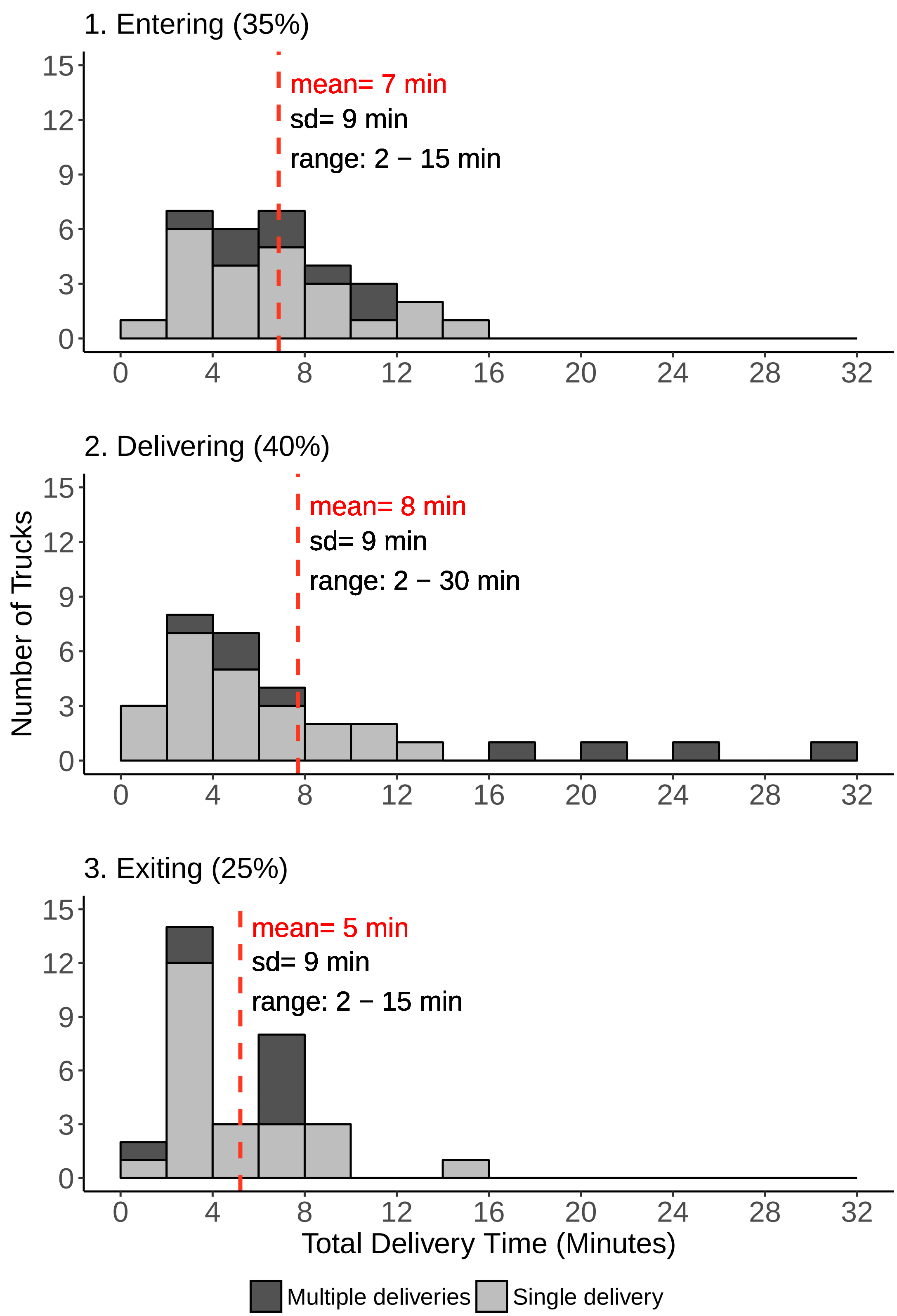
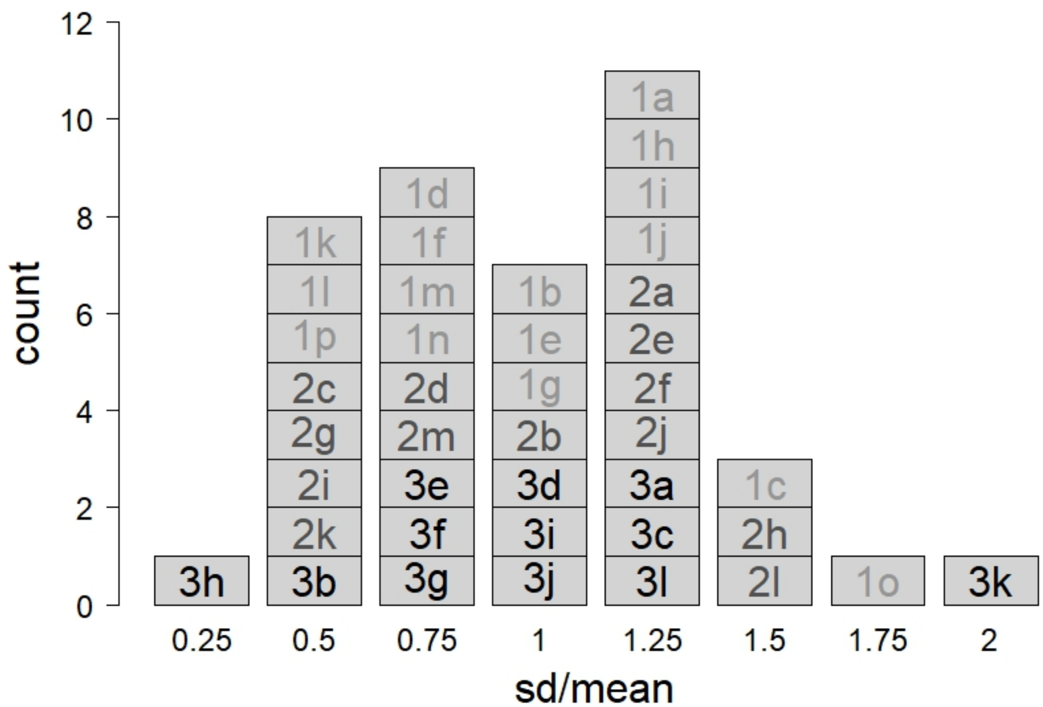


Figure 4.5: Delivery Time by Main Delivery Process Steps (n = 31)

variation (sd) for most processes was close to the mean. The highest variations (sd/mean ¿ 1.5) was observed in the activities, ‘walk to front of truck’ and ‘wait for freight elevator (to destination)’. The six tasks with the largest sd/mean are discussed further in this section.



Note: The letters and numbers within the horizontal bars denote the tasks and subtasks identified in Table 4.1. For example, *3k* represented Task 3 (Exiting) and Subtask k (Walk to front of truck).

Figure 4.6: Ratio of standard deviation and mean (sd/mean) of delivery time.

Task 3k (sd/mean=1.8). Walk to front of truck

The high variation in the activity, ‘Walk to front of truck’ was due to one specific case, which may not be as common in other normal delivery processes. A delivery worker failed to deliver the goods but spent 210 seconds lingering in the loading bay, walking back and forth between the front and the end of the truck. While this is not common, it is important to examine because it is associated with a failed delivery.

Task 1o (sd/mean=1.56). Waiting for freight elevator (to destination)

Time spent while waiting for the elevators increased the overall truck dwell time. The wait time at the bottom floor (loading bay or main lobby) may include elevator travel distance over the entire building and is impacted by use during peak periods. Wait times from the office floor can be much quicker for deliveries to the middle floors of the building.

High variation in the wait time for freight elevator could also be related to the elevator age. Both freight elevators in the observed office building were installed in 1990 (27 years ago). The frequent breakdowns and slow speeds can contribute to bottlenecks observed. Weather was also an observed factor. Strong winds from outside the building would come in through the wide opening of the loading bay entrance, and prevent the freight elevator doors from being fully close, causing delays on the loading bay level. In these situations, a security guard would request that the delivery workers press the ‘close’ button until the door was fully closed. However, those delivery workers that were not familiar with this defect may instead wait an excessively long time for the elevator to automatically close.

Task 2h (sd/mean=1.41), Receiver signs for goods

Out of all the deliveries, 71% of the drivers were required to obtain a signature from the receiver. The time it took for the receiver to sign for the received goods varied greatly and depended on the quantity and type of received goods. For regular deliveries, the receivers anticipate certain types and amounts of goods being delivered, resulting shorter time in signing for goods. When the multiple types of delivered goods are not organized before the delivery, the receiver took a long time to sort and count each item, increasing the total dwell times for the delivery workers at the final destination.

Task 2l (sd/mean=1.34), Walk with empty cart from destination to elevator

The walk time within the final destination also showed high variation, especially for those who walked with hand trucks or dollies, referred as 'cart' in the tables and figures. Depending on the size and types of a cart, maneuvering the office areas with dollies and hand trucks could be time-consuming because the delivery workers required extra time to hold the office doors for hand trucks or dollies. By sharing the building infrastructure information such as the size limits of the hallways or office doors could help the delivery workers to plan out the deliveries ahead of time. Using standardized carts for deliveries could be another way to expedite the delivery process, avoiding any undesirable situations such as being stuck in doors or hallways.

Task 1c (sd/mean=1.28), Exit truck from front door

The high variation in 'exit truck from front door' could be due to the time inside the vehicle to complete paperwork or review receiver lists while the vehicle's door was open. In some cases, the drivers were eating or using their cell phone while exiting the truck. However, most drivers did not take long to exit the vehicle (mean duration was 14 seconds).

4.4 Summary

Freight movement is changing rapidly and it is essential to understand the process flow of goods globally, regionally, and locally. This paper focuses on the movement of goods locally and more specifically within an office building in the Seattle central business district. There has been increasing demand for deliveries in central business districts, but there is limited space with which to move, both structurally and operationally.

The final 50 feet of the supply chain extensively involves a vertical movement of the delivery process as deliveries and pick up activities occur mostly while the drivers are out of the vehicle from the loading zone to the end customer. This chapter introduces a systems approach to measure and observe detail tasks of the current final 50 feet of the supply chain by using a unique tablet application and a process flow map. An office building in downtown Seattle was observed by using this approach. Process flow map decomposes actions of the delivery workers, which helps the researchers identify bottlenecks in the current delivery process and where improvements can be made. The improvements can easy-to-implement solutions such as an information board to notify delivery workers of imperfections in the freight elevator to more high cost solutions such as a building redesign.

While the study included only 31 observations, they still provide substantial insights on the variations that can occur for a one week period within an office building, while also demonstrating that some steps are consistent regardless of carrier type. A future goal is to be able to compare the variations observed in this building to other building types and operations (e.g., shopping center, hotel, residential building). It would also be of interest to examine different operation types. Future process flow maps could also showcase temporal differences with respect to seasons, holidays, and weekend vs weekdays.

The scope of this study was also limited to the most common paths of the delivery process performed at one office building in downtown Seattle. However, this study would provide insights on the average delivery duration for other similar-sized office buildings in urban areas. Also, the focus of this paper is to understand the overview of the final leg of the delivery and pick-up activities by using the new systems approach; process flow maps with quantitative measures on dwell times. The quantitative measures of delivery time for each delivery task can enable researchers to identify the tasks with the high coefficient of variation value being bigger than 1. This provides insights on the tasks that can be performed faster by others, which can be improved for other workers with a better understanding of the current delivery process flows. Further research on the final 50 feet of the pick-up and delivery process in different types of buildings could capture unique characteristics of different delivery procedures.

Chapter 5

EMPIRICAL ANALYSIS OF COMMERCIAL VEHICLE DWELL TIMES AROUND FREIGHT-ATTRACTING URBAN BUILDINGS IN DOWNTOWN SEATTLE

With rapid growth and evolution in supply chain practices, cities around the world are experiencing an influx of goods pickup and delivery activities. The additional related traffic has added pressure to already congested urban roads. A popular method for managing commercial vehicle parking behaviors is to restrict vehicle dwell time, which is defined as the time delivery workers spend performing out-of-vehicle activities while the truck is parked. However, there are challenges in managing dwell time restrictions. The high number of commercial parking fines issued in New York City (NYC) is an example of the challenges in managing the current dwell time restrictions. In 2018, the total amount of commercial parking fines in NYC was $181.5 million, with major delivery companies such as FedEx and UPS responsible for 20 to 30 percent of them [23].

Understanding urban freight parking behaviors is particularly difficult because several underlying factors influence vehicle dwell time. Data on such factors are often proprietary to independent private companies, and are therefore, not shared with researchers and city planners. For this reason, most current parking policies overlook the complexity of urban freight parking behaviors. This paper aims to provide insights on factors that influence dwell time for commercial vehicles and estimate the magnitude of their influences. Parking characteristics for urban freight deliveries are fundamentally different from commuter parking [18]. Urban freight delivery needs close proximity to destinations and requires more space and time to load and unload goods and to maneuver and park the commercial vehicles [18].

Lengthy dwell time at limited curbside spaces could negatively affect the travel times of other commercial vehicles, searching for parking spaces. Rhodes et al. (2012) noted that quantifying and addressing both horizontal and vertical “last mile” inefficiencies are important from a planning perspective [129]. Kim et al. (2018) introduced a process flow for delivery and pick-up activities inside a building in the Seattle central business district and noted that many factors may affect vehicle dwell time, emphasizing the importance of accounting for the vertical movement in understanding the fundamental aspects of urban goods movement [90].

The goal of this chapter is to identify the factors correlated with commercial vehicle dwell times and quantifying their impacts. This goal was achieved by using a generalized linear regression approach with data collected at five different buildings in downtown Seattle: a residential tower, a hotel, a historical building, an office tower, and a shopping mall. Insights gained from our analysis can be used in the decision making process for urban freight policies in many cities.

5.1 Summary statistics

There were 157 observations from the five buildings (see Table 3.1). Figure 5.1 shows the histogram of the dwell times in minutes. Most commercial vehicle parking in this area are limited to 30 minutes or less. Most of the observed vehicles (90 %) had dwell times less than 30 minutes. Only 16 observations (about 10 %) had dwell times longer than 30 minutes. Although the parking fines were not monitored (as it was out of the scope for this study), we did note the number of vehicles that exceeded the parking time limit in order to meet their delivery schedules. Long dwell times can have a negative impact on parking capacity in the neighborhood [138]. Providing a good estimate of dwell times can assist the city to more effectively allocate parking facilities with solutions that are tailored for vehicles based on their expected dwell times.

The observed dwell times used in the analysis ranged from 1.5 minutes to 107.4 minutes. Several past empirical studies showed similar ranges between 1 minutes and 90 minutes for the on-street parking study by Schmid et al. (2018) [138] and from 1.5 minutes to 180

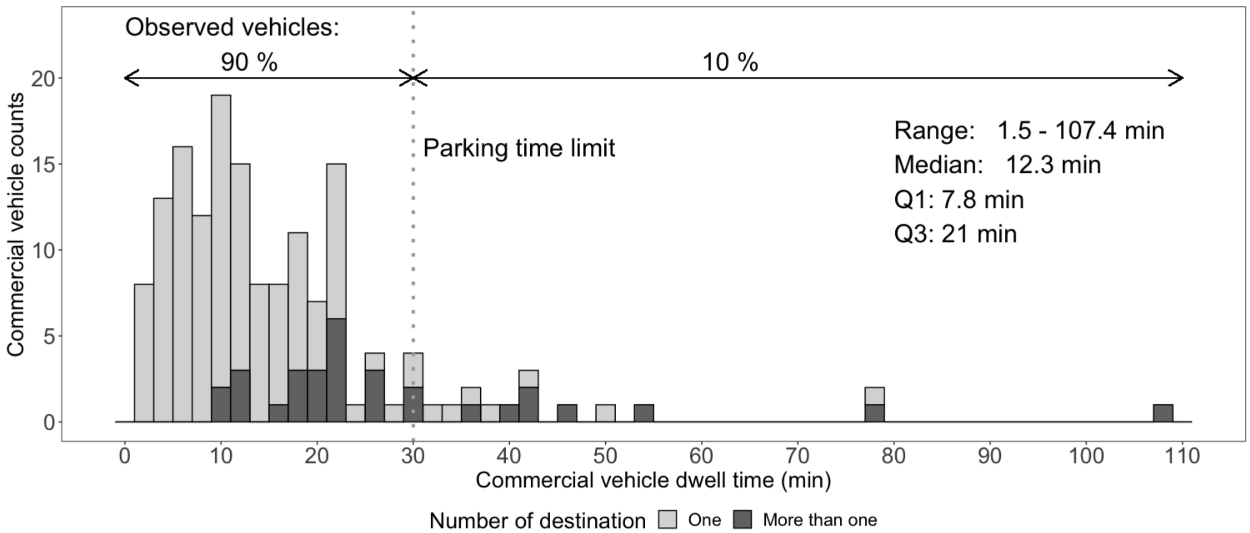


Figure 5.1: Commercial vehicle dwell times for all five buildings combined

minutes for the off-street parking study by Dalla-Chiara et al. (2017) [44]. Campbell et al. (2018) used the estimated dwell times between 30 minutes and 90 minutes in calculating the number of on-street parking spaces [35].

The distribution of observed dwell times was right-skewed with a mean of 16.4 minutes and a median of 12.3 minutes (1st quartile: 7.8 minutes and 3rd quartile: 21.1 minutes). The distribution of dwell times by each building also showed right-skewed trends (see Figure 5.2). This right-skewness was expected as past models also showed right-skewed trends in dwell time distributions [44, 138]. Our data showed a peak dwell time around 10 minutes including both on and off-street parking spaces while past studies showed peaks at 5 minutes for on-street parking [138] and 15 minutes for off-street parking [44].

