Optimizing shared-use curbside spaces in connected transportation networks accounting for uncertainty

by

Shanjeeda Akter

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Civil Engineering
Carl R. Ice College of Engineering

KANSAS STATE UNIVERSITY
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Abstract

For the past two decades, shared-use mobility (SUM) has been changing the landscape of urban transportation. The efficient use of shared-use mobility services to promote the sustainability of a transportation system largely relies on the effective use of curbside spaces. As the use of shared-use mobility services keeps growing, it is challenging the traditional approaches used to manage curbside spaces. The task of managing the curbside is often challenging as it is hard to predict the demand for those spaces. Also, most cities prefer to allocate curbside spaces for long-term parking needs. However, the lack of accessibility of these spaces often leads SUM services to complete their pickup and dropoff services in the active travel lanes making the network congested and worsening the emissions. The use of time-restrictions-based flexible curb-use strategies have gained popularity as it has been able to provide a solution to address the needs from various services while reducing congestion stress from the street. However, the curbside managers often allocate the spaces based on historical demand without using any optimal strategy.

The optimal allocation of these spaces can help provide better access to different modes of transportation and maximize productivity. This research aims to develop an optimization module to help the curbside managers allocate spaces rationally while maximizing the benefits. It is critical to assess the impact of the shared-use services on mobility and the environment when different variables, such as road available curbside spaces and stopping time restrictions, are in effect. This research also aims to evaluate the mobility and environmental impacts of time restriction-based curbside practices considering these dimensions. Lastly, this research explores the performance of

the developed optimization model in field condition when drivers can have real-time communication with the RSUs[1].

We used a fine-resolution simulation framework to evaluate curbside management strategies for ride-sourcing and delivery vehicles. Utilizing microsimulation tools Vissim and EPA-MOVES, we analyzed mobility and environmental impacts in both a small hypothetical network and a complex real-world urban network in Chicago, Illinois. Our results show that eliminating long-term parking can worsen congestion but reduce vehicular emissions. Post-trajectory analysis revealed that increased vehicle speed due to reduced curbside spaces impacts emissions. Key findings of this part also highlight trade-offs between congestion and emission reduction, the effect of adjusting dwelling time windows on curbside productivity, and the relationship between curbside space reduction and energy consumption. Additionally, fleet electrification scenarios indicate that increased electric vehicle adoption decreases emissions, mitigating environmental impacts while meeting mobility needs.

Later we developed a linear mathematical model using a knapsack constraint to allocate spaces optimally. For this purpose, Curb Productivity Index developed by Fehr & Peers has been used as objective function. The mathematical models were developed in AMPL to solve it using the IBM CPLEX Solver. This model was tested across various scenarios to obtain solutions under different variables. The results directed the impact of different variables on curbside productivity and optimal allocation. The results indicate that the curb productivity index (CPI) is highly sensitive to the number of passengers served. When arrival demand is constant, shuttles get priority at curbside spaces if they serve more passengers. If shuttle demand increases but serves fewer

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[1] Road Side Unit- Device usually installed alongside road to facilitate communication between vehicles and transportation infrastructure. [What is a Roadside Unit (RSU)? RSU Meaning | Isarsoft]

passengers, their space allocation decreases. This variation in CPI is due to the number of passengers served. Dynamic optimization shows that CPI changes with vehicle arrivals at each interval, allowing for various allocation strategies. By minimizing the loss of Expected Mean CPI, we can select an optimal allocation for greater real-world benefits.

In the final part of the dissertation, we developed a microsimulation model to estimate curbside productivity variations from the theoretical model. Using PTV Vissim, we assessed the impact of curbside location relative to intersections and data connectivity on productivity. The average Total CPI in the simulation model is about 32% higher than in the theoretical model, although the number of TNCs (Transportation Network Company) served is around 14% less, indicating CPI depends heavily on distribution. It also showed that, curbside productivity improves significantly when curbsides are located farther from intersections, enhancing network productivity. Information availability to drivers also boosts curbside productivity.

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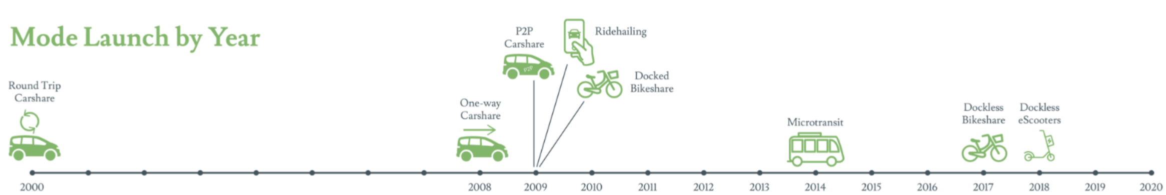
Chapter 1 - Introduction

Background

Shared-Use Mobility

Shared-Use Mobility (SUM) has reshaped the urban transportation landscape in the U.S. in the last two decades by promoting the sharing of transportation modes by users rather than owning them. SUM refers to the concurrent shared use of transportation services or resources among its users (Shared-Use Mobility Center). The accentuating need for sustainable transportation alternatives due to the growing environmental, energy, and economic concerns has created a favorable environment for shared-use mobility to flourish (Shared-Use Mobility Center). Moreover, data sharing and wireless technology advances have influenced transportation network companies to produce novel solutions, including bike sharing, scooter sharing, car sharing, ride-sourcing, and micro-transit, which eventually created the momentum for Mobility-as-a-Service (MaaS). This trend was also motivated by the recent developments of driverless cars, which have the potential to increase economic benefits as they become more affordable. Figure 1. 1 shows the gradual rise of different forms of SUM in the U.S. from 2000 to 2020.

Figure 1. 1 Launching different shared-use mobility modes in the U.S. in the last two decades (Image source: Shared-Use Mobility Center)



Benefits of SUM

SUM can offer multiple benefits to develop a more efficient, sustainable, and equitable transportation system (Shared-Use Mobility Center, 2015). Shared-use mobility services such as ride-sourcing and carpooling can decrease individual trip length, leading to fewer vehicle miles traveled (VMT). This can effectively help to reduce emissions and energy consumption from transportation systems. Research showed that car-sharing members often use newer vehicles that are more fuel efficient, resulting in lower fuel costs and greenhouse gas emissions (Shared-Use Mobility Center, 2015). Table 1. 1 Environmental benefits of car sharing in different cities of the U.S. (Shared-Use Mobility Center, 2015). Table 1. 1shows the environmental benefits of car-sharing in different cities when at least 10 percent of the households subscribe to car-sharing. As newer technologies emerge, the adoption of electric vehicles by car-sharing and ride-sourcing companies could significantly impact the environment by reducing greenhouse gas emissions. Moreover, SUM has the potential to improve public health as bike sharing and scooter sharing will encourage active transportation significantly. Additionally, promoting non-motorized modes has the potential to reduce emissions (Table 1. 2). The SUM services also help the community complete the last-mile trips that complement public transit. According to a study from 2014 conducted by Susan Shaheen and Elliot Martin (Shared-Use Mobility Center, 2016) 14 percent of bike-share users increased rail and bus use due to better first-last mile connections. Therefore, SUM can potentially improve transit accessibility for riders and transit efficiency, especially in underserved neighborhoods. As cities have been trying to provide accessible transportation for people, SUM can potentially serve low and medium-income communities (Shared-Use Mobility Center, 2015) and contribute towards the equitable transportation system. Overall, SUM has the potential to move goods and people from one place to another without the need for active vehicle ownership. In some cases, it may reduce transit ridership. However, it has the potential to improve local mobility while providing flexible services to consumers. Finally, SUM services can reduce long-term parking needs on the streets (curbside) as they are demand-responsive and not owned by individuals.

Table 1. 1 Environmental benefits of car sharing in different cities of the U.S. (Shared-Use Mobility Center, 2015)

If 10% Households became carshare members, there would be:					
	San Francisco Bay Area	Chicago	Houston	Atlanta	Salt Lake City
Fewer Vehicles	50,000	31,000	30,000	5,000	3,000
Fewer Vehicle Miles Traveled Millions annually	267	165	158	27	13
Fewer Gallons of Gasoline Used, thousands annually	12,000	8,000	7,000	1,000	600
CO_2 Reductions Metric tons reduced annually	109,000	67,000	54,000	11,000	5,000

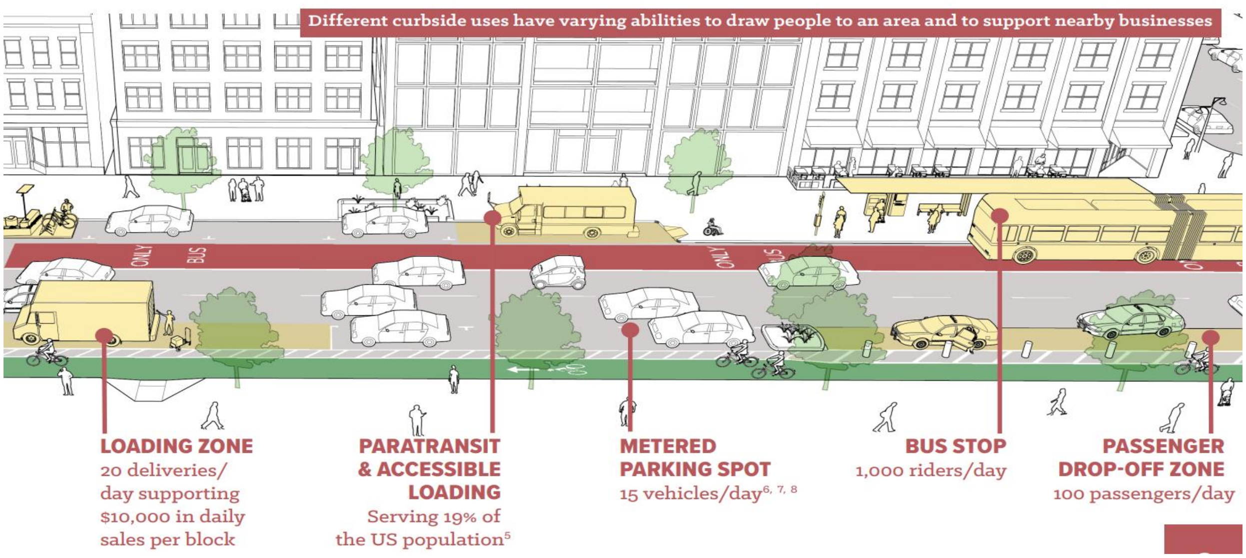
Table 1. 2 If there were a bikeshare dock every ½ miles, the reduction in emissions that could be achieved in different cities of the U.S. (Shared-Use Mobility Center, 2015)

If 10% Households became carshare members, there would be:					
	San Francisco Bay Area	Chicago	Houston	Atlanta	Salt Lake City
Fewer Vehicles	20,000	1,000	5,000	1,000	1,000
CO_2 Reductions Metric tons reduced annually Millions annually	8,000	500	2,000	400	400

While SUM services pose unique challenges for cities (elaborated in the next section), they are also bringing more accessible and equitable alternatives for users. To summarize, SUM has the potential to expand transportation services in cities while meeting increasing travel demand, improving accessibility for low to medium-income communities, and reducing emissions and parking pressure economically and efficiently. Many cities have started to promote SUM as an effective way to implement sustainable and equitable mobility services for users.

Evolving Curbside Operation Due to SUM

Figure 1. 2 Evolving curbside to accommodate newer mobility needs (Source: NACTO)

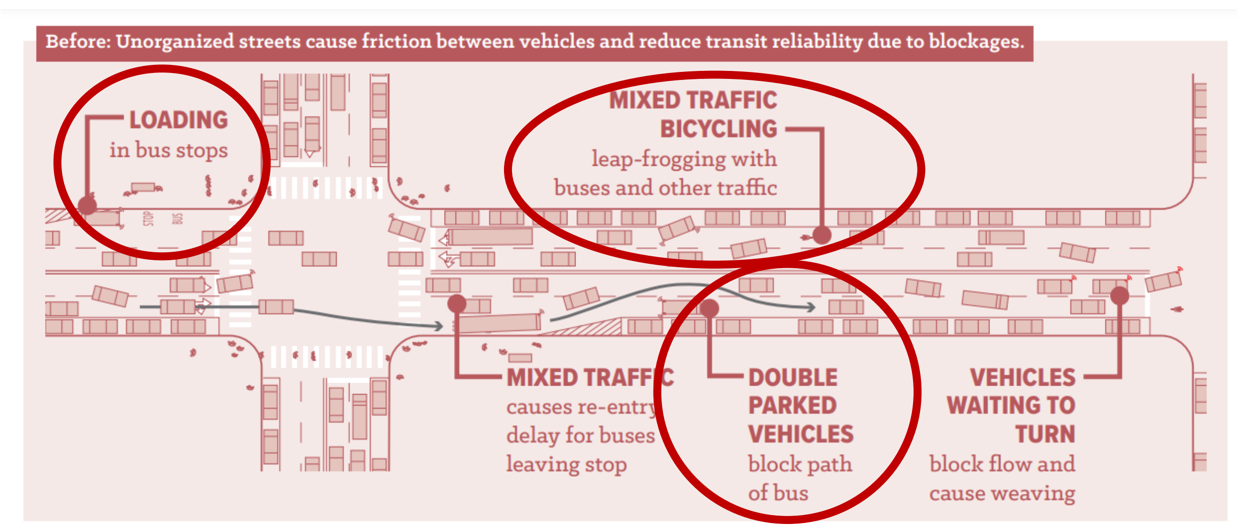


With the realization of potential benefits from SUM and its rising market shares in the transportation market, cities are rethinking the present transportation landscape to accommodate these newer services in the streets. Different metropolitan organizations (MPOs) are reorganizing the roads, especially the curbside, to promote SUM. The main roadway element that makes SUM services accessible to people is the curbside. Curbside refers to the space near the travel lanes which provides a transition zone between multiple functionalities for specific transportation modes includes parking lanes and the spaces adjacent to the physical curb (Abel et al. 2021). Hence, cities have been working to redesign and optimize the curbside to accommodate SUM services. NACTO

(National Association of City Transportation Officials) provided an example of how the curbside can be reorganized to provide accessibility for all (Figure 1. 2). To achieve the greater goal of SUM, it is important to integrate them into the network seamlessly, which depends on the proper management of the curbside.

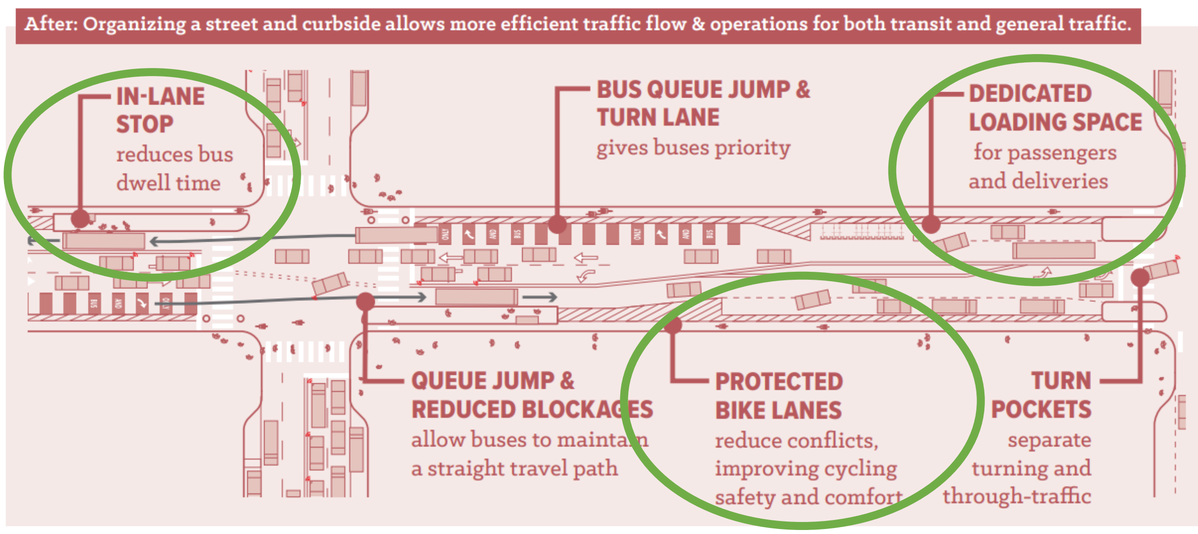
Curbside management is a crucial factor in improving urban transportation systems' efficiency. As urban mobility evolves rapidly and newer technologies emerge with time, the demand for seamless mobility solutions is increasing. The escalating demand for various mobility solutions, especially SUM services, has elevated the need for curbside management to alleviate congestion, reduce environmental impacts, and improve the overall quality of life for urban commuters.

Figure 1. 3 Improper management of curbside can create mobility concerns in the streets (Source: NACTO)



When the curbside is not managed rationally, different user groups may find it difficult to complete their services near the curbside and may disrupt the existing traffic. Figure 1. 3 shows a few examples of disrupting the through traffic when different SUM services do not have designated spaces. One can observe that separating non-motorized vehicle modes from the motorized traffic at the curbside can also make the curbside work in an efficient manner. Figure 1. 4 represents an efficiently functioning curbside scenario provided by NACTO. It shows different spaces for different modes can keep the main traffic stream uninterrupted.

Figure 1. 4 Curbside can be reorganized to accommodate multimodal transportation needs (Source: NACTO)



However, the local governments require more information on the impact of SUM at the curbside to integrate the modes in the planning and allocate the limited resources optimally. This research aims to understand the complexities associated with curbside management, offering insights into challenges, and exploring opportunities to address them with technology and innovation.

<u>In this dissertation, we aim to provide a comprehensive understanding of the challenges and innovative strategies that can transform the way cities manage their curbside spaces to meet the emerging climate and sustainability goals relevant to shared-use transportation systems</u>**.** The rest of this chapter is organized as follows: the next section defines the problem and identifies the

issues rising as curbside demand increases from various mobility solutions. Then we explore the challenges with optimal curbside management. The last section discusses approaches to be considered for overcoming the challenges associated with optimal curbside management.

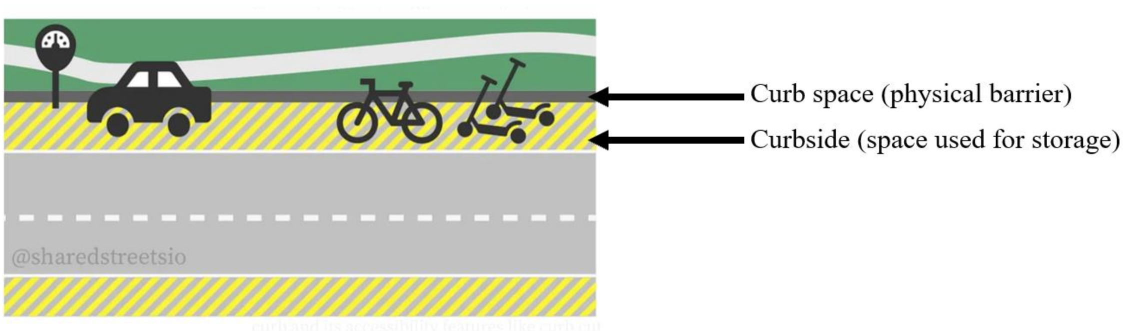
Motivation and Problem Definition

Managing curbside (Figure 1. 5) operations is a complex task in the urban environment due to its *zero-sum* nature—multiple shared-use mobility services compete for the same limited space. Curbside can be used for storage (parking) of bicycles and e-scooters, private vehicles, accommodation of bus bays, and pickup and dropoff (PUDO) activities in dense urban centers. The goal of this research is to explore the impact of functional curbside management strategies resulting from SUM and the potential for optimal allocation of these spaces.

Rise of Curbside Activities

As technology continued to play a significant role in shaping commuters' travel behavior, emerging curbside services started offering more convenient mobility options to their consumers. The use of Mobile Apps and online platforms for e-commerce are two major contributors to escalating curbside demand. In recent years, the use of shared micromobility services saw a rise of about 12 times by 2016 from 2010, while Uber use increased by 6% year-over-year (Figure 1. 6, Figure 1. 7, Figure 1. 8). The shared micromobility market size reached 35 million USD in 2017 from 321,000 USD in 2010. Moreover, urban freight (last-mile) activities have increased during the COVID-19 pandemic (and not slowing down) (Ranjbari et al., 2020; Trivedi & Zulkernine, 2020). This industry continued to grow in the past few years and is expected to reach 1415.78 billion USD revenues by 2027. As a result, emerging mobility services such as ride-sourcing, urban pickup and deliveries, and micromobility (e-scooter and e-bikes) (FHWA) have increased the demand for curbsides (DDOT, 2019).

Figure 1. 5 Curbside vs curb space (Eros, 2019)



The increasing trend of shared-use mobility services demonstrates that more people are using these services; hence, the demand for curbside usage from these services is also increasing substantially, making it crucial to manage curbside spaces in an efficient manner.

Figure 1. 6 Yearly trends in ride hailing services (indexed to sales) in the US (Kaczmarski, 2023)

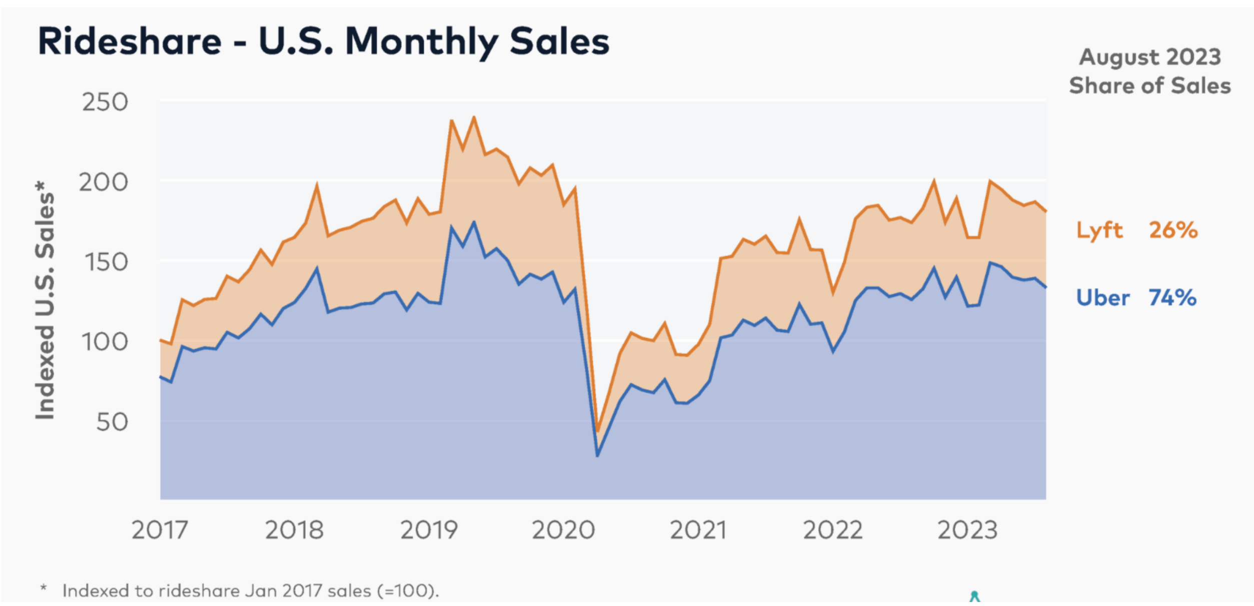


Figure 1. 7 The growth of shared micromobility ridership in the US (NACTO, 2019)

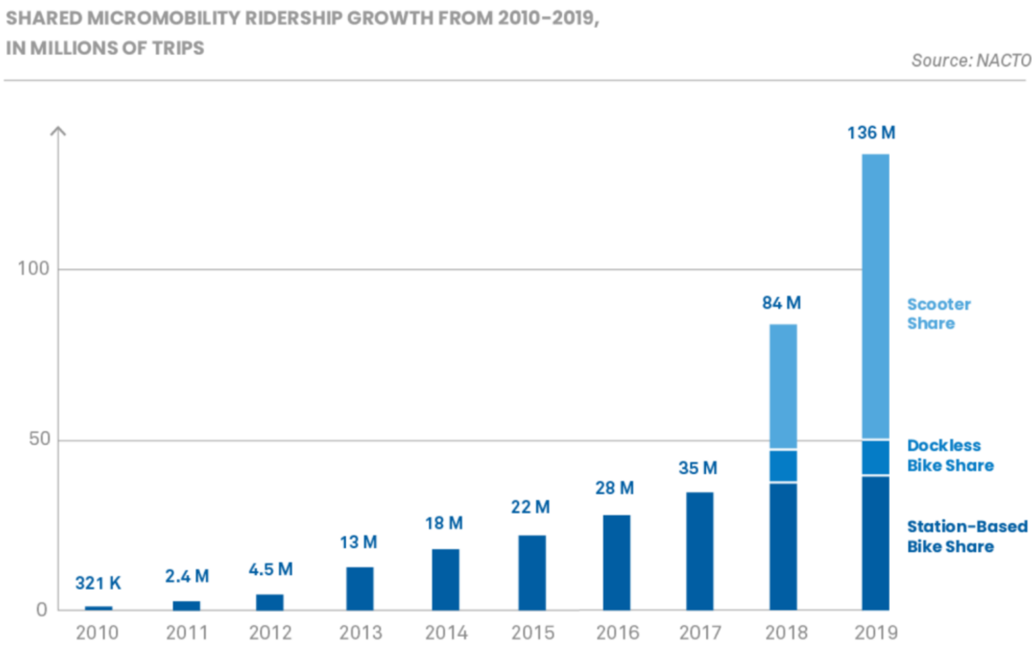
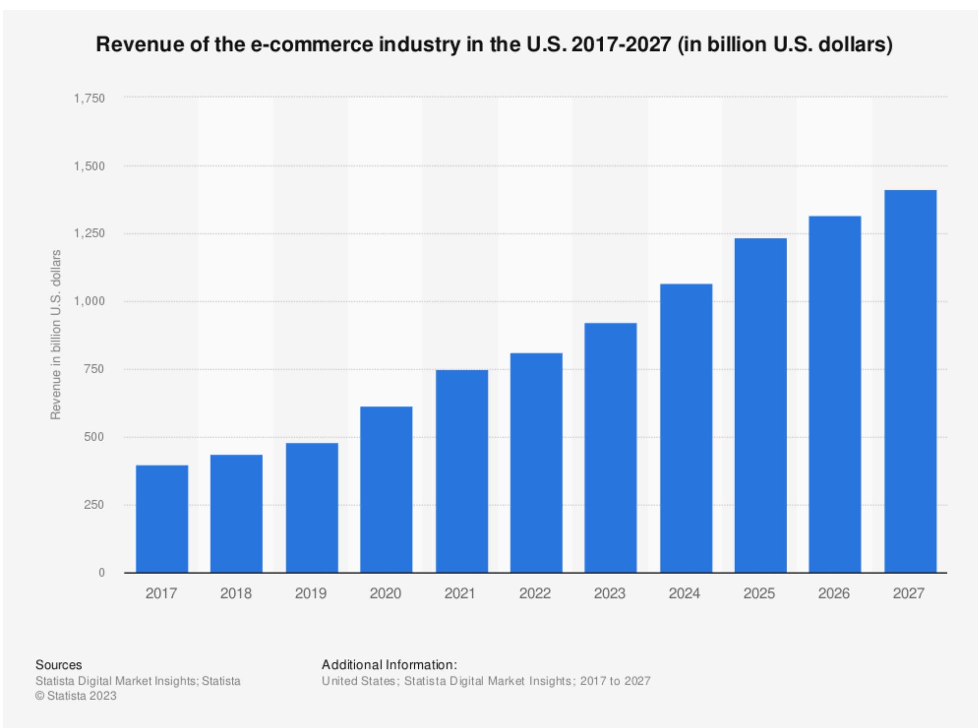


Figure 1. 8 Trends in growth of e-commerce industry in the US (Statista, 2023)



Curbside Management

The suboptimal management of curbside spaces in transportation networks can exert a negative impact on user experience (e.g., out-of-vehicle waiting time), operations and planning by service providers (parking inconveniences for urban delivery trucks), and system performance (e.g., effect on through traffic flow at a network level). These can lead to congestion near curbside, longer commute times and heightened frustration of users. Moreover, inadequate curbside management can constrain accessibility for the elderly and disabled users, thereby diminishing the overall quality of their experience. On the other hand, the service providers may also face operational inefficiencies because of limited or unclear pickup and drop-off zones, which can lead to increased vehicle idle times and reduced customer satisfaction. Moreover, regulatory challenges arising from curbside management issues may disrupt service operations and pose financial risks for providers, impacting their ability to offer reliable and sustainable mobility services. Improper curbside management poses substantial challenges and impacts for curbside managers also. It can hinder data collection and analysis, impeding the ability to make informed decisions and implement data-driven curbside policies and improvements. A lack of effective curbside management may undermine the broader goals of enhancing urban mobility, economic vitality, and sustainability, thereby declining the effectiveness of curbside management entities. Increasing demand for curbside spaces is also resulting in newer issues in the existing traffic system that are discussed in the following sections.

Impeding the Through Traffic

Oftentimes, PUDO activities (involving passengers and goods) occur near the active travel lanes when curbsides are already occupied by parked vehicles (DDOT, 2019). This would impede the flow of through traffic leading to an increase in the road users' travel time and delays. The effects are not linear and homogeneous in nature. The impact will be influenced by factors including availability of parking spaces, parking duration, and geometric configuration (number of lanes, alignment, etc.) of the network.

Contributing to Higher Vehicular Emissions

Further, the roadside PUDO activities while disrupting the traffic flow will also reduce the speed of vehicles. Speed is a major contributing factor affecting the on-road emissions and fuel consumption of motorized vehicles. Fuel consumption and emissions are generally lower when the speed profiles of the motor vehicles remain steady, and there is a smaller oscillation in the acceleration patterns (Aziz & Ukkusuri, 2012; Yin & Lawphongpanich, 2006). PUDO activities may cause the nearby vehicles (on the same or adjacent lanes) to lower their speed and brake irregularly. Ergo, suboptimal curbside operations can lead to undesirable environmental impacts– emissions and fuel consumption.

The above discussions underscore the need for assessing and optimizing curbside operations in cities, accounting for efficient SUM services that lead to sustainability goals. Next, we discuss the primary challenges associated with curbside management.

Challenges with Optimal Curbside Management

As cities are trying to cope with the growing traffic, increasing curbside demands, and evolving mobility trends, effective management of curbside spaces has become a critical urban planning and transportation consideration. Owing to their evolving role in accommodating diverse mobility needs, the lack of comprehensive data and insights relating to curbside spaces makes curbside management a challenging task. This section identifies the existing challenges inherent in curbside management and innovative approaches that can help in addressing them.

Stochasticity (Spatio-Temporal) in Curbside Demand

The lack of fully observed data about curbside usage poses a significant challenge to cities/transportation authorities in managing curbside spaces. Without detailed and up-to-date information on curbside occupancy, usage patterns, spatial-temporal demand from diverse services and compliance with regulations, decision-makers are forced to implement suboptimal policies that may lead to inefficient use of the limited curbside spaces. Simultaneously, these data deficiencies obstruct researchers from developing accurate models for the curbside spaces. The data can be grouped into two broad categories: travel behavior (transportation mode choice, compliance with the regulations, change in trip planning as a function of curbside flexibility) and operations data (spatial-temporal frequency of the services, types of shared-use mobility services, connectivity and data-sharing at infrastructure—user levels). <u>This dissertation focuses on the latter one—operations-related data uncertainty, and the spatial-temporal demand is modeled as stochastic distribution</u>. We acknowledge the complexity of the driving behavior near curbside (e.g., compliance with curbside regulations and choice of multimodal shared-use services) and we consider these variables exogenous (only modeled as user-defined input).

Stochastic Nature of Curbside Demand

Due to insufficient data and policy assessment, allocating curbside spaces becomes challenging. This becomes even more challenging when curbside demand varies for different services throughout the day. For example, demand from ride-hailing services is higher during evening peak congestion hours, while demand from urban freight delivery peaks around 11.00 AM (Figure 1. 9, Figure 1. 10). Also, ride-sourcing vehicles utilize curbside for a shorter period than private vehicles (1 minute vs 30 minutes) at various locations (e.g., at airports, commercial districts, and downtown public places) (R. M. Lu, 2019). The spatio-temporal spikes in the demand can make the curbside operating at a suboptimal manner (Loa et al., 2021; Ranjbari et al., 2020). To accommodate this demand pattern dynamic allocation strategies, need to be implemented that can adapt to different time periods and user needs. However, due to these fluctuations in demand it becomes more challenging to allocate curbside space optimally.

