Technical Report

A Data-Friendly Mesoscale Network Model for Road-Curb Systems: Travel Behavior, System Impacts, and Policy Interventions

Jiachao Liu[1] and Sean Qian[*1,2]

[1]Department of Civil and Environmental Engineering, Carnegie Mellon University
[2]Heinz College, Carnegie Mellon University

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1 Introduction

The explosive growth of transportation network company (TNC) services, e-commerce with on-demand deliveries, micro-mobility services and on-street electric vehicle charging station has transformed curb spaces into high-demand infrastructure. ride-hailing vehicles grew from under 40,000 in 2010 to over 120,000 in 2019—nearly 30% of city traffic [1]. These vehicles frequently occupy curbs for pickups and drop-offs, exemplifying the growing curbside pressure. Meanwhile, e-commerce growth and changes of consumer habits have transformed delivery patterns, with residential deliveries rising from 40% before pandemic to 80% today and 90% of freight deliveries are conducted via trucks [2]. Unlike quick PUDO stops by ride-hailing, delivery vehicles, especially trucks often occupy curb spaces for longer periods and require more space to conduct door-to-door deliveries, further intensifying the competition of limited spaces. Without proper regulations, these increasing utilization of scarce curbs by different traffic modes is exacerbating both curbside and transportation system congestion, contributing to rising number of illegal parking, inefficiency of traffic ecosystem and increased urban environmental pollution. However, existing models often fail to comprehensively consider the various types of stops and occupancy at curb spaces by multiple modes, as well as the location choice of stops on curbside spaces nearby. Each curb user profoundly impacts how other travelers make trips. The location choice of curbside stops for different users depends on both curb and traffic conditions, which are influenced by other users' choices. Therefore, it is essential to analyze the system-level impacts associated with multi-modal curb usage across time and space, and gain a comprehensive understanding of the spatio-temporal characteristics of travel behavior patterns related to curb utilization. This helps facilitate proper curb management strategies that are not only efficient but also promote high compliance rates among users.

Recent advances in sensing and communication technologies have generated vast amount of high-resolution data from various sources, presenting unprecedented opportunities to address these challenges in managing curb infrastructure and transportation systems. Traditional traffic data, collected from fixed detectors, mobile detectors and surveys, can be used in curb-aware network models to capture travelers' preference and network flow patterns. As more investments are made in curb management, emerging technologies are providing new data sources that can be leveraged to facilitate data-driven curb optimization. The City of Pittsburgh launched a pilot Smart Loading Zone (SLZ) program in 2022, which marked curb spaces as

*Email: seanqian@cmu.edu

purple and charged parking fee based on time spent in the zones. The SLZs use license plate reading technology to track curb events occurring in the zones, monitoring how long vehicles remain in the zone and charge registered users for the amount of time spent, according to the posted rates. These monitoring data offers a new opportunity to model the spatio-temporal curb usage patterns and choice preferences. Although multi-source data are available, most remain underutilized and isolated within specific zones or applications. Bridging this gap requires a robust theoretical framework to integrate multi-source data together, unlocking the full potential of big data and enabling smart decision-making across networks and systems.

This research project aims to design a data-friendly framework to model coupled curb-road networks. The framework integrates theories, models and algorithms to model system-level externalities of extensive curb usage and fuse multi-source data including emerging curb data to estimate curb-related travel patterns of multi-modal users. Based on the network model calibrated from data, scenario analysis can be conducted to evaluate different curb intervention policies and optimal operational strategies are identified to improve both system and local mobility efficiency. The project demonstrates the effectiveness and replicability of the models and algorithms in Pittsburgh network.

2 Literature Review

Curb space is evolving into a multi-functional public asset, beyond its traditional role as spaces for temporary on-street parking and vehicle storage. It has been witnessing a convergence of diverse and competing uses with various purposes, including private vehicle parking, commercial deliveries, passenger pick-up/drop-off (PUDO), public transportation, and other emerging mobility services. Initial studies primarily focused on on-street parking function especially in dense urban areas, modeling parking-related behaviors such as on-street parking, queuing, cruising for parking [3, 4], and competition between different parking options [5], and explore corresponding management strategies [6, 7, 8, 9, 10, 11, 12]. Some research has also explored associated congestion impacts [13, 14] and dynamic pricing mechanisms [15, 16, 17]. However, many of these studies address curb usage from the perspective of isolated users, lacking a systemic view of multimodal curb usage.

Since the usage of curbside spaces involves a wide spectrum of stakeholders, the curbside management is usually conceived as achieving a balance for all participants in curbside usage. [18] made a comprehensive review of existing projects of curbside usage and policies, summarizing incoming challenges, demands and opportunities. Several pilot studies have been conducted for different individual components in curbside management, including efforts on commercial loading/unloading [19], on-street parking [20] and residential parking [21]. There are also studies identifying the supply and demand dynamics with respect to the curbside usage, such as the competitions between curbside parking and downtown garage parking under different parking demands [22, 23] and the impacts of regular parking spillovers at popular destinations on curbside usage [24]. However, early studies on curb management did not capture the relationship between curb space usage and network traffic dynamics. It was unclear how curb use would impact the traffic flow and thus the system-level network performance.

In recent years, more research has been conducted to build refined models for curbside management strategies, but mostly focusing on single traffic mode. [25] used agent-based simulation to study the performance of curbside parking and examined if reservation systems outperform come-and-find approaches. [26] examined interactions between bikes and curbside and revealed the fact that there is a strong correlation between bike crashes and parked vehicles on curbs, and further discussed how to design bike-lane/curbside space aiming to reduce bike crashes. On the same topic, [27] proposed a microscopic examination on the curbside parking to capacity reduction of bike lanes. [28] studied the impact to traffic at destination blocks with dedicated PUDO curbs for TNC services. Riders' different levels of correspondence to this policy was also examined when different measures have been taken to reinforce dedicated curbside PUDOs. [29] introduced a network of finite capacity queues to model curbside parking behavior. [30] studied the impact of curbside bus stops to roadway traffic flow under heterogeneous traffic conditions and found out that curbside bus stops reduce roadway capacity depending on bus arriving rate. [31] developed a queuing network considering both dedicated bays and curbside parking to emphasize the allocation of scarce curbside space. [32] utilized real-world datasets to compare regulations and violations of commercial vehicle parking in areas with different land use characters, suggesting that current curb regulations are inadequate for the growing demand. [33] conducted case studies to analyze regulations affecting curbside parking spaces. [34] proposed a deep learning approach to predict diverse spatial-temporal curb usage considering various dependencies. [35] proposed a framework for optimal curbside zoning including changing type limitations and prices with respect to the measurement of curb usage demand. [36] developed a tool to allocate curb space with demand constraints. [37] proposed a reinforcement learning method to dynamically dispatch parking areas to accommodate short-term PUDOs. [38] developed a curbside space management considering infrastructure autonomy, connectivity, and flexibility. [39] analyzed the impact of curb parking behavior on road capacity and the influence mechanism of various factors related to curb parking on traffic capacity. [40] developed a micro-simulation based framework to simulate and evaluate curbside traffic managements policies. Most existing research on curbside management policies studied the curbside area solely, and very few work integrated the curbside space into general transportation networks where a complete trip is made or modeled.

3 Research Gaps and Tasks

Based on the literature review, the main research gaps lie in:

- To the best of our knowledge, very few existing studies explore how curb-related traffic patterns evolve across time and space, and how various curbside management strategies (i.e., pricing and space allocation) impact system-level traffic and accessibility dynamically. The curb-related behavior of multi-modal transportation has diverse spatio-temporal characteristics across the network, necessitating dynamic curb management strategies based on modeling the utilization of curbs in a dynamic network.

- Very few existing simulation models integrate spatial usage of curbs into DNL, and they are not able to model the dynamics of curb utilization of vehicles and the effect of potential curb/road congestion (i.e., double parking) on network traffic. Simulation should be able to model impact of extensive curb usage and the systematic externalities of potential curb/road congestion (i.e., double parking) on network traffic.

- Although emerging curb data is available, there is a lack of theories and models to fuse them with large-scale traditional multi-source data to understand spatio-temporal network flow and curb usage patterns, and how individual travelers make choices regarding routes, time, and curbs in dynamic network models.

To address these research gaps, we propose a comprehensive mesoscale modeling framework for road-curb networks in the City of Pittsburgh. This framework integrates multi-modal travel behavior related to curb and route choices, evaluates the system-wide impacts of localized curb usage, and support the assessment of various curb management interventions. It leverages emerging high-resolution curb activity data collected by Automotus Inc. at Smart Loading Zones in Pittsburgh to establish a base model that reflects current network and curb usage conditions. Based on this base model, the framework enables scenario testing to simulate how traveler behavior may respond to different policy interventions. It also supports the evaluation of both network-level and curb-level performance using metrics of varying spatial and temporal resolutions. These capabilities offer valuable insights to inform policy decisions for the deployment and management of new and existing SLZs. The framework is designed to be adaptive and sustainable, improving over time as additional data becomes available and as curbside dynamic model and behavior model evolve. By leveraging standardized data and modular components, the framework can be easily adapted to other cities with similar curb management challenges and support decision-making at scale. Figure 1 demonstrates key components of the proposed framework.

The project is divided into four major tasks:

Task 1: Identify multi-source data and emerging curb data for in-depth data analytics

The following data are collected, processed, and integrated for modeling curb-road system of Pittsburgh network, shown in Figure 2.

