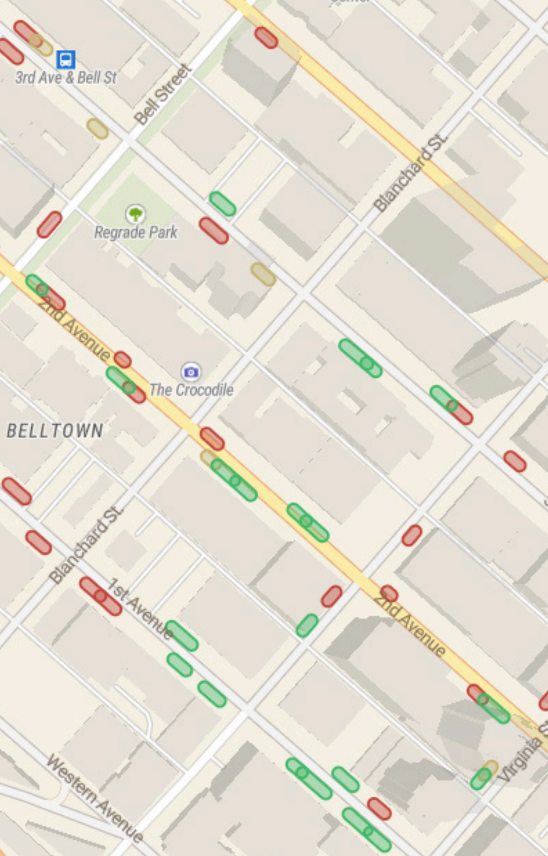

Technology Integration to Gain Commercial Efficiency for the Urban Goods Delivery System, Meet Future Demand for City Passenger and Delivery Load/Unload Spaces, and Reduce Energy Consumption

EERE Award Number: DE-EE0008462

Sponsoring Program Office: Vehicle Technologies Office

Principal Investigator: Dr. Anne Goodchild, University of Washington, Supply Chain Transportation and Logistics Center

Consortium/Team Members: Dr. Andisheh Ranjbari (UW), Dr. Ed McCormack (UW), Ms. Barb Ivanov (UW), Dr. Giacomo Dalla Chiara (UW), Mr. Klaas Fiete Krutein (UW), Ms. Elizabeth Guzy (UW), Ms. Katie Wolf (PNNL), Dr. Vinay Amatya (PNNL), Ms. Amelia Bleeker (PNNL), Dr. Milan Jain (PNNL), Mr. Mike Estey (City of Seattle), Ms. Mary Catherine Snyder (City of Seattle), Mr. Michael Solheim (City of Seattle), Mr. Chris Long (City of Bellevue), Mr. Chris Iverson (City of Bellevue)

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Executive Summary

1.0 EXECUTIVE SUMMARY

This three-year project supported by the U.S. Department of Energy Vehicle Technologies Office has the potential to radically improve the urban freight system in ways that help both the public and private sectors. Working from 2018-2021, project researchers at the University of Washington's Urban Freight Lab and collaborators at the Pacific Northwest National Laboratory have produced key data, tested technologies in complex urban settings, developed a prototype parking availability app, and helped close major knowledge gaps.

All the fruits of this project can be harnessed to help cities better understand, support and actively manage truck load/unload operations and their urban freight transport infrastructure. Project learnings and tools can be used to help make goods delivery firms more efficient by reducing miles traveled and the time it takes to complete deliveries, benefitting businesses and residents who rely on the urban freight system for supplies of goods. And, ultimately, these project learnings and tools can be used to make cities more livable by minimizing wasted travel, which, in turn, contributes to reductions in fuel consumption and emissions.

Cities today are challenged to effectively and efficiently manage their infrastructure to absorb the impacts of ever-increasing e-commerce-fueled delivery demand. All delivery trucks need to park somewhere to unload and load. Yet today's delivery drivers have no visibility on available parking until they arrive at a site, which may be full. That means they can wind up cruising for parking, which wastes time and fuel and contributes to congestion. Once drivers do find parking, the faster they can unload at the spot, the faster they free up space for other drivers, helping others avoid circling for parking. This makes the parking space—and thus the greater load/unload network—more productive.

To this end, the research team successfully met the project's three goals, developing and piloting strategies and technologies to:

1. Reduce parking-seeking behavior in the study area by 20%
2. Reduce parcel truck dwell time (the time a truck spends in a spot to load/unload) in the study area by 30%
3. Increase curb space, alley space and private loading bay occupancy rates in the study area

The research team met these goals by creating and piloting on Seattle streets OpenPark, **a first-of-its-kind real-time and forecasting curb parking app customized for commercial delivery drivers**—giving drivers the "missing link" in their commonly used routing tools that tell them how best to get to delivery locations, but not what parking is available to use when they get there. **Installing in-ground sensors** on commercial vehicle load zones (CVLZs) and passenger load zones (PLZs) in the 10-block study area in Seattle's downtown neighbourhood of Belltown let researchers glean real-time curb parking data. The research team also met project goals by **piloting three parcel lockers** in public and private spaces open to any delivery carrier, creating a consolidated delivery hub that lets drivers complete deliveries faster and spend less time parked. Researchers collected and analysed data to produce the first empirical, robust, statistically significant results as to the impact of the lockers, and app, on on-the-ground operations. In addition to collecting and analyzing sensor and other real-time and historical data, researchers **rode along with delivery drivers** to confirm real-world routing and parking behavior. Researchers also surveyed building managers on their private loading bay operations to understand how to boost usage.

Key findings that provide needed context for piloting promising urban delivery solutions:

- After developing a novel model using GPS data to measure parking-seeking behavior, researchers were able to quantify that, on average, a delivery driver spends 28% of travel time searching for parking, totaling on average one hour per day for a parcel delivery driver. This project offers the first empirical proof of delivery drivers' cruising for parking.
- While many working models to date have assumed that urban delivery drivers always choose to double-park (unauthorized parking in the travel lane), this study found that behavior is rare: Double-parking happened less than 5% of the times drivers parked.
- That said, drivers do not always park where they are supposed to. The research team found that CVLZ parking took place approximately 50% of the time. The remaining 50% included mostly parking in "un-authorized" curb spaces, including no-parking zones, bus zones, entrances/exits of parking garages, etc.
- Researcher ride-alongs with delivery drivers revealed parking behaviors other than unauthorized parking that waste valuable time and fuel: re-routing (after failing to find a desired space, giving up and doubling back to the delivery destination later in the day) and queuing (temporarily parking in an alternate location and waiting until the desired space becomes available).
- Some 13% of all parking events in CVLZ spaces were estimated as overstays; the figure was 80% of all parking events in PLZ spaces. So, the curb is not being used efficiently or as the city intended as many parking events exceed the posted time limit.
- Meantime, there is unused off-street capacity that could be tapped in Seattle's Central Business District. Estimates show private loading bays could increase area parking capacity for commercial vehicles by at least 50%. But surveys show reported use of loading bays is low and property managers have little incentive to maximize it. Property managers find curb loading zones more convenient; it seems delivery drivers do, too, as they choose to park at the curb even when loading bay space is available.

Key findings from the technology and strategies employed:

Carriers give commercial drivers routing tools that optimize delivery routes by considering travel distance and (often) traffic patterns—but not details on parking availability. Limited parking availability can lead to significant driver delays through cruising for parking or rerouting, and today's drivers are largely left on their own to assess and manage their parking situation as they pull up to deliver.

The project team worked closely with the City of Seattle to obtain permission to install parking sensors in the roadway and communications equipment to relay sensor data to project servers. The team also developed a fully functional and open application that offers both real-time parking availability and near-time prediction of parking availability, letting drivers pick forecasts 5, 15, or 30 minutes into the future depending on when the driver expects to arrive at the delivery destination. Drivers can also enter their vehicle length to customize availability information.

After developing, modeling, and piloting the real-time and forecasting parking app, researchers conducted an experiment to determine how use of the app impacted driver behavior and transportation outcomes. They found that:

- **Having access to parking availability via the app resulted in a 28% decrease in the time drivers spent cruising for parking**. Exceeding our initial goal of reducing parking seeking behaviour by 20%. In the study experiment, all drivers had the same 20-foot delivery van and the same number of randomly sampled delivery addresses in the study area. But some drivers had access to the app; others did not.
- **Preliminary results based on historic routing data show that the use of such a real-time curb parking information and prediction app can reduce route time by approximately 1.5%**. An analysis collected historic parking occupancy and cruising information and integrated it into a model that was then used to revise scheduling and routing. This model optimally routed vehicles to minimize total driving and cruising time. However, since the urban environment is complex and consists of many random elements, results based on historic data underly a high amount of randomness. Analysis on synthetic routes suggests including parking availability in routing systems is especially promising for routes with high delivery density and with stops where the cruising time delays vary a lot along the planned time horizon; here, route time savings can reach approximately 20.4% —conditions outlined in the report.
- **The central tradeoff among four approaches to parking app architecture going forward is cost and accuracy**. The research team found that it is possible to train machine learning models using only data from curb occupancy sensors and reach a higher than 90% accuracy. Training of state-space models (those using inputs such as time of day, day of the week, and location to predict future parking availability) is computationally inexpensive, but these models offer limited accuracy. In contrast, deep-learning models are highly accurate but computationally expensive and difficult to use on streaming data.

Common carrier lockers create delivery density, helping delivery people complete their work faster. The driver parks next to the locker system, loads packages into it, and returns to the truck. When delivery people spend less time going door-to-door (or floor-to-floor inside a building), it cuts the time their truck needs to be parked, increasing turnover and adding parking capacity in crowded cities. This project piloted and collected data on common carrier lockers in three study area buildings.

From piloting the common carrier parcel lockers, researchers found that:

- The implementation of the parcel locker allowed delivery drivers to increase productivity: 40%-60% reduction in time spent in the building and 33% reduction in vehicle dwell time at the curb.
- While the sample size is small, the results are promising. A larger-scale locker deployment likely reduces dwell time since locker deliveries improve efficiency.

Key takeaways:

Today's urban infrastructure is not designed nor managed to meet the demands of ever-growing urban delivery. Consequently, a delivery driver spends, on average, more than one hour a day in parking-related delays.

Currently, available technology can improve the urban logistics system by giving delivery drivers curb parking visibility in real-time, predicting curb availability information, and increasing delivery density through common carrier parcel lockers. This study demonstrates that using these technologies can reduce/help reduce/reduce parking-seeking behavior and truck dwell time. This frees curb space and saves wasted time and fuel (and related pollution).

Sensor network-based parking information systems and parcel lockers are solutions that lie between public and private spaces. Both technologies are distributed and operated by private companies but must be installed on the public right-of-way and/or shared among multiple carriers and users. The authors hope that these research results provide a scientific basis for wider discussion on considering the urban logistics system as a fundamental, open, and shared infrastructure needed to guarantee efficient and sustainable urban deliveries to the benefit of all.