5.1.1 Data observations

On the basis of past commercial vehicle studies, the researchers identified potential factors that may influence dwell time ([115]-[165],[90]). Factors that were included in our study were the delivery day of the week, arrival time, total floor area, receptionist presence at

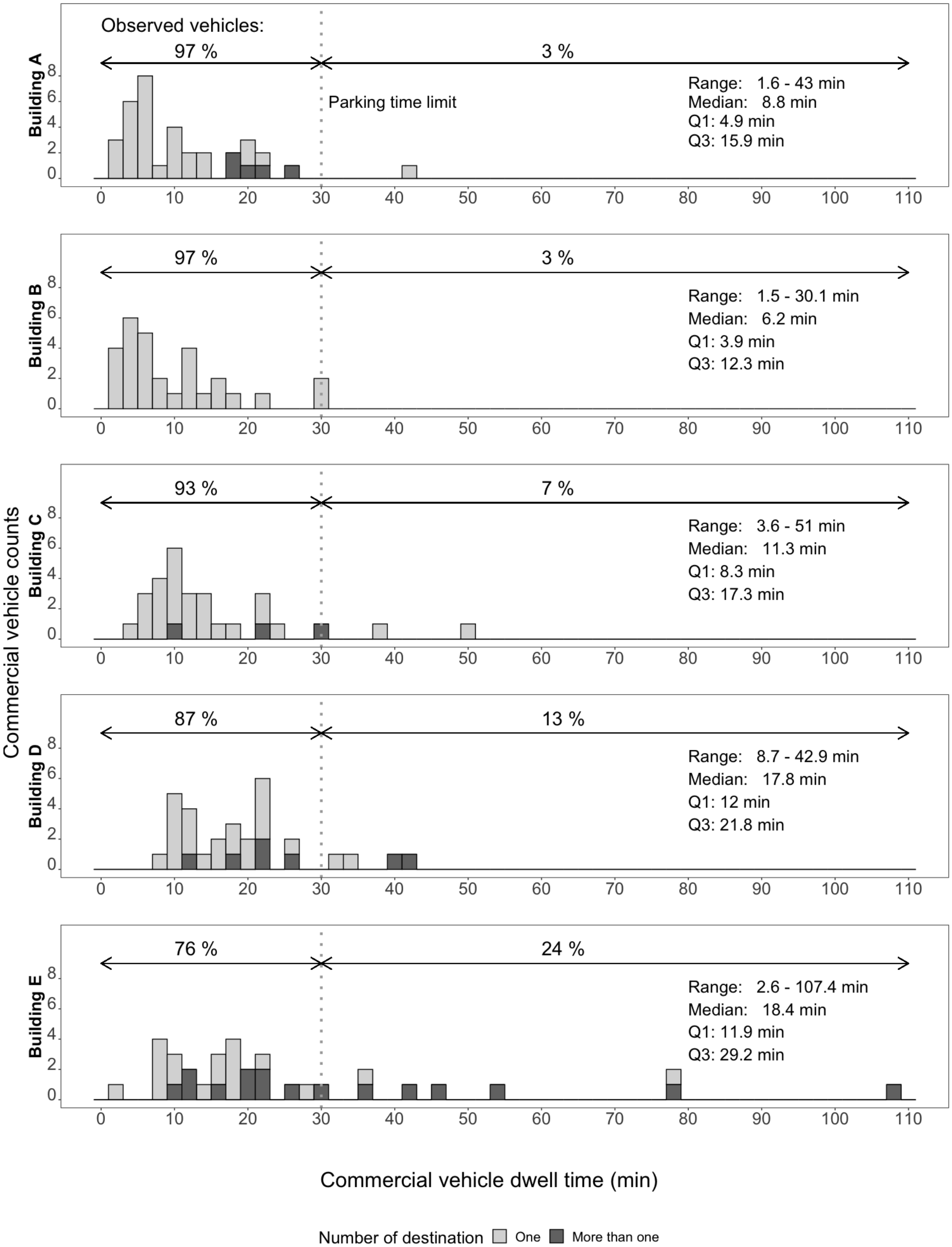


Figure 5.2: Commercial vehicle dwell times for each building

lobby, parking location, delivery vehicle type, type of goods being delivered, number of delivery workers, and number of destinations within each building. The summary statistics of observed variables are shown in Table 5.1.

Table 5.1: Summary statistics (n= 157), dependent variable: dwell time

No.	Variable	Categories	Total sample (%)	Group mean duration (in minutes)	Group SD duration (in minutes)
1	Day	Mon	13 (8.3)	25.6	19.5
2		Tues	39 (24.8)	17.7	16.5
3		Wed	23 (14.6)	13.6	9.1
4		Thurs	37 (23.6)	16.4	17.3
5		Fri	45 (28.7)	13.9	9.4
6	Vehicle arrival time	6:30–9:30	33 (21)	17.2	18.1
7		9:30–11:30	79 (50.3)	17.5	13.5
8		11:30–15:00	45 (28.7)	13.8	13.5
9	Total floor area	31,000 m^2	29 (18.5)	15.1	10.4
10		38,000 m^2	29 (18.5)	9.7	7.7
11		45,000 m^2	34 (21.7)	26.1	23.1
12		89,000 m^2	35 (22.3)	11.0	8.8
13		92,000 m^2	30 (19.1)	19.2	9.0
14	Receptionist presence	No	93 (59.2)	20.4	16.5
15	at lobby	Yes	64 (40.8)	10.4	8.3
16	Parking location	Off-street	82 (52.2)	19.1	17.5
17		On-street	75 (47.8)	13.4	9.8
18	Vehicle type	Roll-up door	89 (56.7)	18.4	16.9
19		Swing doors	53 (33.8)	15.2	10.8
20		Passenger	15 (9.6)	8.2	5.2
21	Type of goods	Oversized supplies	18 (11.5)	20.5	10.6
22		Office supplies	34 (21.7)	17.9	10.7
23		Parcels	39 (24.8)	17.4	22.4
24		Documents	12 (7.6)	14.3	11.1
25		Food	54 (34.4)	13.7	10.7
26	No. of workers	One	135 (86)	15.8	14.9
27		Two or more	22 (14)	19.7	11.8
28	No. of destinations	One	126 (80.3)	13.2	10.7
29		Two or more	31 (19.7)	29.1	20.5

Day of the week

In this study, the delivery day of the week included only Mondays through Fridays (excluded Saturdays and Sundays). Through interviews with building managers, we learned that the office and historical buildings were closed and the other buildings had minimal freight activities on Saturdays and Sundays. Therefore, we limited our data collection to Mondays through Fridays. Mondays had the longest dwell times (mean = 25.6 minutes). The majority of our Monday observations were from Building E which showed the longest mean dwell times of 26.1 minutes. This may be pulled the average dwell times for Monday to the highest while the average dwell time for the other weekdays was 15 minutes. The longest dwell time (107.4 min) was observed on a Thursday. To account for the imbalanced size of observations from each building for Monday, the days of the week were categorized into two levels in our dwell time models: 1) Monday and Tuesday (early week- Group mean:19.7 min, Group SD: 17.4 min), 2) Wednesday, Thursday, and Friday (late week- Group mean: 14.7 min, Group SD: 12.7 min). As can be seen in Table 5.1, the percentage of deliveries was the lowest on Mondays (8.3 percent) and highest on Fridays (28.7 percent). A similar trend was observed in other studies. Cherrett et al. (2012) showed that freight activity was busiest on Fridays and quietest on Mondays [38]. Han et al. (2005) showed that Thursdays and Fridays had the most pick-ups and deliveries, whereas Mondays and Tuesdays had the lowest numbers of deliveries [67]. Some studies showed that weekends or the middle of the week can also be popular days for deliveries. In the UK, deliveries of wholesale produce were concentrated on Saturdays, and Tuesdays and Wednesdays were shown to be popular for freight deliveries [39].

Vehicle arrival time

Figure 5.3 shows the histogram of the commercial vehicle arrival time for all five buildings combined. 25 % of observed vehicles arrived before 9:39 AM while 90 % of them arrived before 12:25 PM. The distributions of arrival times for each building type are shown in

Figure 5.4. As shown in Figure 5.4, Building B and Building E showed 25 % of commercial vehicles to be arrived before 9:00 AM, earlier than other buildings. Presence of restaurants in these buildings may have contributed to the early arrival time as the delivered goods in the morning at Building B and E were mostly food and oversized materials (e.g., construction or utility materials, etc.). 25 % of deliveries at Building C and D were arrived at the buildings before 10 AM. 90th percentile of vehicle arrival time for Building C and D were around 12:00 PM and 1:00 PM respectively. The goods delivered at Building C after 12:00 PM were mostly food (e.g., lunch, catering) for the offices whereas the delivered goods after 1:00 PM at Building D were mostly parcels and documents. Among the five buildings, the Building A (which had residential units) showed that 25% of deliveries (mixed types of food, parcels and oversized goods) arrived at the building before 11:00 AM, the latest 25th percentile compared to other buildings. In our models, vehicle arrival time was grouped into three levels: 1) 6:30–9:30, 2) 9:30–11:30, 3) 11:30–15:00. The average dwell time for the first group of 6:30–9:30 (17.2 minutes) and the second group of 9:30–11:30 (17.5 minutes) were longer than those for deliveries made in the third group of 11:30–15:00 (13.8 min). The observed deliveries were concentrated in the AM period, sharing a similar trend with other studies. According to an extensive analysis of 30 UK surveys over 15 years (1996-2009) by Allen et al. (2012), most urban delivery activities were concentrated in the morning between 6:00 AM and 12:00 PM [15]. A study conducted by Morris and Kornhauser (2000) that observed delivery activities in New York City's central business district (which was defined as south of 59th street to the tip of Manhattan from the river to river) showed a delivery peak in the morning, with an average dwell time of 33 minutes or more [114]. In 1999, McKinnon observed a large number of food deliveries in the the early time period between 5:00 and 9:00 AM [107]. However, Winchester study in 2008 argued that there is no significant difference in delivery arrival time among business categories, as that study found that 26 percent of businesses had no scheduled delivery arrival time [38]. The study suggested that the commercial vehicle arrival time was more likely determined by suppliers or carriers more than by the receiving businesses [38].

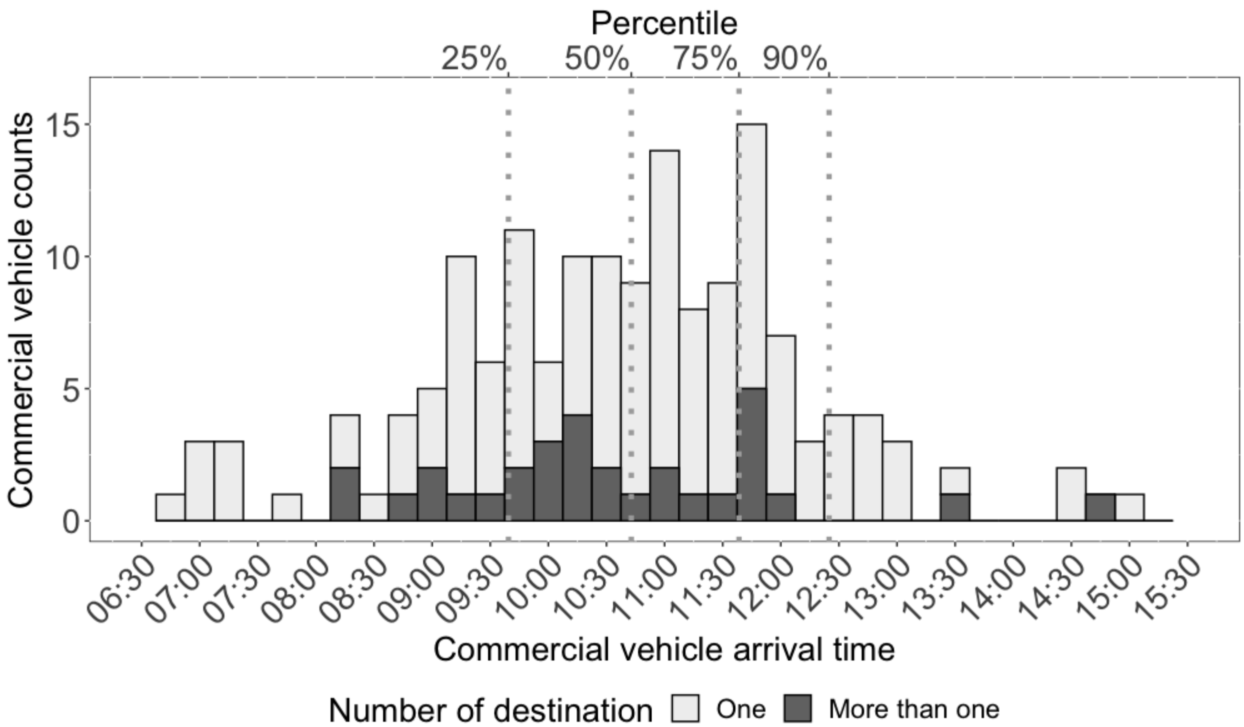


Figure 5.3: Arrival times for all five buildings combined

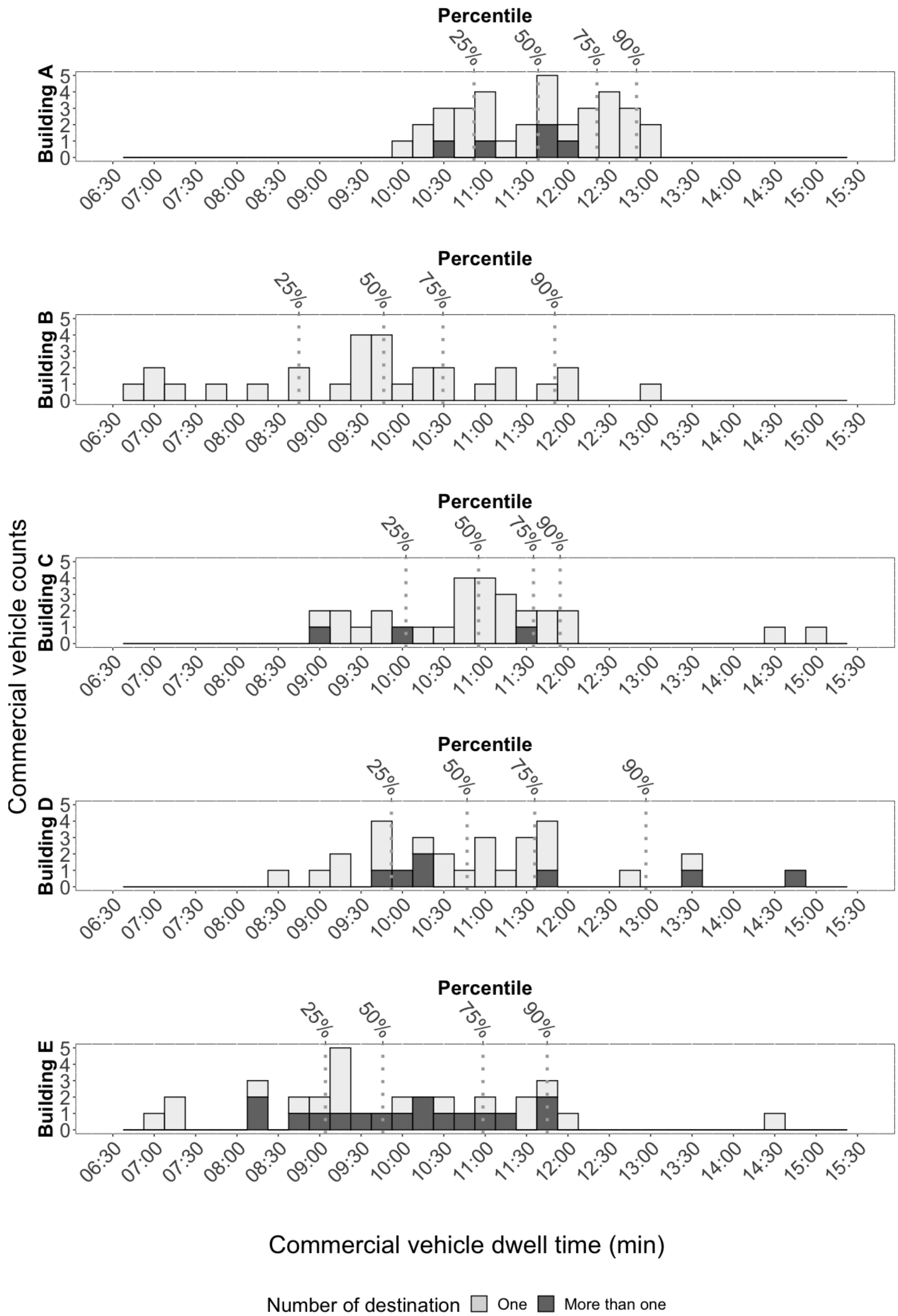


Figure 5.4: Arrival times for each building

Total floor area

Total floor areas for the observed building differed between 31,000 and 92,000 m^2. The total floor area of the building was assumed to be a good indicator to estimate commercial vehicle dwell time as a bigger sized building may attract larger sizes and quantities of goods which require additional time for navigating and handling inside of buildings. However, the number of floors and total floor area did not follow a linear trend with overall dwell time. For example, the mean dwell time at Building A with 89,000 m^2 and 41 floors - 11 minutes - was less than that at Building E with 45,000 m^2 and 25 floors - 26 minutes. This could be due to different building configurations and delivery policies, such as having a concierge service or building configurations that were difficult to maneuver around and inside. Although Building C had the smallest number of floors (15) and 31,000 m^2, both mean and median dwell times were longer than those at Building A and B where concierge services were offered.

Receptionist presence at lobby

Building A and B had concierge services that allowed delivery workers to drop off their goods at a designated location close to the entrance of the building and loading bay. In this way, delivery workers could avoid vertical activities (e.g., taking freight elevators, navigating inside of the building). Some deliveries at Building A still required travel inside of the building in case the goods could not be dropped off (e.g., lunch or dinner food deliveries and deliveries that required a signature from the receiver directly). As expected, the buildings with receptionists at the lobby showed 10 minutes lower mean dwell time than the buildings without receptionists at the lobby. This intuitively makes sense because the extra time to travel to the final destination could be minimized by consolidating goods at the concierge location. Because the delivery workers had to navigate inside the building, longer dwell times were expected for other buildings in comparison to deliveries at buildings with concierge services.

Parking location

Parking location can affect the length of dwell time. Our observed parking options included on-street and off-street parking. Alternatively, unauthorized parking such as double parking could have occurred. However, our observations did not distinguish the unauthorized parking option, as our focus was on the dwell times either on the street curbs (on-street parking) or at loading bays (off-street parking). While observed proportions between off-street and on-street parking were similar, off-street parking showed a longer mean dwell time - 19 minutes - than on-street parking with an average of 13.4 minutes. Given the parking location, delivery workers will leave their cargo compartments open or closed. At loading bays, most delivery workers left their doors open, as a security guard or a surveillance camera was present. On the other hand, on the street, some delivery workers kept the cargo compartment closed or locked when they left their vehicles for deliveries. Closing or locking mechanisms could add extra time to dwell time. The levels of conflict with other roadway users (e.g., pedestrians, bicyclists, and other vehicles) would also vary depending on parking location, which could potentially add extra dwell time. Campbell et al. (2018) studied the impact of on-street parking locations on dwell times and found that the middle of the block is an optimal location for parking needs, minimizing walking time [35]. Butrina et al. (2017) stated that the decision of parking location could be influenced by package size and weight, as well as the distance to the recipient's location [32]. Depending on the types of locations served, the number of parking facilities might differ [38]. According to Cherrett et al.'s review of recent UK urban freight studies, shopping centers had a higher percentage of off-street parking facilities whereas local shops tended to have more on-street parking [38].

Vehicle type

While most of the commercial vehicles were vans or trucks with either swing doors or roll-up doors, about 10 percent of the observed vehicles were passenger vehicles with commercial vehicle logos or vehicles performing crowd-sourced delivery services (e.g., 'Uber eats', 'Amazon

Flex'). The average dwell time for passenger vehicles was around 8 minutes, lower than that for trucks or vans with roll-up and swing doors (around 17 minutes on average). Delivery vehicles such as trucks and vans were categorized on the basis of the types of cargo compartments; roll-up doors and swing doors. Roll-up doors are often found on trucks (e.g., trailer trucks, single-unit trucks, box trucks) while swing doors are often found on vans. When parking, delivery workers had to consider extra space for loading and unloading, especially for swing doors or liftgates. Some trucks had a hydraulic or electric powered liftgate at the rear of the vehicle that moved up and down to assist in unloading and loading heavy cargo. When swing doors were blocked by a loading bay wall or parked vehicles behind, delivery workers had to adjust parking to allow extra space. Additional time required for operating the lift-gate or adjusting parking could be added to the total delivery vehicle dwell time.