Figure 1. 9 Variation in curbside demand from commercial vehicles (Kim et al., 2021)

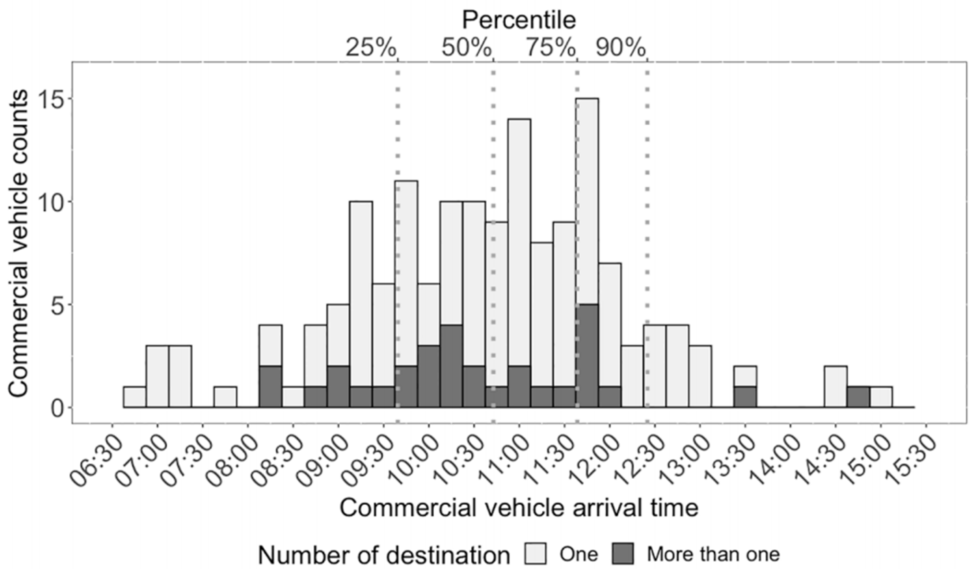
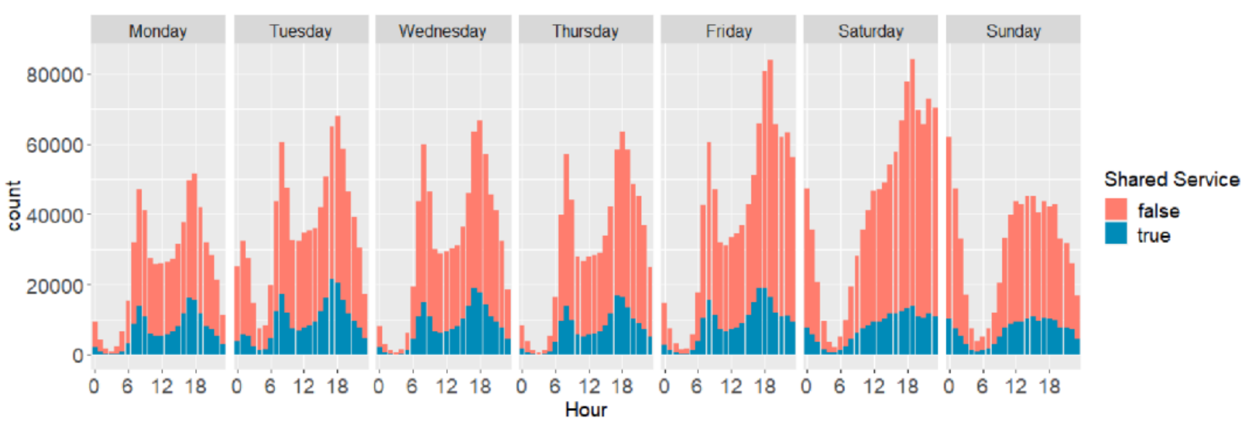


Figure 1. 10 Variation in curbside demand from ride hailing services in Chicago in January 2019 (Dean & Kockelman, 2021)



Lack of Comprehensive Assessment Framework: Models and Metrics

While curbside-focused operational strategies can influence congestion and roadside emissions, their impact remains uncertain as they have not been assessed prior to implementation. Furthermore, the absence of a standardized policy and the existence of various strategies in different cities make it challenging to determine which ones are most effective which complicates the optimal curbside space allocation under varying demand conditions. Furthermore, the efficacy of these policies varies with shifts in roadway geometries within a traffic network, making the curbside space allocation more complex for the decision-makers when considering diverse road configurations. As curbside behavior varies across users and services, macroscopic models will not be sufficient to represent these user characteristics, hence a microscopic modeling approach is required to represent the curbside behavior and evaluate their effect on surrounding traffic. However, extensive data requirement to develop a microscopic model make the curbside allocation problem more complex.

Further, it is important to quantify the changes in curb productivity for effective assessment and execution for implementing flexible use curbside strategies. Fehr and Peers developed a curb productivity index (CPI) to understand the productivity of a curbside space (Fehr & Peers, 2018a). The CPI assesses curbside productivity based on number of passengers. However, using a passenger-based comparison for urban delivery may not be suitable, given the differing impacts of urban deliveries on businesses and the local economy compared to TNC (Transportation Network Companies) and private parking. Balancing the use of metrics that effectively evaluate productivity for both urban freight and ride-hailing services poses a challenge to researchers and urban practitioners. Further, the existing metrics do not consider the environmental impacts—direct emissions or the effect of electrification of the mobility services.

Scalability of the Curbside Management Approaches

Curbside management gets into more complexity when we consider a network of curbsides instead of an isolated one. With dense shared-use mobility services, it is critical to consider a networked approach to optimize curbside space allocation. Oftentimes the impact of one policy/regulation on a curbside impacts other nearby curbside(s)—the demand shifts due to the adaptation of the users/service providers. At the same time, this could lead to an undesired impact at the system level. Moreover, these concerns extend when diverse urban contexts exist within the same network, from busy downtown areas to residential neighborhoods or mixed commercial areas. The existing curbside management approaches (discussed in Chapter 2 – Literature Review) do not account for the diversity of land uses within the same transportation network while developing policies for curbside allocation which makes optimal curbside allocation challenging.

This research aims to address these challenges and the next section will briefly describe the proposed novel approaches.

Proposed Research Approach

It is important for curbside managers in cities to revisit their existing strategies and make necessary shifts to accommodate changing mobility needs. Effective curbside management not only addresses traffic congestion but also supports economic vitality and sustainability. This section discusses our research approaches and considerations in curbside management, exploring how data-driven solutions, optimizations, and technology integration can be used to shape the future of curbside space allocation and regulation. Research goals are later described in the next chapter.

Develop Microsimulation-based Assessment Framework

Microsimulation can play a pivotal role in enhancing curbside allocation by providing a detailed and dynamic modeling approach that captures the intricate behavior of curbside users and the flow of traffic in urban areas. The level of detail in a microscopic simulation ensures a more realistic depiction of the curbside dynamics and evaluates different curbside allocation strategies, allowing for changes in traffic and curbside demand patterns. At the same time, the behavior of curbside users, stopping patterns, pick-up and drop-off activities, and the impact of pricing or time restrictions can be incorporated in a microsimulation model. This will provide valuable insights into how different curbside management policies may affect the traffic flow and the environment. Hence, it is beneficial to develop microsimulation models to help urban planners and decision-makers optimize curbside allocation strategies as well as align curbside management with broader urban planning goals.

Optimize Curbside Space Allocation Considering Uncertainty

Many cities currently deploy curbside management strategies in a somewhat suboptimal manner, relying on demand data without the support of a definitive analytical tool. Efficient use of these spaces has the potential to increase the economic and social benefits (Pochowski et al., 2022). Given the limited nature of curbside resources and the increasing demand for multi-use and multimodal curbside applications, it is important to maximize the efficiency of these spaces. Optimizing these spaces will ensure a rational distribution of these spaces among various road users. The existing allocation tools fall short in accounting for the dynamic and fluctuating curbside demand patterns that evolve over the course of a day (Pochowski et al., 2022). Hence, it is important to develop an optimization tool that not only accommodates stochastic demand variations but also integrates temporal restrictions, facilitating a comprehensive and adaptive approach to curbside space allocation.

Leverage Connected Vehicle Technology: Smart Curbside

To accommodate the dynamic nature of curbside demand, the allocation of curbside spaces needs to evolve as a dynamic element. As curbside allocation adopts a dynamic role, the absence of timely and comprehensive information can compel drivers to navigate within a geofenced area in search of curbside spaces. This scenario has the potential to exacerbate traffic congestion and contribute to increased emissions levels. To mitigate these challenges, it is imperative that curbside management and operations are facilitated by the availability of accurate information pertaining to curbside availability and the intentions of drivers regarding curbside usage locations. The effective deployment of technological solutions, including mobile applications, roadside units (RSUs), Global Positioning System (GPS), Dedicated Short-Range Communication (DSRC), and Cellular Vehicle-to-Everything (C-V2X) communication, holds the promise of enabling the dynamic management of curbside spaces with greater ease and precision.

Smart curbside will provide an easier way to communicate the latest curbside regulations with the users as well as facilitate the implementation since it limits the need to update and maintain signage. With connectivity, users can be informed instantly based on their location, service type, expected dwelling time, or any other criteria. The integration of such technologies into curbside management not only has the potential to enhance curbside productivity but also exerts an indirect influence on the overall operational efficiency of vehicular traffic in the vicinity, which, in turn, can impact emissions levels. Consequently, the careful implementation of technology in curbside management represents a comprehensive approach with far-reaching implications for both curbside operations and broader transportation and environmental considerations.

Summary

This chapter explores the key motivations, challenges, and opportunities related to optimal curbside allocation. As SUM services penetrate the curbside, the potential for frequent Pickup and Drop-off (PUDO) activities near active travel lanes increases when SUM services do not have designated spaces near the curbside. This can disrupt the network’s traffic flow, and also reduce vehicle speeds, thus affecting on-road emissions and fuel consumption. To make the curbside work in an efficient manner the local government needs accurate information about the usage of curbside (duration of services, demand from different services). However, the lack of proper curbside data makes it difficult to assess the curbside strategies as well as model the curbside behavior. The lack of assessment for the existing curbside allocation strategies results in inefficient curbside allocation and makes it difficult to manage the curbside spaces. The dynamic nature of curbside demand, coupled with the lack of an assessment tool, makes the curbside allocation task even more challenging. To address these issues, this dissertation aims to

A. Develop microsimulation-based curbside assessment models that can evaluate the effectiveness of different curbside strategies.

B. Build a curbside optimization model that can take care of the stochasticity of the curbside demand.

C. Explore the role of connected vehicle technologies that can make curbside management easier and assess their effectiveness in managing curbside.

The next chapter will discuss the existing gaps in the literature, research questions, and specific research tasks of this dissertation.

Organization of the Dissertation

The organization of the dissertation is as follows.

Chapter 1 establishes the context of this research by highlighting the current practices, and developments in curbside management practices. It discusses the current issues related to curbside management setting the stage for the research problem. It explains why solving these problems is important and explores the inherent challenges in solving those problems. Finally, it discusses some research approaches that can be adopted to overcome the issues with optimal curbside management stating the opportunities with curbside optimization research.

Chapter 2 discusses the existing practices adopted by different cities to manage curbside spaces. It reviews the existing literature relevant to the topic and summarizes the key findings. By reviewing the literature and current practices, it identifies the gaps leading to some research questions. In the end it justifies how this research will address those gaps.

Chapter 3 presents the methodologies to develop assessment models that can evaluate the efficiency of curbside management practices. Following the development of such models, this chapter sheds light on how time-restriction-based policies can help better manage curbside spaces. It also summarizes the impact of those strategies on emissions and curbside productivity.

Chapter 4 develops a mathematical optimization model to allocate curbside spaces rationally and explores the efficacy of the model to improve curbside productivity. Later, the optimization model was used for a dynamic allocation strategy considering the variation in curbside demand establishing the need for consideration of sources of uncertainty in this research. Later a decision-making process based on the optimization results are shown in this chapter.

Chapter 5 evaluates the efficacy of the curbside optimization model in field conditions. This chapter explores the impact of traffic elements and data connectivity on curbside productivity.

Chapter 6 summarizes the major findings of this research and explains the limitations of this study. Later it suggests some recommendations for future research and provides direction for extending this study.

Chapter 2 - Literature Review

In recent years, the management of curbside spaces has emerged as a critical and multifaceted challenge to transportation practitioners and city managers. With evolving mobility trends and growing concerns about congestion, the efficient allocation and regulation of curbside spaces have obtained increasing interest from researchers, policymakers, and city officials. This literature review seeks to investigate the existing curbside management strategies in cities, exploring research efforts that focus on the dynamics of curbside shared-use mobility activities. By synthesizing the existing body of research, this chapter aims to identify the gaps in curbside management research specific to the goals described in the previous chapter and develop research questions for this dissertation accordingly. We will briefly explore the existing practices and then dive deep into the research goal-specific literature review.

Curbside Management Practices

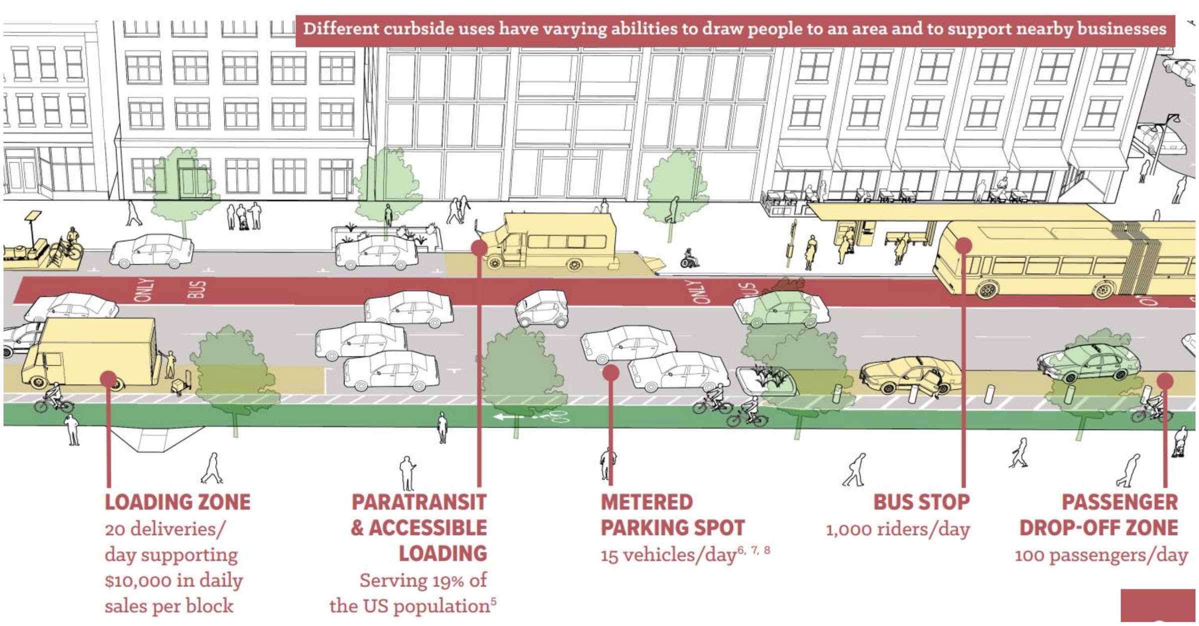
Planners, curbside practitioners, and researchers have been trying to find newer solutions to curbside management. These efforts can be divided into two categories. The first discusses the current practices undertaken by various geographic regions to deal with the increasing curbside demand. The second sheds light on the research efforts made with curbside operations and policies.

Current Practices in Cities

The shared-use mobility paradigm has changed the role of curbside–an element of flexible use compared to only private parking. To improve traffic flow and optimize curbside operations, several cities in the U.S. (Boston, MA; San Francisco, CA; Minneapolis, MN; and Seattle, WA) have reshaped their curbside management policies from a parking-oriented system to a flexible-use management system (Roe & Toochek, 2017). These policies include short-term loading zones for delivery vans and parking zones for ride-sourcing and privately owned vehicles, depending on their mobility needs, to promote multi-use multimodal activities at the curbside (Figure 2. 1).

This flexible use curbside policy aims to meet road users' expectations and minimize traffic flow disruptions near the curbside. A pilot project in Boston, MA, changed the dedicated four private parking spots (two per block) to PUDO designated from 5 PM to 8 AM which increased the curb use rate (PUDO PILOT 2019). This study indicates about a 350% increase in the curb utilization rate (measured by vehicles per hour in the curbside) compared with the existing case (2-hour parking). This study assessed curbside efficiency for one direction of travel without considering goods delivery or passenger access to the curbside. Based on these results, more pickup and drop-off zones were installed on three more streets to reduce congestion in travel lanes due to ride-sourcing services.

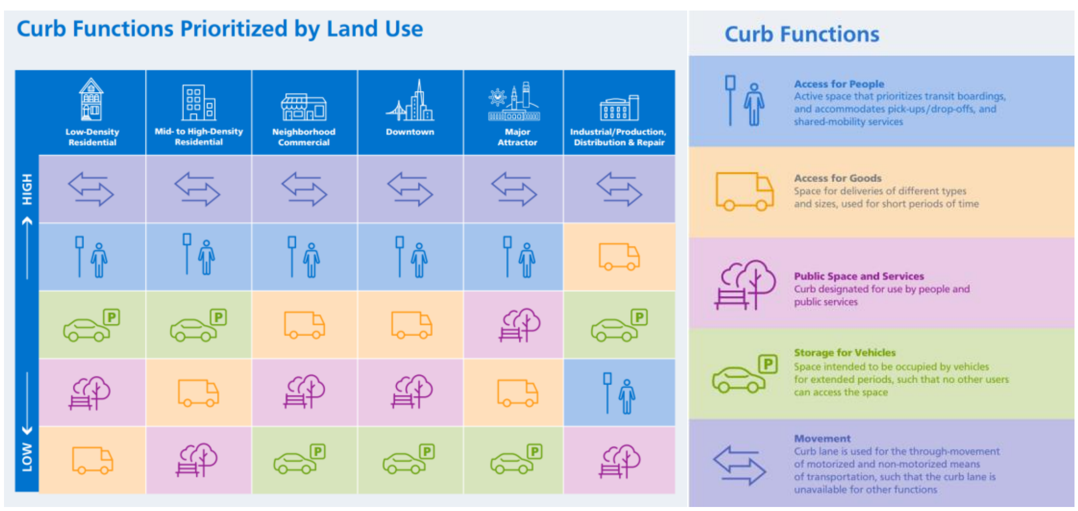
Figure 2. 1 Organized curbside spaces support multimodal services (Roe & Toochek, 2017)



Likewise, San Francisco, CA, responded to its growing shared mobility service demands by reallocating its limited curbside to multiple functions (SFMTA, 2020). San Francisco Municipal

Transportation Agency (SFMTA) divided curbside functions into five categories and prioritized them depending on land uses (Figure 2. 2). Fehr & Peers conducted a study (Fehr & Peers, 2018b) to identify common trends and behaviors in five case study locations in San Francisco and developed broad strategies to improve curbside productivity for a variety of roadway typologies. Curb performance was quantified using the curb productivity index as a function of passenger loading activity, passenger loading impact, and passenger loading curb demand (number of vehicles & number of spaces). The report suggested three primary strategies to improve curb productivity: reallocation, conversion, and flexibility.

Figure 2. 2 Curb functions prioritized by land uses in San Francisco (SFMTA 2020)



The Institute of Transportation Engineers (ITE) describes various curbside management strategies focusing on community values and safety in the practitioners' guide to optimize curbsides (ITE, 2018). Examples include flex zones, freight parking pricing, off-peak delivery, the time limit for loading or unloading, and time of day restrictions. The guide reports insights from San Francisco, CA; Washington D.C. and Toronto, Canada studies. In the city of Toronto, 18 strategies have been identified to optimize the curbsides over the next few years, including the designation of formal delivery vehicle parking zones, taxi stands at fire hydrants (taxis are allowed to park in front of specific fire hydrants to clear up the curbside), and motorcycle parking zones (ITE, 2018). An evaluation of the pilot in San Francisco found that dynamic pricing for on-street parking ensures greater availability of spaces and reduces congestion and vehicle miles traveled due to decreased cruising phenomena (ITE Case Study San Francisco). Further, in a Washington D.C. study, the Golden Triangle Business Improvement District (BID), with the District Department of Transportation (DDOT) and six other stakeholders, identified nightlife activities as the primary reason for congestion and conflicts at Dupont Circle as ride-sourcing services block the travel lanes after 10 PM on weekends (ITE Case Study Washington). Based on observation, parking spaces were reallocated from long-term parking to the nighttime PUDO zone (10 PM - 7 AM) from Thursdays to Saturdays, which was followed by the positive outcome of reducing congestion.

Key Findings

- More cities (San Francisco, CA, Seattle, WA, Bostom, MA, etc.) are implementing flexible use curbside strategies to accommodate newer mobility needs.
- Flexible curbside strategies seem to be effective in meeting the various types of demand from different services.
- Most flexible curbside management strategies are implemented based on land use type in the surrounding area.
- Dynamic pricing for on-street parking ensures greater availability of spaces and reduces congestion and vehicle miles traveled due to decreased cruising phenomena.

Curbside Assessment Methods and Metrics

Curbside has increased its appeal to researchers, mainly due to the increasing volume of shared mobility services, growth in vehicular traffic on streets, expansion in online businesses, and their growing competition for space on roads. International Transport Forum modeled and analyzed a few curbside-specific impacts due to the rise in shared mobility services in 2018 (ITF, 2018). The study investigated the Lisbon (Portugal) area to understand how the diversion of current car users to shared modes may impact curbside activity in the future and suggested dynamic and adaptive use of curbsides to reduce congestion on streets. Lu (R. Lu, 2018a) conducted a study based on descriptive analysis of field data in Los Angeles, CA, to understand how ride-sourcing vehicles utilize curbsides compared to other modes and whether providing loading space can reduce the frequency of double-parking incidents and increase the productivity of curbside. This study suggests that passenger loading zones on curbsides could be utilized four times more by ride-sourcing vehicles than private vehicles. Another study evaluated the influence of vehicles parked at the curbside and parking maneuver on the capacity of an intersection and viability of a curbside parking area (Zhao et al., 2020). The study found that the increase of curbside parking area length, the loss of intersection capacity also increases. While many other congested cities were dealing with the consequences of the massive rise of ride-sourcing like Uber and Lyft, Seattle was not any different from them. Ride-sourcing activities increased by around five times in Seattle from 2015 to 2018.

Researchers (Zhao et al., 2020) evaluated two strategies aiming to reduce blocking active travel lanes, unauthorized stops in the curbsides, and dangerous traffic maneuvers. These include: (a) Changing more parking zones to passenger loading zones (PLZs) 7- 10 AM and 2–7 PM, and (b) Geofencing Uber and Lyft services. The study reported a reduced number of pickups and dropoffs in the active travel lanes. The dwell time for ride-sourcing drivers became smaller, though no substantial changes in safety (measured by the number of conflicts before and after implementing PLZs) and speed was observed in this study. This study aimed to identify factors associated with dwell time for commercial vehicles by employing generalized linear models and data gathered from five buildings known for commercial vehicle activities in downtown Seattle, Washington, USA. Kim et al. (2021) revealed that buildings with concierge services tended to have shorter dwell times, as did deliveries of documents compared to oversized supplies deliveries. Passenger vehicle deliveries also exhibited shorter dwell times than deliveries made with vehicles featuring roll-up doors or swing doors (e.g., vans and trucks). Moreover, when multiple locations within a building received deliveries, dwell times were significantly longer compared to deliveries made to a single location within a building. These findings suggest the potential for refining future parking policies for commercial vehicles by considering various factors, including building types, delivered goods, and vehicle types, based on data analysis. Machado-León et al. (2023) in Seattle, Washington, analyzed over 6,000 passenger vehicle PUDO dwell times using hazard-based duration modeling. The research also conducted a before-after study to evaluate the effects of two curb management strategies: introducing PUDO zones and geofencing. The results indicated that several factors significantly affected PUDO dwell times, including the number of passengers, type of activity (pick-up vs. drop-off), vehicle trunk accessibility, curbside stops, and the time of day (afternoon). While more vehicles at the curb and in adjacent lanes correlated with shorter PUDO dwell times, the practical significance was limited. Ride-hailing vehicles tended to spend less time on PUDO activities compared to other passenger vehicles and taxis. Additionally, the implementation of PUDO zones and geofencing was associated with faster PUDO operations. The study suggests that future curb management strategies should consider these findings to better accommodate ride-hailing operations and optimize curb use for various user needs. Maxner et al. (2023) conducted a simulation-based analysis to assess the impacts of different curb use allocations on curb performance. The study introduces three metrics to evaluate curb performance, considering the efficiency of passenger and goods transportation as well as the reduction of CO2 emissions. These metrics are applied across various scenarios that involve different input parameters, such as traffic volume, parking rates, vehicle dwell time, and street design speed. The results are then compared to a baseline scenario. This research aims to provide municipalities with valuable tools for analyzing and assessing various curb management strategies. It assists cities in making informed policy decisions that align with their specific goals, whether related to productivity, accessibility, or environmental concerns.

Key Findings

- Dynamic and adaptive use of curbsides reduces congestion on streets (ITF, 2018).
- Increasing curbside parking area length increases the loss of intersection capacity (Zhao et al., 2020).
- Curbside spaces can be used more if designated spaces are provided for different services (Lu 2018).
- PUDO dwell times are affected by the number of passengers, type of activity (pick-up vs. drop-off), vehicle trunk accessibility, curbside stops, and the time of day (afternoon) (Machado-León et al. 2023).

Limitations

Most assessed policy scenarios quantify traffic performance and curbside utilization with little or no focus on the environmental impact–emissions and energy consumption. Jaller (2021) estimated emissions in residential, commercial, and mixed-use neighborhoods in San Francisco, CA, for different curb management strategies. The emissions were estimated using factor-based polynomial equations. Very few studies evaluate the effect of curbside allocations strategies when roadway patterns change. Also, comparative studies analyzing the effectiveness of different curbside policies across diverse urban contexts can provide valuable insights for policymakers which is missing in literature. Also, the curb productivity metric by Fehr and Peers measures the amount of people being served per ft of curbside space per hour to calculate productivity, which may not be very effective for different services. For example, an urban delivery vehicle occupies a curbside space for a longer time and carries fewer passengers than public transit or ride-hailing vehicles. While this metric may be helpful to measure the curbside productivity for passenger-carrying vehicles, this metric may not be rational to measure the productivity of a curbside space when an urban delivery vehicle. Also, existing studies lack insights into how curb productivity varies across different curbside management strategies under different time restrictions. Also, only a few studies assessed operational scenarios to quantify the environmental impact–emissions and energy consumption. Using simulation, Maxner et al., (2023) estimated the effects of various curb usage allocations on curb performance. The curb effectiveness was assessed through CO_2 emissions, productivity, and goods and passenger accessibility. Jaller (2021) estimated emissions in San Francisco, CA's residential, commercial, and mixed-use neighbourhoods for different curb management strategies. The emissions were estimated using factor-based polynomial equations. These studies provide valuable insights into the carbon impact of curbside strategies. However, while assessing the carbon impact, these studies do not consider factors like vehicle fleet compositions, vehicle age, model years, or meteorological information. These factors directly impact the emissions and energy consumption of a network.

Research Gaps

From the above discussion, we can identify the following research gaps that we are going to address in our research.

RG1. An assessment framework that integrates fine-resolution microscopic models—both for mobility and emissions—is needed to represent the heterogeneous attributes associated with curbside operations.

RG2. Most existing studies and relevant practices focus only on the mobility dimension. To ensure the desired benefits from curbside operational strategies, we need to account for mobility, environmental, and productivity metrics and the trade-off among these metrics.

RG3. The impact of electrifying the shared-use mobility fleet has not been studied at a fine resolution. It is important for service providers and curb managers to estimate the impact of making both operational and investment decisions.

Research Questions

Hence, our research aims to answer the following questions RQ1 to RQ3, to address the research gap between RG1 and RG3.

RQ1. What are the mobility and environmental impacts of time restriction-based curbside management strategies? Are they effective in improving the network's mobility? Also, are the strategies effective in reducing emissions?

RQ2. How does the flexible-use curbside strategy impact the services at the curbside? Based on different time restrictions applied to different services, can it serve more people? Will it improve curbside productivity that accounts for the number of passengers served?

RQ3. As electric vehicle market share increases in the network, it may impact the environment and mobility differently as they have different powertrains compared to gasoline-driven vehicles.

In these circumstances, when curbside operates with a time restriction-based flexible use strategy, what would be the impact on mobility and the environment?

Research Tasks

To address these needs, we aim to complete the following research tasks:

RT1. Build a fine-resolution assessment framework to quantify the effectiveness of time restriction-based curbside allocation strategies on mobility, productivity, and environment incorporating PTV Vissim (microscopic traffic simulation) and EPA-MOVES (modal-based emissions estimate using speed profiles),

RT2. Apply the framework to estimate and understand the trade-off among mobility, emissions, and curbside productivity metrics of time restriction-based curbside management strategies in real-world testbeds in Chicago, Illinois, USA.

RT3. Estimate the environmental impact of shared-use mobility fleet electrification near curbside using a fine-resolution emissions model, namely, the EPA-MOVES. A general framework to estimate the environmental impact of curbside activities with vehicle fleet electrification will be developed, and major pollutants, including greenhouse gas emissions, will be estimated for the transportation network.

Curbside Optimization Accounting for Uncertainty

With the advent of new transportation modes and technologies like ride-hail apps, e-commerce deliveries, and micromobility services, the allocation of curbside space has become a critical consideration for jurisdictions like Arlington County, Virginia. They aim to develop tools that can optimize curb space allocation to maximize economic and societal benefits within their transportation system (Pochowski et al., 2022). While some jurisdictions and researchers have explored theoretical approaches to reallocating curb space away from on-street parking, Arlington County has taken a practical approach tailored to its context. Arlington County has created a curb space allocation tool consisting of six modules: (i) ride-hailing services, (ii) commercial loading, (iii) on-street parking, (iv) transit service, (v) micromobility, and (vi) non-transportation uses (e.g., parklets/streateries). These modules can be updated with new data or models as they become available. The tool uses each module to estimate the demand for different transportation modes and then allocates curb space to maximize economic or societal value, focusing on serving the highest number of people. This initiative has allowed Arlington County to lay the foundation for a tool that aids in determining the optimal allocation of curb space based on the existing or proposed land uses and transportation services in a given block. Additionally, it has highlighted areas for further research and data enhancement to improve the tool's usability and effectiveness.

An empirical study (Ma et al. 2018) proposed repurposing the curbsides at Austin, TX for the benefit of a larger community. They developed an optimization framework using the classical bid-rent theory to allocate the curbside by providing more accessibility to the higher-valued activities (activities that demand for the greatest accessibility in the central business district) (Ma et al. 2018).

Ye et al. (2022) conducted a study whose primary objective is to optimize the allocation of curbside space to accommodate various parking behaviors, with a focus on maximizing parking service rates and curbside occupancy. To achieve this, the study employs a partially learning Deep Deterministic Policy Gradient (DDPG) algorithm, which operates in real-time while being trained off-policy. The significant contribution of this research lies in its innovative approach to optimizing the sequential dispatching of curbside space, considering both short-term and long-term parking needs. Furthermore, the study's findings provide insights into the relationship between parking demand patterns and curbside performance, offering valuable information for city administrators to efficiently manage their limited curbside resources strategically.

Key Findings

- Arlington County, VA uses existing or proposed land uses and transportation services in a given block to optimize their curbside spaces. They maximized the economic and societal benefits within their transportation system to optimize the curbside spaces (Pochowski et al., 2022)
- Ye et al. (2022) used a partially learning Deep Deterministic Policy Gradient (DDPG) algorithm to optimally allocate curbside spaces to accommodate various parking behaviors, with a focus on maximizing parking service rates and curbside occupancy.

Limitations

The current curbside optimization tools exhibit some significant limitations that warrant critical consideration. Firstly, they do not incorporate parking restrictions specific to geographic areas. Secondly, these optimization tools have demonstrated proficiency in optimizing curbside allocation within smaller and relatively homogenous regions. However, their efficacy tends to lessen when confronted with the complexities of variable land use patterns within the same geographic area. Consequently, their application in such diverse urban environments may result in suboptimal outcomes. Thirdly, the existing curbside optimization tools fail to take into consideration the dwell time restrictions associated with a diverse array of mobility services. Dwell time, a critical factor in curbside management, differs significantly among various modes of transportation. By not factoring in these variances, the tools may lead to inefficient curbside resource allocation. Moreover, the existing literature does not talk about the parameters and constraints that should be considered while developing an optimization tool for multi-use curbside activities accounting for temporal and geographic restrictions.

Finally, the existing models and techniques do not account for uncertainty in several dimensions, including arrival demand, dwell time, and passenger occupancy specific to the SUM services. Furthermore, the current tools do not adequately address two other essential factors. The dynamic nature of demand from different mobility services throughout the day remains unaccounted for. Mobility service utilization experiences temporal fluctuations and optimizing curbside resources without considering these temporal patterns can result in suboptimal outcomes. The vehicle arrival pattern, incorporating the timing and distribution of vehicles seeking curbside access, is another crucial aspect often disregarded by existing tools. Overlooking this parameter can lead to congestion and inefficiencies at the curbside.

Research Gaps

From the above discussion, the following research gaps can be shaped.

RG4. The current literature lacks a comprehensive analysis of the parameters and constraints that should be considered while developing an optimization tool that accounts for the temporal and geographic restrictions. Also, no comprehensive optimization tool is available for curbside use, regardless of the area and type of curbside usage. Insights on the effectiveness of those tools are also absent.

RG5. The current curbside optimization tools do not consider uncertainty in demand throughout the day from different mobility services. To ensure that the optimization tool can capture the uncertainties of demand in terms of time and duration, a curbside optimization tool capable of accounting for the temporal variations of demand from various mobility services is required.

RG6. The current curbside optimization tools lack insights into how curbside productivity improves after optimization. Evaluating the efficacy of the developed tools is important to understand their effectiveness and usefulness in the face of varying uncertainties.

Research Questions

To address the research gaps on optimization (**RG4** to **RG7**), there is a pressing need for the development of more comprehensive curbside optimization tools that consider the multifaceted nature of curbside management, incorporating geographic variations, dwell time constraints, temporal demand dynamics, and vehicle arrival patterns to enhance the overall efficiency of curbside resource allocation. To develop a comprehensive optimization tool, in this research we aim to answer the following questions to address these research gaps,

RQ4. Which inputs and parameters must be considered when formulating an optimization model that effectively addresses geographic disparities and dwell time limitations? How do we develop a comprehensive optimization tool to allocate space rationally among various curbside services? What would be the approach for developing the optimization model (simulation-based, mathematical)? What type of services are these parameters capable of representing? Do we need to consider different types of parameters to develop a curbside optimization model depending on the type of services?

RQ5. How will the optimization model address temporal demand fluctuations and vehicle arrival patterns? When temporal demand variations are considered, will the optimization model enhance curbside efficiency?

RQ6. How will the tool impact overall curb productivity? Will it improve the performance of the existing allocation strategies? Also, what would be the most suitable way to make decisions in the real world based on this optimization model?

Research Tasks

We intend to develop tasks associated with each research question to address these research questions.

RT4. Firstly, we are going to develop a curbside optimization model incorporating a comprehensive set of parameters and constraints to accurately represent dwell time limitations and effectively accommodate temporal demand fluctuations. Initially, we will develop a series of hypothetical scenarios for evaluation purposes to assess the potential for the developed optimization model to enhance overall curbside efficiency.

RT5. Once we complete the assessment of the curbside optimization model's efficacy in enhancing curbside efficiency, we will test whether the model can react to different demand patterns. For interpreting the results, we will consider a stochastic optimization technique that can take into account different vehicle arrival rates and patterns along with varying dwelling times. The different stochastic optimization techniques being used in transportation-related research are discussed later in this chapter.

