Methods for Quantifying Urban Freight Infrastructure Capacity and Utilization

Griffin Kearns Donnelly

A thesis

Submitted in partial fulfillment of the

Requirements for the degree of

Master of Science in Civil Engineering

University of Washington

2022

Committee:

Anne V. Goodchild, Chair

Linda Ng Boyle

Edward McCormack

Program Authorized to Offer Degree:

Civil and Environmental Engineering

University of Washington

Abstract

Methods for Quantifying Urban Freight Infrastructure Capacity and Utilization

Griffin Kearns Donnelly

Chair of the Supervisory Committee:

Professor Anne V. Goodchild

Civil and Environmental Engineering

Two major components of urban freight infrastructure, curb space and off-street commercial vehicle parking, will be analyzed to provide novel methods for estimating their respective capacity in Seattle's downtown commercial core. This report will also look to develop a framework for estimating parking events from sensor data collected from occupancy detectors place along a curb face using hierarchical clustering. This framework will be tested on existing video data and its performance will be assessed using metrics including but not limited to total occupancy over time, length of parking overstay, and true positive parking event identifications.

First, Seattle's Central Business District (CBD) was studied to compare off-street parking capacity in urban loading bays and loading docks with on-street parking at curb segments designated for commercial vehicle loading and unloading. The Federal Highway Administration's vehicle classification criteria was used to distinguish parking capacities by vehicle class. Upper and lower bounds of vehicle dimensions were researched for each vehicle class to utilize a parallel parking formula to determine commercial vehicle occupancy for each CVLZ and Loading/Unloading segment in Seattle's CBD. Utilization scenarios were created for off-street loading bays to calculate the total off-street parking capacity. The two results, for off-street and on-street commercial parking capacities, were compared to see the significance of off-street parking capacity in Seattle's CBD. In 25 out of the 40 cases, the facilities in off-street operations had equal to or greater capacity than the space dedicated to commercial vehicle deliveries at the curb. In all scenarios tested, off-street parking consisted of at least one in every three potential commercial vehicle loading spaces that exist in Seattle's CBD.

The development and implementation of a sensor data clustering algorithm that turns sensor activity into estimated parking events will also be discussed. This process is done by determining the time and spatial dissimilarity between any two sensor events caused by parking activity at the curb. Optimal configurations of space and time factors demonstrate the potential for application in certain situations, specifically those with smaller study areas with uniform parking activity. The quantification of certain parking metrics from estimated sensor data is also

discussed, specifically in overstay and total curb occupancy over time. These metrics are calculated for parking events estimated from both video and sensor data. The former is used to calibrate the latter for several days of video recordings at different block faces in Seattle's Belltown district. Calibrating the hierarchical clustering algorithm with estimated parking events from video recordings means the algorithm is validated by visual estimations of parking events, which are treated as a baseline for performance in this research. It also serves as an assessment for the quality of the clustering algorithm and can determine whether the clustering algorithm provides useful information on parking activity for a given area.

Chapter 1

Comparison of Off-street and Curbside Commercial Parking Capacity in Seattle's Central Business District

Introduction

Understanding how to better utilize the urban transportation network, specifically in downtown areas where space is most scarce, will allow for more efficient movement of people and goods within the city and reduce the impact of these movements on both local ecosystems and the global climate [1-3]. The central business district (CBD) has been observed to be a strategic factor in promoting urban densification, which is conventionally assumed to be correlated to environmental improvements, but this relationship is complex [4]. Urban density is not necessarily environmentally beneficial on its own, only when coupled with policies that utilize its complexity can compact urbanization be sustainable [5]. This paper will quantify both the on and off-street components of urban delivery parking infrastructure. Urban loading bays and loading docks are a key asset in off-street parking infrastructure that will become more valuable as on-street, curbside parking becomes scarcer.

Quantifying capacity for both on and off-street commercial vehicle parking can provide insight into the upper limit of a given infrastructure's utilization, or the maximum amount of users a given system can facilitate at a given time. This process will be agnostic of all factors outside of the infrastructure itself. Location, time of day, and other variables that could impact the demand for parking infrastructure will be excluded from the curb capacity calculation process. Existing literature on calculating curb capacity will be discussed, along with research on management strategies for urban loading bays. Since the method for calculating both on and off-street parking is generalized by vehicle class, potential applications exist with data collection from cordon counts like that conducted by Giron-Valderrama and Goodchild [22]. Curb parking impacts on the road network have also been explored by Cao et al. and illustrate potential in understanding the relationship between utilization of curb space and urban street congestion and roadway performance [41]. The impacts of high curb demand in relation to available commercial curb supply can be explored to better understand how high commercial vehicle activity in an area can impact road network congestion, and potentially how off-street commercial loading and unloading facilities can mitigate it.

To understand the problem of inadequate curbside parking for commercial vehicles, and how loading bay management can mitigate it, the concepts of commercial vehicle cruising for parking and current practices in loading bay management will be reviewed.

Literature Review

Commercial Vehicle Parking Duration, Curb Demand, and Cruising

This section Jaller et al. discusses a method for calculating commercial parking demand and space availability, using freight trip generation. The analysis of freight trips in New York City and the existing curb capacity determined that 10 out of 41 zip codes in the metropolitan area did not have enough parking space to meet demand [31]. Shoup establishes that cities promote cruising for parking through undercharging of parking spaces in comparison to the cost of off-street parking nearby. Drivers will save money by cruising and will therefore be incentivized to spend more time in the road network then to access available off-street parking [6]. Hampshire and Shoup summarized 22 studies of cruising that had a range of 8 and 74 % share. Given the difficulty of replicating these studies, Hampshire and Shoup formulated a statistical method for estimating the traffic share of cruising vehicles, using the reciprocal of the average number of cars that pass a newly vacated parking space before it is occupied [7]. Dalla Chiara and Goodchild model commercial vehicle cruising using trip time, the time difference from arrival and departure, and subtracting driving time, the time it takes a second car in perfect circumstances to park [8]. Using trip data from a delivery company in Seattle, it was determined that, on average, commercial vehicles in the data set spent 2.3 minutes cruising per trip, representing 28% of the total trip time on average.

Loading Bay Management

Understanding the state of literature for loading bay management is important for recognizing the potential impact off-street commercial parking facilities can have in improving delivery efficiency in urban areas. McLeod and Cherrett put forward a method for booking urban loading bays that allows drivers to reserve 15-minute time segments at a loading bay, while also allowing for active management to accommodate late delivery arrival and early departures [9]. A system of 1 and 2 connected loading bays was simulated and compared to unmanaged loading bays, where the booking program outperformed uncontrolled loading bays in all scenarios with 2 loading bays in the control system. Dalla Chiara and Cheah illustrate driver preference and parking behaviors when it comes to what commercial parking facilities they choose and how this, along with other factors, affect parking durations. Insights for managing loading bays are discussed, specifically in how loading bay managers can reduce the number of "balks", where commercial drivers leave the loading bay queue to park and deliver elsewhere, through off-hours delivery planning and centralized receiving stations. [10]. Comi et al. discusses a planning framework methodology aimed at allowing delivery operations at loading bays to be simulated and evaluated for performance [11]. This framework, named DynaLoad (Dynamic Management of Urban Loading and Unloading Areas), allows a variety of users and stakeholders to observe how their aspect of the urban freight delivery process would perform given a set of system constraints. Letnik et al. focuses on the last mile delivery system for dynamic loading bay management and proposes the delivery process be split into two parts [12]. The first part is handled by delivery truck and taken to an available loading bay where the delivered goods will be unloaded for the second stage, where goods are delivered to the last destination either manually or by bike.

Quantifying Parking Curbside Capacity

Literature on determining commercial curb parking capacity is sparse, but certain aspects of the curb parking process have been mathematically formulated. Arnott et al. calculates the curbside parking restraint, or maximum parking throughput of a given unit area as parking space density over the common visit duration [32]. Blackburn derives an equation for calculating the minimum necessary space for parallel parking was for single-unit vehicles [13]. This equation uses the turning radius of a vehicle, the length from the center of the front wheel axis to the back wheel axis, the length from the center of the front wheel to the front of the vehicle, and the width of the vehicle in front of the potential parking spot as variable inputs for determining the amount of space needed for a vehicle to parallel park, in addition to the given length of the vehicle itself. Wenneman et al. use a distance-decay-weighted method for measuring the spatial relationship between the location of on-street and off-street parking locations and illegal parking events, demonstrating that more off-street parking facilities and improved access to these locations can help reduce illegal parking activity [39].

Opportunity for improving the resolution, or granularity in quantifying curb parking exists based on the results from this literature review. Current methods do not calculate capacity on a segment basis, rather, perform their analysis on block faces to determine how many commercial vehicle parking spaces exist at the curb. There are studies on counting the number of loading bays in an area, but insight in how much capacity each individual facility can provide is not demonstrated. Thus, the relationship in capacity between on-street and off-street commercial vehicle parking has not been explored.

Methodology

Study Area

A framework for collecting parking data in the downtown Seattle area has been designed by the Puget Sound Regional Council (PSRC) with a designation for the central business district [14]. These partitions have been used in other studies, including a survey of supply and occupancy of off-street commercial parking facilities by Heffron Transportation [15]. PSRC organized the downtown Seattle area into 13 distinct sectors, with numbered regions 4,5,7, and 8 representing Seattle’s CBD (**Figure 1**).

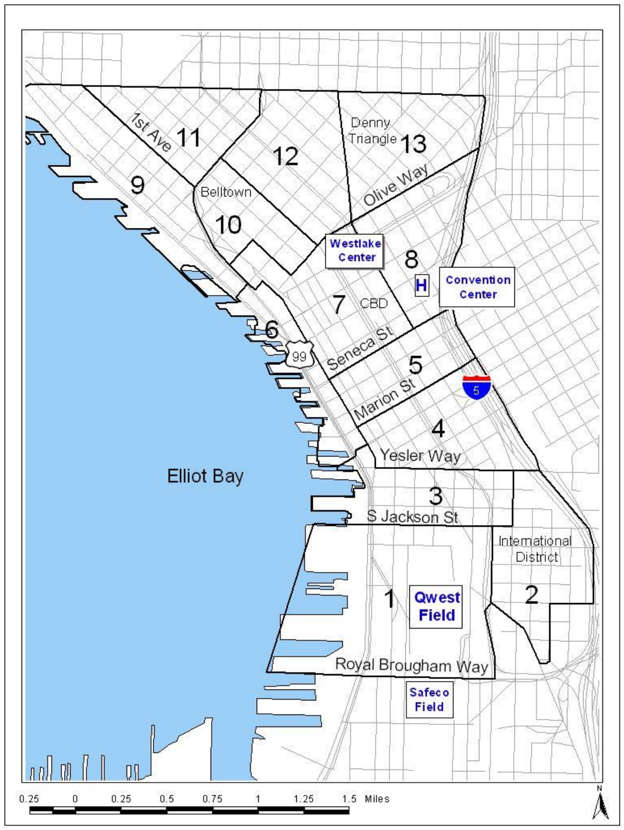

Figure 1; Map of downtown Seattle survey areas defined by PSRC

The datafile for these survey areas was provided by the PSRC and uploaded to ArcMap where regions 4, 5, 7, and 8 were selected as a boundary for the CBD study area.

