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Simulation-based analysis of different curb space type allocations on curb performance

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ABSTRACT

Curbspace is a limited resource in urban areas. Delivery, ridehailing and passenger vehicles must compete for spaces at the curb. Cities are increasingly adjusting curb rules and allocating curb spaces for uses other than short-term paid parking, yet they lack the tools or data needed to make informed decisions. In this research, we analyse and quantify the impacts of different curb use allocations on curb performance through simulation. Three metrics are developed to evaluate the performance of the curb, covering productivity and accessibility of passengers and goods, and CO_2 emissions. The metrics are calculated for each scenario across a range of input parameters (traffic volume, parking rate, vehicle dwell time, and street design speed) and compared to a baseline scenario. This work can inform policy decisions by providing municipalities tools to analyse various curb management strategies and choose the ones that produce results more in line with their policy goals.

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Introduction

There are many uses of curb space: paid parking, load/unload zones, and transit stops are regularly encountered, while new technologies and economic pressures are creating even more competition for curb spaces, from increased ridehailing pick-up/drop-off and on-demand deliveries to businesses leveraging outdoor curbspace as a result of pandemic response efforts (Girón-Valderrama, Machado-León, and Goodchild 2019; Honey-Rosés et al. 2021). With such increased pressure has come more complex consequences of policy decisions, with unclear downstream impacts on congestion, emissions, city revenue, and so on. Thus, with so many different use cases, municipalities are in need of a means to analyse different curb allocation scenarios (Butrina et al. 2020). Comparing various curb configurations and their prospective performance (congestion, emissions, etc.) in simulation is faster and much more cost effective than physical pilot testing of existing curb real estate (Fellendorf and Vortisch 2010).

In this paper we use an agent-based microsimulation platform, VISSIM, to simulate a wide range of curb allocation scenarios on a given blockface. Simulation inputs are based on field data collected in a downtown Seattle neighbourhood, and simulations are performed over a synthetic grid network derived from the typical layout of a network in the business core of Seattle. Then, building on the work of Butrina et al. (2020) and Young and Henao (2020), we develop various curb metrics to measure impacts of each scenario as observed in simulation. These include the number of passengers loaded

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and unloaded or goods delivered per space per hour (Curb Productivity Index), the share of vehicles that successfully park in the study area (Curb Accessibility) and CO_2 emissions within the study area. Simulations are run across a range of parameters and a series of scenarios where curb allocation and parking rules are changed from a baseline of all paid parking spaces. We then calculate the curb performance metrics for each scenario and evaluate the passenger- and goods-related improvements or reductions that can occur by changing curb allocations and rules, in addition to estimating the impact of curb allocation on carbon emissions.

This work contributes to the literature by (a) developing new curb metrics for parking emissions and goods accessibility and productivity (on top of existing passenger-related metrics) and (b) quantifying the trade-offs across a wide range of curb space allocations and parking rules by simulating various potential scenarios and measuring the curb performance through the state-of-the-art curb metrics. Hundreds of potential combinations are simulated, covering a wide range of traffic inputs (e.g. vehicle volume, street design speed, parking demand rate, and vehicle dwell times), curb space allocations (e.g. paid parking, passenger pick-up/drop-off zones, commercial vehicle load zones, bus stops), and parking rules (e.g. restricted space access, illegal parking). This holistic approach to curb performance is the first of its kind in the scientific literature related to parking and curb management. Much attention has been paid to how to better manage curb spaces for traditional uses such as paid parking, or how curb space can be allocated to for-hire transportation services, but not how that allocation then impacts other road uses and eventually the performance of the curb. This study seeks to fill in this research gap.

The remainder of the paper is organized as follows. The next section, Literature Review, describes the body of work in assessing curb performance and simulating curbspace parking. Next, the data and simulation inputs are described in the Simulation Overview and Data section. The methodological approach is then explained, followed by Results and Discussion sections. Concluding remarks are included in the final section.

Literature review

Curbspace allocation for competing curb users

Recent work focuses on allocating curb space for varying uses (e.g. long-term parking, passenger pick-up/drop-off, goods delivery, etc.) and formulates it as an optimization problem. Jaller et al. (2021) and Nazir et al. (2022) suggest optimal curb layouts for case study neighbourhoods in San Francisco and Seattle, respectively. Much of the curb allocation optimization work theorizes adjacent land use as the primary driver for the type of curb access demand. Young and Henao (2020) takes this further by integrating the Bid-Rent theory into curbspace allocation.

Other work centers around particular curb users, such as passenger pick-up/drop-off or goods delivery. Several studies have explored the use of passenger loading zones (PLZs) to accommodate passenger pick-up/drop-off demand on a single or series of blockfaces (Fehr & Peers 2018; Fehr & Peers 2019; Ranjbari et al. 2021; Lu 2019). A few others focus on the need for spaces dedicated to commercial use (Girón-Valderrama, Machado-León, and Goodchild 2019; Schmid, Wang, and Conway 2018; Zou et al. 2016); however, these studies focus on the difficulties commercial vehicles have in finding legal parking, rather than how commercial vehicle loading zones (CVLZs) can improve accessibility. The passenger-based research often overlooks the role of public transit stops in curb performance, or focuses on case studies without transit access at the curb.

Curbspace simulation models

As a cost-saving alternative to pilots, simulation has been exploited to study the impacts of potential curb allocations. Martens and Benenson (2008) uses a curb user's walking time from the best available parking space to their end destination as a measure of the accessibility drivers have to destinations in a fixed vicinity. The study demonstrates simulation's suitability in applying parking decisions, availability of suitable curbspace, and local traffic conditions as controlling variables. Microsimulation has also been used to understand the impacts of double parking, parking outside the designated spaces, and poor parking manoeuvring on congestion and roadway throughput (Portilla et al. 2009). Cao and Menendez (2015) similarly use microsimulation of short duration bottlenecks caused by parking manoeuvres on the performance of nearby intersections measured by delay. With the desire to better manage the curb itself, as opposed to the adjacent transportation network, there is a gap in the simulation body of work that may help cities understand the benefits of curb allocation in terms of people served and goods delivered.

There are recent examples of macroscopic simulation studies that model drivers' parking seeking behaviour. Using simulation Arnott and Williams (2017) find that cruising-for-parking times may be underestimated in previous, non-simulation-based studies when real-world parking occupancy rates are approach or exceed 85%. Dowling, Ratliff, and Zhang (2019) and Liu, Ma, and Qian (2022) use queuing simulators that model parking behaviour to predict driver time lost to seeking for parking. These studies demonstrate the value of simulation tools in understanding how improved access to the curb can improve productivity for road users. In this study we build upon previous studies and utilize microsimulation to study curb performance in terms of productivity for both passengers and goods, as well as emissions.

Curb performance evaluation

Empirical analysis of parking activity can assist city officials in making parking allocation decisions. Their reasons for seeking curb management strategies cited by cities in visionary planning documents include congestion reduction (City of Chicago 2019; San Francisco Planning Department 2017; PBOT 2019), providing shared space or improving accessibility (PBOT 2019, Austin DOT 2019, Atlanta Mayor's Office 2019), reducing emissions (NYCDOT 2021; DDOT 2021; Maxner, Dalla Chiara, and Goodchild 2022), or improving economic output of the city (City of Chicago 2019; Saint Paul PED 2009). Butrina et al. (2020) conducts structured interviews with US cities to catalogue the curb performance metrics used by these cities. The findings suggest both curb performance (in terms of passengers loaded or unloaded per hour) and emissions related to parking activities are increasingly important for Departments of Transportation to calculate and understand. There is not a universal metric or set of metrics that have been used to assess the outcomes of curb-related policy changes, nor do cities have the capability of collecting all required data (Butrina et al. 2020; Young and Henao 2020). Young and Henao (2020) outlines a framework where the curb performance metrics – illegal parking, parking-related collisions, parking revenue, and curb occupancy – developed in Butrina et al. (2020) can be applied to cities based on their street network organization.