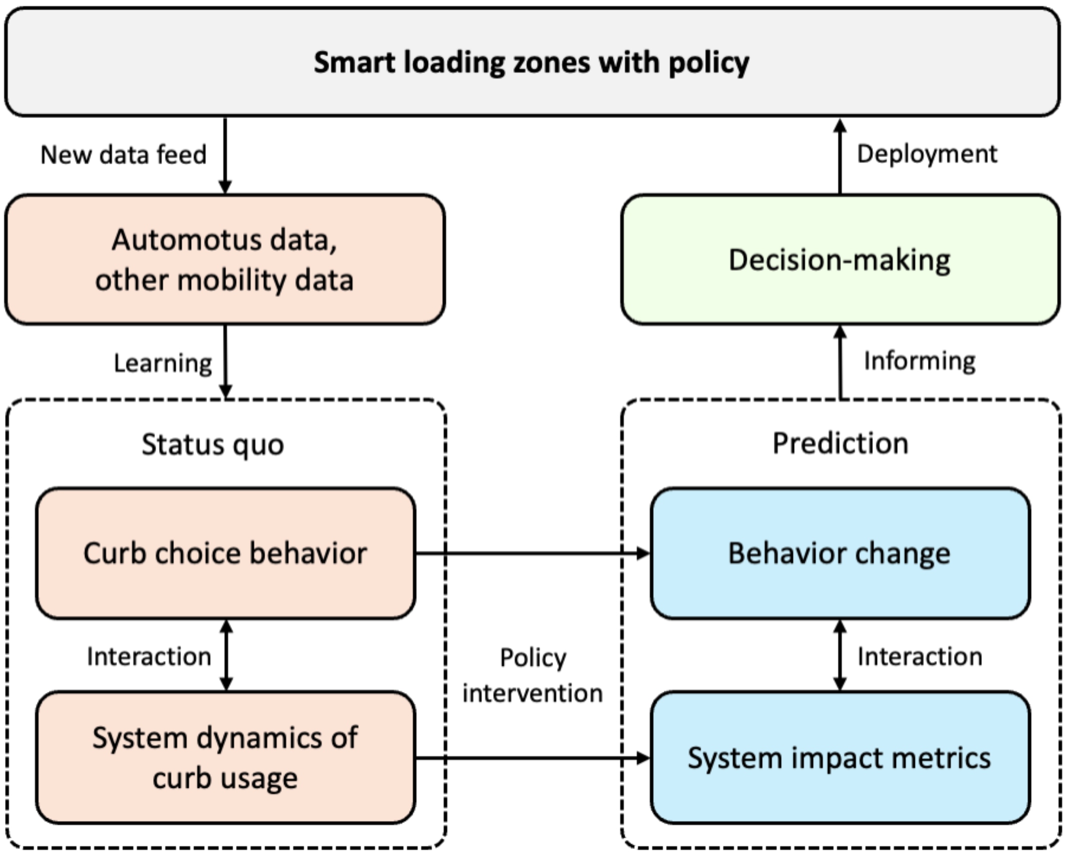


Figure 1: Modeling Framework

- Transportation network data (GIS model) for the City of Pittsburgh
- Traffic counts by vehicle classes on local streets, intersections, and highways in Pittsburgh area.
- Traffic speed data for highways in the region and major arterials within the Pittsburgh area
- Automotus curb data which tracks class-specific curb activities (vehicle class, parking duration etc.) at Smart Loading Zones within Pittsburgh area.

Task 2: Develop a meso-scale multi-modal network simulation to model passenger and freight trips in the roadway-curb network

An open-source mesoscopic network analysis tool, MAC-POSTS (Mobility Data Analytics Center - Prediction, Optimization, and Simulation toolkit for Transportation Systems)[1], developed by Mobility Data Analytics Center (MAC) at Carnegie Mellon University (CMU) is used to simulate the dynamic traffic flows over time in the Pittsburgh network. To model curb choices and impact of curb parking on through traffic, the simulation tool integrates new developed functions for curb parking dynamics within link dynamic model and introduce truncated fundamental diagram to capture curb parking impact on traffic.

Task 3: Develop curb-road network model for Pittsburgh network using multi-source data

Based on curb-aware MAC-POSTS developed in Task 2, a dynamic model for road-curb network of Pittsburgh is established that provides estimated 15-min origin-destination demand among all street segments and curb usage demand at smart loading zones that vary by time of day. The travel and curb demands in the area are calibrated using multi-source data sets collected in Task 1, through a state-of-the-art computational graph approach. With the estimated demand, the network model is then able to replicate the close-to-real-world traffic dynamics and curb usage patterns. This model adopts state-of-the-art traffic models and is much more computationally efficient than other microscopic models that are extremely labor-intensive to establish. It should be noted that this dynamic network model can be leveraged for City of Pittsburgh to make optimal decisions on smart loading zone expansion, curb management and control and other ITS strategies in general. Moreover, the general modeling framework can be easily transferred to other cities using standardized data inputs.

Task 4: Scenario analysis of various curb management policy

Building on the calibrated model in Task 3, we test various curb interventions including pricing, space allocation and reservation, and evaluate the effectiveness based on system-level and localized metrics. The performance metrics include emissions, energy use, vehicle-miles traveled, travel time, congestion attributed to highway or local roads, and curb conditions such as curb parking number and double parking number. This is completed in a simulation environment but can serve as a benchmark of curb management performance and offer recommendations for optimal curb policy developed in the future.

The rest of the report details the methodologies to complete these tasks and discusses the results and findings.

4 Multi-source data collection and processing

The Pittsburgh region has rich granular multi-source data available for traffic analysis and the smart loading zone program provides emerging curb data to model in-depth curb behaviors. This section briefly describes the multiple data sources used in this project, including network topological data, traffic count data, traffic speed data and curb data collected by Automotus Inc.

[1]https://github.com/maccmu/macposts

4.1 Network Consolidation

The network used in this project is a trimmed version of the original regional network provided by the Southwestern Pennsylvania Commission. The trimming focuses on the City of Pittsburgh, where the Smart Loading Zone (SLZ) program is deployed, as indicated by the green dots in Figure 2. The final network has 3,834 road segments, 1,580 intersections and 126 traffic analysis zones (TAZs). The total number of OD pairs is 14,517.