Curb Parking Data

Seattle's Department of Transportation (SDOT) maintains an inventory of curb spaces on the Seattle GeoData page titled, "Paid Area Curbspaces" [16]. This data set, which contains a shapefile of all curb spaces in the downtown Seattle area, along with curb space types and block face IDs, was downloaded on May 28, 2021. The dataset was then opened in ArcMap and clipped to the PSRC partitions for the CBD area. Once clipped, the curb dataset was then selected for all potential commercial vehicle parking segments, this selection included all space types with the prefix "CV", specifically "CVLZ" and included "L/UL" as commercial vehicles can use these spaces for loading and unloading operations [17]. Loading and unloading spaces are not exclusive for commercial vehicle operations, which distinguishes them from "CVLZ" curb space. Since the study conglomerated all potential parking locations for commercial vehicle delivery operations, this nuance was not considered in the analysis. Any curb space designation that allowed for commercial vehicle delivery activity was included in the estimate for potential on-street parking capacity. Further research can be done on the impact non-commercial parking has on commercial vehicle space for "L/UL" segments, as this type of curb space contributed to class 8 and 9 commercial trailer parking space. As a final adjustment, any two curb segments that shared a start or end point, that connected continuously, and were of the same block face ID, were joined for a combined segment length. This is because three curb segments were split into two separate data entries in the SDOT inventory for the CBD area. For the sake of the analysis, it was assumed that these segments were continuous. This process was also checked through inspection in ArcMap.

Off-street Parking, Private Loading Infrastructure

A typology for off-street commercial vehicle infrastructure on private property was defined by Goodchild et al. [18]. The typology includes internal loading bays, exterior loading docks, and external loading areas [18]. These categories were used to classify off-street commercial loading and unloading facilities for data collection in the greater downtown Seattle area. The result of the data collection was an inventory of off-street loading and unloading facilities that serves as the primary source of information for off-street commercial parking in this report. The original dataset, which specified infrastructure type, vehicle spaces, entrance/exit dimensions, and location was provided by University of Washington's Supply Chain Transportation & Logistics Center (SCTL). The dataset was uploaded to ArcMap and clipped to the CBD partition area. The attributes of the clipped data set were downloaded and review for missing data. Locations of missing data in the CBD were aggregated and used for a second data collection effort, which was conducted in July of 2021. The results of the second data collection attempt yielded loading bay space counts for 19 unique, commercially available off-street loading facilities in Seattle's CBD.

Locations with "Not loading bay access" and "Undefined" entries in the infrastructure type variable were removed from the data set resulting in 71 total documented locations. 10 of the remaining locations were found to be redundant, in some cases entrances and exits were counted separately for the same internal loading bay, or located in government-owned buildings. Of the remaining 61 locations, 17 were missing information on spaces or entrance dimensions. A second data collection process was conducted in late June to fill in all necessary variables in the loading bay inventory for comparison with curb parking. The second data collection effort resulted in 14 locations being filled in with missing information. This resulted in a final loading bay location count of 58 from a usable dataset of 61 for the analysis, the coverage of the analysis is 95% of recorded off-street commercial parking infrastructure in the CBD area. Of the 58 locations that had full data for the analysis, 10 were exterior loading docks and the remaining 48 locations were internal loading bays. There were no external loading areas in the CBD region.

TABLE 1; Number of Off-street Commercial Parking Facilities

	Alleyway Access	One-way alley Access	Street Access
Exterior Loading Docks	9	8	6
Internal Loading Bays	38	2	161

Alleyway Infrastructure

Alley infrastructure in the CBD area was also acquired from SDOT's GeoData portal, which originated from the same report that collecting the off-street loading facility inventory data used in this report. [18,19]. This dataset was also clipped to the CBD area. Every off-street loading facility designated with "Alleyway" in the road access variable had the alley ID and width connected from the adjacent alleyway that it is accessible from. This process was done manually due to the lack of congruent identifying factors between alleys and loading bay facilities and the small size of the study area. The combined on and off-street infrastructure can be seen in **Figure 2.**

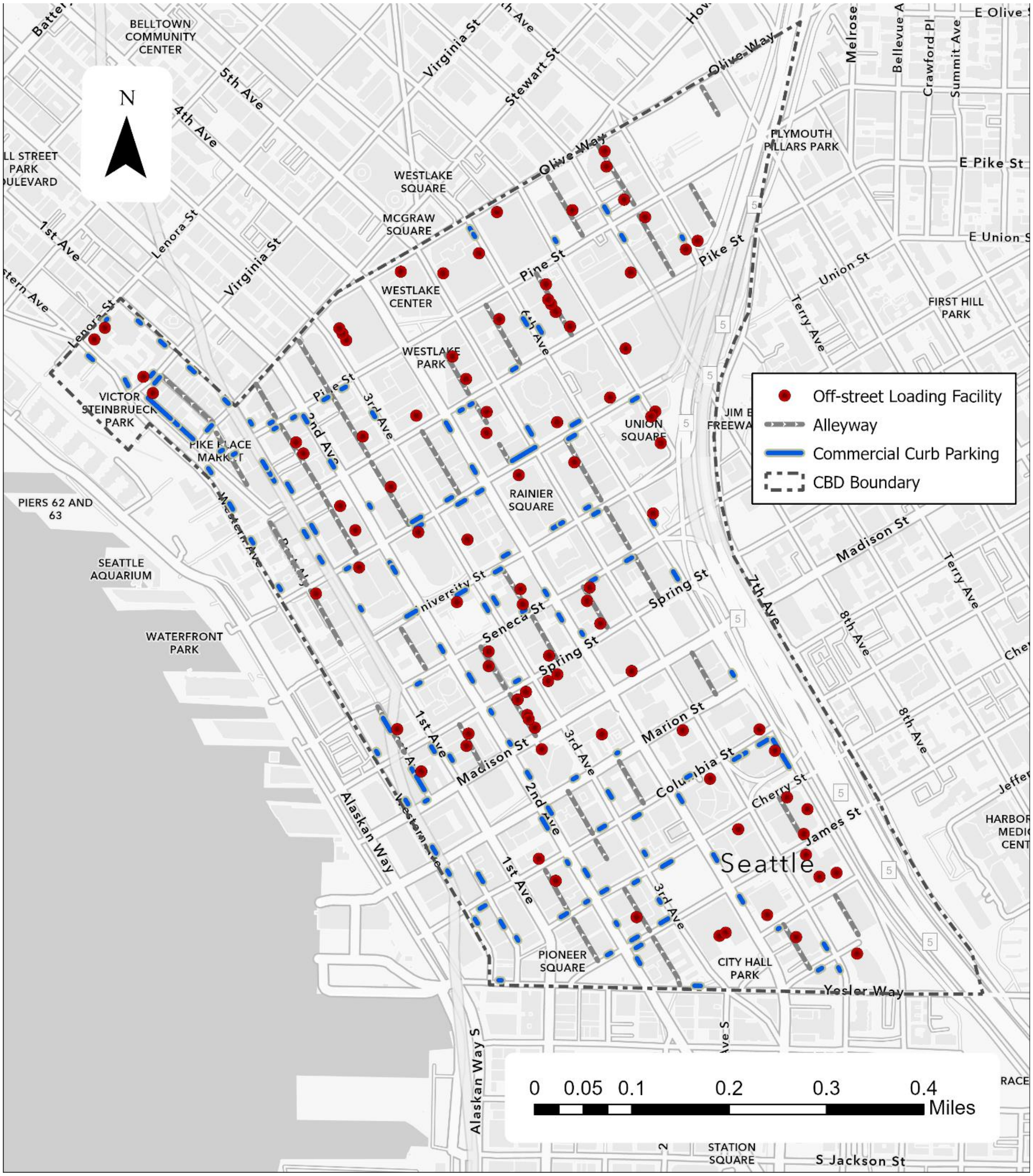

Figure 2; Map of Seattle with Curb and Off-street Commercial Vehicle Infrastructure

The vehicle typology defined by Giron-Valderrama et al. was used as a basis for categorizing commercial vehicles that use both curb and off-street loading facilities [20]. The Federal Highway administration's (FHWA) vehicle classifications were used for further specificity, allowing commercial vehicle types to be broken down in terms of axle counts (**Figure 3**) [21]. A technical report on a commercial vehicle cordon study in the Seattle area by Giron-Valderrama et al. connects vehicle typology with axle count, which was used for the final commercial vehicle categories in this report [22].

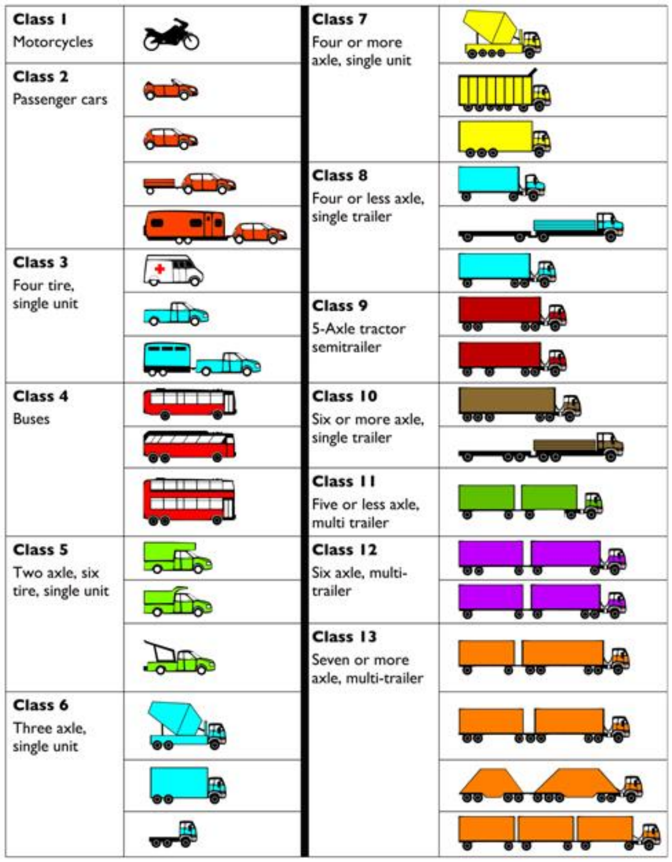

Figure 3; FHWA vehicle classification chart

For curb parking, the FHWA vehicle classes of 3,5,6,8, and 9 were selected to represent possible commercial vehicle types that will enter the downtown Seattle area. Although multi-trailer vehicles have been observed in the fleet composition of the Seattle area, they were not considered in this study due to small percentage of the overall fleet [22]. Commercial vehicle typology for off-street loading collected FHWA's classes into the typology from Giron-Valderrama et al.'s studies [21-23] Class 3 vehicles were determined to be equivalent to vans, class 5 and 6 vehicles equivalent to single-unit box trucks, and 7 and 8 class vehicles to semitruck trailers. The dimensions for each vehicle class were done in coordination with the variables required to fulfill Blackburn's parallel parking equation (**Equation 1**) [13]. This meant overall vehicle length, turn radius, length between front and back wheel, front axle to front of vehicle, height, and width had to be determined for both the curb parking and loading facility capacity analysis. To capture the range of vehicle dimensions that can occur from each class, a minimum and maximum value was assigned to each dimension variable (**Table 2**). All measurements are in feet.