Curb productivity has been evaluated in many studies and is useful in recommending the number of long-term parking spaces that may be replaced by passenger loading zones (Fehr & Peers 2018; Fehr & Peers 2019; Lu 2019). A study in Seattle uses curb productivity in conjunction with space occupancy to show that a pilot curb allocation had an oversupply of passenger loading zones (Ranjbari et al. 2021). However, these studies all focus on productivity from the perspective of passengers served by the curb, leaving a research gap for goods-related curb productivity. Prior studies also exclude transit passengers, so the total passenger productivity of a blockface is unknown.

Occupancy, impacts on congestion, safety, and dwell time are also used in previous studies to support space allocation recommendations (Fehr & Peers 2018; Ranjbari et al. 2021). Impacts on congestion, measured in the number of vehicles double parked or the delay caused by parking activities, can also be used as safety metrics. Another example of a safety metric is the number of traffic conflicts in a study area (Ranjbari et al. 2021).

Parking revenue appears to be a metric declining in importance. Though included in the Curbside Management Practitioners Guide produced by the Institute of Transportation Engineers (ITE 2018) as a performance metric, Butrina et al. (2020) found cities have not experienced declines in revenue despite re-allocating curb space for PLZs and other uses. Separate from parking revenue, yet still a source of income for cities are traffic citations. A few studies, including Dalla Chiara et al. (2021), Wenneman, Habib, and Roorda (2015), and Kawamura et al. (2014) investigate parking citations to understand commercial parking behaviour, but those types of studies do not necessarily address lack of access to the curb.

Finally, studies that estimate emissions related to parking often focus on emissions related to cruising for parking (Kilbert 2011), and do not account for other parking related emissions, such as idling to pick up/drop off passengers, queuing or acceleration/deceleration for entering/exiting a curb space.

This study uses a set of metrics to better assess the performance of the curb that are derived from the goals of cities – improving access to the curb, increasing productivity and economic activity, and reducing emissions.

Simulation and data overview

Simulation overview

Microsimulation provides the means to test a wide variety of curb space allocations and related curb management policies without the time and financial commitments of field testing. These policies can be simulated across a range of parameters to represent any given link in a network as well as incorporating hard-to-measure variables like parking behaviour and choice. This study utilizes the microsimulation software VISSIM, which is capable of obtaining driving and parking state data at minute time increments, making it ideal for this use of microsimulation. Previous researchers have used VISSIM to model on-street curb lane parking based on a number of built-in features including PLZs, CVLZs, public transit stops, and flexibility in modelling a range of driver behaviours (Maciejewski 2010; Gettman and Head 2003). Curb performance metrics can be calculated using vehicle records data extracted as a direct output of the VISSIM software. These metrics and the data used will be described in subsequent sections.

Data and inputs

Simulations for each scenario are generated across a fixed set of parameters: traffic volume entering the network, parking rate, roadway design speed, and commercial vehicle mean dwell time. The parameters and their ranges are presented in Table 1.

Table 1. Simulation parameters.

Parameter	Description	Range	Unit
Volume	The number of vehicles entering the network at each entry point (14 total)	[50:300], 50 vph increments	Vehicles per hour (vph)
Parking rate	The proportion of all vehicles in the network that decide to attempt to park in the study area curb lane.	[0:25%], 5% increments	Proportion of veh. choosing to park
Speed distribution	The design speed of the network (through lanes) independent of congestion and signal queuing.	20 or 30	miles per hour (mph)
Mean commercial vehicle dwell time	Mean dwell time of parked commercial vehicles. Dwell times are normally distributed around the values identified. Mean dwell time remains the same in each simulation but standard deviation varies according to the number of vehicles of the associated vehicle class within vehicle composition	300 or 850	seconds (s)

The range of traffic volumes are selected based on typical evening peak hour flow rates on minor arterials in Seattle (SDOT 2020). Major downtown arterials can experience traffic volumes more than double the simulated max value. However, during test simulations it was determined that maximum parking occupancy was achieved between 200 and 300 vehicles per hour (vph). The volume was restricted to 300 vph and further discretized to measure the impact of volume changes on the curb performance metrics. Parking rate – the percentage of drivers in the network seeking to park – and commercial vehicle dwell times, as well as inputs that were kept static across all simulations (vehicle type composition, dwell time distributions, and passenger distributions) are based on data collected in the South Lake Union area of Seattle (Ranjbari et al. 2021).

Five vehicle types are defined for the simulation study: PUDO (passenger pick-up and drop-off) vehicles, personal vehicles, buses, heavy-duty commercial vehicles, and medium-duty commercial vehicles. The PUDO vehicle category includes any ridehailing vehicle (e.g. Uber or Lyft) in the South Lake Union data as well as all personal vehicles observed loading or unloading passengers without the driver leaving the vehicle. Personal vehicles included in the PUDO category outputs also stopped for five minutes or less. The personal vehicle category therefore includes any passenger vehicle parking for greater than five minutes and often includes a driver that exits the vehicle in addition to a passenger. Passenger distributions are assigned by vehicle type as simulation inputs. Each is normally distributed around the means of 2, 1, and 10 for personal vehicles, PUDO vehicles, and buses, respectively. The commercial vehicle subtypes (heavy- and medium-duty) will henceforth be referred to as a single type: commercial vehicles. Two subtypes are defined in the simulation model to capture the range in sizes of goods delivery vehicles. Heavy-duty vehicles include Class 6–8 trucks while medium-duty vehicles include vans and box trucks up to Class 5 (FHWA 2014). Regarding the quantity of goods delivered, Allen et al. (2018) and Jaller, Holguín-Veras, and Hodge (2013) each state that the dwell time and quantity of goods delivered is dependent on the size of vehicle and the type(s) of goods delivered. To acknowledge these findings and to simplify comparisons between scenarios, all simulated commercial vehicles are assumed to deliver goods at the curb and are assigned one of two parcel counts linked to 'short' or 'long' dwell times of ≤ 30 min (5 parcels) or > 30 min (10 parcels).

Study area emissions are calculated based on emissions rates for a variety of driving states. Each vehicle type is assigned an emissions profile derived from the findings of Frey, Rouphail, and Zhai (2008), Qu et al. (2021), and Liu and Frey (2015). Acceleration and speed, both aspects of driver behaviour, are key elements to determining emissions (Qu et al. 2021; Bishop et al. 2016; Wang et al. 2008). VISSIM outputs include instantaneous acceleration and speed for every trajectory, which allows us to develop emissions profiles based on those states and parking state. These driving states are shown in Table 2 along with the emissions factors. To calculate emission factors for each vehicle type category in the simulation model, first, synthetic representations of the fleet compositions for each vehicle type are defined based on national vehicle sales (BTS 2019) and projected future sales assuming vehicle manufacturers follow emissions standards set by NHTSA (2022). The basis of PUDO vehicles is a compact vehicle and includes a share of mid-sized sedans, cross-over SUVs, and SUVs based on a truck platform. Hybrids, plug-in hybrids and electric vehicles were included in the PUDO fleet based on Uber's self-reported trip-miles from these vehicles (Uber 2022). Although these figures cannot be confirmed in the scientific literature, they do serve as an acceptable baseline for the purpose of this study. The personal vehicle category is based on national sales and therefore have a higher share of SUVs and other large vehicles, thus leading to higher average emission factors. Using national sales figures is another limitation of the study as sales and registration data are not available for the Seattle-area specifically. Synthetic buses and commercial vehicles are similarly generated. The basis for medium-duty commercial vehicles is the Seattle data from Ranjbari et al. (2021) where roughly 80 percent of delivers arrived in medium-duty or step-side box trucks and 20 percent in light-duty vans. Emissions profiles for transit buses were not available in the literature, but the profile is based on an unloaded heavy-duty truck, the weight of which is equivalent to a partially loaded transit bus. Next, emission rates for each model included in the vehicle type composition are gathered from the US DOE's (2022) vehicle fuel economy database. These are then extrapolated into gram per second emissions from the

Table 2. Vehicle type CO_2 emissions factors for each driving or parking state (g/s).

