Models and System-Level Coordination Algorithms for Power-in-the-Loop Autonomous Mobility-on-Demand Systems

PI: Marco Pavone[1]; Co-PI: Mahnoosh Alizadeh[2]

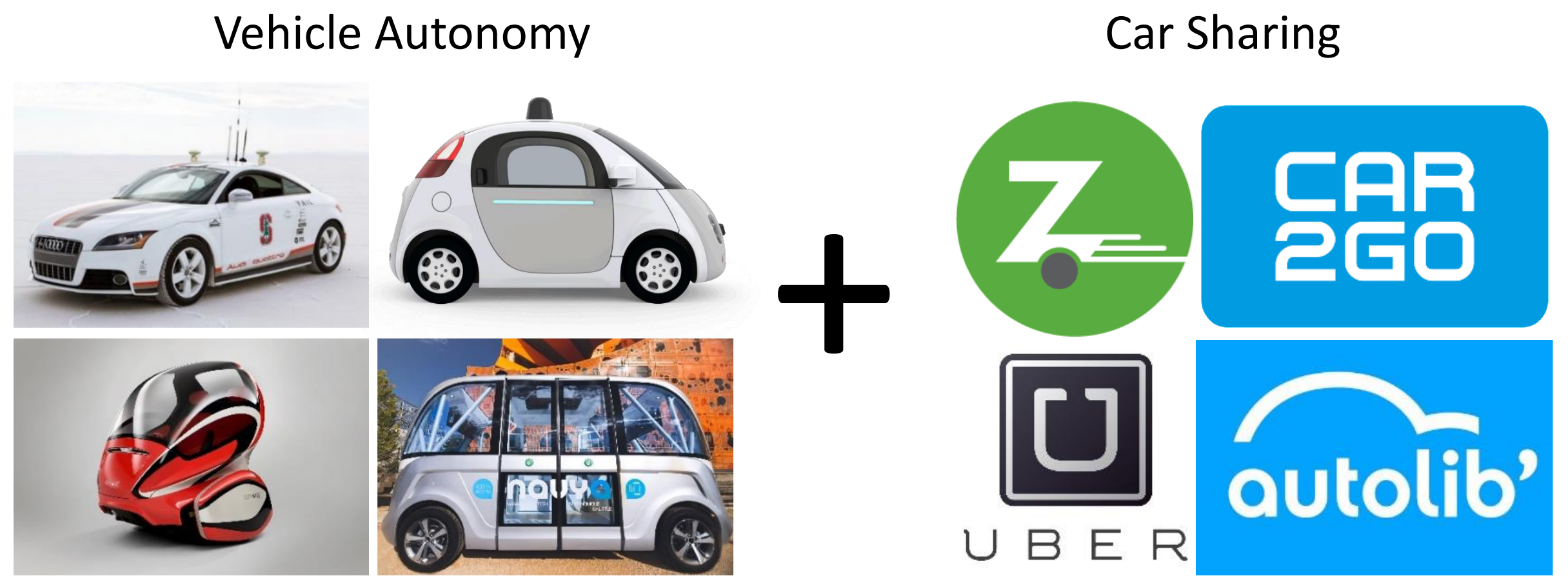
[1] Department of Aeronautics and Astronautics, Stanford University

[2] Electrical and Computer Engineering Department, University of California, Santa Barbara

Contact: pavone@stanford.edu, alizadeh@ucsb.edu

Introduction: Autonomous Mobility-on-Demand (AMoD)