Type of goods

The types of goods - including oversized supplies, office supplies, parcels, documents, and food - were studied. The average dwell time for oversized supplies was 20 minutes, which was much longer than times for other delivered goods, which ranged between 14 minutes and 18 minutes. Oversized supplies included furniture and construction materials that required special moving equipment. Parcels represented the deliveries that were packaged in cardboard boxes and for which data collectors could not identify the type of items inside. Office supplies included papers, toilet papers, electronics such as computers, and monitors identified by data collectors. Deliveries of documents accounted for mail and small documents that were more likely to require a signature from a recipient. Food deliveries included both large quantities for restaurants or catering services and small quantities for individuals, such as grocery deliveries and lunch/dinner deliveries. Differences in the quantity of food deliveries could be accounted for by the vehicle type because small food deliveries tended to be performed by passenger vehicles. Because of their similar delivery process characteristics, office supplies, and parcels were grouped into one category in the model for simplicity.

Number of workers

Typically, one delivery worker performed deliveries (approximately 86 percent) with an average dwell time of 16 minutes. When two or more delivery workers were involved in deliveries, the goods were more likely to be large and numerous in quantity, which may increase the overall dwell times due to longer handling times (e.g., loading and unloading, navigating). Since we do not have a volume-controlled variable in our models, the number of workers was used as a proxy to a large volume of goods. As expected, the mean dwell time for the deliveries with two or more delivery workers (20 minutes) was higher than deliveries performed by one worker.

Number of destinations

Most of the deliveries (80 percent) went to one location within the building. As expected, multiple deliveries with two or more destinations within one building had a much larger mean dwell time (13 minutes vs. 29 minutes). When visiting multiple locations within a single building, delivery workers may be required to maneuver through unfamiliar floor plans and to cope with different delivery policies between departments and floors. Also, certain building types may naturally have a large number of destinations and attract large volumes of goods to be delivered. For example, Building E has a large shopping mall area with several restaurants where goods are being delivered in large quantities to multiple locations within the building. Even when there is only one destination, the delivery may require multiple trips from a vehicle to the same destination due to a large quantity being delivered. This had led some deliveries at Building E to have dwell times longer than 50 minutes.

5.2 Regression model approach

The study objectives were to identify factors correlated with dwell time for commercial vehicles and measure their level of impact on dwell times. We hypothesized that dwell time is a function of independent variables such as day of a week, vehicle arrival time, building type, parking location, vehicle type, type of goods, number of workers and number of destinations within a building. We used two main modeling approaches. The first approach estimated models with combined data from all of five building types. The second approach further analyzed the effects of the independent variables on dwell time in different building types by applying five separate models.

As was shown in Figure 5.1, the distribution of dwell times was right-skewed. Hence, right-skewed distributions (log-normal and gamma) were examined in comparison to the normal distribution. Figure 5.5 shows the distribution fit for the data sets. Gamma distribution often associates with the concepts of random or neutral processes, including queuing models, climatology, and financial services [58]. Gamma distribution is frequently used to predict wait time until k_th arrival [88]. The Shapiro-Wilk test (Table 5.2) confirmed that the log-normal and gamma distributions would be good fits for the observed dwell times, as almost all the data sets failed to reject the null hypothesis (p-value ¿0.05) that the observed data would follow theoretical densities.

Table 5.2: Shapiro-Wilk test result (P-value)

Distribution	Combined	Building A	Building B	Building C	Building D	Building E
Normal	2.66e-15	1.42e-04	1.47e-03	7.81e-05	4.23e-03	4.67e-06
Log-Normal	0.1555	0.6864	0.5121	0.796	0.2977	0.7127
Gamma	0	0.35	0.44	0.1	0.14	0.07
Total observations	157	35	29	29	30	34

Null hypothesis: True cumulative distribution function equals the tested distribution.

General linear models with a gamma-distributed and log-normal dependent variable were created by using the 'GLM' function in the R statistical software package (version 4.0.2). The probability density function of gamma-distributed data y_i, given scale parameter (θ_i)

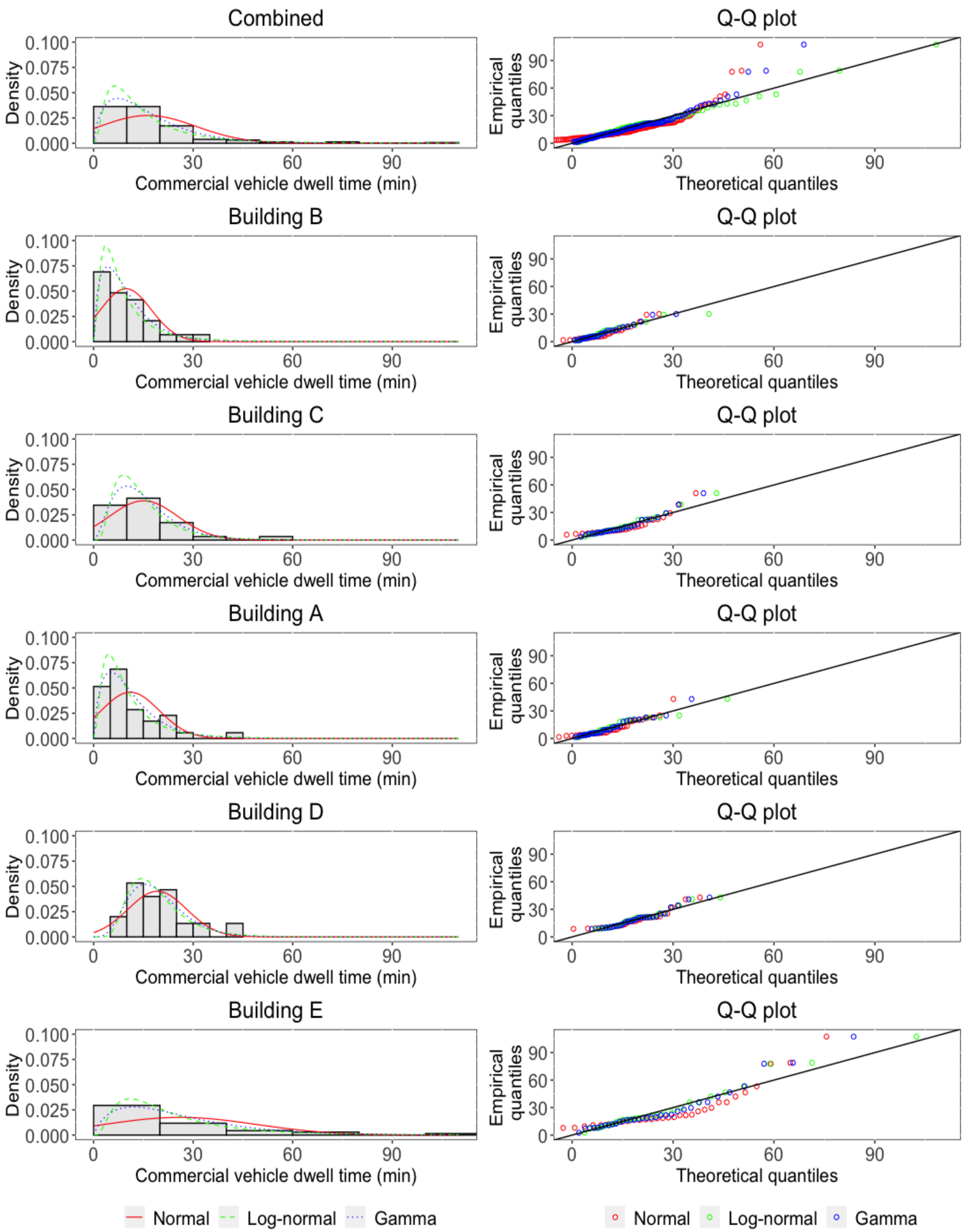


Figure 5.5: Histogram with fitted distributions

and shape parameter (κ) is:

$$\begin{aligned} f(y_i) &= \frac{y_i^{\kappa-1} e^{-y_i/\theta_i}}{\theta_i^{\kappa}\Gamma(\kappa)} \text{ where } y_i, \theta, \kappa > 0 \\ \Gamma(\kappa) &= \int_0^{\infty} y^{\kappa-1} e^{-y} dy \end{aligned}$$

The multivariate gamma-distributed variable can be presented by y_i and the vector size, p, which is a function of independent variables x_1, x_2,....,x_α. Assuming that the link function of "log" that was used in our dwell time models (g(μ) = log(μ)) and the shape parameter α was constant throughout the process, then each element in y can be expressed as:

$$y_i \sim GAMMA(shape = \kappa, scale = [\beta_0 + \beta_1 * x_1 + \beta_2 * x_2 + ...\beta_\kappa * x_\kappa]/\kappa])$$

for *i* = *1,...,p.* The mean and standard deviation for the gamma distribution are then:

$$\begin{aligned} \mu = E(y_i) &= \kappa * \theta = g^{-}1(\beta * x_i') = exp(\beta * x_i') \\ Var(y_i) &= \kappa * \theta^2 \end{aligned}$$

5.2.1 Correlation analysis

A correlation analysis was conducted to ensure there were no issues with multicollinearity. Since the variables are categorical, chi-square tests of independence and Cramer's V values were calculated to test the correlations and strength of these associations. Figure 5.6 shows the Cramer's V values with p-values of the chi-square test (in shades of grey).

The correlation analysis shows high correlations in total floor area and parking location with other variables. Especially, the correlation between total floor area (building specific) and parking location variables was significant showing a high Cramer's V value of 0.83.

This is anticipated because parking location availability was highly dependent on different buildings. For example, Building C was built in 1924 and did not have any off-street parking facility (e.g., loading bay). On the other hand, Building B had a full-time staff member who received goods at the loading bay, deliveries always went to that off-street parking locations. Both the total floor area and parking location variables had strong correlations with the vehicle type and vehicle arrival time variables.

As a result, we removed the total floor area and parking locations from our models and ensured that the association does not exceed the Cramer's V value of 0.3 among explanatory variables [9, 40].

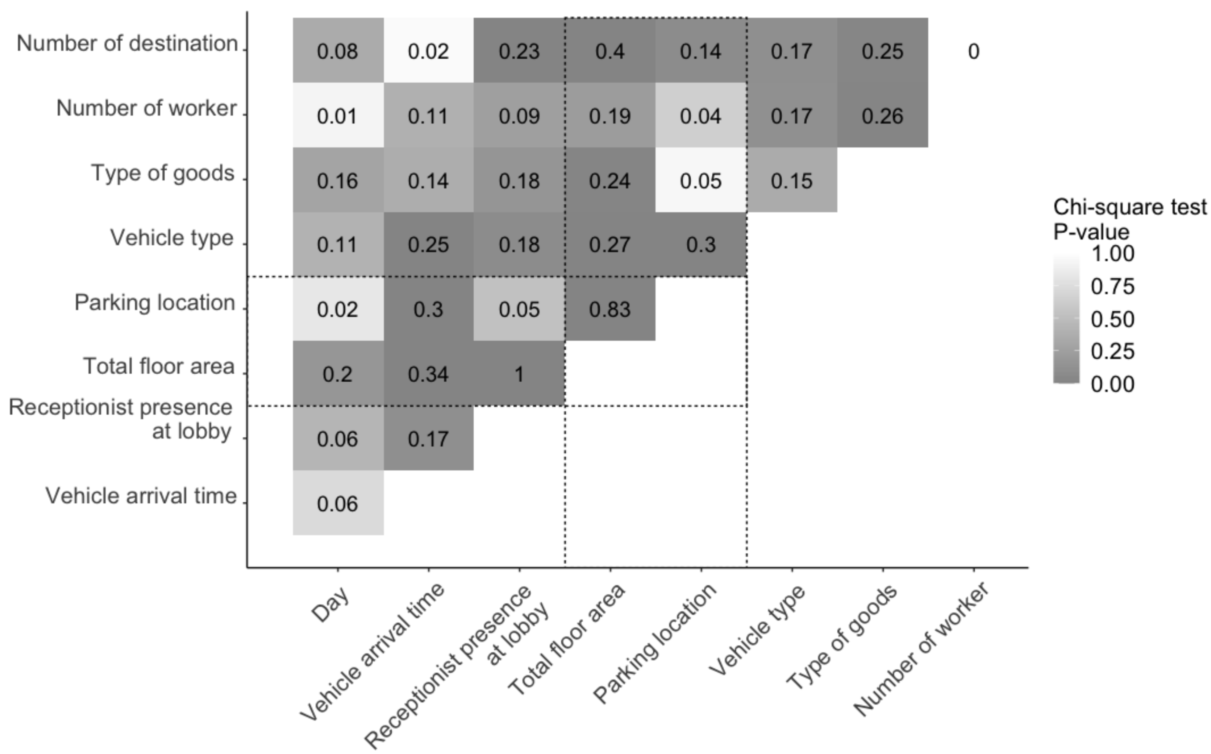


Figure 5.6: Correlation between explanatory variables

5.3 Regression model results

The full models contained days of the week, vehicle arrival time, receptionist presence at lobby, vehicle type, type of goods, number of workers, and number of destinations within a building as independent variables. Using a stepwise algorithm ('stepAIC' function with both directions in MASS package) for feature selection, the full models were further refined into the refined models that include valuable variables that are significantly or marginally correlated with dwell times [132]. To examine the model assumptions for the final models, the 'simulateResiduals' function in the DHARMa package was used to plot residual diagnostics [68].

Different types of models (i.e. Linear, Log-linear, Gamma regressions) were generated for model comparison. For all of our dwell time models, the linear and log-linear models showed the worse fit than the Gamma model. The Gamma model showed the least negative log-likelihood value, indicating the best fit in estimating coefficients with minimal errors.

5.3.1 Combined dwell time models - using data from all five buildings

The combined data (n=157) from the five buildings was used for the models in this section and referred as 'combined dwell time models' throughout the paper. The results are summarized in Table 5.3. The days of the week, vehicle arrival time, and number of workers were not significant in explaining dwell times for commercial vehicles. However, receptionist presence at lobby, vehicle type, type of goods, and number of destinations within a building were significantly associated ($p < 0.05$) with dwell times. Residual diagnostics plots (shown in Figure 5.7) and Nagelkerke pseudo-R-squared values showed strong goodness of fit for both full and refined dwell time models. The refined model showed lower Alkaike Information Criterian (AIC) value, indicating a better fit. Therefore, the refined model was chosen as the final model, and results were analyzed based on the refined model.

The estimates from the refined model (see Table 5.3) showed that deliveries to the buildings with receptionist presence at the lobby were significantly correlated with a 44 % shorter dwell time than deliveries to buildings without a receptionist. Deliveries made by passenger vehicles had 44 % shorter dwell times than deliveries made by vehicles with roll-up doors (e.g., trucks). Deliveries of documents were correlated with shorter dwell times (36 percent shorter) than deliveries of oversized goods. Deliveries that were delivered to multiple (two or more) destinations within a building had longer dwell times (1.83 times) than deliveries to one destination.

Table 5.4 shows the log-likelihood values for different types of dwell time models with the variables used in the final refined model.

Table 5.3: Results of the combined dwell time models

Variables	Categories	Full model			Refined model		
		Exp(β)	95% CI	p-value	Exp(β)	95% CI	p-value
Intercept		**25.13**	**16.59 - 38.94**	**<0.001**	**22.14**	**17.38 - 28.51**	**<0.001**
Day	Mon, Tues (Ref)						
	Weds, Thurs, Fri	0.80	0.64 - 1.01	0.068	0.80	0.64 - 1.01	0.063
Vehicle arrival time	9:30–11:30 AM (Ref)						
	6:30–9:30 AM	0.90	0.68 - 1.20	0.465			
	11:30 AM–15:00 PM	0.89	0.69 - 1.17	0.410			
Receptionist presence at lobby	No (Ref)						
	Yes	**0.57**	**0.46 - 0.72**	**<0.001**	**0.56**	**0.45 - 0.70**	**<0.001**
Vehicle type	Roll-Up doors (Ref)						
	Swing doors	0.86	0.67 - 1.10	0.214	0.83	0.66 - 1.04	0.109
	Passenger vehicle	**0.58**	**0.40 - 0.88**	**0.011**	**0.56**	**0.39 - 0.82**	**0.003**
Type of goods	Oversized (Ref)						
	Office S.&Parcels	0.87	0.59 - 1.27	0.471			
	Documents	**0.58**	**0.34 - 0.99**	**0.039**	**0.64**	**0.43 - 0.99**	**0.035**
	Food	0.86	0.57 - 1.25	0.420			
Number of workers	One (Ref)						
	Two or more	1.14	0.83 - 1.61	0.419			
Number of destinations	One (Ref)						
	Two or more	**1.87**	**1.40 - 2.52**	**<0.001**	**1.83**	**1.40 - 2.44**	**<0.001**
Nagelkerke Pseudo R^2		0.459			0.444		
Deviance		59.08			60.53		
Log-Likelihood		-541.71			-543.72		
Akaike information criterion (AIC)		1109.4			1103.4		
Sample size (N)		157			157		

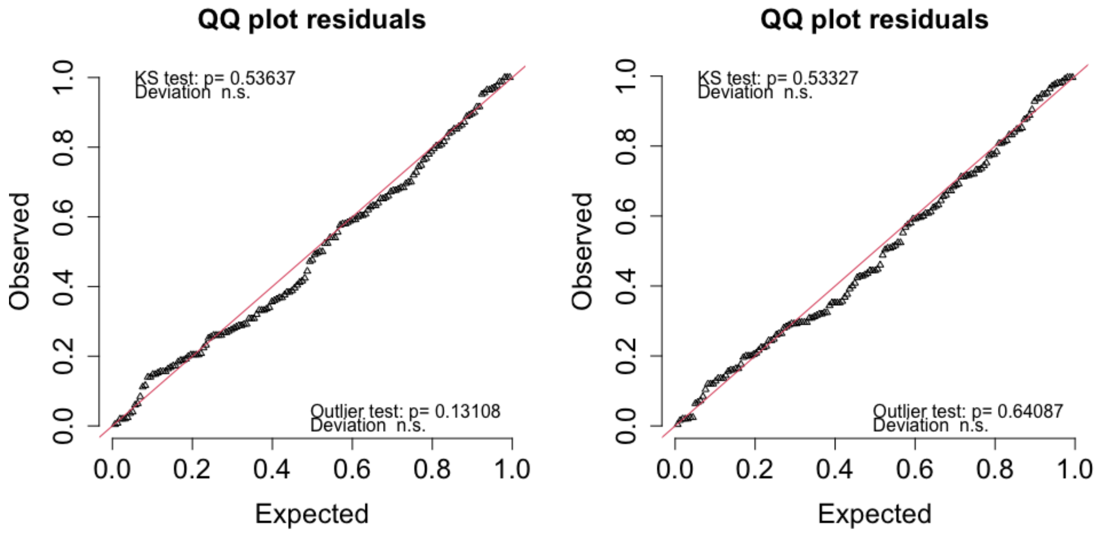


Figure 5.7: Residual diagnostics QQplots for the combined dwell time models - left (full model), right (refined model)

Table 5.4: Combined dwell time model comparison

Model	Log-Likelihood
Linear	-614.38
Log-linear	-614.03
Gamma	-543.72

5.3.2 Dwell time models for each building type

The findings from dwell time models for each building type are summarized in Table 5.5. Apart from the combined dwell time models from the previous section, dwell time models in this section were built for each building type to separately investigate the relationship between independent variables and dwell times for the individual building types. The final dwell time models were selected using a stepwise algorithm. Residual diagnostics plots (shown in Figure 5.8) and Nagelkerke pseudo-R-squared values showed strong goodness of fit for the models.

