Parking Spaces in the Age of Shared Autonomous Vehicles: How Much Parking Will We Need and Where?

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UPE Conference | June 3rd, 2016

Study Objectives & Method

The impact of SAVs system on urban parking demand & parking land use under different parking price scenarios

Data from Atlanta Regional Commission

- Origin & Destination (OD) Matrix
- Local Travel Survey
- Transportation Network With Calibrated Link Level Travel Speed

Scenarios

- **Charged** vs. **Free** Parking Scenarios

Study Method

- Discrete Event Simulation Model

3

Sustainable Cities and Society 19 (2015) 34–45

Contents lists available at ScienceDirect

Sustainable Cities and Society

journal homepage: www.elsevier.com/locate/scs

Exploring the impact of shared autonomous vehicles on urban parking demand: An agent-based simulation approach

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ARTICLE INFO

Article history:
Received 29 April 2015
Accepted 9 July 2015
Available online 20 July 2015

Keywords:
Shared autonomous vehicle
Parking
Agent-based model

ABSTRACT

Although recent studies of Shared Autonomous Vehicles (SAVs) have explored the economic costs and environmental impacts of this technology, little is known about how SAVs can change urban forms, especially by reducing the demand for parking. This study estimates the potential impact of SAV system on urban parking demand under different system operation scenarios with the help of an agent-based simulation model. The simulation results indicate that we may be able to eliminate up to 90% of parking demand for clients who adopt the system, at a low market penetration rate of 2%. The results also suggest that different SAV operation strategies and client's preferences may lead to different spatial distribution of urban parking demand.

1. Introduction

There is compelling research to suggest that advances in transportation technology has a powerful and irreversible impact on urban form. The development of streetcars in the 1950s triggered the initial wave of suburbanization, which accelerated with the advent of the automobiles in the 20th century. Today, we are at the cusp of the emergence of autonomous vehicles (AVs), that is, vehicles that can drive themselves. These driverless vehicles are expected to introduce more fundamental changes to human travel behavior, which may lead to different social structures and urban forms. AVs will facilitate car-sharing and ride-sharing behavior, as the technology can overcome some key barriers, especially automatically navigate to locations from where trips will originate, thereby reducing parking demand.

In this study we estimate the various levels of parking demanded under SAV systems characterized by varying fleet sizes and passenger wait times. These estimates are based on an agent-based model of a 10 mi × 10 mi hypothetical city laid out in a grid network of 0.5 mi street segments. We develop scenarios with fleet sizes between 500 and 800 vehicles, with various levels of willingness for ride-sharing, and with different empty vehicle cruising strategies. The simulation results indicate the amount of parking spaces saved when compared with conventional systems. The results also show where the most parking reductions can be expected under different assumptions in the stylized city described above.