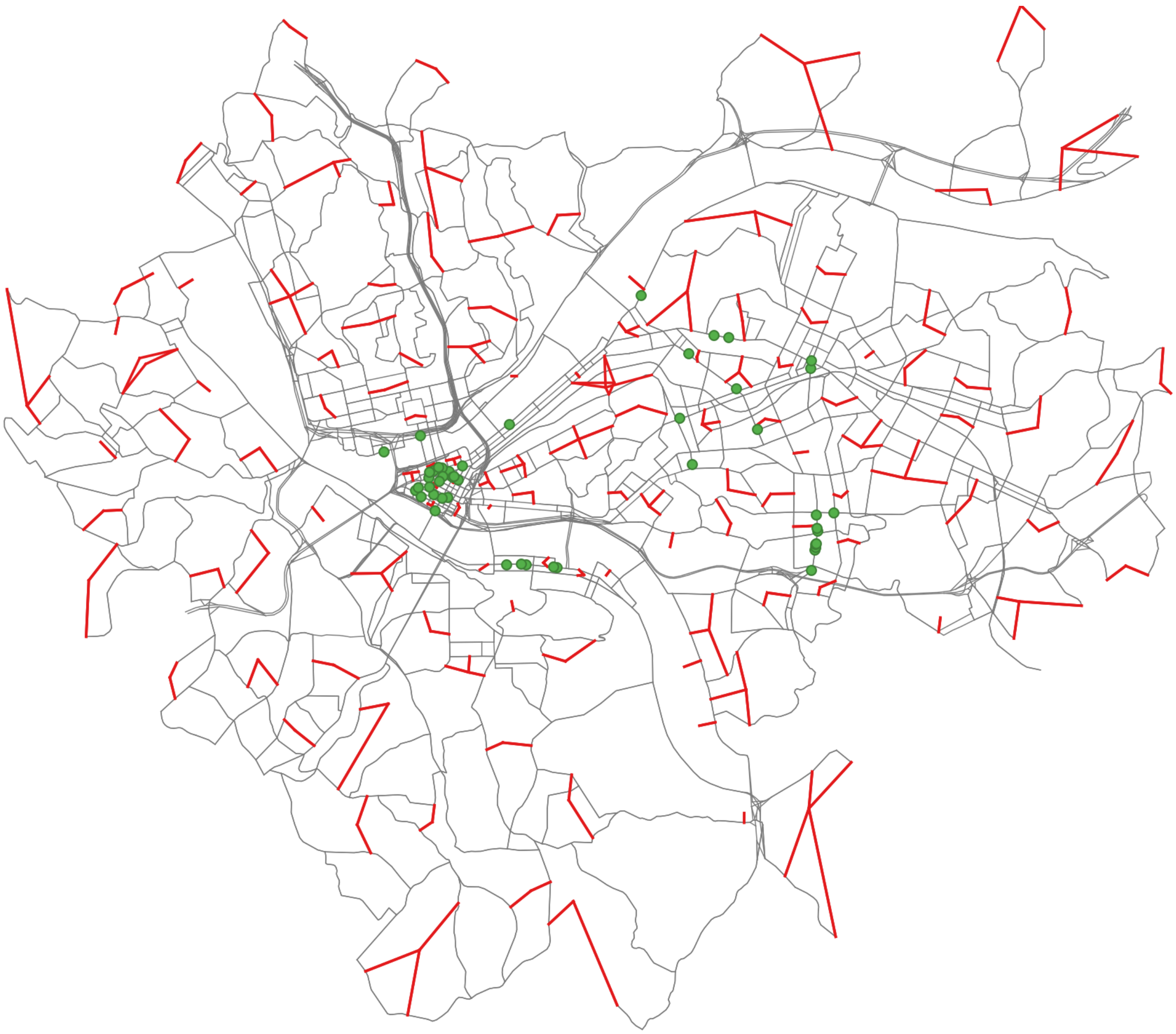


Figure 2: An overview of the Pittsburgh network

4.2 Traffic count and speed data

Multi-class traffic count data represents the vehicle counts passing by a certain location, categorized by vehicle types (i.e., cars and trucks). This data is usually collected by loop detectors or manual counting. The count data used in this project contains historical traffic volumes for different vehicle types at selected locations in this region in the years of 2018-2022. The count data is carefully examined and aligned with the corresponding links of the network. Two vehicle classes, i.e., cars and trucks, are counted separately, representing smaller private or ride-hailing vehicles, and larger freight or delivery trucks, respectively. The count data is consolidated into 15-minute intervals for simulation purposes, enhancing the granularity and accuracy of the traffic analysis. In total, there are 102 locations with valid car and truck counts.

Traffic speed data is provided by INRIX for the year of 2023. Speeds of different vehicle types are measured separately, and hence both passenger car speeds and freight truck speeds are available. The speed data is measured every 5 minutes of each day, and we average the data for different days in 2023 and aggregate the data to 15-minute intervals excluding the outliers. There are a total of 922 links with valid car and truck speed measurements.

4.3 Automotus data

Besides the traffic counts and traffic speed data to model network traffic conditions, we also obtained curb data at specific locations to model localized curb activities. The curb data is collected by pilot Smart Loading Zone program deployed in Pittsburgh, supported by the City of Pittsburgh Department of Mobility & Infrastructure and Automotus Inc. We analyze the curb event data and aggregate the curb arrivals by vehicle classes. Because the smart loading zones has limited spaces (usually 2 parking spots at each location), the hourly arrival rate is small and we aggregate the total arrivals during the whole modeling period to calibrate curb usage demand. In this study, we use data from 62 links with smart loading zones which are consistent with the topology of the network.

5 Curb-aware Meso-scale Network Model

This section presents the mesoscale network model for the coupled road-curb network of the City of Pittsburgh. We first introduce the method used to model curb/route choices of three travel modes, followed by a description of mesoscopic simulation models with curb functions. Finally, we describe the data-driven model calibration process using multi-source data and demonstrate the calibration results.

5.1 Modeling multi-modal curb usage

Consider a general roadway network denoted by $G = (N, A)$, which consists of a node set N and a link set A. Define $T_d = [1, 2, ..., T]$ as the assignment horizon and time interval as $t \in T_d$. R and S are sets of origin and destination nodes. Between each OD pair rs, where $r \in R$ and $s \in S$, there are three categories of demand, departing at time t, separately represented by three travel modes: private driving demand $q^{rs}_{\mathscr{D},t}$, ride-hailing demand $q^{rs}_{\mathscr{R},t}$ and commercial truck demand $q^{rs}_{\mathscr{T},t}$. Travelers of each mode make choices of routes associated with stop location choice at curb spaces. $f^{rs}_{m,k,t}, m \in C$ indicates the flow of path k leaving at time t from origin r to destination s of travel mode m and $C = \{\mathscr{D}, \mathscr{R}, \mathscr{T}\}$ is the set of three modes.

We model the route choice associated with curb stop location choice separately for different modes. The generalized travel costs of three modes are defined and used to govern route and curb choices. A private driving trip starts from an origin node $r \in R$ and ends at either a destination node $s \in S$ (parking at the garage at the destination) or curb spaces nearby (on-street parking at curbs), and these two options might have different parking fees. $P^{rs}_{\mathscr{D}}$ denotes the path set between OD pair rs. The generalized cost of a driving trip $k \in P^{rs}_{\mathscr{D}}$ departing at time t is defined as follows:

$$c^{rs}_{\mathscr{D},k,t} = \alpha w^{rs}_{\mathscr{D},k,t} + p^k_c \sigma^k_c + (1 - \sigma^k_c) p^k_s + \xi, \ \forall k \in P^{rs}_{\mathscr{D}} \tag{1}$$

where $w^{rs}_{\mathscr{D},k,t}$ denotes the travel time on path k obtained from the DNL. σ^k_c is the indicator variable and equals one if the driving traveler parks the car at the curb space (i.e., on-street parking) and pays a parking fee of p^k_c, otherwise $\sigma^k_c = 0$ when he/she parks the car at the destination and pays a parking fee of p^k_s. ξ is the other cost for the driving mode. Following [9], this term can be indicator of accessibility to a private car. If the traveler has access to a car then $\xi = 0$, otherwise it can be set to a large constant. Alternatively, ξ can be other general cost of driving such as fuel costs, flat toll charges, vehicle depreciation and insurance fees. These costs can be allocated evenly to each trip.

The generalized cost for ride-hailings using the k-th tour is defined in Equation (2). $P^{rs}_{\mathscr{R}}$ is the set of generated tours between OD pair rs for ride-hailing vehicles based on exogenous information. In a tour $k \in P^{rs}_{\mathscr{R}}$, there are $N_{\mathscr{R},k}$ trips with quick stops for PUDO and each trip has a location-based curb use fee p^i_c. The curb usage fee p^i_c depends on curb occupancy at predictive arrival time. It can be normal curb fee or penalty for illegal double parking. We consider the choice behaviors for ride-hailing drivers and passengers are consistent and governed by the generalized cost defined based on tour k, denoted by $c^{rs}_{\mathscr{R},k,t}$, which is the summation of trip travel costs $c^{i}_{\mathscr{R},t^i},\ i \in [N_{\mathscr{R},k}]$.

$$
\begin{aligned}
c^{rs}_{\mathscr{R},k,t} &= \sum_{i \in [N_{\mathscr{R},k}]} c^{i}_{\mathscr{R},t^i},\ \forall k \in P^{rs}_{\mathscr{R}} \\
c^{i}_{\mathscr{R},t^i} &= \alpha w^{i}_{\mathscr{R},t^i} + \rho^i(d^i_{\mathscr{R}}, w^{i}_{\mathscr{R},t^i}) + p^i_c
\end{aligned}
\tag{2}
$$

where $c^{i}_{\mathscr{R},t^i}$ denotes the generalized cost of ride-hailing trip i within tour k. t^i represents the start time of trip i which is the end time of last trip (considering curb stop duration). ρ^i is the service cost of trip i and related to the distance $d^i_{\mathscr{R}}$ and travel time $w^{i}_{\mathscr{R},t^i}$ of trip i [41, 42]. Parameters in ρ^i can vary depending on whether trip i is occupied or vacant.

Similarly, the generalized cost of a commercial truck is also tour-based, meaning that a truck driver makes route choices considering travel costs of all trips in a tour, defined as:

$$
\begin{aligned}
c^{rs}_{\mathscr{T},k,t} &= \sum_{i \in [N_{\mathscr{T},k}]} c^{i}_{\mathscr{T},t^i},\ \forall k \in P^{rs}_{\mathscr{T}} \\
c^{i}_{\mathscr{T},t^i} &= \alpha w^{i}_{\mathscr{T},t^i} + p_f d^i_{\mathscr{T}} + p^i_c
\end{aligned}
\tag{3}
$$

where $c^{i}_{\mathscr{T},t^i}$ denotes the generalized cost of commercial truck trip i within tour k. t^i represents the start time of trip i which is the end time of last trip considering the curb stop duration. p_f is fuel cost rate with respect to travel distance and $d^i_{\mathscr{T}}$ is the travel distance of trip $i \in [N_{\mathscr{T},k}]$. $P^{rs}_{\mathscr{T}}$ is the set of tours for commercial trucks between rs, generated from exogenous information.