TABLE 2; Commercial vehicle dimensions by FHWA class

Class	Min. length	Max length	Min. turn radius	Max turn radius	Min. total axle length	Max total axle length	Min front to axle length	Max front to axle length	Width	Height
3	19	26	24	40	11	16.67	2.33	4	8.5	8.5
5	22	33	28	45	12	23	2.33	4	8.5	8.6
6	22	35.5	28	45	12	25.5	2.33	4	8.5	11.2
8	44.5	68.5	NA	NA	NA	NA	2.33	4.33	8.5	13.5
9	55	68.5	NA	NA	NA	NA	2.33	4.33	8.5	13.5

Minimum and maximum values for vehicle dimensions were used to capture the range of typical measurements found in commercial vehicle documentation. AASHTO's Minimum Turning Radii of Design Vehicles was used to approximate all turn radii values, while providing expected lengths for front to back axle measurements in single unit vehicles [24]. In class 3 vehicles, axle and vehicle length of a typical delivery van was expected to be no shorter than a typical passenger vehicle. McCormack et al. developed a report on delivery vehicle envelops that defines the higher bound for delivery van vehicles in the UPS package car footprint that also provides lower and upper bound dimensions for class 5 single unit box trucks [25]. Class 6 vehicles are equivalent to class 5 vehicles in almost all aspects, but have an additional axle, FHWA's LTPP Vehicle Classification rules designate measurements to axle length [26].

In the case of differences between class 5 and 6 vehicles, the spacing requirement for axles 2 and 3 of a class 6 vehicle was added to class 5's length dimensions. Maximum allowable lengths for class 8 and 9 vehicles are determined by the FHWA, with the state of Washington limiting trailer lengths to 48 feet [26]. Dimensions for front of vehicle to first axle were taken from the AASHTO turn radii guidelines, along with vehicle heights for class 3,8, and 9 from McCormack et al. [24-25]. Heights for class 5 and 6 box trucks were derived from national rental truck measurements [27]. All vehicle widths were set to 8.5 feet from AASHTO turn radii guidelines, as the dimension fluctuated between 8 feet and 8.5 feet, the larger value was chosen and applied to all vehicles.

Analysis

Curb Parking Capacity

To capture the range of vehicle lengths in each class, columns for low and high bound curb capacities for each class were appended to the table. Blackburn's parallel parking equation (**Equation 1**) was used to write a function in the R program that took vehicle dimension variables as inputs (in feet) and output the length of available curb segment needed to conduct a parallel parking maneuver. Since Blackburn's parallel parking equation can only be applied to single unit vehicles, turn radius and axle dimensions were not used for vehicle classes 8 and 9 semitrailer trucks [13]. Instead, an additional 10 feet was added to the total vehicle length to approximate how much space a semitrailer truck would need to fit in, a length recommended by CDL College for performing parallel parking maneuvers with a tractor semitrailer [28].

The R program then looped through each curb segment, low bound and high bound of each vehicle class (**Table 2**) to determine how many spaces the class would have at the segment. Each curb segment was converted to several parking spaces using Blackburn's parallel parking equation. If the available parking space at a given segment was equal or greater than the vehicle length plus a parallel parking buffer, a space is added to the parking count for that segment and the length of the vehicle is subtracted from the existing curb length. The equation for calculating the parallel parking buffer is displayed in **Equation 1** below.

$$d' = \sqrt{(r^2 - l^2) + (l + k)^2 - (\sqrt{r^2 - l^2} - w)^2} - \mathrm{l} - \mathrm{k} \qquad \textbf{(1)}$$

$r =$ turning radius
$l =$ distance from front wheel axle to back wheel axle
$k =$ distance from front wheel axle to front of vehicle
$w =$ width of vehicle in front of parking space
$d' =$ difference between space of length needed for parallel parking maneuver and total vehicle length

In this study, **Equation 1** will be used to estimate available parking space along a curb in each curb segment. All variables are units of length, including the result, and must be consistent for all variables. Applications of parking capacity modelling for commercial vehicles were not found in our research, this report will look to use Blackburn's parallel parking equation for a novel method of determining commercial curb parking capacity. Minimum and maximum lengths on vehicle dimensions provided upper and lower bounds on the number of spaces for the vehicle class that the curb segment could provide, respectively. Originally, it was assumed that a parallel parking maneuver would be the minimum amount of space required for the vehicle to fit. If a parallel park could be conducted by the vehicle, it would add to the space count for the corresponding segment row and subtract only the length of the vehicle from the curb segment length and loop through the function again for the segment until the space remaining was less than the parallel parking maneuver. With this method, 48 curb segments were too short to fit one vehicle from the smallest class dimension, the upper bound of class 3 delivery vans. This meant 35.0% of the curb segments designated for commercial vehicle operations in Seattle's CBD were unusable in the first iteration of the curb analysis.

The number of segments deemed unusable by the analysis led to a revision in the program. A new method, where the first vehicle parking maneuver would be assumed to have open space in the entering side of the curb, so that only the length of the vehicle would be required for the first parking space, was put in place of the original curb allocation process and ran for each vehicle class. The results provided higher levels of curb utilization, with only 12.4%, of the commercial curb segments returning 0 spaces for all vehicle sizes.

Off-street Parking Capacity

The off-street loading facility survey from “The Final 50 Feet of Urban Goods Delivery” was used as the data for off-street commercial parking infrastructure [18]. A scenario-based analysis was chosen for determining the capacity of these off-street facilities based on observations made in the field during the second iteration of data collection done in late June. Four scenarios were determined to cover a range of potential loading bay configurations. The variables that the scenarios were designed around include number of truck spaces, spaces with loading docks, entrance angle, clearance (if applicable), and commercial infrastructure type. Each scenario takes into consideration the relative maneuverability of each vehicle type in comparison to the other classes, for example, class 8 and 9 vehicles handle parking infrastructure differently due to the higher degree of movement from the trailer connection, where classes 3,5, and 6 are single unit vehicles. The scenarios also cover the unique features of the infrastructure itself, such that loading spaces with docks, lifted platforms designed to aid delivery operations in vehicles with elevated cargo holds such as those of classes 5,6,8, and 9, will be more effective for said classes. Since this method of approximation takes into consideration the differences between vehicle type, classes 5 and 6 were conglomerated together as box trucks, and classes 8 and 9 were conglomerated together as semitrailer trucks. The following scenarios were iterated for each off-street parking location and determining the scenario’s capacity for class 3 vans, class 5 and 6 box trucks, and class 8 and 9 semitrailer trucks. All conditions from previous scenarios are included in subsequent scenarios, all Scenario 1 conditions apply to Scenario 2, all Scenario 2 apply to Scenario 3, etc. Off-street parking facility spaces are never double counted with the implementation of any scenario.

Scenario 1 (Baseline):

- Delivery vans, class 3, can utilize internal loading bays, both street and alley accessible, for 50% of the total spaces at each location, rounded up if a decimal value is originally returned. If there are less than 3 spaces at a loading bay, all spaces are counted.
- Box trucks, classes 5 and 6, can utilize both internal loading bays and external loading docks, both street and alley accessible, for 50% of the total spaces at each location, rounded down. If there are less than 3 spaces at the location, all spaces are counted.
- Semitrailer trucks can stage deliveries in the alleys with loading bay entrances or external loading docks. Alleyways must have a width of 13.83 feet to accommodate the delivery operations of the vehicle, only one truck can utilize an alley at a time.

Scenario 2 (> S1):

- Delivery vans, class 3, can utilize internal loading bays, both street and alley accessible, for 67% of the total spaces at each location, rounded up if a decimal value is originally returned.
- Box trucks, classes 5 and 6, can utilize both internal loading bays and external loading docks, both street and alley accessible, for 50% of the spaces without a loading dock at each location, rounded down. The number of spaces with loading dock infrastructure is utilized to 67% it's true value.
- Semitrailer trucks can use street accessible exterior loading docks and internal loading bays if the loading bay entrance fits the width and clearance dimensions of vehicle class 9 in **Table 1**. The facility must have more than 4 spaces with loading docks to be counted as 1 space for the semitrailer truck capacity.

Scenario 3 (> S1, S2):

- Vans can utilize exterior loading docks that are angled and have no gate.
- The number of spaces with loading dock infrastructure at internal loading bay and exterior loading dock facilities is now utilized to 75% it's true value, rounded down. If there are less than 3 spaces at the location, all spaces are counted.
- Street-accessible facilities with more than 6 loading dock spaces can accommodate 2 semitrailer trucks.

Scenario 4 (> S1, S2, S3):

- Delivery vans, class 3, can utilize all spaces for internal loading bays if there are no loading docks if the location has less than 4 spaces in total. Otherwise, class 3 vehicles count 75% of the spaces at the location towards their total CBD off-street parking capacity.
- All loading dock-equipped spaces are counted towards the overall capacity for class 5 and 6 box trucks.
- Street-accessible facilities with more than 8 loading docks can creates 4 spaces for semitrailer trucks, more than 6 creates 3, more than 3 creates 2, and all other street-accessible facilities with at least 1 loading dock space provide 1.

Results & Discussion

Curb Parking Capacity

The results from the curb capacity program returned available parking spaces for each curb segment for each vehicle class's lower and upper bounds. All segments were summed by class bounds and returned the total vehicle spaces that each class had, displayed in **Table 3**.