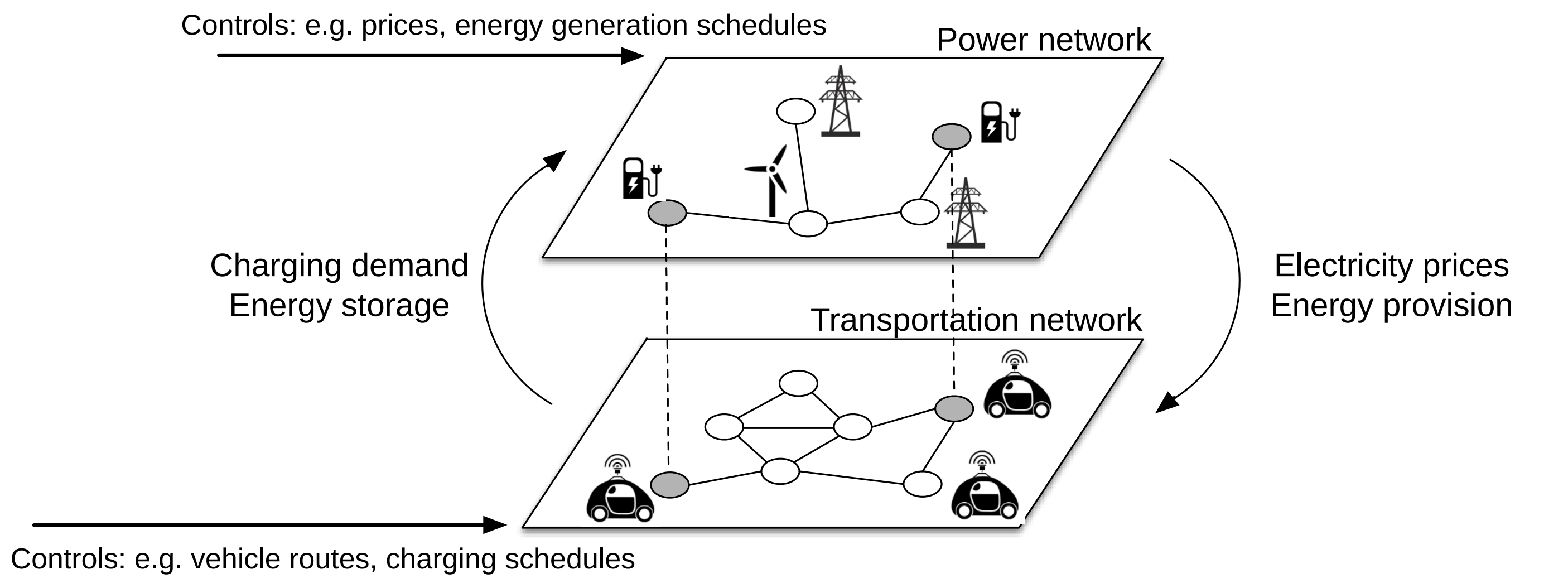
AMoD: mode of transportation wherein **self-driving, electric vehicles** transport passengers on demand in a given environment



Autonomous Mobility-on-Demand (AMoD)

Couplings between AMoD and the Power Network

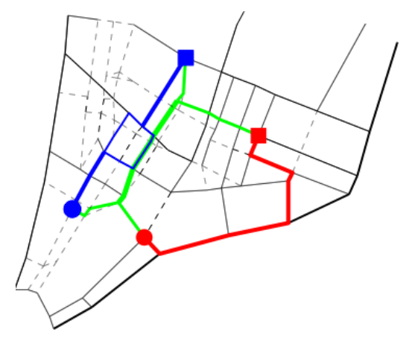
Key observation: AMoD will give rise to complex couplings between the power and transportation networks over a wide range of temporal and spatial scales



Project goal: devise computational methods for the optimal coordination of power-in-the-loop AMoD (P-AMoD) systems, that is methods to jointly determine routes for the autonomous vehicles, charging schedules, electricity prices, and power generation schedules

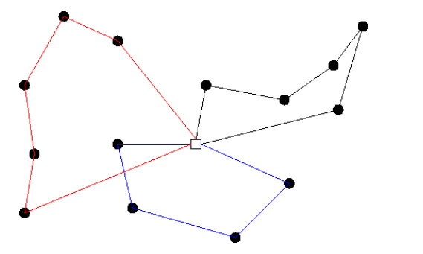
Project Objectives

Objective 1: Modeling



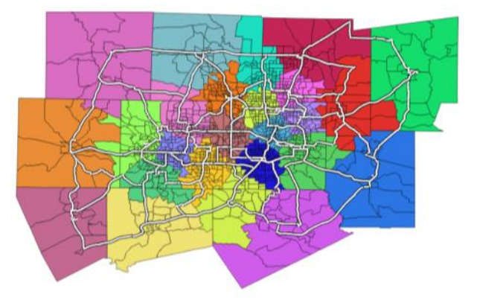
- Devise models that capture the couplings between AMoD systems and the electric power network and are amenable to efficient optimization