The generalized costs $c^{rs}_{m,k,t}, m \in C$ are computed based on the local traffic conditions at the link level (i.e., link travel time $w^{rs}_{m,k,t}$, curb usage fee p^i_c depending on predicted curb occupancy) which are modeled by the simulation. When some links have intensive curbside parking, the local traffic conditions can be impacted, leading to increases in both curb occupancy and link travel time. The increased travel time and the larger curb usage fees (i.e., penalty for double parking) contribute to the overall travel costs of routes passing through these links, thereby altering travelers' route and curb choice behaviors on a macroscopic scale. The route choice behavior of all travelers in the system is modeled using user equilibrium conditions

$$
\begin{aligned}
c^{rs}_{m,k,t} - \mu^{rs}_{m,t} = 0 \text{ if } f^{rs}_{m,k,t} > 0, \forall k \in P^{rs}_m, rs \in RS, m \in C \\
c^{rs}_{m,k,t} - \mu^{rs}_{m,t} \geq 0 \text{ if } f^{rs}_{m,k,t} = 0, \forall k \in P^{rs}_m, rs \in RS, m \in C
\end{aligned}
\tag{4}
$$

where $\mu^{rs}_{m,t}, m \in C$ are equilibrium costs of travel mode m from r to s departing at time t. $f^{rs}_{m,k,t}$ is the flow of path k for mode m from r to s departing at time t. The total flow of each mode between OD pair rs departing at time t is

$$
q^{rs}_{m,t} = \sum_{k \in P^{rs}_m} f^{rs}_{m,k,t} \tag{5}
$$

Let $\boldsymbol{f}$ be the vector of all path flows, $\boldsymbol{f} = \{f^{*rs}_{m,k,t}\}_{rs,m,k,t}$, the Equation (4) can be further reformulated as the following variational inequality (VI) problem, denoted by $\mathbf{VI}(\tilde{\Lambda}, \Omega)$

$$
\begin{aligned}
&\text{Find } \boldsymbol{f}^* \text{ such that } \quad \tilde{\Lambda}(\boldsymbol{f}^*)^T \cdot (\boldsymbol{f} - \boldsymbol{f}^*) \geq 0, \forall \boldsymbol{f} \in \Omega \\
&\text{where } \tilde{\Lambda}(\boldsymbol{f}) = \left\{ \tilde{\Lambda}^{rs}_{m,k,t}(\boldsymbol{f}) = c^{rs}_{m,k,t}(\boldsymbol{f}) \right\}, \Omega = \left\{ \boldsymbol{f} \middle| \sum_k f^{rs}_{m,k,t} = q^{rs}_{m,t} \right\}.
\end{aligned}
\tag{6}
$$

In each DNL run, we obtain cumulative curves of all links and calculate travel time experienced by each vehicle class based on arrival times on each link. We define **Pre-trip Route Choice**, denoted by π_p, as the mechanism where travelers make decisions among the pre-defined route set based on the predictive travel costs before departure and adhere to their choices in the network. In this study, the DUE formulation can be seen as pre-trip route choice.

$$
\begin{aligned}
&\pi_p : \left(r, s, I^{1:T}\right) \mapsto k \in P^{rs}_m \\
&\text{where } I^{1:T} = \left\{ c^{rs}_{m,k,t}\left(w^{rs}_{m,k,t}\right) \right\}_{k \in P^{rs}_m, t \in T_d, m \in \{\mathscr{D}, \mathscr{R}, \mathscr{T}\}}
\end{aligned}
\tag{7}
$$

Pre-trip route choice may not be realistic due to the fact that travelers at time t should be only aware of the traffic states before time t and make choices based on the current states of the network. Here we define an **En-route Route Choice** policy to model this behavior. Travelers existing link a at time t and going to destination s or intermediate destination s' make the decision of next link b based on the current traffic state information at time t. The next link b is the first link in the shortest path heading to the desired destination s or s'. The shortest path is generated on the network where the weight of each link is mainly calculated based on link travel time and curb usage fee for specific travelers. This policy can be denoted as follows:

$$\begin{aligned}&\pi_e : \left(a, s^{(')}, I^t\right) \mapsto b \in A \\ &\text{where } I^t = \left\{h^t_{m,a}, p^t_{m,a}\right\}_{a\in A, m\in\{\mathscr{D},\mathscr{R},\mathscr{T}\}}\end{aligned} \tag{8}$$

where $h^t_{m,a}$ is link travel time for mode m on link a at time t and $p^t_{m,a}$ is the curb usage fee of link a for mode m at time t.

Hybrid Route Choice. A fraction (θ_{rs}) of habitual travelers between OD pair r-s follow pre-trip route choice within pre-defined path sets. The other adaptive travelers, with fraction of $1 - \theta_{rs}$, follow en-route route choice and use time-varying traffic states to explore shortest paths on the network, where generalized travel costs, including curb prices, are used as link weights. This definition follows the work of [43]. We use hybrid route choice to efficiently model simultaneous curb/route choice in the Pittsburgh network model.

5.2 Mesoscopic multi-class traffic flow model considering curb dynamics

In this project, the traffic dynamics in Pittsburgh are simulated in high spatio-temporal resolutions. The MAC at CMU develops an open-source multi-class dynamic network modeling tool, MAC-POSTS, which is capable of simulating network-wide traffic dynamics for any general networks consisting of freeways, arterials, and local streets [44]. MAC-POSTS adopts the state-of-art mesoscopic traffic flow model and can scale up to regional-level transportation networks. MAC-POSTS can be calibrated to replicate real-world traffic conditions and predict the impact of different traffic scenarios.

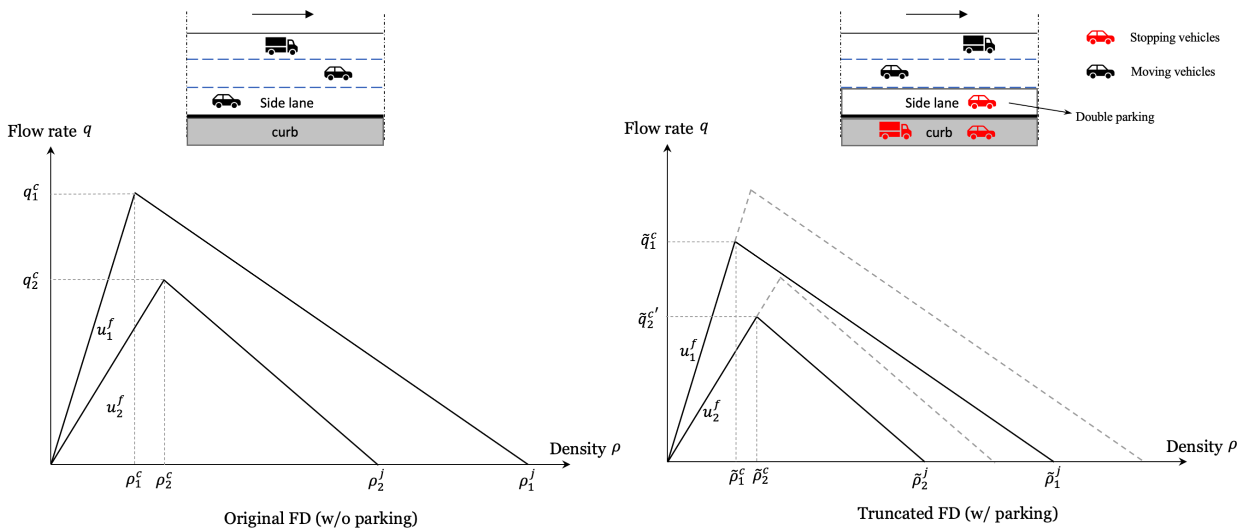
For modeling the heterogeneous vehicle flow on links, MAC-POSTS adopts a multi-class traffic flow model proposed in [45], which can model the flow dynamics consisting of multiple classes of vehicles with distinct flow characteristics. It pragmatically generalizes the cell transmission model (CTM) to multi-class heterogeneous vehicle flow. It includes the concept "physical space split" for each class, which is the fraction of physical space that each vehicle class occupies and uses to progress. Then the "perceived equivalent density" of each class is calculated, representing the equivalent density perceived by some vehicle class, if converting all other class vehicles to this class based on the space they occupied. At each loading time interval, vehicles move through cells following the relations between upstream demand and downstream supply computed using the "physical space split" and "perceived equivalent density", as well as the fundamental diagram of each class.

Traditional CTM uses a homogeneous fundamental diagram (FD) for each cell of the same link to indicate cell-level traffic states and compute flow flux between cells. However, a recent study by [46] found that FD changes as a function of exogenous curb utilization along the road segment, meaning that FDs for different locations of the same road may not be identical and depend on the specific location-based curb utilization conditions. In this study, we use a pragmatic approach with a truncated FD to model the curb utilization effect as partial lane closure and relate the change of FD with curb occupancy. If curb cell i has stopping vehicles at curb space or double parking vehicles on the side lane, the FD of this cell will be truncated by reducing the flow capacities, critical densities, and jam densities for separate classes. The truncation scalar (also called effect scalar in this study) of cell i on link a at time t, denoted by $\eta_a(i,t)$ is determined by the curb space occupancy $o^c_a(i,t)$ and the side lane occupancy $o^d_a(i,t)$ of the cell, which reads,

$$\eta_a(i,t) = \frac{n_a - \tau_c o^c_a(i,t) - \tau_d o^d_a(i,t)}{n_a} \tag{9}$$

where n_a is the total lane number of link a. τ_c and τ_d are the effect scalars of curbside stops and double parking respectively. These two parameters should satisfy $\tau_c o^c_a(i,t) \le 1$, $\tau_d o^d_a(i,t) \le 1$ and $n_a - \tau_c o^c_a(i,t) - \tau_d o^d_a(i,t) \ge 0$. The effect scalars can vary based on locations, segment configuration, and time-varying traffic conditions. They can be calibrated exogenously and separately for different links and times of day using real-world

Figure 3: Illustration of truncated FD considering curb occupancy



observations. The truncated FD has the following parameters

$$\begin{aligned}\tilde{q}_{m,a}^{c}(i,t) &= \eta_a(i,t)q_{m,a}^{c}(i,t)\\ \tilde{\rho}_{m,a}^{c}(i,t) &= \eta_a(i,t)\rho_{m,a}^{c}(i,t)\\ \tilde{\rho}_{m,a}^{j}(i,t) &= \eta_a(i,t)\rho_{m,a}^{j}(i,t)\end{aligned} \tag{10}$$

The illustration of FDs before and after truncation is shown in Figure 3. The flow flux between cells is computed using the FD parameters of adjacent cells. The impact of stopping vehicles on travel time is captured by the link dynamics with truncated FDs. More specifically, the stopping vehicles will truncate the link cell's FD and flux entering and leaving this cell may be smaller,. As a result, some vehicular quanta may queue in their current cell for a longer time before being moved to the next cell. Consequently, these vehicular quanta will experience larger delay, and the link travel time is increased. Thus, link dynamics are related to curb conditions, and curb usage might contribute to traffic congestion on the link. We also develop curb space searching process for vehicles of different modes within their destination links and more details can be found in [47].