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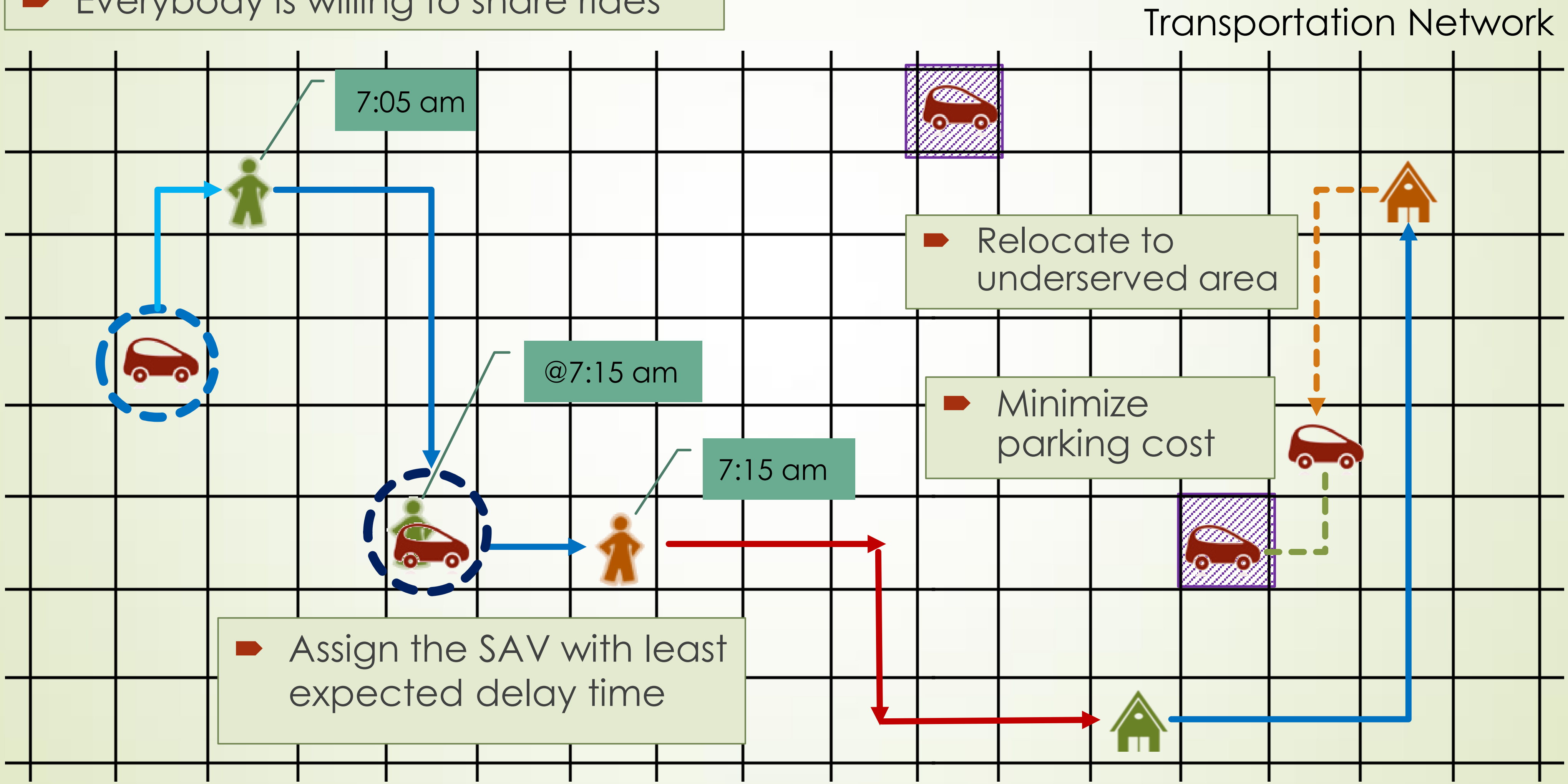
Google Autonomous Vehicle

Simulation Conceptual Model

- Everybody is willing to share rides



Model Assumptions

- 5% of the residents will give up their vehicle and use SAV system instead, which is similar to the assumption used by Fagnant and Kockelman (2014) and Burns et al. (2012);
- There will be no induced travel demand after the implementation of SAV system;
- All users are willing to share rides;
- The cost of SAV is $0.5 per minute with no startup fees (Burns et al., 2012);
- The cost of SAV is $0.3 per minute for each onboard client when two people are sharing rides to encourage ridesharing;
- Fuel cost $0.05 per mile (assuming using electricity)
- The clients will switch to other modes of transportation after waiting for more than 15 minutes.

Model Implementation

About Atlanta

Capital of State of Georgia

Population: 447,841 (2013)