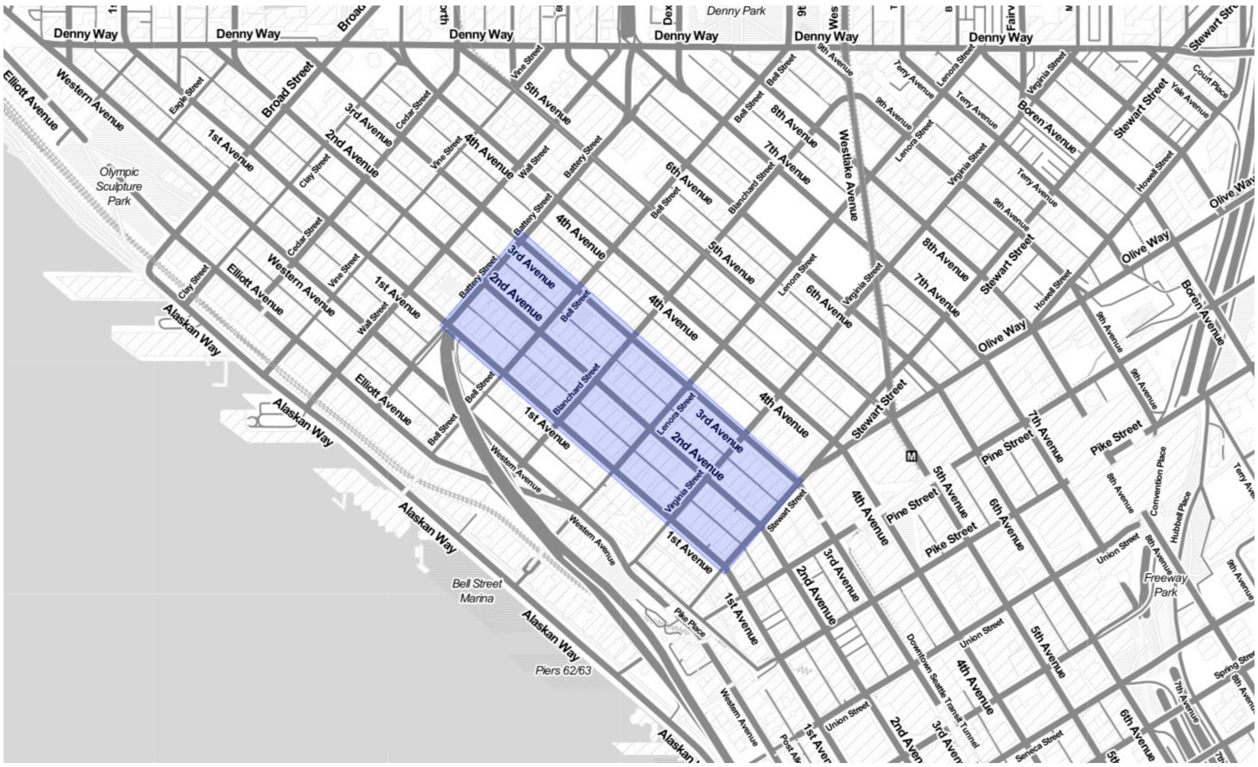
2.0

Study Area

2.0 STUDY AREA

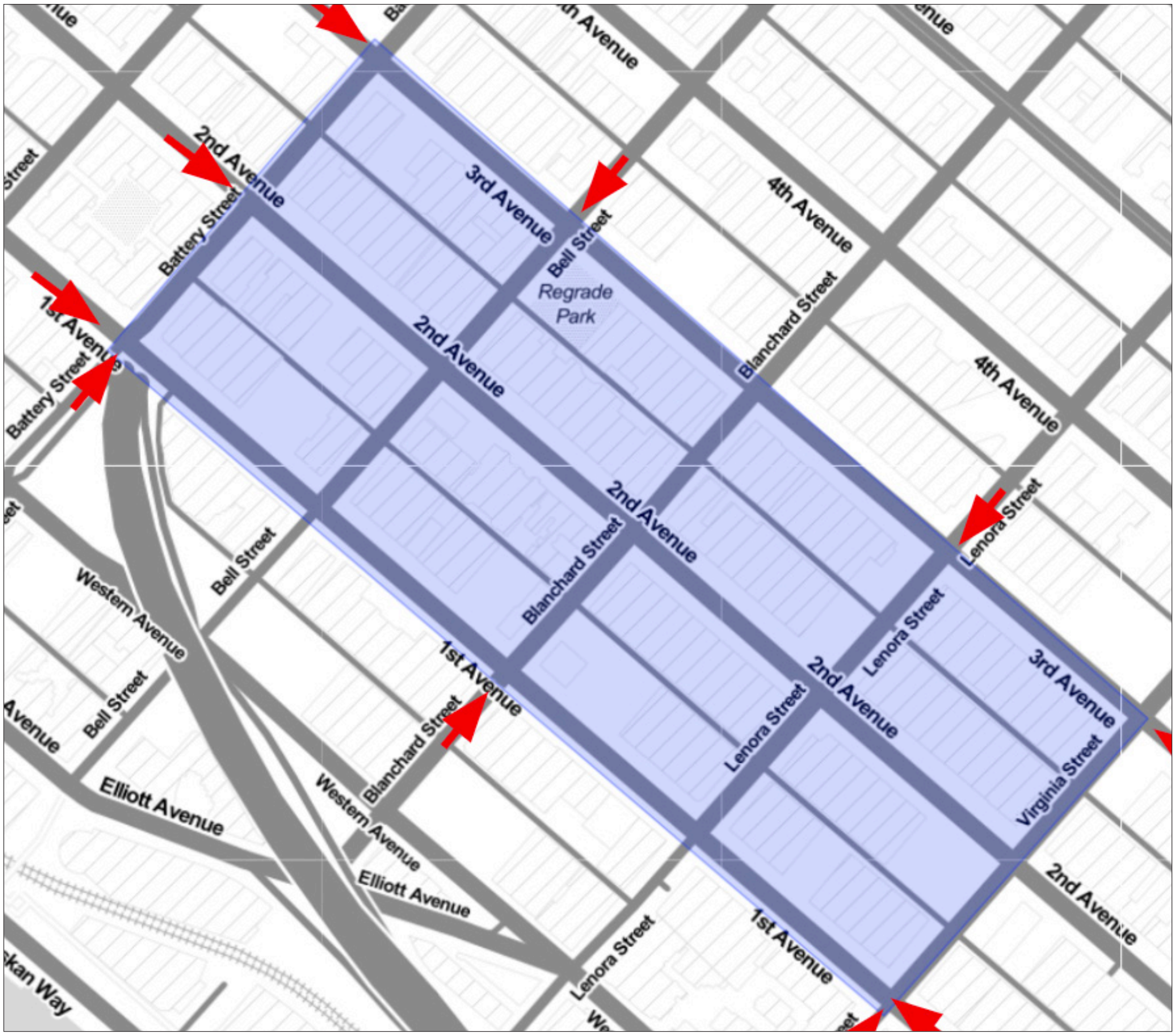
In partnership with the Seattle Department of Transportation, a 10-block study area was selected in the Belltown neighborhood of Seattle, Washington, displayed in Figure 1. The buildings in the area are characterized as mixed-use and consisted of both high-density residential units (e.g. apartment buildings), and commercial units (e.g. retail, lodging, entertainment, and restaurants). However, there were no large freight traffic generators.

Figure 1. Study Area Highlighted in Blue within Seattle Downtown Area



As Figure 2 illustrates, the study area can be accessed through 11 road axes. The size of the study area was approximately 0.05 square miles, with a width of 0.1 miles and a length of 0.5 miles.

Figure 2. Access points to study area in Belltown

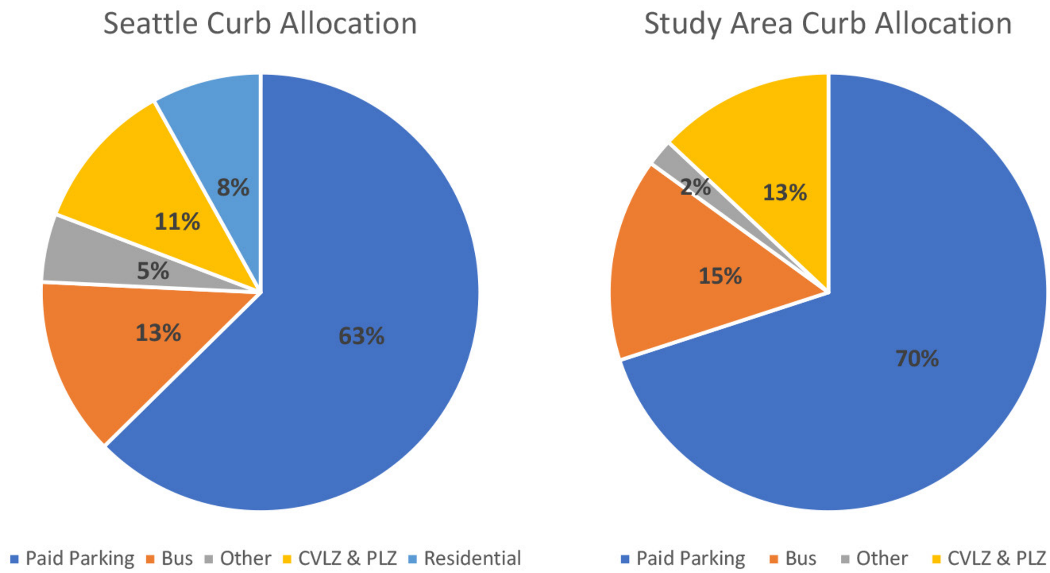


The curb space in the study area hosted different types of designations that give different user groups access. The total length of all curb in the study area was 1.3 miles, which made up approximately 2.5% of all allocated curb space in the central part of Seattle (53 miles). The density of curb spaces was quantified as about 1 space per 6 establishments, which shows the high density of activity in the study area. Figure 3 shows the spatial distribution of the allocation of curb space in the study area.

Figure 3. Curb Space Allocation in Study Area

The curb space allocation in the study area was quite diverse. While large parts of the curb were designated no parking zones, the remaining part of the curbs was accessible for different uses. Figure 4 visualizes the share of allocated curb space in all of Seattle compared to the allocated curb space in the study area. Paid parking made up the largest share of curb space designations in the study area, with 70% in the study area and about 63% in Seattle overall. Bus stops and waiting areas made up 15% and 13% of curb space respectively in the study area and Seattle overall. Most importantly for this study, the study area contained approximately 13% of Commercial Vehicle Loading Zones (CVLZ) and Passenger Loading Zones (PLZ), which are commonly used for delivery activities. CVLZs are specifically designated to commercial vehicles and usually have a parking limit of 30 minutes and require a permit, which can be obtained from the Seattle Department of Transportation (SDOT). PLZs allow drivers to perform passenger loading activities and are usually limited to 3 minutes stopping time, where drivers are supposed to stay in the vehicle. These curb spaces were originally designed for cab and ride-hailing use, but are frequently also used by delivery vehicles. The corresponding CVLZ and PLZ value for Seattle overall was 11%. Another key characteristic of the study area is that there was no designated residential parking unlike Seattle overall, which designated 8% of the curb to residential parking.

Figure 4. Curb Allocation in Seattle vs. Study Area



3.0

Commercial Parking Behavior

3.0 COMMERCIAL PARKING BEHAVIOR

3.1 Do commercial vehicles cruise for parking?

3.1.1 Introduction

A well-known consequence of lack of available parking is cruising for parking. In the absence of available curb space, drivers circle around their destinations searching for available parking. The cost of cruising for parking is two-fold. First, the time spent searching for parking could be used for other, more useful purposes, and therefore represents a direct cost to drivers and carriers. Second, cruising vehicles contribute to traffic, thus increasing congestion and pollution and generating negative externalities to other vehicles and city dwellers.

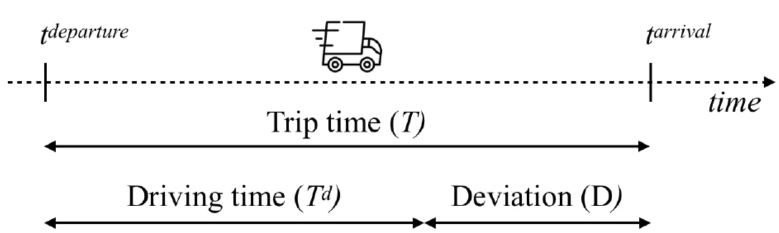
The cruising costs of parking are difficult to measure. As Donald Shoup wrote, "cruising is invisible" (Shoup, 2006), as cruising vehicles are mixed with other vehicles that are headed elsewhere and not searching for parking.

In this section, the research team proposed a novel method to measure cruising for parking for commercial vehicle drivers in urban areas. The team then applied the method to a sample of GPS data from a commercial carrier performing deliveries and pick-ups in Seattle to obtain an empirical distribution of the estimated cruising for parking times. Finally, the results obtained by performing urban ride-alongs with delivery drivers are discussed. For further details on methods and results contained in this section, we refer the reader to (Dalla Chiara et al., 2021, 2020).

3.1.2 Methodology

Consider a trip performed by a commercial vehicle between two delivery/pickup locations, depicted in Figure 5, where: $t^{departure}$ is the departure time and $t^{arrival}$ is the arrival time. *Trip time* (T) is the time difference $T = t^{arrival} - t^{departure}$. Suppose that, in a hypothetical scenario, an identical vehicle departs at $t^{departure}$ from the same location but, this time, its driver knows in advance where the available curb space is. Therefore, he/she will directly drive towards the available space without spending time searching for parking. We define *driving time* (T^d) as the time it takes to reach the available parking lot in this scenario with perfect information. Then, the trip time *deviation* (D) is the difference between the trip time and the respective driving time, $D = T - T^d$, which estimates the time spent cruising for parking.