Objective 2: Control



- Design algorithms for real-time, *congestion-aware*, *power-in-the-loop* routing, rebalancing, and charging of autonomous vehicles at a city-wide scale

Objective 3: Case studies



- Evaluate models and algorithms via large-scale case studies based on real-world data

AY20-21 Contributions

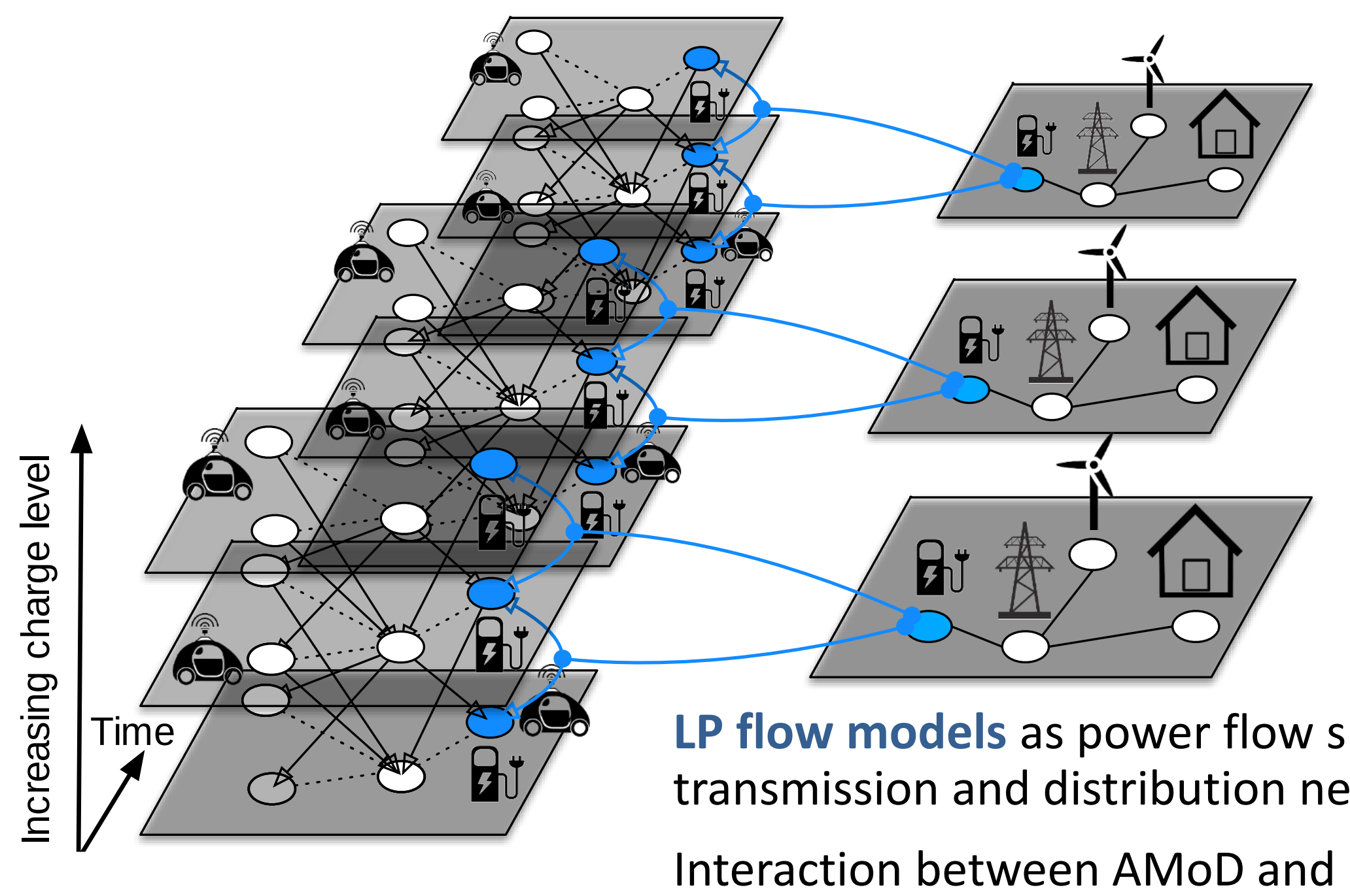
1. Network flow optimization that coordinates a P-AMoD fleet with the power distribution network
2. Study of competition in electric AMoD (E-AMoD) by comparing monopoly and duopoly equilibrium
3. Real-time control of an E-AMoD fleet in a stochastic environment with dynamic pricing
4. Network flow optimization that jointly optimizes charging station siting and E-AMoD operations

