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

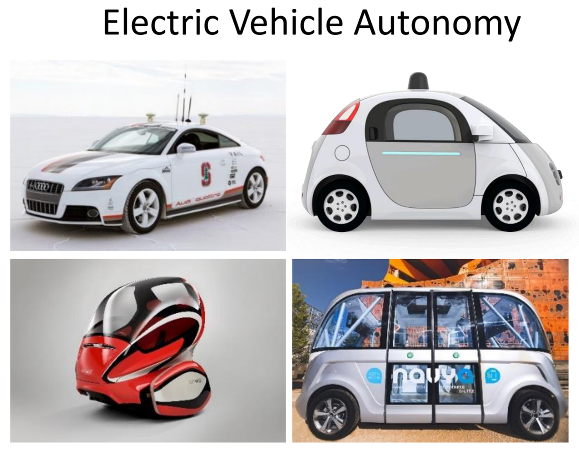
[2] Electrical and Computer Engineering Department, University of California, Santa Barbara

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

Introduction: Autonomous Mobility-on-Demand (AMoD)

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

Electric Vehicle Autonomy



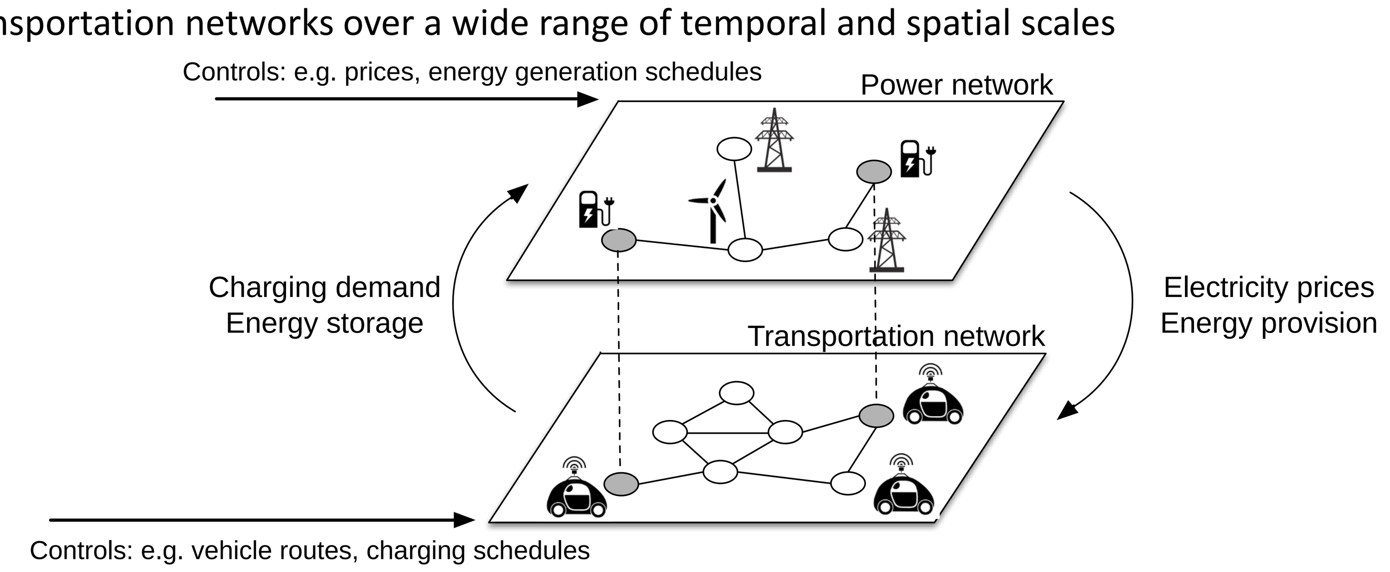