Figure 5. Decomposition of the trip time *(T)* into driving time *(T^d)* and trip time deviation *(D)*



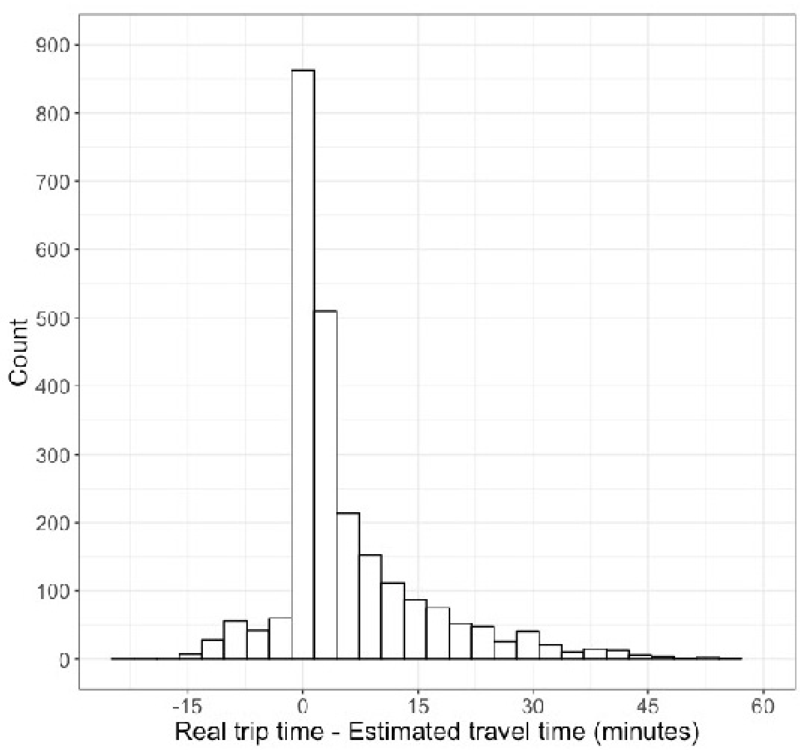
3.1.3 Measuring cruising for parking

A set of 2,477 real trip times (T) was obtained from GPS data from commercial vehicles delivering/picking up goods in downtown Seattle. The team estimated the respective driving times (T^d) by querying the Google Maps Distance Matrix API, using the same trip origin, destination, departure time, day of the week, and month as those of the respective observed trip time. Then, trip time deviations were estimated by subtracting from the observed trip times the respective driving times estimated by the Google Maps API.

Figure 6 shows the empirical distribution of the cruising for parking time estimates. The team observed a right-skewed distribution with a peak around 0 minutes, indicating that driving times often corresponded to their respective trip times. Approximately 16% of trips were characterized by negative deviations, showing that the observed commercial vehicles were not necessarily slower than an average vehicle driving downtown, and sometimes were even faster. However, the right-skew (84% were characterized by positive deviations) shows the presence of a positive trip time deviation. The mean estimated cruising for parking time was 5.8 minutes, the median was 2.3 minutes, and the first and third quartiles were respectively 0.5 minutes and 8.4 minutes.

Therefore, considering the median (2.3. minutes) as a robust estimate of average cruising for parking time, and that an average observed trip length from the GPS data was 8.21 minutes, cruising for parking represented on average 28% of the trip time. Moreover, considering that drivers were observed performing 31 trips per day on average, the total amount spent cruising by a delivery driver per day amounted to 1.1 hours per day, per driver.

Figure 6. Empirical distribution of estimated cruising for parking time



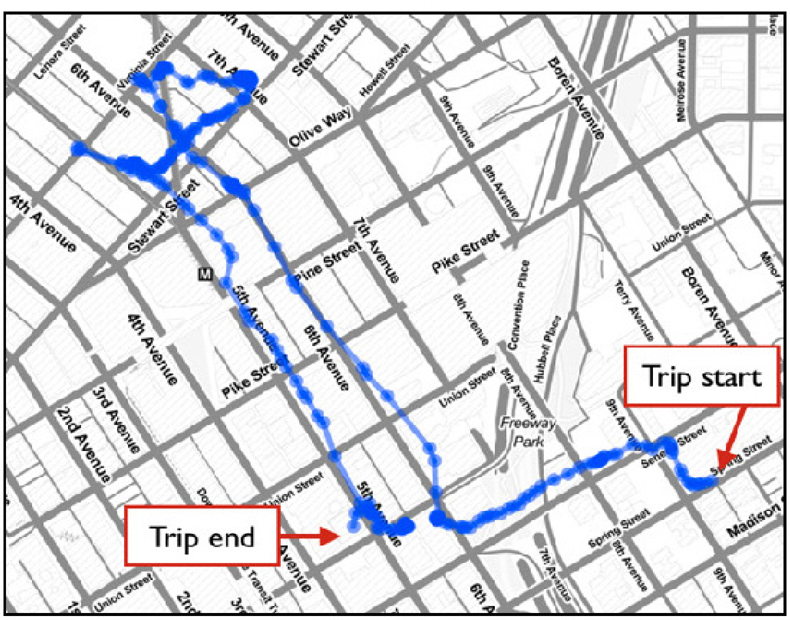
3.1.4 Results from urban ride-alongs

To corroborate the results obtained from GPS data analysis, six ride-alongs with different carriers performing deliveries and pick-ups in Seattle were performed. For each ride-along, an observer followed the delivery driver for the whole day, collecting GPS data as well as contextual data by experiencing first-hand drivers' driving and parking behaviors.

From the data and observations collected during the ride-alongs, four types of parking behaviors were identified.

- *Double-parking*. While it is commonly assumed that urban delivery drivers always choose to double-park, i.e., parking on the travel lane, from empirical data collection (see Dalla Chiara et al., 2021) we observed that double-parking takes place less than 5% of the times drivers park. This does not mean that drivers always park in the dedicated commercial vehicle load zones (CVLZ). In fact, in our studies, CVLZ parking took place approximately 50% of the time. Therefore, while drivers do not always strive to park in curb zones dedicated to commercial vehicles, they still prefer to park on the curb lane and not on the travel lane.
- *Cruising for parking*. When a driver reaches the vicinity of a destination and no curb space is readily available in front of the delivery address, he/she might choose to circle the block in search of available curb space, which is often referred to as cruising for parking.
- *Re-routing*. If, after spending some time searching for parking, still no available curb space can be found, a driver might choose to "give up" and drive to the next destination, coming back later in the day. We defined this parking behavior as "re-routing". Figure 7 shows GPS traces from a vehicle that performed re-routing.
- *Queueing*. Vehicle drivers that are not able to find an available space might choose to temporarily park in an alternative location and wait until the desired space becomes available, hence creating an "invisible" queue of vehicles waiting to access a given space.

Figure 7. GPS traces from a delivery vehicle that re-routed due to unavailable curb parking



3.2 Dwell time and overstay analysis

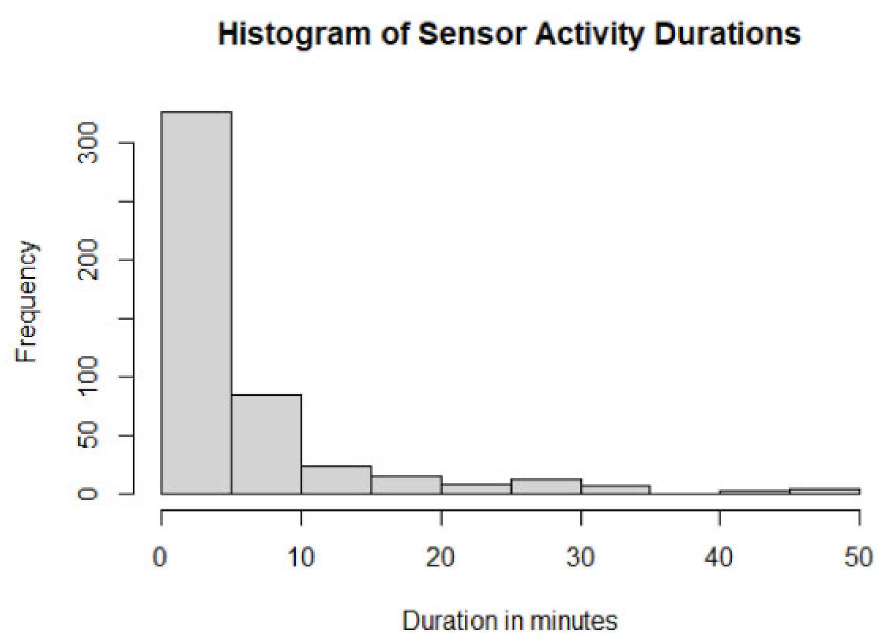
In this section, data from in-ground sensors deployed in the study area is used to analyze the empirical distribution of parking dwell times and the overstay behavior at different curb space types.

The objective of the overstay analysis was to determine the frequency and duration of parking events that occurred in the study area that went over the time allowed for a parking event of a certain curb space type. The maximum allowed parking time at a commercial vehicle load zone (CVLZ) is 30 minutes, while at a passenger load zone (PLZ) is 3 minutes.

Sensor data deployed on CVLZs and PLZs in the study area was processed to obtain start and end times of each vehicle parking event. An algorithm was developed to estimate parking durations from individual sensor events. Since a single parking event can have more than one individual sensor event, the algorithm was designed to combine individual sensor events to estimate parking events at the curb.

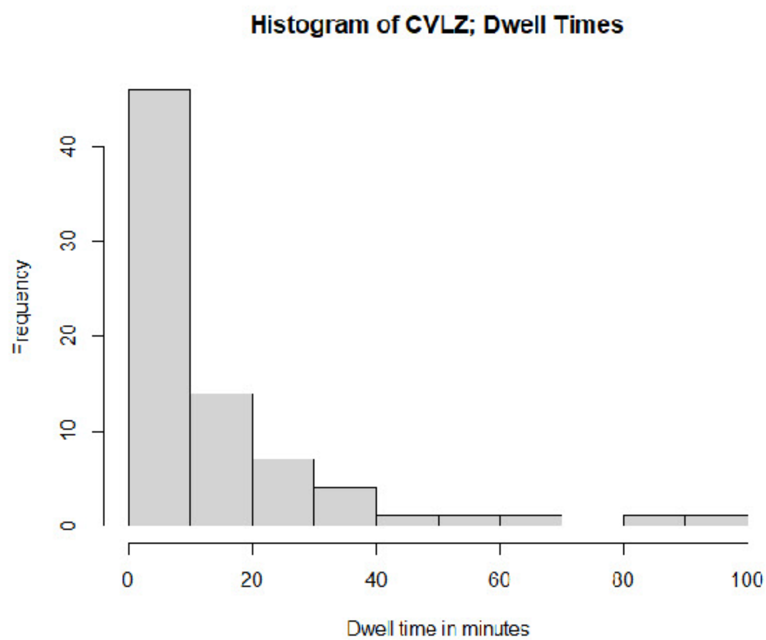
The distribution of the time sensors spent activated, referred to as sensor events, for one blockface in the study area over the span of one week is shown in Figure 8. The mean and median sensor events are 5.57 and 2.17 minutes, respectively.

Figure 8. Histogram of parking dwell time in CVLZs and PLZs in the study area



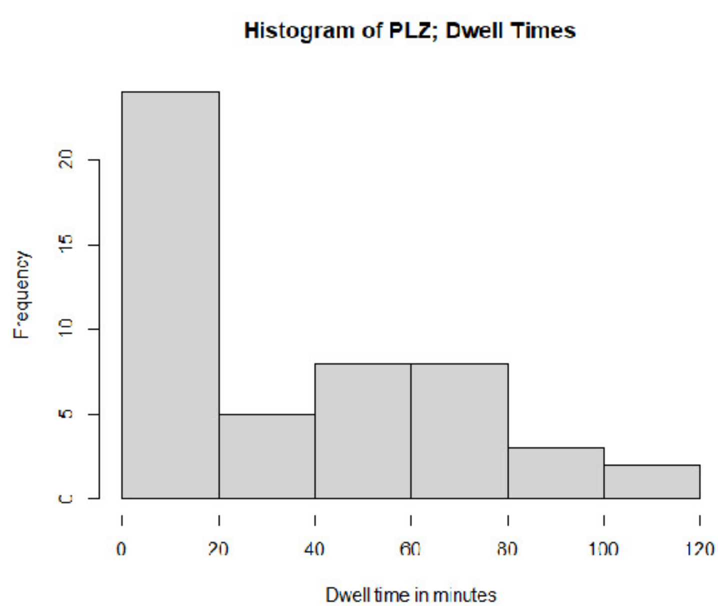
These sensor events were used to estimate dwell times for vehicle parking at the blockfaces. The histogram in Figure 9 shows the distribution of dwell times of vehicles that parked at CVLZs only. The mean and median dwell times are 15.02 and 6.81 minutes, respectively.

Figure 9. Histogram of parking dwell time in CVLZs in the study area



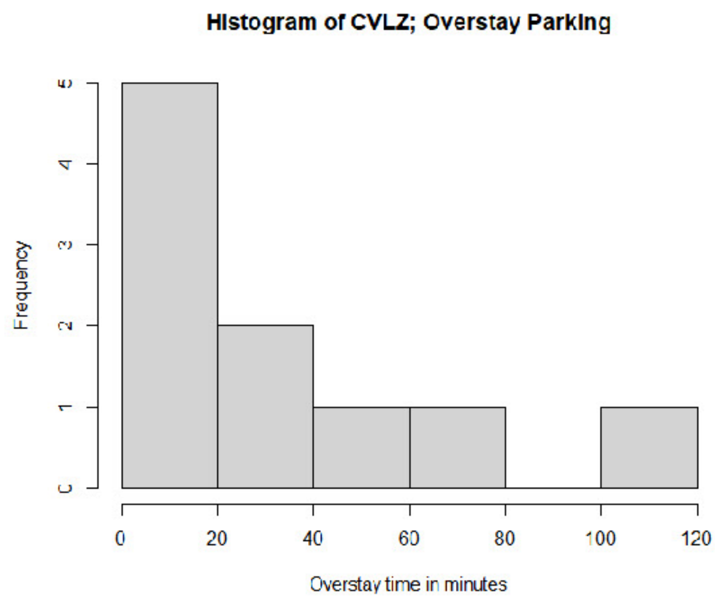
The histogram in Figure 10 shows the distribution of dwell times of vehicles that parked at PLZs. The mean and median dwell times are 47.96 and 28.54 minutes, respectively.