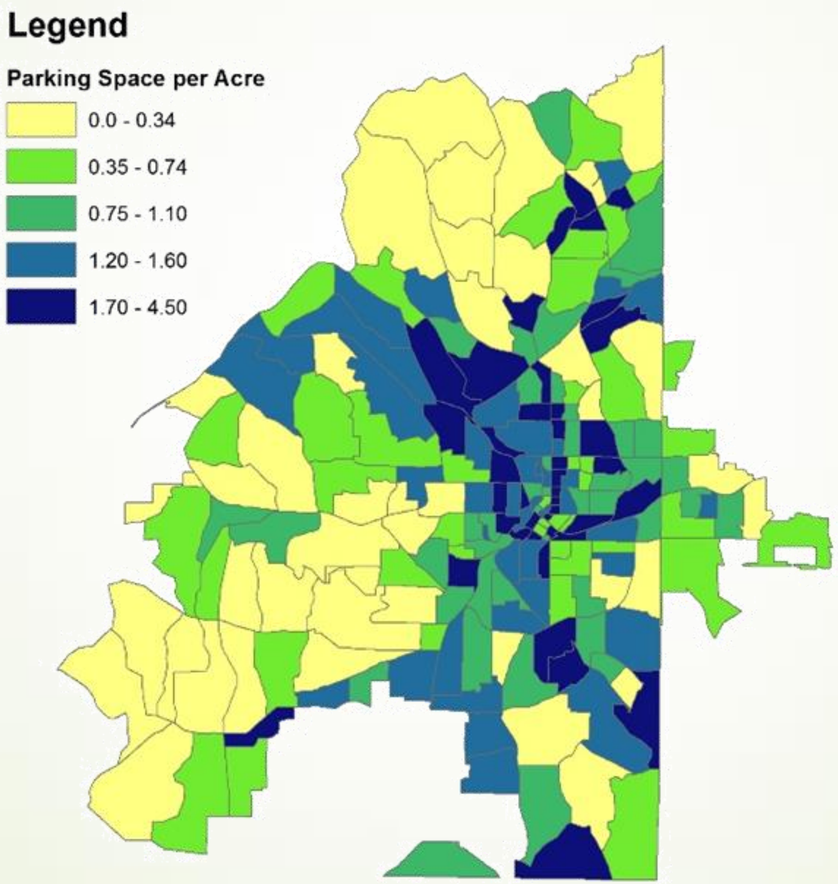
Area: 134 miles^2

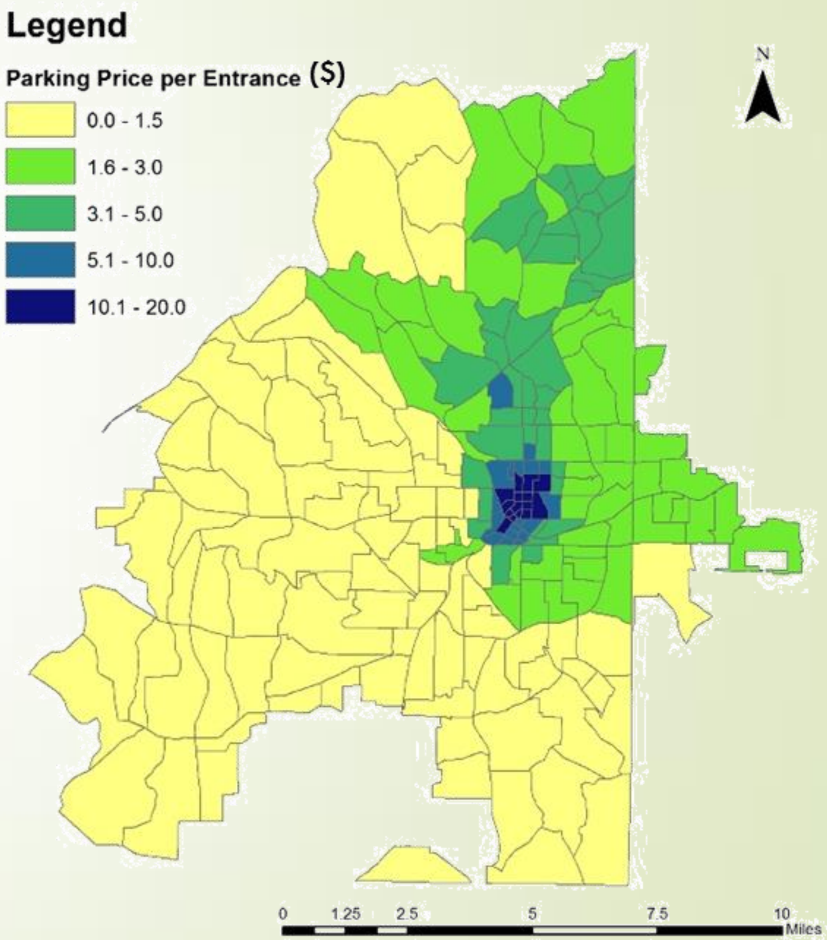
208 Traffic Analysis Zones

92.2% Commuting Trips by Automobile (2011)

Parking in Atlanta

93,000 parking lots in downtown (2014)





Model Initialization

Trip Profile Initialization

- Generate trips by OD pairs (ARC OD MATRIX)
- Assign departure time based on local travel survey

SAV Initialization

- Randomly Distribute the SAVs in the network at the beginning of the simulation

Final Model Results Analysis

- Ran the model for 50-consecutive days
- Discard the results from the first (warm-up) simulation day

