Abstract

In this paper we explore city-level traffic and parking data to determine how much cruising for curbside parking contributes to overall traffic congestion. To this end, we describe a new kind of queueing network and present a data-informed model based on this new queuing network. We leverage the data-informed model in developing and validating a simulation tool. In addition, we utilize curbside parking and arterial traffic volume data to produce an estimate of the proportion of traffic searching for parking along high occupancy arterials. Somewhat surprisingly, we find that while percentage increase in travel time to through traffic vehicles depends on time of day, it does not appear to depend on high volumes of through traffic. Moreover, we show that the probability of a block-face being full is a much more viable metric for directly controlling congestion than average occupancy rate, typically used by municipalities.

1 Introduction

Searching for parking presents a challenging task in urban districts around the world. Drivers in dense urban areas frequently find that desirable parking close to their destination is unavailable or prohibitively expensive. As a result, the act of cruising for parking can arise from any number of situations: desirable parking near a destination being at capacity, price differences between public curbside parking and private garage parking

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or simply a driver’s lack of familiarity with their surroundings. Studies have suggested that a majority of drivers spend anywhere between 3.5 to 14 minutes in a typical search[30]. These times quickly add up to cause significant productivity losses in cities. For example, a single 15 block district of Los Angeles services over 8,000 cars in day, which leads to 470 to 1870 hours of lost time looking for parking[29]. In addition to bringing a high degree of frustration to the individual drivers, cruising for parking is believed to have a even more detrimental impact to the efficiency of the whole transportation system.

The major impact of circulating vehicles looking for parking is increased congestion. An often cited anecdotal figure—whose source is not entirely clear—is at any time, 30% of vehicles on surface streets of major cities are looking for parking[29]. This is an astounding

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The discrepancy between curbside parking and off-street parking can be very significant. For example, in some areas of Seattle, parking in a garage costs upwards of $9/hour compared to the roughly $2/hour cost of on-street parking[15]. In addition to price discrimination caused by time-dependent fees, an entire day in a garage is approximately $30.
Fig. 1: Occupancy over the course of the day for two adjacent blocks in Belltown for a representative weekday (Wednesday) and Saturday. The occupancy plots show that there is spatial and temporal heterogeneity even for nearby blocks. In the case of these two blocks, the disparity is likely due to the fact that the Southeast side (yellow) is parallel parking whereas the Northwest side (purple) is back-in angle parking and thus has more capacity. In addition, between 15:00-17:00 there is no legal parking on the Northwest side on weekdays to allow for King County Metro buses to pick-up passengers.

number: because of the highly nonlinear relationship between traffic volume and travel time, 30% more vehicles could double or triple the throughput delay of urban areas. For a mile long surface street, these circulating vehicles could easily add 10 to 20 minutes of travel time for the through traffic. If 2,000 vehicles traverse a surface street in during commuting hours (a typical number for Seattle), a 15 minute increase in travel time leads to an additional 500 hours lost per street, per day. Consequently, cities and industries have started major initiatives to better manage parking [22, 1, 37, 10].

For cities and urban planners to take concrete actions, a nuanced understanding of the impact of parking on congestion is required. New tools and policies like dynamic pricing [38, 23, 13] and location based pricing [16, 5] can potentially mitigate cruising for parking, but they require a detailed spatial-temporal characterization of cruising behaviors. Without this type of understanding, cities are forced to apply blanket policies. For example, the Seattle Department of Transportation (SDOT) divides its control areas into large zones and implements uniform parking prices and time limits in each of the zones that largely reflect traditional neighborhood boundaries and not transportation system, much less parking occupancy, features. Fig. 2 shows 8 distinct neighborhoods that SDOT uses for parking policy deployment; even a cursory look at Seattle’s parking data shows us that parking occupancy can vary considerably across space and time—even between neighboring block-faces (see Fig. 1).

In this paper, we combine new sources of data with a novel queueing network model to provide a detailed picture—both in space and time—of the impact of cruising for parking on congestion. We develop a city-scale, data-informed model and data-validated simulation tool that can be used in policy design and analysis. To our knowledge, this is the first tool for exploring the parking-congestion relationship that is based on system-level data, can be used at scale, and provides high granularity of actionable spatio-temporal information.