TABLE 3; Estimated commercial vehicle curb spaces by FHWA class, upper and lower bounds

Type	Class 3 Low	Class 3 Hi	Class 5 Low	Class 5 Hi	Class 6 Low	Class 6 Hi	Class 8 Low	Class 8 Hi	Class 9 Low	Class 9 Hi
L/UL	33	52	27	44	26	44	8	20	8	13
CVLZ	87	120	66	98	53	98	2	15	2	8
Total	120	172	93	142	79	142	10	35	10	21

Commercial Vehicle Loading Zones (CVLZ) were the predominant source of parking for vehicle classes 3, 5, and 6, were loading and unloading zones (L/UL) provided larger commercial semitrailers with a majority of their curbside parking capacity. This is because L/UL spaces are longer segments of continuous curb face than CVLZ spaces. The median of L/UL curb segments was 42.5 feet, with a maximum value of 233 feet. There were 4 L/UL segments of greater than 100 feet in length, where CVLZ segments only had 1, the maximum for the group at 128 feet. Segment continuity increases the parking capacity for all FHWA classes on the basis that it minimizes the opportunity for unused space. For example, class 9 higher bound vehicle dimensions see 16% of their unused space come from L/UL segments, where smaller, class 3 upper bound vehicle dimensions see L/UL segments create 20% of their total unused space.

The scenarios each returned a numerical value of spaces per location, per vehicle type. The results provide a spectrum of possible off-street parking capacities in a format comparable to the FHWA classification used in the curbside parking capacity analysis. **Table 4** displays the results of the scenario testing for off-street commercial parking facilities.

TABLE 4; Estimated commercial off-street parking spaces by FHWA class and vehicle type

Class (Type)	Scenario 1	Scenario 2	Scenario 3	Scenario 4
3 (Van)	98	127	144	173
5,6 (Box truck)	114	137	145	192
8,9 (Semitrailer)	18	19	23	29

Results from the scenario analysis show that vehicle classes 5 and 6 have, across all scenarios, the most capacity for commercial vehicle operations in off-street parking of the three tested vehicle types. This is a result on box trucks being designed for loading dock deliveries, where vans cannot use said infrastructure as effectively, see **Figure 4**. Although vans can park in spaces with docks, they will require additional square footage to stage deliveries, restricting which spaces can be used due to the increased delivery envelope. Both box trucks and semitrailer trucks reduce their delivery envelope when utilizing loading docks, since they will not need to lift or lower goods from the elevated cargo hold.

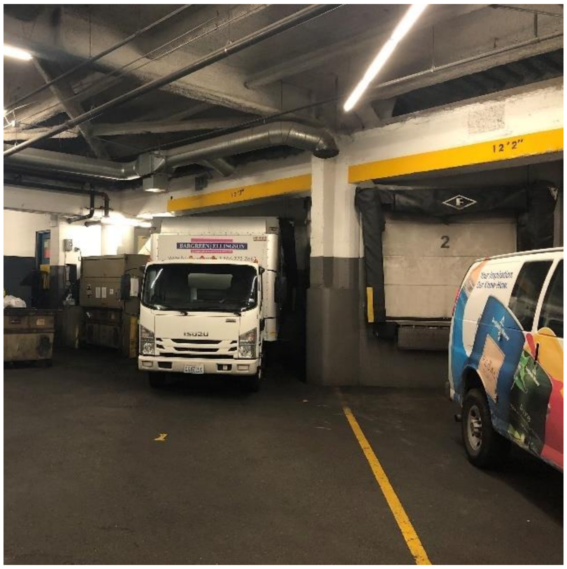

Figure 4; Box Truck Utilizing Elevated Loading Dock vs Van Spaced for Delivery

Once on-street curb capacity and off-street parking capacity were calculated for each FHWA class, the number of off-street parking facilities was divided by the equivalent class for curb spaces, returning a lower and upper bound ratio of off-street to on-street parking for each FHWA class. Note that although off-street delivery capacity was determined using vehicle typology, each type had an equivalent class or set of classes that corresponds to the FHWA standards set in **Figure 3**. The ratio of off-street commercial vehicle parking to on-street curb capacity by FHWA class, with upper and lower bounds, is displayed in **Table 5**.

TABLE 5; Table of off-street parking capacity as a percentage of FHWA class equivalent CVLZ curb spaces

Off-street : Curb Ratio	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Class 3 LB	81.7%	105.8%	120.0%	144.2%
Class 3 HB	57.0%	73.8%	83.7%	100.6%
Class 5 LB	122.6%	147.3%	155.9%	206.5%
Class 5 HB	80.3%	96.5%	102.1%	135.2%
Class 6 LB	144.3%	173.4%	183.5%	243.0%
Class 6 HB	80.3%	96.5%	102.1%	135.2%
Class 8 LB	180.0%	190.0%	230.0%	290.0%
Class 8 HB	51.4%	54.3%	65.7%	82.9%
Class 9 LB	180.0%	190.0%	230.0%	290.0%
Class 9 HB	85.7%	90.5%	109.5%	138.1%

Discussion

Parking demand and traffic congestion from delivery operations are expected to increase globally [29]. Coupled with steady urbanization and increasing activity in e-commerce, urban areas should expect to see a rising demand on their commercial delivery infrastructure, specifically in the demand for loading and unloading of goods at the curb. Curb space is a finite resource, and solutions that alleviate or redirect this demand to other available facilities near the destination can help reduce externalities caused by relatively low on-street commercial parking supply. These externalities can include increased traffic and emissions from commercial vehicles searching for parking, known as cruising for parking. An imbalance between urban freight infrastructure supply and delivery demand can also impact road safety due to an increase in interactions between commercial delivery vehicles and other users of the road network. [30]

The results of this study show that off-street parking facilities in downtown Seattle, specifically internal loading bays and external loading docks in commercial buildings, can provide a source of delivery space comparable to existing curb facilities. Existing literature on loading bay management discusses methods for optimizing the booking of loading bay spaces and management of these facilities to improve their usage. Optimization of loading bay scheduling has the potential to be implemented systemically in dense urban environments where destinations are within walking distance to several potential loading bay delivery points, increasing the complexity and potential upside of improving the usage of these facilities. It should also be noted that off-street commercial vehicle parking facilities like loading bays and external loading docks are specialized for commercial vehicle operations, where on-street curb space is not designed explicitly for commercial vehicle deliveries, providing another potential benefit to emphasizing the usage of off-street parking facilities.

Conclusion

The results from the off-street loading facility and curbside commercial vehicle capacity analysis display that off-street parking can accommodate at least 50% of commercial vehicle deliveries in comparison to its on-street counterpart, the curb. Only the upper bound of class 8 semitrailer truck curb capacity remains above all off-street parking capacity scenarios. Although the occupancy rate of off-street loading bay occupancy is not known for the downtown Seattle area, studies have been conducted in the region on passenger vehicle parking facilities [15]. Similar data collection processes can be used for loading bay facilities to better understand how much extra space is available in the off-street commercial infrastructure. The relative size of off-street parking in the Seattle CBD area warrants further study and consideration, as increases in commercial delivery volumes will put stress on curbside availability. Off-street parking may serve as an underutilized source for delivery space, reducing the need for commercial vehicles to cruise, potentially lowering congestion in the downtown urban core and reducing emissions from freight activity in the CBD. Research exists in understanding how curb parking utilization affects the street network, specifically with regards to congestion, while phenomena like cruising for parking have also been observed [22, 6-8]. In the study of off-street commercial parking, specifically regarding loading bays, management techniques are explored to maximize the efficiency of this space in servicing commercial vehicle deliveries [10-12].

The results of this research, in quantifying both on and off-street commercial vehicle parking capacity, and comparing the two values, demonstrates the potential for a holistic approach to decreasing curbside parking demand by looking at both components of the parking inventory in on and off-street facilities. In the Seattle area, off-street commercial vehicle parking represents a significant portion of the CBD's estimated commercial parking capacity, the application of novel methods for managing loading bays and other off-street parking facilities may represent a systemic solution, or mitigation for the problem of low commercial vehicle parking supply at the curb.

Further improvements can be made to the analysis done in this study by determining exact dimensions of delivery footprints for each vehicle class. This will provide a more accurate estimation of available L/UL and CVLZ curb space, although the capacity will be decreased due to a larger vehicle footprint, further improving the off-street share of commercial parking. As discussed earlier, incorporation of cordon counts in determining vehicle fleet composition can compliment this curb capacity quantification by providing a heuristic method for estimating fleet-specific on and off-street commercial parking capacity. Utilizing cordon counts can allow for capacities in each vehicle class to be aggregated into a single composite value representing an approximate potential parking capacity for both on and off-street parking in a designated area, for this research work, Seattle's CBD. Currently, the results of this study display homogenous results by vehicle class, but data collection on fleet composition can allow for heterogenous results that better reflect parking activity for a given area.

Chapter 2

Estimating Curb Parking Events with Sensor Data Using Hierarchical Clustering Algorithm

Introduction

The implementation of smart parking sensors and other methods of automated data collection has increased the necessity for appropriate processing methods to convert this data into useful information for both the users of the urban road network and those responsible for its management [33]. Estimating parking events from sensor data, specifically sensors that utilize Internet-of-Things (IoT) protocols, is increasing in importance as cities and their respective transportation infrastructure systems become more digitized and networked [42]. The ability to not only interpret real-time information, but use it to predict trends in parking patterns like occupancy rate can provide users of the urban transportation network with information can lead to better informed decisions when attempting to find parking space in a congested road network with high parking demand [44].

This chapter will detail the process of implementing, testing, and evaluating a cluster analysis of sensor data from occupancy sensors that detect presence at a point. The results of this chapter will look to provide a framework for collecting and formatting sensor occupancy data and converting the sensor events into estimated parking events. The results of the hierarchical cluster analysis on real sensor data collected from December 8th to December 10th of 2020 will be shown in terms of how it compares to collected video data. Potential use cases of the hierarchical clustering algorithm will be discussed. Several clustering linkage methods will be tested to determine which method is best for estimating curb parking using sensor occupancy data. Potential uses, directions for improvement, and future work will be discussed. The results from the hierarchical clustering algorithm demonstrate highest levels of accuracy relative to the video data in estimating parking overstay, or, how long over the legally allocated time for a single parking event a vehicle idles. Accurate estimation of overstay times displays use cases for municipalities in determining locations with high illegal parking activity. This information can potentially assist authorities in deterring overstay parking in locations where it is prone to occur.

Literature Review

Gomari et al. conduct a cluster analysis of parking events detected by on-street parking information (OSPI) systems in Munich to understand parking behavior dynamics in the city [34]. Parking purpose was categorized by duration and parked-in time using density-based spatial clustering of applications with noise (DBSCAN). Teodorovic et al. discuss a parking space inventory management system that utilizes fuzzy logic and integer programming to make real-time decisions for accepting parking requests [35]. Diaz Ogas et al. surveyed 274 publications from January 2012 to December 2019 to categorize existing smart parking systems (SPS) by detection method, type of algorithm used, and stage of implementation. The two most common forms of SPS are parking lot reservation schemes and parking guidance and information systems [36]. The application of big data collection from sensors is discussed as well as its application to problems in urban environments like pollution, assisted living, and disaster management by Ang et al. [37]. Dey et al. survey potential methods for detecting parking events at curb space, and specify "in-ground sensors" with occupancy detection capability as a potential method for detecting parking occupancy, however, it is stated that spaces must be "demarcated" in order to create discrete sensor events that represent parking events [40]. Estimating parking events using a neural network from data collected by 400 magnetic parking sensors was explored by Vlahogianni et al., which demonstrated an ability to predict available parking spots, and determine the probability of parking availability for a given area [43].