		Vehicle Type				
Driving state	Speed (mph)	PUDO vehicles	Personal vehicles	Light- and medium-duty commercial vehicles	Heavy-duty commercial vehicles	Buses
Parked, engine off	0	0	0	0	0	0
Ignition after parking [Eff_{Ig}]	0	6.179	7.133	28.220	53.514	43.383
Idling (parked or stopped in through lane) [Eff_I]	0	1.504	1.737	6.870	13.029	10.562
Fast acceleration	0–10	3.008	3.473	13.741	26.057	21.124
	10–20	3.761	4.342	17.176	32.571	26.405
	20–30	4.513	5.210	20.611	39.086	31.686
	30+	5.265	6.078	24.046	45.600	36.967
Moderate acceleration	0–10	2.256	2.605	10.306	19.543	15.843
	10–20	3.008	3.473	13.741	26.057	21.124
	20–30	3.008	3.473	13.741	26.057	21.124
	30+	3.761	4.342	17.176	32.571	26.405
Slow acceleration	0–10	2.256	2.605	10.306	19.543	15.843
	10–20	2.256	2.605	10.306	19.543	15.843
	20–30	2.256	2.605	10.306	19.543	15.843
	30+	3.008	3.473	13.741	26.057	21.124
Free flow at design speed	20–30	2.256	2.605	10.306	19.543	15.843
Deceleration/braking	all	1.504	1.737	6.870	13.029	10.562

profiles developed by Frey, Rouphail, and Zhai (2008), Qu et al. (2021), and Liu and Frey (2015). Total emissions in the model are calculated by multiplying the driving-state-based emissions factor by the amount of time each vehicle remains in that state.

Methodology

The data and inputs described in previous section are used to simulate traffic and parking activity in a downtown neighbourhood of Seattle, Washington, USA. The parking area within the simulated network contains a set number of parking spaces, which can be allocated to specific uses (i.e. goods delivery, long-term parking, etc.), and the users of each curbspace allocation can be controlled in the simulated environment. By changing allocations and calculating the same metrics across each allocation, we aim to measure the impact of these changes on passenger and goods movement and emissions. This section describes the simulated network, curbspace uses included in allocations, details of changes made to allocations and parking rules within each simulated scenario, and metrics by which we measure curbspace performance.

Network and study area

The simulated network represents a series of typical blocks in the downtown core of Seattle, Washington, USA and is shown in Figure 1. Each block in the downtown area is roughly 400 feet by 300 feet (Dowling, Maxner, and Ranjbari 2022). The study area blockface is located on the North side of the street and includes two travel lanes and a parking or curb lane. The curb lane includes ten parking spaces, each measuring 20 feet in length plus one bus stop measuring 65 feet in length (SDCI 2015). The larger network is simulated to prevent artifacts due to vehicle generation and removal at the simulation boundaries from influencing the results of the study area in the centre.

Curbspace allocations

The allocation of curbspace chosen for simulation is based on the findings from Dowling, Maxner, and Ranjbari (2022). In this study k-means clustering is used to determine typical curb configurations in Seattle. About 22% of the study area blockface is dedicated to no-parking uses (crosswalks, driveways, etc.), leaving adequate space for one bus stop and ten standard parking spaces. Seattle is one of many US cities that has dedicated curbspace to passenger or commercial vehicle load/unload zones, yet seven of the top ten blockface configurations described in Dowling, Maxner, and Ranjbari (2022) show paid parking remains the majority share of parking area in a typical Seattle curb lane. This finding is the basis for the curb allocation of the baseline scenario – described in the following section – upon which additional curbspace allocations are developed for simulation scenarios.

Curb performance metrics

Five metrics are used to measure the impact of different curb allocations on curb performance: (a) Passenger curb productivity index (CPIp), (b) goods curb productivity index (CPIg), (c) passenger vehicle curb accessibility (CAp), (d) goods vehicle curb accessibility (CAg), and (e) CO_2 emissions. In addition to calculating these metrics for passenger and goods, metrics are also calculated by vehicle type – PUDO, personal vehicles, heavy goods vehicles, delivery vans, and transit buses – to illuminate the underlying causes of metric value increases and decreases based on curb allocation changes. This would be of use to cities seeking to understand certain vehicle type behaviour such as by Transport Network Companies (TNC) including Uber and Lyft.

The curb productivity indices are defined as the number of passengers or parcels serviced per hour per parking space (roughly 25-foot length of curb) (SDCI 2015). The metric is adapted from Fehr & Peers (2018), Fehr & Peers (2019), Ranjbari et al. (2021), and Lu (2019) and uses the SDOT standard for

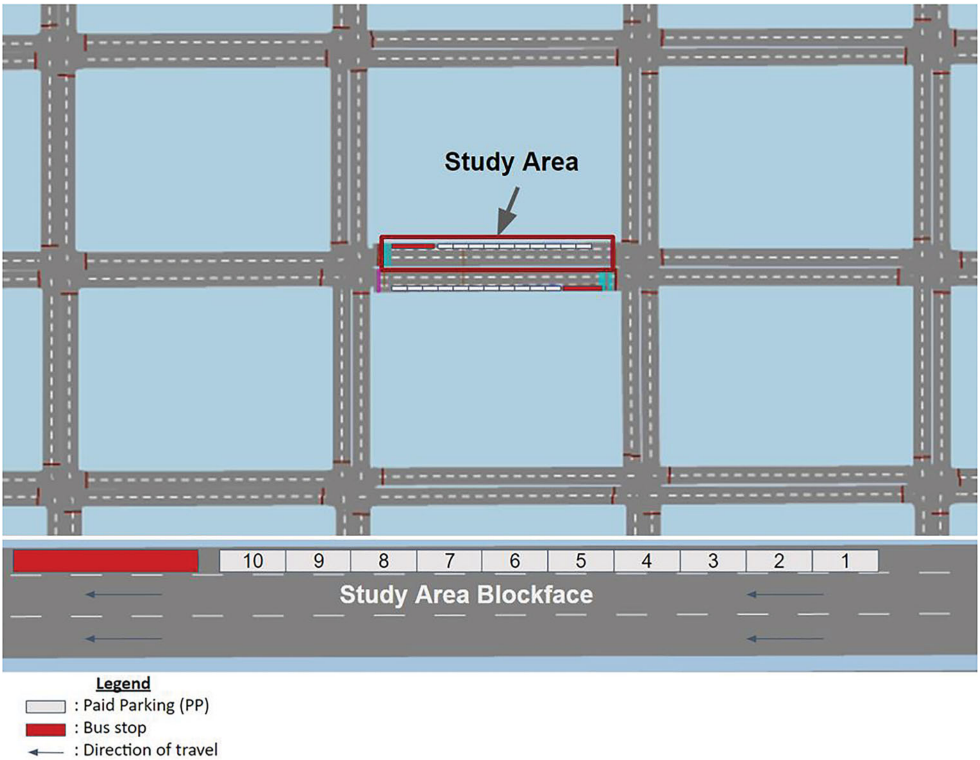

Figure 1. The synthetic Seattle downtown grid network (top) used in VISSIM parking simulations. The inset shows the Study Area in the baseline scenario (bottom), which includes 10 parking spaces, one bus stop, and adequate space to represent alleyways, crosswalks, etc.

space length. Equations (1) and (2) are used to calculate these metrics, where *vi* represents vehicles that successfully park, *pi* is the number of passengers loading or unloading from vehicle *vi*, *gi* is the number of parcels delivered by vehicle *vi*, *t* is the simulation time in seconds divided by the simulation period (2.5 h), and *sp* is the total number of spaces at the curb excluding the bus stop:

$$CPIp = \left(\sum vi * pi\right)/t/sp \tag{1}$$

$$CPIg = \left(\sum vi * gi\right)/t/sp \tag{2}$$

Curb accessibility is defined as the ratio of successful parking attempts to total parking attempts. It is calculated for passenger or goods delivery vehicles using equations (3) and (4), where CAp and CAg are the accessibility measures of passenger traffic and goods movement, respectively. *spp* is the number of successful parking attempts made by passenger vehicles (personal, PUDO, and transit buses) and *tpp* is the total number of parking attempts made by these passenger vehicle types. Similarly, *spg* is the number of successful parking attempts made by goods-carrying vehicles (heavy goods vehicles and delivery vans), and *tpg* is the total number of parking attempts made by goods vehicles:

$$CAp = \sum spp/\sum tpp \tag{3}$$

$$CAg = \sum spg/\sum tpg \tag{4}$$

VISSIM records the parking status ('Parking state') of each vehicle at defined time intervals, which include 'driving to parking space', 'parked', 'back to route, 'parking request declined', etc. We use these statuses to define parking attempts. A *parking attempt* is determined when the status for a unique vehicle changes from 'none' to 'driving to parking space'. When that status changes to 'Parked', it is counted as a *successful parking attempt*. Failed parking attempts are defined by the status 'Parking request rejected', which can occur when all spaces are occupied or if an open space is blocked by a double-parked vehicle for more than one minute. After one minute of waiting, the vehicle will exit the study area unless a space further along its trajectory during the vehicle's transit of the study area becomes available (i.e. a parked vehicle exits the curb lane in front of the transiting vehicle).