5.3 Model calibration

Before deployed for scenario analysis, the dynamic network model needs to be calibrated in order to approximately reproduce the actual traffic and curb conditions. To this end, multiple data sources collected in Section 4 are used and a computational graph-based approach is adopted to calibrate the model.

5.3.1 Curb-aware dynamic origin-destination demand estimation

This calibration is referred to as the curb-aware dynamic OD demand estimation (C-DODE) problem, which aims to estimate the time-dependent vehicle demand and curb usage demand for each OD pair in the study period. The C-DODE is formulated as an optimization problem aiming to estimate travel demand to minimize the discrepancy between the observed data and the simulation results (i.e., traffic count and travel speed). The objective function is as follows:

$$
\begin{aligned}
\min_{\{\mathbf{q}_{\text{car}},\mathbf{q}_{\text{truck}},\mathbf{q}_{\text{rh}}\}} \quad \mathcal{L} =& \mathcal{L}_1 + \mathcal{L}_2 + \mathcal{L}_3 + \mathcal{L}_4 + \mathcal{L}_5 + \mathcal{L}_6 + \mathcal{L}_7 \\
=& w_1(\|\mathbf{x}'_{\text{car}} - \mathbf{x}_{\text{car}}\|_2^2) + w_2(\|\mathbf{x}'_{\text{truck}} - \mathbf{x}_{\text{truck}}\|_2^2) \\
&+ w_3(\|\mathbf{t}'_{\text{car}} - \mathbf{t}_{\text{car}}\|_2^2) + w_4(\|\mathbf{t}'_{\text{truck}} - \mathbf{t}_{\text{truck}}\|_2^2) \\
&+ w_5(\|\mathbf{c}'_{\text{car}} - \mathbf{c}_{\text{car}}\|_2^2) + w_6(\|\mathbf{c}'_{\text{truck}} - \mathbf{c}_{\text{truck}}\|_2^2) + w_7(\|\mathbf{c}'_{\text{rh}} - \mathbf{c}_{\text{rh}}\|_2^2)
\end{aligned}
\tag{11}
$$

where $\mathbf{q}_{\text{car}}$, $\mathbf{q}_{\text{truck}}$ and $\mathbf{q}_{\text{rh}}$ are the car, truck and ride-hailing demands, respectively; $\mathbf{x}'_{\text{car}}$ and $\mathbf{x}_{\text{car}}$ are the observed and estimated car flows (both private driving and ride-hailing cars), respectively; $\mathbf{x}'_{\text{truck}}$ and $\mathbf{x}_{\text{truck}}$ are the observed and estimated truck flows (both background trucks and delivery trucks parking at curbs), respectively; $\mathbf{t}'_{\text{car}}$ and $\mathbf{t}_{\text{car}}$ are the observed and estimated car travel times, respectively; $\mathbf{t}'_{\text{truck}}$ and $\mathbf{t}_{\text{truck}}$ are the observed and estimated truck travel times, respectively; $\mathbf{c}'_{\text{car}}$ and $\mathbf{c}_{\text{car}}$ are observed and estimated curb arrivals of private driving mode, respectively; $\mathbf{c}'_{\text{truck}}$ and $\mathbf{c}_{\text{truck}}$ are observed and estimated curb arrivals of delivery truck mode, respectively; $\mathbf{c}'_{\text{rh}}$ and $\mathbf{c}_{\text{rh}}$ are observed and estimated curb arrivals of ride-hailing mode, respectively; w_1, w_2, w_3, w_4, w_5, w_6, and w_7 are the weights to balance the seven terms in the optimization. The constraints of C-DODE is behavior model depicting multi-modal curb/route choice and network loading model based on MAC-POSTS with curb functions. More details of the calibration framework and the computational-graph-based solution method are omitted here, and interested readers are referred to our previous studies [47].

5.3.2 Calibration results

Simulated traffic and curb usage conditions are calibrated to match the observed afternoon peak hour (3 PM - 6 PM) conditions. MAC-POSTS simulates the movements of all vehicles and curb usage at smart loading zones in the studied network with high spatial (around 50 meters) and temporal (5 seconds) resolution. As with the information provided, we assume 70% of cars and trucks are adaptive to the traffic information, while 30% of cars and trucks stick to the pre-scribed routes. Note that C-DODE aims to estimate the baseline travel and curb usage demand on a recurrent traffic day. As for non-recurrent traffic patterns, time-varying travel demand in the Pittsburgh network is assumed to be the same as the baseline scenario.

Figure 4 presents the comparison between simulated 15-min traffic volumes and observed 15-min traffic volumes, in which the vertical axis is the simulated counts and the horizontal axis is the observed counts. The coefficient of determination R^2, as a measure of goodness of fit, is 0.75998 and 0.77202, for the car flow and truck flow, respectively. The calibration results are considered reasonably good for a large-scale network and outperform many prior studies attempting to replicate real-world traffic conditions through simulation.

Discrepancies between observed and simulated flows arise mainly from two factors: (1) O-D connectors at the network periphery may direct flow through links with volume counters without significantly influencing route choices within the broader network, leading to observed volumes which can be unusually high or low; and (2) simplifications in traffic flow dynamics and routing behavior can limit model realism. The first issue can be mitigated by aligning O-D connector placement with counter locations. The second can be improved by adopting more advanced traffic modeling approaches. Both limitations will be addressed in future work.

Figure 5 demonstrates the comparisons between the observed and estimated hourly curb arrivals for cars and trucks. It can be seen that despite we aggregate the curb arrivals in the whole modeling period, but some of the observed values remain relatively small, with fewer than 10 vehicles for both cars (private driving and ride-hailing) and trucks due to the limited sizes of smart loading zones. The hourly arrival number is relatively small, potentially resulting to high variances of traffic flows related to curb usage. This can be considered as the primary factor contributing to the lower estimation accuracy for curb arrivals. The low R-square value can also be attributed to the variance in stop durations and stochasticity in the simulation process.

Overall, our model shows relatively good performance in capturing the trend of the observed data and this indicates that the proposed regional model can reflect the actual traffic dynamics and curb usage patterns in Pittsburgh area to some extent. The calibrated model lays the ground for the following development and assessment of different curb management strategies. More sensitivity analysis of the modeling framework can be found in [47].

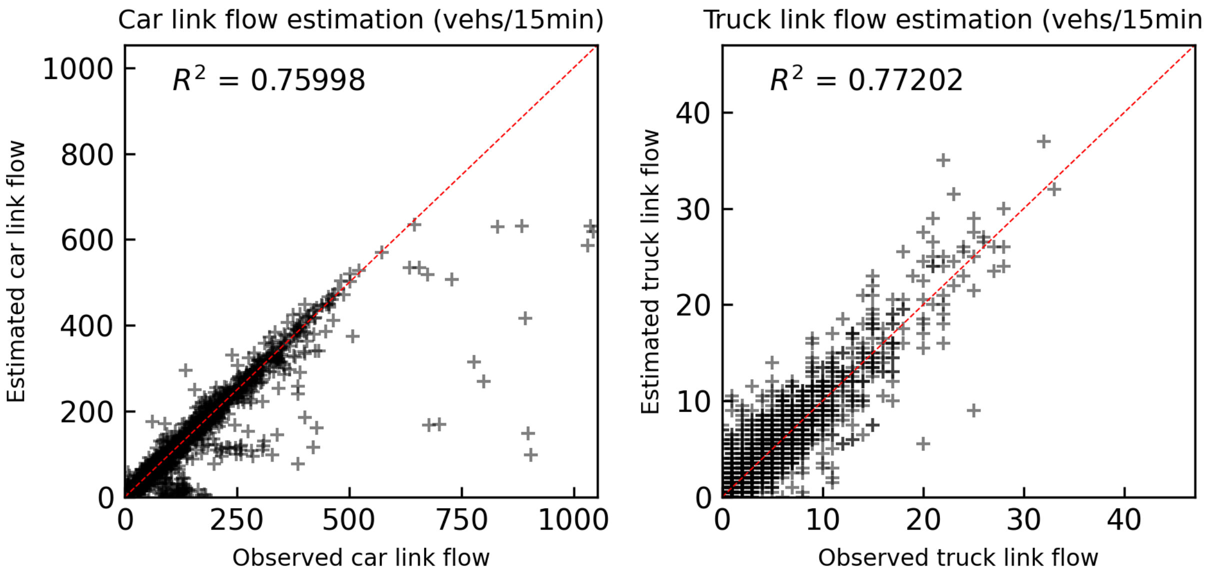


Figure 4: Traffic count calibration (left: car, right: truck)