RT6. To answer **RQ6**, we are going to develop a set of scenarios to compare the differences in curbside productivity before and after implementing the optimization tool to understand its performance. Later, we will discuss strategies to translate the optimization tool's results into real-world implementation.

Smart Curbside

"Smart curbside" is an innovative concept gaining traction in urban planning and transportation management. It involves leveraging technology to optimize curbside space in cities, aiming to enhance efficiency, reduce congestion, and improve the overall urban experience for residents and visitors alike. One of the primary objectives of innovative curbside initiatives is to address the growing challenges associated with urban mobility. As vehicle ownership rises, traditional uses of curbside areas for parking, loading zones, and pick-up/drop-off points often lead to inefficiencies and conflicts. By implementing intelligent curbside solutions, cities can better manage and allocate curbside space based on real-time demand and specific use cases. For instance, advanced sensors and data analytics can provide insights into parking occupancy, enabling dynamic pricing schemes to encourage turnover and reduce congestion. Moreover, designated loading zones can be optimized to accommodate deliveries, ride-sharing services, and other commercial activities, minimizing disruptions to traffic flow. Furthermore, intelligent curbside initiatives can promote sustainable modes of transportation, such as cycling and public transit. By designating bike lanes and transit priority zones along curbsides, cities can encourage alternative modes of travel and reduce reliance on private cars, thereby mitigating emissions and improving air quality.

However, the successful implementation of intelligent curbside strategies requires careful planning, collaboration, and investment. City authorities must consider various factors, including local regulations, community needs, and technological infrastructure. Privacy and equity considerations also play a significant role in developing smart curbside initiatives. Cities must ensure that data collection and usage adhere to strict privacy regulations and prioritize equitable access to curbside resources for all community members, regardless of socioeconomic status or mobility needs.

In conclusion, smart curbside represents a promising approach to optimizing urban mobility and enhancing the efficiency of curbside space in cities. By leveraging technology, data-driven insights, and stakeholder collaboration, cities can create more sustainable, accessible, and livable urban environments.

Research Gaps

The current academic literature on curbside management is deficient in studies that empirically illustrate the impact of technology integration on both curbside management practices and the broader traffic dynamics within the vicinity. This deficiency reflects a significant gap in our understanding of how incorporating technological solutions influences curbside resource allocation, the overall flow of vehicular traffic in urban environments, and the productivity of the curbside spaces.

RG7. The existing literature lacks proper insights into the difference between the theoretical curbside productivity index and the curbside productivity index when results from an optimization model are implemented in the network.

RG8. Existing literature does not shed any light on the impact of a smart curbside and curbside productivity depending on overall traffic dynamics for the surrounding area, for example, how the upstream signal control or congestion will impact it.

RG9. The existing literature lacks insights into the impact of smart curbside**,** which enhances the efficacy of curbside productivity when an optimization tool is used to allocate curbside spaces.

Research Questions

Based on the existing research gaps, we are going to answer the following questions.

RQ-7. How much will CPI values differ between optimization solutions and observations from actual deployment?

RQ-8. When implemented, will the presence of network elements like signal control, and the location of curbside location have a major impact on curbside productivity?

RQ-9. Will connectivity (C-V2X) influence the CPI and service rates (request served)?

Research Tasks

To answer each research question related to smart curbside, we are going to complete the following tasks.

RT-7. To answer RQ7, we are going to evaluate the solutions from the optimization algorithm in PTV Vissim and compare them to simulated real-world results.

RT-8. Once RT-7 is complete, we are going to vary the location of curbside locations in the simulation model to assess its impact on curbside productivity.

RT-9. Later we are going to model connectivity between vehicles and curbside—so that more information about demand and dwelling time (in Vissim) can be achieved. We are also going to test the impact of data availability and the complex urban nature (signal control, bus stops, congestion) on the anticipated curbside productivity.

Summary

This chapter discusses the recent efforts with curbside management practices and relevant research. Despite the progress made in curbside management research and practice, several challenges and opportunities for future investigation remain. These include the need for robust data collection and analysis methods and the development of scalable and adaptable curbside management frameworks that can incorporate uncertainties. The reviewed literature highlights a range of strategies and tools for effective curbside management, including curbside allocation algorithms, and innovative curb space design. These approaches aim to optimize curb utilization, reduce congestion, improve safety, and enhance accessibility for all users. Moreover, advancements in data analytics and modeling techniques offer new opportunities for real-time monitoring and adaptive management of curb space. In Addition, the literature review discusses the research gaps in the existing literature and opportunities for this research.

Chapter 3 - Mobility, Environmental, and Productivity Impacts of Curbside Prioritization Strategies

Introduction

Curbside managers in cities need to revisit their existing strategies and make necessary shifts to accommodate changing mobility needs. Efficient curbside management is important to ensure passenger accessibility while potentially reducing traffic congestion for economic growth and sustainability. Microsimulation can significantly improve curbside allocation by offering a detailed and dynamic modeling approach that accurately reflects the behavior of curbside users and traffic flow in urban areas. Microscopic simulations are capable of providing a highly detailed and realistic representation of curbside dynamics. This also allows the evaluation of different allocation strategies and accommodating changes in traffic and curbside demand patterns. At the same time, the behavior of curbside users, stopping patterns, pick-up and drop-off activities, and the impact of pricing or time restrictions can be incorporated in a microsimulation model. This will provide valuable insights into how different curbside management policies may affect the traffic flow and the environment. Now, evaluating all possible curbside management strategies will be intractable in single research. This chapter focuses on one of the most utilized strategies– time-dependent allocation of curbside space and duration (which mobility service can use the curbside spaces and for how long). In this chapter, we will develop a microsimulation model to evaluate time restriction-based curbside allocation strategies and their impact on mobility, environment and spaces usages. The methodology section discusses the tools and methods used to develop microsimulation-based assessment models. Later in the results section, a detailed analysis has been presented to understand the impact of time-restriction-based curbside strategies.

Methodology

Our proposed assessment framework integrates three major elements: (a) microsimulation at the vehicular level, (b) modal-based emissions simulation using EPA-MOVES and (c) curbside performance quantification. The following sections provide details about each element.

Traffic microsimulation

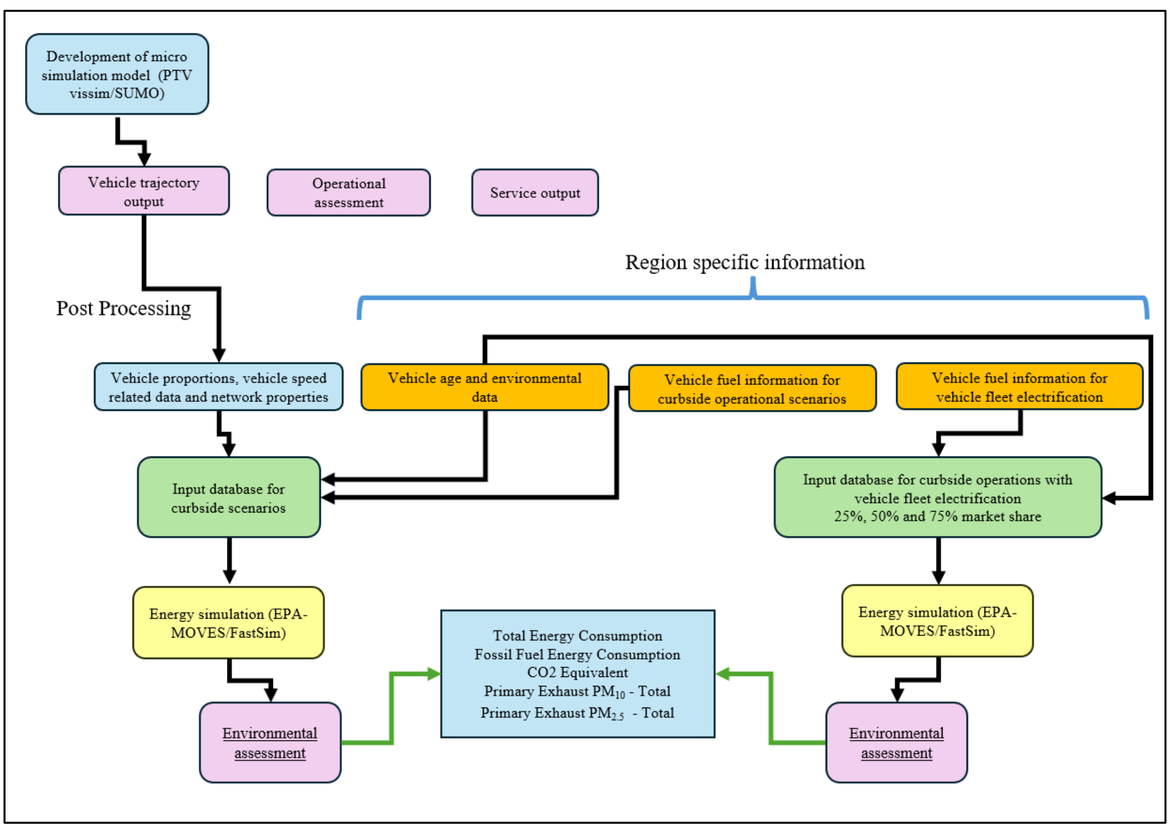
The curbside management strategies (discussed later) and the associated scenarios (Table 3. 1) are simulated using PTV VISSIM (PTV Group, 2022). The microsimulation follows the Wiedemann'74 car following model (Z. Lu et al., 2016). Since PTV VISSIM has no direct feature to replicate the PUDO activities, we used parallel parking lots to model a few continuous stopping zones in the street. Also, we used a dwelling time distribution for the stopping vehicles. The minimum stopping time for vehicles is assumed to have a Gaussian distribution. For buses, the minimum dwell time is 30 s, and the minimum dwelling time for personal vehicles in the base case is 60 minutes. Network level mobility performance metrics are reported, including travel delays, number of stops, and stopped delays.

Existing studies (Ponnambalam & Donmez, 2020) indicate that drivers slow down while searching for a curbside space, drive closer to the curbside, and maintain a speed lower than 9.32 miles/hr. To replicate this behavior near the curbside, we have used a reduced speed zone next to the curbside for drivers looking for a curbside space. We have restricted the driving speed at those locations for vehicles looking for curbside spaces to 9.32 miles/hr. The length of this reduced speed zone has been taken as equal to the available curbside length.

Vehicular emissions estimation

This research uses the U.S. Environmental Protection Agency's MOtor Vehicle Emissions Simulator (EPA-MOVES) model (EPA, 2012) to estimate the emissions and energy consumption from the test networks. EPA-MOVES requires detailed geographical information about the road network of interest. Based on the test-network information, we use the data from Cook County, Illinois; unrestricted urban roads: gasoline-driven passenger cars and trucks and diesel-driven urban freight and buses; analysis period: 6.00 – 7:00 pm of June 2016 (consistent with the traffic volumes used as input). We have estimated emissions and energy for all the links of the network. Link-specific information, i.e., link volume, average link speed, the proportion of different classes of vehicles on each link, and link drive schedule information, has been used to build the input database for each scenario. This information has been collected and processed from the microsimulation results obtained from VISSIM. The process of developing environmental assessment framework is shown in Figure 3. 1.

Figure 3. 1 Schematic diagram for environmental assessment framework



Statistical testing of simulation outcome

Accounting for the stochastic nature of the simulation outputs, we collected data for 30 simulation runs, each with a different seed value from VISSIM. For each performance metric, we conducted F-test followed by Student's t-distribution tests since the variances are unknown. The mean values of the performance metrics are reported for 95% confidence intervals. The range of means values has been estimated from the following equation.

$$\bar{X} - t_{\frac{\alpha}{2}}\left(\frac{s}{\sqrt{n}}\right) < \mu < \bar{X} + t_{\frac{\alpha}{2}}\left(\frac{s}{\sqrt{n}}\right) \qquad (3.1)$$

$\bar{X}$: mean of the sample, s: standard deviation of the sample, μ: mean of the population, n: sample size (30 in our case), $t_{\frac{\alpha}{2}}$: value from t distribution using degrees of freedom (n − 1).

Measuring curbside performance

Curbside productivity can be measured in different ways, and no consensus is found in the existing literature. Based on the type of usage of curbside, the metric can vary. These metrics include the number of bike riders per day (docking station), the number of truck deliveries supporting sales per block (delivery truck loading zones), the number of meals or income per day for food trucks, and pickup drop offs per hour (TNCs). For simplicity, we adopted the curb productivity index metric presented by Fehrs and Peers (Fehr & Peers, 2018a) for the Cincinnati Uber study.

$$\text{Curb Productivity Index}, \vartheta = \frac{\text{Activity}}{\text{Space x Time}} = \frac{S}{T\ x\ L} \qquad (3.2)$$

S: Number of services complete either passengers or delivery in a given time period (typically an hour); T: Dwelling time the amount of time the curbside space was occupied (in hour); L: Length of the curbside (in ft). The curb productivity index, ϑ takes the form of services per unit time per unit curbside space.

Experimental Setup: Curbside Operational Strategies

The strategies evaluated in this research are motivated by varying time restrictions of curbside usage based on the multi-functional priorities for shared-use services. The proposed strategies involve purpose based curbside allocations prioritizing services such as ride sourcing PUDO activities and delivery van parking over private parking. For instance, when dedicated locations are provided for PUDO services, the through traffic is expected to be less impacted due to a reduction in the roadside disruptions and the mid- block congestion (PUDO Pilot, 2019; Swasey, 2019). Further, this may improve traffic operations by increasing network wide speed and reducing vehicle delays. We evaluated scenarios with reduced long-term parking and dedicated spaces for ride sourcing and urban truck deliveries. Then, the system level metrics and curb productivity indices are compared with the legacy curbside operations with only private parking options.

Experimental scenarios

Our evaluated strategies consider three dimensions: time restriction, space availability, and the number of lanes. Following the findings of Lu (2019) regarding the dwelling time of different vehicles for curbsides at Melrose Avenue and Santa Monica Boulevard in California, we chose the maximum dwelling time of ride sourcing vehicles as five minutes, and the maximum allowed dwelling time for the urban freight as 30 minutes. Maximum dwelling time for the ride sourcing vehicles were reported as approximately 1 minute by Lu (2019). Here, a longer dwelling time has been considered to account for more extended pickup or dropoff times when passengers with disabilities or babies use ride-sourcing vehicles. The dwelling time is modeled as a Gaussian distribution with the maximum permitted dwelling time as the upper bound within the traffic simulation. In addition, we also evaluated the effect of space availability by changing the number of spaces in each scenario. Table 3. 1 lists the six experimental scenarios.

Table 3. 1 Description of experimental scenarios

Scenario Label	Curbside Spaces Available	Dwelling Time Restrictions
HS-T1	8	30 min (freight); 5 min (Ride sourcing)
HS-T2	8	20 min (freight); 2 min (Ride sourcing)
MS-T1	6	30 min (freight); 5 min (Ride sourcing)
MS-T2	6	20 min (freight); 2 min (Ride sourcing)
LS-T1	4	30 min (freight); 5 min (Ride sourcing)
LS-T2	4	20 min (freight); 2 min (Ride sourcing)

Further, to assess the effect of network geometry, all the scenarios listed in Table 3. 1 are also tested with varying number of lanes (ranging from three to five) for the roads near the curbside. With fewer lanes, the traffic is expected to experience more disturbance due to PUDO activities. This stress may be milder when we have a higher number of lanes compared to the base condition.

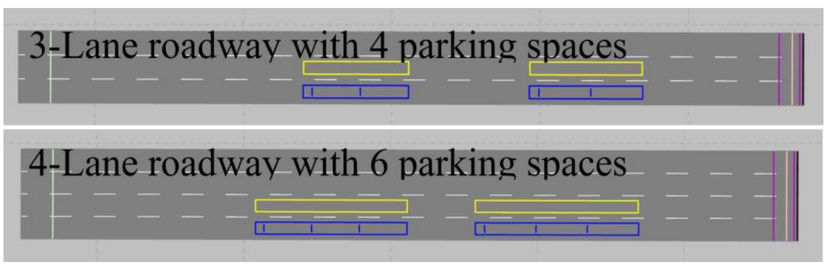
Test Networks

Our study evaluates the strategies on two networks: (i) a hypothetical long stretch of road (minimal or no complexity in the network configuration), and (ii) a real-world network from Chicago, IL (presence of signal controllers and high PUDO activities).

Small hypothetical network

Road network configurations near the curbside can be complex (e.g., the presence of traffic signals, complex channelization, and other control devices). To understand the impact of the strategies without the direct influence of complexities of the road configurations, we used a 345 ft (105 m) stretch of a roadway (Figure 2) to evaluate curbside operations with varying time restrictions, number of spaces, and lanes. We have two vehicle classes: passenger cars (including the TNCs) and delivery vans. The hourly traffic rate was taken as 4000 vehicles per hour to capture the mobility impacts under heavy traffic. The number of lanes for the roadway has been changed throughout the testing process (3, and 4 lanes) to investigate the overall congestion impact corresponding to curbside strategies.

Figure 3. 2 Test network: Long stretch of road without any network complexity



Real-world network from Chicago, Illinois

We selected a real-world network in Chicago, Illinois. Before site selection, we explored the data provided by the transportation network providers (City of Chicago, 2022) to find out the street with a high concentration of pickup and drop off activities. The data showed the location of pickup and drop off activities during June 2019. The pickup and drop off activities were maximum near W Monroe St from Downtown Chicago, IL. About 12,000 pickups and 14,000 drop offs occurred around W Monroe St in June 2019 (Figure 3. 3). The area around this street is highly commercial and congested, which can be affected by the pickup and drop off activities. Therefore, the location was a perfect candidate for testing our proposed strategy. We took the intersection of W Monroe St with S La Salle St to the corner of West Monroe St with S Clark St (Figure 3. 3).

Since W Monroe St is a one-way street, we selected W Madison St to consider the opposite direction of traffic. La Salle St has two-way movements, while Clark St is a one-way St. The intersection of the streets is controlled with a traffic signal. The on-street curbside locations have been identified (Figure 3. 3) using satellite images obtained from Google Earth.

Figure 3. 3 Real-world network: Chicago, IL, curbsides with high pickup and drop off activities

The satellite image showed no curbside spaces on W Monroe St and W Madison St during peak hours. The three curbside spaces on W Madison St is designated for private parking. La Salle St has seven curbside spaces, and more than ten curbside spaces were located in Clark St. These spots are occupied with on-street parking by personal vehicles and urban freight. In this situation pickup and drop offs from ride sourcing and urban freight occur in the active travel lanes, which impedes the traffic flow. As W Madison Street has an exclusive bus lane with an exclusive right turning lane and W Monroes St has an exclusive left turning lane, stopping activities may also hinder those operations.

Table 3. 2 Traffic volume data for Chicago, IL network

Street Name	Direction	Traffic Volume
W Monroe St	Eastbound (one-way)	18,500
W Madison St	Westbound (one-way)	11,500
Clark ST	Northbound (one-way)	15,500
La Salle St	Northbound	8,500
La Salle St	Southbound	7,700

The Average Daily Traffic (ADT) volume (Table 3. 2) for the network was collected from Average Daily Traffic Count Map of Chicago (City of Chicago, 2022). The ADT volume was used to determine the peak hour volume for the streets. Based on the American Association of State Highway and Transportation Officials (AASHTO) (Green Book, 2018) the peak hour volume is estimated using the standard range of 8 - 10% (we use 8.4% for our scenarios).

Three different vehicle classes are considered for the simulation: car, delivery truck, and bus. We have used DL-23 type for delivery trucks, which is commonly used for package delivery (inner and outer turning radii are 22.5 ft and 29 ft respectively) (NACTO, 2023). The selected network's exact mode share was not available for analysis. Chicago, IL, is similar regarding the dense-urban traffic activities and closely identical to New York City, NY. As the close approximation of the traffic demand, we adopted the mode share in New York City, NY, for our experimentation (NYC Open Data, 2018). We acknowledge that this does not represent the actual mode share in our test network. At the same time, all the cases (existing and proposed strategies) are evaluated with identical demand distribution. Thus, the comparison is statistically sound. The proportion of cars, buses, and delivery trucks are 97%, 2%, and 1%, respectively. While developing simulation models, we assumed some changes in the base distribution to represent vehicles looking for curbside spaces. The distribution when curbside activities were present in the network is, 1-2% parking class delivery trucks, 1% delivery trucks, 15-16% parking cars, 80-81% cars and 1% buses. We created a scenario where all vehicles under the parking class will be looking for curbside spaces and slowing down near the curbside so they can stop if a space is available.

Considering the pre-existing geometric configuration of this real-world network from Chicago, IL, scenarios with different lanes are not evaluated. Due to the induced demand and complexity of the network (unlike a long stretch of road), it will be challenging to distinguish between the effects caused by lane increase compared to a change in capacity by increasing the lanes.

Simulation-based Results

We report our results–mobility and emissions metrics–for both the small hypothetical road (Figure 3. 2) and the real-world Chicago network (Figure 3. 3). Please note that the HS cases are only evaluated for the small network to assess the results for a hypothetical scenario with higher availability of curbside space (Table 3. 1). The additional spaces for the Chicago network may create inconsistencies in the overall space distribution and may not represent the real-world conditions. Therefore, we did not test HS cases for the Chicago network.

Results: Mobility

Our mobility metrics include: average stopped delay (s/veh), average number of stops, average vehicular delay (sec/veh), and average speed (miles/hr). The results from both small hypothetical network and the Chicago network are reported in the next subsections.

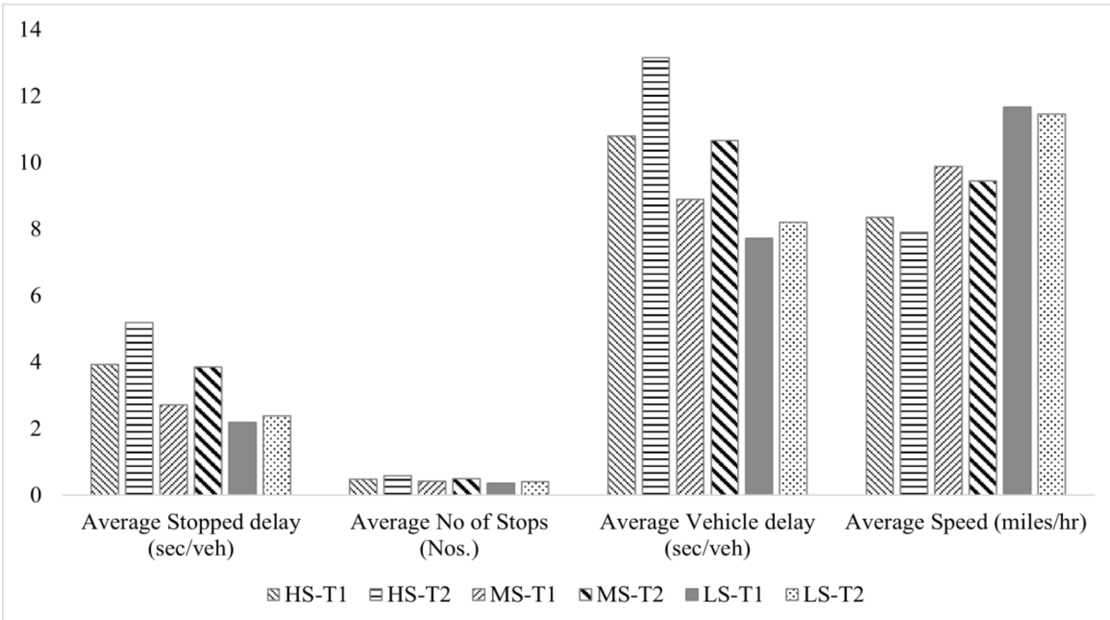
Small Network–Mobility Metrics

Our results indicate that the network performance is likely to deteriorate when the dwelling time is reduced while number curbside spaces remain unchanged. This pattern is seen for all the scenarios when time restriction is implemented. Figure 3. 4(a) reports (for a 3-lane roadway) that scenario with T2 dwelling time has a higher value of average vehicular delay. This pattern also exists for the average stopped delay and the average number of stops. Figure 3. 4(b) also shows a similar pattern of mobility metrics for a 4-lane roadway, respectively. The only difference between scenarios with T1 and T2 (Table 1) is their different dwelling time restrictions. All the scenarios with T2 have a smaller dwelling time allowed for vehicles than those with T1. A shorter dwelling time means more vehicles can stop at the spots, substantially increasing curbside activities. Also, a shorter dwelling time means curbside spaces will be available within a shorter period, so drivers will have a higher expectation of getting curbside spaces available. All these phenomena combined may deteriorate the mobility condition of the network.

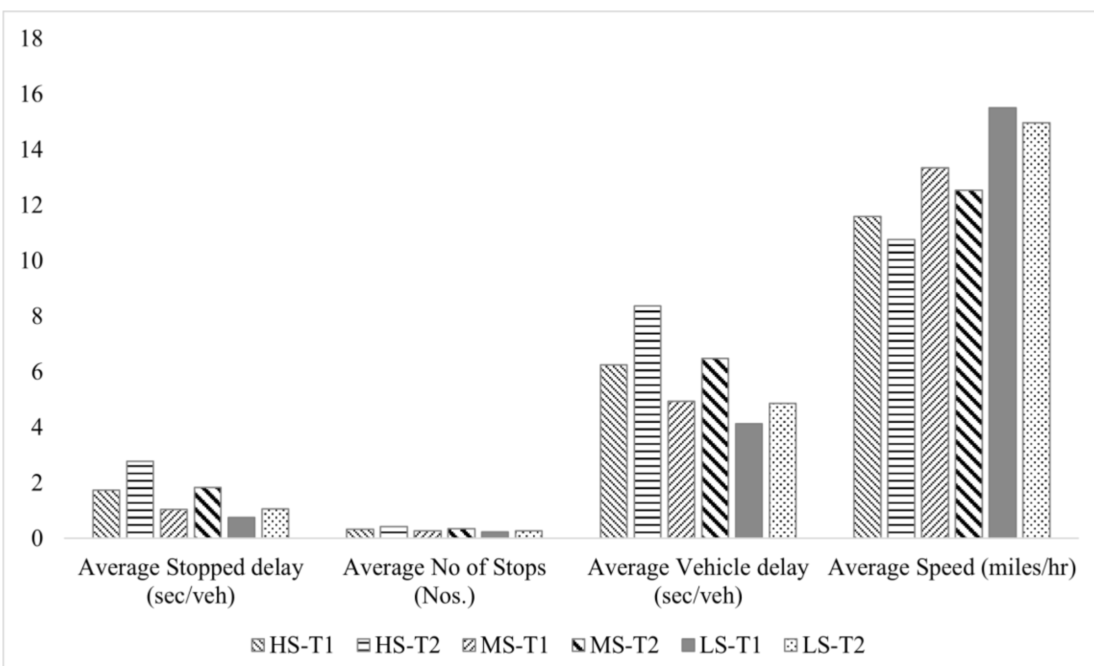
The results from Figure 3. 4(a) and Figure 3. 4(b) also indicate that, when the number of spots supplied at the road is reduced, the network performance starts improving. The difference among scenarios with HS, MS and LS (Table 1) is the number of curbside spots. The lower number of curbside spaces allow lower curbside activities interrupting less traffic. So, the network performance improves when lower curbside spaces are supplied.

Figure 3. 4 Mobility metrics (small network)

(a) Comparison of mobility metrics (three lanes)



(b) Comparison of mobility metrics (four lanes)



Chicago Network–Mobility Metrics

For the real-world Chicago network (Figure 3. 3), we report results at network and link levels for the MS and LS scenarios described in Table 3. 1 Description of experimental scenarios. The mobility metrics were compared with the base case where only private parking spaces are available.Figure 3. 5(a) shows the network level mobility metrics for the Chicago network. Our results indicate that, when compared to the base case, the network performance worsens for all scenarios. This may have been triggered by the changes in curbside activities from the base case. The base case does not represent any curbside activities except for long term parking. It is assumed that vehicles will park at the designated spaces at the start of the simulation and will remain parked for the entire simulation period. This indicates the through traffic will not be impacted in base case. However, for other scenarios, the time restricted curbside activities will interrupt more traffic. Hence, it deteriorates the network performance.

The results in Figure 3. 5(a) also show that the network performance for real-world networks is not consistent with the findings of Figure 3. 4. This may have occurred due to the complexity of the real-world network. The small network we tested only consisted of one link with no downstream signal, no changes in lane distribution or absence of bus stops. The real-world network shows these complexities which may have induced these results.

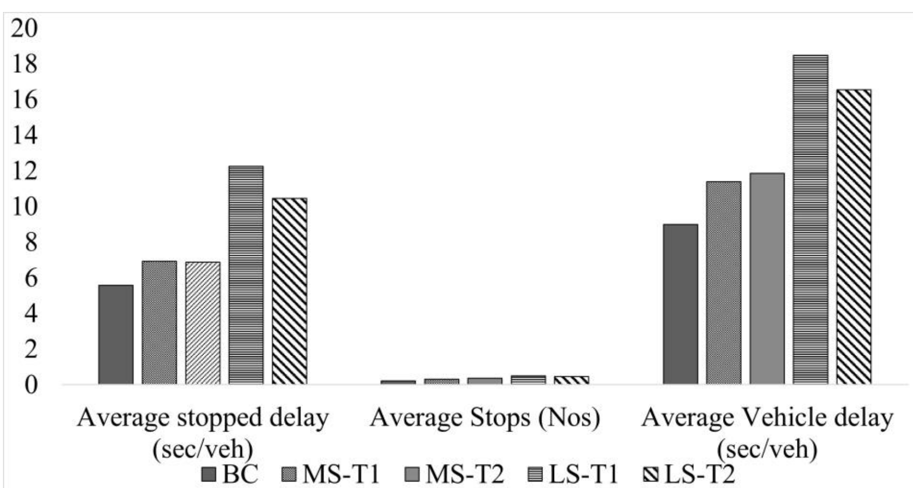
The network level results do not always reflect the link level dynamics and it is essential to investigate link level metrics alongside the network level average metrics. To understand the effects at the link level, we also report results from three different links. Figure 3. 5(b),Figure 3. 6(a) and Figure 3. 6(b) show the mobility results for link-14, link-20 and link-23. The results for individual links indicate an overall trend like the network-level results observed in Figure 3. 5(a).

When curbside activities are introduced, the network performance worsens. However, the results for the network and Link-14 follow different directions from the small network (Figure 3. 4). For this link 14 (Figure 3. 3), the lane configuration and geometric setting may be responsible for this behavior. Link-14 link has two major lanes, including an exclusive left turning lane that diverges from the mid length and signal controllers at both ends. One of the lanes is occupied with long-term parking and a bus stop leaves only one operational lane for traffic (Figure 3. 7). As a result, despite reducing curbside spaces and dwelling time, the delay increases. And when the number of spots is reduced, the link performance gets better.

For link-20 and link-23, comparison between scenario MS- T1 and MS-T2 shows consistency with the previous lane sensitivity results from Figure 3. 4. However, the direction for LS-T1 and LS-T2 was different. This can be potentially explained through the variation in lane configuration–Link-20 has four lanes (Figure 3. 8) with the curbside lane and merged to another link of 5 lanes with a signal controller downstream.