With respect to data, we leverage technologies such as smart meters and embedded traffic volume sensors. In particular, we use data provided by SDOT, collected by the paid transaction smart parking meters. We also use travel time and traffic volume data for arterial streets in Seattle provided the IDAX corporation. These types of data are becoming widely
available in many cities around the United States. Recent initiatives—LA Express Park in Los Angeles [22] and SFpark in San Francisco [1], for example—are providing both city planners and researchers with a wealth of new data. SFpark is a now concluded pilot study that evaluated the effectiveness of spatially and temporally adjusted pricing for on-street and off-street parking\(^2\). Similarly, LA Express Park is an ongoing program that utilizes smart technologies and demand-based pricing to manage parking in downtown LA.

Barring these few examples of pilot studies, cities most often have neither a) crowdsourced data on parking availability nor b) real-time sensing capabilities that can provide information on driver behavior (e.g., search or common destination patterns) and supply (which can be dynamic in cities like Seattle that do not demarcate curbside parking spaces). This is largely due to the fact that such initiatives come at a high price; it is not cheap to install and maintain city-wide spot-level sensors and web-based information access. Moreover, cities often experience push back from constituents when installing new technologies [6, 14]. Residents often fear the result will be more congestion in their neighborhood or inequitable pricing that adversely effects low-income drivers. Thus, the roll out of technology for many cities is slow. In Seattle, like many cities, there is data available from smart meters, yet it only provides information on paid transactions (disabled placard holders, government vehicles, and the drivers of car-sharing vehicles do not pay for parking in Seattle) and does so only at the block-face level, rather than individual spaces. It does, however, provide a

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\(^2\)The pilot study was conducted on approximately 25% of SF’s smart meters and due to its success, the program will be rolled out across SF mid-2017.
window into historical usage so that real-time estimates of availability can be made.

Hence, the key challenge lies in generating actionable models that take into consideration data currently available to city planners. Moreover, there is a clear need for generalizable techniques that leverage available data streams in order to provide a foundation for control design—e.g., pricing, maximum duration, and other policies. This highlights the need for approaches that balance model-based with data-driven techniques.

**Contributions & Impact:** Our contribution can be summarized in the following points: 1) we present a new *data-informed model* for urban parking that leverages *available* data streams and considers spatio-temporal heterogeneity and 2) we present a *data-validated simulation tool* based on this model. More specifically, using parking transaction and traffic volume data from Seattle, we estimate the parameters of a queuing-theoretic model of parking and demonstrate that there are large spatial and temporal differences in the number of cars on the street searching for parking. Using the data-informed model, we estimate the marginal cost of congestion created by cruising for parking at various times of day in the city of Seattle. An example of our result is shown in Fig. 3, which plots the percentage delay increase in a arterial surface street in Seattle throughout the day.

In addition, using our data-informed model, we show that the metric most commonly adopted by cities when designing parking policy—namely, *average occupancy*—does not correlate with congestion as well as the probability of a block-face being full.

While our study focuses on Seattle, spatio-temporal heterogeneity is not unique to Seattle. The techniques we develop have the potential to be quite useful in the design of demand-based pricing schemes that depend on spatial and temporal heterogeneity. Curb-side parking is an important, flexible resource to businesses looking to attract customers and to drivers that may not be able to afford garage prices.

The remainder of this paper is organized as follows. In Sec. 2, we briefly overview related work in order to place our work in the context of the *state-of-the-art*. We describe the data we utilized in Sec. 3. We describe our novel queuing network model and the simulation tool we developed in Sec. 4 and Sec. 5 respectively. In Sec. 6, we present the main results, including model estimates and simulations. We conclude with a discussion and overview of future avenues for research in Sec. 7 and Sec. 8 respectively.

## 2 Background

We discuss related works as they pertain to developing *data-informed models* and *data-validated simulation* as these are the two salient aspects of the work presented in this paper.
Far from data-driven approaches, there exists a number of approaches to modeling parking and driver behavior and their impact on congestion and the environment. In [7] and [25], the authors examine accidents related to parking and parking maneuvers and how these factors impact congestion. The authors of [34] study parking-related driving and its production of pollutants. In [2], from an economic perspective, an integrated model of parking and congestion is introduced. On the other hand, the authors of [35] examine parking from a physical design perspective in relating parking occupancy and load to number of lanes and capacity. Moreover, many of the existing parking models tend to be stylistic and assume homogeneity.