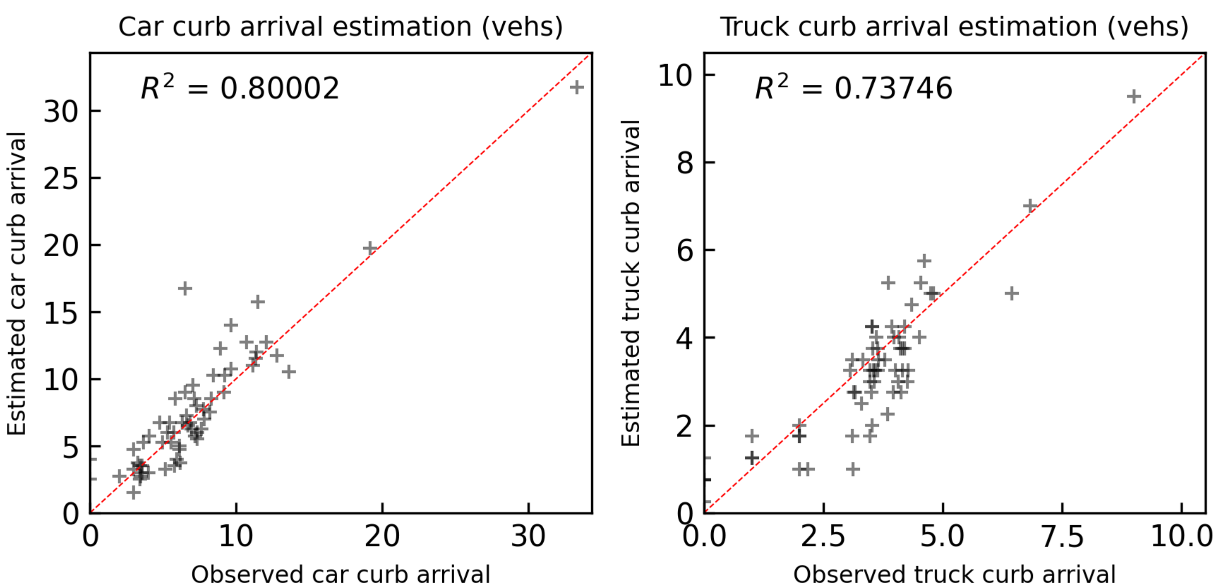


Figure 5: Curb arrival calibration (left: ride-hailing, right: delivery truck)

6 Scenario analysis of curb management strategies

This section presents the evaluation of some selected curb management strategies in synthetic scenarios under simulation environment. The analysis aims to inform the design of effective curb policies for real-world implementation, particularly in the context of deploying new Smart Loading Zones in Pittsburgh City and associated management policies. The strategies tested include variations in pricing and curb space allocation. We first outline the setup of these synthetic scenarios, followed by a summary of results and practical recommendations for real-world curb policy design.

6.1 Scenario set-up

In this project, we develop several synthetic scenarios in simulation model to evaluate the effectiveness of curb management strategies and reflect practical implementation considerations. The baseline scenario uses calibrated demand in which all users are directed to Smart Loading Zones (SLZs), reflecting observed curb usage patterns at these locations. In other scenarios, users are given the option to choose between SLZs and nearby curb alternatives, allowing us to assess how different strategies influence curb choices.

Demand Scaling: Given that the SLZ program is relatively new in Pittsburgh City, increased demand is expected as more residents become familiar with the policy. In this scenario, total travel demand is scaled by a factor of 1.5, while other parameters remain unchanged, which helps assess system performance under increased demand.

Pricing: To understand how pricing influences curb choice behavior, three pricing scenarios were tested: (1) equal pricing: SLZs and nearby curb options have identical fees; (2) Higher SLZ Pricing: SLZs are priced overall$2 higher than nearby alternatives for each usage; (3) Lower SLZ Pricing: SLZs are priced $2 lower than nearby options. These tests examine user compliance and the potential of pricing to shift demand toward or away from new smart loading zones or existing zones with new prices.

Space Allocation: Two strategies were evaluated: (1) Demand-Responsive Allocation: curb spaces are adjusted to ensure availability for all arriving users. (2) Truck Reservation: Trucks are given priority over cars when allocating SLZ space, reflecting their need for longer dwell times. This scenario simulates a basic reservation system by giving priority upon arrival, which can be enhanced in future studies using more precise Estimated Time of Arrival (ETA), curb condition prediction and pre-trip booking mechanisms.

6.2 Evaluation metrics

This section presents three categories of metrics used in simulation-based scenarios to evaluate system performance comprehensively.

System-level Metrics: These metrics are used to evaluate overall network performance under different curb management strategies, including:

- Trips (by class): The total number of completed trips in the simulation which traverse the link of interest, broken down by vehicle class (e.g., cars, trucks).
- Vehicle Hours Traveled (VHT, hours): The cumulative time all vehicles spend traveling on the network.
- Vehicle Miles Traveled (VMT, miles): The total distance traveled by all vehicles in the network.
- Average Travel Time (minutes): The average travel time per vehicle spent during trip.
- Average travel Distance (miles): The average distance per trip.
- Fuel (gallons): The total fuel used by all vehicles during the simulation.
- Carbon Dioxide Emissions ($CO2$, kg): Total $CO2$ emitted from vehicles by class.
- Hydrocarbon Emissions (HC, kg): HC emissions from vehicles by class.
- Carbon Monoxide Emissions (CO, kg): CO emissions from vehicles by class.
- Nitrogen Oxide Emissions (NOX, kg): NOX emission by vehicle class.

Local-level metrics: These metrics are the same as system-level metrics but is restricted to road segments containing Smart Loading Zones (SLZs) and adjacent curb areas. These localized metrics are used to evaluate the impact of curb strategies on the performance of roadway segments around SLZs.

Curb usage Metrics: The curb usage metrics focus on evaluating localized curb parking conditions under different management strategies. For each scenario and vehicle class, we track three key metrics: (1) the total number of parking events at Smart Loading Zones (SLZs), which reflects utilization of designated zones; (2) the total number of parking events at other nearby curb spaces, which helps evaluate alternative choices when SLZs are not available or less preferred than other options; and (3) the total number of double parking events at SLZs, which serves as an indicator of curb space saturation and potential illegal behaviors. We do not consider double parking at other curb options because it is assumed vehicles can finally find parking spots (on-street or off-street) on them if smart loading zones are occupied fully. This can be further enhanced by advanced cruising for parking models in the future. Together, these metrics provide insights for how different strategies influence curb choice and the effectiveness of interventions in reducing illegal double parking.

6.3 Experiment results

This section summarizes the results under synthetic scenarios and discusses insights to inform real-world smart loading zone expansion and policy design.

Based on the results shown in Table 1, the impact of different curb interventions on system-wide traffic performance is relatively small. Key performance metrics such as VHT, VMT, fuel consumption, and emissions remain largely consistent across all scenarios. This suggests that the overall Pittsburgh network is not significantly sensitive to changes in curb intervention or at least under the tested scenarios.

One primary reason for this is that Smart Loading Zones (SLZs) represent only a small portion of the total roadway segments and usually at locations of short local segments. Meanwhile, the curb users (e.g., delivery trucks and ride-hailings) make up a relatively small share of the total vehicles in the network as the data we observed and used for modeling come from a limited number of SLZs. Therefore, interventions targeting these users influence only a small portion of the traffic flow. For example, in all tested scenarios, total trips, VHT, and VMT for both cars and trucks show marginal variations—typically less than 1–2%. This implies that even with changes in pricing, space allocation, or reservation for trucks, the macroscopic network-level metrics remain stable, which is good for conducting some pilot testing without interrupting the network-wide traffic in real world. The minor fluctuations in average travel time and average travel distance also support this finding. Although we scale the curb demand by 1.5, the network conditions is not effected too much, only with a slight increase of average travel time, which may stem from the stochastic nature of simulation models. Average travel distances also vary only slightly across all scenarios. These stable metrics suggest that overall route choices and travel patterns are not substantially disrupted by curb interventions alone. In terms of environmental impact, emissions and fuel use also remain steady, further reinforcing the findings.

Table 2 summarizes local performance metrics for cars and trucks under different curb management scenarios. In the baseline scenario, both vehicle classes exhibit relatively high travel times (2.44 min for cars, 1.96 min for trucks) and elevated emissions, reflecting congestion and double parking due to limited Smart Loading Zone (SLZ) capacity. The scaled demand scenario shows that car travel time slightly improves while truck travel time increases, indicating that moderate demand growth does not significantly degrade local network performance. Among the strategies tested, the equal pricing scenario performs best, reducing car travel time to 1.89 minutes, while maintaining stable truck performance. This suggests that pricing parity between SLZs and nearby curbs can balance curb usage more evenly and reduce local congestion. In contrast, lower pricing of SLZs attracts more users but leads to longer travel times and higher emissions, suggesting that underpriced zones can become overcrowded and inefficient as the capacity of these loading zones are limited. The space allocation scenario increases total curb capacity and reduces emissions but results in the highest travel times, possibly due to extensive usage of curbs affect the through traffic most. Finally, the truck reservation scenario effectively reduces car travel time (2.08 min) though truck dwell time and emissions increase slightly. These results highlight that combining various operational controls can be more effective than pricing alone for improving local curb performance.

Table 3 summarizes the curb usage metrics under different scenarios. These results reflect travelers' responses to curb policy changes and their impacts on curb-related illegal behaviors such as double parking. In the baseline scenario, all curb users are constrained to Smart Loading Zones (SLZs), resulting in a total of 398 car and 176 truck parking events within 62 SLZs, with no parking at alternative curbs and a total of 127 double parking incidents (91 by cars, 36 by trucks), meaning approximately 18% of parking events are illegal.