Figure 3. 5 Mobility metrics for Chicago network (Figure 3. 1)

(a) Comparison of mobility metrics (Chicago network–average over all links)



(b) Comparison of mobility metrics (Chicago network: link-14)

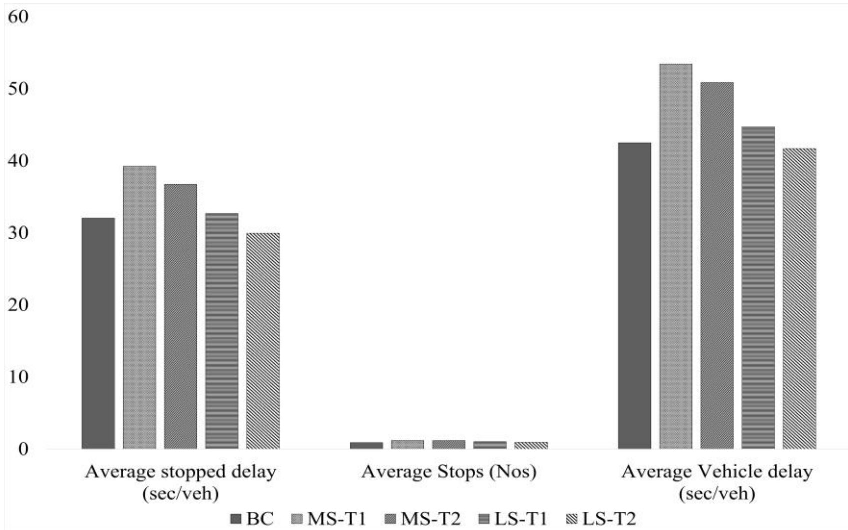
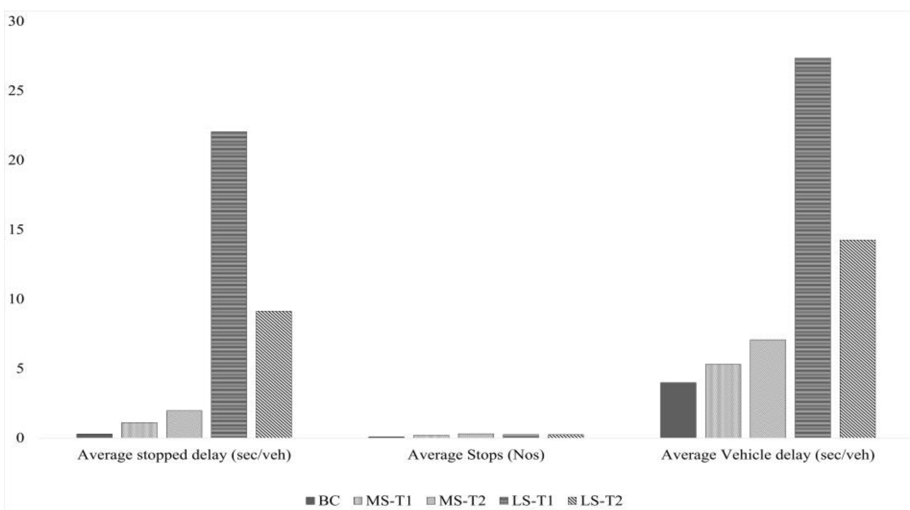


Figure 3. 6 Mobility metrics for Chicago network–Links 20 and 23

(a) Comparison of mobility metrics (Chicago network: link-20)



(b) Comparison of mobility metrics (Chicago network: link-23)

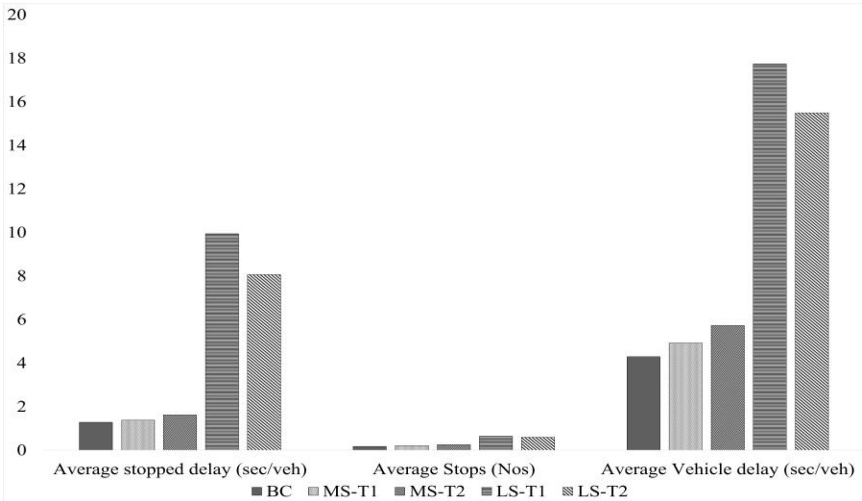


Figure 3. 7 Link-14 from real-world network: Chicago, IL

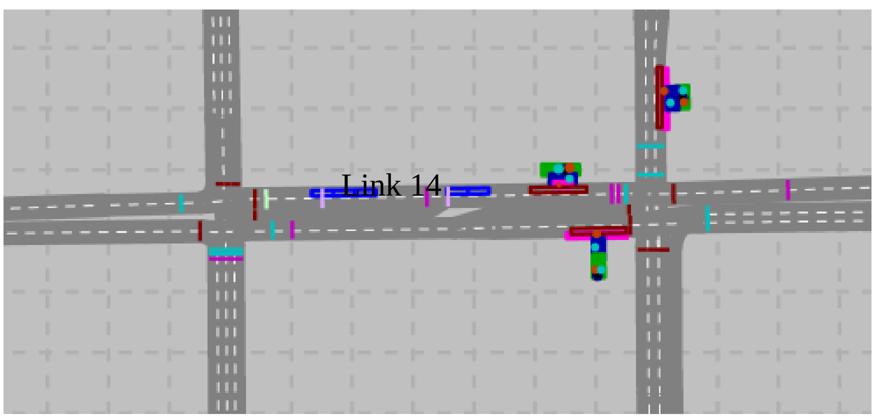
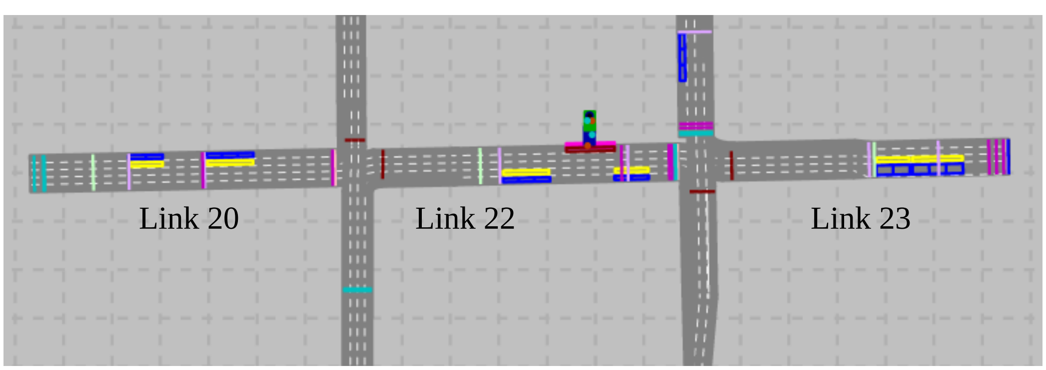


Figure 3. 8 Link-20, 22and 23 from real-world network: Chicago, IL



Results: Emissions and Energy

For environmental impacts, our reported metrics include CO2 equivalent (unit), primary exhaust PM10 (gm/hr), PM2.5 (gm/hr) total energy consumption (M.J./hr), and total fossil fuel energy consumption (M.J./hr). The pathway to environmental assessment is presented in Figure 3. 9.

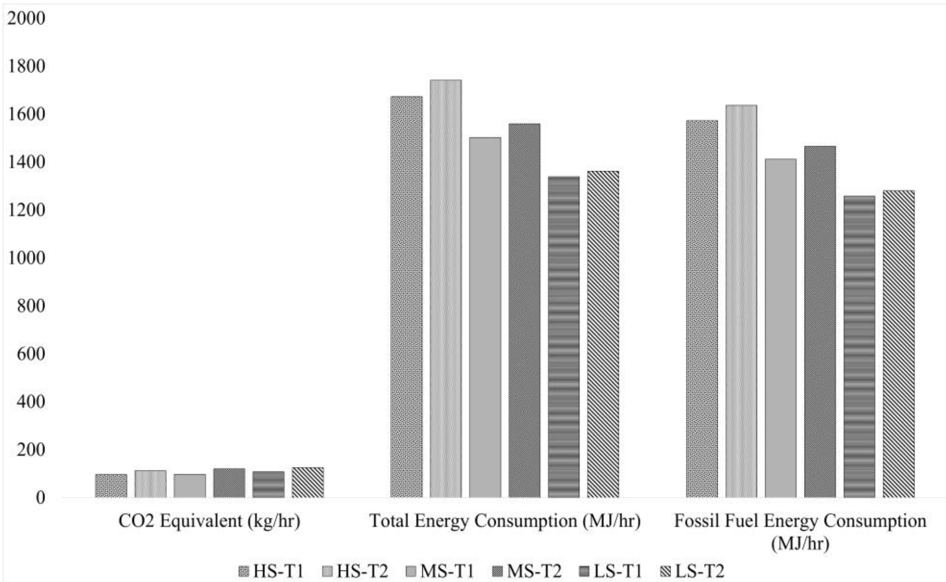
Small Network Environmental Impacts

Figure 3. 9(a) and Figure 3. 9(b) show the environmental metrics for the three and four lane roadways respectively. From Figure 3. 9(a), we can observe that, as the dwelling window becomes shorter, the GHG emissions and energy consumption increase. The energy estimation estimated by EPA-MOVES highly depends on the average link speed. As the allowed dwelling time goes down, the average speed of the network decreases below optimal (Figure 3. 4(a)) leading to more energy consumption. In addition, curbside stopping activity requiring vehicles to start and stop the engine may have contributed to GHG emissions and energy consumption.

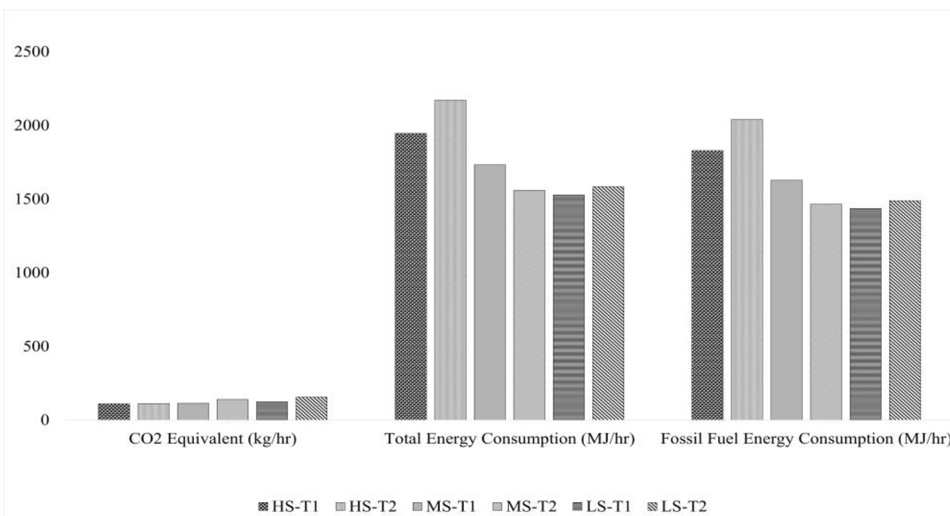
The impact of the number of spaces can also be seen in energy consumption and GHG emissions. Figure 3. 9 shows that energy follows a downward trend when the number of spaces is reduced. For a 3-lane roadway, the curbside spaces are reduced to 6 from 8 (MS-T1 to HS-T1), and the total energy consumption reduces to 1502.26 MJ/hr from 1672.92 MJ/hr (about 10.2% reduction). A similar trend is also prominent for a 4-lane roadway. As the number of spaces reduces, the disruption level by the curbside activities gets smaller. The through traffic will be able to maintain a steady speed, and there will be fewer braking phenomena. This may have contributed to the reduction of total energy consumption.

Figure 3. 9 Comparison of energy metrics (small network - Figure 3. 2)

(a) Comparison of energy metrics (small network with three lanes)



(b) Comparison of energy metrics (small network with four lanes)



Chicago network–Environmental impacts

We used EPA-MOVES to estimate the emissions and energy consumption from the Chicago network. The analysis in EPA-MOVES was conducted at link level with the link-driving-schedule as the input. Similar to the mobility results, we report the results for Link-14, Link-20, and Link-23.

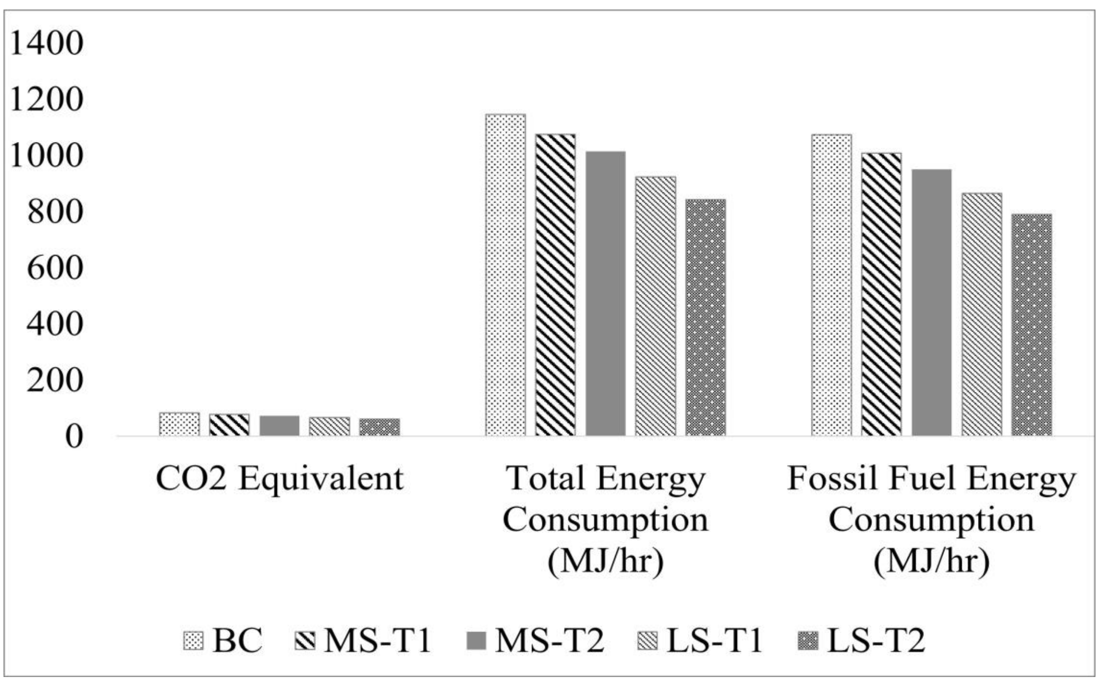
Figure 3. 10(a) and Figure 3. 10(b) show the energy and emissions metrics respectively for Link-14. Our results indicate that, when curbside long-term parking is removed from the street the overall emissions in the network reduces significantly and energy consumption becomes smaller compared with the base case. This improvement in emissions and energy can be explained by means of the improvement in speed distribution with reducing the number of curbside spaces in the streets. Figure 3. 11(a) and Figure 3. 11(b) show the speed distribution of the vehicles for the base case and scenario LS-T1 in Link-14, respectively. In the base case, we can observe that the frequency is maximum at a significantly lower speed of 0-5 km/hr, and frequency is very low at speeds higher than 20 km/hr. In scenario LS-T1, the frequency for speed ranges 0-5 km/hr reduces in scenario LS-T1 and the frequency for speeds higher than 15 km/hr increases significantly. This redistribution of speed-bins led to lower energy consumption and emissions. Several studies found that speed range 0 – 5 km/hr is associated with higher speeds (Aziz & Ukkusuri, 2012).

Figure 3. 12 and Figure 3. 13 report the energy and emissions results for Link-20 and Link-23, respectively. The results show that as restrictions are applied on the curbside space and timing, the energy consumption and emissions improve for Link-20. One of the primary reasons for the energy reduction, even though the delay went up for Link-20, might be the reduction in curbside spaces. As curbside spaces went down, the impact area of curbside activities on the passing vehicles was reduced. As a result, the link speed improved. Since link speed improvement is

directly related to energy consumption and emissions, energy consumption decreased. Link-23 has a trend like Link-20. Energy consumption and emissions keep going down as more restrictions are applied. However, Link- 20 and Link-14 showed a gradual linear decrease in energy consumption and emissions when Link-23 showed a spike in the scenario in LS-T1. While further investigating the reason behind this, we found that Link-23 has three active travel lanes with a wide lane dedicated to curbside activities. This link merges into a new link with five busy travel lanes. These changes force vehicles to slow down and reduce their operating speed. As a result, the energy consumption goes up to 1025.80 MJ/hr from 835.34 MJ/hr.

Figure 3. 10 Comparison of environmental impacts Chicago network–Link-14

(a) Comparison of energy metrics (Chicago network: link-14)



(b) Comparison of energy metrics (Chicago network: link-14)

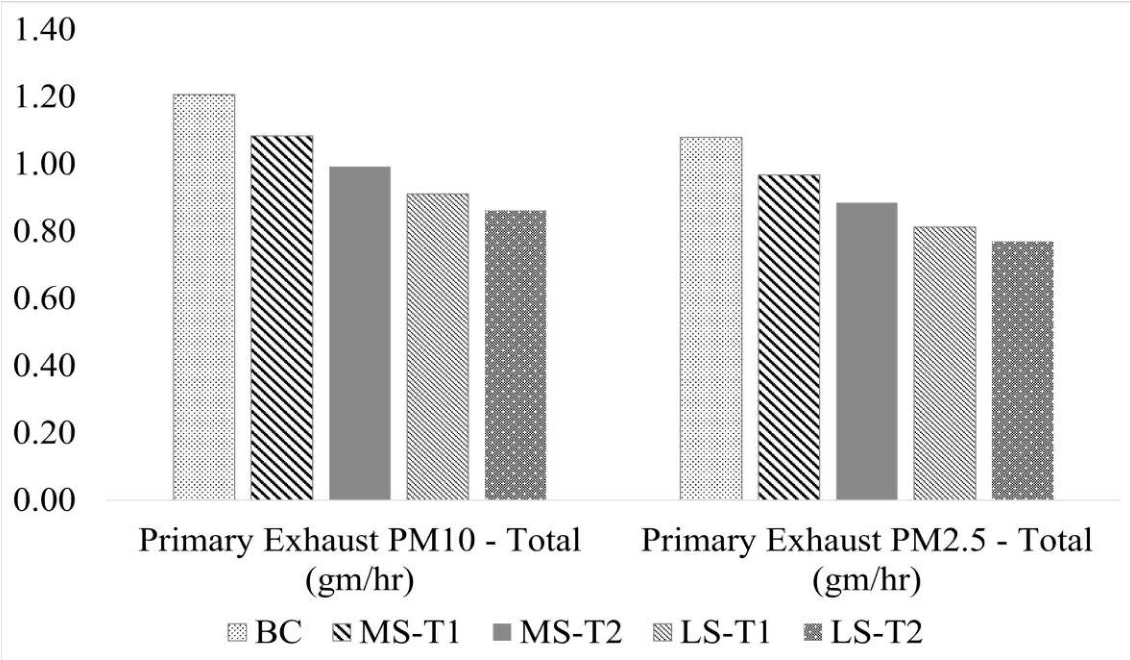
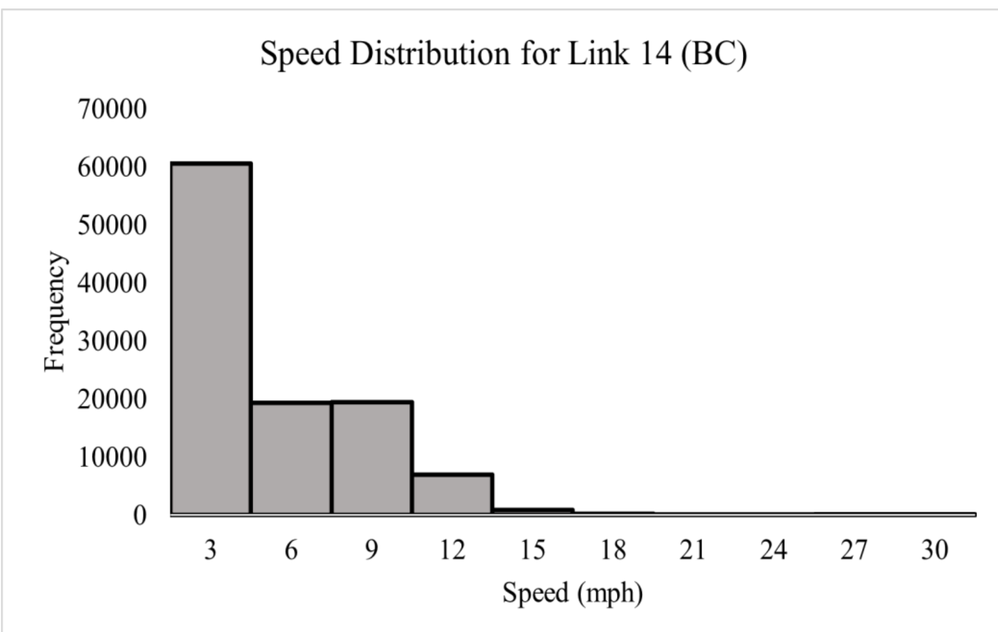


Figure 3. 11 Comparison of speed profiles Chicago network–Link-14

(a) Speed distribution (Chicago network: link-14 - Base Case)



(b) Speed distribution (Chicago network: link-14 - LS-T1)

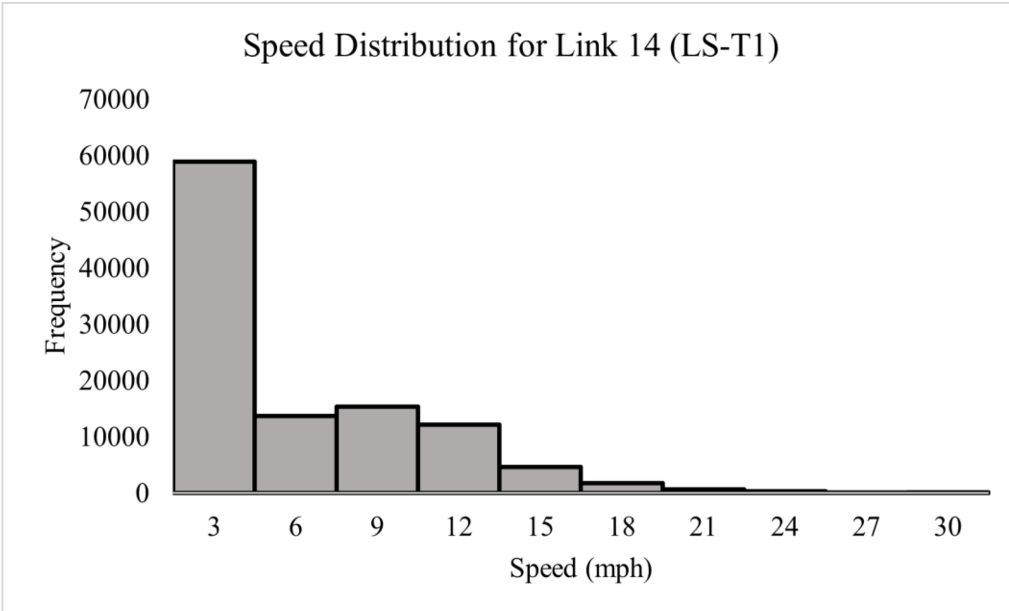
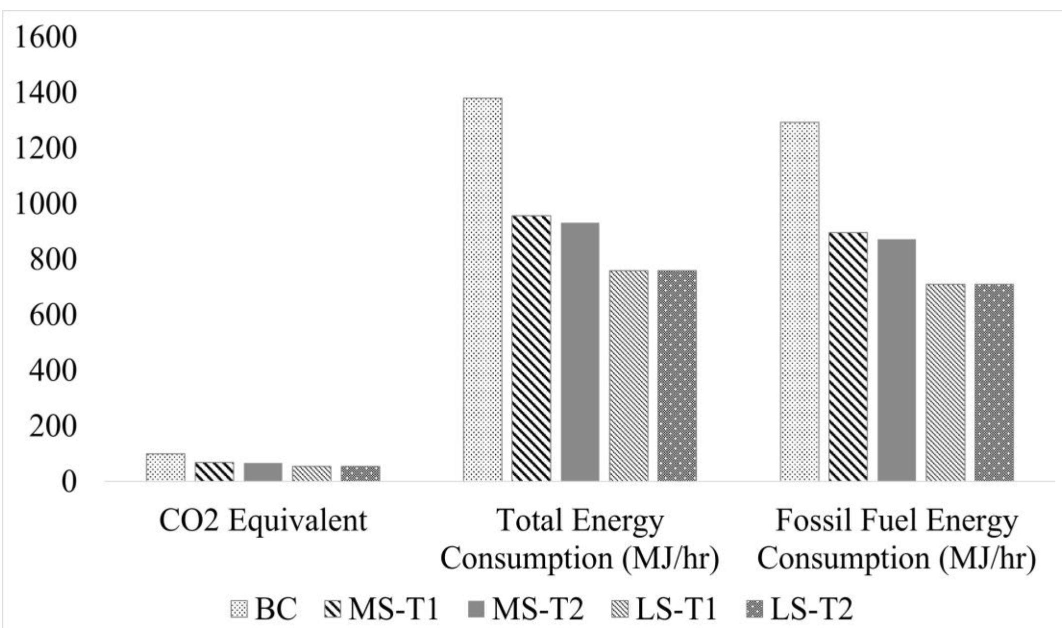


Figure 3. 12 Comparison of environmental impacts Chicago network–Link-20

(a) Comparison of energy metrics (Chicago network: link-20)



(b) Comparison of energy metrics (Chicago network: link-20)

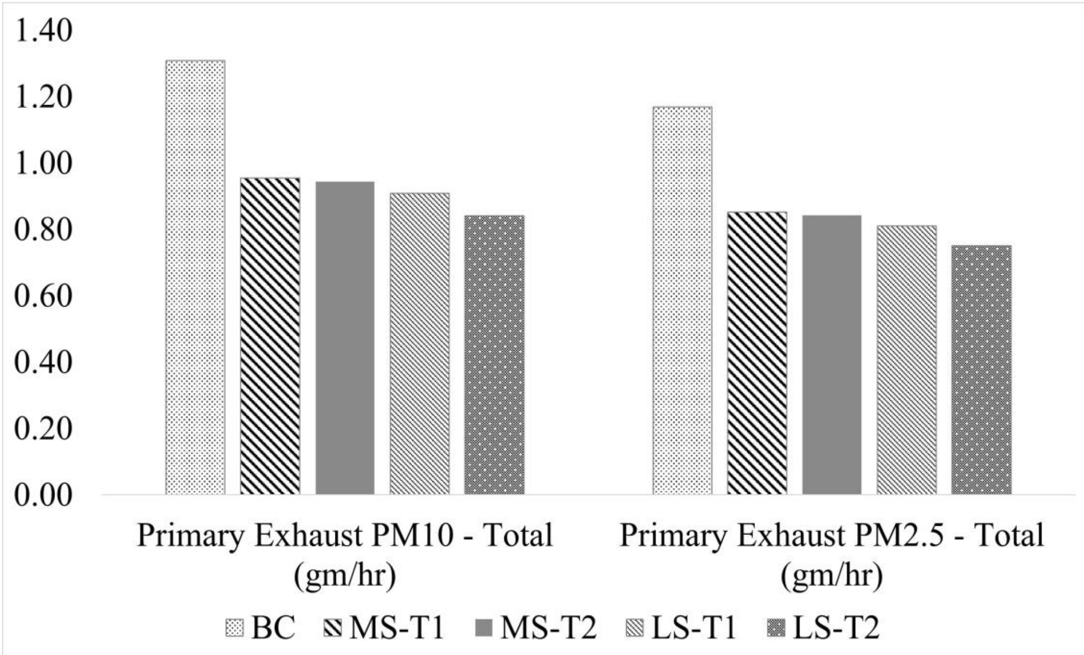
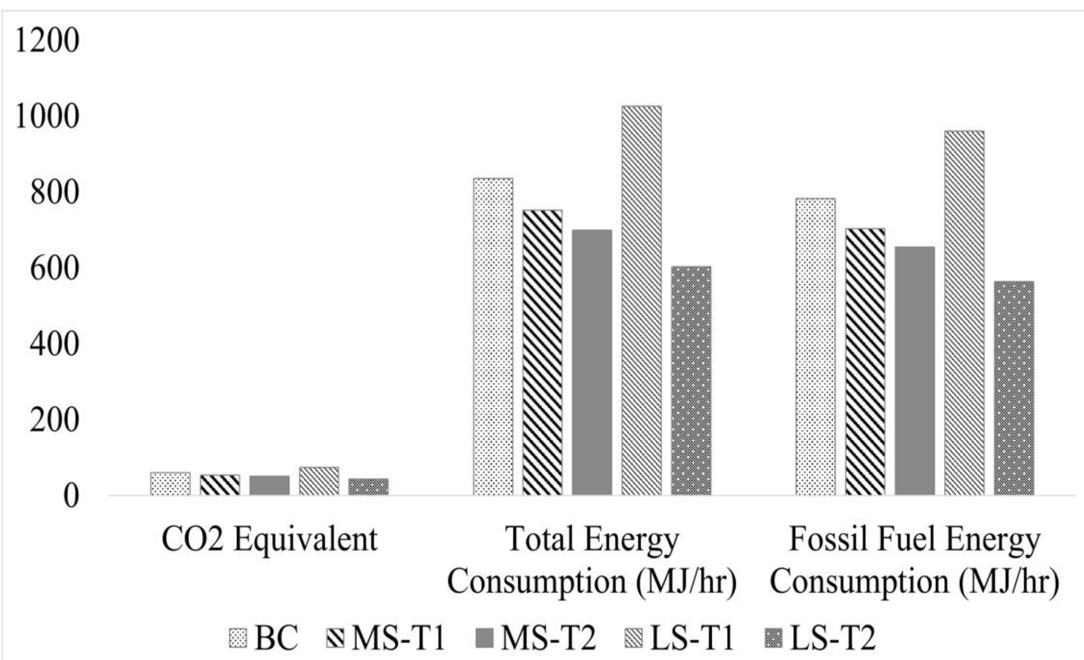
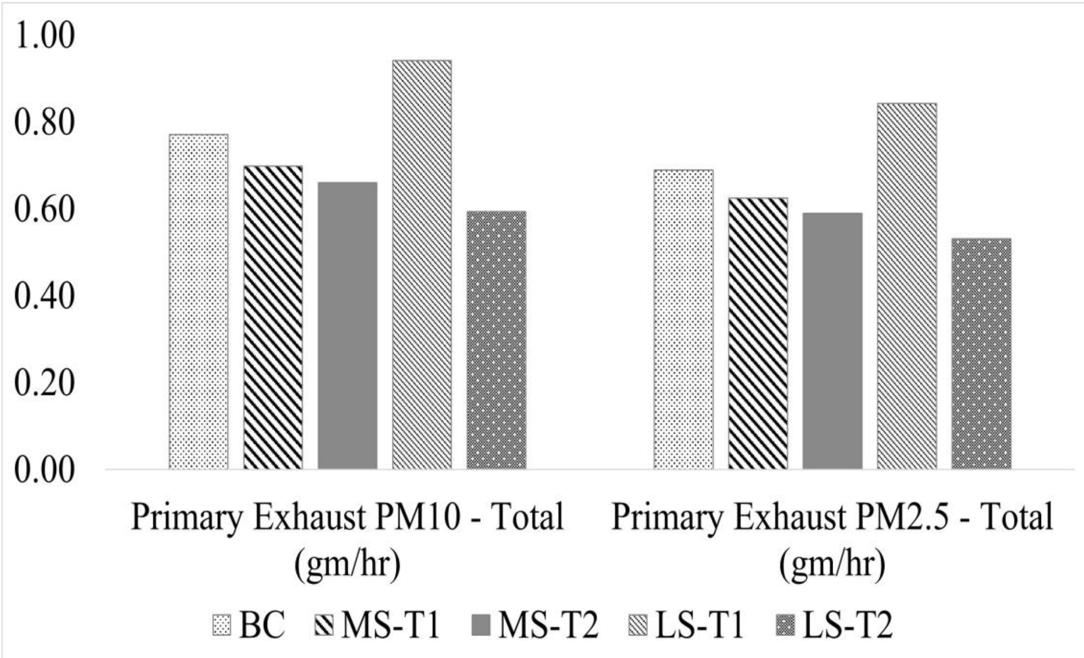


Figure 3. 13 Comparison of environmental impacts Chicago network–Link-23

(a) Comparison of energy metrics (Chicago network: link-23)



(b) Comparison of energy metrics (Chicago network: link-23)



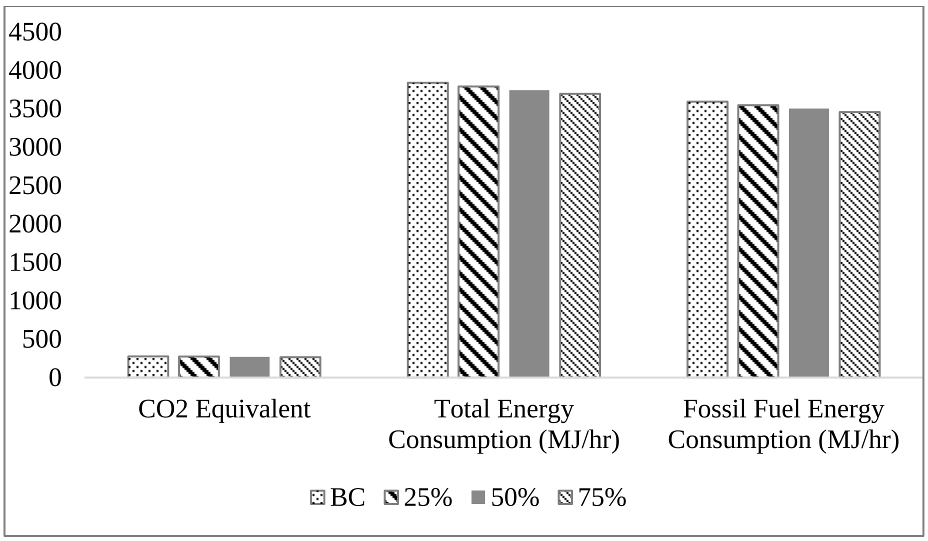
Chicago network–Environmental impacts due to electrification

To understand the effect of fleet electrification of shared-use mobility services we developed three experimental scenarios with varying electric vehicles (EV) market shares. The market share of EV near the curbside depends on the market adoption rate and the usage pattern. Modeling full-size adoption and usage patterns are not within the scope of this research. We only focus on the proportion of EVs near the curbside for specific shared-use mobility services. We assumed three market shares—25%, 50%, and 75%--of EVs replacing conventional gasoline-driven vehicles in the network near the curbside. This section only reports the MS-T1 scenario for analysis and presents results for link-14, 20, 22, and 23 (Figure 3. 14).

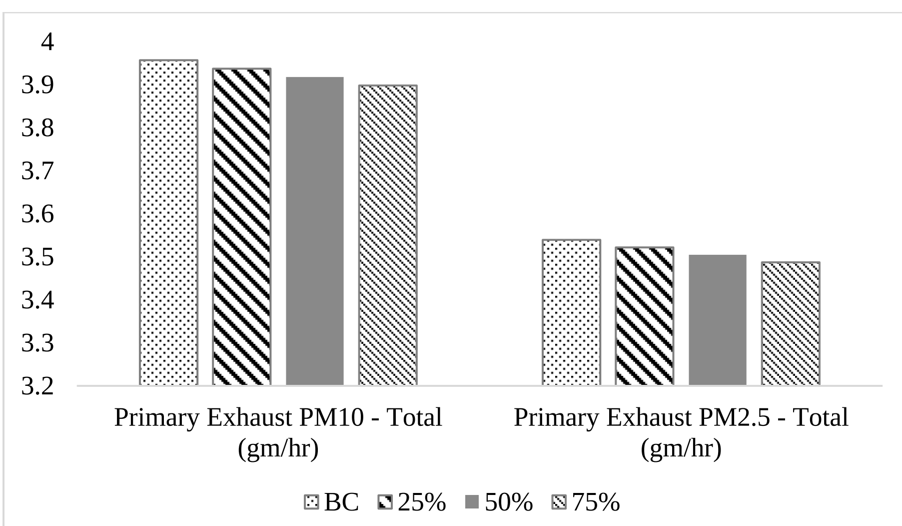
The results show that with fleet electrification, the environmental emissions and energy consumption are reduced compared to the base case. As the market share of electric vehicles increases, the emissions and energy consumption gradually decrease. Therefore, it can be inferred that while more curbside activities will have a negative effect on traffic operations, the environmental impact can be mitigated through the use of vehicle electrification.