The emissions index is measured in pounds of CO_2 per hour (lb CO_2/hr) for all vehicles that travel along the study blockface within the study area. This metric is called the emissions index because we cannot be sure of the exact composition of each vehicle type fleet, model years, or various other factors that can impact emissions. It is intended as a baseline tool for cities to understand how emissions may increase or decrease based on curb allocations. Vehicle trajectories are assigned an emission state based on acceleration, speed, parking or dwell time, and parking state (see Table 2). It is assumed that some vehicles that park remain idling (buses and PUDO vehicles). Vehicles that park and do not idle (turn the vehicle off) also include an ignition factor assigned to the vehicle type. For that reason, emissions for parking and driving are calculated separately then added together as shown in equation (5), where Eff_{ds} is the emissions rate for each driving state (Table 2), DS is the acceleration- and speed-based driving state, tds is the time in that driving state, Eff_I is the emissions rate for each vehicle type while idling, tI is the time spent idling, Eff_{Ig} is the measure of emissions released during engine ignition, and Ig is a binary variable describing the ignition of the vehicle before it leaves its parking space. Ig equals 1 when a vehicle parks for greater than 5 min and turns the engine off, and equals 0 if the vehicle idles while parked.

$$\text{Emissions Index} = \sum(Eff_{ds} \times (DS \times tds)) + \sum(Eff_I \times tI) + \sum(Eff_{Ig} \times Ig) \tag{5}$$

Simulation scenarios

Curb performance is analysed across nine scenarios, described in Table 3, representing changes to curb use allocations, parking rules, and driver compliance to those rules. These scenarios are based on pilot curbspace allocations conceived and tested by US cities (Butrina et al. 2020) as well as existing curb configurations in the case study city of Seattle (Dowling, Maxner, and Ranjbari 2022). Scenarios where a portion of drivers ignored parking rules and time limits or double parked were developed to capture known parking behaviour in many US cities (Butrina et al. 2020; Ranjbari et al. 2021; Cao and Menendez 2015).

Scenario 1 acts as the baseline to which all other scenarios are compared. In this scenario all parking is designated as paid parking (PP) with a 2-hour time limit. Each of the four vehicle types (see simulation input section) are allowed to park in any available space and it is assumed that all vehicles comply with the paid parking time limit. Additionally, the study area includes one bus stop in which only transit vehicles may park. All vehicles adhere to the paid parking time restriction and no vehicles exhibit illegal parking behaviour such as double parking or attempting to park in the bus stop.

Scenarios 2, 2a, 3, and 3a modify parking allocation, add a single parking rule each, and preserve 100% driver compliance with the parking rules. Scenarios 2 and 2a replace paid parking spaces with Passenger Load Zones (PLZ). These spaces are restricted to PUDO vehicles and personal vehicles parking for less than 5 min. Scenarios 3 and 3a replace paid parking with Commercial Vehicle Loading Zones (CVLZ). These spaces are restricted to commercial vans and heavy goods vehicles. In all four scenarios any vehicle type can park in an unoccupied paid parking space.

Scenarios 4, 4a, and 5 introduce multiple new parking uses as well as varying parking rules and driver compliance. In each scenario paid parking is replaced by one PLZ and one CVLZ. Scenario 4 allows all vehicle types to park in unoccupied paid parking spaces. Scenario 4a places a restriction on this rule: only passenger vehicles dwelling for greater than 5 min may park in a paid space. 100% of drivers comply with parking rules in Scenarios 4 and 4a. Scenario 5 introduces noncompliance. Shares

Table 3. Simulation scenarios and descriptive information.

Scenario: name	Description	Curb allocation (PP/PLZ/CVLZ/BS)	Driver compliance
1: Baseline	Curbspace defaults to paid parking	9 PP, 1 bus stop	
2: 1 PLZ	1 PP space replaced by 1 PLZ. Any vehicle can use PP. Only PUDOs and personal vehicles with dwell time $<$ 5 min can use PLZ.	8 PP, 1 PLZ, 1 bus stop	All drivers comply with 5-minute PLZ time restrictions. All drivers comply with space type assignment.
2a: 3 PLZs	3 PP space replaced by 3 PLZ. Any vehicle can use PP. Only PUDOs and personal vehicles with dwell time $<$ 5 min can use PLZ.	6 PP, 3 PLZ, 1 bus stop	All drivers comply with 5-minute PLZ time restrictions. All drivers comply with space type assignment.
3: 1 CVLZ	1 PP space replaced by 1 CVLZ. Any vehicle can use PP. Only commercial vehicles can use CVLZ.	8 PP, 1 CVLZ, 1 bus stop	All drivers comply with 30-minute CVLZ time restrictions. All drivers comply with space type assignment.
3a: 3 CVLZs	3 PP space replaced by 3 CVLZ. Any vehicle can use PP. Only commercial vehicles can use CVLZ.	6 PP, 3 CVLZ, 1 bus stop	All drivers comply with 30-minute CVLZ time restrictions. All drivers comply with space type assignment.
4: Utopia / PP Open	2 PP replaced by 1 PLZ and 1 CVLZ. Any vehicle can use PP. Only PUDOs and personal vehicles with dwell time $<$ 5 min can use PLZ. Only commercial vehicles can use CVLZ.	7 PP, 1 PLZ, 1 CVLZ, 1 bus stop	All drivers comply with 5-minute PLZ and 30-minute CVLZ time restrictions. All drivers comply with space type assignment.
4a: Utopia / PP Restricted	2 PP replaced by 1 PLZ and 1 CVLZ. Only personal vehicles can use PP. Only PUDOs and personal vehicles with dwell time $<$ 5 min can use PLZ. Only commercial vehicles can use CVLZ.	7 PP, 1 PLZ, 1 CVLZ, 1 bus stop	All drivers comply with 5-minute PLZ and 30-minute CVLZ time restrictions. All drivers comply with space type assignment.
5: Fury Road	2 PP replaced by 1 PLZ and 1 CVLZ. Any vehicle can use PP. Only PUDOs and personal vehicles with dwell time $<$ 5 min can use PLZ. Only commercial vehicles can use CVLZ. Introduces illegal parking behavior.	7 PP, 1 PLZ, 1 CVLZ, 1 bus stop	90% of drivers comply with 5-minute PLZ and 30-minute CVLZ time restrictions. 10% PUDO and personal vehicles park in CVLZ or bus stops or double park in travel lanes.
6: Replace Bus Stop	1 PP replaced by 1 CVLZ and the bus stop replaced by 1 PP and 1 CVLZ. Any vehicle can use PP. Only commercial vehicles can use CVLZ.	9 PP, 2 CVLZ	All drivers comply with 30-minute CVLZ time restrictions. All drivers comply with space type assignment.

Nomenclature used in the above table: PP = paid parking; PUDO = passenger pick-up/drop-off; PLZ = passenger loading zone(s); CVLZ = commercial vehicle loading zone(s).

of personal vehicles and PUDO vehicles park in any unoccupied space regardless of designation, park beyond the time restrictions, block the bus stop and double park in the travel lane. To simulate double parking in the travel lane, we create a series of artificial parking spaces in the travel lane adjacent to the parking lane. Blocking the bus stop is similarly achieved by overlaying a parking space on the defined bus stop area. The spaces are associated with a parking decision element separate from the original ten spaces that initiate a parking attempt from a share (10%) of the PUDO and personal vehicles attempting to park on the blockface. This percentage is reflective of the share of PUDO and personal vehicles that parked in through lanes or in transit-designated curb space (9-11% per blockface) in the data collected by Ranjbari et al. (2021). Though less explicit in their definition of 'affecting the flow of traffic', Fehr and Peers (2018) report 4-14% of passenger parking events inhibit through traffic from passing parked vehicles. Reflecting the behaviour of vehicles that parked in the through lane during data collection by Ranjbari et al. (2021), the dwell time of double-parked cars in normally distributed around three minutes.