Parking is naturally amenable to being modeled as a queue—drivers arrive, enter service (park) if a server (spot) is available and wait (circle) if one is not. In an attempt to capture the parking-congestion relationship, several approaches based on queuing theory have been introduced [18, 3, 24, 19, 28] where roads (or segments), parking spaces, or both are modeled as queues. Some of these works claim that drivers seeking parking create a significant amount of congestion, yet little is known about how the parking-congestion relationship depends on network topology, neighborhood characteristics, and external stimuli (price) among other factors (recall Fig. 1). Previous work has not had access to high resolution data to consider spatial heterogeneity in parking supply and congestion. Data availability will be a key in learning models of parking that not only reflect actual consumption patterns but also capture spatial and temporal heterogeneity.

More broadly, much of the existing work is purely model-based [3, 4]. Very few works utilize real-world data in learning a model for the relationship between parking and congestion. Those that do take advantage real-world data sets focus almost exclusively on occupancy prediction [36, 26] or parking difficulty (e.g., Google’s new parking feature based on a logistic regression model of difficulty [9]). Moreover, many of these approaches are based on data that is either proprietary or otherwise not as rich as that provided by spot-level sensing technologies. Due to the recent increasing availability of data, however, we can revisit the modeling problem to learn data-informed models that capture the parking-congestion relationship more realistically. Such models have the potential to provide better insight into parking utilization across different cities and provide a base on which a policy design (e.g., pricing changes) can be built.

Leveraging these data source in developing simulation environments that enable analysis and design will be necessary for capturing a parking system’s diversity. Existing simulation tools tend to be agent-based [5, 12] or discrete event-based [39, 40], simulating driving and parking related behaviors. These simulation tools tend to model individual driver behavior and while useful, often do not scale well. Our simulation tool, is validated against true occupancy data and can be applied at a city-wide scale. Data-informed, scalable simulation tools offer cities the opportunity to not only better understand how parking and congestion are related but also test policy changes before deploying them in the real-world.

3 Data

We utilize on-street paid parking transaction data collected from April, 2015 through October, 2015 by the SDOT to inform our model. The paid parking transaction data includes
both pay-station and pay-by-phone records at a block-face level of granularity. In Belltown, there is a total of 256 block-faces across the neighborhood each with a number spaces range of one to 20 parking spaces. Spaces are not demarcated, as parking is paid for at a digital meter and a permit is displayed in the vehicle’s passenger window. To estimate supply, SDOT divides the length of the legal parking zone along the block-face into 25 foot sections.

Paid parking is active from 8 AM–8 PM, Monday through Saturday. As an exception to this, there are a select number of block-faces along downtown arterials in which no paid parking is allowed during portions of the morning and evening commutes to allow for more roadway capacity and for buses to stop. The pricing model for each block-face includes four separate rate intervals: 8 AM - 11 PM weekday, 11 AM–8 PM weekday, 8 AM–11 PM Saturday, and 11 AM–8 PM Saturday. Prices range between $1.50 - $2.50 per hour. The time limit for paid parking is two or four hours depending on location. From our data we observe that drivers typically park for the maximum allotted time allowed whether the limit is two or four hours.

We measure occupancy by counting the number of spaces paid for at each block-face at each minute. We then convert the number of paid spots at each minute to a load which is defined to be the number of spaces paid for at a block-face divided by the supply of the block-face, as estimated by SDOT. We then aggregate the loads to be at 1-hour granularity. These loads do not give the true occupancy due to several categories of vehicles which may park curbside for free (e.g., disabled placard holders, government vehicles, car-sharing services). Further, the load can be greater than 1; this is the result of 1) cars leaving before their paid time is expired, and 2) SDOT’s estimated 25 feet of parking space per vehicle being too large for small compact cars and motorcycles.