Figure 10. Histogram of parking dwell time in PLZs



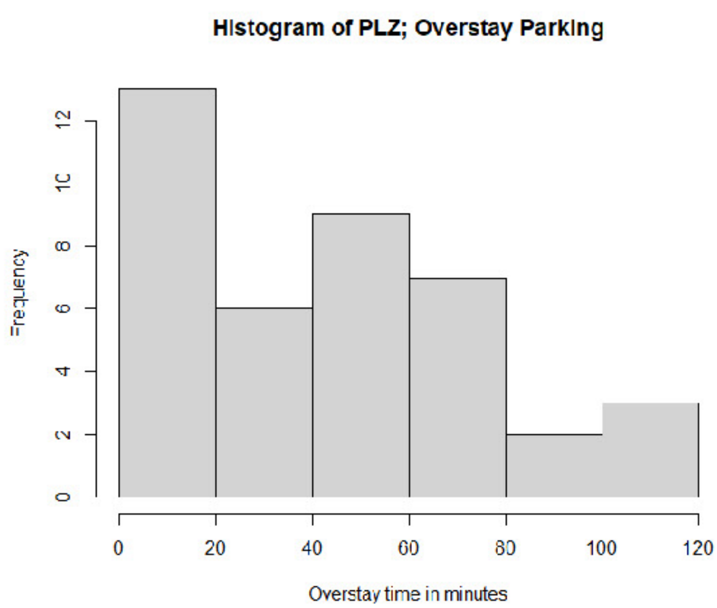
Using the above distributions, the team computed the overstay time which is defined as the additional time spent in a space beyond the maximum allowed time. The maximum allowed time for CVLZs is 30 minutes, and for PLZs is 3 minutes. The histogram in Figure 11 shows the distribution of overstay time at CVLZs. The mean overstay duration is 33.59 minutes and the median is 22.35 minutes.

Figure 11. Histogram of overstay time at CVLZs



The histogram in Figure 12 shows the distribution of overstay time at PLZs. The mean and median overstay durations are 56.43 and 43.2 minutes, respectively.

Figure 12. Histogram of overstay time at PLZs



CVLZ curb space reported 13% of all parking events as overstays, and PLZ curb space had 80% of all parking events as overstay in the estimation.

3.3 Loading bays and curb

Off-street loading bays are parking facilities for commercia delivery vehicles that assist a building's operations with loading and unloading goods inside of a property. This space is internal and separated from public access, unlike curb parking at the street. Loading bays are typically controlled by a property manager or operations specialist designated by the building owner. These facilities can be accessed directly from the street via building entrance or through alleyways. For the first stage of the investigation on loading bay usage in Seattle, commercial building managers in the city's Central Business District and Belltown area were interviewed to gauge internal loading bay utilization and potential interest in sensor implementation for data collection.

Building managers universally stated that loading bays are not utilized to their fullest capacity, as the building either does not have the demand to achieve full utilization or accessing the facilities is less convenient for deliveries than delivering to the curb. One building manager noted that service operations, like garbage pickup, in the parking lot outside the internal loading bay entrance would occasionally prevent trucks from using their off-street facilities, leaving the driver to park on the curb in front of the building. It was determined that the current state of practice in loading bay operations leaves off-street commercial loading and unloading facilities underutilized as building managers have no incentive to improve their loading bay management, as it does not impact daily building operations significantly.

The results of the interviews, as well as the literature review that accompanied it, directed research efforts to study the capacity of off-street commercial parking in comparison to curb parking in Seattle's Central Business District. Results from the analysis showed that off-street commercial vehicle parking is 50% the capacity of curb parking for semitrailer trucks, and 96% for the most conservative estimation of off-street parking capacity for box trucks. This means that every two estimated curb spaces for semitrailer trucks have one estimated loading bay space in the study area. The comparison analysis demonstrated that off-street parking is a significant source of loading and unloading space in the Seattle Central Business District and efforts should be increased for utilizing off-street facilities more effectively.

Figure 13. Example of an off-street loading bay in Seattle's Central Business District

4.0

Parcel Lockers

4.0 PARCEL LOCKERS

4.1 Introduction

In this section, the deployment of three parcel locker systems aimed at consolidating deliveries in congested urban areas and their ability to mitigate last-mile delivery challenges through reducing out-of-vehicle delivery times and consequently vehicle dwell times at the curb is discussed. To empirically demonstrate the environmental and efficiency gains of the parcel lockers, the research team proposed a novel method to measure the causal effects of a common-carrier locker in terms of vehicle dwell time and the time delivery drivers spend inside buildings. Lastly, feedback gathered from the locker users to gauge overall satisfaction and to better understand how the lockers were being used is presented.

4.2 Deployment and marketing

The research team drafted a list of potential locations for parcel lockers in early 2019, and started reaching out to building managers and business owners to obtain approvals. The list included residential buildings, retail properties, light rail transit stations, parking lots, office buildings, and sidewalks (public property). After extensive outreach through phone calls, emails, and in-person visits, three feasible locations for placing the lockers were identified as listed below and started to obtain agreements and conduct installation tasks.

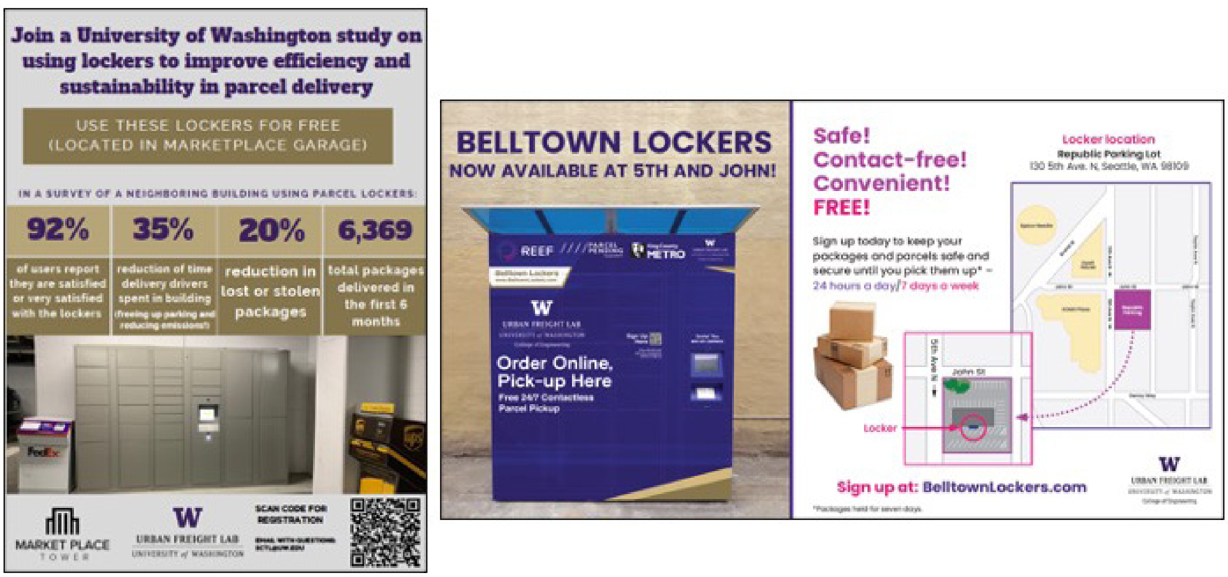
1. Royal Crest Condominium (a residential building)
2. Market Place Tower (a commercial building)
3. Republic parking lot (a publicly accessible location)

Figure 14. Lockers installed in Market Place Tower building (top left), Royal Crest building (bottom left) and in Republic public parking lot (right).

The three parcel lockers (shown in Figure 14) were successfully installed between June-September 2019 in Seattle, WA, and started operation shortly after. The Royal Crest and Market Place lockers were located indoors and accessible only by tenants of the buildings. The Royal Crest locker was in a 26-story residential building, with 133 units, and the Market Place locker was in a publicly accessible parking area underneath a building with a mix of commercial and residential floors. The Republic parking locker was located in a public off-street surface lot and could be accessed by anyone upon registration. All three lockers could receive deliveries from any carrier (e.g. UPS, FedEx, USPS, Amazon, OnTrac and DHL).

The Royal Crest locker located in the lobby of a condominium was utilized at maximum capacity by building residents upon installation. However, due to their non-residential public locations, the Market Place Tower and Republic parking lockers required integrated marketing campaigns to inform building tenants and neighborhood residents of the new amenity. The Market Place Tower mixed-use building location remained open during the Covid-19 pandemic, but related tenant absences presented challenges in gaining active users. Marketing efforts through property management partners and the condo owner's association in the building included posting flyers in the building lobby and personal conversations with tenants by building management. The Republic parking locker marketing campaign was exhaustive, it included: a joint press release with the University of Washington and the locker logistics company, a targeted social media campaign, multiple rounds of direct mailers sent to over 5,000 nearby residents and businesses, posting of flyers in public areas in nearby buildings, sidewalk sandwich board signage at the parking lot, and coverage in local media. Examples of the marketing materials developed can be seen in Figure 15.

Figure 15. Marketing materials developed for Market Place Tower and Republic parking



4.3 Experimental Design

To estimate the effects of parcel lockers a pre-test/post-test control group experiment was designed and applied the difference-in-difference (DiD) analysis framework to estimate the causal impacts of a locker system on (a) delivery vehicle dwell time at the curb and (b) the time delivery drivers spend inside the building.

The study residential building with the locker in it was chosen as the treatment building, and the team selected a residential building with similar characteristics (e.g. floor area ratio, number of units, surrounding loading zones, neighborhood) but without a locker, as the control building.

4.4 Data Collection

Field data was collected for two periods (before and after the installation of locker) from both treatment and control buildings. Moreover, for the treatment building, a short online survey was designed and conducted of residents to solicit feedback about the locker performance. An online community survey was also developed for the Republic parking locker to better understand the public's awareness and impression of the locker.

4.4.1 Field data collection

Data collection was done in three-hour shifts from 8:30 a.m. to 2:30 p.m. on several weekdays in Summer 2020 and Winter 2021, which respectively represent time periods before and after the locker installation.

The collected data included:

- time that commercial vehicles arrived at and departed from the four blockfaces adjacent to and opposite the study building, and whether couriers delivered to the study building
- vehicle type (car, van or truck)
- parking space type (CVLZ, PLZ, paid parking, or no parking)
- time couriers entered and exit the building
- carrier
- type of goods

•estimated volume of goods carried in and out of the building

Figure 16. Data collectors record commercial vehicle parking activity in the study area.

After processing and cleaning the data, the result was a total of 165 deliveries to the two residential buildings. A summary of collected data is presented in Table 1. Since only packages were permitted in the locker, observations related to service visits and mail or meal/grocery deliveries were removed from the analysis dataset, leaving a total of 116 observations. Table 2 presents summary statistics of the packages delivered to the treatment and control buildings, before and after the locker installation.

Table 1. Summary of Collected Field Data on Deliveries to the Study Buildings

	PRE-TREATMENT		POST-TREATMENT	
	TREATMENT BLDG	CONTROL BLDG	TREATMENT BLDG	CONTROL BLDG
Days observed	5	10	8	4
Hours observed	45	51	48	21
Total deliveries	31	56	60	18
Package deliveries	19	39	43	15
Total deliveries per day	6.4	5.6	7.5	4.5
Parking events	121	135	187	56
Parking events per Day	24.2	13.5	23.4	14

Table 2. Summary Statistics for Package Deliveries to Treatment and Control Buildings, Before and After Locker Installation

	PRE-TREATMENT		POST-TREATMENT	
	TREATMENT BLDG	CONTROL BLDG	TREATMENT BLDG	CONTROL BLDG
Package Volume				
Avg. Volume per delivery (m^3)	0.50	0.35	0.26	0.51
Vehicle Type				
Cars	1 (5%)	3 (8%)	2 (5%)	3 (20%)
Trucks	8 (42%)	18 (46%)	21 (49%)	6 (40%)
Vans	10 (53%)	18 (46%)	20 (47%)	6 (40%)
Parking Space Type				
CVLZ	17 (89%)	18 (46%)	29 (67%)	4 (27%)
PLZ	2 (11%)	5 (13%)	7 (16%)	2 (13%)
Paid Parking	0	13 (33%)	2 (5%)	9 (60%)
No Parking	0	2 (5%)	5 (12%)	0

4.4.2 Resident survey

To solicit users' feedback about the performance of the locker, an online survey of residents of the Royal Crest building was developed and administered six months after the locker installation, when it was believed that the locker operation reached a stable condition.