Technical Approach: Multi-commodity Network Flows

Road network: directed graph $G(V, E)$

Congestion model: capacity constraint on each edge

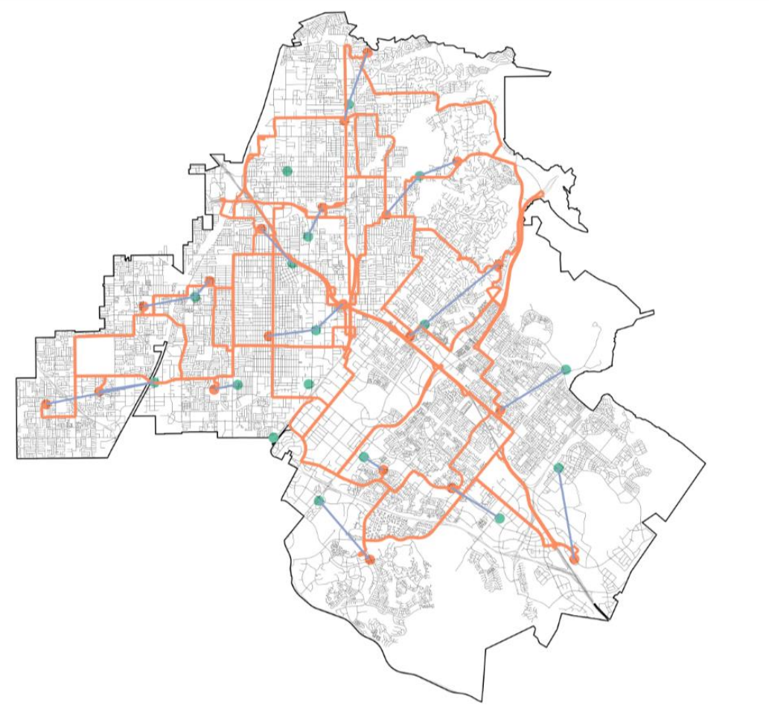
Augmented **network flow model**: time and state of charge

