# Minimizing congestion due to drivers searching for parking

#### Chase Dowling in collaboration with Tanner Fiez, Lillian Ratliff, Baosen Zhang

University of Washington, Department of Electrical Engineering

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### Curbside parking in Seattle



Image credit: Ana Arevalo, CBS, Washington DC

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### Estimated 30% of drivers on city streets searching for parking

### Curbside parking in Seattle

30% is a big estimate

Is it correct? Can we minimize it?



Annual studies of parking resource performance

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- Mobile Applications: SFPark, Go Mobile PGH
- City: places like Oslo banning cars from city center (City) http://www.popsci.com/ oslo-decides-to-ban-cars-from-city-center

Occupancy

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- Once required manual counting, can estimate with digital parking meters
- SDOT aims for an occupancy level in the range of 75%—85% on an hourly basis

Occupancy

11:00 AM 66% occupancy



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Occupancy







83% hourly occupancy

-Problem Statement

Research Questions

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Can we determine the amount of congestion drivers searching for parking are responsible for?

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Let's model downtown curbside parking as a network of interdependent queues.

-Problem Statement

└─ Research Questions

# Contributions

- Wrote a simulator for virtual drivers to search for parking in (github.com/ cpatdowling/ net-queue)
- We've shown that one can optimize parking availability subject to constraints on resulting congestion



Simulated occupancy levels in Belltown on a Monday morning

Preliminaries

### Multi-server Queue



Preliminaries

### Bufferless Multi-server Queue



Problem Statement

Block-face as a Queue

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Problem Statement

└─ As a Network of Queues

### Block-face Queue Network



Data: IDAX, Seattle Dept of Transportation and data.seattle.gov

block-face latitude/longitudes

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- spaces per block (number of servers)

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- spaces per block (number of servers)
- curbside parking transactions since 2012 at each block-face (service times)
- traffic volume by time of day on select arterials (superset of drivers parking)

# SDOT Data



Figure 1: Distribution of transactions by paid parking time.



Results

First we'll gain some intuition in perfectly uniform networks

Results

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- We'll then analyze a real downtown network

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- First we'll gain some intuition in perfectly uniform networks
- We'll then analyze a real downtown network
- Then we'll clearly state the optimization problem to minimize congestion
- And we'll conclude with a hypothetical optimization result

## Symmetric/Uniform Networks



- Uniform occupancy
- Equal in and out degree at each queue
- Equal service times
- Equal number of spaces
- Uniform search behavior

# Symmetric/Uniform Networks



- Total arrival rate to each queue becomes solution to a polynomial
- Prove solution is unique, gives probability queue is full
- Can solve for rejection rate along each edge

Arrival Rates



#### Arrival rate as a function of occupancy, number of servers

number of parking spaces (servers)

Figure 3: Arrival and rejection rate of vehicles is asymptotic in occupancy

### Belltown Occupancy

Occupancy not uniform: github.com/cpatdowling/demandviz



Congestion



└─ Congestion



Congestion



Congestion



Congestion



Congestion

# Congestion Caused by Parkers



Figure 5: Approximation of travel time delay curve for signalized road

Figure 6: Belltown arterials with SDOT traffic volume data

Congestion

### Congestion Caused by Parkers



Figure 7: 2nd and Blanchard in Belltown

Congestion

### Congestion Caused by Parkers



Price Control

### Congestion Optimization

# $\begin{array}{ll} \underset{\mathbf{p}}{\text{maximize}} & \text{Occupancy}(\mathbf{p}) \\ \text{subject to congestion along road } i; i = 1, \dots, m. \end{array}$

Price Control

### Price Control Strategies

- Seattle Parking rates by morning/evening, weekday/weekend
- San Francisco Parking rates by previous rate period's demand, to time of day on a block by block basis

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- Seattle Parking rates by morning/evening, weekday/weekend
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price  $\rightarrow$  desired demand level (occupancy)  $\rightarrow$  queue probability of being full  $\rightarrow$  rate of drivers unable to find parking (congestion)

Everything is convex!

Price Control

# Price Control in Mission District



 Price elasticity estimates from SFPark pilot study and companion 2013 study

Figure 8: Curbside parking data in the Mission District of SF

Price Control

# Price Control in Mission District



Figure 8: Curbside parking data in the Mission District of SF

- Price elasticity estimates from SFPark pilot study and companion 2013 study
- Gradient descent subject to an arbitrarily set maximum allowable rate of vehicles unable to find parking at each block-face.

Price Control

# Price Control in Mission District



Figure 9: Noon weekday occupancy levels and resulting traffic estimates for Mission District, SF  $\,$ 

Price Control

### Price Control in Mission District

Noon weekday price changes to reduce rate of searching vehicles to no more than 1 per 12 minutes: Mission District, SF



Price changes to reduce overall congestion

Price Control

# Price Control in Mission District

Noon weekday controlled occupancy levels and resulting traffic estimates for Mission District, SF



# **Concluding Remarks**

 Sharpen the "30% of traffic" estimate: depends on time of day and location

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- Sharpen the "30% of traffic" estimate: depends on time of day and location
- Not pricing against congestion due to individual drivers parking maneuvers

### Future Work

 Aiming for socially and politically actionable solutions to congestion

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- Data-driven analysis of surface-street congestion: time delay due to volume

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- Data-driven analysis of surface-street congestion: time delay due to volume
- How does location factor into price elasticity?