Scenario 6 replaces the bus stop with two CVLZs restricted to commercial vehicle parking only. All drivers comply with parking rules and time restrictions. This scenario is intended to measure the impact of removing public transit from a blockface.

Results

Curb performance metrics are calculated for every combination of the simulation parameters as shown in Table 1. These values are then averaged for each scenario to generate an aggregate metric value, and the results are presented in Table 4. Additionally, two-tailed t-tests are performed on performance metrics to compare each scenario with the baseline. A p-value of < 0.05 is considered as statistically significant. CPI, CA, and the emission index were calculated for each vehicle type and for the overall study area. The null hypothesis is that the mean of a given scenario's metric is not significantly different from that of the baseline scenario. If the null hypothesis is accepted, additional t-tests are performed on the vehicle type-level metrics in order to determine if metrics for different vehicle types change significantly.

Passenger-based curb performance metrics

Passenger Curb Productivity Index (CPIp) and Passenger Curb Accessibility (CAp) improve from baseline in two of the eight scenarios (2 and 2a). In these scenarios, at least one PLZ is added to the curb space allocation. Vehicle type-level metric calculations show that the increases in CPIp and CAp are driven by increases in PUDO parking activity. In Scenario 2 the CPIp and CAp for PUDO vehicles increase by 42% (equivalent to an additional 8.4 PUDO vehicles loading or unloading passengers per hour) and 29% (equivalent to 9.5 fewer failed parking attempts per hour), respectively. In Scenario 2a PUDO CPIp and CAp increase by 71% (15.0 vph) and 48% (15.9 parking attempts per hour), respectively.

Offsetting the gains in performance attributed to PUDO vehicles are decreases in personal vehicle CPIp and CAp. Because these vehicles do not have access to the PLZs, taking out paid parking spaces (and turning them into PLZs) reduces their parking access. The same number of personal vehicles are now competing for fewer paid parking spaces and continuing to compete for those spaces with commercial vehicles and even some PUDO vehicles that continue to park in unoccupied paid parking spaces. In Scenario 2, personal vehicle CPIp decreases by 5.5% (2.3 vph) and CAp by 6% (2.7 attempts per hour). These figures are significant because the average personal vehicle contributes twice as many passengers to CPIp as a PUDO vehicle. The impact on personal vehicles is more drastic in Scenario 2a where personal vehicle accessibility decreases by 21% and the curb loses 25% of passengers serviced by personal vehicles (almost 50% of the potential curb users).

Unsurprisingly, replacing paid parking with a single or multiple CVLZs results in lower passenger performance metrics. CPIp and CAp decrease for both PUDO and personal vehicles at about the

Table 4. Aggregated results across all simulations: passenger & goods performance metrics.

	Passenger curb productivity index (CPIp)			Passenger curb accessibility (CAp)		
Scenario: name	CPIp (pax/hr/sp)	% Δ from baseline	*t*-test *p*-value	CAp (parking success rate)	% Δ from baseline	*t*-test *p*-value
1: Baseline	11.654	–	–	0.696	–	–
2: 1 PLZ	12.318	5.7%	$p < 0.001$	0.741	6.5%	$p < 0.001$
2a: 3 PLZs	12.290	5.5%	$p < 0.001$	0.724	4.0%	$p < 0.001$
3: 1 CVLZ	11.300	−3.0%	$p < 0.001$	0.656	−5.7%	$p < 0.001$
3a: 3 CVLZs	10.107	−13.3%	$p < 0.001$	0.553	−20.5%	$p < 0.001$
4: Utopia / PP Open	11.141	−4.4%	$p < 0.001$	0.663	−4.7%	$p < 0.001$
4a: Utopia / PP Restricted	11.574	−0.7%	**0.3915**	0.702	0.9%	**0.1743**
5: Fury Road	11.278	−3.2%	$p < 0.001$	0.680	−2.3%	0.0013
6: Replace Bus Stop	7.404	−36.5%	$p < 0.001$	0.726	4.3%	$p < 0.001$

	Goods Curb Productivity Index (CPIg)			Goods Curb Accessibility (CAg)		
Scenario: Name	CPIg (parcels/hr/sp)	% Δ from baseline	*t*-test *p*-value	CAg (parking success rate)	% Δ from baseline	*t*-test *p*-value
1: Baseline	1.830	–	–	0.507	–	–
2: 1 PLZ	1.667	−8.9%	0.0121	0.464	−8.5%	0.0014
2a: 3 PLZs	1.299	−29.0%	$p < 0.001$	0.387	−23.7%	$p < 0.001$
3: 1 CVLZ	2.269	24.0%	$p < 0.001$	0.612	20.7%	$p < 0.001$
3a: 3 CVLZs	3.000	63.9%	$p < 0.001$	0.709	39.8%	$p < 0.001$
4: Utopia / PP Open	1.418	−22.5%	$p < 0.001$	0.395	−22.1%	$p < 0.001$
4a: Utopia / PP Restricted	2.319	26.7%	$p < 0.001$	0.583	15.0%	$p < 0.001$
5: Fury Road	1.335	−27.0%	$p < 0.001$	0.319	−37.1%	$p < 0.001$
6: Replace Bus Stop	2.731	49.2%	$p < 0.001$	0.678	33.7%	$p < 0.001$

Bold *p*-values represent metrics that fail to reject the t-test null hypothesis, that the metric value does not statistically significantly differ from the baseline value (*p*-value > 0.05).

same rate in Scenarios 3 and 3a. Scenario 6 is similar to Scenarios 3 and 3a in that multiple CVLZs exist at the curb. However, in Scenario 6 a paid parking space is also added in place of the bus stop, resulting in 11 total parking spaces compared to 10 in all other scenarios. We can isolate the impacts of each change by considering the CPI from each vehicle class. If the bus stop was removed in Scenario 3 (where a single paid parking space was replaced by a single CVLZ), the resultant CPIp would be 6.2 passengers per hour per space. In Scenario 6, a paid parking is added, increasing the CPIp from 6.2–7.4. However, this increase in CPI is also attributed to a reduction in competition for paid parking spaces from goods vehicles, which now have two dedicated CVLZs. In Scenario 3, goods vehicles park in paid parking spaces 58% of the time versus 54% in Scenario 6. Based on the total successful parking attempts by goods vehicles in each scenario, and controlling for the number of spaces this equates to about 1 fewer successful parking attempts per hour. Given an average dwell time for goods vehicles of 9.6 min across all simulation experiments, and the arrival rate of each passenger vehicle type, this successful parking event could be replaced by 1 personal vehicle parking event or up to 6 PUDO events. This equates to an increase in CPIp of between 0.08 and 0.24. The real impact of adding the paid parking space is therefore 0.96–1.12 passengers per space per hour. Scenario 6 is the only scenario in which an increase in passenger curb accessibility does not result in a corresponding increase in CPIp compared to the baseline scenario because the bus stop contributes about 5.1 passengers per hour per space to the CPI metric. The increase in PUDO CPIp (10% or 2.1 vph) and personal vehicle CPIp (15.5% or 5.0 vph) does not overcome the lost passengers attributed to the bus stop removal.

Scenarios where both a PLZ and a CVLZ are included on a blockface (Scenarios 4, 4a, and 5) show a similar pattern as Scenarios 2 and 2a, where CPIp and CAp related to PUDO vehicles increase as a result of adding PLZs and personal vehicle metrics decrease. However, the implementation of parking restrictions in Scenario 4a creates a difference. In this scenario each vehicle type is assigned to a single space type. When PUDO vehicles are forced to park only in PLZs, CPIp attributed to this vehicle type increases by 38%, three times the rate of increase in Scenarios 4 and 5 where multiple vehicle types compete for paid parking. Correspondingly, personal vehicle CPIp in Scenario 4a decreases by 13% or 2.5 times the decrease rate in Scenario 4. When passenger vehicles illegally park (double park in the through lane or park in the CVLZ and bus stop), passenger vehicle CPIp only marginally (1.6%) decreases. However, vehicles illegally parking in front of the bus stop, results in a significant decrease (12%) in bus CPIp, blocking about one bus per hour.