8 Model Verifications

Chi-square goodness of fit tests

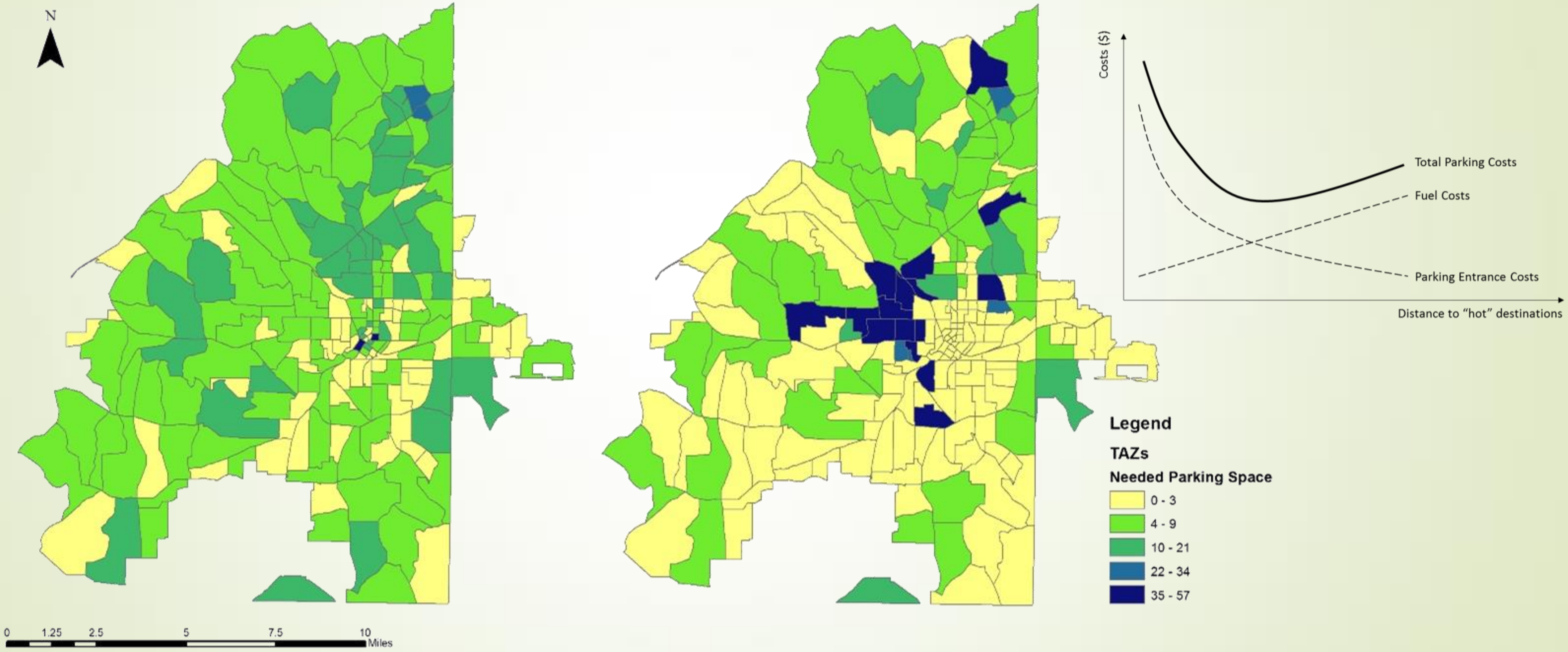
Trip Length Distribution **[0.96]**

Trip Departure Time Distribution **[0.98]**

NOT significantly different from Local Travel Survey

Vehicle Activity Tracing

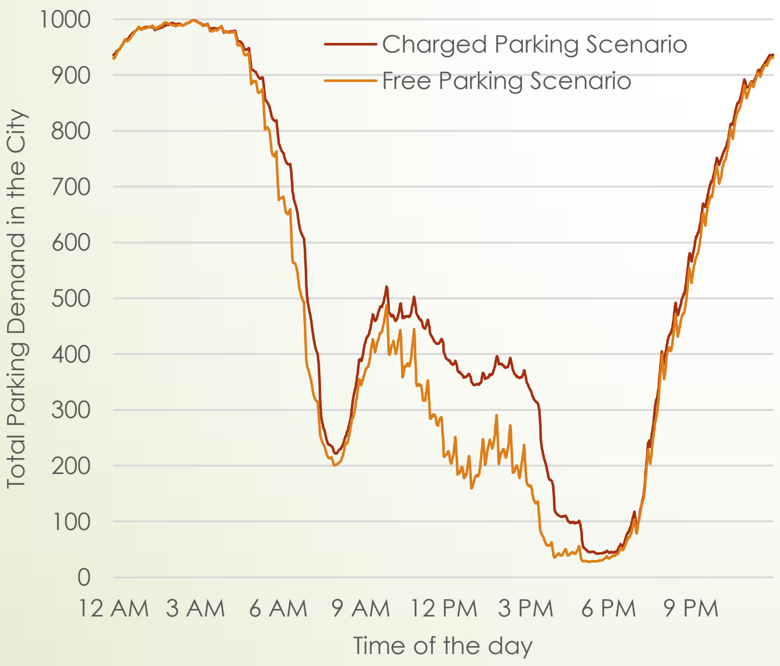
Model Outcome
Spatial Distribution of Parking Land Use