Because of differences in building configurations and operations, a few independent variables were not controlled for particular building types. For example, at Building B, all deliveries were conducted by one delivery worker and vehicles with swing doors or roll-up doors at the off-street loading bay. Because a full-time staff member received goods at the Building B's loading bay, the number of destinations was always one, as deliveries always went to that single location. Therefore, variables such as vehicle types: passenger vehicle, number of workers, and number of destinations were eliminated for Building B. The vehicle type: passenger vehicle was not included in the model for Building E because no deliveries were observed to be made by passenger vehicles. Nevertheless, although a few variables were not controlled for in some models, significant variables correlated with dwell times were still identified, consistent with the combined dwell time models.

Vehicle type: In the full and refined models from the combined dwell time models, vehicles with swing doors, as opposed to vehicles with roll-up doors, were not significantly but only marginally correlated with dwell times. However, they showed significant associations at Building E and D, respectively. At Building E, dwell times for vehicles with swing doors (e.g., vans) were significantly shorter (55 percent) than those for vehicles with roll-up doors (e.g., trucks). On the other hand, the vehicles with swing doors were significantly correlated with longer dwell times (1.45 times) at Building D. Passenger vehicles in combined dwell time models showed more significant association with shorter dwell times than vehicles with roll-up doors. Passenger vehicles at Building A showed similar but marginal associations with shorter dwell times.

Type of goods: In the full and refined models, deliveries of documents were significantly correlated with shorter dwell times than deliveries of oversized supplies such as furniture and construction materials. Deliveries of documents were significantly and marginally correlated with shorter dwell times for Building C and D respectively. Although the full and refined models showed deliveries for food had no significant association with dwell time, food deliveries at Building E showed a significant association with shorter dwell times than oversized supplies.

Number of destinations: For all buildings except Building B, deliveries with two or more delivery destinations showed significant associations with longer dwell times (range between 1.48 and 2.62 times) as compared to deliveries that go to a single destination. These findings aligned with the combined dwell time model results, which showed significant associations with a longer dwell times (1.83 times).

Both the combined dwell time models and dwell time models for each building type revealed that the significant variables related to dwell times were vehicle type, type of goods, and number of destinations, which are discussed further in the following section.

Table 5.6 shows the log-likelihood and AIC values for different types of models with the variables used in the final refined models.

Table 5.5: Results of the dwell time models for each building type

Variables	Categories	Building A			Building B			Building C		
		Exp(β)	95% CI	p-value	Exp(β)	95% CI	p-value	Exp(β)	95% CI	p-value
(Intercept)		**10.69**	**7.94 - 14.78**	**<0.001**	**11.05**	**5.79 - 23.72**	**<0.001**	**16.84**	**12.79 - 22.80**	**<0.001**
Day	Weds, Thurs, Fri				0.58	0.27 - 1.16	0.123			
Vehicle arrival time	11:30 AM–15:00 PM	0.71	0.47 - 1.06	0.111	0.49	0.20 - 1.30	0.109			
Vehicle types	Passenger vehicle	0.61	0.39 - 0.99	0.052						
Type of goods	Office S.&Parcels							0.65	0.39 - 1.12	0.118
	Documents							**0.38**	**0.18 - 0.87**	**0.023**
	Food				1.73	1.01 - 2.94	0.058			
Number of workers	**Two or more**	**2.10**	**1.27 - 3.71**	**0.011**						
Number of destinations	**Two or more**	**2.13**	**1.26 - 3.84**	**0.012**				**2.62**	**1.14 - 6.57**	**0.039**
Nagelkerke Pseudo R^2		0.554			0.240			0.281		
Log-Likelihood		-103.57			-89.44			-96.33		
AIC		219.13			188.89			202.66		
N		35			29			29		

Variables	Categories	Building D			Building E		
		Exp(β)	95% CI	p-value	Exp(β)	95% CI	p-value
(Intercept)		**16.73**	**12.16 - 23.47**	**<0.001**	**29.77**	**20.57 - 44.61**	**<0.001**
Day	Weds, Thurs, Fri	0.83	0.60 - 1.15	0.304			
Vehicle types	**Swing doors**	**1.45**	**1.09 - 1.93**	**0.020**	**0.45**	**0.30 - 0.69**	**<0.001**
Type of goods	Documents	0.76	0.50 - 1.18	0.221			
	Food				**0.57**	**0.37 - 0.88**	**0.018**
Number of destination	Two or more	**1.48**	**1.07 - 2.07**	**0.030**	**1.64**	**1.08 - 2.49**	**0.027**
Nagelkerke Pseudo R^2		0.471			0.554		
Log-Likelihood		-95.07			-129.89		
AIC		202.15			269.80		
N		30			34		

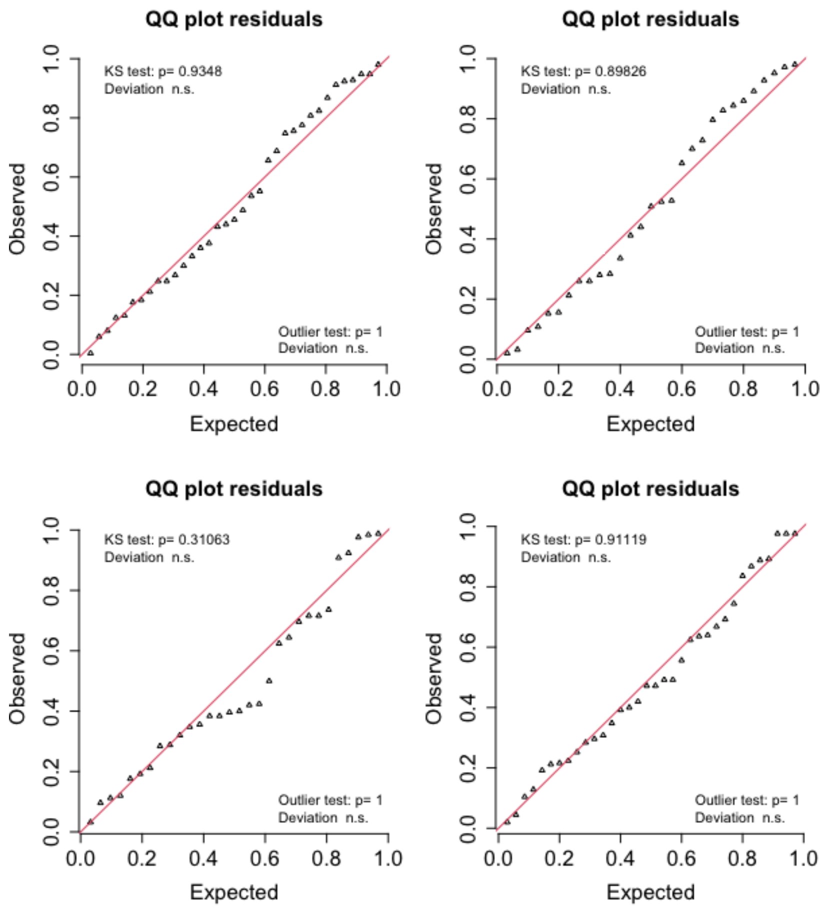


Figure 5.8: Residual diagnostics QQ plots for the five separate dwell time models by different building type (Building A,B,C (top rows from left to right) and Building D,E (bottom rows from left to right))

Table 5.6: Model comparison - five separate dwell time models by different building type

	Log-Likelihood (AIC)				
Model	Building A	Building B	Building C	Building D	Building E
Linear	-113.6 (239.3)	-96.8 (203.6)	-106.9 (221.8)	-99.2 (208.5)	-146.9 (303.9)
Log-Normal	-114.4 (238.9)	-96.5 (203.0)	-106.9 (221.8)	-96.7 (203.4)	-145.9 (301.9)
Gamma	-103.6 (219.1)	-89.4 (188.9)	-96.3 (202.7)	-95.1 (202.1)	-129.9 (269.8)

5.4 Model application

The aim of this study was to examine if there are correlations between commercial vehicle dwell times and characteristics of buildings and deliveries and identify the strength of the correlations. Our analysis showed that there are significant factors that are correlated with shorter or longer dwell times for commercial vehicles. Using data collected at a residential building, a hotel, a historical building, an office building, and a shopping mall in downtown Seattle, we built generalized linear models with attributes that were known to be correlated with dwell times ([90], [115], [38], [13], [138], [165], [44]). Factors such as a receptionist presence at lobby, number of destinations, vehicle type, and type of goods were significantly correlated with dwell times for commercial vehicles. The study shed new light on the effects of these important factors on commercial vehicle dwell time.

5.4.1 Building operations and number of destinations

Dwell times at the buildings with a receptionist presence at lobby were significantly correlated with shorter dwell times as compared to those without. Allen et al. (2000) indicated that the distance from the goods vehicle to the premises being served can influence dwell times [13]. Although there have been several dwell time studies related to commercial vehicles, each study focused on a particular building type (e.g., office buildings [115], shopping malls [44]) or parking location type (on-street parking in New York City [165],[138]). Cherrett et al. (2012) examined the relationship between dwell times and floor areas of different store types (e.g., jewelers, mobile phone stores, food and drink retail) but found no correlations [38]. This motivated us to observe the relationship between dwell times and different building types, rather than business types.

Shorter dwell times were expected for the buildings with a receptionist presence at the lobby, as the physical location for receiving goods was close to the parked vehicles. At Building B, the same loading bay area was used as both a parking location and the drop-off location where full-time concierge staff received goods. Also, dwell times for deliveries to a single destination within a building was significantly correlated with shorter dwell times than deliveries to multiple destinations within a building. The key finding from this result was that not only the physical building characteristics (e.g., location of loading bays, freight elevators) but also delivery operations within buildings can strongly influence dwell times for commercial vehicles. When parking policies are implemented, it is important to consider their relationship with building operations for handling deliveries, as building operations within different buildings can greatly influence dwell time for commercial vehicles.

5.4.2 Vehicle type

Consistent with previous dwell time studies ([165],[44],[138]), vehicles with swing doors (e.g., vans) were correlated with shorter dwell times (significance showed only at Building E) than were vehicles with roll-up doors (e.g., trucks). As we expected, deliveries made by passenger vehicles were significantly correlated with shorter dwell times than were vehicles with roll-up doors, which had not been reported in previous studies. Currently in Seattle, passenger vehicles can be registered as commercial vehicles as company fleets can comprise passenger vehicles. In addition, in recent years, more deliveries have been made by individuals using their own passenger vehicles for deliveries. Documentation of dwell times for deliveries made by passenger vehicles is especially limited. With crowd-sourcing delivery platforms, deliveries by passenger vehicles are certainly growing in number without regulation. The varying levels of influence of different vehicle types on dwell times should be further investigated as more samples are collected.

5.4.3 Type of goods

Deliveries of documents were correlated with shorter dwell times than oversized supplies, as expected. The dwell time model for Building E showed a significant correlation between food deliveries and shorter dwell times. The dwell time model developed by Schmid et al. (2018) [138] using data of on-street parking dwell times in New York City found that deliveries of parcels and food were involved with shorter parking durations than service vehicles and other deliveries. With New York City on-street parking data, Zou (2016) [165] consistently found that food deliveries were correlated with shorter dwell times than other types of deliveries such as furniture.

The knowledge gained from this study can be extended to other cities that have similar types of buildings that attract urban freight activities. In this study, we clearly identified factors that are correlated with dwell times for commercial vehicles and presented detailed data analysis results, along with comparisons with factors found in previous studies.

5.4.4 Parking strategies

Our dwell time models identified factors that can provide good estimates of commercial vehicle dwell times. Being able to estimate commercial vehicle dwell times provides for better predictions of commercial parking needs. Our models provide insights that can enhance parking policies by tailoring time limits and locations based on commercial vehicle needs. Our analysis suggests the following recommendations for the future parking policies; 1) allow passenger load zone use for short commercial deliveries, 2) implement standardized delivery receipt policies aimed to reduce dwell time, 3) consider context-specific commercial vehicle parking time limits. With additional dwell-time studies, cities can develop locally-specific policies that reduce unauthorized parking and its consequences, while best utilizing commercial parking spaces.

1. Allow passenger load zone use for short commercial deliveries

The model results showed that the dwell times were greatly affected by the types of delivery vehicles and goods, and that dwell times for smaller vehicles (e.g., passenger car) were significantly shorter (44% less) than larger vehicles with roll-up and swing doors (e.g., vans, trucks). Deliveries of documents were correlated with shorter dwell times (36% less) than deliveries of oversized goods. Because dwell times for short deliveries are similar to that of passenger drop-offs, allowing passenger load zones for these types of deliveries will allow maximizing the use of passenger load zones, while reserving the limited commercial load zones for longer deliveries.

2. Implement standardized delivery receipt policies aimed to reduce dwell time

Our dwell time models showed that having a receptionist in the lobby is associated with 44% shorter commercial vehicle dwell times. Our models also found that the number of destinations that are two or more locations within a building can result in 1.83 times longer dwell times. Introducing standardized delivery policies such as providing a designated consolidation location (e.g., reception desks, common carrier locker installation at entrances) will reduce the time required to navigate and operate floor-to-floor deliveries inside of buildings. Currently, delivery policies are mostly determined by individual building managers alone. In many cases, different floors or offices in one building may have several different delivery policies for their convenience. Even when there are consolidation areas, they are often haphazardly located. For example, a reception desk can be located on a high floor (e.g., 15th floor) without any consequences from the city. This will lead to high costs for both carriers and cities because carriers are required to learn the specific building configuration to find the location of the reception desk and travel longer routes within the building. Meanwhile, the cities need to manage limited parking facilities for these carriers. In contrast, the locations of mailboxes inside of the urban buildings have been thoroughly considered to be placed conveniently for the United States Postal Service carriers, even before the building construction. With the rapid growth in urban goods movements, consolidation locations such as reception desks or common carrier lockers can be suggested to be designated near main entrances as a standardized delivery policy. With the standardized delivery policies, dwell times can be reduced, as well as more accurately predicted, which will allow planners to better allocate and utilize commercial parking capacity.

3. Consider context-specific commercial vehicle parking time limits

Our five separate dwell time models for each building type showed that significant variables that influence the dwell times can vary by different buildings. Different building types may require longer or shorter dwell times based on the type of goods, vehicle types, number of destinations. This shed new light on the use case for context-specific commercial vehicle parking time limits for commercial vehicle parking. With the current fixed time limits of 30 minutes, we observed Building E had more vehicles that exceeded the parking limits (24%) as compared to Building A (3%). The commercial vehicles may run out of time and have to re-enter the CVLZs because the deliveries at Building E may require more time than those at Building A. This can also be translated into Building A may not require a full parking limit of 30 minutes. Accurate dwell time models like the ones described in this paper can be used for developing context-specific commercial vehicle parking time limits for commercial vehicle parking. The information gained from our dwell time models can enable the cities to develop and apply context-specific commercial vehicle parking time limits. This can also further developed into new parking pricing structures for various types of deliveries or delivery vehicles. This could improve the current one-size-fits-all approach to a more data-driven approach to commercial vehicle parking management.

5.5 Summary

Delivery activities in downtown Seattle were observed at five freight-attracting buildings that include the residential building, the hotel, the historical building, the office building, and the shopping mall. This paper identifies factors correlated with dwell time for commercial vehicles. Generalized linear models with gamma distribution were developed, with commercial dwell time as the dependent variable and several explanatory variables. Dwell times correlated with buildings with concierge services tended to be shorter. As expected, deliveries of oversized supplies tended to have longer dwell times. Deliveries by passenger cars had shorter dwell times. When there were deliveries made to multiple locations within the building, the dwell times significantly increased in comparison to one consolidated delivery.

Our dwell time models provide valuable insights into the correlations between commercial vehicle dwell time and other explanatory variables. Valuable information on factors affecting commercial vehicle dwell time can help in developing future parking strategies. The dwell time model can provide estimated commercial vehicle dwell time with a known delivery day, types of vehicles and goods, whether single or multiple deliveries. Under different policy scenarios, our models can be applied to estimate the percent changes of commercial vehicle dwell time to better understand the effects of the policies on commercial vehicle dwell time. A future goal is to observe these changes based on different policy scenarios using establishment data in a city. Additionally, we plan to apply our dwell time models for optimizing parking operations and building resource allocations. For example, with the estimated dwell times, the number of on and off-street parking lots and the number of receptionists can be optimized based on the number of deliveries made to buildings. At the same time, many logistics and delivery companies can also benefit from estimated dwell time to optimize their delivery routes and the number of deliveries for each delivery worker.

Future improvements can be achieved by expanding the data set by collecting observations around more buildings and for a longer period of time. With a larger data set, the accuracy of the estimates can be enhanced, and specific characteristics could be well-defined. Also, data collection for a long period of time can allow discovering possible temporal differences with respect to seasons, holidays, and weekends vs weekdays. In the future, different types of models (e.g., duration models, etc.) can be developed with the same data set and compared with this generalized linear model results to compare the model performances.

Chapter 6

PREDICTION & OPTIMIZATION OF THE COST DISTRIBUTION FOR ALLOCATING BUILDING AND PARKING RESOURCES WITH INCREASING NUMBERS OF URBAN GOODS DELIVERIES

With rapid global urbanization and the explosion of e-commerce, urban freight efficiency has become highly dependent on the successful management of urban growth and sustainability. Urban freight transport increases accessibility to resources and trade markets by collecting, transporting, and distributing goods within urban areas, playing a crucial role in economic growth and the promotion of sustainable and livable cities [71]. In recent years, urban freight policy has been challenged by the complexity and cost of last-mile deliveries, as well as increasing congestion and pollutant emissions [24]. To better prepare for future urban logistics, researchers have emphasized the importance of innovation in every aspect of traffic management, urban planning, and urban warehouse designs [31]. As past research has recognized that delivery processes rely on transportation networks and systems, the major focus has been on network optimization (e.g., horizontal movement) in last-mile deliveries [134]. However, this has led to a critical research gap in understanding the vertical movements of deliveries (e.g., unloading/loading activities, use of freight elevators, and pick-up/delivery operations) and their impacts on building and parking infrastructure design [89]. Cities' off-street parking requirements are an example of the lack of data-driven approaches to establishing building and parking designs and policies [142]. Through off-street parking policies, building developers are required to provide a minimum number of off-street parking facilities based on the types of development (e.g., residential land use, shopping centers) in addition to on-street parking spaces. Although such parking policies highly impact architecture and urban designs and increase the price of everything around such developments, city planners often propose such design requirements on the basis of instructions from elected officials, other cities' parking requirements, or unreliable surveys, rather than scientific methodologies [142]. A lack of curbside space, because of excessively long stays by delivery workers, can increase urban congestion as other delivery vehicles circle city blocks looking for parking spaces [129]. Not only the number of on– and off-street parking spaces, but also building resources (e.g., number of elevators, building staff) can affect urban freight efficiency significantly. We aimed to close this research gap by providing useful simulation and optimization tools for city planners use to better understand the freight delivery cost dynamics among delivery workers, building managers, and city planners, as well as to estimate adequate numbers of building and parking resources as a way to better to prepare for increasing demand for urban delivery of goods.

