## IOWA STATE UNIVERSITY

# Modeling the Operations of Electric Autonomous Taxis in New York City

Liang Hu and Jing Dong

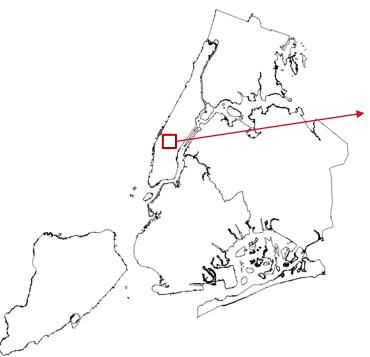
Presented at 2017 INFORMS Annual Meeting, Houston, TX

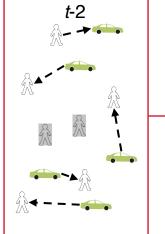
October 23, 2017

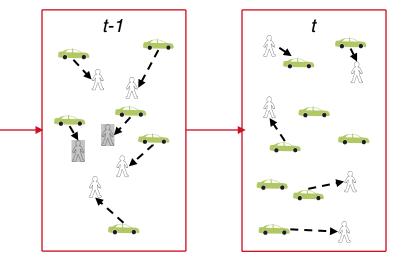
## Why Electric Autonomous Taxis?

	Conventional taxis	Ride-hailing	Electric autonomous vehicles (EAV)
Energy source	<ul><li>gasoline</li><li>some electric</li></ul>	<ul><li>gasoline</li><li>some electric</li></ul>	electric
Search for customers	<ul><li> cruising</li><li> by chance</li></ul>	<ul><li> cruising + waiting</li><li> drivers compete</li></ul>	<ul><li>relocating + waiting</li><li>collaborative</li></ul>
Customers' delay	<ul> <li>unknown to taxis</li> </ul>	<ul> <li>drivers do not care</li> </ul>	<ul><li> optimal dispatch</li><li> reduce delay</li></ul>
Trip distance	<ul> <li>unknown to taxis</li> </ul>	<ul> <li>unknown to taxis</li> </ul>	<ul> <li>taxis w/o sufficient range are not assigned</li> </ul>
ntroduction	Simulation	Optimization Res	sults Summary

## Model EAV Taxi Operations







Model operations based on status of both requests and taxis, over time, area by area

#### Requests

- request time
- location

• wait time

EAV taxis

- location
  - SOC

Summary

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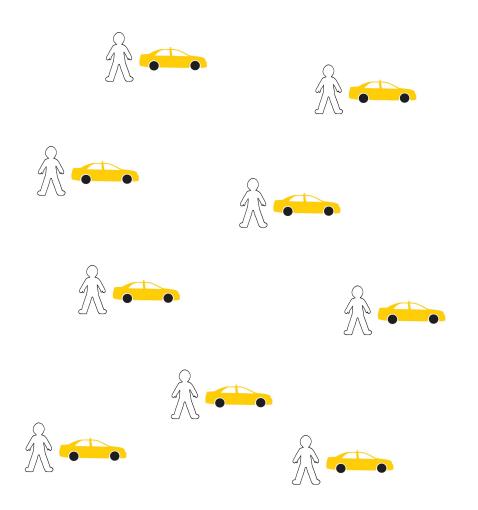
#### Introduction

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## Taxi Trip Data in NYC



### Data fields

- taxi ID
- pick-up GPS
- pick-up timestamp
- drop-off GPS
- drop-off timestamp
- occupied trip distance
- Estimate empty trip dist. by

trip dist. =  $1.4413 \times \text{straight-line}$ dist. + 0.1383 (unit: mi)

Extract data of 500 taxis & the corresponding requests

### Introduction

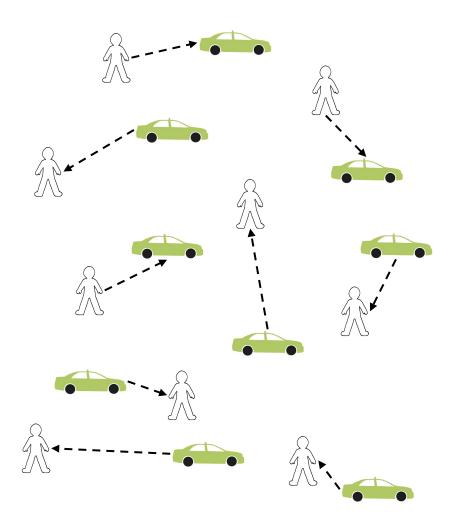
#### Simulation

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Summary

## **Assumptions for Simulation**



Simulation

Introduction

### Requests of customers

- location: pick-up GPS
- time: pick-up timestamp
- dist.: occupied trip dist.