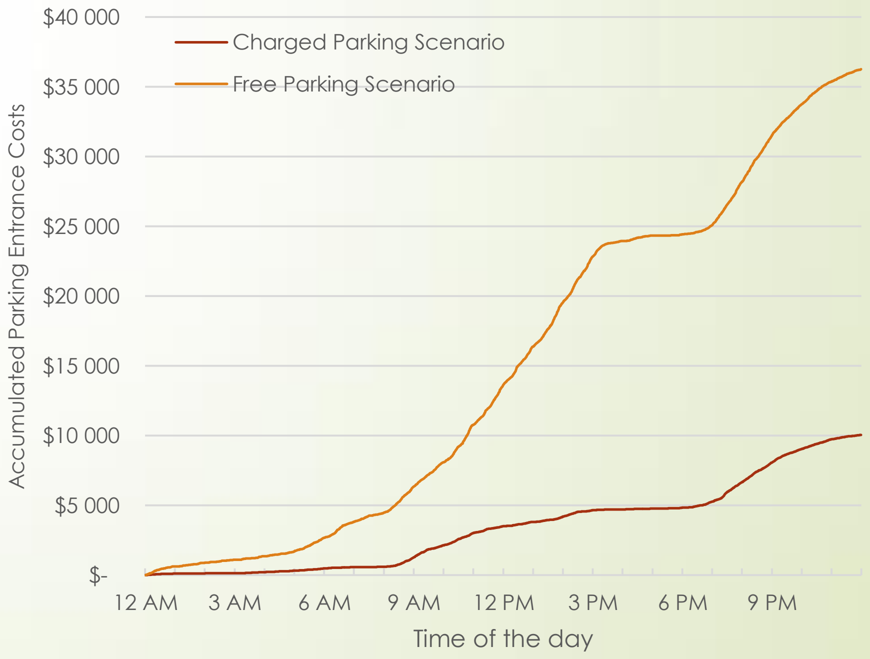


- Free parking Scenario
- Charged parking Scenario

Model Outcome
Temporal Distribution of Parking Demand

- More parking demand in charged parking scenario during day time
  - In free parking scenario, more vehicles cruising in expensive TAZs rendering a smaller parking demand during day time





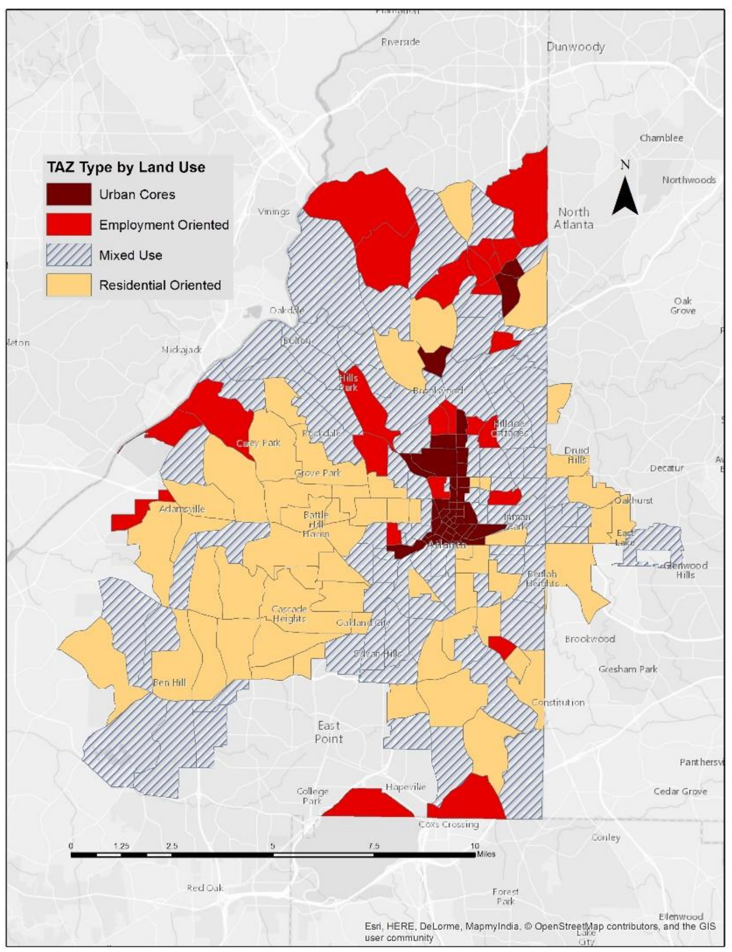
Model Outcome
Total Parking Land Use Required