Goods-based performance metrics

Half the simulated scenarios presented in Table 4 result in higher goods curb performance metrics compared to the baseline. Those scenarios include one or more CVLZ on the blockface with a dedicated use for commercial vehicles. In the baseline scenario, commercial vehicles compete with other vehicles for paid parking spaces. When the number of spaces available to commercial traffic is reduced (Scenarios 2 and 2a), there is a drop in goods productivity that is roughly proportional to the number of spaces to which their access is being restricted (9-10% per space). When curb space is instead allocated to commercial uses (CVLZ), there is a proportional increase in goods productivity (almost 20-25%). In Scenario 3, where a single CVLZ is added, CPIg increases by 24%, or about five parcels per hour.

In the scenarios where both PLZs and CVLZs are added (4, 4a, and 5), goods productivity is dependent on the activity of other vehicles. When commercial vehicles compete with PUDO and personal vehicles for paid parking spaces (Scenario 4), CPIg and CAg decrease. However, when each vehicle type has a dedicated space and only uses that space (Scenario 4a), performance across both passenger and goods productivity metrics improves. However, CAg remains relatively low (58%), because some commercial vehicles arrive at the CVLZ when it is already occupied by another commercial vehicle. Finally, in Scenario 5, where illegal parking occurs in the CVLZs, the goods performance is the lowest of any scenario, even though only about 2.5% of passenger and PUDO vehicles park illegally in the CVLZs. In

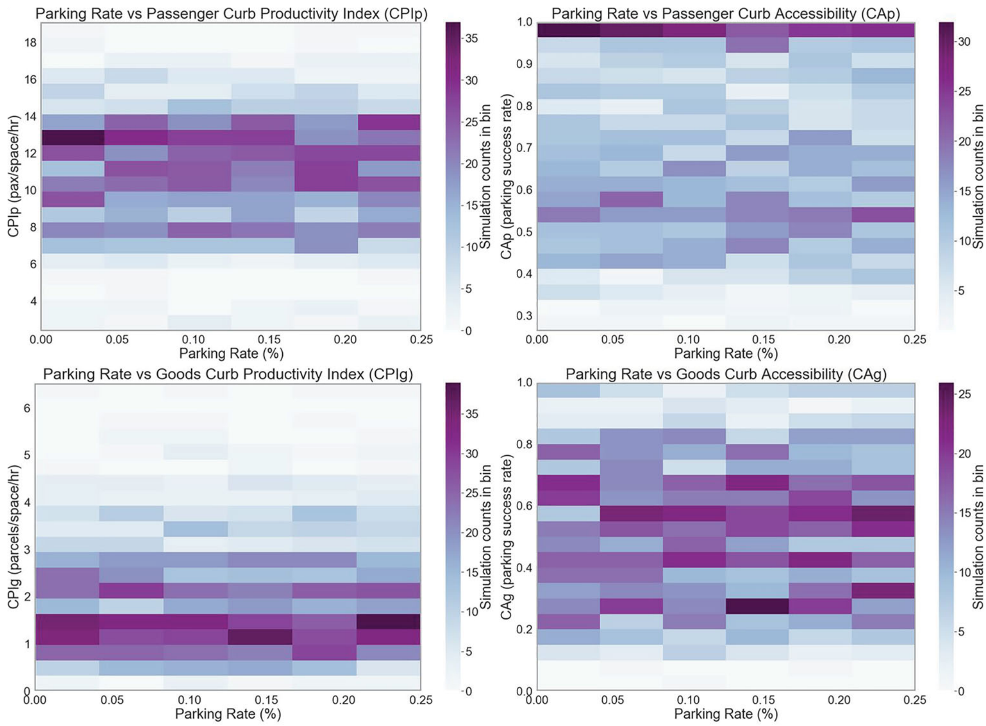

Figure 2. Passenger and goods metrics versus parking rate (%).

this scenario, more than two thirds of commercial vehicles are unable to park, and CPIg decreases by about 5 parcels per hour.

Sensitivity analysis of passenger and goods metrics

As previously noted, the results presented thus far are averaged across all simulations and parameter distributions. To understand how each parameter impacts the four performance metric values, we also perform a sensitivity analysis.

Each of the four metrics (CPIp, CAp, CPIg, and CAg) are plotted against two of the simulation parameters, parking rate and volume (Figures 2 and 3). There is no noticeable trend between metrics and changes in parking rate, but there is substantial correlation between the metrics and changes in volume. This means the average metric values between scenarios change independently of parking rate. To better understand the relationship between the metric values and the volume parameter, the parking rate histograms are binned by volume, and the trends are still clear (Figures 4 and 5). As volume increases, curb productivity increases until the parking in the study area reaches saturation –between 300 and 400 vehicles per hour. The saturation level for commercial vehicles is even lower (150–250 vehicles per hour) due to the longer average dwell time of these vehicles. Curb accessibility conversely declines as volume increases, because there is higher demand for each parking space, and this trend continues for higher volumes.

The remaining two parameters: design speed and commercial vehicle dwell time are not discretized at a level similar as volume and parking rate and therefore plots are not provided. Roadway design speed has limited impact on passenger and goods metrics. The difference between the average CPIp and CAp values at 20mph and 30mph is just 0.4%. This equates to less than one vehicle per hour attempting to park in the study area. Regarding commercial vehicles and goods delivery, the differences in goods metrics as a result of changes in design speeds is even less pronounced. The difference

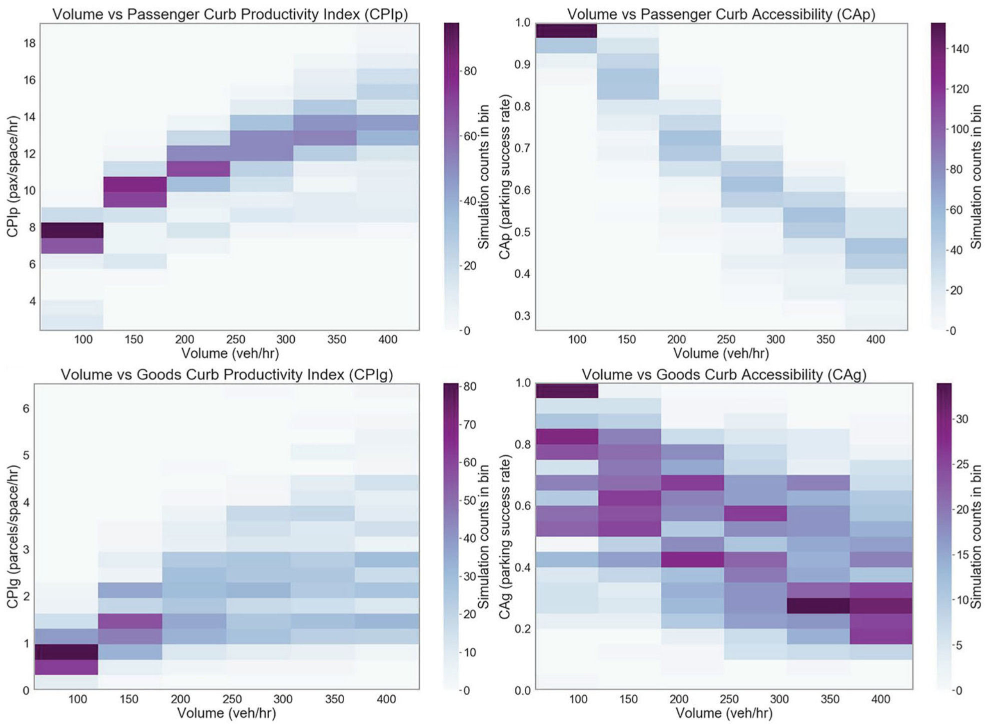

Figure 3. Passenger and goods metrics versus study area volume (veh/hr).