Literature on the application of clustering for analyzing parking activity exists but is not performed for estimating parking events from sensor data. Other methods for converting curb sensor data into estimated parking events includes neural networks, as shown by Vlahogianni et al. [43]. This research will look to apply hierarchical clustering to the problem of grouping sensor events into parking events. Clustering is used to determine macroscopic trends in vehicle parking exclusively, where sensor activity itself does not need to be processed to determine individual parking events.

Methodology

Sensor Data

Sensor data was collected from devices that utilized a magnetic field to detect when a large object occupies the space directly above. In **Figure 5**, a standard configuration of the detection sensors is shown. Each sensor is spaced 10 feet apart and designated by curb space type. Variables provided by sensor activity include start and end time of the occupation event, as well as sensor identification factors including parking space type, unique sensor ID, latitude, and longitude of the sensor.

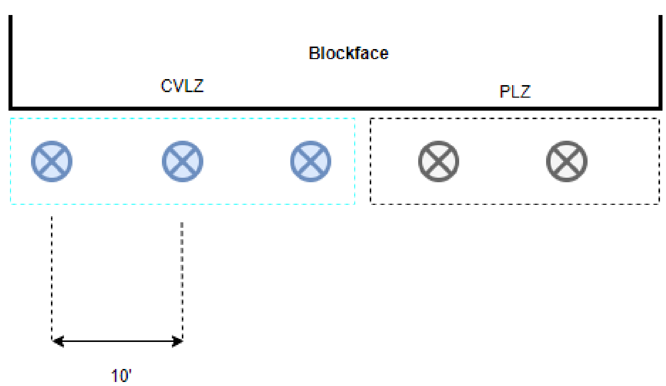

Figure 5; Typical Sensor Configuration in Physical Environment

Estimated Parking Events

Estimated parking events can come from two sources of data. The first source, video data, comes from video recordings of curb space with sensors installed along the face in the typical pattern displayed in **Figure 5**. Video data is used to estimate parking events visually and can be used to confirm when a vehicle enters the curb space and parks. The video recordings provided a sensor interface so sensor events could be displayed simultaneously with the video recordings. This allows the observer to record when sensors are activated and deactivated by a vehicle with visual confirmation. See **Figure 6** below for an example of the video data interface.

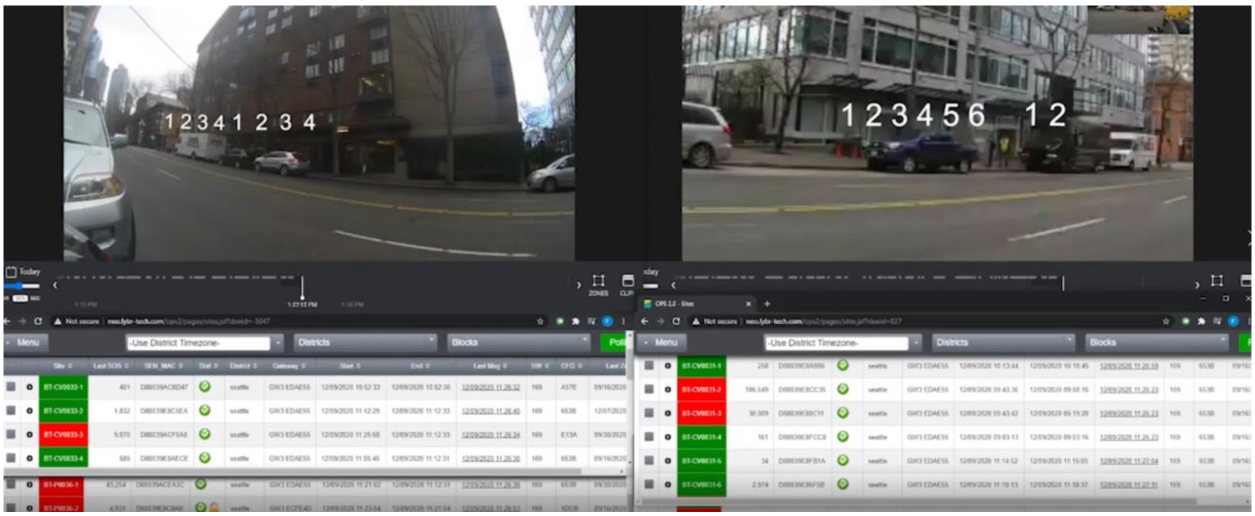

Figure 6; User Interface for Video Recordings of Study Area

Four videos of unique parking events during midday in Seattle's Belltown area were used for visually estimating when a vehicle entered and exited the curb space for parking. These videos cover the 8th, 9th, and 10th of December 2020. The 9th and 10th each record a different block face, while the 8th has two unique videos of different block faces, one of which was shared with the 9th. **Table 6** is sample of the first recorded event for each unique block face day in a table created for video data parking estimation. The variables "sensor ID" and "Space ID" represent a sensor's sequence in the line for a given space and the space identification respectively. Both combined represent a sensor's unique identification in the Belltown sensor framework. These combined variables can locate any individual sensor and provide information on the parking type for the sensor's location at the curb.

Start time and end time of each sensor event is also provided, which displays when the sensor in the event was activated by occupation or deactivated when cleared. For the sake of this study, any parking events that began before the video start were not considered in data collection and by extension the analysis, only parking events that were estimated entirely within the beginning and end of recording time were collected.

TABLE 6; Sample of Estimated Parking Events Dataset from Video Recordings

Sensor ID	Space ID 1	Space ID 2	Space Type	Start Time	End Time	Sensor Count	Block Face ID
1_2	CV0032	NA	cvlz	2020-12-08 10:37:19	2020-12-08 10:40:02	2	31
2_3	P0036	NA	plz	2020-12-08 10:54:54	2020-12-08 11:07:02	2	30
3	CV0033	NA	cvlz	2020-12-09 11:25:38	2020-12-09 11:37:26	1	30
1_2	P0003	NA	plz	2020-12-10 11:14:03	2020-12-10 11:19:50	2	4

Clustering Algorithm

Hierarchical clustering uses a matrix of dissimilarity values between any two pairs of points, *i* and *j*, such that the dissimilarity calculation *d(i,j)* between *i* and *j* is greater than zero, and that the dissimilarity is equal in both configurations of *i* and *j* such that *d(i,j) = d(j,i)* [38]. This analysis will use two variables that differentiate each sensor event, time, and space, to calculate the dissimilarity between any two sensor events represented as *i* and *j*.

The first variable, space distance, is determined by the longitude and latitude of sensor event *i*, and the distance in meters from the geographical position to the altitude and longitude of sensor event *j*. This units of this distance are measured in feet. The sensor event longitude and latitude is provided by the identity of the activated sensor.

In **Equation** 2, the second variable, time distance, is calculated using the start time (S_i, S_j), end time (F_i, F_j), and duration of given sensor events, *i* and *j*. Start time and end time are calculated in seconds from a universal reference point. For example, a sensor event of 30 seconds that occurs 4 minutes from the universal point of reference will have a start time of 240 seconds and an end time of 270 seconds. **Equation 2** displays how time distance was calculated between two sensor events. **Figure 7** displays the time space-relationship between sensor events.

$$t_d(i,j) = \max(F_i, F_j) - \min(S_i, S_j) - (F_i - S_i) - (F_j - S_j) \qquad \textbf{(2)}$$

$t_d(i, j)$ = time distance between sensor events *i* and *j*

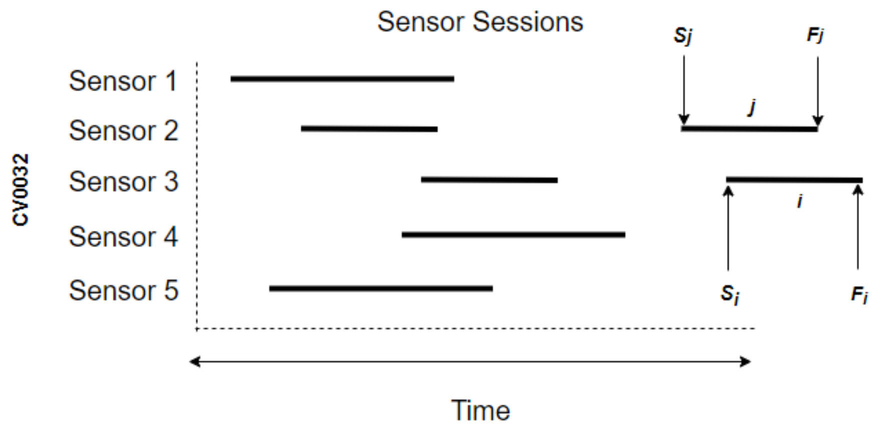

Figure 7; Time-space Relationship Between Sensor Events

A dissimilarity value for each sensor event pair *i* and *j* was calculated for cell C_{ij} in the dissimilarity matrix, such that $i \neq j$. The value of C_{ij} was then used to determine which sensor events would be assigned to which cluster ID groups based on a threshold value of distance, called a cut height. **Equation 3** displays the calculation of C_{ij}, where time and space distance are weighed against each other using a factor, α.

$$C_{ij} = (t_d(i,j) * \alpha) + (e_d(i,j) * (1 - \alpha)) \qquad \textbf{(3)}$$

e_d = Euclidian distance between *i* and *j*

Clustering Validation

For each block face day of video data, the optimal configuration of the alpha parameter (α) and cut height for the resulting diagram was determined through an iterative process. Each alpha value from 0.2 to 0.95 for every 0.05 was run through the clustering process. The resulting dendrogram would be cut from height 5 to 175 every 5 units. This process was repeated on each block face day for five different linkage methods: Average, Single, Complete, Ward, and McQuitty. **Appendix A** displays the results of the clustering validation iterations, with rows sorted by occupancy difference and cut off after the first ten results.

The leading validation metric, occupancy difference, is calculated in vehicle-seconds by finding the difference in area between occupancy curves created by estimated video data of a block face day and estimated parking events from the sensor clustering algorithm for that period. Each occupancy time is bounded by the start of the first parking event and the end of the last parking event. **Figure 8** and **Figure 9** display the resultant occupancy curves of December 9^{th} and December 10^{th} for their best performing parameter configuration, respectively.