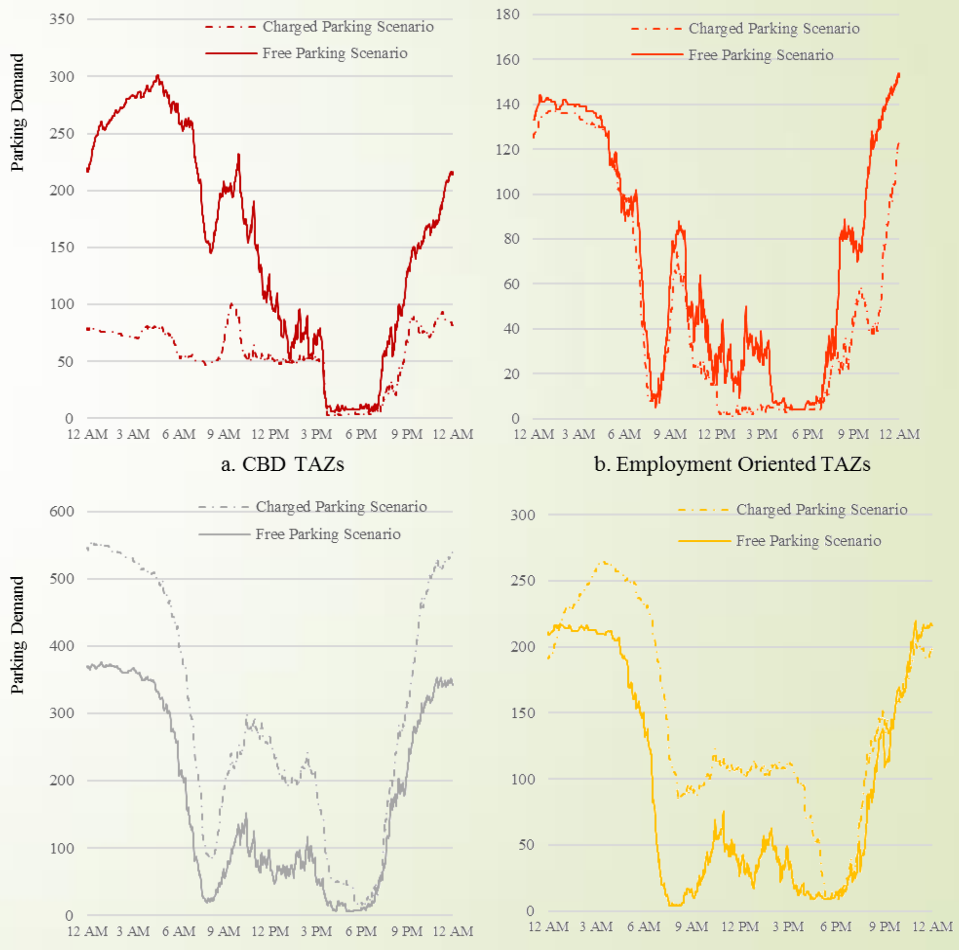
- ~ **4.9%** reduction given **5%** market penetration rate
- **1,371** in Free parking scenario vs. **1,495** Charged Parking scenario
- **Cause**
  - Mismatching of spatial distribution of parking lots during day time and night time
  - More vehicles park in mixed use and residential zones during night and in the CBD during daytime