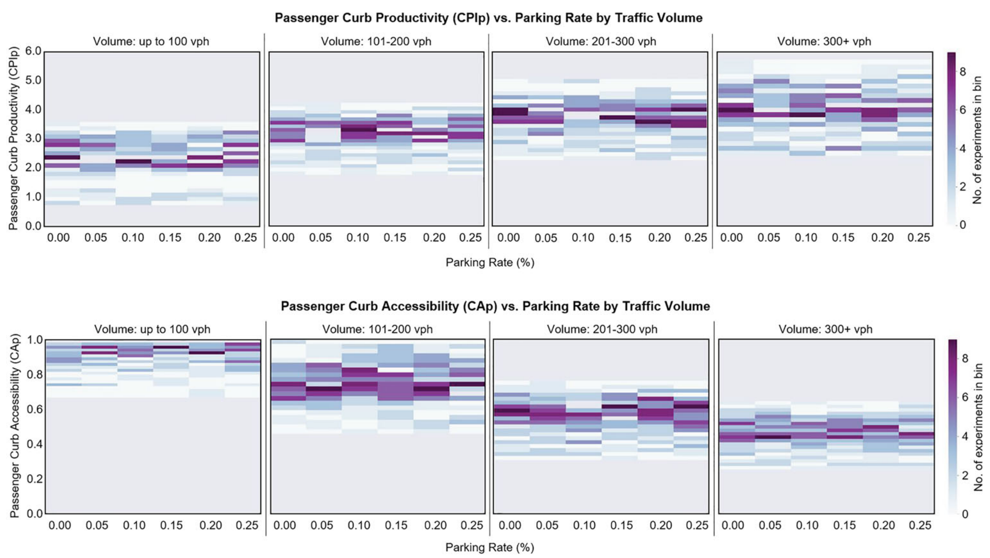

Figure 4. Passenger metrics versus parking rate (%) by volume (veh/hr).

in average CPIg for simulations run at design speeds of 30mph and 20mph is only 1.8%. Average CAg is by 0.9% greater at 30mph. However, these figures bely the small overall share of commercial vehicles in the simulated fleet. The difference in CAg at the two speeds represents a single additional van or truck parking every 5 simulations (out of 640 total simulations at each speed).

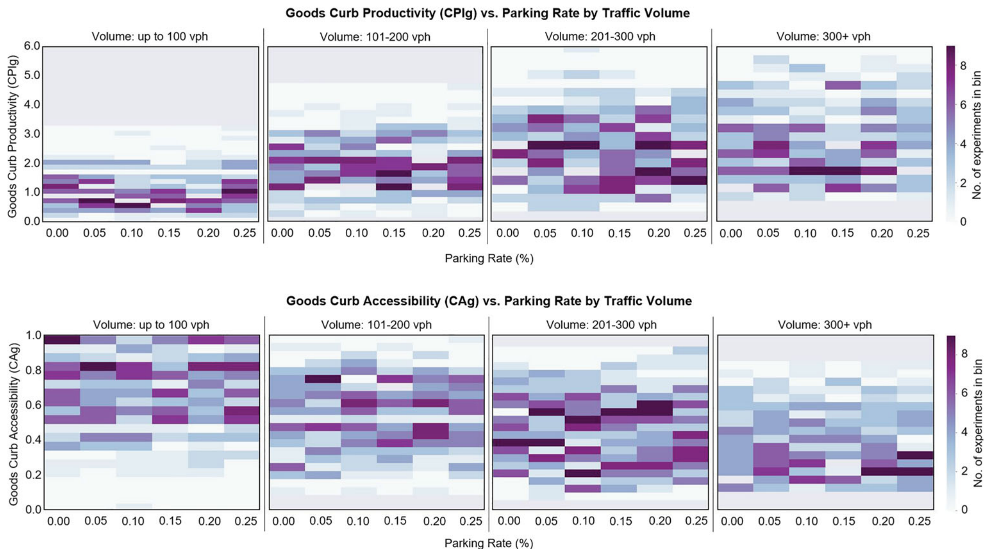

Figure 5. Goods metrics versus parking rate (%) by volume (veh/hr).

The impacts of changing the average commercial vehicle dwell time on the performance and accessibility metrics were larger than the impacts of changing roadway design speed. Increasing commercial vehicle dwell time led to decreases in the number of passenger and commercial vehicles able to park in the study area. Commercial vehicle dwell times are distributed around means of 5 min or 14.2 min, corresponding to small and large deliveries. When a commercial vehicle occupies a parking space for a longer period, we can expect lower vehicle accessibility rates for other commercial vehicles or any vehicle type competing with commercial vehicles for parking. On average five fewer PUDO or personal vehicles and 2.5 fewer commercial vehicles were able to park in the study area when the commercial vehicle dwell time parameter increases from 5 to 14.2 min.

Emissions index

Study area emissions from each scenario are summarized in Table 5. Emissions are reduced from the baseline scenario in two of the eight scenarios: 4 and 6. The emissions reduction in Scenario 6 can be easily explained. With the absence of a bus stop, emissions from buses idling while passenger board and alight are eliminated. While buses still pass through the study area and idle while stopped at the traffic light in Scenario 6, the elimination of idling emissions tied to the bus stop outweigh the increased emissions from personal vehicles (3.8%), PUDO vehicles (2.7%), and commercial vehicles (15.5%) by more than three to one. The changes to emissions from the other three vehicle types are also statistically significant and can be explained by the increased accessibility rate of all three. Vehicle types emit more local CO_2 when more vehicles are able to park in the study area.

Scenario 4 results in lower emissions for different reasons. Only the changes in emissions from personal and commercial vehicles are statistically significant. Personal vehicle emissions are reduced by 3.6% and commercial vehicle emissions are reduced by 9.2%. Although we may expect CO_2 reductions from these vehicle types when they are able to find parking at higher rates because neither type idles while parked and exhibits longer dwell times, the real reason emissions are reduced is because this scenario results in some of the lowest accessibility rates. The act of being turned away from the study area block face because spaces are already occupied is the driver for emissions reductions.

The only scenario that results in significantly higher emissions in Scenario 2. This change rests solely with PUDO vehicles that experience a significantly higher accessibility rate *and* idle while parked,

Table 5. Aggregated CO_2 emission index results across all simulation parameters.

Scenario: name	Emissions (kg CO_2/hr)	% Δ from baseline	*t*-test *p*-value
1: Baseline	25.7	–	–
2: 1 PLZ	26.1	1.5%	0.049
2a: 3 PLZ	25.6	−0.2%	**0.804**
3: 1 CVLZ	25.6	−0.2%	**0.794**
3a: 3 CVLZ	26.1	1.5%	**0.147**
4: Utopia / PP open	24.6	−4.3%	$p < 0.001$
4a: Utopia / PP restricted	25.7	0.0%	**0.962**
5: Fury road	25.4	−1.2%	**0.102**
6: Replace bus stop	22.8	−11.4%	$p < 0.001$

resulting in 18.2% more CO_2 emitted in the study area by this vehicle type. This pattern is confirmed by Scenarios 2a (30.3% increase) and Scenarios 3 and 3a (6.4% and 13.7% decrease, respectively). When PUDO vehicles are able to park at a high rate (Scenarios 2 and 2a), PUDO emissions increase, and when they are unable to park at a high rate (Scenarios 3 and 3a), PUDO emissions decrease. That being said, the overall changes in emissions from Scenarios 2a, 3 and 3a are not statistically significantly different. In those cases, the change in PUDO emissions is offset by changes in personal and commercial vehicle emissions. In Scenario 2a, a combination of failed parking attempts by personal and commercial vehicles offsets the PUDO emissions increase. In Scenarios 3 and 3a, the high rate of parking success by commercial vehicles results in significant increases in truck or van emissions.

The emissions results from Scenarios 4a and 5 are similar to the above. PUDO emissions increase in both cases. In Scenario 4a, more personal vehicles are unable to find parking, resulting in lower emissions from the class. Commercial vehicle emissions changes are insignificant. And in Scenario 5, the opposite is true. Commercial vehicle emissions decrease significantly as a result of parking being blocked by illegally parked cars in the CVLZ or by double parked vehicles, and personal vehicle emissions are not statistically significantly impacted by the curb assignment.