In addition to curbside parking occupancy data, we make use of traffic volume data also provided by SDOT. Data was collected throughout May, 2016 and is a measure of the number of cars that traveled through specific intersections—at 1st Ave and Lenora St and 2nd Ave and Blanchard St—with respect to direction of travel.

## 4 Model Description

As described in Sec. 3, data currently available in Seattle only tells us the occupancy (average number of cars parked at any time) of a block-face and it is not immediately obvious how this measure relates to congestion. Ideally, we would like to have data on the probability of a block-face being full and/or the number of vehicles attempting to park at a block-face over a given time period. The former is difficult to obtain without dedicated sensors, and the latter is perhaps impossible to measure directly. To estimate these quantities based on existing data and to capture the topological dependency of parking and traffic arising from cruising for parking, we model city streets as a network of queues.

Queues and queueing networks have been used to study a wide array of problems, including those in traffic engineering (see, e.g., [27] and the references within). We introduce a new kind of queueing network where, again, customers arrive according to some exogenous input process, but move between queues along the network until an available server is found and exits the system once served. Therefore unlike canonical queueing networks where customers

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3 Measured using the Sensys platform: [http://www.sensysnetworks.com/](http://www.sensysnetworks.com/)
are buffered at individual queues, we assume that customers are buffered or queued along the *network edges*. This behavior reflects the key fact that vehicles which cannot find parking circulate in the network rather than wait at one location.

More specifically, we treat a block-face of curbside parking as a multiserver queue, where the number of servers corresponds to the number of parking spaces along that block-face. Each of the block-faces has an exogenous arrival rate, representing the number of vehicles arriving at that block per unit time from outside the system. In addition to exogenous arrivals, block-faces experience arrivals from vehicles arriving from adjacent block-faces. That is to say, if a driver arrives at a new block-face to check for available parking and finds no empty spaces, the driver immediately moves on to an adjacent block-face and repeats the process.

This type of queueing network differs fundamentally from conventional queue networks. In the open-system version of the latter, a user moves on to an adjacent queue in the network once the current queue *finishes serving the user*. Users are lost to the system with some probability after service [17]. However, in our regime, a user transits between two queues if it is *rejected*, meaning no servers were available, at the previously visited queue. Technically our setting is a more challenging because the rejection process from a queue is not Poisson, even for queues with Poisson arrival rates and exponential service times. This means that celebrated results such as Burke’s theorem and those of Jackson networks cannot be directly applied to analysis of the stationary distribution of our queueing network regime.

To overcome this barrier, we focus on the *average* quantities and rates of *symmetric networks*. For example, instead of characterizing the distribution of the number of vehicles on the street looking for parking, we calculate the mean number of vehicles. In addition, we assume that the underlying network has sufficient symmetry; viz., the topology of the network is a $d$-regular graph (for some degree $d$), and every block-face has the same number of servers, mean exogenous arrival rate, and mean service time. This assumption is somewhat justified by the fact that many urban areas do have a fairly regular topology (e.g., the Seattle Belltown Area shown in Fig. 2). We emphasis this is only a first order approximation of real cities, and much better can be developed. This simple model, however, allows us to use currently available information (see Sec. 3) to provide valuable insights into the role parking plays in urban congestion as shown in Sec. 6.

## 4.1 Symmetric Queue Network

Consider a network of queues that is symmetric. That is, the topology of the network is given by a $d$-regular graph, where all nodes have equal in- and out-degree $d$. Each node models a queue with $k$ i.i.d. servers, each with mean service rate $\mu$. There is no waiting room at the queue. At each node, there is an exogenous Poisson arrival process at rate $\lambda$ modeling the arriving drivers looking for parking. If a queue does not have a server available (i.e., open parking spot), the user is diverted immediately to one of its neighbors with equal probability. A driver chooses with a uniform probability of $\frac{1}{d}$ search any of the neighboring blocks for parking. The mean transit time between two nodes is denoted $t$, modeling the travel time of going from one street to the other. We allow this travel time to be deterministic, random, or even state dependent since it turns out the exact description of the travel time does not enter the analysis, as long as $t$ is bounded [11].
The quantity of interest in this network is the number of vehicles desiring to park being rejected due to full parking queues. Let \( r_{ij} \) denote the rate of vehicle flow from node \( i \) to node \( j \), which is the rate of vehicles being rejected per unit time from node \( i \) traveling to node \( j \) in search of parking. Because the network is symmetric, \( r_{ij} \) is the same for all \( i \) and \( j \) and we drop the subscript. The total arrival rate at a node is then \( \lambda' = \lambda + dr \). Let \( P_{\text{full}} \) be the probability that all parking spots at a queue are taken, then we have the following balance equation:

\[
\lambda' P_{\text{full}} = (\lambda + dr) P_{\text{full}} = dr
\]

where \((\lambda + dr) P_{\text{full}}\) is the total rejection rate of a queue and \( dr \) is the total out flow.

To solve for \( P_{\text{full}} \) in terms of \( \lambda' \), observe that we can think of a queue in the network as a single isolated queue with arrival rate \( \lambda' \). The stationary distribution of this isolated queue can be found. Let \( P_m \) be the probability that \( m \) of the \( k \) servers are currently in use. Then by standard calculations \cite{8},

\[
P_m = \frac{1}{1 + \frac{(\lambda+dr)^2}{2} + \frac{(\lambda+dr)^3}{3!} + \cdots + \frac{(\lambda+dr)^k}{k!}} \frac{(\lambda + dr)^m}{m!},
\]

where \( P_{\text{full}} = P_k \). Then \( r \) can be found by substituting the expression for \( P_{\text{full}} \) into \((1)\). Using Descartes’ rule of signs \cite{21} we can show there is a unique solution for \( r \), and it can be found via bisection or exhaustive search.

The above derivation is of course not rigorous. For example, we did not show the condition\footnote{4} under which a stationary distribution or \( r \) exists. Because of space constraints, we refer the interested reader to \cite{11} for additional details.

### 4.2 Travel Time Delay

From the above discussion we can obtain \( r \), the rate of vehicles traversing between two nodes looking for parking. Our ultimate goal is to relate this flow rate to through-traffic congestion and the additional delay \( r \) causes. Ideally, one would adopt an A/B testing framework, where travel time is compared under different levels of parking rejections while holding everything else constant. However, no study of this type (as far as we are aware) has been conducted. In this paper, we adopt a strategy that leverages the currently available data to quantify the additional delay caused by vehicles searching for parking: we use the idea of fundamental diagrams in traffic engineering \cite{20, 41}.

These diagrams relate the travel time (or travel speed) to the volume of traffic on a street. Many of these fundamental diagrams have been developed in the past several decades, each describing roadways with different numbers of lanes, turns, traffic lights per mile, nominal pedestrian levels, etc. For any given city, a suitable fundamental diagram can be constructed. The interested reader can consult the Highway Capacity Manual for more information \cite{33, Chap. 15}. Here, we use a fundamental diagram of the following functional form:

\[
T(Q) = a \left[ 1 + b \left( \frac{Q}{c} \right)^g \right],
\]

The stability condition of the queue turns out to be the standard requirement that \( \lambda/k\mu < 1 \) plus another technical condition.
where \( T(Q) \) is the travel time as a function of traffic volume; \( a, b \) and \( y \) are constants depending on the street type; \( c \) is the free-flow capacity of the street, where it is defined to be the maximum number of cars that can travel at the same time without congestion; and \( Q \) is the actual number of cars on the street. Therefore as \( Q \) increases, the travel time grows at a nonlinear rate. Once the constants in (3) are obtained, it can be used to characterize the increase in travel time (that is, delay) caused by changes in the number of vehicles from parking circulation. Fig. 4 shows an example of travel time as a function of \( Q/C \) for \( a = 1, b = 0.15, y = 3 \), which we use for our calculations in Sec. 6. We find the parameters in (3) using travel time data and traffic volume data at different times of the day.

4.3 Estimation Procedure

For the purposes of simulation, we require a numerical method of calculating the exogenous arrival rate from an occupancy level. First, given a service time, degree \( d \), and exogenous arrival rate \( \lambda \), we can use the bisection method to calculate the rejection rate \( r \). The stationary distribution \( P_m \) can then be found via (2).