Urbanization is key in creating higher demand for goods movement within urban areas, which is expected to grow continuously. In 2018, 55 percent of the world's population lived in urban areas (a significant increase from only 30 percent in 1950), expected to increase to 68 percent by 2050. Most urbanized countries are in North America (82 percent of its population is in urban areas), Latin America and the Caribbean (81 percent), Europe (74 percent) and Oceania (68 percent) [119]. In this analysis UN followed the definition of urban used in each country, according to national statistical offices in the latest available census [119]. Current urban planning practices encourage urbanization by providing effective transit services or promoting sustainable transportation modes such as walking and biking. While urbanization has environmental and social benefits, it also increases the numbers of goods entering into limited urban spaces, creating slower travel speeds, denser roadway networks, and conflicts among pedestrians, bicycles, and mixed traffic [31]. There is often a disconnection between smart growth strategies and recent land-use, building, and urban freight system designs [158]. As population densities increase in cities, constraints to urban deliveries become more severe, especially because more vehicles increase the demand for limited city roads, parking spaces, and vehicle dwell times (i.e., time required to perform deliveries). An increasing number of commercial parking fines issued in New York City, totaling $181.5 million, is an example of the challenges of managing current parking restrictions. It is evidence of a systematic failure in current infrastructure (e.g., building, parking) designs to accommodate rapidly growing numbers of deliveries. Building a strong, data-driven approach to developing urban designs and policies is important as city policy makers constantly seek solutions to better manage future demands for goods and services.

E-commerce is another key to the fast-growth of urban freight transport. Recent advances in new technologies for the internet of things and smartphones have reshaped retail industries, significantly increasing business-to-business and business-to-consumer urban logistic services at unstoppable speeds [24]. E-commerce has become an indispensable part of the retail framework, resulting in sales totaling more than $3.5 trillion worldwide in 2019, representing 14.1 percent of all global retail sales [145, 144]. These amounts are expected to nearly double to $6.5 billion and 22 percent of total retail sales by 2023 [145, 144]. Emerging countries in the Asia-Pacific - mainly China, India, and Indonesia have had significant e-commerce growth, especially China, which had an estimated $1.9 trillion in e-commerce in 2019 [50]. With various online platforms and easy payment choices, customers have ample options for comparing prices and shopping for goods and services online. The growing use of smartphones is also making online shopping more convenient and easier, even when traveling [41]. By 2021, Statista estimates that 53.9 percent of all e-commerce sales will occur on mobile devices [146]. With advanced technology, consumers expect free or low-cost delivery fees and more transparent information about delayed, damaged, or lost packages, as well as easier return procedures [41]. Nguyen et al. (2019) pointed out that consumers' purchase decisions are highly influenced by delivery fees, delivery speeds, time slots and delivery dates, and delivery time windows (e.g., daytime/evening) [120]. The delivery fee is known to influence e-commerce purchases [100, 99]. Lepthien and Clement (2019) found that threshold-based free shipping, however, leads to more returns [99]. As advanced technologies have progressed, consumers' expectation for delivery speeds, delivery time windows, and shipment individualization have reached ever higher standards [24]. This has led to high supply chain costs for corporations and trucking and logistics companies as the costs of shipping goods and services have risen [43]. Without proper design of urban freight infrastructure, unintended consequences such as congestion, high logistics costs, and parking and safety issues will be aggravated, as both urban freight flows and public and private vehicle traffic will inevitably increase [24].

This study applies a multi-objective optimization method, combined with a discrete event simulation (DES), also known as simulation-based multi-objective optimization (SMO) [102]. The process of improving urban freight policies involves trading off optimal solutions that take into consideration multiple variables and objectives [151]. Our DES accounts for complex vertical movements that were noted during field observations in an office building in downtown Seattle, U.S. By building a discrete event simulation model, we first aimed to understand the freight cost relationships among delivery workers, building managers, and city planners. With the SMO, we then estimated the numbers of building and parking resources that could minimize costs associated with freight deliveries for all three parties; delivery workers, building managers, and city planners. Three main objective functions are described in the problem formulation:

1. Minimize the costs for delivery workers.

2. Minimize the costs for building managers.

3. Minimize the costs for city planners.

Infrastructure designs optimized through our proposed method could ultimately benefit both the users (e.g., delivery companies) and planners (e.g. city planners, building managers) of building and parking infrastructure.

6.1 Simulation design

Through simulation models, this research aims to understand the complex cost relationships among delivery workers, building managers, and city planners and evaluated the impacts of increasing demand for urban goods deliveries on parking and building operations.

In a previous study, trained data collectors shadowed delivery workers at freight-attracting urban buildings and collected thee time distributions associated with each delivery task, using a customized mobile app [91]. The details of the data collection process can be found in Kim et al. (2018) [89]. Data collected from downtown Seattle, Washington, U.S., were used to model the final 50 feet of the delivery process in our discrete event simulation model. In Python software (version 3.8), the discrete event simulation was built by using a SimPy package (version 4.0.1). A value stream map was used to create a computer simulation model and represent essential process delivery steps in the final 50 feet. Five important variables (i.e., numbers of on– and off-street parking spaces, security guards, elevators, and receptionists) were selected as decision variables to calculate the costs for delivery workers, building managers and city planners.

6.1.1 Problem formulation

The indices, decision variables, boundaries, input parameters of this model, and cost functions are defined in this section.

Indexes:

i :Index of building staff ($i = 1, \ldots, I$) such as security guard, receptionist

j :Index of building resources ($j = 1, \ldots, J$) such as elevator, off-street parking spaces (e.g., loading bay) for commercial parking

k :Index of on-street parking type such as commercial parking, un-authorized parking (e.g., double parking)

Decision variables:

X_i : Number of building staff types i

X : Vector of the number of building staff types, X = $[X_1, \ldots, X_I]$

Y_j : Number of building resource types j

Y : Vector of the number of building resources types, Y = $[Y_1, \ldots, Y_J]$

Z_k : Number of on-street parking types k

Z : Vector of the number of on-street parking k, Z = $[Z_1, \ldots, Z_K]$

Upper and lower boundaries for decision variables:

l_i : Minimum number of building staff type i

l_j : Minimum number of building resources type j

l_k : Minimum number of on-street parking type k

u_i : Maximum number of building staff type i

u_j : Maximum number of building resources type j

u_k : Maximum number of on-street parking type k

Simulation parameters:

R : Total simulation replications

r : Index for simulation replication (r = 1,...,R)

n : Index for delivery vehicle

N : Total delivery vehicle in a building

m : Index for resources used (can be X_i, Y_j, Z_k, W_o)

$Start$: Arrival time of delivery vehicle

End : Departure time of delivery vehicle

f : Total number of goods that failed to be delivered

$unau$: Total number of unauthorized parking occurrences

c_f : Failed delivery cost

c_d : Labor cost for delivery worker n

c_i : Labor cost for building staff i

c_j : Operational cost for building resource type j

c_k : Operational cost for on-street parking type k

c_{unau} : Environmental cost for unauthorized parking

u_{im} : Utilization rate of resource m for the building staff

u_{jm} : Utilization rate of resource m for the building resource type j

u_{km} : Utilization rate of resource m for the on-street parking type k

Cost functions for DC, BWC, CWC:

Delivery worker's cost estimator:

$$DC(X,Y,Z;\xi)_r = \underbrace{(\frac{\sum_{n=1}^{N}(End_n - Start_n)}{N})_r * c_d}_{\text{Length of stay cost}} + \underbrace{(\frac{\sum_{n=1}^{N}(f)}{N})_r * c_f}_{\text{Failed delivery cost}} \tag{6.1}$$

Building manager's waste cost estimator:

$$\begin{aligned} BWC(X,Y,Z;\xi)_r \\ &= \sum_i \sum_{m=1}^{X_i} c_i * (1-u_{im}) + \sum_j \sum_{m=1}^{Y_j} c_j * (1-u_{jm}) \\ &= \underbrace{(\sum_i X_i * c_i + \sum_j Y_j * c_j)}_{\text{Resource costs}} - \underbrace{(\sum_i \sum_{m=1}^{X_i} c_i * u_{im} + \sum_j \sum_{m=1}^{Y_j} c_j * u_{jm})}_{\text{Utilization cost}} \end{aligned} \tag{6.2}$$

City planner's waste costs estimator:

$$\begin{aligned} CWC(X,Y,Z;\xi)_r \\ &= \sum_i \sum_{m=1}^{Z_k} c_k * (1-u_{km}) + \sum (unau) * c_{unau} \\ &= \underbrace{(\sum_k Z_k * c_k)}_{\text{Resource costs}} - \underbrace{(\sum_k \sum_{m=1}^{Z_k} c_k * u_{km})}_{\text{Utilization cost}} + \underbrace{\sum (unau) * c_{unau}}_{\text{Unauthorized parking cost}} \end{aligned} \tag{6.3}$$

Subject to:

$$l_i \quad \leq \quad X_i \quad \leq \quad u_i \quad \forall i \tag{6.4}$$

$$l_j \leq Y_j \leq u_j \quad \forall j \tag{6.5}$$

$$l_k \leq Z_k \leq u_k \quad \forall k \tag{6.6}$$

$$X_i \geq 0 \quad \forall i \tag{6.7}$$

$$Y_j \geq 0 \quad \forall i \tag{6.8}$$

$$Z_k \geq 0 \quad \forall i \tag{6.9}$$

The mathematical models are explained as follows:

Equation 6.10 is the minimal average cost of delivery workers who make deliveries to the building, where ξ indicates the stochastic effect. The minimal average DC includes two parts: (a) minimum length of stay cost, (b) minimum failed delivery cost. Given each simulation replication r, the average DC of all deliveries is estimated according to Equation 6.1. Therefore, the average DC ($\hat{E}[DC(X, Y, Z; \xi)]$) across multiple replications is predicted with Equation 6.10 and is applied to approximate a true DC performance $f_1(X, Y, Z)$ under a given number of all staff and building and parking resources.

Equation 6.11 is the minimal average building manager's costs, where ξ indicates the stochastic effect. The minimal average BWC includes two parts: (a) minimum building resource costs, (b) maximum utilization costs for building resources. Given each simulation replication r, the average BWC of all deliveries is estimated according to Equation 6.2. Minimizing total BWC will result in minimizing resource costs and maximizing the utilization rate simultaneously. Therefore, the average BWC ($\hat{E}[BWC(X, Y, Z; \xi)]$) across multiple replications is predicted with Equation 6.11 and is applied to approximate a true BWC performance $f_2(X, Y, Z)$ under a given number of all staff and building and parking resources. It is important to note that the proposed cost structure for the receptionist (X_2) in building manager's waste cost considers only the cost dedicated for receiving goods and does not account for their opportunity costs for performing productive tasks other than receiving goods. Therefore, the concept of receptionist can be simply considered as the concept of having a parcel locker system or a consolidation location (with the same service time of receptionists) that is solely dedicated to receiving parcel deliveries without opportunity costs.

Equation 6.12 is the minimal average costs for city planners who manage on-street parking and unauthorized parking, where ξ indicates the stochastic effect. The minimal average CWC includes three parts: (a) minimum on-street parking operational costs, (b) maximum utilization costs for on-street parking spaces, and (c) unauthorized parking cost. Given each simulation replication r, the average CWC of all deliveries is estimated according to Equation 6.3. Minimizing total CWC will result in minimizing resource costs and maximizing the utilization rate for resources simultaneously. Additionally, the total unauthorized parking number is multiplied by the environmental costs, as unauthorized parking will affect the surrounding environment (e.g., congestion, noise, etc.). Therefore, the average CWC ($\hat{E}[CWC(X, Y, Z; \xi)]$) across multiple replications is predicted with Equation 6.12 and is applied to approximate true CWC performance $f_3(X, Y, Z)$ under a given number of all on-street parking resources.

6.1.2 Problem description

This study looked at the process flows in the final 50 feet of urban freight deliveries (see Figure 6.1). The delivery workers arrival interval times and service times for each delivery followed specific stochastic distributions based on field observations. Our model presumed that the type of resources such as building staff (e.g. security guard, receptionist) and resources (e.g. parking, elevator) does not change dynamically over time. Under such pre-established conditions, the simulation model was studied. The building and parking resources that were used in this work included the number of building staff (X_1 = security guard, X_2 = receptionist), the number of building resources (Y_1 = off-street parking, Y_2 = elevator), and the number of on-street parking spaces (Z_1 = on-street parking).

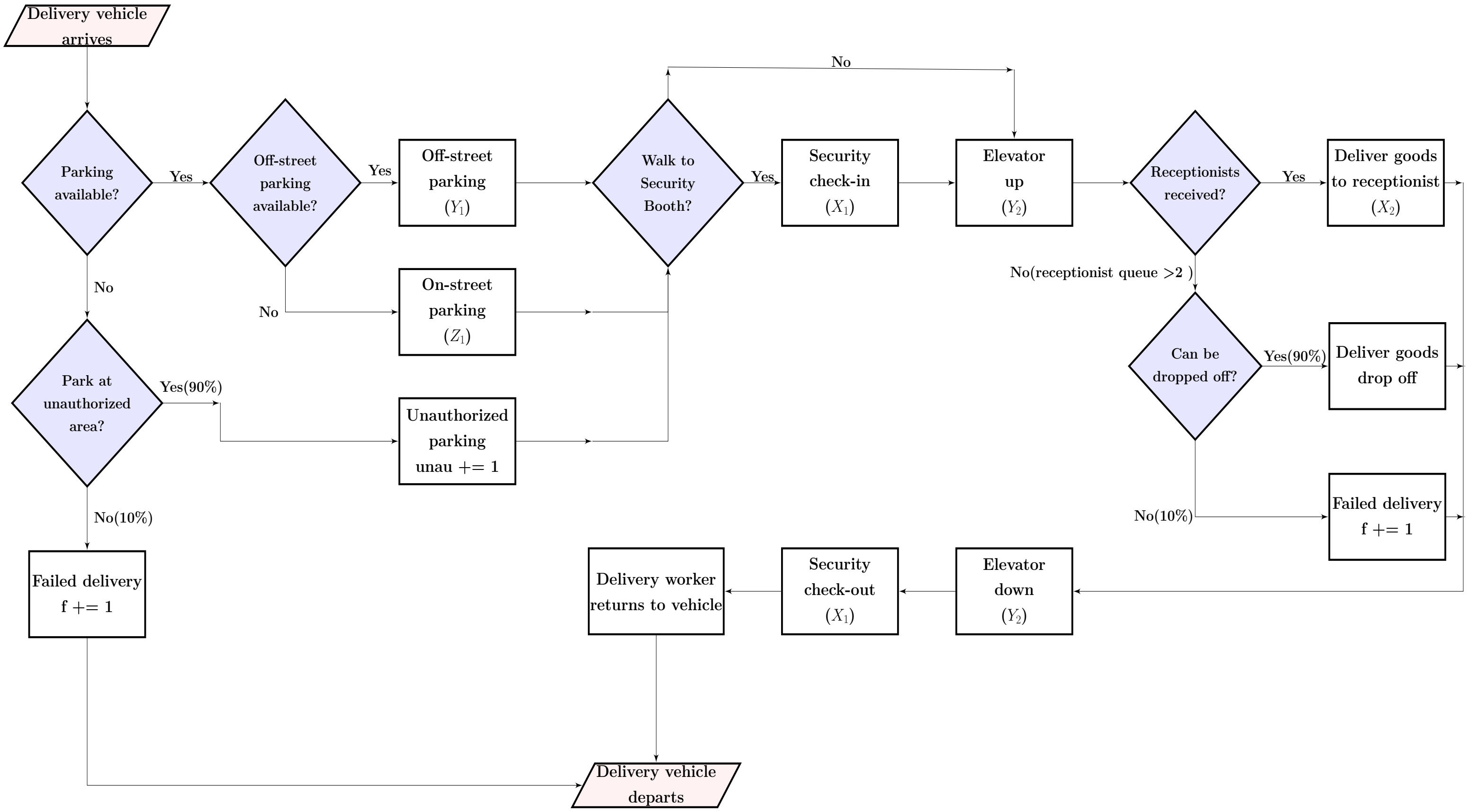


Figure 6.1: Simplified Delivery Process Flow Map

6.1.3 Delivery flow

Delivery workers' out-of-vehicle activities inside urban buildings were simulated based on field observations from an office building in downtown Seattle. Time in the system was categorized into two sections: time associated with parking activities and dwell time (the moment when the vehicle was parked until the vehicle left the site). Figure 6.2 shows the definitions of parking and dwell time referred to in this paper.

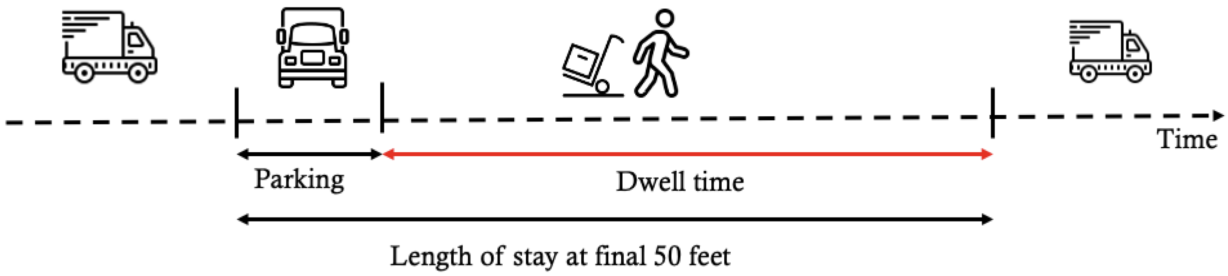


Figure 6.2: Definitions of parking and dwell time

When a delivery worker arrived at the building, on-street and off-street parking spaces were filled first. Both on– and off-street parking were assumed to have no queue, reflecting real-world commercial vehicle parking behaviors. When both on– and off-parking spaces were full, delivery workers were assumed to park at unauthorized areas or leave the building, failing to deliver. Because resources such as security check-in and elevators had to be used in each direction when the building was entered and exited the building, the resources were shared between delivery workers who entered and exited the system. For example, when there were queues at the security booth and elevator, the queues were formed in a first-in-first-out (FIFO) method, containing a mixture of delivery workers entering or exiting the system. Figure 6.1 shows the overall process flow of the simulation model, and the delivery flows are described as follows.

1. Arrival: Delivery workers can park either at off-street parking or on-street parking. In case there is no parking lot available, delivery workers have the option to park at an unauthorized parking area (90 percent of the time) or leave the building which result as a failed delivery (10% of the time).

    1.1. Once parked, delivery workers take time unloading their goods.

    1.2. When unauthorized parking occurs, delivery workers spend extra time walking from the vehicle to the building.

1.3. They walk from the vehicle (or building entrance) to a security booth.

2. Security check-in: Most delivery workers go through a security check-in to obtain a guest pass to the building. Some bypass security check-in as they perform regular deliveries (e.g., UPS, FedEx, etc.).

   2.1. Once checked in, they walk from security booth to elevator.

3. Elevator up: All delivery workers take an elevator up to their delivery destination. Based on the capacity of an elevator, other delivery workers may be required to wait till others finish using the elevator either up or down.

   3.1. They walk from the elevator to a delivery destination.

4. Delivery: Delivery workers can deliver goods to a receptionist. If the receptionist has a queue greater than two, delivery workers either drop off without a receptionist (90 percent of the time) or fail to deliver (10 percent of the time).

   4.1. They walk from the delivery destination to the elevator.

5. Elevator down: All delivery workers take an elevator down. On basis of the capacity of an elevator, other delivery workers may be required to wait till others finish using the elevator up or down.

   5.1. They walk from the elevator to the security booth.

6. Security check-out: Delivery workers are required to return the guest pass that they obtained when entering the building.