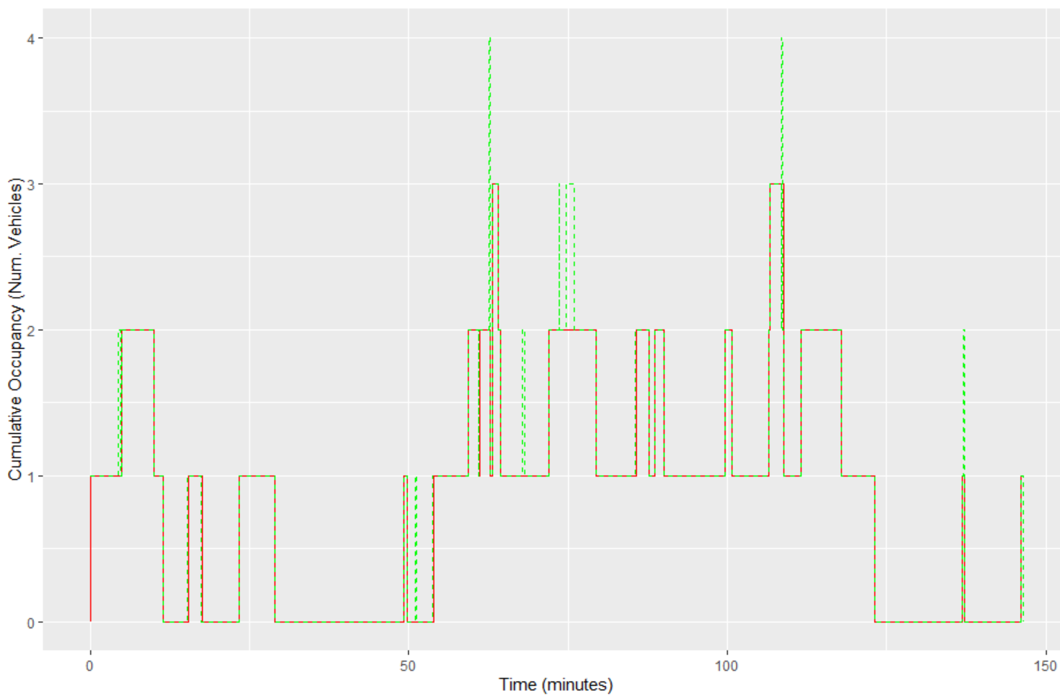

Figure 8; Occupancy Step plot Graph, 12/9/2020, alpha = 0.8, cut height = 30, McQuitty

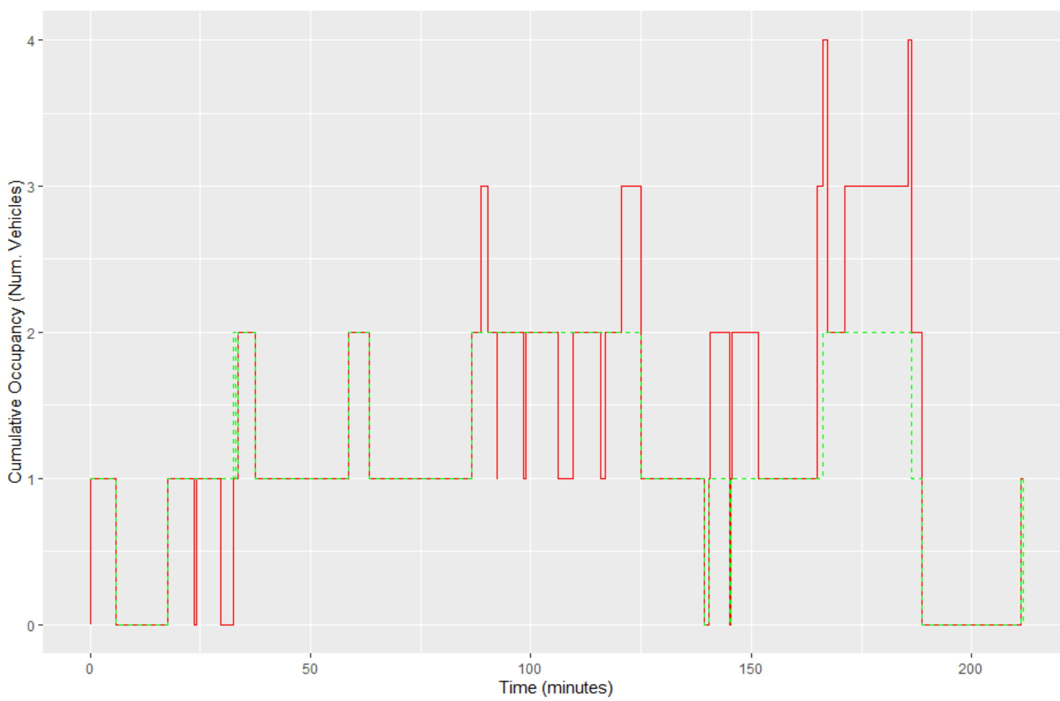

Figure 9; Occupancy Step plot Graph, 12/10/2020, alpha = 0.8, cut height = 105, McQuitty

Overstay Analysis

Overstay is the duration a vehicle spends parked at a curb space above the legally allowed limit. This value differs by curb parking type, as passenger vehicles are only allowed to use passenger load zone curb space for 3 minutes, where commercial vehicles have 30 minutes for parking or idling. Calculating overstay at a given curb face can provide municipal authorities with data on what areas of their jurisdiction see more vehicles over the legal limit of time spent at the curb.

For the McQuitty linkage method, the best fit occupancy parameters for each day of video data collected provided the following overstay analysis results, see **Table 7**.

TABLE 7; Overstay Results for McQuitty Method, Given Optimal Alpha and Cut Height Configurations

	Sensor Estimated (min)	Video Estimated (min)	Percent Difference
12/9, block 30	9.52	11.43	20.1
12/8, block 30	144.15	131.08	9.06
12/8, block 31	88.38	87.9	0.54
12/10, block 4	166.74	172.62	3.52

Results & Discussion

In terms of occupancy difference, the McQuitty linkage method performed the best as an average of all four block face days of video at 2085 vehicle-seconds. The "Average" method performed second-best at 2294.75 vehicle-seconds. All five linkage methods achieved below a 230 vehicle-second threshold for December 9th, while no linkage method was able to achieve below 4500 vehicle-seconds for block face 30 on December 8th.

The best performing clustering configuration for December 9th estimated 17 out of the 19 video data parking events for that day with a buffer zone of 10 seconds from the start and end times of the video events. December 10th saw 7 out of the 23 estimated video events produced from sensor data clustered by the algorithm. Discrepancies in clustering performance may be a product of differing block face lengths, as block face 4 is 144.62 feet long, more than 42 feet longer than the next closest block face, 31, of length 102.55.Although percent differences between sensor estimated parking events and video estimated events can reach up to 34% for their optimal parameter configuration, applying an overstay analysis to the results provides much closer approximations. The clustering algorithm performs better when utilized as a heuristic for calculating parking events from sensor data, especially when trying to capture larger parking events.

Conclusion

This work explored how hierarchical clustering using a time-space dissimilarity matrix can estimate parking events from raw sensor data collected at a curb face. The results demonstrated that the accuracy for detecting curb occupancy is variable between both block faces and days where video data was collected. The percent difference in vehicle occupancy calculated from sensor event clustering is not consistently within 20% of the video data estimates. The clustering algorithm is, however, effective at calculating overstay time from sensor events. 3 of the 4 video data sets reported less than a 10% difference between overstay from estimated parking events from sensors and overstay calculated from video observations. Only one overstay analysis exceeded a 10% difference between sensor clustering and video estimates but said overstay analysis was within 5 minutes of the video estimate, see **Table 7**. The clustering algorithm may serve as a useful heuristic in determining overstay, and potentially predicting future overstay parking events based on trends in previous parking estimates from sensor data.

Given the accuracy of the clustering algorithm in calculating both occupancy and overstay metrics for shorter block face spaces, the clustering algorithm may be a valid method for estimating parking events from occupancy sensors for a curb segment of limited length. Constraints may also exist in terms of expected curb activity, where curb segments with high parking activity are more difficult to estimate with accuracy than curb segments with fewer parking events in an equal timeframe. The impact that parking activity frequency and curb segment length have on the accuracy of the estimated sensor parking metrics was not quantified in this work, and by extension neither were the impacts these factors can have on the different parameters for time and space in calculating the dissimilarity matrix for the clustering algorithm.

Chapter 3

Conclusions

Observing the capacity of on-street and off-street parking in tandem provides insight between the two facilities that has not been explored in previous research. On-street and off-street parking facilities are often observed individually, but their comparison is a distinct feature of this thesis. Although methods for calculating curb space capacity have been conducted, this thesis looks to determine parking capacity for the entire CBD by curb segment, which is a level of detail not conducted in previous research. This is in part due to the area being studied, as not all municipalities collect curb parking inventories by segment. This thesis should demonstrate the benefit of collecting data to segment-level resolution, which allows for more detailed analysis of commercial vehicle parking capacity at the curb. The results of this analysis demonstrate that, even in lowest estimates of off-street parking, at least 1 in every 3 potential parking spaces in Seattle's CBD is found off-street in internal loading bays or exterior loading docks. Off-street capacity scenarios 3 and 4 displayed 80% or more of the on-street parking capacity existed off-street except for FHWA Class 8 in scenario 3. This demonstrates that off-street parking not only serves as a useful infrastructure for separating commercial vehicle deliveries from curb activity, but also represents a considerable portion of a major downtown area's parking capacity. Although these results are specific to Seattle, the methodology used in this analysis can be generalized to any urban area with commercially designated curb space and off-street commercial vehicle parking.

A method for effectively measuring performance of commercial vehicle infrastructure at the curb was also explored. Utilizing sensor data from occupancy detectors located in Seattle's Belltown district, this thesis developed an algorithm that estimates parking activity from sensor occupancy data using hierarchical clustering. This approach is a novel usage of hierarchical clustering and can convert sensor data inputs into estimated parking events with varying degrees of accuracy, between 2.91% and 34.61% difference in vehicle occupancy from estimated parking events from video data. The algorithm performed with higher accuracy to video data results in terms of parking overstay, or time spent by parked vehicles exceeding their legal limit. The four days of overstay analysis demonstrated a percent difference between estimated sensor data and video data ranging between 0.54 and 20.1 percent difference, with an average of 8.31 percent difference. Accuracy in overstay analysis demonstrates the potential use case for hierarchical clustering of sensor data for policy application, where sensor data over days, weeks, or months can be aggregated to determine trends in parking violations to help improve effectiveness of curb usage and prevent prolonged vehicle occupancy of curb space. Future work in this research topic can include predicting future parking activity, specifically overstay parking events, through trends in estimated parking events from sensor activity clustering.