The data available in Seattle provides the occupancy, which is the number of servers in use at any given time, represented as the average number of parking spaces in use weighted by the stationary distribution. Since given a service time and degree \( d \), \( \lambda \) uniquely determines the probability distribution and thus the occupancy, we can exhaustively search for the exogenous arrival rate \( \lambda \) which yields an occupancy level seen in data. Other parameters can then be easily calculated. \(^5\)

5 Simulator

Once we depart from a spatially homogeneous, symmetric queue network, many of our simplifying assumptions are no longer valid and the single node view is inappropriate. In order to quantify the effects on overall congestion by 1) variations in network topology and 2) heterogeneous parking supply and occupancy rates, we developed a simulator that we can use to estimate the volume of drivers searching for parking.

Our simulator is written in Python and is freely available to download and test at [github.com/cpatdowling/net-queue](https://github.com/cpatdowling/net-queue). Requirements and basic instructions, as well as example data and relevant parameters used in this paper are included in the repository. The simulator constructs a network of block-face (drivers in service/parked) and street (drivers

\(^5\)The code to perform these calculations is also available along with the simulator described in Sec. 5 at [github.com/cpatdowling/net-queue](https://github.com/cpatdowling/net-queue).

\(^6\)Our experiments utilize GNU Parallel [32].
waiting/circling) queues linked according to the true street topology. Our simulator is validated against occupancy data provided by SDOT—see Sec. 6.

In line with our model design the simulator treats streets and block-faces independently: once a driver reaches the end of their drive time on a street, they immediately check the entire block-face they’ve arrived at for availability. If no parking is available, the driver chooses a new destination uniformly at random based on the block-faces currently accessible to them according to the street topology. The simulator allows a for a full range of time resolutions. Algorithm 1 provides an overview of the simulator logic.

```
while simulator time < time limit do
    if any arrival occurs then
        if arrival is exogenous then
            block i arrival timer = \( \exp(\lambda) \)
        else
            remove arrival from block j-to-block i street queue
        end
        if any parking space timer at block i < 0 + \( \epsilon \) then
            replace a free parking space timer at block i with service time \( \mu \)
        else
            search an adjacent block k according to uniform probability (legal turns)
            append fixed travel time \( t \) to block i-to-block k street queue
        end
    else
        pass
    end
    increment simulator time by \( \epsilon \),
    subtract \( \epsilon \) from exogenous arrival, street, and parking space service timers
end
```

**Algorithm 1:** Description of queue-network simulator

![Fig. 5: (a) Distribution of parking spaces per block-face in Belltown. (b) Distribution of Paid Parking Time.](image)

The input parameters of our simulator include:

1. **Network Topology.** For every block-face in Belltown, there will be any number of block-faces a driver can reach using only legal maneuvers on one- and two-way streets,
excluding legal U-turns\footnote{Our data and roadway maps currently provide no principled means of determining which intersections allow U-turns and prescribe time-of-day dependent left turns.} and same-street lane-changes. The simulator is given a map of block-face connectivity transcribed from Google Maps.

2. **Service Rate**: The inter-service time dictates how long cars will spend parked on a block-face. Fig. 5b illustrates the distribution of paid parking times across Belltown. In this initial work, we use the mean service time of approximately 105 minutes, just short of the median service time of 120 minutes—see Fig. 5b for a histogram of parking service times. At this point we have no reliable data on the frequency of illegally parked vehicles that have either paid, or overstayed, and further we have no means of measuring how early drivers typically leave before their paid time expires. In our initial simulations, we assume everyone parks legally and early/late departures balance out.

3. **Number of Servers**: The number of parking spaces, or the number of servers in the block-face queue, are extracted directly from data for each block-face, ranging in values according to Fig. 5a. In our data, it is sometimes the case that there may be higher than 100% occupancy at any given block-face as a result of factors described in Sec. 3. In these cases we assume that occupancy is 100% with respect to the estimated number of spaces, and not with respect to the number of vehicles currently in service.