   6.1. They walk from the security booth to their vehicle.

   6.2. Once returned to their vehicle, delivery workers take time loading their tools (e.g., dollies)

7. Departure: Delivery workers leave the site.

Several parameters for the simulation were set up according to the cost parameters in Table 6.1 and processing time distributions in Table 6.2. The labor costs and time distributions were estimated based on the real-world observations and the Seattle area's average labor costs for each occupation according to the U.S. Bureau of Labor Statistics [4]. Operational cost and costs for failed delivery and unauthorized parking were assumed as shown in Table 6.1. Table 6.4 indicates the resource limit parameters, that is, the maximum and minimum amounts of each resource.

A past study found that the average construction costs for parking structures in 2015, excluding land cost, was about \$24,000 per space for above ground parking and \$34,000 per space for underground parking [142]. In 2017, Sound Transit, a public transit agency serving the Seattle metropolitan area in the U.S., estimated \$100,000 per space for park and ride facility, including high land prices and a contractor's market [104]. To provide more realistic options, the costs of on– and off-street parking spaces and elevators included operational costs only, rather than the costs for building new infrastructure (e.g., constructing new parking spaces or installing a new elevator). This means that our scope of work was limited to the re-allocation of existing infrastructure, rather than building new infrastructure, based on the optimized numbers. For example, when the optimized number of parking spaces or elevators is smaller than the current system, city or building managers can decide to transfer the use of parking spaces that were dedicated for commercial vehicles to passenger vehicles or use of freight elevators to passengers, etc., rather than removing the current infrastructure. Therefore, the model results can be still valuable to policy makers for allocating existing resources.

Table 6.1: Resource limit parameters of each building and parking resource

Model resource	Cost ($)
Labor cost of delivery worker	$20 per hour
Labor cost of receptionist	$18 per hour
Labor cost of security guard	$16 per hour
Cost of failed delivery	$30
Operational cost of on-street parking	$1 per hour
Operational cost of off-street parking	$1 per hour
Operational cost of elevator	$1 per hour
Cost of unauthorized parking	$20

Table 6.2: Processing times of each activity within the simulation model

Activity	Processing/Service times (minutes) Triangle distribution (min, mode, max)
On-street parking	Triangle(9, 12, 165) / 60
Off-street parking	Triangle(12, 12, 67) / 60
Walking from unauthorized parking to building	Triangle(5, 8, 20)
Walking from truck (or building entrance) to security booth	Triangle(4, 8, 102) / 60
Security booth	Triangle(2, 9, 156) / 60
Unloading goods from truck	Triangle(20, 30, 300) / 60
Elevator	Triangle(4, 35, 635) / 60
Walking from elevator to destination	Triangle(10, 20, 200) / 60
Receptionist	Triangle(3, 11, 404) / 60
Walking from destination to elevator	Triangle(3, 20, 200) / 60
Walking from elevator to security	Triangle(3, 18, 97) / 60
Loading a tool back to vehicle	Triangle(5, 30, 100) / 60

6.2 Simulation results

The simulation period for this study lasted 8 hours (480 minutes). The first 1 hour (60 minutes) of the simulation constituted the transient period, and the remaining 7 hours represented the steady period. Experimental data were collected during the latter period. The reliability of the simulation results was ensured by applying a sufficient replication number control (n = 100). Currently, four delivery workers per hour were assumed to arrive at the modeled building. The current resource allocations for the building had seven off-street parking spaces (see Figure 6.3), eleven on-street parking spaces, one security guard, four receptionists, and two freight elevators. Multiple simulation runs with various arrival rates of delivery workers were performed to understand the impact of increased numbers of deliveries at an urban building.

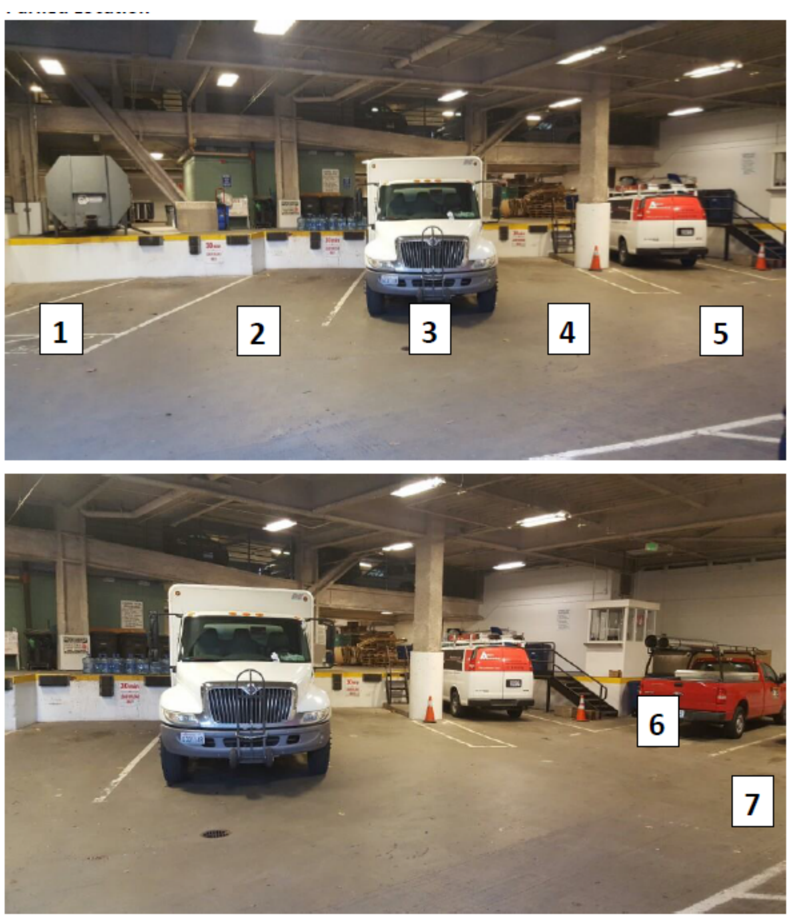


Figure 6.3: Loading bay with seven off-street parking spaces

6.2.1 Validation and verification of the simulation model

To confirm that the delivery process simulation model is an appropriate model that can accurately reflect and represent the conceptual model, the following validation and verification processes were employed.

1. Validation process: The model was mainly developed on the basis of real-world observations of an urban building in Seattle, Washington. Our data collection processes allowed us to obtain very detailed time distributions and delivery task sequences for multiple urban goods deliveries. We also conducted iterative discussions with repre-

sentatives from industry experts from logistics companies who were members of the Urban Freight Lab under the Supply Chain Transportation and Logistics Center at the University of Washington [7].

2. Verification process: This model can trace delivery workers' flows step by step through a time-advance mechanism and can produce simulation animation by printing customized messages for each different step in the model. Multiple checking procedures on the behavior of the model were performed to ensure the quality of the model.

6.2.2 Cost distributions with various arrival rates of delivery workers

The simulation results with various arrival rates are summarized in Figure 6.3. Delivery arrival rates were increased and decreased from the current arrival rate (four deliveries per hour). As expected, the lowest cost for delivery workers resulted when the delivery rate decreased to two deliveries per hour. This makes sense, as there were no queues at the resources, resulting in the shortest average dwell time for delivery workers. On the other hand, building waste costs were the highest because the resources were idling until deliveries arrived at the building. Therefore, the cost for delivery workers kept increasing as the delivery arrival rate increased. Similarly, building waste costs decreased as resource utilization increased with increased numbers of delivery rates until the system overflowed at the rate of 18 deliveries per hour. The high number of queues concentrated at one location (e.g., the elevator), resulted in idling at other locations (e.g., reception). We observed the lowest waste cost for city planners at the arrival rate of ten deliveries per hour. This means that the arrival rate of ten deliveries per hour was the point at which on-street parking was highly utilized, with no or minimum instances of unauthorized parking. The CWC increased again at the arrival rate of 12 deliveries per hour, as the instances of unauthorized parking increased.

With an increased number of deliveries, our simulation model allowed us to better understand the cost relationships among delivery workers, building managers, and city planners. The results showed that the current numbers of resources allocated at the urban building were not designed for the current arrival rate of four deliveries per hour. For example, the current building and parking resources were not utilized at 100 percent capacity with the current arrival rate of four deliveries per hour. We can visualize this by exploring the utilization rate of the resources.

Table 6.3: Simulation results regarding dwell time and cost distribution

Delivery arrival rate (per hour)	Average dwell time (min)	DW ($)	BWC ($)	CWC ($)
2 (lowest cost for delivery workers)	17.5	5.7	605.2	87.7
4 (current arrival rate)	17.7	6	602.8	87.5
6	18.4	6.2	600.5	87.2
8	19.2	6.4	598	86.9
10 (lowest cost for city planners)	20.6	7.1	596.5	86.6
12	24.5	8.1	593.7	89
14	28.4	9.5	591.3	105
16 (lowest cost for building manager)	35.7	12.9	586.4	289.3
18 (system overflow- bad for all)	48.1	15.8	587.7	626.1

Note: Holding decision variables constant at current conditions (X_1=1, X_2=4, Y_1=7,Y_2=2, Z_1=11)

6.2.3 Utilization of resources

At the current arrival rate of four deliveries per hour, the resource utilization rates are visualized in Figure 6.4. As expected, the current numbers of on-street (n = 11) and off-street (n = 7) parking spaces were being used at less than 20 percent of their capacity. Although the security guard (n = 1) was in service at almost 100 percent of capacity, elevators (n = 2) were in service at 60 percent of their capacity, and receptionists (n = 4) were in service at 30 percent of their capacity.

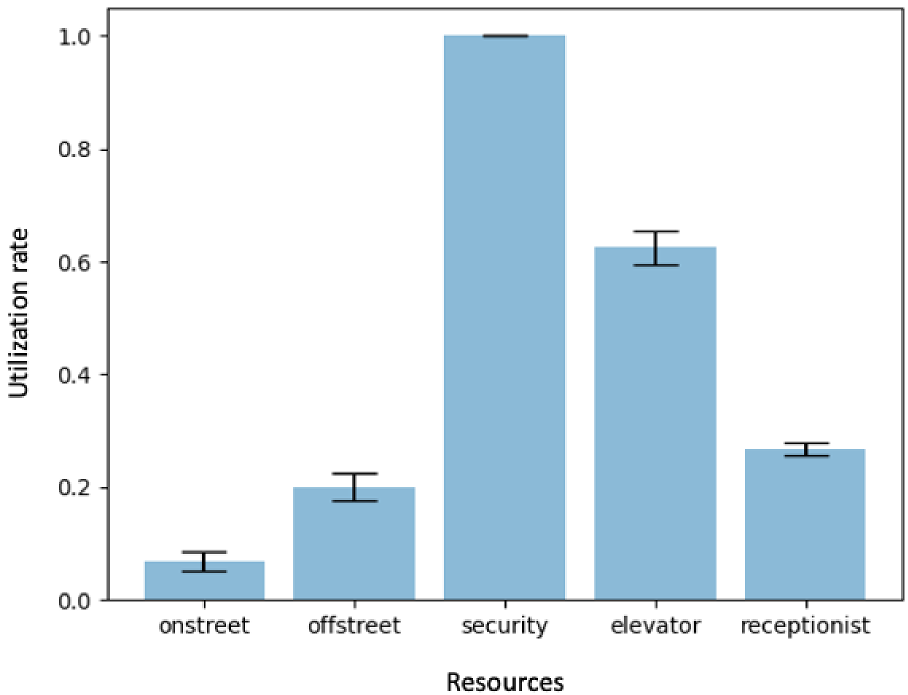


Figure 6.4: Utilization rate of building and parking resources at the arrival rate of 4 deliveries per hour

From the simulation, we could also observe how each resource was utilized by calculating cumulative average counts for active resources over the simulation run time. The usage of resources can also be expressed as instantaneous usage, showing the number of resources in use for a certain period of service time (e.g. shown as spikes each time resources are being used) over simulation run time. In this analysis, cumulative average counts were shown (instead of instantaneous usage). Cumulative average counts can be understood as the average number of resources that are in use on average over the simulation run. For example, when the resources are being used at their capacity for the entire simulation run, then the cumulative average counts would be increased to their capacity quickly at the beginning of the simulation run (but still gradually increase at the beginning) and would stay close to the capacity for the entire simulation run.

In Figure 6.5 and 6.6, each line represents one simulation run. They show the cumulative average counts of on– and off-street parking spaces over time in green. As stated before, we assumed that there was no queue for parking resources. The capacity limits are shown in dotted blue in the figures. As expected, usage of parking spaces increased as delivery arrival rates increased. At the current arrival rate of four deliveries per hour, on– and off-parking spaces were far too many and were underutilized, at far lower than their capacity.

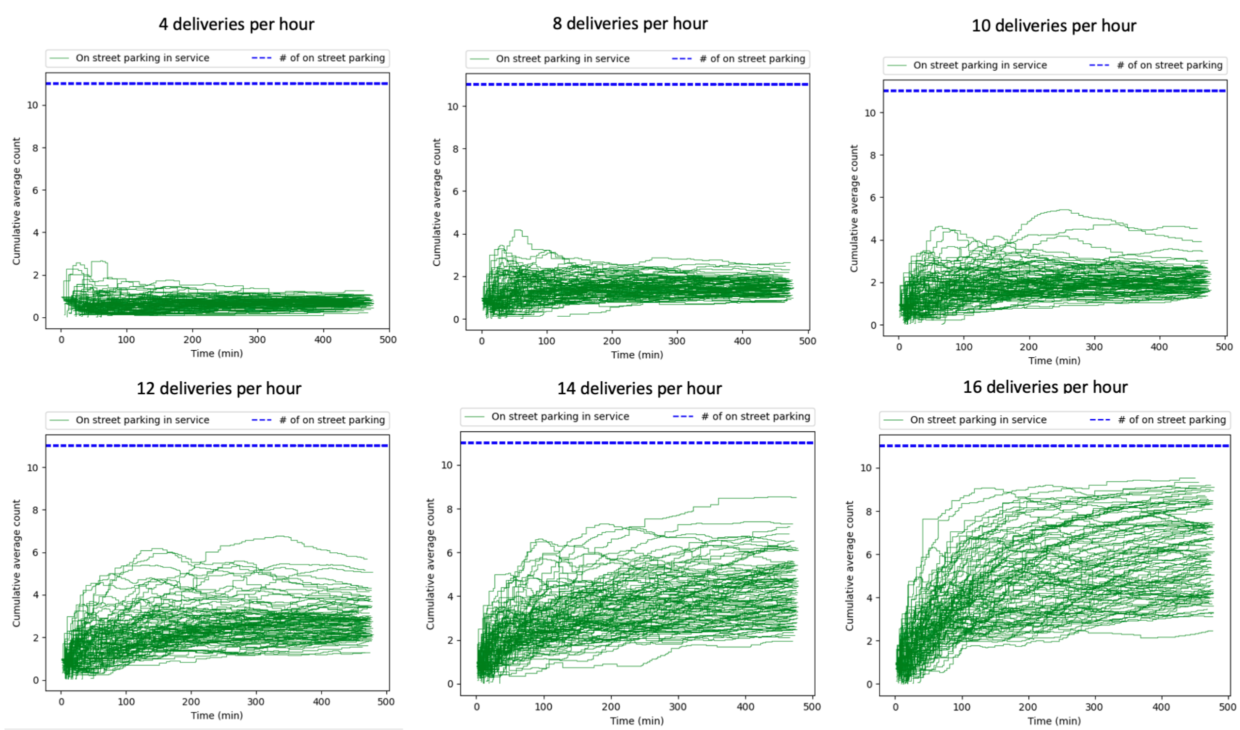


Figure 6.5: On street parking space usage

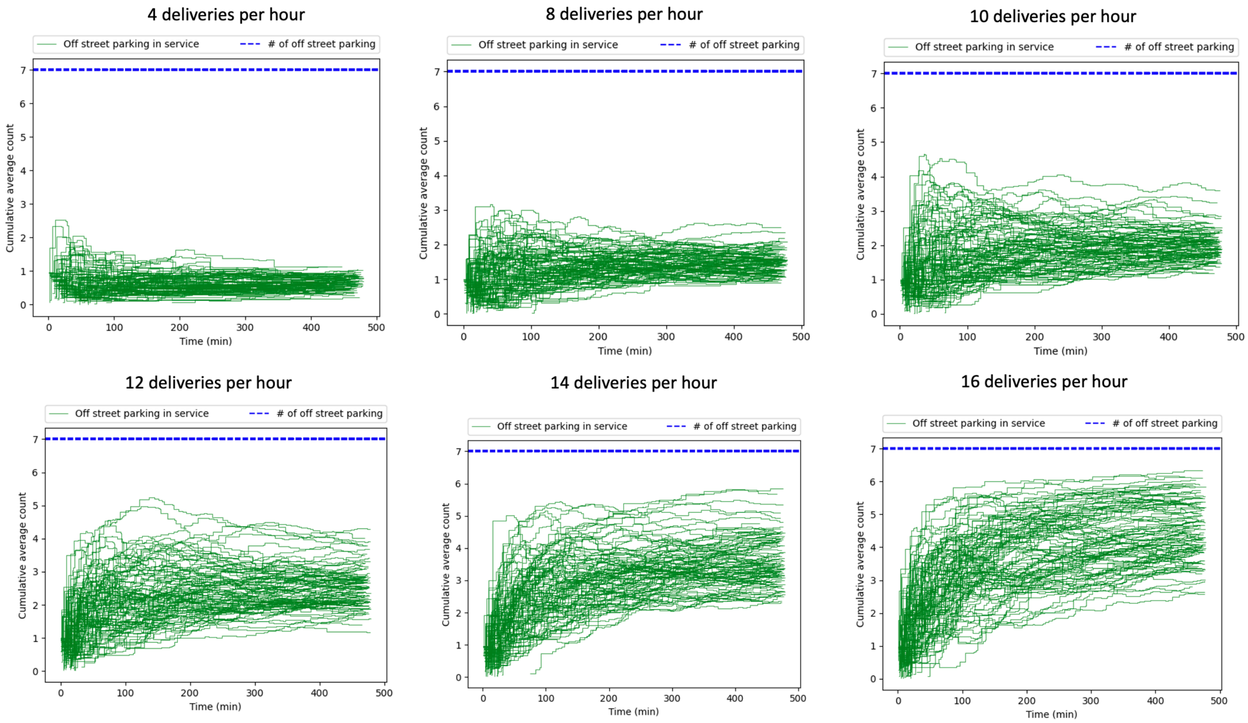


Figure 6.6: Off street parking space usage

Figures 6.7 and 6.8 show the cumulative average counts of security booth and elevator in green and queues in red. Although many queues were generated at the security booth over time, the overall formation of queues did not exceed its capacity most of the time. This is probably because delivery workers spent time loading goods before checking in at the security booth between each delivery, leaving some breathing time for the security guard to check in each delivery worker. Also, some delivery workers could bypass the security guard based on their status (e.g., regular delivery workers such as UPS or FedEx). On the other hand, we can see that the queues at elevators accumulated more than their capacity at the arrival rate of ten deliveries per hour. At 16 deliveries per hour, the average queue length reached up to 20, showing that the elevators were the bottleneck of the current system.