Figure 3. 14 Comparison of environmental impacts Chicago network (levels of electrification)– Link-14

(a) Comparison of energy metrics (levels of electrification) (Chicago network: link-14)



(b) Comparison of energy metrics (levels of electrification) (Chicago network: link-14)



Curb Productivity Metrics

Since the small network only represents a hypothetical scenario without a base case, we only report the curbside productivity for the Chicago network. Table 3. 3 lists the space available for each scenario. Note that the total curbside space length is reduced from the base case in the Chicago network (Figure 3. 3). For TNC pickup-drop off and urban delivery (DL-23 delivery trucks), activities use about 6.5 m (about 22 ft) and 7.0 m (about 23 ft), respectively.

Table 3. 3 Curbside allocation for Chicago network for test scenarios

Scenarios	Number of Curbside Spaces			
	Private	TNC	Urban Delivery	Total
Base Case	40	0	0	40
MS-T1	3	12	8	23
MS-T2	3	12	8	23
LS-T1	3	8	4	15
LS-T2	3	8	4	15

To compute the curb productivity, ϑ, we estimated the total dwelling time for each type of services–private parking, PUDO, and urban delivery. The ϑ is computed using the equation (3.2) to compute the passenger based value of curbside productivity, φ.

Passenger utilization-based curb productivity

Similar to Fehr and Peers (2018), we assumed two passengers per vehicle for private parking and PUDO activities. Note that the passenger-based comparison for urban delivery may not be a sound approach because urban deliveries impact the business and local economy differently than TNC and general private parking. Table 3. 4, Table 3. 5, and Table 3. 6 report the curb productivity index for the Chicago network (for all curbside spaces) based on passenger utilization 2. A higher index, ϑ, indicates a higher utilization rate of the curbside. For the base case, we assume full utilization of the curbside space for private parking–the best-case scenario– to compare with the cases where we reallocate spaces for TNC/PUDO and urban delivery services (Table 3. 1).

The results indicate that shared-use service focused curb utilization is more productive compared to parking only use in all cases. Also, we observe the PUDO service offers higher curbside productivity than the delivery service. Although this comparison is not normalized, an economic evaluation-based comparison would be more appropriate. One approach would be to convert the economic impact of each PUDO and urban delivery service into monetary value and compare the effect for the region (curbside) of interest. Further, our results show that the shorter time window (time restriction) increases curb productivity. This will be more significant for high demand scenarios and lead to more effective curbside utilization.

Table 3. 4 Comparison of curbside productivity based on passenger-based utilization: TNC/PUDO services only

Scenarios	Total number of curbside Services	No. of Passengers served	Total Dwell Time (for all units using the curb for PUDO) (hrs)	Sum of Curb Length (ft) for allocated for TNC/PUDO	Curb Productivity Index (TNC/PUDO) (passengers per hour per 100 ft of curbside)
Base Case (Private Parking Only)	46	92	32.45	898.72	0.32
MS-T1	120	240	12.63	329.64	5.76
MS-T2	222	444	11	329.64	12.24
LS-T1	79	158	9.07	241.08	7.23
LS-T2	147	294	8.09	241.08	15.07

Table 3. 5 Comparison of Curbside productivity based on passenger-based utilization: Urban delivery services only

Scenarios	Total number of curbside Services	No. of Passengers served	Total Dwell Time (for all units using the curb for PUDO) (hrs)	Sum of Curb Length (ft) for allocated for Urban Delivery	Curb Productivity Index (Urban Delivery) (passengers per hour per 100 ft of curbside)
Base Case (Private Parking Only)	46	92	32.452	898.72	0.32
MS-T1	14	28	5.99	183.68	2.54
MS-T2	20	40	5.62	183.68	3.87
LS-T1	7	14	3.3	91.84	4.62
LS-T2	10	20	3.08	91.84	7.07

Table 3. 6 Comparison of curbside productivity based on passenger-based utilization: TNC/PUDO + urban delivery

Scenarios	Total number of curbside Services	No. of Passengers served	Total Dwell Time (for all units using the curb for PUDO) (hrs)	Sum of Curb Length (ft) for allocated for TNC/PUDO + Urban Delivery	Curb Productivity Index (TNC/PUDO + Urban Delivery) (passengers per hour per 100 ft of curbside)
Base Case (Private Parking Only)	46	92	32.452	898.72	0.32
MS-T1	134	268	18.62	513.32	2.80
MS-T2	242	484	16.62	513.32	5.67
LS-T1	86	172	12.37	332.92	4.18
LS-T2	157	314	11.17	332.92	8.44

Table 3. 7 Tradeoff between mobility and curb productivity

Scenarios	Curb Productivity Index (TNC/PUDO + Urban Delivery) (passengers per hour per 100 ft of curbside)	Average stopped delay (sec/veh)	CO2 Equivalent	Total Energy Consumption (MJ/hr)
Base Case (Private Parking Only)	0.32	35.91	359.00	4990.07
MS-T1	2.80	45.50	268.35	3729.99
MS-T2	5.67	47.45	260.70	3623.72
LS-T1	4.18	73.89	263.66	3664.67
LS-T2	8.44	66.16	232.33	3229.10

Tradeoff between Mobility and Curb Productivity

Table 3. 7 reports the tradeoff among the curb productivity, mobility, and environmental metrics averaged over four links (link-14, 20, 22, and 23) in the Chicago network. In the base case scenario, where only parking for personal vehicles is allowed, the curb productivity index is relatively low at 0.32 passengers per hour per 100 feet of curbside, with an average stopped delay of 5.57 seconds per vehicle and 0.22 stops on average. However, as we transition to scenarios MS-T1, where curbside spaces and time restrictions are implemented, we observe a significant boost in curb productivity, with the index soaring to 2.80. However, this sharp increase in curb productivity comes at the cost of increased stopped delay—about 45.50 seconds per vehicle in MS-T1.

Further, we observe reduced emissions and energy consumption for shorter time-restrictions (T1 vs. T2). Our results indicate a consistent decrease in total CO2 equivalent emissions and total energy consumption for the links as curb productivity improves. LS-T2 offers the best curb productivity with the least environmental impact. While enhancing curb productivity can boost passenger throughput and environmental benefits, it may negatively impact the mobility performance near the curbsides. Achieving optimal balance between these factors is essential for shaping effective curbside strategies.

Summary

Integrating shared-use mobility services into urban transportation systems presents a promising route for reducing carbon emissions and promoting sustainability. By offering alternatives to car-based short trips and facilitating resource-efficient practices such as ride sourcing and multiple uses of curbside spaces, these services contribute to a more environmentally friendly and equitable transportation landscape. Proactive planning and collaboration can harness the full potential of shared-use mobility to create more efficient, and inclusive urban transportation systems for the future.

We applied a simulation-based framework to assess the curbside management strategies favoring ride sourcing and delivery vehicles. Using a microsimulation platform, Vissim and EPA-MOVES, we assessed the mobility and environmental impact for different scenarios (Table 3. 1). The scenarios have been tested for two types of networks: (1) a hypothetical stretch of roadway as a small network and (2) an existing traffic network from Downtown Chicago, IL. Later, we also assessed the effect of fleet electrification of shared-use mobility services by analyzing three potential EV market share scenarios. Regarding mobility and environmental impacts, our results lead to the major findings:

- The results indicated that, as electric vehicle adoption rises, emissions and energy consumption decline, offsetting the negative traffic impact of increased curbside activities. Hence, vehicle electrification will offer a solution to mitigate environmental effects while accommodating growing urban mobility demands.
- Removing long-term parking and restricted curbside management policies can increase street congestion stress but reduce emissions and energy consumption.
- Shortening the dwelling time window for ride sourcing services will serve more vehicles. Also, when curbside activities increase, the emissions and delays become higher.
- When the number of curbside spaces is reduced, the energy consumption reduces. The post trajectory analysis shows improvements in vehicle speeds which may have contributed to the reduction of energy consumption and emissions.

- Comparing the small and complex networks showed that the results of an ideal network condition might vary for a complex network. The presence of traffic control turns, multiple interactions, and lane configurations may have led to these differences.

Further, we observed that the mobility and environmental metrics do not follow the similar link and network-level trends. The configuration of the roads–the presence of signal control, bus-bike boxes, and similar–will impact the overall congestion and resulting emissions level. More investigations are needed to develop a general correlation between network geometry and the impact of curbside impacts. We also report the curbside productivity metrics for our test scenarios. The curbside metrics can be used for the optimal allocation of activities through prioritization. The metrics in the literature are not yet robust enough to capture the economic impact of services like urban delivery or food trucks in a central business district.

Chapter 4 - Curbside Allocation Accounting for Uncertainty

Introduction

Optimization refers to the efficient use of limited resources by allocating resources to achieve the maximum benefits. It often involves finding the best solution from a set of alternatives while maximizing or minimizing specific metrics. Curbside optimization is used to allocate the limited curbside spaces to diverse SUM services (e.g., pickup and dropoff of goods and passengers, autonomous shuttles, and bike-sharing). The optimization of curbside spaces is important to achieve the maximum benefit in terms of serving passengers, curb space utilization, and economic productivity in neighboring areas. Efficient curbside management can reduce congestion from the street and reduce emissions while supporting local businesses. Even though curbside optimization is becoming a pressing need these days, the efforts with curbside optimization have been limited in the industry. The existing studies lack mathematical optimization-based methodology and solution framework (a detailed literature review can be found in Chapter 2).

Demand Uncertainty in Curbside SUM Services

The curbside demand for different SUM services varies depending on the time of day (discussed in Chapter 1 and Chapter 2). Even within a specific hour, the curbside demand can change every minute. The demand fluctuations make the curbside allocation task more challenging for the curbside managers. Curbside operations involve uncertainty in several dimensions, including total demand (e.g., 100 TNCs arriving between 7.00 – 8.00 am peak hour), arrival rate distribution (the number of vehicles arriving at 7:19 am), dwell time (PUDO time at curbside), and passenger occupancy specific to the SUM services. If we do not solve the curbside allocation problem accounting for this arrival pattern and changing demand, the curbside will operate in a suboptimal manner. Hence, it is important to develop a curbside allocation tool that accounts for the arrival pattern of SUM services.

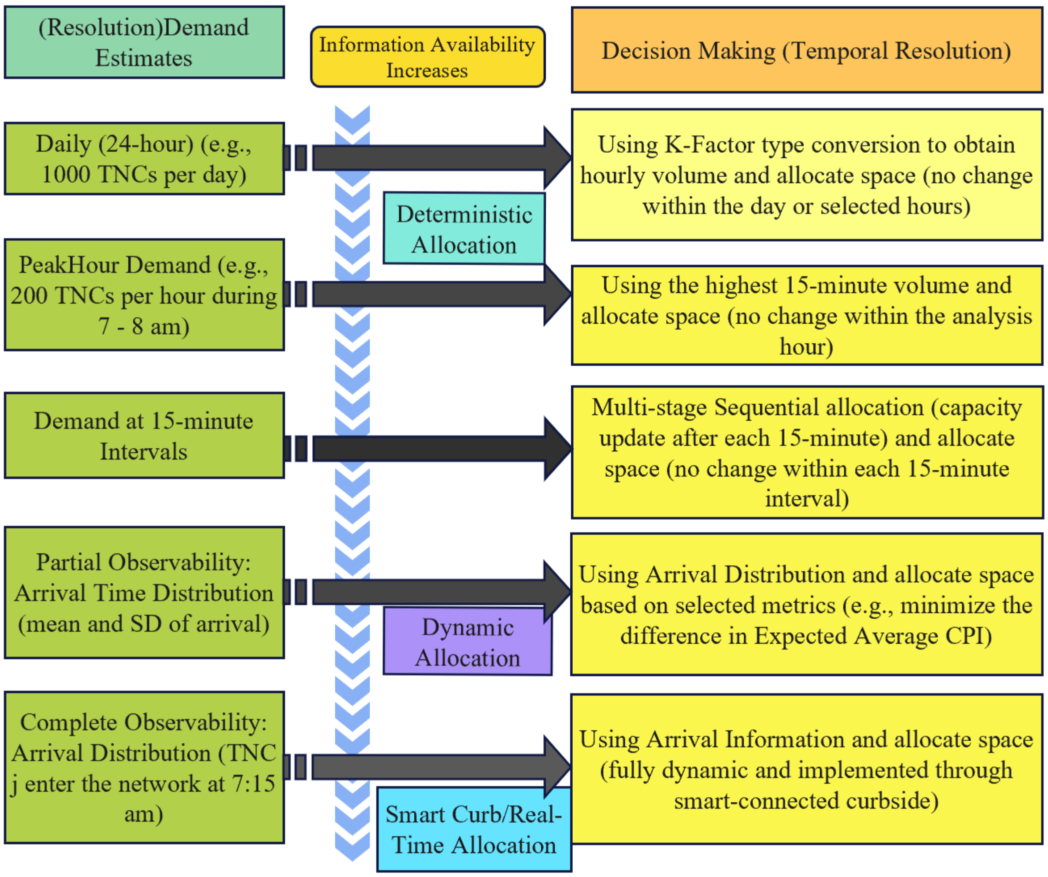
Most existing research works primarily focus on static (zero or limited temporal variation) demand, either on an hourly or daily basis, without considering the variation in the arrival patterns at a high shorter decision interval of the SUM services. Furthermore, the impact of SUM services' varying passenger occupancy and stopping (dwelling) time on the curbside allocation has not been thoroughly investigated. The limited curbside management studies in the literature do not explicitly consider the arrival pattern, dwell time, and number of passengers in an integrated manner (see Chapter 2 for relevant existing studies).

We are going to address these gaps by developing a curbside optimization module that can allocate curbside spaces in a network while capturing the variation in demand, passenger occupancy, and dwelling time for various services. After developing the mathematical formulation, we are going to test the formulation at various decision intervals. The resolution refers to the minimum decision interval at which the optimization model can produce accurate results. At the end, we are also going to discuss the practicality of the solutions.

Curbside Optimization with Multi-Resolution Decision Timeframe

Our goal is to develop an optimization-based solution with multi-resolution capability. Due to the pragmatic nature of curbside management within the context of traffic engineering, it is necessary to develop solutions that can accommodate different decision time frames. This is primarily dictated by the resolution of input data—demand and arrival distribution. The demand input generally is obtained from a regional travel demand model that estimates the daily number of SUM services to expect at certain curbside networks (e.g., a zone with four curbsides in a downtown area). Later the daily demand is converted into hourly demand—the demand during peak hours or similar. The modeling of SUM service demands is not within the scope of this dissertation and will be treated as input to the optimization-based solution presented here. How the resolution can change depending on the availability of information is presented in Figure 4. **1**.

Figure 4. 1 Resolution Depending on Information Availability



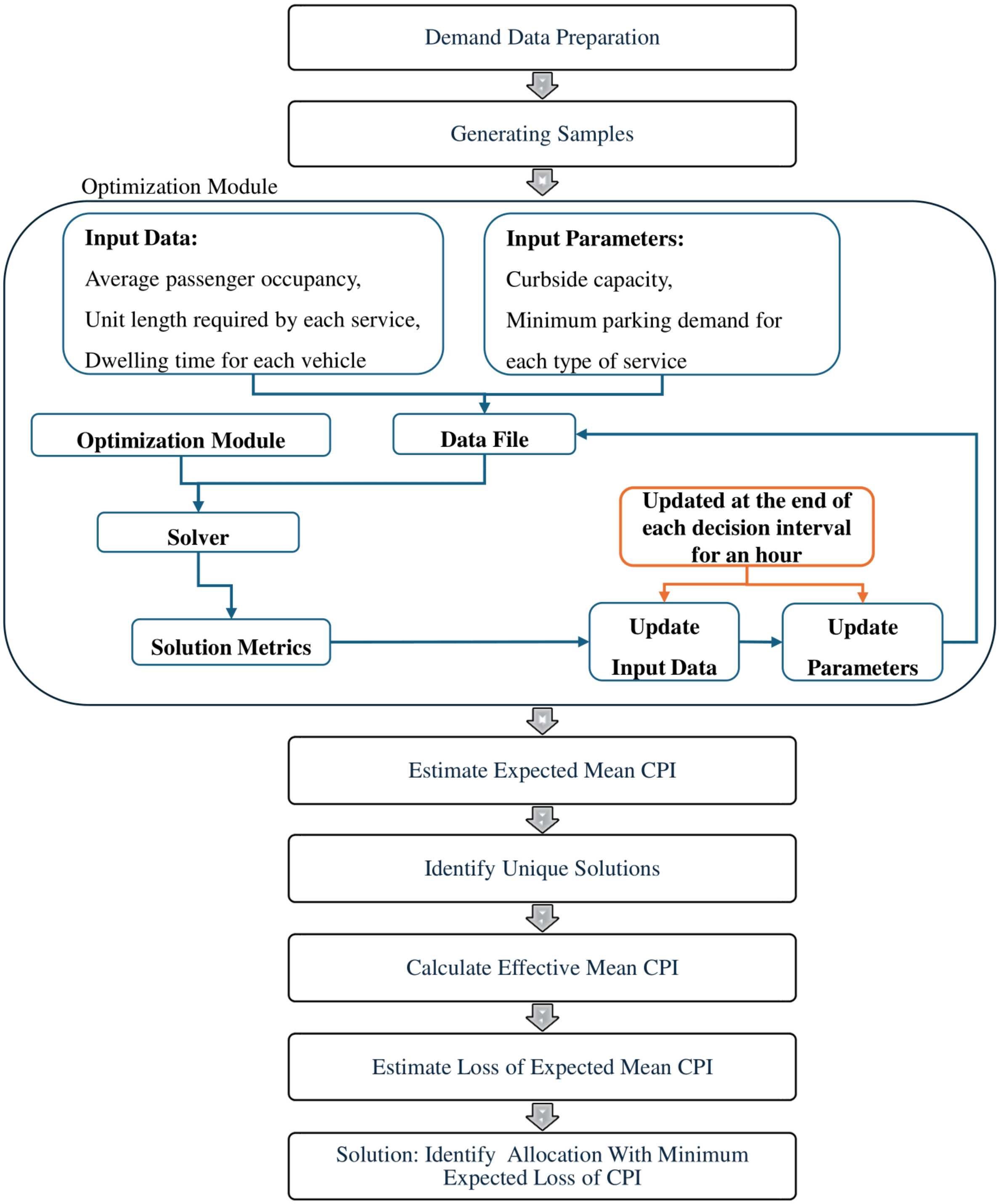
As the availability of information increases the curbside allocation can be solved at a smaller decision interval (Figure 4. 1). When there is data connectivity, the curbside can be allocated dynamically in real-time. However, when real-time information is not available, a decision maker can make decisions for an hour using a sampling heuristic based on the developed optimization model. The sampling heuristic is described later in this chapter.

Solution Framework

We developed a solution framework that can accommodate the uncertainty in demand for SUM services and allow decision-making at multiple resolutions. At the core of the solution framework, we have a base optimization model (which will be described in the next section) and an iterative process to account for the capacity update at curbsides as a function of the decision time resolution. Figure 4. 2 describes the generalized algorithm that involves mathematical program-based optimization and iterative capacity update using the solution from the previous time frame. The algorithm can be applied for any preferred time framework—either hourly or minute-by-minute. More details about the algorithm and the respective steps are provided later in the methodology section.

It is important to specify the resolution of the model, as the curbside capacity will be updated at the end of each decision interval. The resolution refers to the minimum decision time interval for the optimization model to produce accurate results. For example, the optimization input parameters can be updated and the model can be run every 15-minute to reach a single solution for an hour. Hence, the resolution becomes 15-minute for the model. For a 15-minute resolution, there will be four decision intervals within an hour. The resolution may have an impact on the allocation results.

Figure 4. 2 Generalized Framework for Curbside Allocation



The rest of this chapter is organized as follows: first, we describe the mathematical program representing the core curbside optimization problem. After that, the methodology to develop a solution based on the mathematical problem is described. In the last section, we have illustrated two examples, ***Example A: Allocation for a Curbside Network*** and ***Example B: Impact of Resolutions.*** The first example shows how to use the developed mathematical model to reach a solution, while the second example describes the impacts of resolution on the results.

Methodology

Curbside Optimization with *knapsack* Constraint

The curbside optimization can be formulated as an Integer Linear Programming (ILP) problem with a *knapsack* constraint. An ILP involves optimizing a linear objective function with integer decision variables representing the allocation of spaces at curbsides for different services. The *knapsack* constraint ensures that the combination of total allocated spaces for different services does not exceed the available capacity of the curbside, while the objective function aims to maximize some linear quantity, such as the Curb Productivity Index (Fehr & Peers, 2019).

Accordingly, we developed our curbside optimization framework based on the *knapsack* problem (Chu and Beasley 1998). It is written as an ILP with *knapsack* constraints for optimizing the curbside spaces. This mathematical program is developed using AMPL (A Mathematical Programming Language) (AMPL). This process entails defining decision variables, formulating an objective function to maximize or minimize, and specifying constraints that reflect real-world limitations or requirements. The ILP program is then solved using the IBM CPLEX (version 22.1.1) solver through (AMPL) development environment to find the optimal solution.

Mathematical Program

The optimization model determines the allocation for a combination of different services (predefined demand) in a network of curbsides to maximize the passenger-based utilization—the cumulative CPI for the network. We assume that there are $|K|$ curbside locations in the network under consideration, and the set of curbsides is represented as $K = \{1,2,3, \ldots\ldots k, \ldots. |K|\}$. Each curbside location, $k \in K$, had a specific capacity which is denoted by C_k. The capacity of each curbside location C_k, is measured in total available length for that curbside. Within an analysis period, J vehicles seeking spaces at the curbside enters the network, where $J = \{1, 2, \ldots., j, \ldots., |J|\}$. $j \in J$ represents unique vehicle labels. Each vehicle $j \in J$ belongs to a particular curbside activity $i \in I$. Curbside service activities are denoted by an integer $i \in I$ where $I = \{1, 2, \ldots., i, \ldots., |I|\}$, and unique values of $i \in I$ represents a specific type of curbside activity. For example, $i = 1$ indicates TNC pickup and drop off activities, $i = 2$ denotes urban pickup and drop-off activities etc. Hence, values $j\ and\ i$ combined represents the type and service category of a vehicle entering the network.

We have defined a variable x_{ij}^k that indicates if a vehicle $j \in J$ from service $i \in I$ has been assigned to curbside $k \in K$. It is a binary variable that takes on to the value of 1, when a vehicle $j \in J$ from service $i \in I$ is assigned to curbside $k \in K$. It takes on the value of 0, when a vehicle is not assigned to a particular curbside. The objective function maximizes the curb productivity index which is determined by the number of passengers served by unit length of curbside space per hour. It is a function of number of passengers P_i, the dwelling time T_i and the unit length of the curbside space l_i required for each vehicle $j \in J$ from service $i \in I$. For deterministic optimization model, we had assumed the total number of passengers served P_i by each vehicle does not changes across vehicles $j \in J$ within a certain service category $i \in I$. The dwelling time

T_i is measured in hours for this problem and like P_i it also does not change across every vehicle $j \in J$ within a certain service category $i \in I$. Hence, T_i and P_i are service-specific constants for all vehicles belonging to service type i. The dwell time may vary for different services depending on the time of day. For example, for TNCs dwell time is 1 to 2 minutes while for urban delivery vehicle it is 20 to 30 minutes during the peak hour. We will not be considering the dwell time variation based on the time of day in our experimental settings. We will consider only the dwell time for different services for the analysis hour. The service-specific dwell time will be used as an input parameter to the optimization model. The curbside length l_i required by each vehicle $j \in J$ within a certain curbside service category $i \in I$ also varied within each curbside service category $i \in I$. Table 4. 1 describes the notations used for the formulation. P_i, T_i and l_i are constant for each type of service for the deterministic optimization problem. The above-discussed parameters are shown in Figure 4. 3.

Figure 4. 3 Hypothetical network for curbside allocation

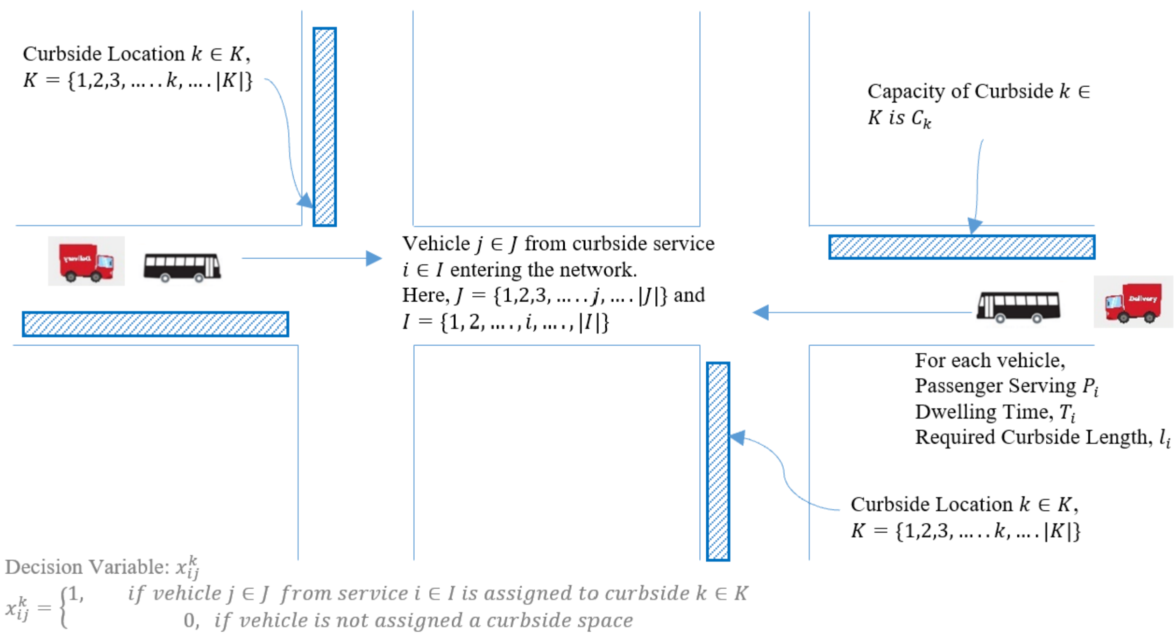


Table 4. 1 Definition of sets, decision variables, and parameters

Set	Description
$I = \{1, 2, \dots, i, \dots, \lvert I \rvert\}$	Set of curbside services
$J = \{1, 2, \dots, j, \dots, \lvert J \rvert\}$	Set of parking seeking vehicles from each service $i \in I$
$K = \{1,2,3, \dots k, \dots \lvert K \rvert\}$	Set of curbside locations, $k \in K$
Variable	**Description**
x_{ij}^{k}	Binary decision variable which indicates if vehicle $j \in J$ from service $i \in I$ has been assigned to curbside $k \in K$
Parameter	**Description**
P_i	Average number of passengers served by each service $i \in I$ at curbside.
l_i	Unit length of a curbside space required for a vehicle from a specific type of service $i \in I$ at curbside.
T_i	Dwell time duration for a particular service $i \in I$. For example, for TNCs dwell time is 1 to 2 minutes while for urban delivery vehicles, it is 20 to 30 minutes. Dwell time varies for different services depending on the time of day. This parameter is flexible but initially, we are going to use this parameter for an hour.
C_k	The capacity of each curbside location $k \in K$, measured in total available length for that curbside.
$D_{min,i}^{k}$	Minimum demand that should be met for a specific service $i \in I$ at curbside location $k \in K$.

<u>Objective function:</u> The objective is to maximize the curbside productivity index (CPI).

$$Max \sum_{i=1}^{|I|} \sum_{j=1}^{|J|} \sum_{k=1}^{|K|} \frac{P_i}{T_i * l_i} * x_{ij}^{k} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \quad (4.1)$$

Constraints

Constraint 1- Curbside Capacity Constraint: For a particular curbside $k \in K$, sum of the length occupied by the number of vehicles assigned does not exceed its total available capacity (C_k). The capacity of a curbside $k \in K$ is represented by its total available length C_k. This constraint addresses the capacity of individual curbside as well as the curbside network.

$$\sum_{i=1}^{|I|} \sum_{j=1}^{|J|} l_i * x_{ij}^k \leq C_k, \qquad \forall k \epsilon K \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots .. (4.2)$$

Constraint 2- Single Vehicle Selection Constraint: When a vehicle enters the network to look for a curbside space the optimization tool will assign it a space. One vehicle cannot be assigned to more than one space during the allocation. Hence, when vehicles are being assigned a curbside space, each vehicle is selected at most once.

$$\sum_{k=1}^{|K|} x_{ij}^k \leq 1, \qquad \forall i \epsilon I, \forall j \epsilon J \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots .. (4.3)$$

Constraint 3- Minimum Demand Constraint: To ensure that each type of service activities at the curbside a minimum demand criterion has been set to the optimization model. For example, if we set the minimum spaces to be allocated to urban delivery vehicles to two, at least two spaces will always be assigned to the urban delivery vehicles. Total assigned vehicles for a particular service $i \epsilon I$ at all curbsides $|K|$ must satisfy the minimum demand for that service. For example, a minimum of two spaces should be allocated for urban delivery.

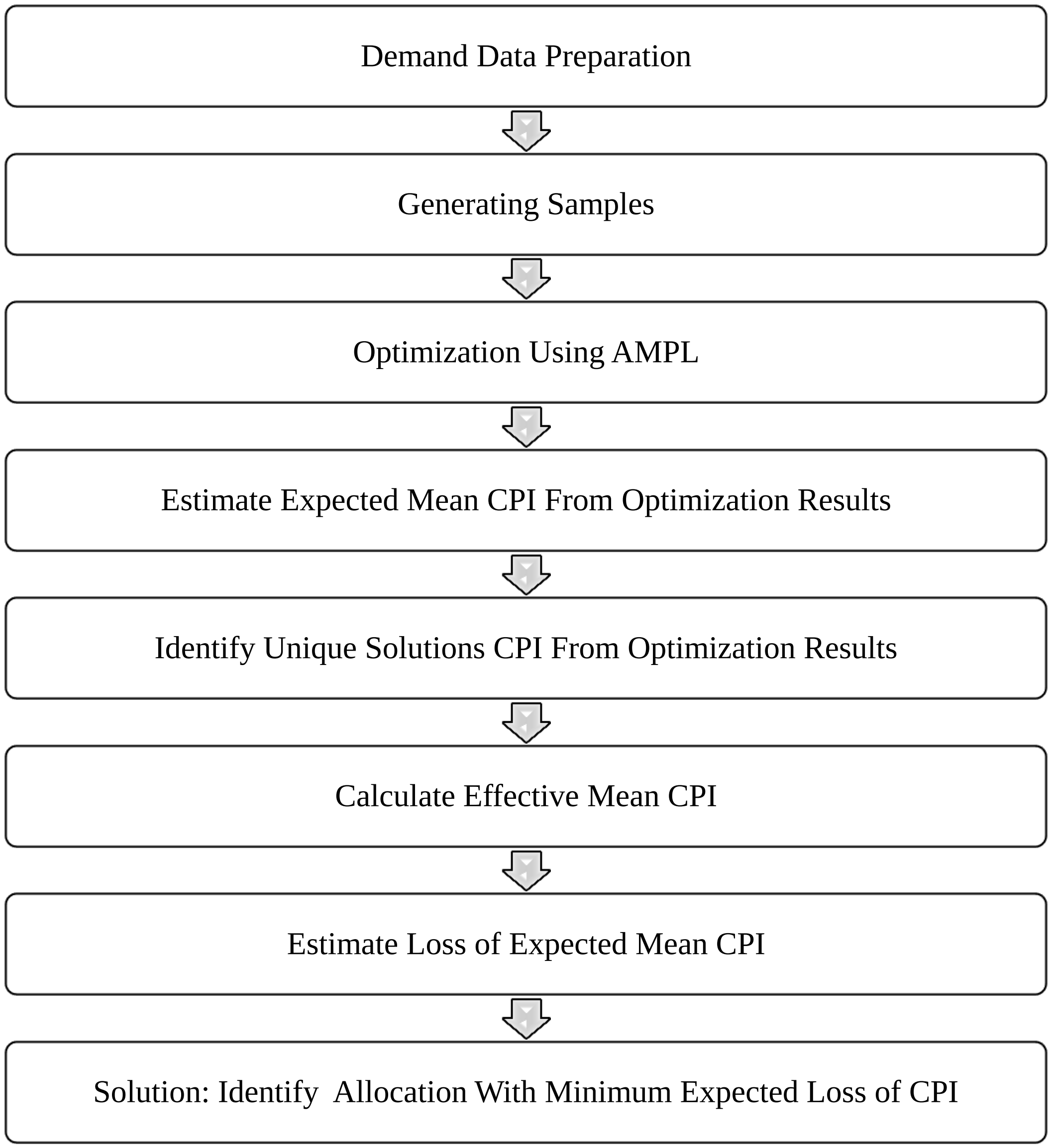
$$\sum_{j=1}^{|J|} \sum_{k=1}^{|K|} x_{ij}^k \geq D_{min,i}, \qquad \forall i \epsilon I \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots .. (4.4)$$

Solution Technique: Sampling Heuristic

The developed optimization model can address the sources of uncertainty (curbside demand, passenger occupancy, and dwell time). We are going to address the uncertainty of demand in this research. To account for the uncertainty, the optimization model was kept unchanged except for the minimum demand constraint (equation 4.4). The minimum demand constraint was relaxed for the stochastic demand as the demand for a service with a larger decision interval could be zero. Allocating space for a service without demand for it might result in underutilization of the curbside. We also modified the curbside capacity in the input data to reflect the multiple use of spaces during a decision interval.

In the next few subsections, we described the methodology for optimizing the model for stochastic demand by preparing the demand data, updating parameters, and selecting a single allocation solution using a sampling-based decision heuristic. The sampling-based decision heuristic is a technique to make decisions based on samples taken from a probability distribution. This technique has been used to avoid the exhaustive evaluation process of all probable solutions during optimization. The solution framework is shown in Figure 4. **4**. Each step of this framework is described in the following sections.

Figure 4. 4 Sampling Heuristic-based Decision Framework



Demand Data Preparation

In this research, we are going to address the uncertainty of demand only. Hence, the dwell time (0.5 minutes for TNCs and 1 minute for shuttles in the example) and occupancy (2 people for TNCs and 7 people for shuttles in the example) for different services tested across different scenarios were kept constant during optimization. It is important to represent the demand in a coherent manner during data preparation. The curbside demand data can be generated upon the availability of local data (Pochowski et al. 2022). Pochowski et al. (2022) mentioned the following list of data sources that if available, could be used to generate curbside demand using a regression model.