Discussion

The developed curb performance metrics in this study and the results presented are intended to aid cities in better managing their curbs, whether their goals are increasing accessibility (Butrina et al. 2020; PBOT 2019; Austin DOT 2019; Atlanta Mayor's Office 2019), maintaining or enhancing economic output (City of Chicago 2019; Saint Paul PED 2009), and/or reducing emissions (NYCDOT 2021; DDOT 2021). The results of this study corroborate findings of Fehr & Peers (2018) and Ranjbari et al. (2021) that PLZs can improve passenger accessibility at the curb, and those of Ranjbari et al. (2021) that curbs can be underutilized if PLZs are placed solely based on the total passenger demand. Rather than leading to a specific recommendation about the number and location of PLZs though, this study quantifies the performance gains/losses of passenger and commercial vehicles as a result of changed PUDO curb access. In the same vein, we measure the passenger and PUDO performance losses as a result of allocating a curb space to commercial vehicles. A key finding, then, is that the importance of each user has to be weighed when allocating spaces at each blockface or series of blockface.

Butrina et al. (2020) and Young and Henao (2020) imply that curb spaces should be allocated according to the most frequent user. Likewise, the planning document Denver Blueprint (2018) states that curb allocation, 'should be based on the highest and best use that services the most number of people'. But those studies imply that multiple users should be given access to the same curb if, for example, the block contains an office building generating passenger demand and a hotel that generates demand for goods delivery. This work shows that neither group of curb users – passenger or commercial – benefits when separate spaces are allocated to each use along the same block. Instead, it may be more effective to place PLZs and CVLZs on different but adjacent/nearby streets to maximize access and productivity while minimizing walking distance.

Importantly, study area emissions are only reduced in two scenarios – where a bus stop is replaced by paid parking and a CVLZ (Scenario 6), and where one PLZ and one CVLZ replace paid parking spaces (Scenario 4). This lends minimal credence to city transportation plans that intend to use curb management as a means to reduce emissions, such as those developed by New York City and Washington, DC (NYCDOT 2021; DDOT 2021). However, reporting that removing a bus stop reduces emissions ignores the fact that the bus stop would likely be placed somewhere else. The low accessibility rates that cause CO_2 emission reductions in Scenario 4 likewise to do not account for the emissions transported somewhere else while vehicles cruise for parking. Despite not accounting for cruising emissions, we have shown that when space is allocated for either goods delivery (CVLZ) or passenger loading/unloading (PLZ) accessibility for the corresponding vehicles types increases. Those configurations result in the highest accessibility rates, implying fewer vehicles needed to cruise for parking, and henceforth lower parking-related emissions.

Curb allocation changes are context specific, meaning each city has their own goals to achieve when making allocation decisions. A city might have a vested interest in improving curb access for only PUDO or goods vehicles, or a city may seek to improve curb access for both user groups. Our results show that only three scenarios: 3, 4a and 6 resulted in improvements across multiple metric categories (passenger, goods, and emissions). In Scenario 3, goods metrics and emissions improved, although the change in emissions was not statistically significant. In Scenario 4a goods metrics improved and more passenger vehicles were able to park, but this did not result in more passengers accessing the curb. In Scenario 6, both goods metrics, emissions, and passenger accessibility were increased, yet the emissions reductions were attributed mainly to the lack of idling buses because the bus stop was removed. The relationship between emissions and other metrics is closely linked with vehicles that idle. When more PUDO vehicles park, emissions likely increase. However, this link, and the link between emissions reductions and curb allocations in tenuous. Only three scenarios produced emissions results statistically significantly different from the baseline suggesting that if a city is seeking to reduce transportation emissions, perhaps curb allocation is not the best way to achieve this goal.

Conclusion

This work provides quantitative performance trade-offs for different space allocations at the curb, taking into account for the first time both passenger and goods metrics, as well as incorporating parking-related emissions. A major contribution of this work is to provide cities with a framework to assess these trade-offs between different curb allocation outcomes and choose the allocation that meets the overarching goals of the city. For example, if their goal is to reduce CO_2 above all other performance factors, Scenario 4 (replace paid parking with 1 CVLZ and 1 PLZ) should be implemented. Or, if addressing inadequate commercial vehicle parking is the only goal, Scenarios 3 or 3a (replace paid parking with CVLZ) should be implemented. However, rather than addressing a single curb management problem such as inadequate commercial vehicle parking, cities can use these methods and findings to justify curb allocation changes, or use the empirical results to determine if a trade-off – such as increasing passenger metric values while decreasing goods-related metric values – is worth the investment. Our methodology can be reproduced by cities and the framework used prior to implementing curb changes. Scenarios provided in this study are sample scenarios, and the methodology would yield different results curb allocations in different cities. Utilizing microsimulation prior to implementing changes to the physical infrastructure can save cities temporal and financial resources. The findings can aid cities in making better curb management decisions, especially in mixed-use urban areas, that enhance their overarching goals, whether it is increasing accessibility and recurring parking congestion, enhancing productivity and economic output, or reducing carbon emissions. The main contribution of this paper is the development of new curb metrics for parking emissions and goods accessibility and productivity and also quantifying the trade-offs across a wide range of curb space allocations and parking rules.

The results confirm findings of Fehr & Peers (2018) and Ranjbari et al. (2021) that PLZs improve the curb productivity in terms of the number of passengers served by the blockface. Simulations demonstrate an increase of almost 6% in passenger productivity by adding just one PLZ in the study area. The single PLZ scenario also improved PUDO accessibility to the curb while decreasing accessibility of personal vehicles. We quantify the loss in goods delivery production as a result of a dedicated space to passenger pickup/drop-off to be roughly 9%. Conversely, goods productivity (24-64%) and commercial vehicle accessibility (21–40%) improves by adding CVLZs, confirming the results of Dalla Chiara et al. (2021) with quantitative evidence. When both PLZ and CVLZ spaces are allocated on the same blockface, however, passenger productivity and accessibility show decreases as a result of increased competition for paid parking amongst personal vehicles. Goods delivery metrics only improve in an idealized scenario – where all drivers adhere to parking rules and park in their designated spaces.

A key contribution to the field of parking research is the incorporation of emissions as a metric of curb performance by accounting for various vehicle states associated with curb parking, such as queuing, entering/exiting a space, and idling when loading/unloading passengers. Such a metric can help cities justify implementing curb management strategies that improve parking efficiency without increasing emissions, and in some limited cases, with lower emissions. Maxner, Dalla Chiara, and Goodchild (2022) determined that more than half of cities with commercial vehicle-related emissions goals are considering changing curb space allocations to provide more parking to these vehicles. This work presents an argument that CVLZs have an insignificant impact on emissions and PLZs should not be created if emissions is the deciding factor, but the metric can also be enhanced by considering the wider neighbourhood.

A limitation to this study is rooted in the analysis of a single blockface. Vehicles that fail to park in the study area would not simply exit the network, rather the drivers would search, or cruise, for parking on nearby blocks. Future work will extend the study area to several blockfaces at the neighbourhood scale. This would enable taking cruising for parking into account, which can increase emissions (Kilbert 2011). Scenarios with low curb accessibility metrics for any vehicle type, could underestimate produced emissions because of this matter. Extending the simulated network to several blockfaces would also allow us to measure the impacts of increased or reduced demand on neighbouring streets. These streets would already have their own parking demand. The CPI and CA metrics do not reflect vehicles that find parking elsewhere in the network. Passengers that walk and goods that are otherwise transported from nearby streets to the study area will be counted in modified productivity and accessibility metrics. Additional factors including driving times during the search for parking, and walking distance to the intended destination will be accounted for. Modelling several blockfaces further allows for exploring the outcomes of prioritizing passenger and commercial vehicle access on separate blockfaces rather than including both on the same blockface. Moreover, future studies could use the developed framework and metrics in this study to simulate additional curb use types (such as electric vehicle charging or flex delivery spaces) and/or other curb policies (such as pricing or maximum dwell time).

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