Introducing pricing strategies significantly affects curb usage patterns. In the equal pricing scenario, where SLZs and nearby curb spaces are priced identically, a clear redistribution occurs: the total parking at SLZs drops to 250 (car) and 227 (truck), while 175 and 130 parkings shift to other curbs nearby. Double parking events drop to 51 (car) and 54 (truck). This suggests that users will voluntarily redistribute when alternative curb spaces are available with same prices, mitigating the pressure on SLZs. Moreover, the fraction of double parking drops to 13%. In the higher SLZ pricing scenario, vehicle parking shifts further away from SLZs (206 cars and 194 trucks), and usage at other curbs increases (242 and 181 respectively). Double parking numbers are lower than baseline. Conversely, in the lower SLZ pricing scenario, offering cheaper SLZs leads to more extensive usage of these zones and a reduced number of users choosing other curb spaces with higher prices. However, double parking events increase again to 145 in total. This indicates that even though lower prices make SLZs more attractive to users, this can exacerbate overuse and congestion at designated loading zones especially without adequate capacity.

The space allocation scenario, where total curb supply is increased, results in the highest number of SLZ parkings and relatively balanced redistribution, with double parking dropping to just one event, meaning all curb arrivals can be accommodated in the loading zones. Reservation for delivery trucks can effectively reduce double parking of trucks but the number of double parking events of cars increases due to lower usage priority. This indicates proper space allocation strategies can effectively regulate double parking behavior, however, the space allocation strategies must be able to accurately predict demand, requiring more research and pilot testing in real applications.

Three key insights are summarized as follows which has potential to achieve optimal curb management in real world deployment:

- Balanced pricing between Smart Loading Zones and nearby curb spaces (or SLZs) promotes more equitable curb usage, helping to mitigate local congestion and reduce illegal double parking without compromising overall system-level performance. When deploying new SLZs in Pittsburgh, they should be strategically located near existing SLZs and use consistent pricing policies to encourage user compliance.
- Implementing space allocation in response to demand and reservation systems that prioritize high-impact users, can reduce curbside conflicts and improve localized traffic flow, particularly in dense urban areas where curb space is limited and demand is high.
- Curb management requires integrated strategies. Relying solely on space expansion or pricing is insufficient. Effective deployment should combine curb allocation, pricing, and user-specific policies (e.g., truck reservations) to adapt to localized demand and ensure operational efficiency.

7 Conclusion

This project develops a mesoscale network model for coupled curb-road networks. The model integrates travel behavior related to curb and captures system externalities related to curb usage. The model is empowered by emerging curb data collected at smart loading zones and other mobility data. First, a behavior model is developed to govern curb/route choices in response to traffic/curb conditions and curb policy. Second, a mescoscopic network simulation model is developed with a curb dynamic module to model curb usage impact on local through traffic. Furthermore, multi-source data are collected and a data-driven framework is adopted to calibrate the dynamic network model for Pittsburgh road-curb network. The result demonstrates the calibrated model has a satisfactory accuracy to reproduce the actual traffic/curb conditions. Last but not least, several synthetic scenarios are created to examine the effectiveness and robustness of various curb management methods. Results show that curb management policies only affect targeted curb users without influencing the overall network traffic performance. Pricing, space allocations and reservation for specific users can effectively reduce illegal behavior at curbs such as double parking and balance the curb usage in local areas. It is recommended to the City of Pittsburgh to consider locate new zones around existing smart loading zones and make sure coordination among policies. When curb space is limited, space allocation in response to demand and reservation systems that prioritize high-impact users can be used to minimize the impact of illegal double parking. Integrated strategies are also recommended to achieve the best performance and equity. The mesoscopic network model developed for this project is easily transferable to other applications and cities with standardized data inputs and modular functions in the framework. The source code of MAC-POSTS with integrated curb management functions is open-sourced on Github at: `https://github.com/jiachaol/macposts-curb`

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References

[1] Taxi and Limousine Commission. Improving efficiency and managing growth in new york's for-hire vehicle sector. Technical report, Technical report, 2019.

[2] NYC Department of Transportation. Loading zone expansion. Technical report, Technical report, 2023.

[3] Nikolas Geroliminis. Cruising-for-parking in congested cities with an mfd representation. *Economics of Transportation*, 4(3):156–165, 2015.

[4] Nan Zheng and Nikolas Geroliminis. Modeling and optimization of multimodal urban networks with limited parking and dynamic pricing. *Transportation Research Part B: Methodological*, 83:36–58, 2016.

[5] Tara Radvand, Sina Bahrami, Yafeng Yin, and Ken Laberteaux. Curbing cruising-as-substitution-for-parking in automated mobility. *Transportation Research Part C: Emerging Technologies*, 143:103853, 2022.

[6] Richard Arnott, Andre de Palma, and Robin Lindsey. A temporal and spatial equilibrium analysis of commuter parking. *Journal of Public Economics*, 45(3):301–335, 1991.

[7] Zhen (Sean) Qian, Feng (Evan) Xiao, and H.M. Zhang. Managing morning commute traffic with parking. *Transportation Research Part B: Methodological*, 46(7):894–916, 2012.

[8] Ludovic Leclercq, Alméria Sénécat, and Guilhem Mariotte. Dynamic macroscopic simulation of on-street parking search: A trip-based approach. *Transportation Research Part B: Methodological*, 101:268–282, 2017.

[9] Xidong Pi, Wei Ma, and Zhen Sean Qian. A general formulation for multi-modal dynamic traffic assignment considering multi-class vehicles, public transit and parking. *Transportation Research Part C: Emerging Technologies*, 104:369–389, 2019.

[10] Ziyuan Gu, Ali Najmi, Meead Saberi, Wei Liu, and Taha H Rashidi. Macroscopic parking dynamics modeling and optimal real-time pricing considering cruising-for-parking. *Transportation Research Part C: Emerging Technologies*, 118:102714, 2020.

[11] Ziyuan Gu, Farshid Safarighouzhdi, Meead Saberi, and Taha H. Rashidi. A macro-micro approach to modeling parking. *Transportation Research Part B: Methodological*, 147:220–244, 2021.

[12] Amir Brudner. On the management of residential on-street parking: Policies and repercussions. *Transport Policy*, 2023.

[13] Richard Arnott and Eren Inci. An integrated model of downtown parking and traffic congestion. *Journal of Urban Economics*, 60(3):418–442, 2006.

[14] Richard Arnott and Eren Inci. The stability of downtown parking and traffic congestion. *Journal of Urban Economics*, 68(3):260–276, 2010.

[15] Zhen Sean Qian and Ram Rajagopal. Optimal dynamic parking pricing for morning commute considering expected cruising time. *Transportation Research Part C: Emerging Technologies*, 48:468–490, 2014.

[16] Ziyuan Pu, Zhibin Li, John Ash, Wenbo Zhu, and Yinhai Wang. Evaluation of spatial heterogeneity in the sensitivity of on-street parking occupancy to price change. *Transportation Research Part C: Emerging Technologies*, 77:67–79, 2017.

[17] Chao Lei and Yanfeng Ouyang. Dynamic pricing and reservation for intelligent urban parking management. *Transportation Research Part C: Emerging Technologies*, 77:226–244, 2017.

[18] Diehl Caleb, Ranjbari Andisheh, and Goodchild Anne. Curbspace management challenges and opportunities from public and private sector perspectives. *Transportation Research Record: Journal of the Transportation Research Board*, 2675(2):1413–1427, Nov 2021.

[19] Ellen Jones, Arun Chatterjee, and Robert L. Marsili. A collaborative plan for curbside freight delivery in washington, dc, usa. *Institute of Transportation Engineers. ITE Journal*, 79(5):22–25, 05 2009.

[20] Adam Millard-Ball, Rachel R. Weinberger, and Robert C. Hampshire. Is the curb 80% full or 20% empty? assessing the impacts of san francisco's parking pricing experiment. *Transportation Research Part A: Policy and Practice*, 63:76 – 92, 2014.

[21] Zhan Guo and Simon McDonnell. Curb parking pricing for local residents: An exploration in new york city based on willingness to pay. *Transport Policy*, 30:186 – 198, 2013.

[22] Richard Arnott and John Rowse. Curbside parking time limits. *Transportation Research Part A: Policy and Practice*, 55:89–110, 2013.

[23] Richard Arnott, Eren Inci, and John Rowse. Downtown curbside parking capacity. *Journal of Urban Economics*, 86:83 – 97, 2015.

[24] M. Olus Inan, E. Inci, and C. Robin Lindsey. Spillover parking. *Transportation Research Part B: Methodological*, 125:197–228, 2019.

[25] Z. Chen, Z. Xu, M. Zangui, and Y. Yin. Analysis of advanced management of curbside parking. *Transportation Research Record*, 2567:57–66, 2016.

[26] Paul Schimek. Bike lanes next to on-street parallel parking. *Accident Analysis & Prevention*, 120:74 – 82, 2018.

[27] Xiaofei Ye, Xingchen Yan, Jun Chen, Tao Wang, and Zhao Yang. Impact of curbside parking on bicycle lane capacity in nanjing, china. *Transportation Research Record*, 2672(31):120–129, 2018.

[28] Anne Goodchild, Don Mackenzie, Andisheh Ranjbari, Jose Machado, and Giacomo Dalla Chiara. Curb allocation change project - final report. Technical report, UNIVERSITY OF WASHINGTON, 2019.