#### EAV taxis

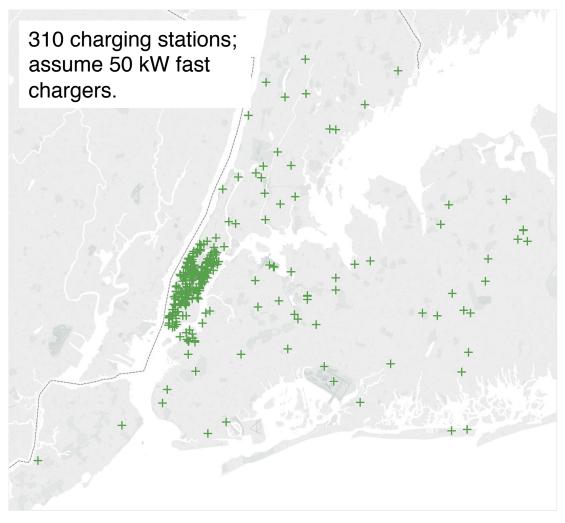
Optimization

- location: drop-off GPS
- time: drop-off timestamp
- dist.: estimated trip dist.

**Results** 

### Summary

# **Charging Stations in NYC**

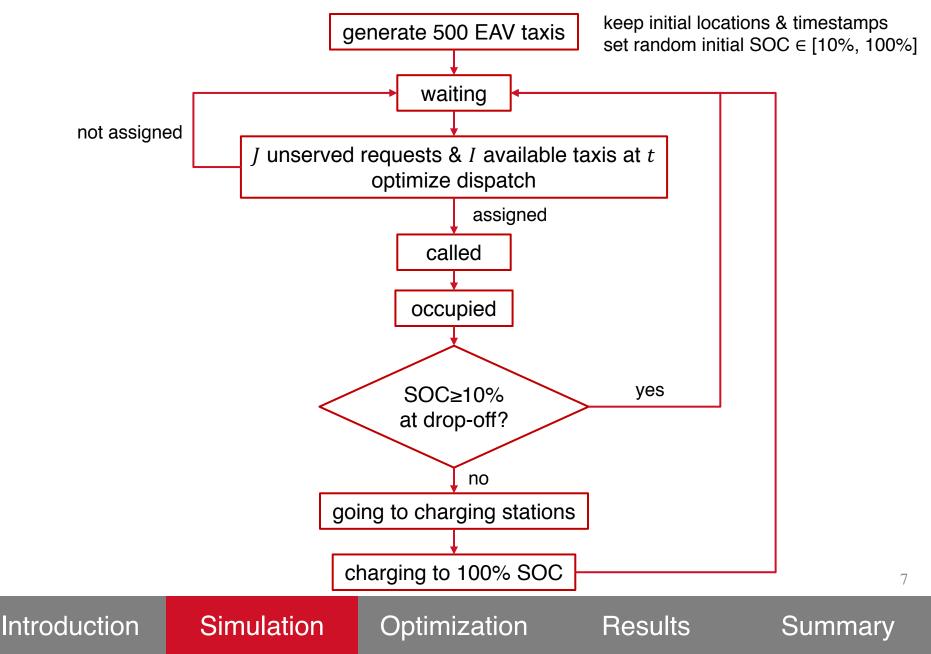


Source: US DOE

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# Introduction Simulation Optimization Results Summary

## **Simulation Process**



### **Decision Variables**

*I* available taxis and *J* unserved requests at *t* Define binary decision variables

 $x_{i,j}$ 

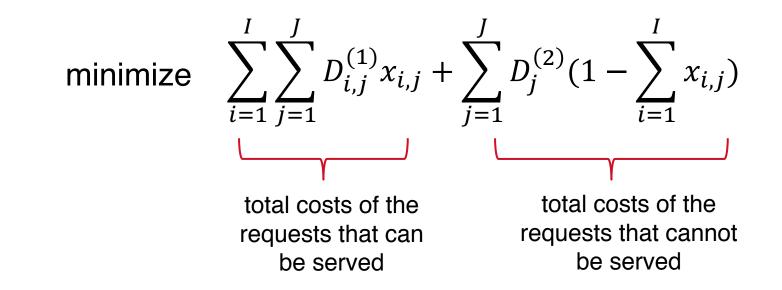
*i*: index of an available taxi,  $i \in I$ *j*: index of an unserved request,  $j \in J$  $x_{i,j} = 1$ : taxi *i* picks up request *j*  $x_{i,j} = 0$ : taxi *i* does not pick up request *j* 