4. **Exogenous Arrival Rate**: The simulator accepts a mean parameter for an exponential random inter-arrival time distribution, simulating vehicles arriving at a specific block-face to begin their search for parking. If a space is available at the block-face they originally arrive at, the driver accepts the first space without contributing to congestion. The estimation procedure from occupancy data is described in Sec. 4. At equilibrium we do not distinguish between an arriving car being a new exogenous arrival to the network, or a car arriving from a neighboring block-face.

5. **Drive Time**: Drivers arrive at a block-face and determine if any spaces are available. If no spaces are available, a drive time is specified to determine how long it takes drivers to reach the next adjacent block-face in their search.

Important output values of our simulator include:

1. **Traffic due to Parking**: Traffic due to drivers searching for parking can be measured as the total number of rejections at a particular block-face (or road, if search strategy is non-uniform) or as rejections per unit time.

2. **Average Wait**: The amount of time a driver spends looking for parking, as a function of drive time between each block-face a driver is rejected from until they find parking.

3. **Occupancy**: The resulting occupancy (referred to as utilization in queueing theory) measures the average number of servers or spaces along a block-face in use at any given time. This value is compared against true occupancy data to ensure the simulator is providing accurate estimates.
6 Results

6.1 Model Estimates

Here we plot the impact of cruising for parking on the travel time of 1st and 2nd Avenues (see Fig. 6) in Seattle. These are major arterials in the Belltown district of Seattle that experience high parking occupancy and for which we have through traffic data. For each arterial, we examine the rejection rate of curbside parking along their high occupancy corridors: 1st Ave (a four lane, two-way arterial) from Stewart to Broad, and 2nd Ave (a three lane, one-way arterial) from Denny to Battery.

For these corridors, we aggregate the rejection rates from block-faces along the arterial itself, as well as block-faces immediately adjacent, feeding into either side of the arterial. We assume drivers follow a search pattern whereby they select a legal turn uniformly at random, and consider only rejected traffic that either feeds into an arterial, or remains on the arterial. For each hour, Monday through Saturday, we calculate the rejection rate based on that day and hour’s occupancy data for each block-face in the corridor.

Traffic data at the 2nd Ave and Broad intersection immediately downstream of the Denny to Battery block-face corridor provides an estimate of traffic volume southbound on the 2nd Ave arterial, while traffic data at the 1st and Lenora intersection provides an upstream estimate of northbound traffic on 1st Ave. Fig. 7 illustrates the proportion of traffic made up of cars searching for parking.

6.2 Travel Time Delay Due to Parking-Related Congestion
After using occupancy data to estimate number of vehicles $N_{park}$ searching for parking along an arterial corridor per hour, we compare this to the total traffic volume $N_{total}$. We use Google Maps data to find the typical travel time along a street at a particular hour of a particular day. Using these times and the traffic count data, we find the parameters in (3). We use equation (3) and the fact that delay is inversely proportional to travel time to calculate the percent delay increase as $\frac{T(N_{total})}{T(N_{total} - N_{park})} - 1$. Fig. 8a shows the percent delay increase on 2nd Ave over a typical Saturday and Fig. 8b shows the percent delay increase on 1st Ave over a typical weekday.

Fig. 8: (a) Percentage delay along 2nd Ave on a typical Saturday due to drivers searching for parking. (b) Percentage delay along 1st Ave on a typical weekday due to drivers searching for parking. (c) Distribution of mean absolute error in simulated and observed percentage occupancy.

### 6.3 Simulation

To capture a broader picture, we utilize our simulator to estimate the total volume of congestion across Belltown caused by searching for parking, rather than directly solving for individual block-face rejection rates by hand.

Note the difference between the northwest and south east sides of Belltown as divided by Battery St, illustrated in Fig. 9 in simulation, using model estimates of exogenous arrival rates at each block-face, the northwest sees higher parking occupancy. As a result we would not expect to see as much congestion caused by people searching for parking on the southeast side of the neighborhood, as the probability of any particular block-face being full diminishes. If this information were accessible in real-time, drivers could adjust their route plans accordingly and effectively help reduce congestion.
7 Discussion

7.1 Validation

We validate our methods by comparing the parking occupancies from the simulator with the occupancies reported by SDOT data. Fig. 10 gives the spatial distribution of the mean absolute error (MAE) of simulated block-faces across Belltown for the duration of a typical week. Although the MAE at each individual block-face across the network increases as more block-faces approach occupancy saturation late in the day, the network-wide average of block-face occupancy by hour and day has an MAE of 2%.