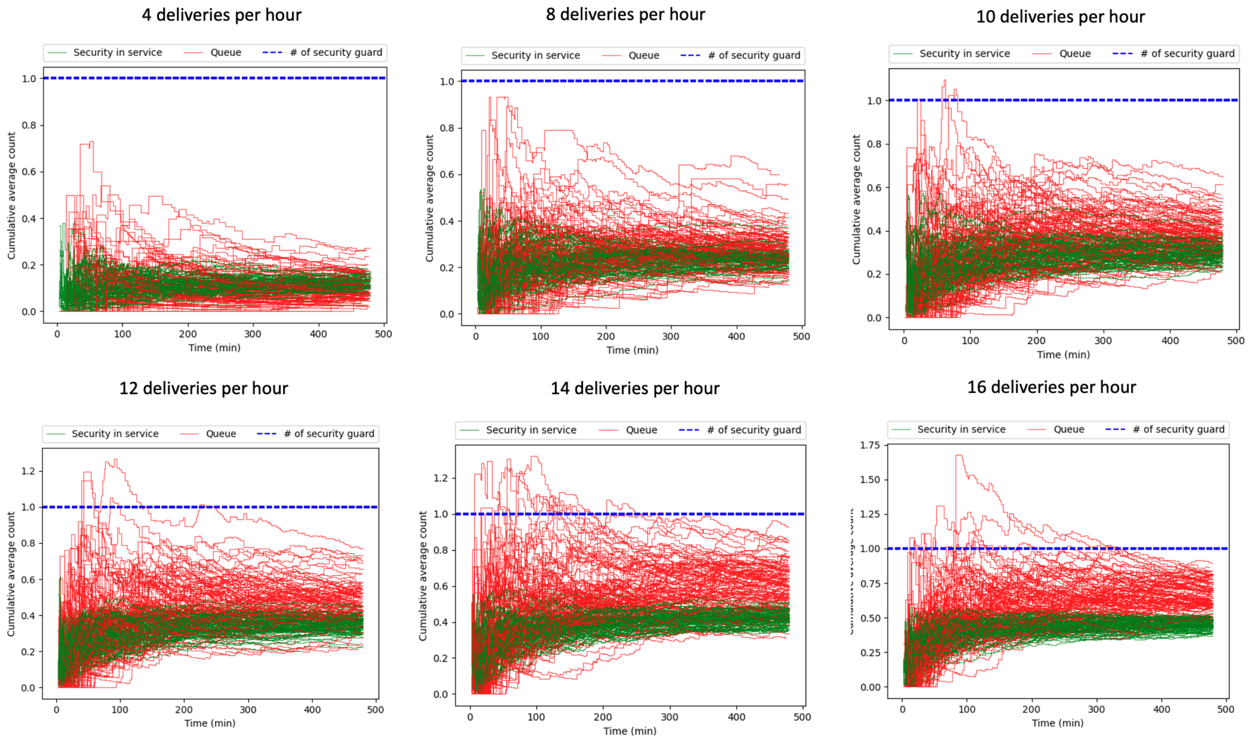


Figure 6.7: Security booth usage

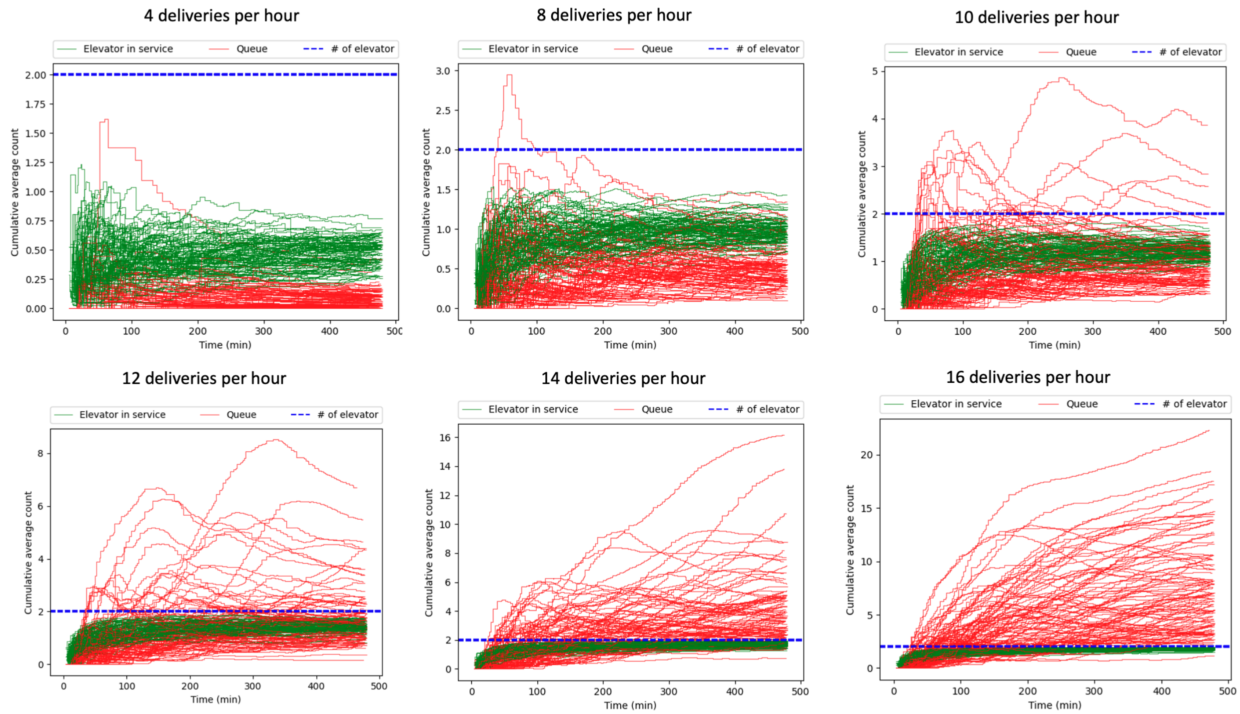


Figure 6.8: Elevator usage

6.2.4 *Failed deliveries and unauthorized parking*

Failed deliveries and unauthorized parking occurred when both on– and off-street parking spaces were full. Additionally, failed delivery could occur when the queue at the receptionist desk was more than two. Figures 6.9 and 6.10 show the cumulative occurrences of failed deliveries and unauthorized parking. Each red line represents each simulation run. Failed deliveries and unauthorized parking started to occur at the arrival rate of 12 deliveries per hour. As expected, as the delivery arrival rate increased, failed delivery and unauthorized parking occurrences increased.

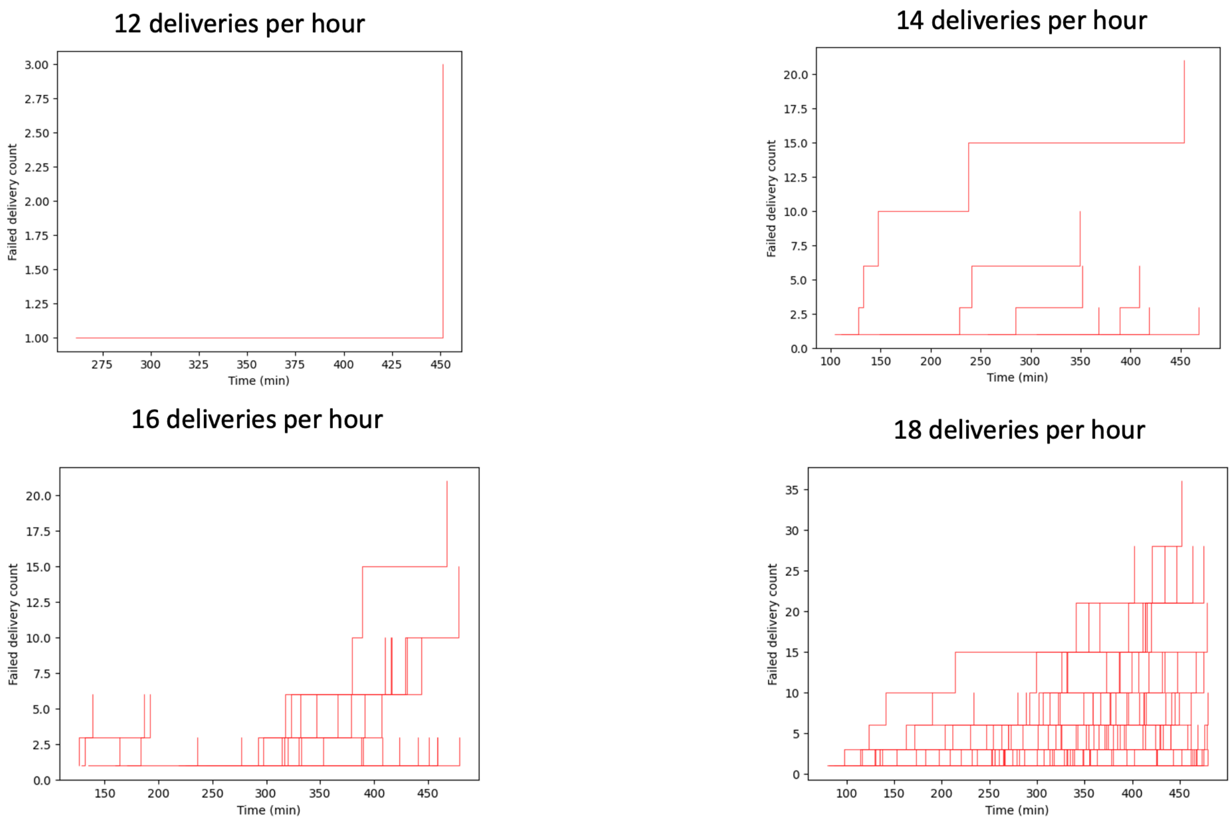


Figure 6.9: Cumulative occurrences of failed deliveries over simulated time

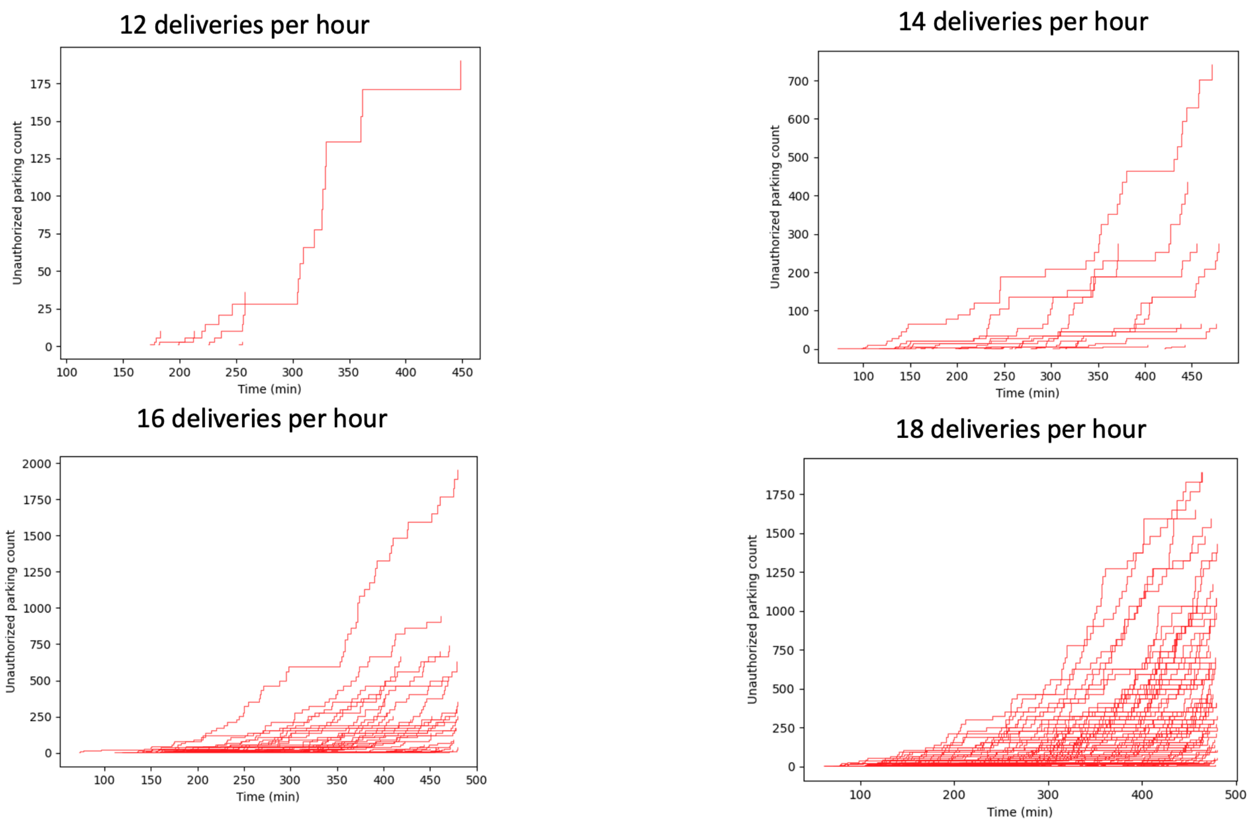


Figure 6.10: Cumulative occurrences of unauthorized parking over simulated time

6.3 Multi-objective optimization design and algorithm

The simulation model results showed that the current building and parking resource allocation system is not designed ideally for the resources (e.g. not at their capacity). When more than 10 deliveries per hour arrive at the current system, the elevator started to suffer, showing the constant queues while the number of on– and off-street parking spaces shows no signs of problems. This means that even if the number of parking spaces are increased due to a high number of deliveries in the future, the bottlenecks of the system are just pushed to the building resources, such as elevators in our case. This emphasizes the importance of collaboration among delivery workers, building managers and city planners because the delivery systems are linked from the street curbs to building elevators. The costs functions from the simulation model show the conflicting objectives of delivery workers, building managers and city planners (see Table 6.3). When there are multiple-objectives, simulation-based multi-objective optimization is known to search for trade-offs between several conflicting objectives to find the optimal solutions [46]. For the future infrastructure designs, we estimated the numbers of building and parking resources that could minimize costs associated with freight deliveries for all three parties; delivery workers, building managers, and city planners. Three main objective functions for this multi-objective problems are shown below.

Multi-objective functions:

1. Minimize delivery worker's costs (DC):

$$f_1(X,Y,Z) = \hat{E}[DC(X,Y,Z;\xi)] = \frac{\sum_{r=1}^{R} DC(X,Y,Z;\xi)_r}{R} \tag{6.10}$$

2. Minimize building manager's waste costs (BWC):

$$f_2(X,Y,Z) = \hat{E}[BWC(X,Y,Z;\xi)] = \frac{\sum_{r=1}^{R} BWC(X,Y,Z;\xi)_r}{R} \tag{6.11}$$

3. Minimize city planner's waste costs (CWC):

$$f_3(X,Y,Z) = \hat{E}[CWC(X,Y,Z;\xi)] = \frac{\sum_{r=1}^{R} CWC(X,Y,Z;\xi)_r}{R} \tag{6.12}$$

Given restricted numbers of building and parking resources, this study aimed to search and obtain the most viable solutions for allocating adequate amounts of resources to better prepare future demand. Twelve deliveries per hour was set as the future delivery demand for our optimization model because we started to see the prominent bottlenecks in the simulation model with the current building and parking allocations. To improve the current system, we searched for optimal numbers of resources within the lower and upper limits shown below.

Table 6.4: Resource limit parameters of each building and parking resource

	Lower limit (LL)	Upper limit (UL)
Number of security guard	1	4
Number of receptionist	1	4
Number of off-street parking	2	10
Number of elevator	1	2
Number of on-street parking	2	15

A multi-objective optimization model was formulated to identify optimum numbers of parking spaces, staff, and elevators to minimize freight delivery costs for city planners, building managers, and delivery workers. Given the large solution space (4*4*9*2*14 = 4,032) and multi-objective nature of our model, this study applied two multi-objective evolutionary algorithms: 1) the population-based NSGA II to search non-dominated solutions (Pareto-optimal solutions) and 2) multi-objective evolutionary algorithm based on decomposition (MOEA/D) through the Pymoo package (version 0.4.1) in R. NSGA II has been used most commonly for multi-objective, simulation-based optimization [22]. Similar multi-objective simulation optimization algorithms have been used for optimizing resource allocation in emergency departments and healthcare systems [52, 75]. In this section, the basic concepts of the selected algorithms are described, while more detailed descriptions can be found in Deb et al. (2002) [45] for NSGA II and in Zhang and Li (2007) [163] for the MOEA/D algorithm.

6.3.1 NSGA II

The non-dominated sorting genetic algorithm (NSGA II) is a population-based algorithm developed by Deb et al. (2002) [45] to search for multiple non-dominated solutions (Pareto-optimal solutions) through evolutionary processes. Multi-objective optimization problems involve conflicting objectives (e.g., one objective increases while the other decreases). Therefore, there is no global solution but a set of solutions.

The first non-dominated sorting generic algorithm (NSGA) was proposed by Deb et al. [45], but three main criticisms followed over the years; 1) the high computational complexity of non-dominated sorting, 2) a lack of elitism, and 3) the need to specify the sharing parameter, σ_{share}, when a parameter-less diversity-preservation mechanism is desirable. The NSGA II algorithm overcomes these drawbacks.

NSGA II is a kind of genetic algorithm, which is an heuristic optimization method inspired by natural evolution that produces better and better approximations. A new population is generated by the process of evaluating individuals based on the fitness levels to identify the elite population (Pareto set) with a non-dominated sorting algorithm [52]. With each generation, the current elite population is selected to generate new offspring through crossover, mutation, and repair operators. The fitness values of the current elite population with the new offspring are reevaluated to create a new elite population. This evolution process is repeated until the approximate non-dominated resource allocation solutions are found (termination condition).

Initialization

The combination of decision variables can be designed as a chromosome or individual. Each chromosome contains segments of decision variables, forming a combination of decision variables. First, the initial population is randomly generated from the minimum and maximum ranges of each decision variable.

Fitness assignment & selection

The initialized population is sorted into each front based on non-domination (elite). A fast non-dominated sorting system partitions all chromosomes into different non-domination fronts. The first front is the completely non-dominant set in the current population, and the second front is dominated by the individuals in the front only. For each front i, all solutions of front (i) always dominate front (i+1). The fitness values are given to each front. For example, the first fronts are assigned fitness values of 1, and the second fronts are given fitness values of 2, and so on (see Figure 6.11). Therefore, the first front is the best level of all fronts among the population.

In addition to fitness value, crowding distance is calculated for each individual, as a new parameter. Crowding distance is a measure of Euclidean distance between two individual chromosomes in the same front based on their multi-objective fitness values. Large average crowding distance will result in better diversity in the population. Parents are selected from the population by using binary tournament selection based on rank and crowding distance.