Model Outcome
Total Parking Land Use Required

TAZ Type by Land Use *

- Urban Cores
- Employment Oriented
- Mixed Use
- Residential Oriented





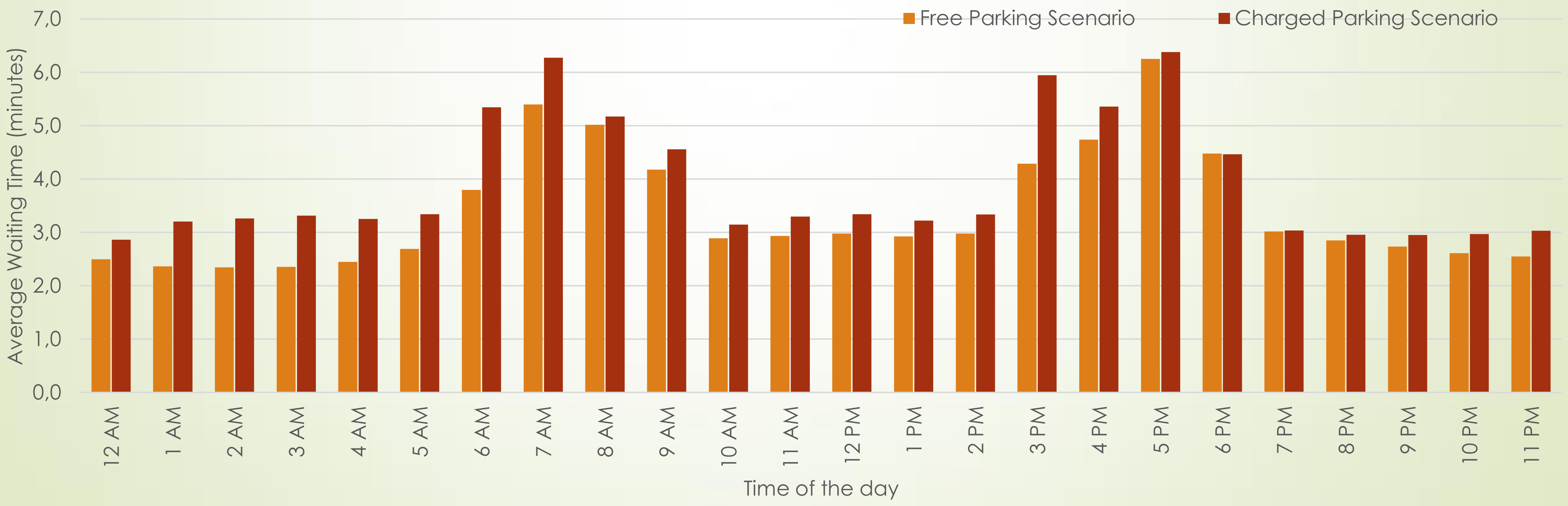
a. CBD TAZs
b. Employment Oriented TAZs
c. Mixed Use TAZs
d. Residential Oriented TAZs

*

CBD TAZs: TAZs with employment density > 3 * population density and recreation employment density >= 9000
Employment Oriented TAZs: TAZs with employment density > 3 * population density and recreation employment < 9000
Residential Oriented TAZs: TAZs with population density > 2 * employment density
Mixed TAZs: TAZs with employment density/population density between 0.5 to 3.

Model Outcome
Average Waiting Time and VMT

- Charged scenario:
  - Longer waiting time especially before peak hours
  - 130,000 more VMT generated during pick up and park process



Model Outputs Summary

- The SAV system can significantly reduce the amount of parking land use by improving vehicle occupancy and reduce vehicle ownership
- Charge parking can significantly reduce downtown parking, however, may lead to larger parking footprint in the city.
- Charge parking scenario may concentrate parking in low-income neighborhoods and need to be cautiously planned to alleviate negative social impacts

Model Limitations & Future Work

- **Model Limitations**
  - Entrance based parking charging system vs. Time based charging system

- **Next Steps**
  - Explore different parking charging systems
  - How land use configuration can change SAV parking demand
  - Integrate with trip assignment model to simulate a large scale implementation of the SAV system

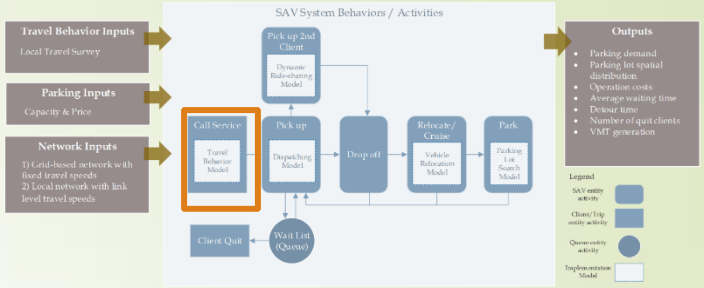
Questions & Comments?

Back up slides

Model Simplification

- The trips always start and end at TAZ centroids;
- The vehicle travel speed is fixed given time of the day on one road segment (but will be updated hourly);
- The average intra-zonal travel time is modeled using the following formula
  - $intra - zonal\ travel\ time = \frac{\sqrt{area_{taz}}}{2 * travel\ speed}$
- Both loading and unloading time are set as 1.5 minutes;
- The clients will never cancel the trip once a vehicle is assigned to the client;
- Empty vehicles will be assigned to serve the closest calling client during peak hours to optimize vehicle use;
- The system doesn't offer reservation service for the general public.