Quantifying urban freight infrastructure in terms of capacity can allow different facility types, like curb space and off-street vehicle parking, to be compared in a manner that reflects a common purpose. These facilities are valued based on how much activity they can support, as well as how effectively they can support said activity. The process developed in this thesis looks to methodize the former in a novel manner that addresses the nuances in how vehicles park for deliveries in on-street and off-street facilities. The latter, determining how effectively urban freight infrastructure can support delivery operations, can be quantified in data collection, and evaluated in the analysis of said data. The process of collecting relevant data for analyzing performance can be tedious and ongoing, creating demand for smart, automated systems that can process information with minimal oversight. This thesis provides a method for converting raw data from internet connected curb sensors into parking events and demonstrates a potential use case for this data in overstay analysis, determining how much time is spent by parked vehicles past what is legally allowed for parking duration at a given curb space. The processes discussed in Chapters 1 and 2 of this thesis demonstrate novel methods for quantifying urban freight infrastructure, both on-street and off-street, that allow stakeholders in the operations of these resources to better understand the performance and potential capacity of their facilities.

BIBLIOGRAPHY

1. Grimm, N.B., S.H. Faeth, N.E. Golubiewski, C.L. Redman, J. Wu, X. Bai, and J.M. Briggs. Global Change and The Ecology of Cities. *Science*, Vol. 319, No. 756, 2008, doi: 10.1126/science.1150195

2. Browne, M., J. Allen, T. Nemoto, D. Patier, and J. Visser. Reducing social and environmental impacts of urban freight transport: A review of some major cities. *The Seventh International Conference on City Logistics*, 2012, doi: 10.1016/j.sbspro.2012.03.088

3. Russo, F., and A. Comi. City characteristics and urban goods movements: A way to environmental transportation system in a sustainable city. *The Seventh International Conference on City Logistics*, 2012, doi: 10.1016/j.sbspro.2012.03.091

4. Saynajoki, E.S., V. Inkeri, J. Heinonen, and S. Junnila. How central business district developments facilitate environmental sustainability – A multiple case study in Finland. *Cities*, Vol. 41, Part A, doi: 10.1016/j.cities.2014.05.010

5. Van Der Waals, J.F.M. The Compact City and The Environment: A Review. *Tijdschrift voor Economische en Sociale Geografie*, December 1999, Vol. 91, No. 2, pp. 111-121.

6. Shoup, D.C. Cruising for parking. *Transport Policy*, November 2006, Vol. 13, Issue 6, pp. 479-486.

7. Hampshire, R.C., and D. Shoup. What Share of Traffic is Cruising for Parking?. *Journal of Transportation Economics and Policy*, July 2018, Vol. 52, Part 3, pp. 184-201.

8. Dalla Chiara, G., and A. Goodchild. Do commercial vehicles cruise for parking? Empirical evidence from Seattle. *Transport Policy*, Vol. 97, October 2020, pp. 26-36.

9. McLeod, F.N., and T. Cherrett. Loading bay booking and control for urban freight. *International Journal of Logistics*, doi: 10.1080/13675567.2011.641525

10. Dalla Chiara, G., and L. Cheah. Data stories from urban loading bays. *European Transport Research Review*, Vol. 9, doi: 10.1007/s12544-017-0267-3

11. Comi, A., B. Buttarazzi, M.M. Schiraldi, R. Innarella, M. Varisco, and L. Rosati. DynaLOAD: a simulation framework for planning, managing and controlling urban delivery bays. *Transportation Research Procedia*, Vol. 22, 2017, pp. 335-344.

12. Letnik, T., A. Farina, M. Mencinger, M. Lupi, and S. Bozicnik. Dynamic management of loading bays for energy efficient urban freight deliveries. *Energy*, Vol. 159, 2018, pp. 916-928.

13. Blackburn, S.R. The Geometry of Perfect Parking. *University of London, Department of Mathematics*, November 30, 2009.

14. Puget Sound Regional Council. Parking Inventory. Retrieved May 21, 2021, from https://www.psrc.org/parking-inventory

15. Heffron, M.C., J. A. Royson. 2018 Downtown Off-Street Parking Study. *Heffron Transportation, Inc*. January 15, 2019

16. City of Seattle Department of Transportation, 2021. Paid area curbspaces. Retrieved May 28, 2021, from. https://data-seattlecitygis.opendata.arcgis.com/datasets/SeattleCityGIS::paid-area-curbspaces/about

17. City of Seattle. Municipal Code, 11.14.295, "Load and unload zone.", Ord. 108200.

18. Seattle Department of Transportation. Private Loading Facilities Inventory. In *The Final 50 Feet Urban Goods Delivery System: Research Scan and Data Collection Project*. Supply Chain and Transportation Logistics Center, University of Washington, Seattle, WA. January 19, 2018, Ch. 3, pp. 59-71.

19. City of Seattle Department of Transportation, 2021. Greater downtown alleys. Retrieved July 7, 2021, from. https://data-seattlecitygis.opendata.arcgis.com/datasets/SeattleCityGIS::greater-downtown-alleys/about

20. Giron-Valderrama, G.C. J.L. Machado-Leon, A. Goodchild. Commercial Vehicle Parking in Downtown Seattle: Insights on the Battle for The Curb. *Transportation Research Record*, doi: 10.1177/0361198119849062

21. Federal Highway Administration. *Office of Highway Policy Information*. "Traffic Monitoring Guide". From: https://www.fhwa.dot.gov/policyinformation/tmguide/tmg_2013/vehicle-types.cfm

22. Giron-Valderrama, G., and A. Goodchild. *Characterization of Seattle's Commercial Traffic Patterns: A Greater Downtown Area and Ballard/Interbay Vehicle Count and Evaluation*. Supply Chain and Transportation Logistics Center, University of Washington, Seattle, WA. December, 2020. http://depts.washington.edu/sctlctr/research/publications/characterization-seattles-commercial-traffic-patterns-greater-downtown-area

23. Giron-Valderrama, G., and A. Goodchild. Cracking the Freight Data Nut: Estimating Center City Inbound and Outbound Vehicle Vehicle Volumes from Cordon Counts. *METRANS International Urban Freight Conference*, October 17, 2019.

24. AASHTO. *Geometric Design of Highways and Streets*. Design Controls and Criteria, 2004, pp. 19-33.

25. McCormack, E., A. Goodchild, M. Sheth, D.S. Hurwitz, H. Jashami, and D.P. Cobb. Developing Design Guidelines for Commercial Vehicle Envelopes on Urban Streets. *Pacific Northwest Transportation Consortium*, 2019. From: https://depts.washington.edu/sctlctr/research/publications/developing-design-guidelines-commercial-vehicle-envelopes-urban-streets

26. Federal Highway Administration. "Verification, Refinement, and Applicability of Long-Term Pavement Performance Vehicle Classification Rules", accessed from: https://www.fhwa.dot.gov/publications/research/infrastructure/pavements/ltpp/13091/002.cfm

27. Enterprise. "26' Box Truck with Lift Gate". Accessed from: https://www.enterprisetrucks.com/truckrental/en_US/vehicles/straight-trucks/26--straight-personal.html

28. CDL College. “CDL Test/Practice Pad Dimensions”. Accessed from: https://cdlcollege.com/courses/test-cone-dimensions/test-practice-cone-dimensions.html

29. World Economic Forum. “The Future of the Last-Mile Ecosystem”. 2020. Accessed from:

http://www3.weforum.org/docs/WEF_Future_of_the_last_mile_ecosystem.pdf

30. Amaya, J., M. Delgado-Lindeman, J. Arellana, J. Allen. Urban freight logistics: What do citizens perceive. *Transportation Research Part E*, 152, 2021.

31. Jaller, M., J. Holguin-Veras, S. Darville Hodge. Parking in the City: Challenges for Freight Traffic. *Transportation Research Record: Journal of The Transportation Research Board*, 2379, 2013, pp. 46-56.

32. Arnott, R., E. Inci, J. Rowse. Downtown curbside parking capacity. *Journal of Urban Econmics*, 86, 2015, pp. 83-97.

33. Piovesan, N., L. Turi, E. Toigo, B. Martinez, M. Rossi. Data Analytics for Smart Parking Applications. *Sensors*, 16, 2016.

34. Gomari, S., C. Knoth, C. Antoniou. Cluster analysis of parking behaviour: A case study in Munich. *Transportation Research Procedia*, 52, 2021, pp. 485-492.

35. Teodorovic, D., P. Lucic. Intelligent parking systems. *European Journal of Operations Research,* 175, 2006, pp. 1666-1681.

36. Diaz Ogas, M. G., R. Fabregat, S. Aciar. Survey of Smart parking Systems. *Applied Sciences*, 10, 2020.

37. Ang, L., K. P. Seng. Big Data Applications in Urban Environments. *Big Data Research*, 4, 2016, pp. 1-12.

38. Murtagh, F. A Survey of Recent Advances in Hierarchical Clustering Algorithms. *The Computer Journal*, 26, 4, 1983.

39. Wennenman, A., K. M. N. Habib, M. J. Roorda. Disaggregate Analysis of Relationships Between Commercial Vehicle Parking Citations, Parking Supply, and Parking Demand. *Transportation Research Record*, No. 2478, 2015, pp. 28-34.

40. Dey, S. S., M. Darst, A. Pochowski, B. O. Perez, E. C. Sanchez. Hunt for Perfect Detection of Parking Occupancy; Evaluation of On-Street Technology and Its Ability to Address Urban Challenges. *Transportation Research Record*, No. 2645, 2017, pp.12-23.

41. Cao, Y., Z.Z. Yang, Z.Y. Zuo. The effect of curb parking on road capacity and traffic safety. *European Transportation Review*. 9**,** 4 (2017). https://doi.org/10.1007/s12544-016-0219-3

42. Provoost, J.C., A. Kamilaris, L.J.J. Wismans, S.J. van der Drift, M. van Keulen. Predicting parking occupancy via machine learning in the web of things. *Internet of Things*, 12, 2020.

43. Vlahogianni E.I., K. Kepaptsoglou, V. Tsetsos, M. G. Karlaftis. A Real-Time Parking Prediction System for Smart Cities. *Journal of Intelligent Transportation Systems*, 20, 2, 2016, pp.192-204.

44. Stolfi D.H., E. Alba, X. Yao. Can I Park in the City Center? Predicting Car Park Occupancy Rates in Smart Cities. *Journal of Urban Technology*, 27, 4, 2020, pp. 27-41.