The survey link was shared with the residents via an email sent by the building management. Flyers were posted containing a QR code to the survey link in the building common areas, such as the lobby and elevators. To promote participation in the survey, a raffle prize of a $100 Amazon gift card was also offered. A total of 76 responses were received, which accounts for about 60% of the locker users. After cleaning the dataset and removing repeated or low quality responses, 69 responses resulted.

4.4.3 Public locker survey

To better understand the public's awareness and impression of the Republic parking locker, the team developed and administered an online community survey available to anyone with the link. The survey was advertised to residents living in nearby apartment buildings and the surrounding neighborhood through posting flyers with a QR code to the survey in nearby buildings and also posting about the survey on neighborhood community webpages. The survey was posted for two months and received over 1,800 responses.

4.5 Data Analysis

Using the DiD modeling framework, the causal impacts of the locker on vehicle dwell time at the curb and time spent inside the building was estimated. Several regression models were built and controlled for the volume of packages carried in and out of the building, time of day, parking space type, and vehicle type.

4.6 Results

4.6.1 Locker impact

The regression results are presented in Table 3. The models showed that installing the locker caused a 50-60% drop in time spent inside the building, controlling for time of day, parking space type, vehicle type, and in some cases, volume of packages carried in and out of the building. Although the exact magnitude of the locker effect varied across models, all models showed a consistent and statistically significant decrease in time spent inside the building.

There was also a 33% decrease in dwell time as a result of installing the locker; however, the effect of locker on dwell time decrease was not statistically significant at the 0.1 level. This could be because of the small sample size or possibly due to drivers spending the additional time on other activities, such as staging packages or delivering to other nearby buildings.

4.6.2 Resident user survey

Royal Crest residents expressed high levels (96%) of overall satisfaction with the locker, reporting lower rates of missed delivery and lost/stolen packages since the installation of the locker in the building. A summary of user survey results is presented in Table 4.

Table 3. Regression model results for the impact of the locker on dwell time and in-building time

OUTCOME VARIABLE	DWELL TIME	IN-BUILDING TIME		
MODEL ESTIMATION METHOD	ORDINARY LEAST SQUARES (OLS)	WEIGHTED LEAST SQUARES (WLS)	GAMMA GENERALIZED LINEAR MODEL (GLM)	GAMMA GLM (W/ GOODS VOLUME)
Treatment Effect	-0.40	-0.70*	-0.92**	-0.72*
Locker effect	-32.97%	-50.3%	-60.12%	-51.45%
Log Likelihood	-143.09	-151.08	-336.20	-331.68
AIC	302.18	316.17	686.39	679.36

Note: *p < .1 **p < .05 ***p< .01

4.6.3 Public locker use survey

Results to the community survey for the Republic parking locker found that 96% of respondents were aware of the public parcel locker and 70% reported being "likely" or "very likely" to use it. Survey feedback included praise for the convenience during the pandemic and concerns about the security of packages, and desire to store refrigerated items in the lockers. Following the community survey, the team saw an 18% increase in people registered for the locker.

Table 4. Summary of locker user survey results collected from residents of Royal Crest building

QUESTION	RESPONSES					
		Never	Once a month or less	A few times a month	A few times a week	
I missed a delivery, and the package was returned	Before	61%	33%	4%	1%	
	After	92%	3%	1%	4%	
A package I ordered online was lost/stolen	Before	70%	29%	-	1%	
	After	90%	6%	1%	3%	
	Very satisfied	Satisfied	Somewhat satisfied	Somewhat dissatisfied	Dissatisfied	Very dissatisfied
How would you rate your overall satisfaction with the locker service?	73%	20%	3%	1%	1%	1%

5.0

Parking Information Systems

5.0 PARKING INFORMATION SYSTEMS

5.1 Curb proximity sensors deployment

To gather real-time curb availability data, i.e. whether curb spaces are currently occupied, in-ground proximity sensors were deployed on commercial vehicle load zones (CVLZs) and passenger load zones (PLZs) in the study area.

Sensors were installed by drilling the curb Figure 17-(a) Each sensor used a magnetometer to detect magnetic perturbations created by vehicles (Lan et al., 2009). Each sensor's status (where the sensor is active – a vehicle is detected in the proximity of the sensor – or inactive – no vehicles detected) is reported in real-time wirelessly to the internet through a gateway (Figure 17-c).

Sensors were placed every 10 feet from each other, and 5 feet from the beginning/end of a curb zone. Figure 17- (b) shows some of the sensors deployed on two contiguous curb zones.

A total of 274 sensors were deployed. Figure 18 shows the study area and the location of each sensor. Note that more than one sensor was installed in each CVLZ and PLZ, depending on the length of the space.

After deployment, several testing procedures were applied to test the accuracy of the sensors in reporting vehicle parking events. Several hours of videos recorded parking activities at selected curb spaces. Videos were manually processed to obtained a list of parking events, their start and end time and curb space identifier. The video data was then compared with the data reported by the sensors.

A total of 74 parking events were recorded, and 72 of those triggered at least one sensor, obtaining a 97% accuracy. During the same time and at the curb spaces recorded on video, sensors were triggered an additional 14 times, without any vehicle parking on the sensors. The primary causes of these events included engine starts, vehicles making small back and forth movements within the space, or drivers entering the vehicle. In one case, a vehicle stopping in a travel lane triggered a sensor.

Figure 17. (a) proximity sensor; (b) sensors deployment on a curb space; (c) gateway receiving sensor data and forwarding it to the internet

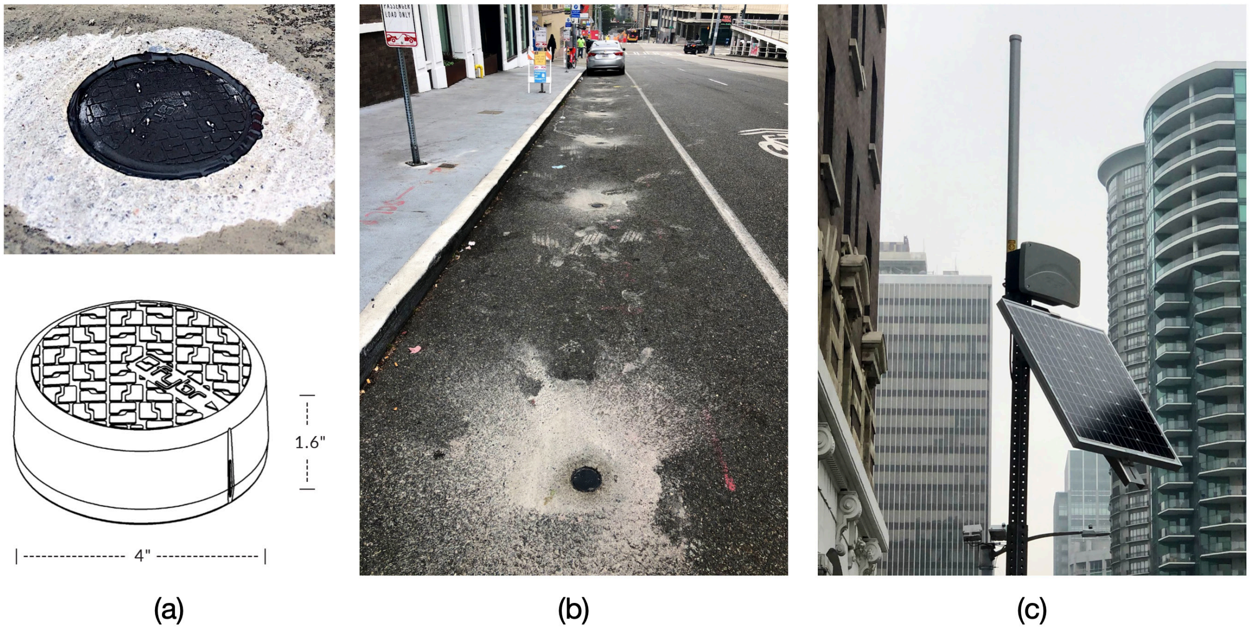


Figure 18. Proximity sensors were deployed on two types of curb spaces: commercial vehicle load zones (CVLZs) and passenger load zones (PLZs)

5.2 Visualizing real-time curb availabilities

An application framework was developed that enabled collecting and processing the raw data recorded by the sensors deployed and to visualize curb parking availabilities in real-time.

The framework was developed using opensource software and APIs for (a) interfacing with the API provided by the sensors' vendor for real-time sensor data, (b) data storage and (c) web based graphical user interface overlaying the vehicle spaces availability on top of a physical map layout of the study area.

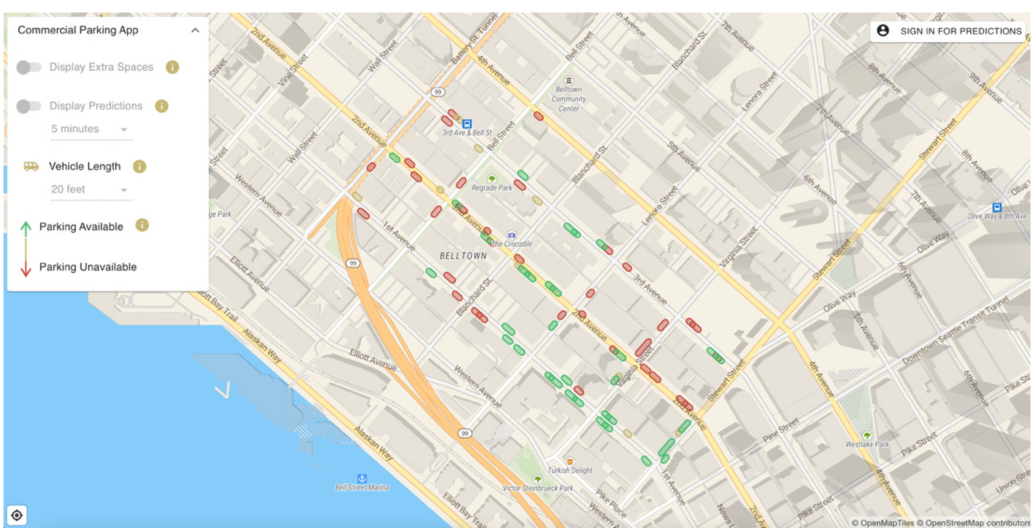
The API interface provides access to real-time sensor data from curb spaces in study area. The API interface is queried by the web-app using a Restful API. The real-time API is queried every five seconds and the resulting spatio-temporal data is stored in MariaDB (based on MySQL) database. In the web-app framework, besides an API for the real-time data, an additional API for historical data was also developed.

The following meta-data information are provided for each sensor:

- block identifier
- blockface identifier
- curb space identifier
- curb space type (commercial or passenger load zone)
- total space length
- geo-coordinates of the sensor
- total number of sensors
- date, time and status of the sensor

A web based graphical user interface was developed (Web App) for commercial vehicle drivers who can access it through an internet browser. The Web App is based on NodeJS runtime environment as a backend server; meanwhile uses Javascript and HTML for the (frontend) web interface. The Web App utilizes OpenStreetMap based map of the study area, on top of which the parking zones of proportional shape and sizes are overlayed. Figure 19 depicts the web-app with real-time data feed for sensor locations.

Figure 19. Web-App GUI showing real-time parking information for commercial vehicle loading zones in Belltown, Seattle.



The developed webapp framework (https://uwtechint.pnnl.gov) was deployed on Pacific Northwest National Laboratory (PNNL) Institutional Computing Infrastructure and was made accessible to outside users. The webpage interface/web-app allowed access to the underlying map with the sensor data. This was done either in the guest mode where no login information is required or in a login mode where a password-based user-id is required[1]. In the guest mode, the user can still access the real-time spaces available. Meanwhile, in the login mode, the user can additionally access occupancy prediction of the loading zones for five, fifteen, and thirty-minutes time horizons. The web-app displayed sensor information from both the Belltown and Bellevue areas. The web-app allowed us to query the availability of spaces by vehicle lengths in feet. The web-app used three color codes for indicating the availability or unavailability of loading zones: a) green, b) yellow and c) red. The green color indicated a contiguous space for the queried available space available; the yellow color indicated queried space is available but may not be contiguous; and the red color indicated queried space is unavailable.

5.3 Predicting future curb availability

This section describes the work done by the PNNL team for the development of a Machine Learning/ Deep Learning (ML/DL) modeling framework that integrated with the Web App for near real-time prediction of curb space availabilities.