[29] Chase P. Dowling, Lillian J. Ratliff, and Baosen Zhang. Modeling Curbside Parking as a Network of Finite Capacity Queues. *IEEE Transactions on Intelligent Transportation Systems*, 21(3):1011–1022, March 2020.

[30] Manish Patkar and Ashish Dhamaniya. Developing capacity reduction factors for curbside bus stops under heterogeneous traffic conditions. *Arabian Journal for Science and Engineering*, 2020.

[31] Abhishek, Benjamin Legros, and Jan C Fransoo. Performance evaluation of stochastic systems with dedicated delivery bays and general on-street parking. *Transportation Science*, 55(5):1070–1087, 2021.

[32] Quanquan Chen, Alison Conway, and Jialei Cheng. Parking for residential delivery in new york city: Regulations and behavior. *Transport Policy*, 54:53–60, 2017.

[33] Sneha Mandhan and Kelly Gregg. Managing the curb–public space and use of curbside cafes during the coronavirus pandemic. *Cities*, 132:104070, 2023.

[34] Haiyan Hao, Yan Wang, Lili Du, and Shigang Chen. Enabling smart curb management with spatiotemporal deep learning. *Computers, Environment and Urban Systems*, 99:101914, 2023.

[35] Nawaf Nazir, Chase Dowling, Shushman Choudhury, Stephen Zoepf, and Ke Ma. Optimal, centralized dynamic curbside parking space zoning. In *2022 IEEE 25th International Conference on Intelligent Transportation Systems (ITSC)*, pages 91–98. IEEE, 2022.

[36] Alek L Pochowski, Stephen Crim, Like Liu, Lake Trask, Christine Sherman Baker, Sarah Woodworth, and Jessica Klion. Solving the curb space puzzle through the development of a curb space allocation tool. *Transportation Research Record*, 2676(10):601–621, 2022.

[37] Qiming Ye, Yuxiang Feng, Jingshuo Qiu, Marc Stettler, and Panagiotis Angeloudis. Approximate optimum curbside utilisation for pick-up and drop-off (pudo) and parking demands using reinforcement learning. In *2022 IEEE 25th International Conference on Intelligent Transportation Systems (ITSC)*, pages 2628–2633. IEEE, 2022.

[38] Shuyi Yin, Zhiyong Cui, and Yinhai Wang. Reinforcement learning for curbside space management with infrastructure autonomy and mixed vehicle connectivity. In *2022 IEEE 25th International Conference on Intelligent Transportation Systems (ITSC)*, pages 3276–3282. IEEE, 2022.

[39] Xiongwei Jin, Liang Yin, Yikang Rui, and Bin Ran. Study on the impact of curb parking on traffic capacity. In *CICTP 2022*, pages 2347–2353. 2022.

[40] Juliette Ugirumurera, Joseph Severino, Karen Ficenec, Yanbo Ge, Qichao Wang, Lindy Williams, Junghoon Chae, Monte Lunacek, and Caleb Phillips. A modeling framework for designing and evaluating curbside traffic management policies at Dallas-Fort Worth International Airport. *Transportation Research Part A: Policy and Practice*, 153:130–150, November 2021.

[41] Zhengtian Xu, Zhibin Chen, Yafeng Yin, and Jieping Ye. Equilibrium analysis of urban traffic networks with ride-sourcing services. *Transportation science*, 55(6):1260–1279, 2021.

[42] Jiachao Liu, Wei Ma, and Sean Qian. Optimal curbside pricing for managing ride-hailing pick-ups and drop-offs. *Transportation Research Part C: Emerging Technologies*, 146:103960, 2023.

[43] Zhen Qian and H Michael Zhang. A hybrid route choice model for dynamic traffic assignment. *Networks and Spatial Economics*, 13:183–203, 2013.

[44] Wei Ma, Xidong Pi, and Sean Qian. Estimating multi-class dynamic origin-destination demand through a forward-backward algorithm on computational graphs. *Transportation Research Part C: Emerging Technologies*, 119:102747, 2020.

[45] Zhen Sean Qian, Jia Li, Xiaopeng Li, Michael Zhang, and Haizhong Wang. Modeling heterogeneous traffic flow: A pragmatic approach. *Transportation Research Part B: Methodological*, 99:183–204, 2017.

[46] James Koch, Thomas Maxner, Vinay Amatya, Andisheh Ranjbari, and Chase Dowling. Physics-informed machine learning of parameterized fundamental diagrams. *arXiv preprint arXiv:2208.00880*, 2022.

[47] Jiachao Liu and Sean Qian. Modeling multimodal curbside usage in dynamic networks. *Transportation Science*, 2024.

Scenario	vehicle class	trips	VHT (hour)	VMT (miles)	Average travel time (min)	Average travel distance (miles)	fuel (gallon)	CO2 (kg)	HC (kg)	CO (kg)	NOX (kg)
Baseline	car	224,583	54,693.65	1,561,697.86	14.62	6.96	52,035,43	462,438.83	1,303.82	1,708.41	1,663.88
	truck	26,448	5,753.53	172,797.75	13.06	6.54	8,719.93	77,494.02	319.88	667.89	1,117.95
Scaled curb demand	car	224,468	55,098.55	1,568,259.31	14.72	6.98	52,281.17	464,622.80	1,310.70	1,712.79	1,669.06
	truck	26,393	5,865.63	176,092.81	13.34	6.68	8,885.82	78,968.26	325.93	681.11	1,139.61
Equal pricing	car	224,350	55,676.81	1,575,831.19	14.90	7.02	52,516.94	466,718.12	1,317.61	1,719.99	1,676.57
	truck	26,545	5,876.44	175,099.71	13.28	6.60	8,836.30	78,528.16	324.573	674.91	1,133.37
Higher pricing	car	224,449	54,736.95	1,571,602.51	14.64	7.00	52,397.16	465,653.59	1,312.35	1,719.46	1,674.26
	truck	26,556	5,678.95	173,471.26	12.84	6.54	8,748.76	77,750.21	320.17	673.27	1,121.20
Lower pricing	car	224,420	54,874.75	1,568,822.43	14.68	7.00	52,239.28	464,250.51	1,307.46	1,713.60	1,668.76
	truck	26,566	5,764.60	173,687.28	13.02	6.54	8,761.42	77,862.70	320.93	672.71	1,122.73
Space allocation	car	224,750	56,082.22	1,555,127.85	14.98	6.92	51,867.47	460,946.18	1,302.72	1,697.41	1,655.03
	truck	26,442	5,934.10	171,115.77	13.46	6.48	8,633.85	76,728.99	318.14	655.22	1,107.46
Reservation for delivery trucks	car	224,499	54,896.50	1,582,038.60	14.67	7.05	52,718.79	468,511.90	1,318.42	1,731.93	1,685.14
	truck										

Table 1: System-level metrics

Scenario	vehicle class	trips	VHT (hour)	VMT (miles)	Average travel time (min)	Average travel distance (miles)	fuel (gallon)	CO2 (kg)	HC (kg)	CO (kg)	NOX (kg)
Baseline	car	75766	3083.13	24405.49	2.44	0.32	865.25	7689.46	25.37	25.08	26.59
	truck	10,346	337.56	3,030.03	1.96	0.29	156.73	1,392.90	6.94	8.61	19.98
Scaled curb demand	car	75,702.5	2,883.80	24,696.84	2.29	0.33	855.99	7,607.25	24.71	25.05	26.46
	truck	10,322	405.03	3,246.96	2.35	0.31	167.02	1,484.32	7.38	9.20	21.35
Equal pricing	car	75,181	2,363.45	25,249.21	1.89	0.34	900.96	8,006.87	26.44	26.02	27.51
	truck	10,335	359.23	3,195.72	2.09	0.31	166.48	1,479.48	7.37	9.17	21.23
Higher pricing	car	75,477	2,748.87	24,270.75	2.19	0.32	856.24	7,609.44	25.03	24.89	26.37
	truck	10,351	361.02	3,149.11	2.09	0.30	163.19	1,450.28	7.25	8.96	20.84
Lower pricing	car	75,711	2,933.69	24,944.26	2.32	0.33	875.42	7,779.86	25.41	25.45	26.86
	truck	10,432	421.55	3,229.71	2.42	0.31	167.32	1,486.98	7.40	9.22	21.35
Space allocation	car	75,741.5	3,228.20	23,668.77	2.56	0.31	824.96	7,331.46	23.94	24.10	25.51
	truck	10,317.5	427.02	3,133.20	2.48	0.30	162.10	1,440.54	7.19	8.90	20.69
Reservation for delivery trucks	car	74,858.5	2,592.58	24,160.85	2.08	0.32	855.14	7,599.69	25.03	24.81	26.28
	truck	10,272	419.81	3,217.46	2.45	0.31	167.93	1,492.39	7.44	9.25	21.43

Table 2: local metrics for scenarios

Scenario	vehicle class	total parking number at SLZs	total parking number at other curbs	total double parking number at SLZs
Baseline	car	398	0	91
	truck	176	0	36
Equal pricing	car	250	175	51
	truck	227	130	54
Higher pricing	car	206	242	34
	truck	194	181	35
Lower pricing	car	272	152	76
	truck	265	72	69
Space allocation	car	358	135	0
	truck	324	92	1
Reservation for delivery trucks	car	232	194	58
	truck	364	95	14

Table 3: Comparison of average vehicle delay on the ramp and downstream highway