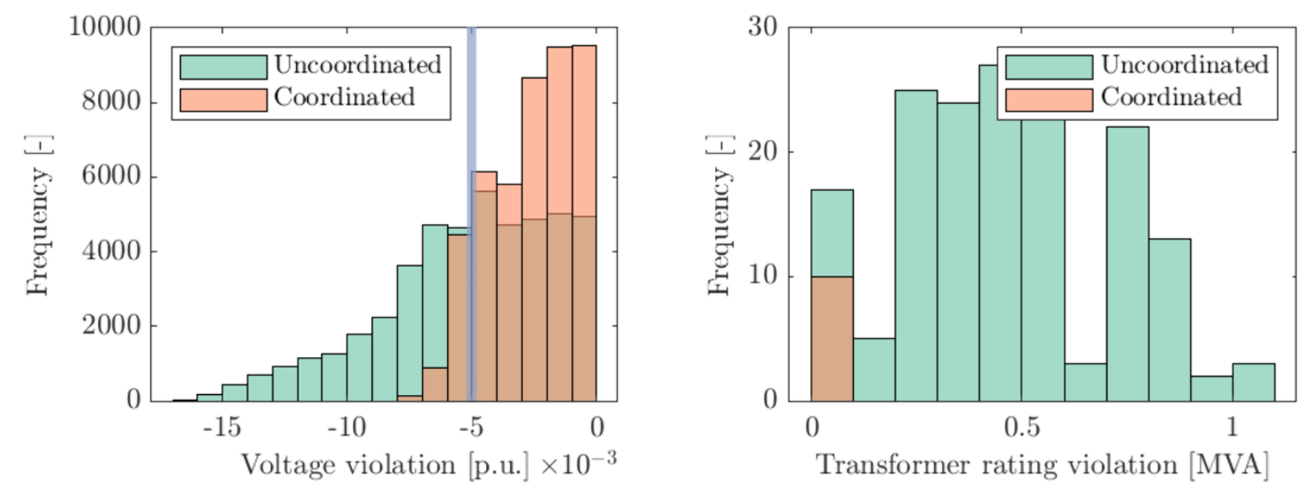


LP flow models as power flow surrogates for transmission and distribution networks

Interaction between AMoD and power network can be optimized as a **linear program**

Results: P-AMoD in Orange County, CA

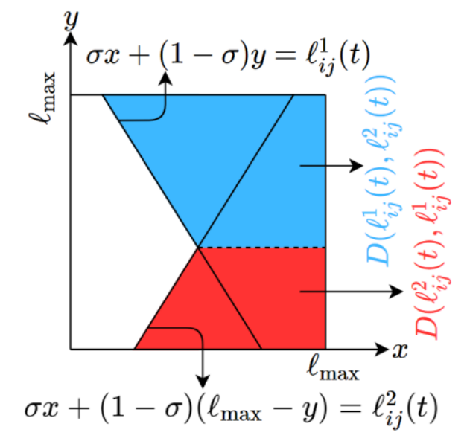




- Uncoordinated electric AMoD causes substation overloads (7.98MVAh) and voltage violations (24.04 p.u.-h) across 14 PDNs over an 8-hr commute cycle
- Coordination **reduces substation overloads by 99.71%** and **voltage violations by 50.28%**, while operating costs increase by only **3.13% (3300 USD)**

[1] A. Estandia, M. Schiffer, F. Rossi, J. Luke, E. C. Kara, R. Rajagopal, and M. Pavone, "On the Interaction between Autonomous Mobility on Demand Systems and Power Distribution Networks – An Optimal Power Flow Approach," *IEEE Transactions on Control of Network Systems*, 2021.

Results: Competition in E-AMoD Systems



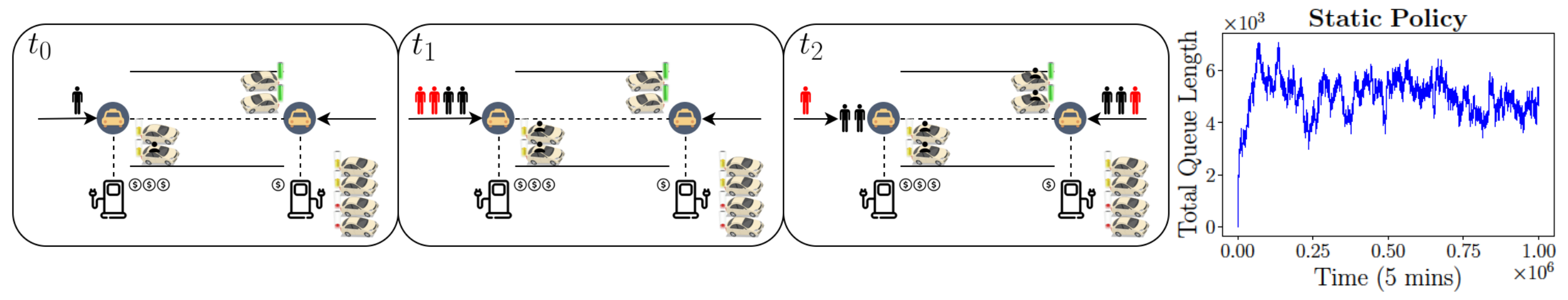
- Study competition in electric AMoD systems by comparing the monopoly and the duopoly in equilibrium.
- Identical competitors can only be in a symmetric equilibrium.
- Closed-form bounds quantify the impacts of the competition on the ride prices, the profits of the firms, the aggregate demand served and the consumer surplus.
- Higher correlation between customers' preferences strengthens the competition and boosts the impacts of competition.