5.3.1 Prediction unit

The prediction unit of the framework predicted curb space availabilities for time horizons of five, fifteen, and thirty minutes into the future. Figure 20 shows the placement of the prediction unit in the full workflow schematic of the framework – starting from data collection till the Web display. The prediction unit is situated independently from the Web-App and interacts with the Web-App using Flask API via data management unit to pull and push the relevant data.

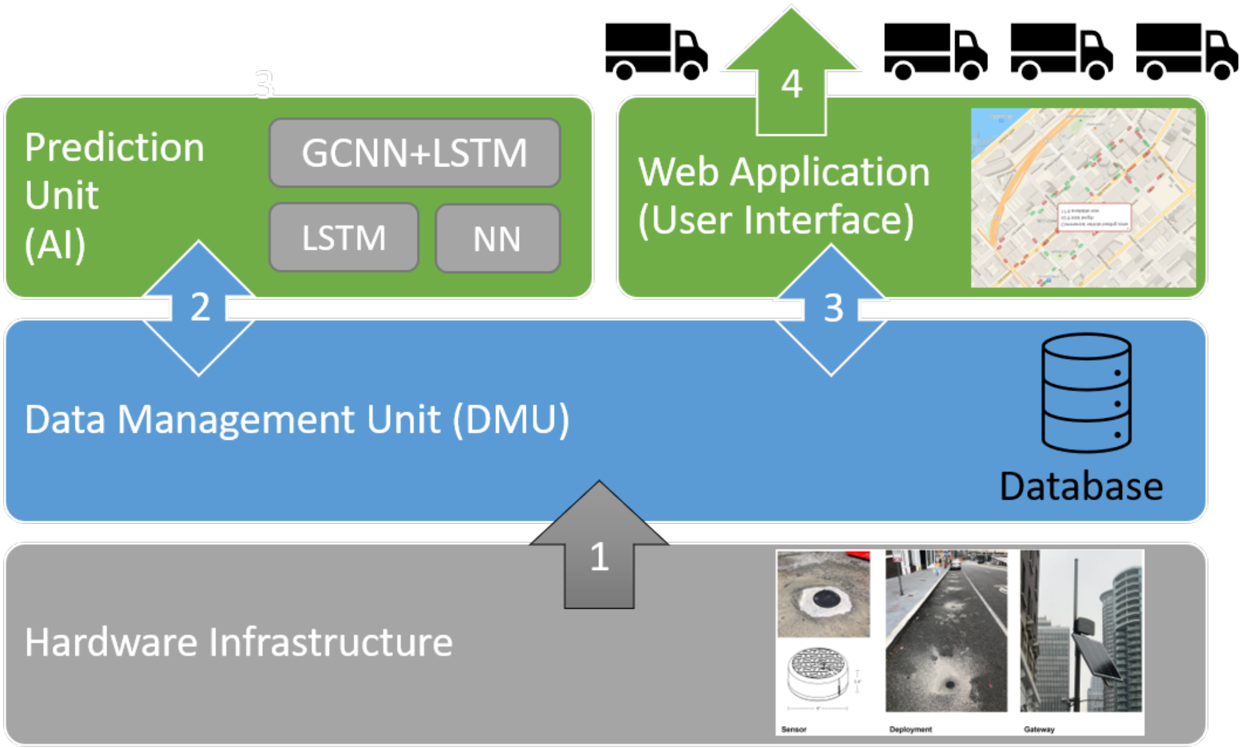
Using the historical spatio-temporal data of the sensors from the loading zones, an offline data model was first developed. The trained models were then used by the Prediction Unit for predicting the availability of nearby loading zones at different time horizons. The predicted value is then passed on to the Web App, which then displayed the predictions on the Webpage.

5.3.2 Statistical analysis of input data

This section summarizes the statistical analysis of the sensor data that was collected between January 2021 and September 2021. The data collection from the sensor is event-driven, i.e., a data point is created whenever there is an event - space being occupied/unoccupied – which makes the data sparse. For time-series analytics and prediction, the sparse event data is transformed into a timeseries and resampled to the data collection frequency - 1 minute - using forward fill, which propagates last valid observation forward.

[1] *The PNNL did not store any personally identifying information.*

Figure 20. Workflow schematic for Web App and Prediction Unit.



1 The Data Management Unit (DMU) uses a Restful API to collect the occupancy data from the deployed hardware in near-real time and store in a MariaDB database.

2 The Prediction Unit takes historical data from the DMU to develop a data model that can predict at 5-, 15-, and 30-min horizons. DMU stores those predictions into the database.

3 The Web API interacts with the DMU to access the historical data and predictions from the database.

4 The commercial fleet can use the web application to visualize the data and check availability of the parking spaces for five, fifteen, and thirty-minutes time horizons.

Figure 21 and Figure 22 show the distribution of mean occupancy of the loading zones at different hours of the day and different days of the week, respectively, using a heatmap. The brighter color implies higher occupancy while darker color implies lower occupancy. In both the figures, the heat maps are grouped together by their Block Face Id. From the figure, further validation that some curb spaces are more utilized compared to the others can be made. While some curb spaces are used across whole day, others are used at a specific time of the day only: time of day impacts utilization of the loading zones.

Figure 21. Daily Occupancy Pattern

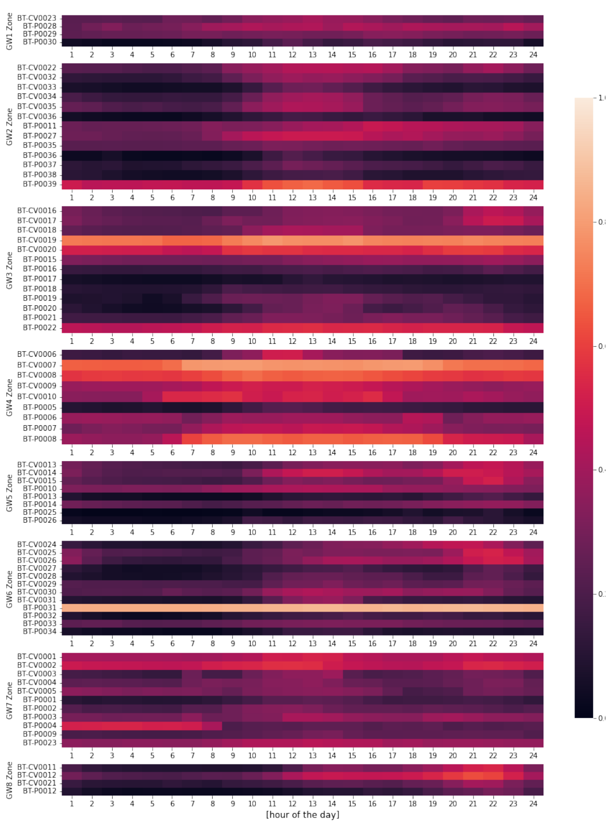


Figure 22. Weekly Occupancy Pattern

This significant variation in the occupancy of a curb spaces can be explained from the fact that their usage depends on several exogeneous factors such as the location, type of businesses located nearby and their operating hours, among others.

Though statistical time-series models (such as ARIMA) can capture the temporal variations, they tend to perform poorly when the data is stochastic and controlled by various unobserved exogeneous parameters. The next section will explore various machine learning and deep learning techniques that were explored to predict curb availabilities at different time horizons.

5.3.3 Prediction modeling

Two types of prediction modeling techniques were explored: State-Space and Time-Series Modeling. The state-space modeling aggregates the data and uses contextual information to predict the system's state at different time horizons. On the other hand, time-series modeling uses a recent sequence of events as input to predict a sequence of future values.

1. State Space Based Modeling

In this technique, regression tasks are applied on the input data for state-space based prediction of the occupancy of each curb space. In addition to the input data, such ensemble learning techniques can take additional input features. The occupancy data was resampled to 5-min and the following input features were considered for the model development: start minute, end minute, start hour, end hour, day, month. K-Nearest Neighbors (KNN), Decision Tree (DT), and Random Forest (RF) were explored under state-space-based modeling. Table 5 summarizes the performance of all three modeling techniques across all the curb spaces. All three techniques are comparable and can predict the system state with an accuracy ~78%.

Table 5. Performance comparison of state-space models

Metrics	KNN	DT	RF
Precision	**0.612**	0.603	0.563
Recall	0.373	0.384	**0.410**
F1-Score	0.463	0.470	**0.475**
Accuracy	**0.782**	0.781	0.771

Light training and quick inference are some of the key benefits of the state-space modeling. However, the aggregated output cannot be used to estimate the amount of continuous space available in the loading zone. The information could be highly useful, especially for commercial vehicles, which vary greatly in shape and size. Sensor-based prediction using time series modeling is one way to resolve this issue.

2. Time Series Prediction

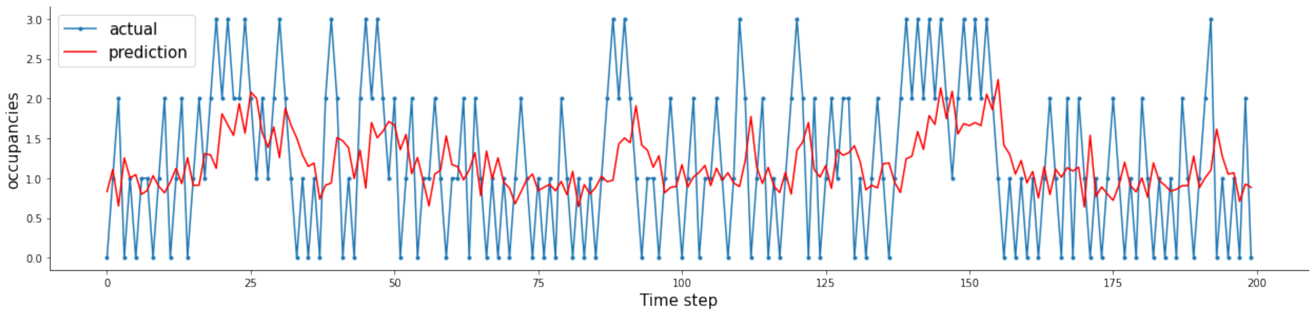
Four timeseries based deep-learning models were explored under this category (as summarized in Table 6. All the models were implemented in TensorFlow.

Table 6. Summary of Model Architectures

	LINEAR	DENSE	CONV	LSTM
# of Hidden Layers:	1	2	2	2
Layer-1:	Input *shape:* (30, 1)	Input *shape:* (30, 1)	Input *shape:* (30, 1)	Input *shape:* (30, 1)
Layer-2:	Dense *# of nodes: 5* *activation:* sigmoid	Dense *# of nodes: 512* *activation:* sigmoid	Conv1D *# of nodes: 256* *activation:* sigmoid	LSTM *# of units:* 32
Layer-3:	Output *shape:* (5, 1)	Dense *# of nodes: 5* *activation:* sigmoid	Dense *# of nodes: 5* *activation:* sigmoid	Dense *# of nodes: 5* *activation:* sigmoid
Layer-4:		Output *shape:* (5, 1)	Output *shape:* (5, 1)	Output *shape:* (5, 1)

A time series model takes a sequence of recent observations (the look-back window) as input and predicts a sequence of future events (the look-forward window). Different sizes of look-back windows (5, 30, and 60 minutes) and look-forward windows (1, 5, 10, 15, and 30 minutes) were analyzed as part of the modeling efforts and the empirical evaluation indicated that increasing the look-back window size slows down the training and decreasing the window size reduces the accuracy. Based on this analysis, the look-back window of 30-mins and the look-forward window of 5-mins were chosen for further evaluation of the modeling techniques. Figure 23 depicts one such example where the model is predicting the occupancy of a loading zone with a look-back window of 30-mins and the look-forward window of 5-mins. The time step interval used is 1 minute, hence the prediction is done every minute in a rolling window fashion. The occupancy value is >1 because a single loading zone contains multiple sensors and the occupancy number here indicates the number of occupied sensors.

Figure 23. LSTM based modeling with 30 mins. look back and 10 mins. look forward window.