- Block-level census data including median age, median income, percent of the population with a bachelor's degree or higher, and population density.
- Socio-economic data including population, industrial employment, retail employment, office employment, and other employment.
- Ride sourcing and pickup and drop off (PUDO) data.

For our case, we are assuming the demand data is available to the curbside managers through an external demand estimation model and the hourly service-specific demand is known. The input data for the optimization model was generated for an hourly volume of curbside demand. We are assuming n number of vehicles for different services i will be entering the curbside network within the morning peak hour (assuming 7.00 AM to 8.00 AM). The headway of vehicles arriving at the curbside is not constant due to its stochastic nature. Hence, the vehicle's arrival times are not known. It is possible to model the vehicle arrival process within a time interval following Poisson distribution. However, in our case, the arrival time of each vehicle will impact the curbside capacity directly. Hence, we are modeling the arrival time of the vehicles as a random variable that will have a probability distribution (with specified mean and standard deviation) instead of modeling the arrival process.

For n number of vehicles from services i arriving at the curbside network with k curbside locations during peak hour, the arrival time has been modeled as a truncated normal distribution (arrival time was modeled between 0 to 60 minutes). A value of mean and standard deviation has been used to produce multiple samples (33 samples) of a distribution. Each probability distribution will represent a specific demand scenario of a curbside demand. We have developed an example with four demand scenarios for four different probability distributions which are discussed in a later section Implementation and Results from Test Networks.

Optimization using AMPL

Once the input demands data and resolution for the optimization is selected, the next step is to prepare the necessary data files for optimization. Depending on the resolution, AMPL input data files have been generated for each demand scenario for every decision interval followed by running the optimization module in AMPL. After running the optimization model for each decision interval, the curbside capacity has been updated to reflect the available capacity of the curbside. A Python module has been used to generate input data files, run AMPL, store allocation results and CPIs, and update parameters (curbside capacity) seamlessly for each decision interval.

Updating Curbside Capacity

For a specific demand scenario, the curbside capacity does not remain the same during each decision interval. The curbside capacity is updated at the end of each decision interval for any resolution. The effective curbside capacity refers to the minimum number of times a curbside can be used by the vehicles during a decision interval. It depends on the number of available spaces at the curbside and the dwelling time of the vehicles. For example, if a decision interval is 5-minute and the maximum dwell time for services arriving at the curbside is 1 minute, then the minimum capacity of one single curbside space is 5. If the curbside network has 8 spaces, the total capacity of the curbside is 40 vehicles for a 5-minute decision interval. However, if one space is occupied by a service in the first minute of the decision interval, the effective capacity of that curbside space becomes 4 for a 5-minute decision interval. The total capacity for the curbside network becomes 39 ($40 - 1$) vehicles for that decision interval. The curbside capacity was updated as the effective capacity at the end of each decision interval during the optimization process. For different decision intervals, the minimum capacity for the curbside network consisting of four curbsides (considering the maximum dwell time is 1 minute), each having two spaces, is shown in Table 4. 2.

Table 4. 2 Curbside Capacity for Different Resolution

Time Resolution	Curbside Capacity for a Decision Interval (No. of Vehicles)
1-minute	$4 * 2 * 1 = 8$
5-minute	$4 * 2 * 5 = 40$
10-minute	$4 * 2 * 10 = 80$
15-minute	$4 * 2 * 15 = 120$
60-minute	$4 * 2 * 60 = 480$

Hourly CPI and Expected Mean CPI

The optimization model estimated the CPIs for each decision interval of an hour for every sample from a demand scenario. The summation of the CPIs for all decision intervals of an hour represents the hourly CPI values for a sample. For example, if optimization is being done at a 5-minute resolution, there will be 12 decision intervals. There will be 12 values of CPIs for each sample within an hour. Adding the 12 CPIs together will result in the hourly CPI for the analysis hour for one sample. If there are m decision intervals for an hour then the hourly CPI can be expressed as,

$$Hourly\ CPI = \sum_{r=1}^{m} CPI_r \dots\dots\dots\dots\dots (4.5)$$

According to the law of large numbers, the mean of a larger sample represents the population mean. For n number of samples (n is a larger number) for each demand scenario, the hourly CPIs can be denoted by $CPI_1, CPI_2, \dots CPI_n$. Then the expected mean CPI will be,

$$E[\overline{CPI}] = \frac{1}{n}\sum_{p=1}^{n} CPI_p \dots\dots\dots\dots\dots (4.6)$$

Unique Allocation combinations

Depending on the resolution, the optimization model will return the best allocation combinations for each decision interval. Allocation for a decision interval is highly dependent on the service demand for that interval. Hence, the allocation changes as the service demand changes across decision intervals. If n samples are drawn from a population, and the analysis hour is split into m decision intervals, then the optimization model will generate $n * m$ solutions. These solutions can be unique or repetitive. Based on the optimization, these solutions will produce the maximum CPI for their respective decision intervals. Since in the real world, it will be challenging to change the curbside allocation at small intervals, it is important to reach a single solution for implementation for a larger time horizon. To find the best solution from the optimization results, we identified the unique solutions from the optimization results for each demand scenario for further assessment.

Estimating Mean Effective CPI

The hourly CPI found from the optimization model represents the maximum CPI achievable for a sample from a specific demand scenario when the allocation will be changed at every decision interval. The hourly CPI obtained based on the dynamic allocation from the optimization model will not remain effective if a single allocation is fixed for the entire hour. Hence, depending on the hourly service demand variation (each sample), the hourly CPI will be different when a single allocation is fixed for the entire hour, and that CPI is denoted as an effective hourly CPI for an hour. We intend to estimate the effective hourly CPI for each allocation as we identify the unique solutions for each demand scenario. Hence, for each unique allocation, an effective hourly CPI was calculated for all samples from a single demand scenario. Following equation 4.6, the mean effective CPI was calculated. A Python module was used to calculate the effective CPIs and mean effective CPI. Theoretically, the mean effective CPI for a single allocation will be less than the Expected Mean CPI. This is because the single allocation is not the optimum allocation for all decision intervals.

Selection of Allocation at Hourly Level

To decide which allocation is the best allocation for an hour, <u>we selected the allocation that have maximum mean effective CPI.</u> We also computed the difference between the expected mean CPI and the allocation-specific effective mean effective CPI for each allocation for a specific demand scenario. The difference is defined as the Loss of Expected Mean CPI. Since expected mean CPI is a constant value for a given demand scenario, this is equivalent to choosing the allocation with the maximum mean effective CPI. The loss has been computed for all possible allocations. Using a spreadsheet, a manual search has been conducted to find out the allocation that has the maximum mean effective CPI. This allocation has been defined as the best solution for the problem.

$$Loss\ of\ Expected\ Mean\ CPI\ =\ Expected\ Mean\ CPI - Mean\ Effective\ CPI \ldots\ldots\ldots\ldots\ldots\ldots (4.7)$$

Implementation and Results from Test Networks

This section reports the computational processes for curbside allocation on a test network using the sampling heuristic-based decision technique. First, we describe ***Example A: Allocation for a Curbside Network***. For this example, we have considered a resolution of 1-minute. The underlying assumption is that when curbside managers have real-time demand available, the curbside can be allocated in real-time. However, when enough information is not available to the curbside managers, the algorithm provided in Figure 4. 2 can be used to reach an hourly solution.

Though we are using a 1-minute resolution, the curbside problem can be solved at a larger decision interval than a 1-minute (5-minute, 10-minute, 15-minute, 30-minute, or 1-hour). In the Curbside Optimization with Multi-Resolution Decision Timeframe section, we have discussed the impact of resolution on the optimization model results. Later in this section, we developed an example (***Example B: Impact of Resolutions***) to test the sensitivity of the results at different resolutions. The results of this example will provide us with insights into how the allocation results and CPI might change depending on resolutions.

Experimental Setup

For developing the examples, we have considered a simple curbside network consisting of four curbside locations like Figure 4. 3. We are assuming that each curbside location has two available spaces that will be serving the SUM services. The length of each curbside space is 23ft (7m). We are also assuming 240 TNCs and 30 shuttles will be arriving at the curbside during the morning peak hour (7.00 AM-8.00 AM). We are assuming that the TNCs will stop at the curbside for 0.5 minutes and the shuttles will stop at the curbside for 1 minute to complete their services. The dwelling time was kept constant for each service in these examples. The length of curbside space required by each service from TNC and shuttles is 23 ft. We are also assuming that the demand will be loaded into the network at the beginning of each decision interval. Based on this setup we have developed the following examples. The capacity will be updated at the end of each decision interval. A fixed value of passengers was considered for each type of service in this example (2 for TNCs and 7 for shuttles). The experiment setup for these examples is provided in Table 4. 3.

Table 4. 3 Experimental Setup

Curbside Location	No. of Spaces at Each Location	Services	Hourly Service Demand (vehicles)	Service Dwell Time	Service Occupancy (No. of Passengers)
4	2	TNC, Shuttle	TNC = 240, Shuttle = 30	TNC: 0.5 minute, Shuttle: 1 minute	TNC: 7, Shuttle: 2

Example A: Allocation for a Curbside Network

In this example, we are assuming that there are four curbside locations (Figure 4. 3) in a curbside network. At each curbside location, there are two curbside spaces available. Since CPI metrics use the number of passengers served to compute the curbside productivity, we have considered two passenger-carrying services TNC and shuttles to allocate curbside spaces among them during the morning peak hour (7.00 AM -8.00 AM). The procedure to develop an hourly solution for the space allocation is described below.

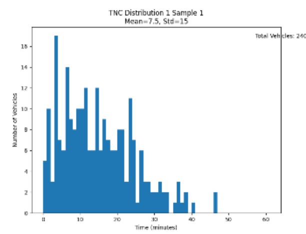
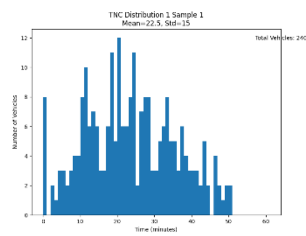
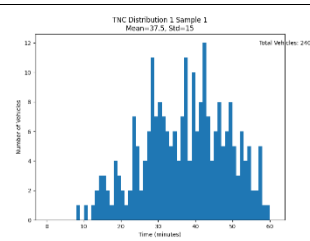
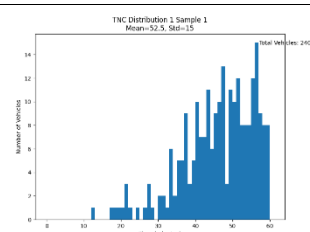
Demand Scenarios

We wanted to address different congestion patterns for a network within the same hour. Congestion patterns reflect when the network will experience a surge in curbside demand. The curbside demand will not be uniform throughout the entire hour. We are assuming the peak demand will occur within a 15-minute window. Peak 15-minute demand data is commonly used to design, analyze, and optimize different elements of a traffic network. Since we do not know when most vehicles will arrive at the network, we are going to develop congestion scenarios for four quarters of the hour, assuming the peak will occur at those four quarters across four scenarios. Each scenario will have a different value of mean, while having the same standard deviation. For each demand scenario we will develop a solution using Solution Technique: Sampling Heuristic.

For each demand scenario, we are assuming two types of services will be arriving at the network, TNCs and shuttles. Each demand scenario will represent a single probability distribution (a truncated normal distribution with specified mean and standard deviation) of arrival times for TNCs. The arrival time of the 240 TNCs within a peak hour (assuming peak hour occurs at 7.00 AM – 8.00 AM) will be produced depending on the mean and standard deviation. Using the same mean and standard deviation, 33 samples will be generated within the same scenario. This will ensure that the samples are taken from the same population.

We assume that 30 shuttles will arrive at the curbside network during the peak congestion hour. We assume that the shuttle services will be arriving on demand within that hour, and the schedule will be known to the curbside modeler/manager. To replicate this, we will produce only one sample of shuttle arrival time using a truncated normal distribution with a specified mean and standard deviation. So, there will be one fixed distribution for the shuttle in each scenario. Hence, for each scenario, there will be 33 combined samples of shuttle and TNCs. The demand scenarios are presented in Table 4. 4.

Table 4. 4 Demand Distributions Across Different Scenarios

Demand Scenario	Description	TNC Arriving	Parameters of Arrival Time Distribution	Example	Shuttle Arriving	Parameters of Arrival Time Distribution
Scenario 1	The peak demand is observed within the first quarter of the hour	240	Mean = 7.5, SD = 15 (33 Samples)		30	Mean = 7.5, SD = 15 (1 Sample)
Scenario 2	The peak demand is observed within the second quarter of the hour	240	Mean = 22.5, SD = 15 (33 Samples)		30	Mean = 22.5, SD = 15 (1 Sample)
Scenario 3	The peak demand is observed within the third quarter of the hour	240	Mean = 37.5, SD = 15 (33 Samples)		30	Mean = 37.5, SD = 15 (1 Sample)
Scenario 4	The peak demand is observed within the fourth quarter of the hour	240	Mean = 52.5, SD = 15 (33 Samples)		30	Mean = 52.5, SD = 15 (1 Sample)

Optimization Model Results

Using a Python module, each demand sample was categorized into 1-minute intervals, and the demand data was formatted appropriately for use as input in AMPL. The optimization model was run in AMPL to obtain allocation results and CPI values for every 1-minute of the peak hour for every sample. For one sample, 60 allocation combinations and CPI values were estimated. The allocation results and CPI values estimated by the optimization model for the first sample of scenario 1 are presented in Table 4. 5.

Table 4. 5 Allocation and CPI Results for Sample 1 from Scenario 1

Interval	TNC Requested	Shuttle Requested	TNC Allocated	Shuttle Allocated	CPI (Passengers Served Per Min Per 20 ft of Space)
1	5	2	5	2	29.62
2	10	1	2	1	13.07
3	3	3	3	3	28.75
4	17	1	4	1	20.03
5	7	0	7	0	24.39
6	6	1	3	1	16.55
7	14	2	5	2	29.62
8	9	3	3	3	28.75
9	8	0	5	0	17.42
10	10	0	5	0	17.42
11	10	2	6	2	33.10
12	12	1	2	1	13.07
13	6	1	6	1	27.00
14	6	0	3	0	10.45
15	12	0	8	0	27.87
16	6	1	6	1	27.00
17	9	0	4	0	13.94
18	7	1	7	1	30.49
19	6	1	3	1	16.55
20	6	0	6	0	20.91
21	8	0	5	0	17.42
22	8	1	6	1	27.00
23	3	1	3	1	16.55
24	11	1	5	1	23.52
25	7	1	6	1	27.00
26	1	3	1	3	21.78
27	6	1	4	1	20.03
28	3	0	3	0	10.45
29	3	1	3	1	16.55
30	2	0	2	0	6.97
31	2	0	2	0	6.97
32	3	0	3	0	10.45
33	2	1	2	1	13.07
34	2	0	2	0	6.97
35	0	0	0	0	0.00
36	1	0	1	0	3.48
37	3	0	3	0	10.45

38	1	0	1	0	3.48
39	2	0	2	0	6.97
40	0	0	0	0	0.00
41	1	0	1	0	3.48
42	0	0	0	0	0.00
43	0	0	0	0	0.00
44	0	0	0	0	0.00
45	0	0	0	0	0.00
46	0	0	0	0	0.00
47	2	0	2	0	6.97
48	0	0	0	0	0.00
49	0	0	0	0	0.00
50	0	0	0	0	0.00
51	0	0	0	0	0.00
52	0	0	0	0	0.00
53	0	0	0	0	0.00
54	0	0	0	0	0.00
55	0	0	0	0	0.00
56	0	0	0	0	0.00
57	0	0	0	0	0.00
58	0	0	0	0	0.00
59	0	0	0	0	0.00
60	0	0	0	0	0.00
Hourly CPI (Passengers Served Per Min Per 20 ft of Space)					705.58

A sample calculation for the CPI values in Table 4. 5 is shown below.

For the first row, the CPI is reported as 29.62 in the table, here,

Available Spaces: 8

TNC requested: 5, $\text{TNC assigned} = 5$

Shuttle Requested: 2, $\text{Shuttle assigned} = 2$

The CPI for each interval is calculated based on individual spaces. The optimization model calculated CPI for each space and then summed them to obtain the CPI for all the spaces in the network. The space allocation is obtained from the optimization model.

Initially, I used the curbside length in meters. So, the optimization model reported the CPI values for each interval in passengers per minute per meter. I converted the results into passengers per minute per 20 ft while reporting hourly CPI. I am providing a direct example from the optimization, so the digits match to eliminate confusion.

When 1 TNC is assigned,

$$\text{Pi} = 2 \text{ passengers}, \text{li} = 7 \text{ m}, \text{Ti} = 0.5 \text{ minutes}$$

$$\text{CPI} = \frac{2}{0.5 * 7} = 0.5714 \text{ passengers per minute per meter}$$

When 5 TNCs are assigned, the optimization modules calculates the CPI as,

$$\text{CPI} = 5 * 0.5714 \text{ passengers per minute per mete}$$

$$= 2.857 \text{ passengers per minute per meter}$$

When 1 Shuttle is assigned,

$$\text{Pi} = 7 \text{ passengers}, \text{li} = 7 \text{ m}, \text{Ti} = 1 \text{ minute}$$

$$\text{CPI} = \frac{7}{1 * 7} = 1 \text{ passengers per minute per meter}$$

When 2 Shuttles are assigned, the optimization modules calculates the CPI as,

$$\text{CPI} = 2 * 1 \text{ passengers per minute per meter}$$

$= 2 \text{ passengers per minute per meter}$

So, CPI for interval 1 is,

$2.857 \text{ passengers per minute per meter} + 2 \text{ passengers per minute per meter}$

$= 4.857 \text{ passengers per minute per meter}$

$= \frac{4.857 * 20}{3.28} \text{passenger per minute per 20 ft}$

$= 29.62 \text{ passengers per minute per 20 ft}$

$26.62 \text{ passengers per minute per 20 ft}$ is reported in the tables. The unit of the column needs to be changed to $\text{passengers per minute per 20 ft}$ which is currently passengers per hour per 20 ft.

Summing up the values of CPIs for a sample from a demand scenario at 1-minute intervals provided us with the hourly CPI for the peak hour (Table 4. 5). Thus, for one probability distribution (demand scenario), $1980\ (33 * 60)$ allocation results and 33 hourly CPI values were obtained. The mean of these 33 CPI values represents the expected value of the mean CPIs for the peak hour. The hourly CPI variation across 33 samples for the four demand scenarios from Table 4. 4 are presented in Figure 4. 5, Figure 4. 6, Figure 4. 7, and Figure 4. 8.

Figure 4. 5 CPI Values Across 33 Sample for Demand Scenario 1

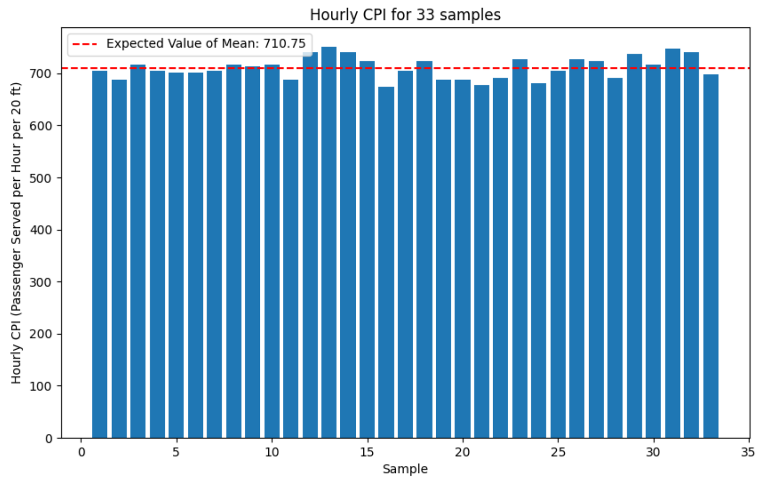


Figure 4. 6 CPI Values Across 33 Sample for Demand Scenario 2

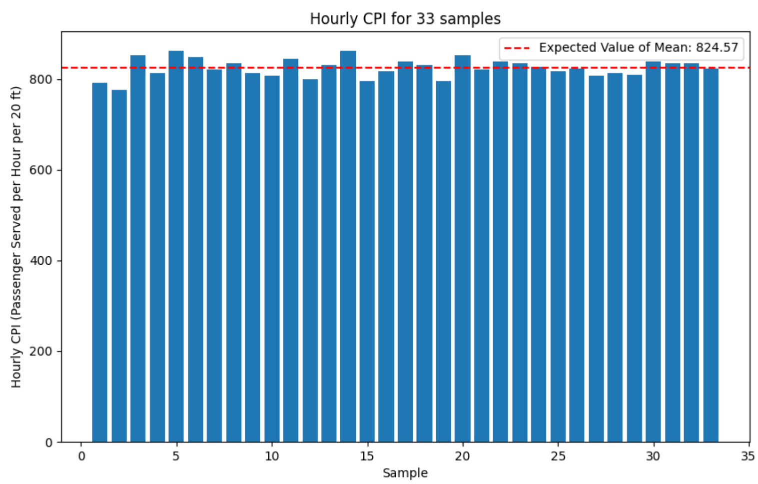


Figure 4. 7 CPI Values Across 33 Sample for Demand Scenario 3

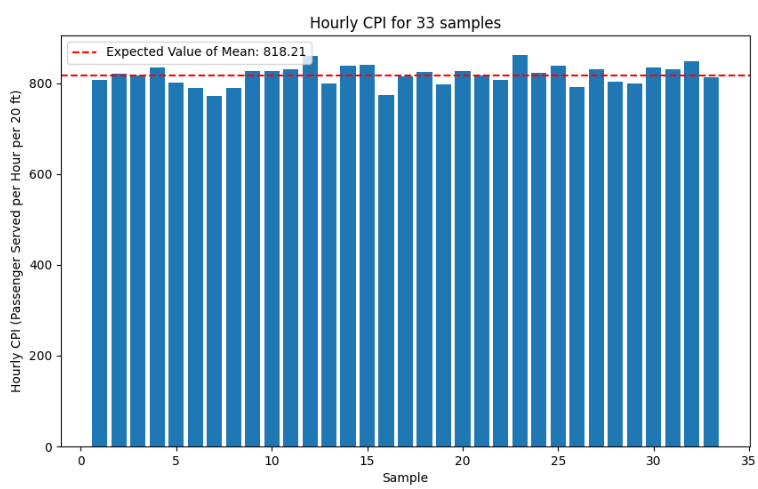
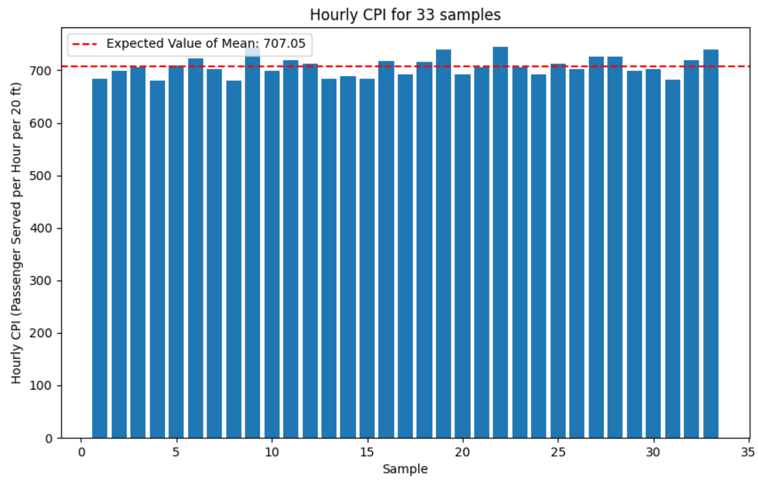


Figure 4. 8 CPI Values Across 33 Sample for Demand Scenario 4



Selecting Allocation Combinations

As mentioned in the previous section, each sample from a demand scenario generates probable 60 solutions. From each demand scenario, we have identified the unique solutions by using a Python Module. The unique solutions for different demand scenarios are presented in Table 4. 6.

Table 4. 6 Unique Solutions Across the Demand Scenarios

	Demand Scenario 1		Demand Scenario 2		Demand Scenario 3		Demand Scenario 4	
Solution	TNC	Shuttle	TNC	Shuttle	TNC	Shuttle	TNC	Shuttle
1	0	0	0	0	0	0	0	0
2	0	1	0	2	0	1	0	1
3	0	2	0	3	0	2	0	2
4	1	0	1	0	0	3	1	0
5	0	3	1	1	0	4	0	3
6	1	1	2	0	1	0	1	1
7	2	0	1	2	0	5	2	0
8	1	2	1	3	1	1	1	2
9	1	3	2	1	2	0	1	3
10	2	1	3	0	1	2	2	1
11	3	0	2	2	1	5	3	0
12	2	2	2	3	2	1	2	2
13	2	3	3	1	3	0	2	3
14	4	0	4	0	2	2	4	0
15	3	1	3	2	3	1	3	1
16	3	2	5	0	4	0	3	2

17	5	0	3	3	3	2	5	0
18	4	1	4	1	5	0	4	1
19	3	3	6	0	4	1	3	3
20	6	0	4	2	4	2	6	0
21	4	2	5	1	5	1	4	2
22	5	1	4	3	7	0	5	1
23	4	3	7	0	5	2	4	3
24	7	0	5	2	6	1	7	0
25	5	2	6	1	8	0	5	2
26	6	1	8	0	6	2	6	1
27	8	0	5	3	7	1	8	0
28	7	1	6	2	0	0	7	1
29	6	2	7	1			6	2

Effective CPI

We have obtained an hourly value of CPIs from post-processing the results from the optimization model. These hourly CPIs are based on the optimum allocation during each minute. However, in the real world when only one allocation combination will be selected, the CPI values will not remain the same across all scenarios. The CPI effective for a single allocation will be different than the estimated CPI. We are defining it as an effective CPI for a specific allocation. Hence, once the unique solutions are identified, the effective CPI across 33 samples for each demand scenario is estimated using a Python module. The mean values of the 33 samples of a scenario will represent the mean effective CPI for an allocation. For each demand scenario, the allocation-specific effective CPI is presented in Table 4. 7, Table 4. 8, Table 4. 9, and Table 4. 10.

Table 4. 7 Mean Effective CPI for Specific Allocations for Demand Scenario 1

TNC Spaces Allocated	Shuttle Spaces Allocated	CPI (Passengers Served Per Hour 20 ft of Curb)
0	0	0
0	1	79.2
0	2	128
1	0	137.2
0	3	158.4
1	1	216.4

2	0	246.6
1	2	265.2
1	3	295.6
2	1	326
3	0	338
2	2	374.8
2	3	405.2
4	0	413.2
3	1	417.2
3	2	466
5	0	477.4
4	1	492.6
3	3	496.6
6	0	533.4
4	2	541.4
5	1	556.6
4	3	571.8
7	0	581.6
5	2	605.4
6	1	612.6
8	0	624.2
7	1	661
6	2	661.4

Table 4. 8 Mean Effective CPI for Specific Allocations for Demand Scenario 2

TNC Spaces Allocated	Shuttle Spaces Allocated	CPI (Passengers Served Per Hour 20 ft of Curb)
0	0	0
0	2	134
0	3	164.6
1	0	166.4
1	1	251.6
2	0	299.4
1	2	300.4
1	3	331
2	1	384.8
3	0	405.6
2	2	433.6
2	3	464
3	1	491
4	0	491.4
3	2	539.8
5	0	563.6
3	3	570.2

4	1	576.8
6	0	623.4
4	2	625.6
5	1	649
4	3	656
7	0	672.6
5	2	697.8
6	1	708.8
8	0	713.8
5	3	728.2
6	2	757.6
7	1	758

Table 4. 9 Mean Effective CPI for Specific Allocations for Demand Scenario 3

TNC Spaces Allocated	Shuttle Spaces Allocated	CPI (Passengers Served Per Hour 20 ft of Curb)
0	0	0
0	1	85.2
0	2	134
0	3	152.4
0	4	164.6
1	0	167.6
0	5	170.6
1	1	253
2	0	300
1	2	301.8
1	5	338.4
2	1	385.4
3	0	405
2	2	434.2
3	1	490.4
4	0	492.6
3	2	539.2
5	0	564.2
4	1	578
4	2	626.8
5	1	649.6
7	0	672.6
5	2	698.2
6	1	709.2
8	0	712.8
6	2	758
7	1	758

Table 4. 10 Mean Effective CPI for Specific Allocations for Demand Scenario 4

TNC Spaces Allocated	Shuttle Spaces Allocated	CPI (Passengers Served Per Hour 20 ft of Curb)
0	0	0
0	1	79.2
0	2	128
1	0	134.6
0	3	158.4
1	1	213.8
2	0	244
1	2	262.6
1	3	293.2
2	1	323.2
3	0	334.2
2	2	372
2	3	402.4
4	0	409
3	1	413.4
3	2	462.2
5	0	472
4	1	488.4
3	3	492.8
6	0	528
4	2	537
5	1	551.4
4	3	567.6
7	0	578
5	2	600.2
6	1	607.4
8	0	621.6
5	3	630.6
6	2	656
7	1	657.4

Solution

The dynamic allocation for 1-minute intervals provided numerous solutions for the allocation of the curbside spaces in the network. However, practically it is not convenient for the curbside managers to change curbside allocation every minute. Depending on the value of the loss of the expected mean CPI, a decision-maker can approach multiple decisions for an entire hour. In this example, we are solving the allocation problem for each demand scenario. Hence, each demand scenario will have a different solution and they are unrelated.

In the previous section (Effective CPI), we have computed the effective CPI for all probable solutions for different demand scenarios. The probable solution refers to the unique solutions obtained from the optimization module. From the Optimization Model Results we have the expected mean value of CPI for each demand scenario. From mean effective CPI values presented in Table 4. 7, Table 4. 8, Table 4. 9, and Table 4. 10 and the expected mean value of CPI presented in Figure 4. 5, Figure 4. 6, Figure 4. 7, and Figure 4. 8, the mean effective CPI for any allocation is lower than the expected mean CPI. This is because the optimization models provide the best possible CPI for a specific demand scenario and that is dynamic allocation. When only one allocation is fixed for the entire hour, it cannot capture the maximum curb productivity. In this circumstance, the best solution for each scenario will be the one that maximizes the mean effective CPI. We have conducted a manual search using an Excel spreadsheet to find out which allocation maximizes the mean effective CPI hence, minimizes the loss of expected mean CPI for each demand scenario.

Demand Scenario 1

For demand scenario 1 the loss of expected mean CPI is reported in Table 4. 11. It shows that when 6 spaces are allocated to TNCs and 2 spaces are allocated to shuttles, the mean effective CPI is maximum. Hence, this is the solution for the peak hour for this specific demand scenario.

Table 4. 11 Loss of Expected Mean CPI for Demand Scenario 1

CPI Unit: Passengers Served Per Hour 20 ft of Curb

TNC Spaces Allocated	Shuttle Spaces Allocated	Mean Effective CPI	Expected Mean CPI	Loss of Expected Mean CPI = Expected Mean CPI – Mean Effective CPI
0	0	0	710.75	710.75
0	1	79.2	710.75	631.55
0	2	128	710.75	582.75

1	0	137.2	710.75	573.55
0	3	158.4	710.75	552.35
1	1	216.4	710.75	494.35
2	0	246.6	710.75	464.15
1	2	265.2	710.75	445.55
1	3	295.6	710.75	415.15
2	1	326	710.75	384.75
3	0	338	710.75	372.75
2	2	374.8	710.75	335.95
2	3	405.2	710.75	305.55
4	0	413.2	710.75	297.55
3	1	417.2	710.75	293.55
3	2	466	710.75	244.75
5	0	477.4	710.75	233.35
4	1	492.6	710.75	218.15
3	3	496.6	710.75	214.15
6	0	533.4	710.75	177.35
4	2	541.4	710.75	169.35
5	1	556.6	710.75	154.15
4	3	571.8	710.75	138.95
7	0	581.6	710.75	129.15
5	2	605.4	710.75	105.35
6	1	612.6	710.75	98.15
8	0	624.2	710.75	86.55
7	1	661	710.75	49.75
6	2	661.4	710.75	49.35

Demand Scenario 2

For demand scenario 2 the loss of expected mean CPI is reported in Table 4. 12. It shows that when 7 spaces are allocated to TNCs and 1 space is allocated to shuttles, the value of mean effective CPI is maximum. Hence, this is the solution for the peak hour for this specific demand scenario.

Table 4. 12 Loss of Expected Mean CPI for Demand Scenario 2

CPI Unit: Passengers Served Per Hour 20 ft of Curb

TNC Spaces Allocated	Shuttle Spaces Allocated	Mean Effective CPI	Expected Mean CPI	Loss of Expected Mean CPI = Expected Mean CPI – Mean Effective CPI
0	0	0	824.57	824.57
0	2	134	824.57	690.57

0	3	164.6	824.57	659.97
1	0	166.4	824.57	658.17
1	1	251.6	824.57	572.97
2	0	299.4	824.57	525.17
1	2	300.4	824.57	524.17
1	3	331	824.57	493.57
2	1	384.8	824.57	439.77
3	0	405.6	824.57	418.97
2	2	433.6	824.57	390.97
2	3	464	824.57	360.57
3	1	491	824.57	333.57
4	0	491.4	824.57	333.17
3	2	539.8	824.57	284.77
5	0	563.6	824.57	260.97
3	3	570.2	824.57	254.37
4	1	576.8	824.57	247.77
6	0	623.4	824.57	201.17
4	2	625.6	824.57	198.97
5	1	649	824.57	175.57
4	3	656	824.57	168.57
7	0	672.6	824.57	151.97
5	2	697.8	824.57	126.77
6	1	708.8	824.57	115.77
8	0	713.8	824.57	110.77
5	3	728.2	824.57	96.37
6	2	757.6	824.57	66.97
7	1	758	824.57	66.57

Demand Scenario 3

For demand scenario 3 the loss of expected mean CPI is reported in Table 4. 13. It shows that when 7 spaces are allocated to TNCs and 1 space is allocated to shuttles, the value of mean effective CPI is maximum. Hence, this is the solution for the peak hour for this specific demand scenario.