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## **Objective Function**

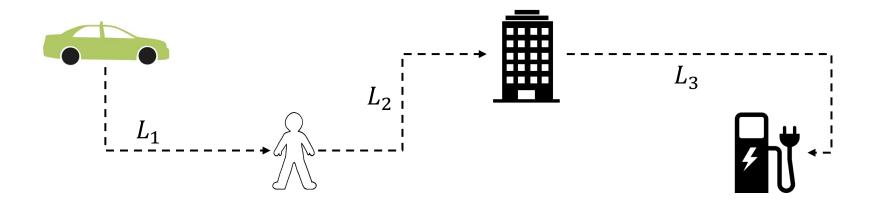


 $D_{i,j}^{(1)}$ : cost matrix (1) = time that has been delayed + time for pick-up  $D_j^{(2)}$ : cost matrix (2) = time that has been delayed + avg. wait time differs by area

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## Constraints (1): Sufficient EV Range

 $\Box$  calculate the distance matrix  $L_{I \times J} = L_1 + L_2 + L_3$ 



 $\Box$  if  $L_{i,j}$  > the taxi's remaining range,

$$x_{i,j}=0$$

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## Constraints (2)

Introduction

Simulation

Each taxi will server at most one customer

$$\sum_{j=1}^{J} x_{i,j} \le 1, \forall l$$

Each customer will be served by at most one taxi

$$\sum_{i=1}^{I} x_{i,j} \le 1, \forall J$$

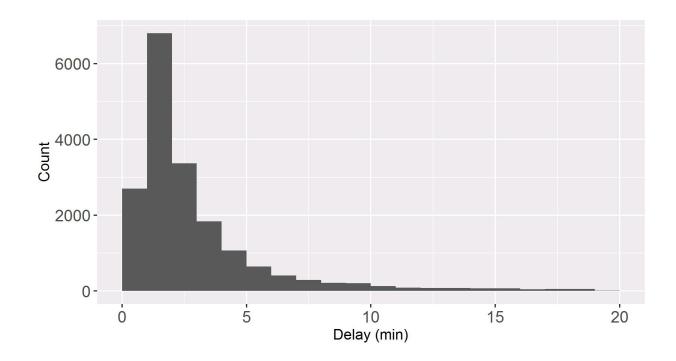
Optimization Results Summary

### Solver

- Gurobi 7.5.1
- integer linear programming (ILP)
- 1440 time intervals
- □ CPU Intel E5-1620 3.70GHz, RAM 16GB
- ~40 minutes

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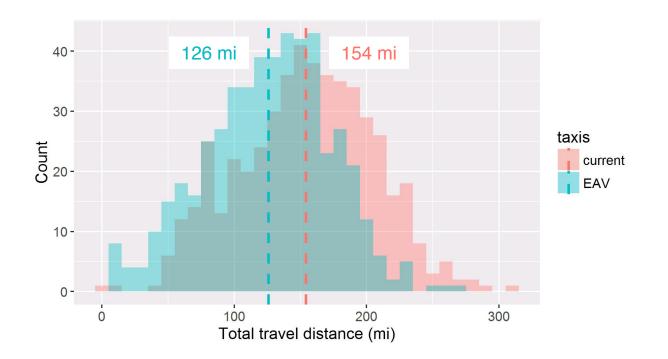
## **Customer Wait Time Distribution**



- Only 0.5% of requests are not served
- Average wait time is 4.7 minutes
- 95% of requests are served within 11 minutes

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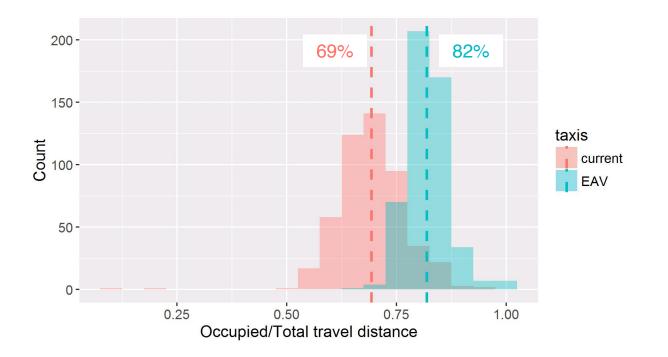
## **Total Travel Distance of Taxis**