	Empirical			Theoretic LB			Theoretic UB		
Correlation Coefficient σ	0.6	0.8	1	0.6	0.8	1	0.6	0.8	1
Price Ratio	0.80	0.42	0.11	0.67	0.29	0	1	1	1
Demand Ratio	1.44	1.73	2.04	1.25	1.11	1	2.26	2.55	4
Profits Ratio	0.57	0.32	0	0.39	0.19	0	0.85	0.74	0
Consumer Surplus Ratio	2.00	2.95	4.18	1.46	1.22	1	5.89	9.22	16

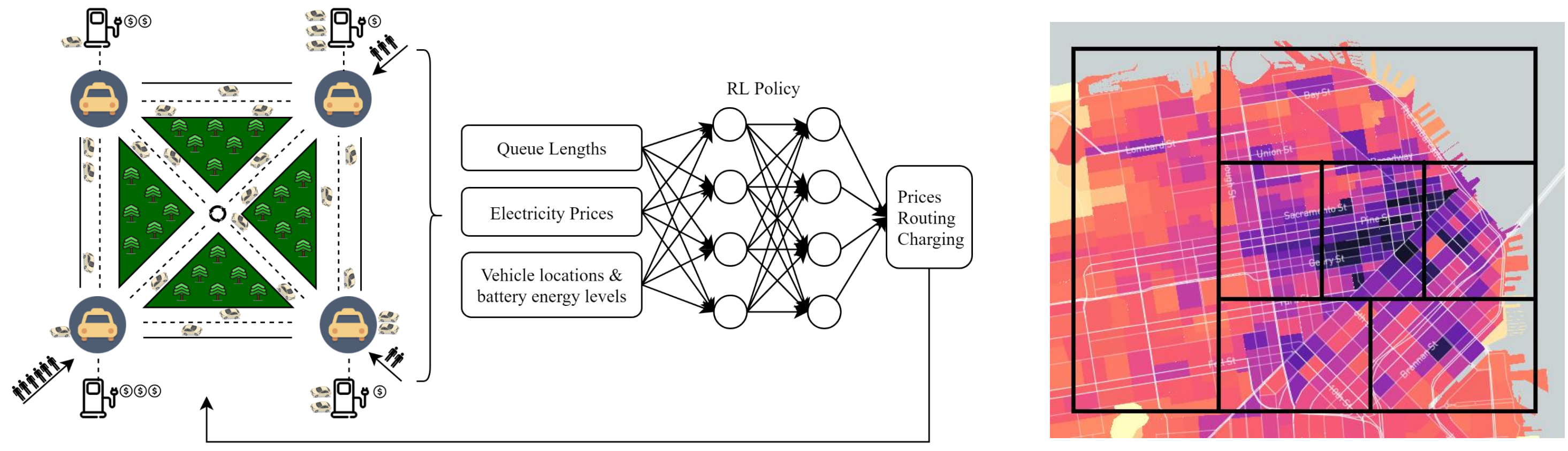
[2] B. Turan and M. Alizadeh, "Competition in electric autonomous mobility on demand systems," *IEEE Transactions on Control of Network Systems,* under review.

Results: Real-time Control

- Develop joint pricing, vehicle routing, and vehicle charging policy.
- Optimal static policy guarantees stability of the queues, however, is oblivious to the stochastic events occurring in the dynamic environment.