Table 4. 13 Loss of Expected Mean CPI for Demand Scenario 3

CPI Unit: Passengers Served Per Hour 20 ft of Curb

TNC Spaces Allocated	Shuttle Spaces Allocated	Mean Effective CPI	Expected Mean CPI	Loss of Expected Mean CPI = Expected Mean CPI – Mean Effective CPI
0	0	0	818.21	818.21
0	1	85.2	818.21	733.01
0	2	134	818.21	684.21
0	3	152.4	818.21	665.81
0	4	164.6	818.21	653.61
1	0	167.6	818.21	650.61
0	5	170.6	818.21	647.61
1	1	253	818.21	565.21
2	0	300	818.21	518.21
1	2	301.8	818.21	516.41
1	5	338.4	818.21	479.81
2	1	385.4	818.21	432.81
3	0	405	818.21	413.21
2	2	434.2	818.21	384.01
3	1	490.4	818.21	327.81
4	0	492.6	818.21	325.61
3	2	539.2	818.21	279.01
5	0	564.2	818.21	254.01
4	1	578	818.21	240.21
4	2	626.8	818.21	191.41
5	1	649.6	818.21	168.61
7	0	672.6	818.21	145.61
5	2	698.2	818.21	120.01
6	1	709.2	818.21	109.01
8	0	712.8	818.21	105.41
6	2	758	818.21	60.21
7	1	758	818.21	60.21

Demand Scenario 4

For demand scenario 4 the loss of expected mean CPI is reported in Table 4. 14. It shows that when 7 spaces are allocated to TNCs and 1 space is allocated to shuttles the value of mean effective CPI is maximum.. Hence, this is the solution for the peak hour for this specific demand scenario.

Table 4. 14 Loss of Expected Mean CPI for Demand Scenario 4

CPI Unit: Passengers Served Per Hour 20 ft of Curb

TNC Spaces Allocated	Shuttle Spaces Allocated	Mean Effective CPI	Expected Mean CPI	Loss of Expected Mean CPI = Expected Mean CPI – Mean Effective CPI
0	0	0	707.05	707.05
0	1	79.2	707.05	627.85
0	2	128	707.05	579.05
1	0	134.6	707.05	572.45
0	3	158.4	707.05	548.65
1	1	213.8	707.05	493.25
2	0	244	707.05	463.05
1	2	262.6	707.05	444.45
1	3	293.2	707.05	413.85
2	1	323.2	707.05	383.85
3	0	334.2	707.05	372.85
2	2	372	707.05	335.05
2	3	402.4	707.05	304.65
4	0	409	707.05	298.05
3	1	413.4	707.05	293.65
3	2	462.2	707.05	244.85
5	0	472	707.05	235.05
4	1	488.4	707.05	218.65
3	3	492.8	707.05	214.25
6	0	528	707.05	179.05
4	2	537	707.05	170.05
5	1	551.4	707.05	155.65
4	3	567.6	707.05	139.45
7	0	578	707.05	129.05
5	2	600.2	707.05	106.85
6	1	607.4	707.05	99.65
8	0	621.6	707.05	85.45
5	3	630.6	707.05	76.45
6	2	656	707.05	51.05
7	1	657.4	707.05	49.65

Example B: Impact of Resolutions

To understand the impact of resolutions, we have compared optimization results at different resolutions. During the process, we have kept the hourly demand data consistent across all resolutions. We have tested the optimization model results at 1-minute, 5-minute, 10-minute, 15-

minute, and 60-minute resolutions for two services, TNC, and shuttles. The experiments done to understand the impact of resolution on optimization results are different from the scenarios described in Table 4. 4.

We have used only one instance of demand for this example. We also assumed that the curbside network would have four curbside locations ($k = 4$), each having two curbside spaces available during the first decision interval. For each resolution, the effective capacity was updated at the end of each decision interval (Updating Curbside Capacity). The input data files were prepared based on the demand data generated for each decision interval. The optimization model was run to obtain the CPI and space allocations for the services for each decision interval. For an hour, based on the resolution, the CPI for all decision intervals was summed to obtain the hourly CPI for the curbside network. The allocation and CPI results for the curbside network at different time resolutions from the optimization model are provided in Table 4. 15. The hourly CPI is presented in Table 4. 16.

Table 4. 15 Allocation and CPI Results for Different Resolutions from the Optimization Model

Legends
Shuttle Allocated
TNC Allocated

TNC Space and Shuttle Space Unit: Numbers
CPI Unit: Passengers Served Per 20 ft Per Hour

No of Spaces

60-minute Resolution

TNC Space	Shuttle Space	Decision Interval	CPI	TNC 1	2	3	4	5	6	7	8	Shuttle 1	2
4	1	1	1019.16										

15-minute Resolution

TNC Space	Shuttle Space	Decision Interval	CPI	TNC 1	2	3	4	5	6	7	8	Shuttle 1	2
1	1	1	82.75										

7	1	2	418.99		
7	1	3	423.35		
2	1	4	90.59		

10-minute Resolution

TNC Space	Shuttle Space	Decision Interval	CPI	TNC	Shuttle
1	1	1	34.84		
5	1	2	176.83		
7	1	3	286.59		
7	1	4	277.00		
3	1	5	130.66		
1	1	6	47.04		

5-minute Resolution

TNC Space	Shuttle Space	Decision Interval	CPI	TNC	Shuttle
1	1	1	27.87		
1	1	2	6.97		
3	1	3	47.91		
6	1	4	128.92		
7	1	5	139.37		
7	1	6	133.28		
7	1	7	130.66		
7	1	8	149.83		
4	1	9	87.11		
2	1	10	43.55		
2	1	11	33.97		
1	1	12	13.07		

1-minute Resolution

TNC Space	Shuttle Space	Decision Interval	CPI	TNC	Shuttle
1	0	1	3.48		
0	0	2	0.00		
0	0	3	0.00		
0	0	4	0.00		
4	0	5	24.39		
0	0	6	0.00		
0	0	7	0.00		
0	0	8	0.00		
1	0	9	3.48		
1	0	10	3.48		
4	0	11	13.94		
3	0	12	10.45		
1	0	13	3.48		
2	0	14	6.97		
2	1	15	13.07		
4	1	16	20.03		
6	1	17	27.00		
1	1	18	9.58		
6	1	19	27.00		
3	0	20	10.45		
7	1	21	30.49		
3	1	22	16.55		
7	0	23	24.39		
3	0	24	10.45		

4	2	25	26.13										
4	0	26	13.94										
4	1	27	20.03										
3	1	28	16.55										
4	0	29	13.94										
6	1	30	27.00										
1	1	31	9.58										
6	1	32	27.00										
5	0	33	17.42										
8	0	34	27.87										
7	0	35	24.39										
6	0	36	20.91										
6	1	37	27.00										
2	1	38	13.07										
4	1	39	20.03										
4	1	40	20.03										
3	1	41	16.55										
4	1	42	20.03										
1	0	43	6.10										
5	0	44	17.42										
4	1	45	20.03										
2	2	46	19.16										
4	0	47	13.94										
1	0	48	3.48										
1	0	49	3.48										
1	0	50	3.48										
1	1	51	9.58										
4	0	52	13.94										
1	0	53	3.48										
2	0	54	6.97										
0	0	55	0.00										
0	0	56	0.00										
1	0	57	6.10										
1	0	58	3.48										
1	0	59	3.48										
0	0	60	0.00										

Table 4. 16 Hourly CPI Obtained from Different Resolution

Resolution	Total CPI (Passengers Served Per 20 ft Per Hour)
60 Minute	1019.16
15 Minute	1015.68
10 Minute	952.96
5 Minute	942.51
1 Minute	754.36

From Table 4. 15, it is evident that when a 1-minute decision interval is considered, the optimization model produces a dynamic allocation for the curbside. For a single sample, the solution will consist of 60 possible results. The results can consist of unique allocations while some allocations may repeat. In the real world, curbside managers do not allocate spaces for every minute. The space allocations are usually done daily or for a 2–3-hour period. Depending on the preferences of a city and its requirements, allocations can be made for a longer or shorter period. The allocation decision can be made using the Solution Technique: Sampling Heuristic.

Table 4. 16 shows that hourly CPI is highly sensitive to the resolution being considered. As the resolution for decision interval gets higher (smaller decision intervals) the CPI value reduces. The reason behind this can be described by the demand data and updating of capacity. When a larger decision interval is considered, the capacity of the curbside network gets updated only at the end of a decision interval. This results in an inflated capacity of the curbsides compared to the available capacity. As a result, more vehicles are assigned to the curbside when they were supposed to be discarded from the CPI estimation upon not finding a space. For example, for the 5-minute resolution, the total capacity of the curbside for eight curbside spaces is 40 vehicles. So, the curbside can accommodate 8 vehicles at the same time. The multi-use of the curbside inflates the capacity of the curbside to 40 vehicles. If the curbside has a demand of 40 vehicles within 5 minutes, the optimization model will assign all of them to the curbside. However, it might happen that within a shorter period (say 1 minute), more than eight vehicles arrive at the curbside. After assigning the first eight of them, there will be no space left at the curbside. Hence, the effective capacity of the curbside will be zero. In this circumstance, the vehicles left after assigning the first eight vehicles will need to be discarded from allocation and CPI estimation. The optimization

model at a 5-minute resolution cannot address this resulting in a higher CPI value. However, this issue will be resolved as smaller time intervals are considered.

During the 5-minute resolution, the optimization allocated spaces among the vehicles without considering their arrival time. Though the capacity is updated every 5 minutes, the model cannot recognize which vehicles will be arriving at the same time. Hence, it assigns the vehicles to curbside spaces regardless of their arrival time and includes them for CPI calculation. For example, Table 4. 17 shows the demand data from 30 to 35 minutes for the morning peak hour (7.00 AM-8.00 AM). The column 'Arrival Time in Minutes.' shows the arrival time of each vehicle within this 5-minute interval. The TNC demand for each minute within this 5-minute interval has been highlighted consecutively by blue and green cells in Table 4. 17. When the optimization model is run at 5-minute resolution, it allocates the first 34 vehicles (red colored text) (TNCs) (Table 4. 17) and 50th to 51st vehicles (red colored text) (shuttle) (Table 4. 17) (7 spaces allocated to TNCs and 1 space allocated to shuttles), while it is not possible to assign the first 34 of them as the curbside capacity will be zero after the first 7 TNCs and the 1st shuttle is assigned. However, when the 9th (TNC) and 51st (Shuttle) vehicles arrive according to their arrival time they will not find a space and be discarded from the network. However, the optimization model assigns both of them to a space and includes them in the CPI calculation. This has happened to multiple vehicles. Hence the 5-minute resolution model overestimates the CPI.

However, the overestimation issue is resolved for the 1-minute resolution model, hence the hourly CPI value is less than the hourly CPI obtained from the 5-minute resolution. Also, during the 1-minute resolution, the optimization model assigned the first 7 TNCs and the first shuttle arriving between 30th-31st minute. After allocating those vehicles it discarded all other vehicles arriving during that decision interval (blue heighted cells in Table 4. 17). However, the 8th and 11th

TNC was supposed to get a space for this allocation. This also contributes to the lower CPI observed for the 1-minute decision interval. However, this issue can be resolved if a smaller decision interval is considered for the optimization. A resolution equal to the minimum dwell time will resolve this issue.

From these observations, we can conclude that the optimization model cannot consider the arrival time of vehicles when run at a smaller decision interval and makes an overestimation of CPI. So, when considering the uncertainty of demand, running the optimization model at a smaller decision interval will result in improved accuracy of estimation and it will also update the capacity at regular intervals ensuring proper space utilization.

Table 4. 17 Five Minutes of Demand Data Used as an Input for the Optimization Model

Vehicle No.	Arrival Time in Minutes	Dwell Time in Minutes	Required Curbside Length in ft	Occupancy in No. of People	Services (1= TNC, 2= Shuttle)	Arrival Time in Minutes	Arrival + Dwell Time in Minutes
1	30.14	0.5	23	2	1	0.14	0.64
2	30.46	0.5	23	2	1	0.46	0.96
3	30.55	0.5	23	2	1	0.55	1.05
4	30.56	0.5	23	2	1	0.56	1.06
5	30.60	0.5	23	2	1	0.60	1.10
6	30.61	0.5	23	2	1	0.61	1.11
7	30.63	0.5	23	2	1	0.63	1.13
8	30.67	0.5	23	2	1	0.67	1.17
9	30.77	0.5	23	2	1	0.77	1.27
10	30.92	0.5	23	2	1	0.92	1.42
11	30.97	0.5	23	2	1	0.97	1.47
12	31.19	0.5	23	2	1	1.19	1.69
13	31.27	0.5	23	2	1	1.27	1.77
14	31.31	0.5	23	2	1	1.31	1.81
15	31.39	0.5	23	2	1	1.39	1.89
16	31.64	0.5	23	2	1	1.64	2.14
17	31.65	0.5	23	2	1	1.65	2.15
18	31.80	0.5	23	2	1	1.80	2.30
19	31.81	0.5	23	2	1	1.81	2.31
20	31.85	0.5	23	2	1	1.85	2.35
21	31.95	0.5	23	2	1	1.95	2.45
22	32.09	0.5	23	2	1	2.09	2.59

23	32.17	0.5	23	2	1	2.17	2.67
24	32.21	0.5	23	2	1	2.21	2.71
25	32.27	0.5	23	2	1	2.27	2.77
26	32.27	0.5	23	2	1	2.27	2.77
27	32.34	0.5	23	2	1	2.34	2.84
28	32.43	0.5	23	2	1	2.43	2.93
29	32.51	0.5	23	2	1	2.51	3.01
30	32.84	0.5	23	2	1	2.84	3.34
31	32.92	0.5	23	2	1	2.92	3.42
32	33.01	0.5	23	2	1	3.01	3.51
33	33.07	0.5	23	2	1	3.07	3.57
34	33.16	0.5	23	2	1	3.16	3.66
35	33.22	0.5	23	2	1	3.22	3.72
36	33.26	0.5	23	2	1	3.26	3.76
37	33.43	0.5	23	2	1	3.43	3.93
38	33.43	0.5	23	2	1	3.43	3.93
39	33.65	0.5	23	2	1	3.65	4.15
40	33.70	0.5	23	2	1	3.70	4.20
41	33.81	0.5	23	2	1	3.81	4.31
42	33.91	0.5	23	2	1	3.91	4.41
43	34.14	0.5	23	2	1	4.14	4.64
44	34.14	0.5	23	2	1	4.14	4.64
45	34.16	0.5	23	2	1	4.16	4.66
46	34.33	0.5	23	2	1	4.33	4.83
47	34.43	0.5	23	2	1	4.43	4.93
48	34.77	0.5	23	2	1	4.77	5.27
49	34.92	0.5	23	2	1	4.92	5.42
50	30.47	1	23	7	2	0.47	1.47
51	31.21	1	23	7	2	1.21	2.21

The current study does not investigate the impact on the allocation decision when the resolution is changed, which is necessary for fully understanding the implications of the resolution choice. This task can be done in future research.

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Summary

This chapter describes the steps to formulate the mathematical curbside optimization model as an integer linear program (ILP). The formulation has been tested across different scenarios to demonstrate the application of the algorithm. The summary of results obtained for different scenarios is described in the following.

- The dynamic allocation strategy reveals that the CPI will vary depending on the vehicle arrival at each interval, hence, we can have numerous allocation strategies. However, using sampling heuristic, it is possible to select an optimal allocation to achieve a greater benefit in the real world.
- Initial assessment reveals that the developed optimization model is highly sensitive to the decision interval being selected. The optimization model overestimates the CPI when run in a smaller decision interval.
- The CPI is higher at smaller decision interval because the optimization provides a theoretical estimation of CPI during the optimization. However, the CPI will be lower when the stochasticity in arrival time will be considered.
- The optimization model can produce more realistic results of CPI when run at a larger decision interval because the stochasticity in arrival time is properly considered and the issue with over-estimation of CPI is resolved.
- The optimization model makes an underestimation of CPI at 1-minute decision interval. However, this can be avoided by considering a larger decision interval (equal to the minimum dwell time of SUM services).

Chapter 5 - Curbside with Connectivity

Introduction

The previous chapter discusses the methodology and outcome for theoretical optimization for a network of curbside. While theoretical models are important for decision-making, real-world scenarios can differ greatly from theoretical scenarios. As transportation networks are dynamic, the presence of various uncertainties may lead to new observations for the optimization results computed in the previous chapter. In this chapter, we will test the optimization results obtained in Chapter – 4 in a simulation-based scenario where the curbside will have impacts from the surrounding environment. For example, depending on the signal timing and traffic demand of the network, vehicles may have difficulty stopping at the nearby curbside spaces. In a busy urban street, the nearby curbside spaces can also be inaccessible due to queue spillback from the downstream intersection. We are assuming that in this type of situation, the productivity of the curbside will drop. Though this is a logical assumption, there is no evidence of this claim in the literature. Hence, we are going to develop a microsimulation model where we are going to estimate the variation of curbside productivity in the real world from the theoretical model. Later, we are going to assess how the physical elements, mainly the curbside location impacts the productivity of the network. Also, drivers having the exact availability information about the curbside may impact the curbside productivity. Technological advancements have made data sharing among drivers and infrastructure (roadside units- RSUs) a lot easier than before. With the help of smartphones, and mobile apps, communication is possible in real-time. Hence, it is possible to inform the drivers about the availability of spaces at a certain curbside location. This has the potential to reduce the cruising of vehicles in the network in search of spaces to complete PUDO activities. At the same time, having this information will also reduce the congestion stress from the network while improving emissions for the network. The existing literature also lacks insights into how data connectivity can improve curbside productivity. Hence, in the last section of this chapter, we are going to assess the impact of drivers having the exact information on curbside productivity and how much it will vary from the theoretical optimization results.

Methodology

This section describes the process of developing the simulation model and the scenarios for test cases. The simulation model has been developed using PTV Vissim (PTV Group, 2022) as PTV vissim can model individual vehicle behavior. With the modifications of the features of the PTV Vissim, it is possible to model the curbside locations and control their behavior. This section is divided into two parts. The first part discusses the modeling methodology, and the second part describes the scenarios.

Development of Microsimulation Model

We have developed the network shown in Figure 1 from Chapter 4 in the Vissim platform. The scenarios in Vissim have been modeled using Wiedemann'74 car following model as it is suitable for urban arterials (Z. Lu et al., 2016). Vissim has a unique driving behavior model for the curbside lanes. The curbside lane driving behavior has been used for the lanes adjacent to the curbside location. Since PTV VISSIM has no direct feature to replicate the curbside PUDO activities, we used parallel parking lots to stop zones in the street. From the optimization results, we have chosen the allocation results from demand scenario 1 and demand scenario 2. These two demand scenario results have been selected to represent the two unique optimization results across four demand scenarios. Hence, two base microsimulation models were prepared based on the demand pattern and space distributions of these scenarios, one with 6 spaces for TNCs and 2 spaces for the shuttles and another with 7 spaces for TNCs and 1 space for shuttles as these allocations showed the maximum productivity for the curbside spaces. The 4 curbside locations and space distributions are shown in Figure 5. 1. For results from demand scenario 1, the curbside distribution is as follows:

Allocation 1:

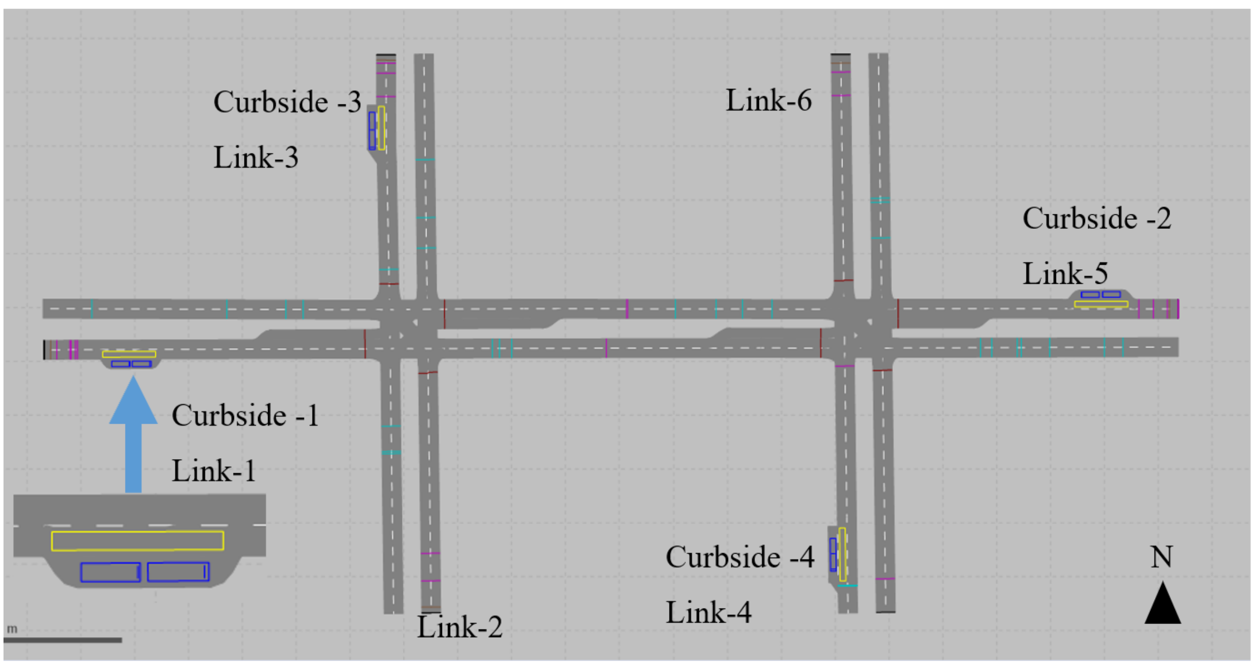
- Location-1 & 2: 1 TNC space, 1 Shuttle Space
- Location-3 & 4: 2 TNC Spaces

For results from demand scenario 2, the curbside distribution is as follows:

Allocation 2:

- Location-1: 1 TNC space, 1 Shuttle Space
- Location-2: 2 TNC Spaces
- Location-3 & 4: 2 TNC Spaces

Figure 5. 1 Modeled network and spaces in the microsimulation network



The shuttle spaces are provided in the north-south direction only as it is assumed to be the shuttle route. The traffic demand has been taken as hourly 500 vehicles in all directions. Both intersections are modeled in Synchro and the signal timing is Vissim has been used as an input from there. The directional volume for regular traffic has been assumed as 60% for through, 30% for left, and 10% for right turns during the process. The speed limit of the network has been 30 mph as we assume this is a commercial urban corridor. The TNC and shuttle demand have been used from one of the distributions generated during the optimization process from each demand scenario (Demand Scenario-1, Distribution ID-1 and Demand Scenario-2, Distribution ID-1). Later, using the random seed, 30 different samples were created within Vissim using the same probability distribution. As, from five entry points the curbside locations are accessible for the network, the TNC distribution has been uniformly divided into five input distributions. As we have used during the optimization, the TNC and shuttle distribution have been split into 1-minute intervals before using them as input for the simulation model. The hourly TNC and shuttle demand is 240 and 30 vehicles. A separate vehicle composition for TNC and shuttle class vehicles has been used to model them in Vissim. Here, the samples generated in Vissim are not exactly same as the samples used in the optimization. Only one sample from them was used to ensure the same demand distribution is used across different scenarios. Replicating the samples in Vissim was not possible because of the randomness within Vissim.

We also used a dwelling time distribution for the stopping vehicles. The minimum stopping time for vehicles is assumed to have a Gaussian distribution. For buses, the minimum dwell time is 60 seconds, and the minimum dwelling time for TNCs is 30 seconds as used during the optimization. Existing studies (Ponnambalam & Donmez, 2020) indicate that drivers slow down while searching for a curbside space, drive closer to the curbside, and maintain a speed lower than 9.32 miles/hr. To replicate this behavior near the curbside, we have used a reduced speed zone next to the curbside for drivers looking for a curbside space. We have restricted the driving speed at those locations for vehicles looking for curbside spaces to 9.32 miles/hr. The length of this reduced speed zone has been taken as equal to the available curbside length.

Scenario Description

We have modeled three scenarios for each allocation to assess curbside productivity for each base model. The first scenario provides insights into the difference in curb productivity from a theoretical scenario to a real-world scenario. The second scenario is modeled to compute the impact of location on curbside productivity while the third scenario is modeled to show the impact of data connectivity on curbside productivity. The results are computed as the number of space requests and number of requests served along with the productivity of each space.

Scenario 1: Curbside Near Intersection

This scenario represents when curbside locations are placed in the network according to the space allocations from optimization results. Regardless of the location of the curbside, the TNCs are routed to arrive at each curbside location. Upon arrival, they request to park at the curbside location and leave if the space is not available. Their routes are randomly defined by the model. If they find another curbside location on their way out of the network, they can request a space. In this scenario, the drivers do not have any information about the curbside space availability. The shuttles are running in the north-south direction. The results of this scenario will be compared to the optimization results to understand the differences between both.

Scenario 2: Curbside far from Intersection

The routing logistics of this scenario is the same as Scenario 1. The only difference in this scenario from the previous one is the curbside locations are moved far from the intersection. We hypothesize that when the curbside locations are situated far from the intersection, they will be free from the impact of the traffic signals and queues. Hence, more vehicles will be able to stop at the curbside and the curbside productivity will go higher.

Scenario 3: Curbside with Data Connectivity

In this scenario, we assume that drivers will get exact information about the availability of spaces upon requesting a space at a curbside location. They will be informed about the availability of spaces. Having the exact information will help more vehicles to find a stopping location in the network, hence the curbside productivity will go higher. The routing logistics for this scenario are as follows.

- If a vehicle enters from link 1, it can request a space at curbside 1, if the space is available, it can stop. Otherwise, the vehicle sends a request to curbside 4 to stop. If the request gets accepted; it goes there to stop and leave the network afterward.
- If a vehicle enters from link 2, it can request a space at curbside 4, if the space is available, it goes there to stop, otherwise leaves the network as there are no other curbside spaces on route.
- Similarly, if a vehicle enters from link 3 or 5, it can request a space at curbside on link 3 and 5, if the space is available, it can stop. Otherwise, the vehicle sends a request to curbside 4 to stop. If the request gets accepted; it goes there to stop and leave the network afterward.

Productivity Results

30 runs of the microsimulation model were run for 75 minutes for a random starting seed. The vehicle stopping information was collected from 15 minutes to 75 minutes to compute the productivity outcome. The results for each demand scenario are presented in the subsections.

Allocation-1:

Scenario 1: Curbside Near Intersection

The optimization results for the distribution used to model the curbside scenarios are shown in Table 5. 1. The results show that the average total CPI for the same distribution is around 79 percent higher than what is estimated in the theoretical model though the number of TNCs served is about 36 percent less than the optimization model and shuttle served is about 24 percent lower than the optimization model. The differences in results can be explained by the randomness of the simulation model. In the optimization model, we have assumed thirty realizations of the distribution while for the same parameters, numerous distributions can occur in the real world. Though we have used the same distribution as the input, the random numbers are generated by Vissim. Hence, the total number of TNCs in the optimization model and simulation model do not match. Also, the number of TNCs served for simulation shows a greater chance of multiple vehicles arriving at the curbside within a small interval, which is why fewer vehicles are served by the simulation model. Another explanation for the mismatch of the curb productivity index lies in the stopping time for each vehicle. As assumed in the optimization model, the vehicle stopping times in the simulation model are not constant.

Table 5. 1 Difference between the optimization and simulation results

	TNC Requested	TNC Served	Shuttle Requested	Shuttle Served	Total CPI (Passenger Per Hour Per 20 ft)
Optimization	240	154	30	21	661.4
Simulation	254	98	24	16	1185.03
Difference	5.83%	36.36%	20.00%	23.81%	79.17%

Scenario 2: Curbside far from Intersection

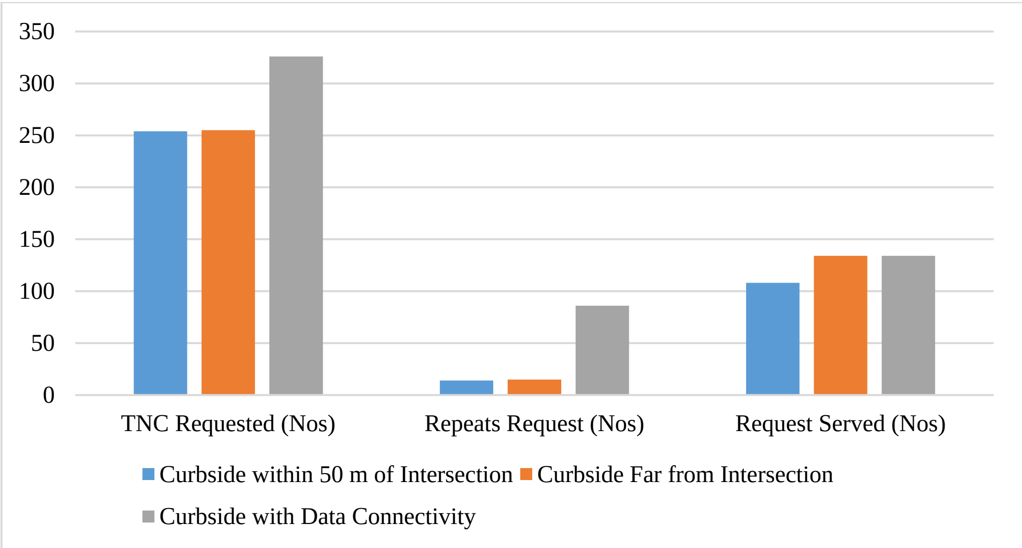
Table 5. 2 and Figure 5. 2 present the results for all scenarios which also contain the results for curb productivity when curbside spaces are situated far from the intersection. It shows that

when curbside locations are located far from the intersections, more vehicles can find spaces in the curbside and stop. Hence, the curb productivity has gone up from the previous scenario where the curbsides were located near the intersections. The shuttle productivity remains the same as the number of shuttles entered and served does not change.

Table 5. 2 Curb productivity results for all curbside scenarios.

Scenario	TNC Entered in the Network (Nos)	TNC Requested (Nos)	Repeats Request (Nos)	Request Accepted (Nos)	Request Declined (Nos)	TNC Served (Nos)	CPI (Passenger Per hr Per 20 ft of Curbside Space)
Curbside within 50 m of Intersection	240	254	14	108	146	98	629.93
Curbside Far from Intersection	240	255	15	134	121	125	745.68
Curbside with Data Connectivity	240	326	86	134	192	129	760.20
Scenario	Shuttle Entered in the Network (Nos)	Shuttle Requested (Nos)	Repeats Request (Nos)	Request Accepted (Nos)	Request Declined (Nos)	Shuttle Served (Nos)	CPI (Passenger Per hr Per 20 ft of Curbside Space)
Curbside within 50 m of Intersection	24	24	0	18	6	16	555.10
Curbside Far from Intersection	30	30	0	21	9	21	553.20
Curbside with Data Connectivity	30	30	0	21	9	21	558.01

Figure 5. 2 Vehicle Served Across Different Scenarios



Scenario 3: Curbside with Data Connectivity

Table 5. 2 also shows that, when drivers have exact information about the curbside availability, the curbside can serve more vehicles hence, more people. This means data connectivity has the potential to improve the curb productivity of the network. The results show that data connectivity allowed 129 TNCs to stop for PUDO activities which is 31 vehicles more than when drivers did not have exact information.

Allocation-2:

Scenario 1: Curbside Near Intersection

The optimization results for the distribution used to model the curbside scenarios are shown in Table 5. 3. The results show that the average total CPI for the same distribution is around 76 percent higher than what is estimated in the theoretical model though the number of TNCs served is about 39 percent less than the optimization model and shuttle served is about 32 percent lower than the optimization model. The differences in results can be explained by the randomness of the simulation model. In the optimization model, we have assumed thirty realization of the distribution while for the same parameters, numerous distributions can occur in the real world. Though we have used the same distribution as the input, the random numbers are generated by Vissim. Hence, the total number of TNCs in the optimization model and simulation model do not match. Also, the number of TNCs served for simulation shows a greater chance of multiple vehicles arriving at the curbside within a small interval, which is why fewer vehicles are served by the simulation model. Another explanation for the mismatch of the curb productivity index lies in the stopping time for each vehicle. As assumed in the optimization model, the vehicle stopping times in the simulation model are not constant.

Table 5. 3 Difference between the optimization and simulation results

	TNC Requested	TNC Served	Shuttle Requested	Shuttle Served	Total CPI (Passenger Per Hour Per 20 ft)
Optimization	240	179	30	22	758
Simulation	248	110	30	15	1337.46
Difference	3.33%	38.55%	0.00%	31.82%	76.45%

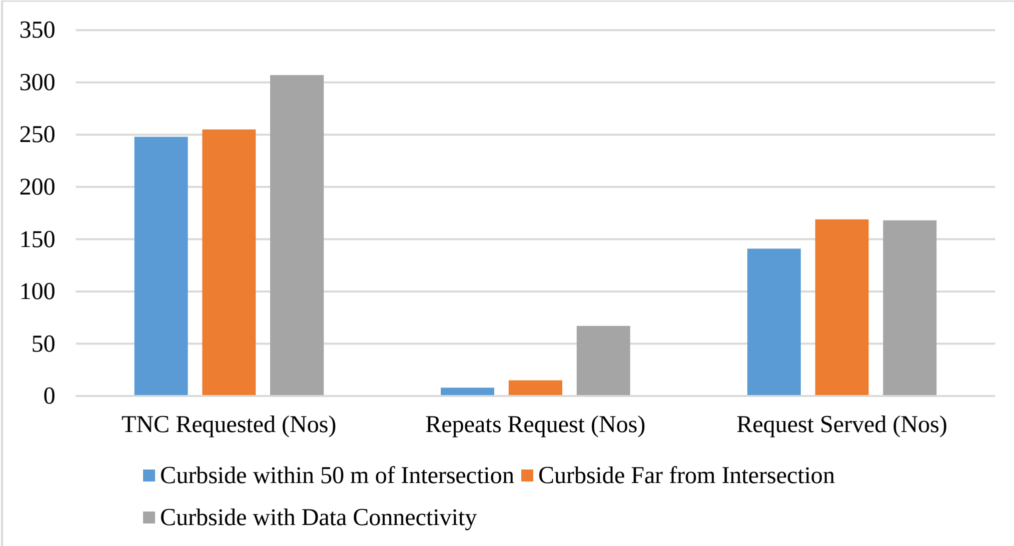
Scenario 2: Curbside far from Intersection

Table 5. 4 and Figure 5. 3 present the results for all scenarios which also contain the results for curb productivity when curbside spaces are situated far from the intersection. It shows that when curbside locations are located far from the intersections, more vehicles can find spaces in the curbside and stop. Hence, the curb productivity has gone up from the previous scenario where the curbsides were located near the intersections. The shuttle productivity remains the same as the number of shuttles entered and served does not change.