APPENDIX A

TABLES 8-11; Table of Performance Metrics for Evaluating parking Event Estimation with Video Data, Linkage Method: McQuitty

12/8/2020 (McQuitty)	Cut height	alpha	Occupancy Diff. (veh-sec)	Percent Diff.	Est. Parking events
Block: 31	40	0.55	448	4.26	12
	40	0.6	754	7.16	17
	45	0.7	777	7.38	15
	40	0.5	785	7.46	11
	45	0.6	986	9.37	12
	45	0.65	986	9.37	12
	50	0.7	986	9.37	12
	25	0.3	1273	12.10	12
	30	0.35	1273	12.10	12
	35	0.45	1273	12.10	12

12/9/2020 (McQuitty)	Cut height	alpha	Occupancy Diff. (veh-sec)	Percent Diff.	Est. Parking events
Block: 30	30	0.8	215	2.91	12
	30	0.85	235	3.18	17
	30	0.75	282	3.81	15
	30	0.9	337	4.56	11
	25	0.65	388	5.25	12
	25	0.7	388	5.25	12
	25	0.75	556	7.52	12
	30	0.95	556	7.52	12
	35	0.9	569	7.70	12
	35	0.95	569	7.70	12

12/10/2020 (McQuitty)	Cut height	alpha	Occupancy Diff. (veh-sec)	Percent Diff.	Est. Parking events
Block: 4	105	0.8	2916	17.72	10
	110	0.85	2916	17.72	10
	115	0.85	2946	17.90	9
	90	0.7	3143	19.10	11
	110	0.8	3625	22.03	9

	100	0.8	3649	22.17	13
	65	0.5	3820	23.21	13
	70	0.55	3820	23.21	13
	95	0.75	3915	23.79	12
	35	0.95	569	21	12

12/8/2020 (McQuitty)	Cut height	alpha	Occupancy Diff. (veh-sec)	Percent Diff.	Est. Parking events
Block: 30	155	0.95	4761	34.61	8
	170	0.95	4916	35.73	4
	175	0.95	4916	35.73	4
	170	0.85	4950	35.98	3
	175	0.85	4950	35.98	3
	160	0.95	5081	36.93	7
	165	0.95	5096	37.04	5
	165	0.2	5847	42.50	1
	170	0.2	5847	42.50	1
	175	0.2	5847	42.50	1

TABLE 12-15; Table of Performance Metrics for Evaluating parking Event Estimation with Video Data, Linkage Method: Ward

12/8/2020 (Ward)	Cut height	alpha	Occupancy Diff. (veh-sec)	Percent Diff.	Est. Parking events
Block: 31	45	0.65	258	2.45	15
	45	0.7	268	2.55	16
	50	0.7	339	3.22	14
	40	0.45	477	4.53	13
	40	0.5	477	4.53	13
	40	0.55	477	4.53	13
	45	0.55	477	4.53	13
	45	0.6	477	4.53	13
	50	0.65	477	4.53	13
	40	0.6	754	7.16	17

12/9/2020 (Ward)	Cut height	alpha	Occupancy Diff. (veh-sec)	Percent Diff.	Est. Parking events
Block: 30	30	0.7	225	3.04	27
	35	0.8	370	5.00	24

	35	0.85	370	5.00	24
	30	0.75	386	5.22	27
	30	0.8	434	5.87	30
	30	0.85	454	6.14	34
	25	0.55	546	7.38	27
	25	0.75	556	7.52	35
	30	0.9	556	7.52	35
	30	0.95	556	7.52	35

12/10/2020 (Ward)	**Cut height**	**alpha**	**Occupancy Diff. (veh-sec)**	**Percent Diff.**	**Est. Parking events**
Block: 4	50	0.35	3936	23.92	15
	110	0.8	4021	24.43	13
	75	0.65	4354	26.46	20
	65	0.55	4419	26.85	19
	70	0.6	4419	26.85	19
	95	0.85	4465	27.13	20
	100	0.9	4465	27.13	20
	105	0.95	4465	27.13	20
	80	0.75	4484	27.25	29
	65	0.6	4518	27.45	28

12/8/2020 (Ward)	**Cut height**	**alpha**	**Occupancy Diff. (veh-sec)**	**Percent Diff.**	**Est. Parking events**
Block: 30	100	0.65	7179	52.18	23
	95	0.6	7289	52.98	21
	100	0.6	7327	53.26	19
	105	0.65	7327	53.26	19
	85	0.55	7566	55.00	25
	90	0.6	8005	58.19	30
	90	0.5	8043	58.46	17
	95	0.55	8043	58.46	17
	105	0.6	8106	58.92	18
	110	0.65	8106	58.92	18

TABLE 16-19; Table of Performance Metrics for Evaluating parking Event Estimation with Video Data, Linkage Method: Average

12/8/2020 (Average)	Cut height	alpha	Occupancy Diff. (veh-sec)	Percent Diff.	Est. Parking events
Block: 31	40	0.6	754	7.16	17
	45	0.6	957	9.09	11
	40	0.55	986	9.37	12
	45	0.65	986	9.37	12
	30	0.35	1146	10.89	11
	50	0.6	1167	11.09	9
	25	0.3	1273	12.10	12
	35	0.45	1273	12.10	12
	40	0.5	1294	12.30	10
	45	0.55	1294	12.30	10

12/9/2020 (Average)	Cut height	alpha	Occupancy Diff. (veh-sec)	Percent Diff.	Est. Parking events
Block: 30	30	0.8	215	2.91	29
	30	0.85	235	3.18	33
	30	0.75	282	3.81	25
	30	0.9	337	4.56	34
	25	0.65	388	5.25	33
	25	0.7	388	5.25	33
	25	0.75	556	7.52	35
	30	0.95	556	7.52	35
	35	0.9	569	7.70	21
	25	0.6	620	8.39	27

12/10/2020 (Average)	Cut height	alpha	Occupancy Diff. (veh-sec)	Percent Diff.	Est. Parking events
Block: 4	105	0.8	3625	22.03	9
	110	0.85	3625	22.03	9
	100	0.8	3649	22.17	13
	90	0.7	3852	23.41	10
	110	0.8	3895	23.67	8
	65	0.5	3915	23.79	12
	70	0.55	3915	23.79	12
	95	0.75	3915	23.79	12
	115	0.8	4263	25.90	7

	80	0.75	4484	27.25	29

12/8/2020 (Average)	**Cut height**	**alpha**	**Occupancy Diff. (veh-sec)**	**Percent Diff.**	**Est. Parking events**
Block: 30	170	0.75	4585	33.33	2
	175	0.75	4585	33.33	2
	170	0.8	4585	33.33	2
	175	0.8	4585	33.33	2
	170	0.85	4585	33.33	2
	175	0.85	4585	33.33	2
	175	0.9	4585	33.33	2
	155	0.95	4713	34.26	7
	175	0.95	4876	35.44	4
	150	0.95	4905	35.65	9

TABLE 20-23; Table of Performance Metrics for Evaluating parking Event Estimation with Video Data, Linkage Method: Single

12/8/2020 (Single)	**Cut height**	**alpha**	**Occupancy Diff. (veh-sec)**	**Percent Diff.**	**Est. Parking events**
Block: 31	35	0.45	1167	11.09	9
	40	0.5	1167	11.09	9
	40	0.55	1167	11.09	9
	40	0.6	1217	11.56	14
	35	0.5	1316	12.50	11
	35	0.6	1423	13.52	19
	20	0.25	1577	14.98	12
	30	0.4	1655	15.73	10
	35	0.55	1932	18.36	18
	30	0.45	2093	19.89	16

12/9/2020 (Single)	**Cut height**	**alpha**	**Occupancy Diff. (veh-sec)**	**Percent Diff.**	**Est. Parking events**
Block: 30	30	0.8	192	2.60	26
	30	0.85	293	3.96	32
	30	0.9	337	4.56	34
	25	0.7	388	5.25	33
	25	0.75	556	7.52	35
	30	0.95	556	7.52	35
	30	0.75	559	7.56	19
	25	0.65	618	8.36	31

	35	0.95	623	8.43	16
	35	0.9	721	9.75	15

12/10/2020 (Single)	Cut height	alpha	Occupancy Diff. (veh-sec)	Percent Diff.	Est. Parking events
Block: 4	45	0.35	4225	25.67	5
	60	0.55	4619	28.07	26
	65	0.6	4619	28.07	26
	95	0.75	4629	28.13	5
	75	0.7	4767	28.96	27
	70	0.65	4799	29.16	24
	65	0.55	4964	30.16	10
	70	0.6	4964	30.16	10
	75	0.65	4964	30.16	10
	80	0.7	4964	30.16	10

12/8/2020 (Single)	Cut height	alpha	Occupancy Diff. (veh-sec)	Percent Diff.	Est. Parking events
Block: 30	140	0.95	5776	41.99	10
	145	0.95	5790	42.09	3
	110	0.2	5847	42.50	1
	115	0.2	5847	42.50	1
	120	0.2	5847	42.50	1
	125	0.2	5847	42.50	1
	130	0.2	5847	42.50	1
	135	0.2	5847	42.50	1
	140	0.2	5847	42.50	1
	145	0.2	5847	42.50	1

TABLE 24-27; Table of Performance Metrics for Evaluating parking Event Estimation with Video Data, Linkage Method: Complete

12/8/2020 (Complete)	Cut height	alpha	Occupancy Diff. (veh-sec)	Percent Diff.	Est. Parking events
Block: 31	45	0.65	258	2.45	15
	45	0.7	268	2.55	16
	40	0.55	339	3.22	14
	40	0.45	448	4.26	12
	35	0.4	477	4.53	13
	35	0.45	477	4.53	13
	40	0.5	477	4.53	13

	40	0.6	754	7.16	17
	50	0.75	777	7.38	15
	30	0.35	963	9.15	14

12/9/2020 (Complete)	**Cut height**	**alpha**	**Occupancy Diff. (veh-sec)**	**Percent Diff.**	**Est. Parking events**
Block: 30	30	0.8	215	2.91	29
	30	0.75	225	3.04	27
	30	0.85	235	3.18	33
	30	0.9	337	4.56	34
	25	0.65	388	5.25	33
	25	0.7	388	5.25	33
	30	0.7	389	5.26	26
	25	0.55	466	6.30	26
	25	0.6	536	7.25	29
	25	0.75	556	7.52	35
12/10/2020 (Complete)	**Cut height**	**alpha**	**Occupancy Diff. (veh-sec)**	**Percent Diff.**	**Est. Parking events**
Block: 4	100	0.75	2877	17.48	12
	105	0.8	2877	17.48	12
	70	0.5	3048	18.52	12
	75	0.55	3048	18.52	12
	80	0.6	3048	18.52	12
	110	0.8	3359	20.41	10
	115	0.8	3625	22.03	9
	85	0.65	3649	22.17	13
	90	0.7	3649	22.17	13
	95	0.75	3649	22.17	13

12/8/2020 (Complete)	**Cut height**	**alpha**	**Occupancy Diff. (veh-sec)**	**Percent Diff.**	**Est. Parking events**
Block: 30	75	0.45	7266	52.82	21
	85	0.5	7304	53.09	19
	80	0.5	7641	55.54	22
	70	0.4	8317	60.46	20
	80	0.45	8536	62.05	15
	90	0.5	8536	62.05	15
	150	0.95	8723	63.41	12
	155	0.95	8732	63.47	10
	70	0.45	8861	64.41	29
	170	0.95	8950	65.06	7