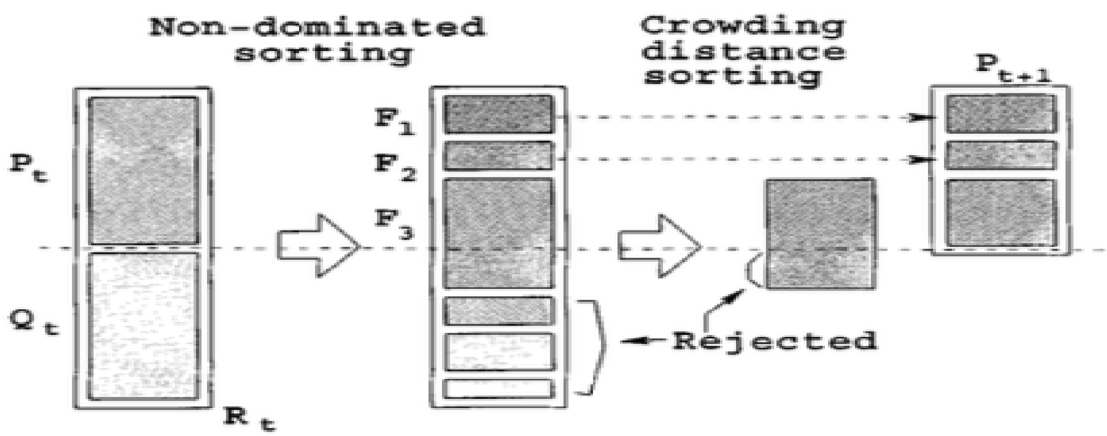


Figure 6.11: NSGA II Procedure [45]

Crossover

The selected population generates offspring with crossover and mutation operators. Crossover is performed to swap parts of a solution with another in chromosomes to provide mixing of the solutions and convergence in a subspace. Crossover occurs on two chromosomes at a time and generates two offspring by combining the features of both chromosomes under a cross over rate, (p_c). There are many different types of crossover. For example, uniform cross-over operates by uniformly selecting genes from either of two chromosomes and copying them to offspring 1, and the remaining genes are copied to offspring 2. By default, NSGA uses the real-coded genetic algorithm simulated binary cross-over (SBX) method, which uses a probability density function that simulates the single-point cross over operator of the binary-coded genetic algorithm. The mixture of population that consists of the current population and offspring is sorted again based on non-domination, and only the best N (population size) individuals are selected.

Mutation

As the crossover operator can generate offspring very similar to the parents, the new generation may lack diversity. As a way to solve this issue, the mutation operator randomly changes the value of some feature of offspring. A random number between 0 and 1 is generated to pick which feature is mutated. If this number is lower than a value called the mutation rate, that variable is flipped. The mutation rate is usually chosen to be 1/m, where m is the number of features. This means we mutate one feature of each individual. For NSGA II, the polynomial mutation is used (further described by Deb and Deb (2012) [47]).

6.3.2 MOEA/D

The multi-objective evolutionary algorithm based on decomposition (MOEA/D) is an evolutionary algorithm that decomposes multi-objective optimization problems to several single-objective sub-problems [163]. MOEA/D attempts to optimize these sub-problems simultaneously. Each sub-problem has its own best solution, which is determined by comparing all solutions found by the algorithm. Among these sub-problems, the neighborhood relations are constructed based on the distances between the aggregation coefficient vectors. Each sub-problem is optimized in MOEA/D by using information from its neighboring sub-problems. We used the penalty boundary intersection method for decomposition which minimizes a penalized distance value of the form $d_1 + \theta \mathrm{d}_2$ for a solution x with respect to a weight w $(\theta = penaltyvalue)[154]. Figure 6.12 shows the distances in penalty boundary intersection method.$

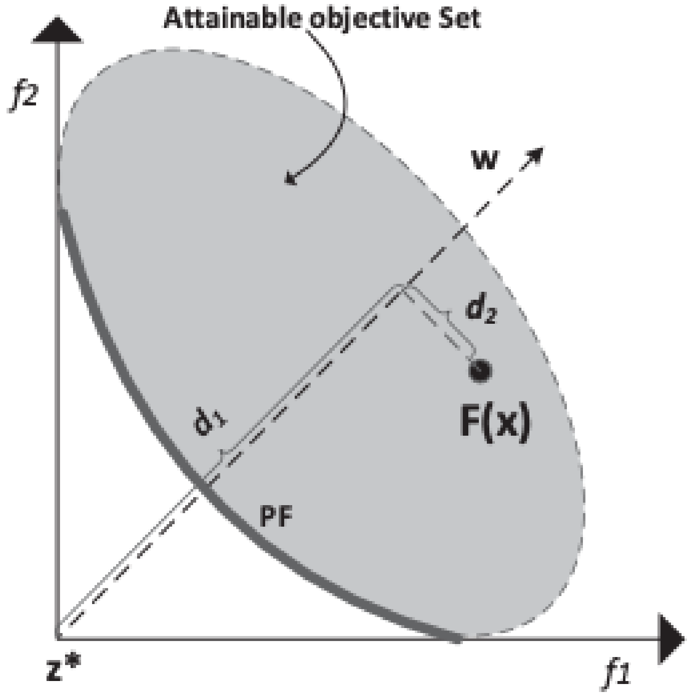


Figure 6.12: The d1 and d2 distances in the penalty boundary intersection method [154]

The major advantages of MOEA/D over Pareto dominance-based MOEAs (e.g. NSGA II) is that single objective local search techniques can be readily used in MOEA/D [125].

6.4 Optimization results

This section summarizes the results obtained by the two optimization algorithms, MOEA/D and NSGA II, to minimize costs for delivery workers, building managers, and city planners. Our optimization models used the delivery arrival rate of 12 deliveries per hour (higher than the current arrival rate of four deliveries per hour), given probable growth in urban deliveries in the future. Therefore, our models could be beneficial in developing building and parking designs that could improve current resource allocations in urban cities. Figures 6.13 show Pareto frontiers obtained by using the NSGA II and MOEA/D, respectively. As one can infer from the figure, the sets of Pareto optimal values from each algorithm seemed very similar (a BWC of between \$220 and \$250, a DC of between \$8 and \$10, and a CWC of between \$60 and \$150), although the NSGA II produced extremely high BWC values of between \$400 and \$600. We can see that MOEA/D provided more targeted ranges for the Pareto frontiers.

Policy makers can choose any point from the Pareto-optimal solutions presented in Figure 6.13 by creating a proper cost distribution strategy. Currently, the exact cost distributions among delivery workers, building managers, and city planners are unknown and very complex, as there is no data-driven approach for implementing regulations for managing building and parking resources in light of the rapidly growing demand for urban deliveries. Our optimization model minimizes costs for all three parties, preventing biased policies that could benefit only one or two parties. By comparing the costs of the alternative solutions, policy makers can consider a broad decision spectrum and consequently take the advantage of more flexible decision making.

For example, policy makers may want to reduce a city's waste costs more than building managers and delivery workers. In this case, policy makers can choose the options (one of the dots in the Pareto frontiers) with lighter grey color, which represents a low CWC in Figure 6.13 while increasing other costs for BWC or DC or both. Our systematic approach to cost distributions can provide flexibility to policy makers because it considers cost distributions under multiple objectives.

On the basis of polity decisions, policy makers can decide on the appropriate resource allocations associated with the chosen cost distributions. For example, policy makers could choose one of the Pareto frontiers from NSGA II and MOEA/D that are marked in red circles in Figure 6.13. They are picked as they are shown the similar cost combinations for DC, BWC, CWC.

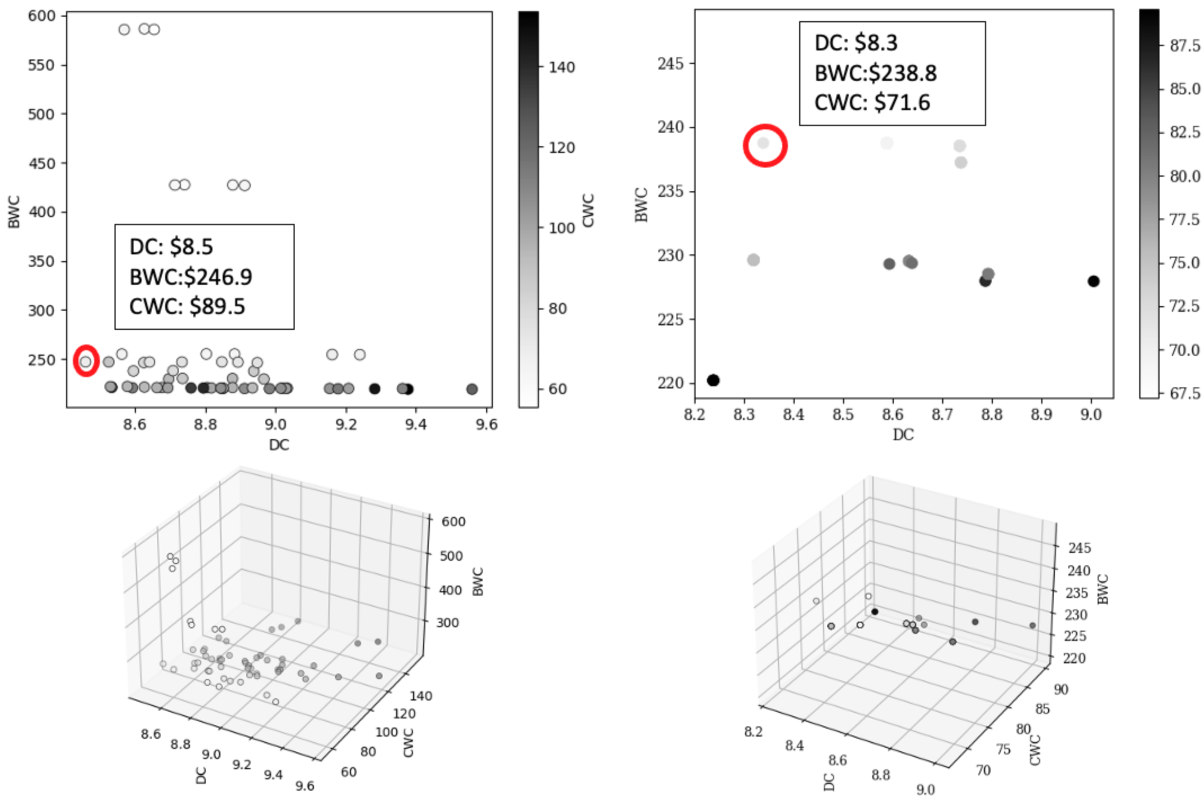


Figure 6.13: Pareto frontiers obtained from the NSGA II (left) and MOEA/D (right)

Table 6.5 shows the combination of decision variables resulted from the selected examples marked in red circle in Figure 6.13. Although numbers of on– and off-street parking are slightly different from each other, the combination of corresponding decision variables were similar except for the number of on-street parking. The information gained from the optimization results can be applied to future decision making processes for building and parking operations.

Table 6.5: Resource limit parameters of each building and parking resource

	NSGA II	MOEA/D
Number of security guard	1	1
Number of receptionist	2	2
Number of off-street parking	5	4
Number of elevator	2	2
Number of on-street parking	11	8
Delivery worker's cost (DC)	\$8.5	\$8.3
Building manager's waste cost (BWC)	\$246.9	\$238.8
City planner's waste cost (CWC)	\$89.5	\$71.6

Through our optimization model, we could add, remove, or reallocate the building and parking resources to tailor them to each different Pareto frontier on the basis of their own policy needs.

6.5 Summary

A multi-objective, simulation based optimization framework was developed to aid decision makers in determining the building and parking resource allocations that yield the best cost distributions for delivery workers, building managers, and city planners. The proposed framework was developed with a simulation phase and an optimization phase. In the simulation phase, analysis of current parking and building infrastructure with different delivery arrival rates was conducted to better understand the dynamics of freight delivery cost distributions among delivery workers, building managers, and city planners. In the optimization phase, results obtained with two popular multi-objective optimization algorithms, NSGA II and MOEA/D, were compared to find the optimized numbers of resources at the fixed delivery arrival rate of 12 deliveries per hour.

This study contributes to the policy making process of allocating building and parking resources, by considering three key players involved in urban deliveries: delivery workers, building managers, and city planners. First, it offers a complex simulation that reflects complicated final 50 feet of delivery processes and real-world time distributions. From the simulation model, we can learn how cost distributions for different parties are related to increasing numbers of urban deliveries. Second, it applies multi-objective optimization algorithms to provide insights into possible optimal cases that would minimize the costs for all three parties.

The proposed framework can support policy makers in determining the best combination of building and parking resources that can minimize costs. As the proposed framework considers all of the costs for different parties, it enables policy makers to determine the best trade-offs between the objectives related to these resource allocations. Because the multi-objective evaluation provides several alternative solutions, policy makers make decisions making within a broad decision spectrum. Additionally, utilization of optimization algorithms ease the computational burden of the simulation phase of the proposed framework.

Our study sheds new light on the opportunities for delivery workers, building managers, and city planners to work together to better prepare for increased demand for urban deliveries. Our research effort will continue to integrate the proposed data-driven approach into policy making procedure. The proposed framework can also be improved by normalizing the costs for each party and applying weights to different parties to account for different priorities. For example, the city may assign higher weights to the city's waste costs and may want to investigate how the relationships with building managers and delivery workers may change.

Chapter 7

CONCLUSION

This dissertation focused on understanding urban freight deliveries and aimed to contribute to provide insights and approaches that are based on data to support future freight plans. The goal of this research was to establish systematic methods to better understand cities' rapidly changing urban freight deliveries which will ultimately help to take a more data-driven approach to urban freight management in the future. To achieve this goal, several tools were used to analyze the collected data including 1) Value Stream Mapping, 2) statistical (regression) models, 3) a discrete event simulation and optimization algorithms.

The first part of this dissertation focused on discovering the process associated with the final 50 feet of the urban freight delivery using value stream mapping. This chapter introduced the lean philosophy and value stream mapping (VSM) approaches to examine the delivery process flows in an office building in downtown Seattle. The final 50 feet of the supply chain extensively involves a vertical movement of the delivery process as deliveries and pick up activities occur mostly while the drivers are out of the vehicle from the loading zone to the end customer. This chapter introduces a systems approach to measure and observe detail tasks of the current final 50 feet of the supply chain by using a unique tablet application and a process flow map. An office building in downtown Seattle was observed by using this approach. Process flow map decomposes actions of the delivery workers, which helps the researchers identify bottlenecks in the current delivery process and where improvements can be made. The improvements can easy-to-implement solutions such as an information board to notify delivery workers of imperfections in the freight elevator to more high cost solutions such as a building redesign. Because the freight delivery process consists of many steps, applying this new approach can help measuring the delivery time for each process accurately, especially when the delivery process needs to consider the number of carriers, types of goods, and types of delivery vehicles. With VSM approach, dwell times and failed deliveries can be better understood as it decomposes the delivery process in micro level.

The second part of this dissertation explored contributing factors associated with dwell time for commercial vehicles using statistical models. This chapter provided statistical models with explanatory variables based on the information gathered from the first part of the dissertation. The models provided insights on the levels of influences of each factor on dwell times, which could help the cities on developing policies and priorities that are specific to delivery characteristics. Dwell time is defined as the time that delivery workers spend performing out-of-vehicle activities while their vehicle is parked. Restricting vehicle dwell time is widely used to manage commercial vehicle parking behavior. However, there is insufficient data to help assess the effectiveness of these restrictions. This makes it difficult for policy makers to account for the complexity of commercial vehicle parking behavior. The current study aims to identify factors correlated with dwell time for commercial vehicles. This is accomplished by using generalized linear models with data collected from five buildings that are known to include commercial vehicle activities in the downtown area of Seattle, Washington, USA. Our models showed that dwell times for buildings with concierge services tended to be shorter. Deliveries of documents also tended to have shorter dwell times than oversized supplies deliveries. Passenger vehicle deliveries had shorter dwell times than deliveries made with vehicles with roll-up doors or swing doors (e.g., vans and trucks). When there were deliveries made to multiple locations within a building, the dwell times were significantly longer than dwell times made to one location in a building. The findings from the presented models demonstrate the potential for improving future parking policies for commercial vehicles by considering data collected from different building types, delivered goods, and vehicle types.

The third part of this dissertation focused on predicting and optimizing the cost distribution between delivery workers, building managers, city planners with increasing numbers of deliveries in urban buildings. The number of package deliveries and more varied delivery options are increasing rapidly in the cities annually. This may lead to an imbalance of supply and demand of the current building and parking resources to prepare for the future demands of urban freight activities. Along with urban building managers, the city's policy makers seek solutions to better manage the future demands for goods and services in the cities. Given the limited spaces and costs, increasing parking and building resources in urban cities can be challenging. Therefore, optimizing resource allocation (e.g parking spaces and building staffs) is important to minimize the costs for both the users (e.g. carriers) and planners (e.g. city planners, building managers). This chapter introduced a multi-objective simulation-based optimization model for building and parking resource allocation to minimize the costs for delivery workers, building mangers, and city planners. As delivery process and performance in the final 50 feet of urban freight activities are stochastic, our multi-objective mathematical models were performed using a non-dominated sorting genetic algorithm NSGA II (NSGA II) and multi-objective evolutionary algorithm based on decomposition (MOEA/D), in conjunction with a discrete-event simulation model to estimate the expected performance values of each building and parking allocation solution. Finally, optimized numbers of parking and building resources were obtained to minimize the costs for both building managers and delivery companies to work together as a team to better prepare for the future demands for urban goods deliveries in the cities. The main contributions of this chapter include not only simulation and optimization models but also the realizations how building and parking management are related on the efficiency of urban delivery system. For example, a large number of parking spaces does not solve the urban freight problems while it may cause a large queues at the elevator. More data-driven approach that is proposed in this research will allow policy makers to consider proper cost distributions between key players in urban freight deliveries.

The generalizability of this study is limited to the particular sample of buildings used in this research, which was selected to ensure sufficient variability in urban freight activities. Further research is needed with an increase in the numbers of sample buildings, including more high-rise buildings as well as mid-rise buildings, to verify our findings. This research is also limited to the information of the numbers of floors visited by delivery workers, rather than the volume of packages that were delivered. Therefore, this study does not consider potential economies of scale in the delivery of multiple packages to individual buildings. This will be an important area of future research regarding sustainable urban freight delivery systems. The proposed cost structure for the receptionist in building manager's waste cost in simulation models may also be an issue because receptionists can perform productive tasks other than receiving goods. Our data collection was limited to the activities that receptionists performed for deliveries only. Therefore, our model considered the receptionist desks as the resource of collective package delivery locations only, disregarding such opportunity costs for receptionists. Having the concept of receptionists in building managers' waste costs could be more complex than our proposed cost functions, which can be more systematically modified and added in the future. Alternatively, the proposed cost function for receptionists can be replaced by the concept of having a parcel locker system or a consolidation location that is solely dedicated to receiving parcel deliveries without opportunity costs.

While there are limitations, this study shows that there may be conflicting priorities between the different actors in the public and the private sectors, pushing the urban freight delivery costs to each other. For the extreme scenarios, if on-street parking (e.g., curb space) went away entirely, urban freight delivery costs are transferred to delivery workers who will have a difficult time finding parking and building managers who provide off-street parking (e.g., loading bay) spaces which will be the only parking options for delivery workers. On the other hand, if there are too many parking spaces with a large number of deliveries, there will cost pushed to the building managers as there will be a lot of queues at the building resources such as security guards, elevators, and receptionists. This research contributes to the new understanding of the urban freight system as a whole, connecting between parking and building operations, with complex cost relationships among delivery workers, building managers, and city planners. This study shows that actors in the public and private sectors will need to work together and negotiate future arrangements to reduce the costs for all parties and improve the efficiency of urban freight and package deliveries to individuals and businesses in cities. Collaborative efforts are desperately required in managing parking spaces, regulating building managers in building designs, and instructing freight delivery entities for effective operation systems in urban buildings. This research provides insights into understanding the complex final 50 feet of delivery processes and the impact of increased urban freight deliveries in the current urban systems. Multiple tools suggested in this research can be used for policy makers to obtain better information and improve communications between public and private sectors prior to actual policies, which can be scaled and applied to other urban cities.

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