Table 5. 4 Curb productivity results for all curbside scenarios.

Scenario	TNC Entered in the Network (Nos)	TNC Requested (Nos)	Repeats Request (Nos)	Request Accepted (Nos)	Request Declined (Nos)	TNC Served (Nos)	CPI (Passenger Per hr Per 20 ft of Curbside Space)
Curbside within 50 m of Intersection	240	248	8	141	107	110	615.84
Curbside Far from Intersection	240	255	15	169	86	162	747.38
Curbside with Data Connectivity	240	307	67	168	139	161	746.60
Scenario	Shuttle Entered in the Network (Nos)	Shuttle Requested (Nos)	Repeats Request (Nos)	Request Accepted (Nos)	Request Declined (Nos)	Shuttle Served (Nos)	CPI (Passenger Per hr Per 20 ft of Curbside Space)
Curbside within 50 m of Intersection	30	30	0	15	15	15	721.62
Curbside Far from Intersection	30	30	0	15	15	15	718.22
Curbside with Data Connectivity	30	30	0	15	15	15	719.41

Figure 5. 3 Vehicle Served Across Different Scenarios



Scenario 3: Curbside with Data Connectivity

Figure 5. 3 also shows that, when drivers have exact information about the curbside availability, the curbside can serve more vehicles hence, more people. This means data connectivity has the potential to improve the curb productivity of the network. The results show that data connectivity allowed 161 TNCs to stop for PUDO activities which is 51 vehicles more than when drivers did not have exact information.

Summary

This chapter evaluates the impact of location and data connectivity on curbside productivity. For this purpose, a microsimulation model has been developed by modifying the basic features in PTV Vissim to represent PUDO activities. Based on the microsimulation model, three scenarios were developed to assess the impacts. The results show that the location of the intersection has a significant impact on curbside productivity. If the curbside is designated far from the intersection, it can improve network productivity. Results also show that apart from the location, the availability of information to the drivers can also improve curbside productivity.

Chapter 6 - Conclusion And Future Directions

Summary

Shared-use mobility (SUM) has changed the landscape of urban transportation in the U.S. over the past twenty years. The growing demand for sustainable transportation, stimulated by environmental, energy, and economic issues, has encouraged a favorable environment for SUM's expansion. Technological advancements have enabled transportation network companies to create innovative solutions such as bike sharing, scooter sharing, car sharing, ride-sourcing, and micro-transit, contributing to the emergence of Mobility-as-a-Service (MaaS).

Integrating shared-use mobility services into urban transportation systems presents a promising route for reducing carbon emissions and promoting sustainability. By offering alternatives to car-based short trips and facilitating resource-efficient practices such as ride-sourcing and multiple uses of curbside spaces, these services contribute to a more environmentally friendly and equitable transportation landscape. Proactive planning and collaboration can harness the full potential of shared-use mobility to create more efficient and inclusive urban transportation systems for the future. However, the lack of assessment for existing curbside allocation strategies results in inefficient use and management of these spaces. The dynamic nature of curbside demand and the absence of an assessment tool make curbside allocation even more challenging. In this study, we focused on developing a microsimulation-based curbside assessment model that can evaluate the effectiveness of different curbside strategies. Later, we developed a curbside optimization model that can take care of the stochasticity of the curbside demand. Finally, we explored the role of connected vehicle technologies that can make curbside management easier and assess their effectiveness in managing curbside. The significant findings of this research, limitations, , future research directions, and research contributions are presented in the following sections.

Major Findings

Microsimulation-based Framework:

In this work, we applied a simulation-based framework to assess the curbside management strategies favoring ride sourcing and delivery vehicles. Using a microsimulation platform, Vissim, and EPA-MOVES, we assessed the mobility and environmental impact for different scenarios. The scenarios have been tested for two types of networks: (1) a hypothetical stretch of roadway as a small network and (2) an existing traffic network from Downtown Chicago, IL. Later, we also assessed the effect of fleet electrification of shared-use mobility services by analyzing three potential EV market share scenarios. Regarding mobility and environmental impacts, our results lead to the major findings:

- The results indicated that as electric vehicle adoption rises, emissions and energy consumption decline, offsetting the negative traffic impact of increased curbside activities. Hence, vehicle electrification will offer a solution to mitigate environmental effects while accommodating growing urban mobility demands.
- Removing long-term parking and restricted curbside management policies can increase street congestion stress but reduce emissions and energy consumption.
- Shortening the dwelling time window for ride-sourcing services will serve more vehicles. Also, when curbside activities increase, emissions and delays become higher.
- When the number of curbside spaces is reduced, energy consumption decreases. The post-trajectory analysis shows improvements in vehicle speeds, which may have contributed to reducing energy consumption and emissions.

- Comparing the small and complex networks showed that the results of an ideal network condition might vary for a complex network. The presence of traffic control turns, multiple interactions, and lane configurations may have led to these differences.

Further, we observed that the mobility and environmental metrics do not follow similar link and network-level trends. The configuration of the roads–the presence of signal control, bus-bike boxes, and similar–will impact the overall congestion and resulting emissions level. More investigations are needed to develop a general correlation between network geometry and the impact of curbside impacts. We also report the curbside productivity metrics for our test scenarios. The curbside metrics can be used for the optimal allocation of activities through prioritization. The metrics in the literature are not yet robust enough to capture the economic impact of services like urban delivery or food trucks in a central business district.

Optimization Framework:

After developing the assessment model, we formulated a mathematical curbside optimization model as an integer linear program (ILP). Later we tested the formulation across different scenarios to understand the efficacy and applicability of the model. The summary of results is as follows:

- Initial assessment revealed that the curb productivity index (CPI) is highly sensitive to the number of passengers being served by the service. When arrival demand by various services is unchanged but they are serving different numbers of passengers, shuttles get priority at the curbside spaces. When shuttle demand increases but it serves fewer passengers, the allocation of spaces for shuttles reduces. This is because the CPI varies depending on the number of passengers being served.

- Comparison of Curb Productivity Index (CPI) between the long-term parking dominated allocation and an optimal allocation shows that CPI is consistently lower when more vehicles are parked for longer times.
- The optimized allocation strategy ensures an increase in curb productivity within the same space. Depending on service demands, this optimization model can elevate productivity by up to 5.1 times.
- The dynamic optimization reveals that the CPI will vary depending on the vehicle arrival at each interval, hence, we can have numerous allocation strategies. However, depending on the loss of Expected Mean CPI, it is possible to select an optimal allocation to achieve a greater benefit in the real world.

Connected Curbside:

In the last part of the dissertation, we developed a microsimulation model where we estimated the variation of curbside productivity in the real world from the theoretical model. Later, we assessed the impact of curbside location relative to the intersection and data connectivity on curb productivity using PTV Vissim.

- The results show that the average Total CPI for the same distribution is around 32 percent higher in the simulation model than what is estimated in the theoretical model though the number of TNCs served is about 14 percent less than the optimization model. The result confirms that CPI will highly depend on the distribution.
- The results show that the location of the intersection has a significant impact on curbside productivity. If the curbside is designated far from the intersection, it can improve network productivity.

- Results also show that apart from the location, the availability of information to the drivers can also improve curbside productivity.

Limitations

While we conducted this research in three segments, it was not possible to address all the elements in a single study. Hence, this study has some limitations described below.

Curbside Assessment

This assessment framework utilizes the shared vehicle demand from real-world data and the shared-use services demand as a fraction of it to estimate the impacts of curbside prioritization strategies. Although this approach represents the critical demand state of shared-use mobility services, the demand is not extracted from real-world data. The complexity of determining the demand from different shared-use services per se is a topic of research and not within the scope of this work.

One critical assumption made in our work is the public acceptance and enforcement of curbside strategies. We acknowledge that the results from the assessment model developed in this study will only be realized when proper curbside regulations are into effect. Hence, curbside enforcement is integral to the effectiveness of this assessment model, as it will ensure that curbside spaces are utilized efficiently. Curbside enforcement can also be crucial in monitoring and ensuring compliance with curbside regulations, such as long-term parking restrictions, time limits, and designated use for services like PUDO for TNCs, public transportation, urban delivery, etc. It will help to maintain the priorities and accessibility of the curbside spaces while discouraging violations.

Optimization

The curbside optimization formulation that we developed in this study is solely applicable to services for passenger PUDO services. This curbside optimization model cannot directly be used for goods-carrying services as the objective function is dependent on the number of passengers being served. So, this optimization model limits itself to the passenger-carrying services only.

The static optimization module was later used for optimizing the curbside spaces when the demand is stochastic. While this model can address the variation in demand effectively, the model was not tested for variability in other stochastic parameters like stopping time, and passenger occupancy. Further research is needed to estimate the impact of these variable parameters on curbside optimization and its productivity.

Connected Curbside

The results obtained from the dynamic optimization have been used in microsimulation scenarios to check the difference between the CPI from optimization and a real-world scenario. The scenarios tested in connected curbside have been tested for only one instance of demand while the dynamic optimization was done for 35 different distributions. Though the results have been tested for the demand distribution that has been used, more experiments for different demand instances may lead to newer observations.

Also, in the connected curbside, while modeling it was assumed that the drivers will communicate first with the infrastructure to request for spaces. This communication, though instant may result in excessive stopping requests to the RSUs for the same number of vehicles. This may mislead the curbside managers about the instant demand for the spaces if not handled carefully.

Another limitation of this research is that, while testing the impact on curbside productivity from the surrounding environment, only the location of the intersection and the presence of signal timing have been assessed. Many other factors like the presence of bus bays, driver behavior, cruising for stopping spaces etc. that may be available in the real world has not been evaluated.

Future Directions

As we look toward the future of curbside operations research, several vital directions can significantly contribute to addressing the challenges posed by the increasing complexity of urban mobility.

- Incorporating predictive models that analyze user behavior, traffic patterns, and service preferences will provide decision-makers invaluable insights into the dynamic nature of curbside demand. Demand Models will enable more accurate forecasting of future demand, allowing for proactive and efficient allocation of curbside space.
- As urban landscapes evolve and become more intricate, it is essential to consider networks with complex geometry and curbside operations. Traditional approaches to curbside management often need to pay more attention to the nuanced spatial characteristics of urban environments, leading to suboptimal utilization of curbside space. By developing advanced modeling techniques that account for the intricate interplay between road layouts, land use patterns, and curbside dynamics, researchers can devise more robust strategies for optimizing curbside operations in complex urban settings.
- Additionally, incorporating vehicle-systems models like FASTSim or Autonomie presents a promising avenue for advancing the environmental sustainability of curbside operations. These models provide advanced tools for calculating vehicle emissions at a detailed level,

considering factors such as vehicle attributes, driving habits, and operational circumstances. By integrating these models into curbside management frameworks, decision-makers can devise strategies that prioritize eco-friendly vehicles and encourage sustainable transportation practices, ultimately lessening the environmental footprint of curbside operations.

- The static optimization module can be further developed to consider the other sources of variation in the network like stopping time, and passenger occupancy. Incorporating these parameters is important as they will directly impact curbside productivity, changing the optimal allocation.
- This study has developed the initial model to optimize curb productivity for passenger-carrying services. Developing a new objective function that can address the productivity for the good carrying services can help optimize the whole curbside for all services. For this, it is important to find a common ground to compute benefits from both passenger-carrying and goods-carrying services. It can be independent research itself as the availability of data representing benefits for both is missing. One approach can be using benefits in monetary terms while using different optimization techniques like Pareto optimization. Apart from passenger occupancy, metrics like environmental and mobility benefits can also be incorporated into the objective function to develop an integrated optimization module for the network.
- The microsimulation model for curbside connectivity can be further extended to test for different demand scenarios while each demand scenario can be simulated multiple times. As autonomous vehicles will potentially be penetrating the market in the future it will be

beneficial to understand the changes in curbside occupancy and productivity for connected autonomous vehicles.

- This research can be further extended to evaluate how the curbside productivity will change when vehicles approach the curbside and vehicles completing services at the curbside can inform their expected dwelling time through to the approaching vehicle through vehicle-to-vehicle (V2V) communication. This research can also be extended to see how curbside pricing will impact overall productivity.

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APPENDIX

Appendix A - Mobility Results

Table 3. 8 Mobility Results for the Hypothetical Small Network (3 Lane Roadway)

	Average Delay (Bus) (sec/veh)	**Average Stopped Delay (Bus) (sec/veh)**	**Average Speed (Bus) (kmph)**	**Average Stops (Bus) (Nos.)**
HS-T1				
Average	11.19	3.89	13.43	0.52
Standard deviation	0.75	0.72	0.43	0.06
Minimum	9.84	3.09	12.52	0.31
Maximum	13.74	6.76	14.52	0.66
HS-T2				
Average	13.51	5.13	12.71	0.62
Standard deviation	0.86	0.57	0.38	0.04
Minimum	11.25	3.58	11.85	0.54
Maximum	15.30	6.24	13.83	0.70
MS-T1				
Average	9.36	2.71	15.91	0.46
Standard deviation	0.45	0.29	0.40	0.03
Minimum	8.50	2.28	14.69	0.41
Maximum	10.46	3.30	16.51	0.56
MS-T2				
Average	9.67	4.27	16.47	0.38
Standard deviation	11.09	3.83	15.20	0.54
Minimum	1.24	1.08	0.64	0.07
Maximum	9.52	2.85	13.47	0.38
LS-T1				
Average	8.18	2.18	18.77	0.41
Standard deviation	0.75	0.65	0.59	0.03
Minimum	7.55	1.67	16.48	0.35
Maximum	11.57	5.37	19.65	0.49
LS-T2				
Average	8.81	2.53	18.44	0.22
Standard deviation	0.84	0.72	0.74	0.04
Minimum	7.60	1.71	15.69	0.15
Maximum	12.41	6.06	19.54	0.34

Table 3. 9 Mobility Results for the Hypothetical Small Network (4 Lane Roadway)

	Average Delay (Bus) (sec/veh)	**Average Stopped Delay (Bus) (sec/veh)**	**Average Speed (Bus) (kmph)**	**Average Stops (Bus) (Nos.)**
HS-T1				
Average	6.49	1.65	18.67	0.35
Standard deviation	0.70	0.42	0.48	0.04
Minimum	5.24	1.05	17.82	0.28
Maximum	7.70	2.64	19.48	0.42
HS-T2				
Average	8.72	2.81	17.33	0.45
Standard deviation	0.65	0.38	0.49	0.04
Minimum	7.31	1.99	16.51	0.37
Maximum	9.87	3.46	18.29	0.53
MS-T1				
Average	5.26	1.06	21.48	0.29
Standard deviation	0.47	0.21	0.49	0.03
Minimum	4.53	0.79	20.11	0.24
Maximum	6.59	1.70	22.24	0.38
MS-T2				
Average	6.86	1.88	20.19	0.37
Standard deviation	0.62	0.49	0.77	0.05
Minimum	6.03	1.36	18.41	0.20
Maximum	8.37	3.55	22.79	0.46
LS-T1				
Average	4.44	0.77	24.95	0.24
Standard deviation	0.46	0.19	0.69	0.04
Minimum	3.41	0.37	23.72	0.17
Maximum	5.24	1.37	26.77	0.31
LS-T2				
Average	5.21	1.10	24.08	0.29
Standard deviation	0.57	0.34	0.75	0.04
Minimum	4.33	0.67	22.02	0.23
Maximum	6.99	2.07	25.44	0.38

Table 3. 10 Mobility Results for the Real World Network from Chicago

	Average Delay (Bus) (sec/veh)	**Average Stopped Delay (Bus) (sec/veh)**	**Average Speed (Bus) (kmph)**	**Average Stops (Bus) (Nos.)**
Base Case				
Average	60.60	44.18	11.48	1.41
Standard deviation	4.73	3.60	0.55	0.13
Minimum	52.10	37.29	10.71	1.13
Maximum	67.53	48.98	12.56	1.68
MS-T1				
Average	63.57	46.09	12.52	1.52
Standard deviation	4.08	3.14	0.54	0.13
Minimum	56.13	40.53	11.78	1.26
Maximum	69.63	50.76	13.53	1.74
MS-T2				
Average	63.23	45.52	12.75	1.53
Standard deviation	4.99	3.75	0.69	0.15
Minimum	53.65	38.66	11.78	1.25
Maximum	70.94	52.05	14.18	1.73
LS-T1				
Average	71.40	52.86	1.61	12.12
Standard deviation	9.84	7.90	0.27	1.20
Minimum	54.36	39.27	1.21	9.74
Maximum	94.37	69.32	2.42	14.61
LS-T2				
Average	66.23	48.21	12.89	1.54
Standard deviation	8.99	7.01	1.14	0.26
Minimum	55.18	39.76	10.00	1.23
Maximum	92.22	67.07	14.65	2.40

Appendix B - Proof of Concepts for Optimization

To illustrate the effectiveness of the proposed optimization model, we evaluated the performance with multiple scenarios using both hypothetical and networks based on real-world data. First, we present the results from the deterministic models that do not account for temporal variation in the SUM services arrival pattern. Later, we offer the solution framework to account for demand uncertainty and report results for the hypothetical network.

Deterministic Optimization—Hypothetical Network

To evaluate our optimization model [equation (4.1) – (4.4)], we developed four demand scenarios for a hypothetical network (Figure 4. 3). In this hypothetical network, we are considering four block faces each consisting of a curbside space. We assumed that two types of services—shuttles and TNCs—are seeking parking spaces at those curbsides. The Navya shuttle characteristics have been considered for this experiment. Navya shuttle has the same length as cars, hence, the parking space required by both types of services can be served with a 22ft (7m) spot. Each curbside has a limited length capacity. We assumed that the TNCs arrive at the network with an average headway of 5 minutes and the shuttle buses arrive with an average headway of 10 minutes. The arrival of these services follows Poisson distribution. The TNCs are looking to park at those spaces for an average of 2 minutes with a standard deviation of 1 minute and the shuttle buses are looking to park for an average of 1 minute with a standard deviation of 1minute. Each type of service can serve a limited number of passengers. The number of passengers has been assigned using a normal distribution. The TNCs have a normal distribution of passengers with a mean of 2 and a standard deviation 1. The shuttle buses have a passenger range from 1-8. The minimum demand for the curbsides that should be met for TNCs, and shuttle buses is 1 space each service. We have assessed four scenarios, each for 15 minutes. The TNC demand for these scenarios has been kept constant while both vehicular and passenger demand for the shuttles have been varied. The assumed demand for the TNCs and shuttle buses has been taken as three times more than the actual demand to assess the sensitivity of the model for different demand patterns. The detailed scenarios and the space allocations are presented in Table 4. 18 and Table 4. 19.

Initial assessment reveals that the curb productivity index (CPI) is highly sensitive to the number of passengers being served by the service. Findings derived from both scenario 1 and scenario 2 indicate that, when arrival demand by various services is unchanged but they are serving different numbers of passengers, shuttles get priority at the curbside spaces. When shuttle demand increases but it serves fewer passengers, the allocation of spaces for shuttles reduces. This is because the CPI varies depending on the number of passengers being served.

Table 4. 18 TNC and Shuttle Bus Input Demands

Scenario	Demand (no.)		Curb Length (ft)	Assign Minimum Space (no.)		Passenger Range (no.)	
	TNC	Shuttle	Available	TNC	Shuttle	TNC	Shuttle
1	251	11	512	1	1	1-2	5-8
2	251	11	512	1	1	1-2	1-5
3	251	19	512	1	1	1-2	1-5
4	251	7	512	1	1	1-2	5-8

Table 4. 19 TNC and Shuttle Allocation Results

Scenario	Assigned Spaces		Curb Length (ft)	
	TNC	TNC	Used For Assignment	Unused
1	11	11	506	7
2	17	5	506	7
3	13	9	506	7
4	15	7	506	7

Deterministic Optimization—Network based on Real-World Data

To illustrate the effectiveness of the proposed optimization model, it is necessary to observe its performance in real-world relevance. This example has been developed for three types of services with data from the real world. The objective of this scenario assessment is to compare the curbside productivity before and after optimization. The real-world curbside data has been collected from a study conducted by Machado-León et al. (2023). According to this study, for a total of 560 ft curbside at three block faces, the space distribution is shown in Table 4. 20.

Table 4. 20 Space Allocation for an Existing Case Scenario

Parking Type	Assigned Spaces	
2-hour paid parking	450	ft (19 spaces)
PUDO Zones	20	ft (1 space)
Commercial vehicle loading zones	40	ft
Shuttle bus/Taxi/Charter bus loading zones	50	ft (2 spaces)

In this example, we are going to optimize the spaces for all the above-mentioned services except for commercial vehicles. So, for four block faces, the total curbside length would be 159 m (520 ft). We are assuming the curbside location at each location is shown in Table 4. 21.

Table 4. 21 Assumption of Space Allocation for Each Curbside Location

Curbside Location	Length (ft)
Curbside 1	155
Curbside 2	141
Curbside 3	148
Curbside 4	115

Figure 4. 3 shows the hypothetical curbside locations at four block faces. The demand for the above-mentioned services is described in the following section.

Demand for Curbside Services

Demand estimation for curbside SUM services involves estimating the number of users who will utilize the service within a certain time frame and geographic area. The curbside demand can be estimated by analyzing arrival patterns at the designated locations. This involves collecting data on the frequency and timing of arrivals over a certain period, typically using observational studies or historical records. For this study, we have utilized existing studies--Machado-León et al. (2023)—to estimate curbside demand for our network.

Machado-León et al. (2023) observed pickups and dropoffs at three block faces adjacent to the downtown of Seattle, WA. The data were collected on weekdays for three different weeks over six hours (8.00 AM to 10.00 AM and 2.00 PM to 6.00 PM) from December 2018 to early January 2019 (total of 90 hrs). A total of 6024 valid TNC pickup and dropoff events were recorded during that time. From the above information, we can assume that on average 67 ride hailing vehicles per hour entered the network during peak hours. The average dwell time recorded for TNC trips was 44 seconds. The minimum and maximum dwell time of the TNC services were found to be 4 seconds and 130 seconds. The average number of passengers being picked up or dropped off by the TNCs was 1.15 individuals. The minimum and maximum number of passengers picked up and dropped off by TNCs and other types of services during this time were 1 individual to 13 individuals. However, these observations do not reflect the actual demand, instead, it reflects a portion of the demand that was met by the existing infrastructure.

In another study, Lu (2018b) collected data for stopping of ride hailing/sourcing vehicles on four blocks of Santa Monica Blvd and two blocks of Melrose Avenue of Los Angeles, CA, for 24 hrs from late January to early February 2018. These streets had the highest level of ride sourcing activities on weekend evenings due to vibrant nightlife and retail activities. The data was collected from 7.00 PM to 11.00 PM at Santa Monica Blvd and from 2.00 PM to 6.00 PM at Melrose Avenue on Friday and Saturday evenings for three weeks to capture the weekly variation of ride sourcing demand. Lu found that about 131 ft of curbside space (13%) on Melrose Avenue and 40 ft of curbside space (5%) on Santa Monica Blvd was designated for passenger pickup and dropoff activities. During this study period (24 hrs), Lu (2018b) found that 2067 ride sourcing vehicles stopped at Santa Monica Blvd and 174 ride sourcing vehicles stopped at Melrose Avenue. From this information, we can derive that about 87 ride sourcing vehicles per hour stopped at Santa Monica Blvd and 8 ride sourcing vehicles per hour stopped at Melrose Avenue during peak hours.

Since we are trying to understand the peak demand from the TNCs at a curbside network, depending on the information above, we assumed that 87 ride sourcing vehicles will arrive at four block intersections for our experiment. The TNC demand can be more than 87 vehicles in real network as these numbers only reflect the observed demand. The actual demand was not captured in these studies. According to this study, 176 transit stopped during this analysis period, making it 8 transit per hour on average. The study also mentioned that demand from the private cars on these four blocks was 827 vehicles during the analysis period, which is 35 private cars in an hour. The average dwell time for the ride sourcing vehicles was recorded to be 0.8 minutes, while the mean stopping time for the private cars and transit vehicles was found to be 30 minutes and 0.4 minutes respectively. Here, instead of transit, we are considering Navya shuttle as shuttle buses (SB) for this example. The parking space requirement for this shuttle is the same as for private cars and TNCs. According to Akter and Aziz (2021), the hourly demand for the shuttles is 17 in two blocks. Hence, we assume the hourly demand for the shuttles at four block faces will be more, hence assuming 24 shuttles will be stopping having the same dwell time as the transit provided by Lu (2018b).

Once we had a proper assumption of the arrival rate for each type of service, we estimated the average gap time [3]for the arrival of those services. Depending on the average gap time we were able to produce a vehicle arrival distribution pattern for each type of service for every 15-minute interval within an hour. An exponential distribution was used to produce the gap time between vehicles. This distribution was used because an exponential distribution is usually used to model time between events in a Poisson process. This was generated by producing random numbers in Python. Using a random number generator, we also generated dwelling time associated with each service at the curbside. The dwelling time was generated using a distribution presented in Table 4. 22. Here, dwell time has been used as a normal distribution. This has been produced with a Python module using the mean and standard deviation values provided in Table 4. 22. For the passenger occupancy, the range provided in Table 4. 22 is used to assign the occupancy to different services randomly. The service demand within a 15-minute period was kept constant.

Scenario Description:

We are going to optimize the spaces for 1 hour using multi-stage planning: run the model for every 15 minutes of demand and evaluate productivity based on allocation. We are considering each 15-minute demand as an individual scenario. Here, it is assumed that the demand for different services will vary at different quarters of the hour. The details of the demand that has been used as an input for the optimization model are provided below in Table 4. 22.

[3] The gap time is a terminology used in Traffic Engineering. This can also be assumed as interarrival time of vehicles.

Table 4. 22 Details of parameters used for the optimization model

Scenarios			**TNC**		
	Service Demand (veh/15 min)	**Average Gap Time (min)**	**Mean Dwell Time (min)**	**Dwell Time (Standard Deviation) (min)**	**Passenger Range Served (Nos.)**
SC-1	15	1	1	0.5	1-2
SC-2	20	0.75	1	0.5	1-2
SC-3	17	0.9	1	0.5	1-2
SC-4	35	0.4	1	0.5	1-2
Scenarios			**Shuttle**		
	Service Demand (veh/15 min)	**Average Gap Time (min)**	**Mean Dwell Time (min)**	**Dwell Time (Standard Deviation) (min)**	**Passenger Range Served (Nos.)**
SC-1	7	2.1	0.4	0.5	1-15
SC-2	7	2.1	0.4	0.5	1-15
SC-3	5	3	0.4	0.5	1-15
SC-4	5	3	0.4	0.5	1-15
Scenarios			**Private Car**		
	Service Demand (veh/15 min)	**Average Gap Time (min)**	**Mean Dwell Time (min)**	**Dwell Time (Standard Deviation) (min)**	**Passenger Range Served (Nos.)**
SC-1	16	0.9	30	15	1-2
SC-2	5	3	30	15	1-2
SC-3	6	2.5	30	15	1-2
SC-4	8	1.9	30	15	1-2

Input Data Preparation for AMPL:

In AMPL, we used several files to run the mathematical optimization model. These files included a model file, a data file, and a command file. The model File (*.mod) file contained the mathematical representation of our optimization model. It consists of the objective function, decision variables, and constraints. The data file (*.dat or *.dat.txt) contained specific data values that have been used as input to our model. These values included parameter values, and any other data required to solve the optimization problem. The commands File (*.run or *.run.txt) contain AMPL commands that instruct the AMPL solver on how to solve our model. It included commands to load the model file, read the data file, specify the solver to use (CPLEX), and request the solution of the optimization problem.

We prepared the input data for the *.dat file to solve the proposed optimization model using Python. We assume that the demand is fixed over 15 minutes, so, we generated a gap time distribution for the arrival of different services using the mean value in Python. The gap time distributions are critical to measuring productivity. It is dependent on the dwell time and the gap time if a vehicle is going to find an available space upon arrival. To prepare the input data for the optimization, we used Python to generate data for each vehicle, containing information about the passengers they were carrying and the duration of their stays. The mean, standard deviation, and passenger range values provided in Table 2 are used to generate these data. We also used the capacity of the various curbsides as an input for the model. These values have been updated at the end of every allocation stage (15-minute intervals). This is because some vehicles will arrive near the end of the analysis period to dwell more than the time left of the current stage which keeps the space occupied at the start of the next stage. Thus, the residual capacity of curbside changes at the end of each stage, so it needs to be updated. Hence, if a space is occupied at the beginning of the 15-minute window, then no other vehicle will be assigned during the entire 15-minute. The minimum demand to be met for each type of service was set to 1 in the optimization model to ensure each service gets a space during allocation.

Results: Space Allocation:

The allocation of spaces for each stage is provided in Table 4. 23. If we compare this space allocation with the existing space allocations in Table 4. 20 (19 spaces for private cars, 2 spaces for transit, and 1 space for TNC PUDO), then we can observe that, the optimization model prioritizes the allocation for PUDO services from the TNCs and the on-demand shuttles in each scenario. This is because the model maximizes the curb productivity index which has the passengers served and dwell time as major influencing variables in the equation. Prioritizing TNCs and on-demand shuttles will ensure more people are being served, hence, the model results reflect that in the outcome. During this process, the model used for this analysis does make the same capacity constraint adjustment used in the main part of the chapter. However, this is done manually after each scenario is run and results are obtained rather than done directly in the optimization model.

Table 4. 23 Space Allocation for the different scenarios from the optimization model

SC-1	**Parking Lot 1**	**Parking Lot 2**	**Parking Lot 3**	**Parking Lot 4**	**Sum**
TNCs	4	3	3	4	14
Shuttle	2	2	2	1	7
Private Car	0	1	0	0	1

SC-2	**Parking Lot 1**	**Parking Lot 2**	**Parking Lot 3**	**Parking Lot 4**	**Sum**
TNCs	3	4	3	3	13
Shuttle	3	1	1	2	7
Private Car	0	0	1	0	1

SC-3	**Parking Lot 1**	**Parking Lot 2**	**Parking Lot 3**	**Parking Lot 4**	**Sum**
TNCs	3	6	4	3	16
Shuttle	2	0	0	2	4
Private Car	1	0	0	0	1

SC-4	**Parking Lot 1**	**Parking Lot 2**	**Parking Lot 3**	**Parking Lot 4**	**Sum**
TNCs	3	4	3	5	15
Shuttle	1	2	1	0	4
Private Car	1	0	0	0	1

Results: Curb Productivity Index:

After the allocation, we estimated the curb productivity index (CPI) using the model's results as well as for the existing allocation. Only 1 instance for each scenario is solved in this example. The comparison of the curb productivity index is presented in Table 4. 24 and Figure 4.

9. The values of the curb productivity index are presented as passengers served per 100 ft of curbside space per hour. The allocation results from the optimization model were post-processed using an Excel spreadsheet to consider the arrival time and dwell time of vehicles in CPI estimation. Since the optimization model did not account for the multi-use directly in the model, we used an Excel spreadsheet to estimate the effective CPI for an allocation where the multi-use of spaces was considered and capacity for the next model was calculated. This CPI is reported in the results instead of directly reporting the CPIs from the optimization model. For the multi-stage framework, I estimated effective CPI using the allocation obtained from the optimization model for each stage. For each allocation and respective demand, the CPI was estimated at four stages for each 15-minute while the multi-use of spaces was considered. Summing up the CPIs for four stages provided us with the hourly CPI. For the base case, the hourly allocation and hourly demand (that was split into 15-minute demand for stage-based estimation) were considered to estimate the CPI, while muti-use was also considered. The results show that, for each demand scenario, the value of the curb productivity index is lower in the base case where most spaces are designated for private vehicles than in the optimized case where private vehicles get the least priority. The optimization model ensures the curb productivity increases by at least 3 times for the same available space. Depending on the demand from different services, productivity can be increased by 5.1 times when curbside optimization is done. Hence, we can conclude that the curbside optimization model will have a positive impact on the management when implemented.

Figure 4. 9 Comparison of Curb Productivity Index Across Different Scenarios

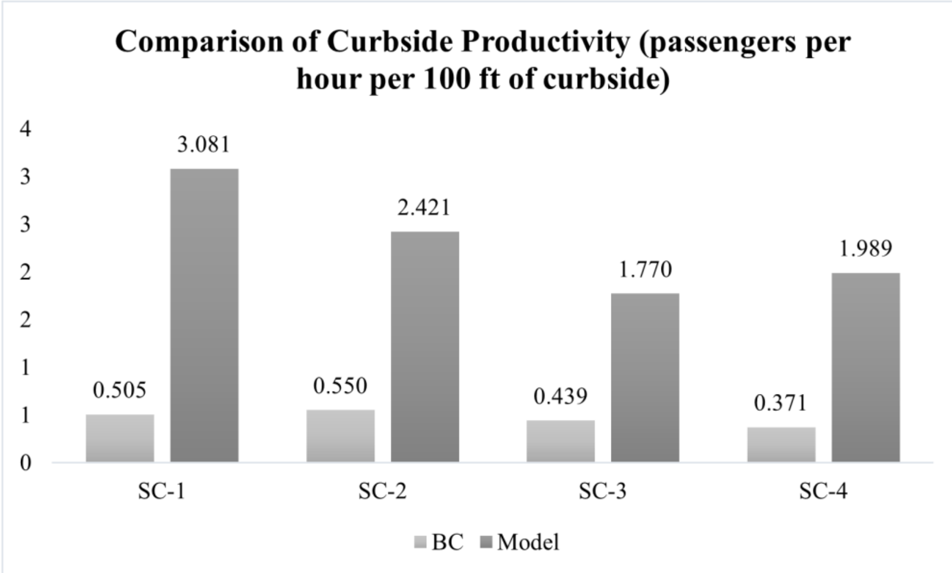

Table 4. 24 Comparison of Curb Productivity Index

Scenario	Curb Productivity Index (passengers per hour per 20 ft of curbside)		Multiplies Productivity By
	BC	Model	
SC-1	0.505	3.081	5.1
SC-2	0.550	2.421	3.4
SC-3	0.439	1.770	3.0
SC-4	0.371	1.989	4.4