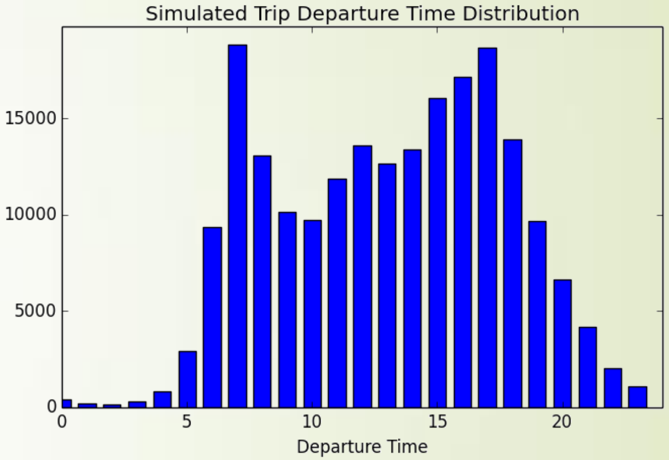
Implementation Algorithms

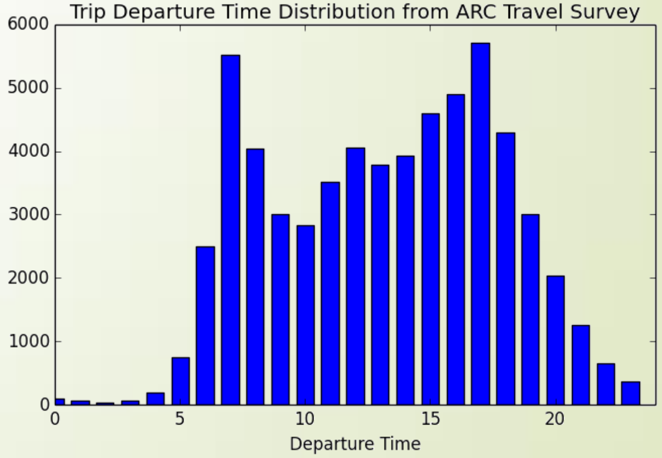


Travel Behavior Model

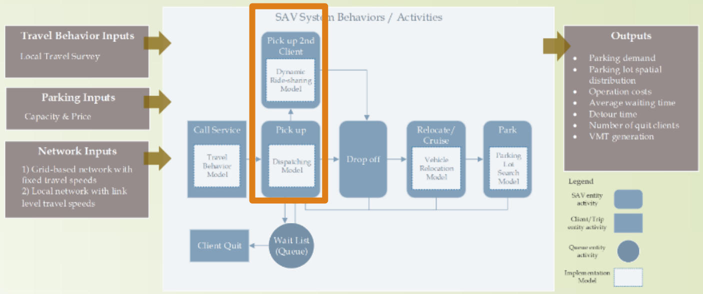
- Synthesized travel profile for the city of Atlanta, based on OD matrix and Atlanta Travel Survey (2009)

- $NumTrip_{ij} = Random.Poission(\lambda_{i,j})$
- $DepartureTime_k = CDF_{dt}^{-1}(r)$





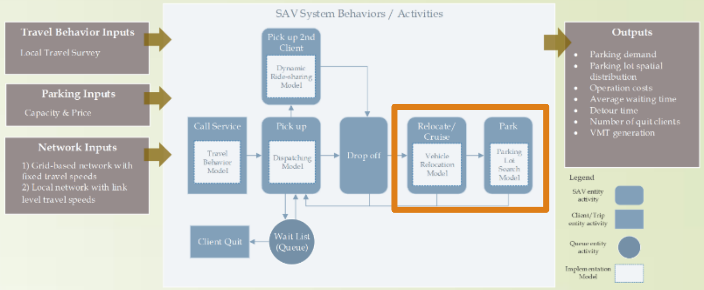
Implementation Algorithms



- **Dynamic Ride-sharing Model** - whether two trips can be pooled together to benefit both clients.
  - The detour time for each client is equal or smaller than 15% of travel time without ride-sharing;
  - For short intra-zonal trips, the acceptable maximum detour time is set as 3 minutes;
  - The ride-sharing induced detour time should be compensated by the decrease in SAV fare for both clients.
  - Recommend the SAV that minimizes total detour time

- **Dispatching Model** - Assign SAVs to serve calling clients.
  - Empty vehicle: closest vehicle – [pickup time 1]
  - Sharing vehicle: identified by DRS model – [pickup time 2 – benefits provided by ride sharing]
  - Assign the one with lower cost to client

Implementation Algorithms



- **Relocation Model** – Rebalance the distribution of SAV in the city
  - Balance value calculation for each TAZ:

$$TAZ\ Balance = \frac{SAVs_{TAZ}}{SAVs_{Total}} - \frac{Demand_{TAZ}}{Demand_{Total}}$$

  - the SAVs will relocate from zones with 1.25% excessive supply to zones with the largest shortage in SAV
- **SAV Parking Model** – Find the parking lot to park
  - $\min_{j \in J_A}(fuel\ cost_{i,j} + entrance\ cost_j)$