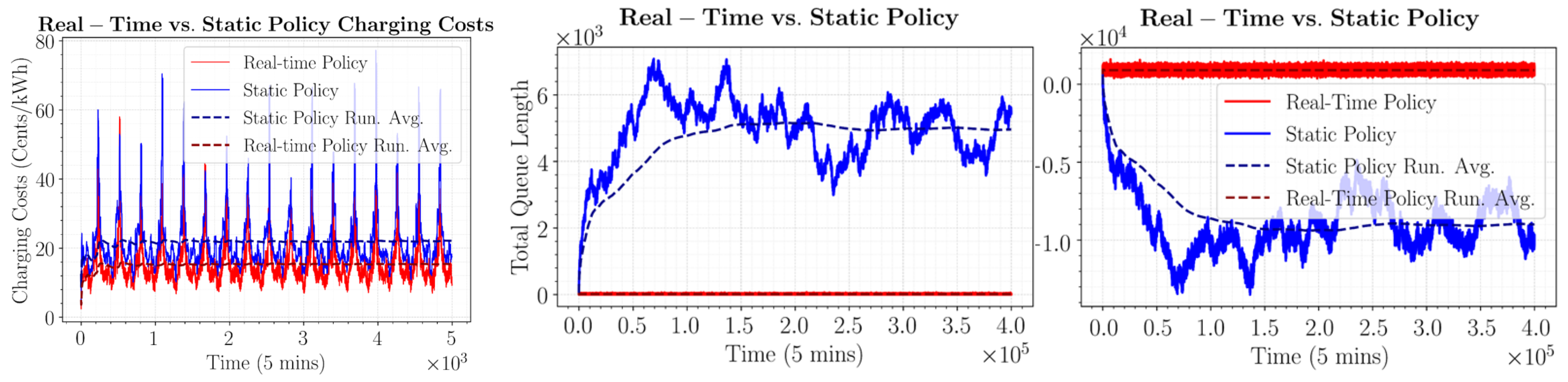


- A real-time control policy can perform better in the stochastic environment.
- Due to the curse of dimensionality, intractable to solve for the optimal policy.
- Utilize deep reinforcement learning to establish a near-optimal policy.



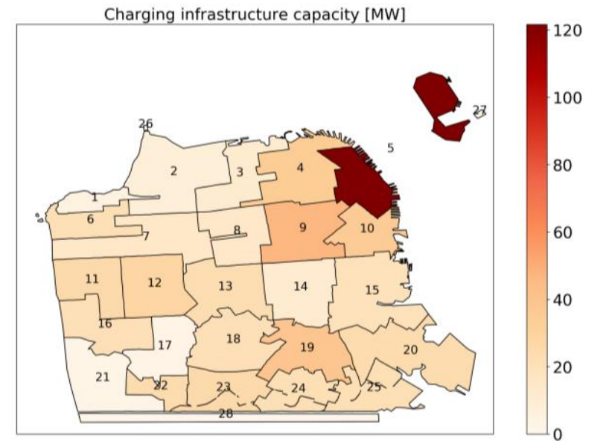
Case Study in Bay Area

- Using real network and demand data, develop and implement RL policy.
- 400x shorter queues, 25% less charging costs, increased profits.



[3] B. Turan, R. Pedarsani, and M. Alizadeh, "Dynamic pricing and fleet management for electric autonomous mobility on demand systems," *Transportation Research Part C: Emerging Technologies*, vol. 121, p. 102829, 2020.

Results: E-AMoD Systems with Charging Station Siting



- Planning and operations optimized jointly: station siting, fleet sizing, charging, routing, and rebalancing solved using LP flow model
- Case Study in San Francisco: joint siting of stations **reduces empty-vehicle distance traveled, peak charging demand, and total fleet costs by 10%** compared to scaled up present-day siting

[4] J. Luke, M. Salazar, R. Rajagopal, M. Pavone, "Joint Optimization of Electric Vehicle Fleet Operations and Charging Station Siting," *24th IEEE International Conference on Intelligent Transportation,* under review.

Conclusions

AMoD systems can act as mobile storage units in the power network

- Cooperation results in near elimination of substation overloads and halving of voltage violations with a modest cost increase (OC case study)
- Reinforcement learning model controls pricing and fleet operations in a stochastic real-time environment with reduced queues and charging costs
- Charging station siting sensitive to where vehicles are available at times of low electricity rates and travel demand, and to management of power demand

2021 NSF Cyber-Physical Systems Principal Investigators' Meeting
June 2-4, 2021

Award ID#: 1837135