Outliers in the block-face network topology are the greatest source of error for individual block-face MAE: SDOT estimates the parking space supply of two reporting areas at the intersection of 1st Ave and Stewart St. to be 1 space each. These areas of low supply have the largest MAE by far at +60% each. Fig. 8c illustrates the distribution of MAE for individual block-faces for all days and times, with a mean around 20%. We observe a much more favorable MAE with respect to the network wide simulated occupancy because these low-supply outliers contribute little to the neighborhood-wide total supply, and thus occupancy level. Future work will be aimed at improving accuracy at high occupancy levels and for atypical block-face types.

7.2 Comparison of Parking Utilization Metrics

Many existing parking initiatives focus on maintaining the average parking occupancy at around 80% [1, 22]. However, although easy to measure, this is not the quantity that directly relates to congestion due to cruising for parking.

Our results suggest there is a major drawback in using the average occupancy as a metric
as it may lead to an under-utilization of parking resources. A few high occupancy blocks may be responsible for a high rate of vehicles searching for parking being forced to congest the nearby network, while low occupancy block-faces will skew the average network occupancy downward. For a block-face with a supply of 10 parking spaces, a service rate of 2 hours, and 2 legal maneuvers available leading into and out of the block, at 80% occupancy, there is only a 25% chance of the block-face being full. At 90% occupancy, the probability of being full doubles and rejections occur three times faster. This is to say the average network occupancy does not capture the spatial heterogeneity in cities. If all blocks in a city are symmetrical and have 25% chance of being full, very few vehicles would be rejected. However, due to heterogeneity, the rejections tend to concentrate at a few high occupancy blockfaces which, in turn, may result in severe increases in travel time due to the highly nonlinear relationship between traffic and delay. Measuring the average occupancy rate is a misleading goal for city planners to target as it potentially masks these impact of these high occupancy block-faces. The results and tools in this paper allow for a much more refined understanding of the system.

7.3 Spatio-temporal Dependency of Parking-Related Congestion

Fig. 7 shows that congestion due to people searching for parking in the Belltown neighborhood is negligible during the morning rush hour commute along the 2nd Ave arterial. This could be due to a number of factors: 1) Belltown is a highly residential neighborhood (a population density of 47.9 people per acre [31], among the highest in Seattle); 2) the 1st and 2nd Ave arterials lead directly into the Central Business District, where morning commuters have no reason to park along these routes. Congestion due to parking, however, is much
higher in the evening hours which may be due to the high concentration of restaurants and bars, as this behavior extends into the weekend as seen in Fig. 8a. High occupancy levels correspond with high exogenous arrival rates of people in need of parking, but as we observe they are not necessarily dependent on the total traffic volume, as total evening volume can be lower than morning rush hour, but a larger proportion of that volume is searching for parking based on observed occupancy levels.

8 Conclusion

In sum, we have demonstrated a new model for urban parking that considers spatial and temporal heterogeneity. This model provides a means for city planners and traffic engineers to analyze a network of curbside parking at a much higher resolution that previously possible. Using our data-informed model, we identify a more viable metric for controlling congestion via parking—namely, the probability of a block-face being full—and show that it more directly captures parking resource consumption. Secondly, we presented a validated simulation tool based on this model to analyze full networks of curbside parking to estimate congestion caused by drivers searching for parking. Lastly, using city traffic volume data, we estimated the percent delay increase due to congestion created by cruising for parking and find that the marginal costs are not always highest during peak traffic volume periods. These results help provide a basis for future work designing and exploring new parking scheduling and pricing regimes to minimize delays caused by cruising for parking while leaving open a flexible resource to drivers and businesses.

Future work includes further vetting our simulator by collecting more nuanced data; these include frequency of illegally parked vehicles, vehicles not required to pay, etc. Other information to incorporate will include typical driver search behavior, as well as the distribution, occupancy, and price of parking garages (also modeled as large capacity queues in the network). We anticipate using this simulator to test control strategies and new parking policies.

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