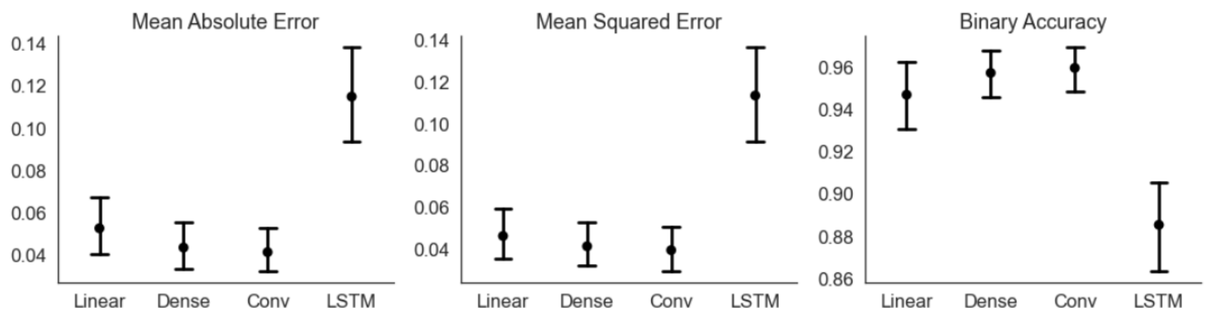
To get predictions at a higher resolution, all four models (from Table 5) were trained at the sensor level i.e., one model for each sensor. Therefore, the target label could either be 0 or 1, where 0 indicates that the space is unoccupied and 1 indicates that the space is occupied. Binary cross-entropy loss between the target label and the predicted label was optimized using the Adam optimizer. An early stoppage criterion was applied on the validation loss with a patience value of 5 i.e., if the loss doesn't improve in 5 consecutive epochs, the training will stop early. The data was split into 70:30 – 70% for training and 30% for testing. 20% of the training data was used for validation between the epochs.

Table 7 summarizes the results averaged across all the parking zones for both the training set and the testing set. The results indicate that the convolution architecture has the least prediction error and highest accuracy, when averaged across all the loading zones. Closest to the Conv architecture is the Dense architecture. For all the four architectures, Figure 24 depicts variation in error and accuracy metrics across all the loading zones. LSTM seems to have the highest variability and least accuracy among the four, and therefore is the least robust model.

Table 7. Performance comparison of time series prediction models

		LINEAR	DENSE	CONV	LSTM
MAE (lower is better)	Train	0.042 (±0.03)	0.036 (±0.02)	**0.036 (±0.02)**	0.070 (±0.05)
	Test	0.054 (±0.08)	**0.042 (±0.06)**	0.040 (±0.06)	0.111 (±0.11)
MSE (lower is better)	Train	0.038 (±0.02)	0.035 (±0.02)	**0.033 (±0.02)**	0.068 (±0.05)
	Test	0.047 (±0.07)	**0.040 (±0.06)**	0.038 (±0.06)	0.110 (±0.11)
Accuracy (higher is better)	Train	0.959 (±0.03)	0.964 (±0.02)	**0.965 (±0.02)**	0.930 (±0.05)
	Test	0.944 (±0.09)	**0.959 (±0.06)**	**0.961 (±0.06)**	0.89 (±0.11)

Figure 24. Performance comparison of different time series prediction models



5.3.4 Discussion

The statistical analysis of the occupancy data showed that the parking events are highly stochastic in nature and depended upon several exogeneous parameters. Different ML/DL models were explored for the prediction unit, which can be categorized into two types: State-space Modeling and Time Series Prediction. While the training of state-space models is computationally inexpensive, the state-space models offer limited accuracy. Moreover, the output is at a very low resolution – both spatially and temporally. The shortcomings of state-space modeling can be addressed through deep-learning models, which are deep and complex in architecture. Four different architectures were explored as part of this study and the evaluation of these models over the real-world data indicated that these models can predict with an accuracy of ~96%. However, since these models are computationally expensive - the training time and the inference time is significantly higher as compared to the state-space model – it would be a challenge to use them on the streaming data. Depending upon the hardware architecture and its compute capability, the inference time for deep learning models could be significant. Given this tradeoff, benchmarking ML/DL models against the real-world deployment is critical and warrants additional investigation. The current version of the prediction app uses the Dense network for highly accurate results.

5.4 Routing with curb availability information

5.4.1 Introduction

Through the introduction of routing tools, carriers have provided commercial vehicle drivers with optimized delivery routes that consider travel distance and often also traffic patterns. However, details on parking availabilities have not been part of these tools. Even though limited parking availability can lead to significant delays through cruising for parking, or result in rerouting, these assessments still have to be made mostly in real-time by the driver (Dalla Chiara et al., 2020). With technology such as the proximity sensors used in this study, data on curb parking availabilities can be collected systematically. Some research questions resulted from this is whether and how this information can be used to improve routing tools and what value it delivers. This research combined cruising for parking predictions from real-world data with routing to investigate the added value of the consideration of parking availabilities in commercial vehicle routing.

5.4.2 Modeling framework

The material this research used consists of multiple steps:

1. A set of historic route data was obtained from a beverage company that operates in the Seattle area. The dataset contained two years of route data from 50 drivers that delivered to 2,000 customers performing more than 60,000 deliveries.
2. A time dependent travel distance matrix for all delivery addresses in the dataset was generated from travel time data provided by the Google Travel Distance API (Google Maps Platform, 2021).
3. Using the data from step 1 and 2, cruising times for all delivery addresses for each time of the day were predicted based on the cruising model presented by Dalla Chiara and Goodchild (Dalla Chiara et al., 2020) that considers the built environment around the delivery address and the curb space allocation. With these predictions, an alternative travel time matrix to the one generated in step 2 that considers the parking delays at the curb was created.
4. To calculate optimal routes, a version of the Time-Dependent Traveling Salesman Problem with Time Windows (TD-TSP-TW) (Albiach et al., 2008) was used. Due to the high structural complexity of the TD-TSP-TW, a metaheuristic approximation method, the Biased Random Key Genetic Algorithm (BRKGA) (Andrade et al., 2021) was implemented to approximate optimal routes for the TD-TSP-TW.

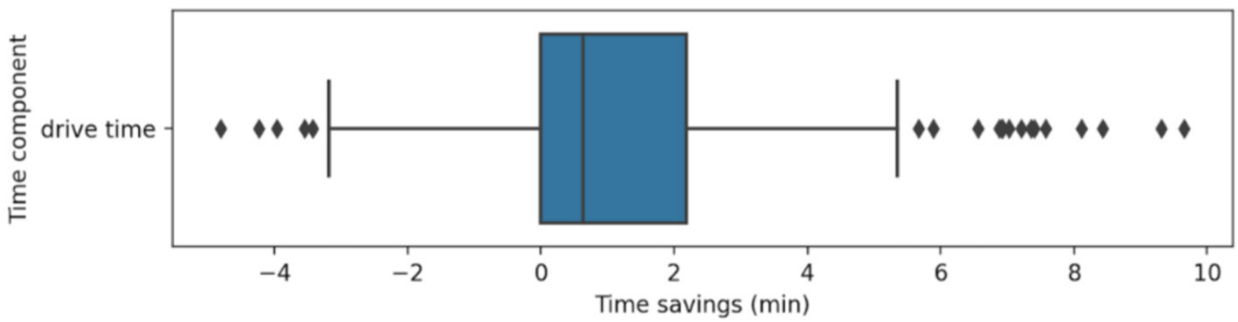
5.4.3 Simulation set up

The simulation analysis was conducted in four steps. A base case, where cruising delays are not considered, was generated with the TD-TSP-TW and the default travel distance matrix from the Google Travel Distance API (Google Maps Platform, 2021). To simulate the reality, where drivers actually experience cruising delays, even if these were not considered during route optimization, the results from the base case were retroactively updated by the corrected travel time matrix. However, the order of deliveries was not changed. The treatment case where cruising delays are considered during route generation was obtained through solving the TD-TSP-TW directly with the corrected travel time matrix. Lastly, the results from both cases were compared for each delivery manifest.

5.4.4 Results

The main finding was that considering cruising delays in route optimization based on historic data reduced the mean drive time by 1.5 % (1.02 min per route) in the tested dataset. Figure 25 illustrates the result distribution and shows that not all runs showed a reduction in drive time. The main reason for this is that the TD-TSP-TW was solved with a heuristic that does not guarantee optimality. Therefore, in some cases it is possible not to find the optimal route. For the majority of route manifests however route time savings could be generated, in some cases with quite significant impact.

Figure 25. Savings From Considering Cruising for Parking in Routing



5.4.5 Discussion and conclusions

After investigating the route manifests that delivered the largest and smallest savings in more detail, it was identified that route time savings generally are larger in the following circumstances:

- If the number of stops in the manifest is large as more alternatives for routing exist.
- If the addresses are distributed in a homogeneous space, where travel distances are similar in between addresses and thus savings on cruising times can be leveraged to improve routes.
- If the cruising delays vary substantially between different time intervals, as this leads to larger efficiency gains when considering cruising times.

Figures 26 and 27 below show examples of routes that illustrate the extremes of these observations.

Figure 26. Example Route with Linear Shape and Few Stops, Base (left), Treatment (right)

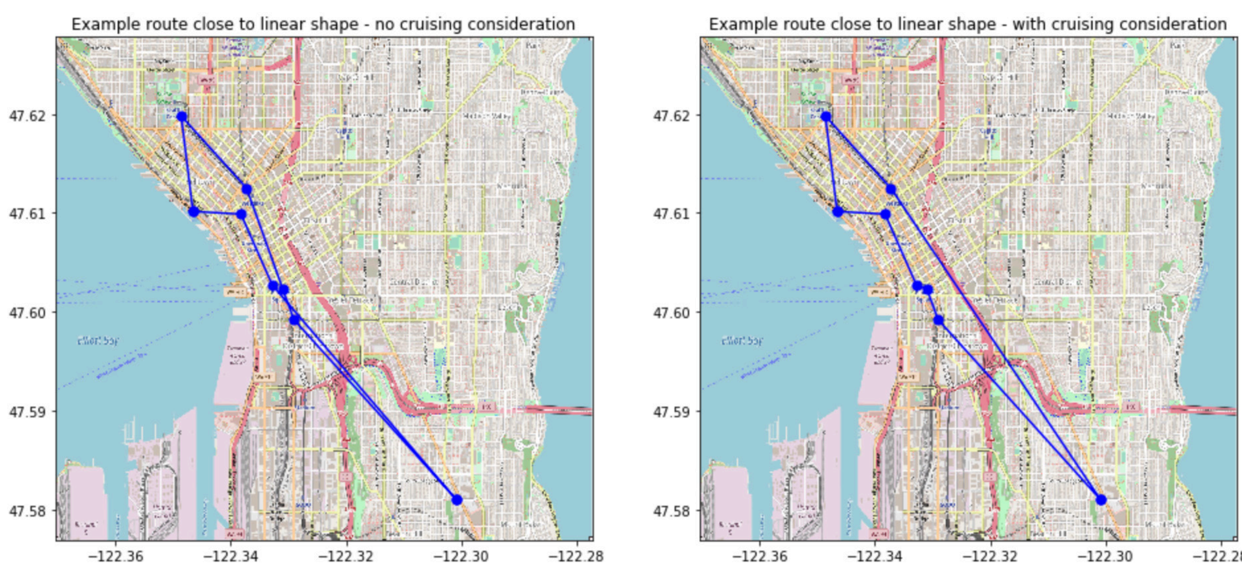
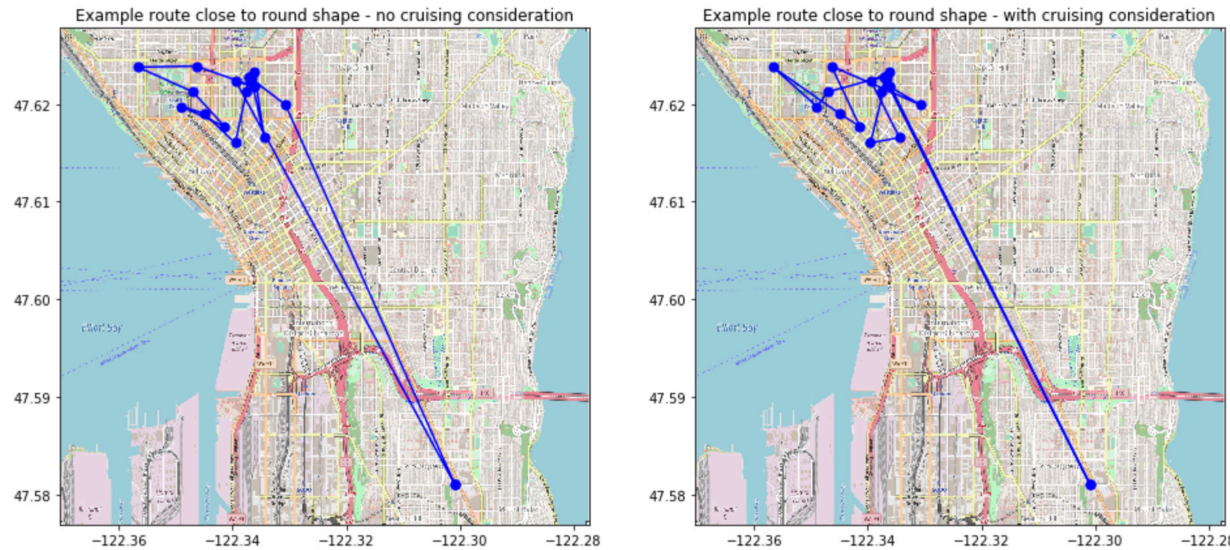


Figure 27. Example Route with Compact Shape and More Stops, Base (left), Treatment (right)



The route presented in Figure 26 has relatively few stops and the addresses are distributed in a more linear shape, where gains obtained through the consideration of cruising times cannot offset the large differences of travel times in between the addresses, as the similarity of the routes resulting from the different approaches show. The route presented in Figure 27 shows a route with more stops and the addresses are distributed in a more homogeneous shape, where there are many viable alternatives for routing. Figure 27 further shows that the routes generated by the two different approaches provide very different solutions, and thus delivery higher route time savings. Most route manifests from the test dataset, however, follow a linear shaped geographic distribution. Reversing a part or the entire route is therefore often the only viable alternative, thus resulting in low time savings. Furthermore, historic data collected in urban environments is noisy and thus not ideal to predict route time savings. Further analysis on a synthetic route set provides evidence that the consideration of cruising delays in routing delivers added value for routes with a high delivery density and high variance of cruising time along the planning time horizon, confirming the findings visualized in Figures 26 and 27 above. This can be used to generate trip time savings of approximately 20.4%.