• Average travel distance reduces by 18%

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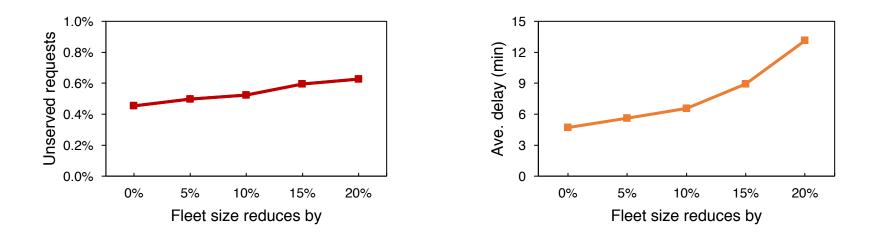
## Ratio of Occupied/Total Travel Distance



- EAV taxi system reduces empty trip distance from 49 mi to 23 mi
- Average ratio of occupied distance increases from 69% to 82%

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### **Implications of Fleet Size**



Reduces fleet size by 5%~20%

Simulation

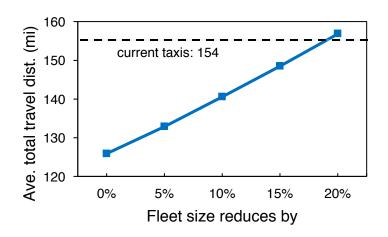
Introduction

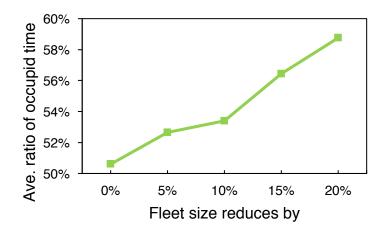
- Unserved requests remain at 0.5%~0.6%
- Average delay is within 9 minutes when fleet size reduces by ≤15%
- Average delay increases more significantly at 20% reduction

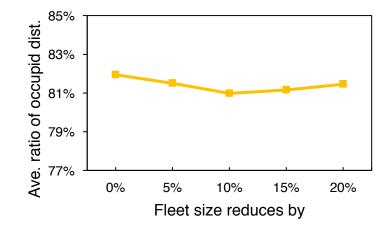
Optimization

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## **Implications of Fleet Size**



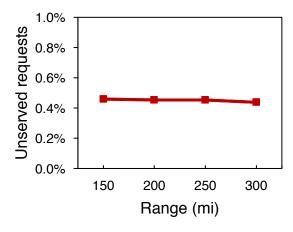




- With smaller fleet size, EAV taxis become busier
  - travel distance & ratio of occupied time increase almost linearly
- Efficiency of current taxi system ≈ EAV taxis with 80% of fleet size
- Ratio of occupied distance remains stable at 81%~82%

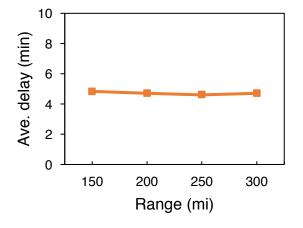
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## Implications of Electric Range



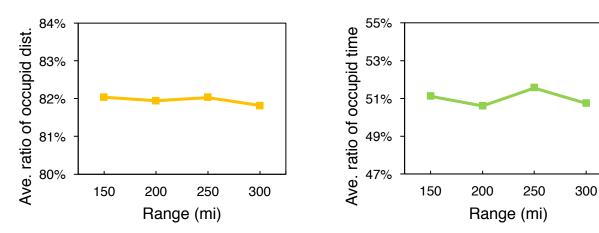
unserved requests: 0.5%

Introduction

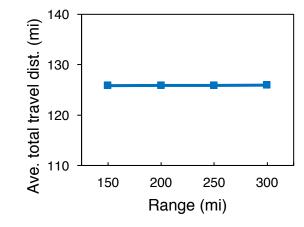


avg. delay: 4.6~4.8 min

Optimization



Simulation



avg. total travel dist.: 126 mi

 Range does not have considerable implications on request delays nor efficiency of EAV taxi systems

Results

avg. ratio of occupied dist.: 82% avg. ratio of occupied time: 51%~52%

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## Summary

EAV taxis improves efficiency of taxi systems

- less empty trips
- less energy consumption

EAV taxis has potential to reduce fleet size, while keep wait time at an acceptable level

 average delay is within 9 min when the fleet size is reduced by 15%

Results

# Thank you

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Modeling the Operations of Electric Autonomous Taxis in New York City