5.5 The impact of curb availability information on delivery drivers' cruising for parking behavior

5.5.1 Experimental design

To empirically test whether curb availability information affects delivery drivers' cruising for parking behaviour, a real-world experiment was performed. Drivers were hired to perform "artificially-generated" deliveries, where delivery addresses were randomly sampled from the list of addresses in the study area. The driver had to walk to the entrance of the building without entering and performing a real delivery. Each driver was provided with a 20-foot delivery van and 3 delivery manifests, each manifest contained a list of 15 addresses located within the study area.

Each driver started a delivery manifest from a parking lot located near the study area and received a tablet displaying a map of the study area and the locations of the deliveries to be performed. On some of the tours, drivers were also provided with the OpenPark app. A driver would then drive to the vicinity of the first delivery, park the vehicle and walk to the entrance of the building. A box was given to the driver to simulate a real delivery. Multiple delivery addresses could be visited from a single parking stop. Drivers were free to choose the sequence of deliveries and where to stop the vehicle.

A total of 11 drivers were hired and 10 different manifests were generated. Manifests were allocated to drivers such that each manifest was performed at least once with the app, and once without. Each driver performed 3 different manifests, at least once with the app and once without.

An observer followed each driver collecting GPS traces, distinguishing in-vehicle segments (traces collected while driving) from out-of-vehicle segments (traces collected while walking). For each in-vehicle segment, the trip start/end times, and total trip time were obtained. The controlled experiment was performed on weekdays between July and November 2021. A total of 33 routes were performed (11 drivers, each performing 3 different delivery manifests out of a set of 10 different manifests), completing 494 deliveries. Drivers performed 177 trips to reach the delivery destinations (more than one delivery can be performed from a single stop). The length of each trip in minutes is used as the experimental unit in the following analysis.

5.5.2 Modeling cruising for parking time

To understand the impact of curb availability information on cruising for parking behaviour of delivery drivers a mixed-effect random intercepts model was used, shown in Equation 1. Consider driver i, performing manifest j, driving the vehicle to a new stop location k. The total trip time it took the driver to reach the k stop is $Trip_{ijk}$, measured in minutes. This trip time is regressed over: the expected driving time $Drive_{ijk}$, i.e. the time it takes to reach a given destination without having to cruise for parking; an indicator variable $1[App_{ijk}]$ taking value $=1$ whenever the app displaying curb availability information was available to the driver, and 0 otherwise; and two vectors of indicator variables, $1[Day_{ijk}]$ and $1[Hour_{ijk}]$, which control for the day of the week and the time of the day. Parameters $\beta_0, \beta_1, \beta_2, \gamma'$, and δ' represent the regression fixed effects, u_i and u_j are the random intercept for driver i and manifest j, and ε_{ijk} is the zero-mean Gaussian error term.

Equation 1. Mixed effect random intercept model for the logarithm of trip time

$$\text{Log}\,Trip_{ijk} = (\beta_0 + u_i + u_j) + \beta_1 \log Drive_{ijk} + \beta_2 1[App_{ijk}] + \boldsymbol{\gamma}'\mathbf{1}[Day_{ijk}] + \boldsymbol{\delta}'\mathbf{1}[Hour_{ijk}] + \varepsilon_{ijk}$$

We are particularly interested in β_2, the effect of the use of the web-based app showing curb availability information on the total trip time $Trip_{ijk}$, controlling for the driving time $Drive_{ijk}$, Trips times are obtained from the in-vehicle GPS traces collected. Driving times are estimated by querying the Google Maps Distance Matrix API (Google Maps Platform, 2021), which returns the expected time it takes to drive between two locations considering historical travel time data, for a given time of the day and day of the week, but it does not consider the additional time spent searching for available curb parking. A similar method was used by Dalla Chiara and Goodchild (Dalla Chiara et al., 2020).

The regression coefficients are estimated using the sample of 177 trip times collected during the experiment by Restricted Maximum Likelihood (REML), using the Lme4 package (Bates et al., 2015), coded in R language (R Core Team, 2017).

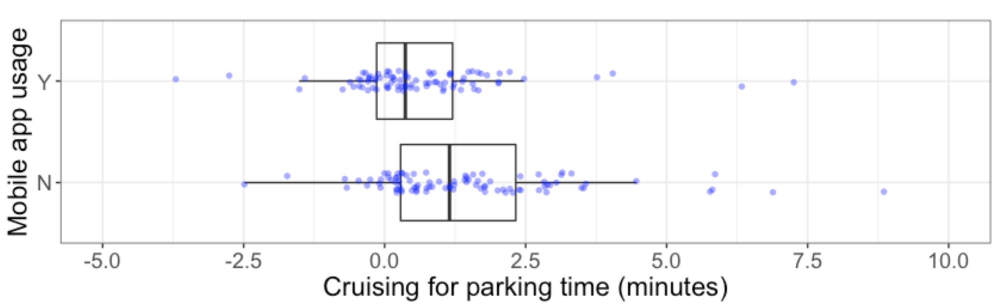
5.5.3 Experiment results

The cruising for parking time experienced by a driver to reach and park at a given stop location is estimated by subtracting the driving time obtained from the Google Maps Distance Matrix API from the respective observed trip time obtained from the GPS data collection. Figure 28 shows the empirical distributions of the estimated cruising for parking times for each trip performed with the app ("Y"), providing the driver with real-time curb availability information, and without ("N"). The median cruising for parking time for trips performed with the app is 0.37 minutes, while the median cruising for parking time for the trips performed without the app is 1.15 minutes. The sample data collected showed a 68% decrease in median cruising for parking time when curb availability information is available to the drivers. We also observe a reduced interquartile range for the trips performed with the app.

To obtain the marginal effect of providing curb availability information to drivers on their cruising for parking behaviours, the regression model in Equation 1 was estimated. The estimated coefficient for the usage of the curb availability information app (β_2), is -0.33. When the app was used, the sample data showed a 28% decrease in total trip time $100 \cdot [e^{-0.33} - 1]$, controlling for driving time.

For further details on methods and results contained in this section, we refer the reader to Dalla Chiara et al. (2022).

Figure 28. Empirical distribution of cruising for parking times for routes performed with ("Y") and without ("N") curb availability information



6.0 CONCLUSION

The increase in delivery demand in urban areas has not been met with a change in the urban infrastructure that supports the delivery processes, on which private carriers rely. Consequently, a delivery driver spends time searching for parking, parking in unauthorized spaces, or walking longer distances and spending time inside buildings to meet customers' demand for home deliveries.

The three-year research project sponsored by the U.S. Department of Energy Vehicle Technologies Office and carried out by researchers at the Urban Freight Lab of the University of Washington, Pacific Northwest National Lab (PNNL), and other collaborators aimed at quantifying the key challenges of the urban delivery system, such as the impact of parking-seeking behavior, and improving system efficiency by using two currently available technology solutions:

- After an agreement was reached with the Seattle Department of Transportation, a *curb parking information system* was deployed in a 10-block study area in the Belltown neighborhood of Seattle, WA, where 274 in-ground proximity sensors were installed in the curb in commercial vehicle load zones and passenger load zones. Data from sensors was transmitted to servers, processed, and made visible a web-based application. The application was developed by PNNL to visualize in real-time curb parking availabilities and models were developed to provide accurate curb parking availability predictions.
- *Common carrier parcel lockers* are automatic lockers to temporarily store parcels, allowing receivers to be notified when a parcel arrives and to pick-up the package anytime. After securing agreements with private landlords in the Belltown neighborhood, three common carrier parcel lockers were installed in both publicly accessible and private space.

<u>The objectives of the project were to:</u>

1. Reduce parking-seeking behavior in the study area by 20%
2. Reduce parcel truck dwell time (the time a truck spends in a spot to load/unload) in the study area by 30%
3. Increase curb space, alley space and private loading bay occupancy rates in the study area

To quantify the impacts of the curb parking information system and common carrier parcel lockers, and therefore to test the above stated project objectives, several data sources were used. The parking information system itself used a network of curb proximity sensors, which recorded more than 600,000 curb activities since their installation. The common carrier parcel lockers also automatically recorded more than 6,800 delivery and pick-up transactions. To process and analyze curb sensor data, several hours of video recordings were taken and manually processed, to calibrate an algorithm to estimate real parking events from sensor data. To study cruising for parking behaviors GPS data from real delivery vehicle activities from different delivery carriers were obtained, and more than 3,000 vehicle trips were analyzed. The research team also performed 10 ride-alongs, following 10 different delivery drivers for entire working days, collecting the most detailed set of data on urban delivery operations ever obtained, matching GPS tracking data with qualitative data and interviews. Finally, to estimate the impacts of the parking information system and common carrier parcel lockers, a designed experiment was conducted and implemented, manually collecting data on the parking and delivery operations of carriers in the study area.

The key outcomes of the project are summarized below.

- A model framework was developed and implemented to provide the first measurement of cruising for parking times for urban commercial vehicles. When applied to Seattle, the researchers were able to quantify that, on average, a delivery driver spends 28% of travel time searching for parking, totaling on average one hour per day for a parcel delivery driver.
- By riding along with urban delivery drivers, researchers obtained detailed data through first-hand experience of the urban delivery process. They found that while double-parking (parking in the travel lane) represented a minor share of total parking choices (less than 5% of the time), unauthorized parking is indeed frequent (more than 20% of the time).
- Researchers classified commercial vehicles' curb parking behaviors of delivery drivers facing curb parking congestion into four categories.
  - *Cruising for parking*: searching for available curb spaces by cruising around the block.
  - *Unauthorized parking*: parking in non-authorized curb spaces or in the travel lane.
  - *Queueing*: temporarily parking in an alternate location and waiting until the desired space becomes available.
  - *Re-routing*: after failing to find the desired space, giving up, and doubling back to the delivery destination later in the day.
- Some 13% of all parking events in CVLZ spaces were estimated as overstays; the figure was 80% of all parking events in PLZ spaces.
- By running an experiment in which some delivery drivers had access to real-time curb availability information while others did not, it was found that having access to this information reduced cruising for parking by 28%.
- By including forecasting of cruising times within a vehicle routing algorithm it was estimated that total route time can be reduced on average by 1.5% using historic data. Further analysis suggested that including parking availability in routing systems is especially promising for routes with a high delivery density and a high variance of cruising time over the planned time horizon of approximately 20.4%.
- Common carrier parcel lockers were found to significantly decrease the time a delivery driver spends inside a building by 40 to 60%, and reducing the vehicle parking dwell time up to 33%. These statistics are the first quantitative evaluation of the impact of common carrier parcel lockers on urban delivery operations and clearly show how lockers can increase delivery driver efficiency and vehicle parking turnover.

This study represents the first and most detailed evaluation of currently available technologies – curb parking information systems and common carrier parcel lockers – by deploying them in situ – and empirically evaluating the results. These technologies have the potential to reduce cruising for parking and delivery times, therefore impacting urban parking and road congestion and related vehicle emissions.

Sensor network-based parking information systems and parcel lockers are solutions that lie in between public and private spaces. Both technologies are distributed and operated by private companies but can be installed on the public right-of-way, shared among multiple carriers and users, and encouraged by public support and policy. It is the authors' hope that the results from this research provides a scientific basis for a wider discussion on considering the urban logistics system as a fundamental, open, and shared infrastructure needed to guarantee efficient and sustainable urban deliveries.

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SUPPLY CHAIN TRANSPORTATION & LOGISTICS CENTER

UNIVERSITY *of* WASHINGTON

Urban Freight Lab

SCTL CENTER

UNIVERSITY OF WASHINGTON

BOX 352700

SEATTLE, WA 98195

Phone: 206.221.6407

Email: sctl@uw.edu