\+

Car Sharing

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

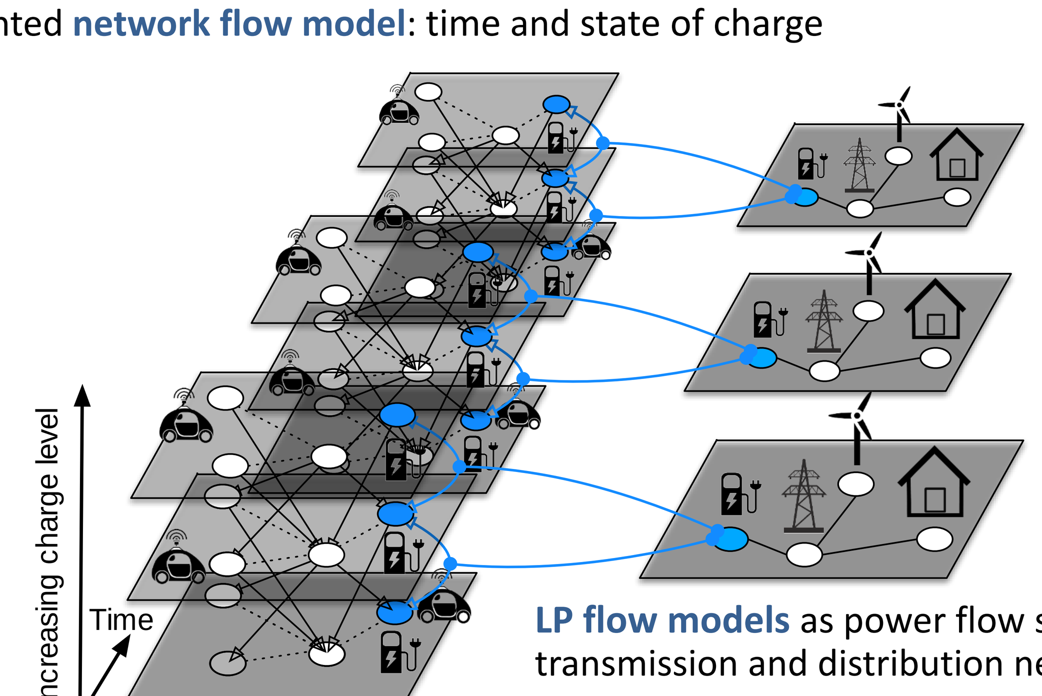


Technical Approach: Multi-commodity Network Flows

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

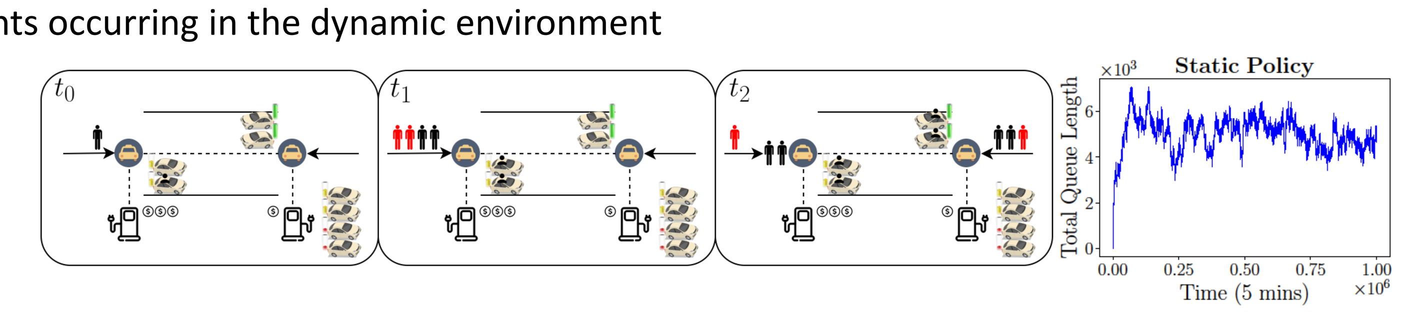
Interaction between AMoD and power network can be optimized as a **linear program**

Summary of Recent Objectives and Results

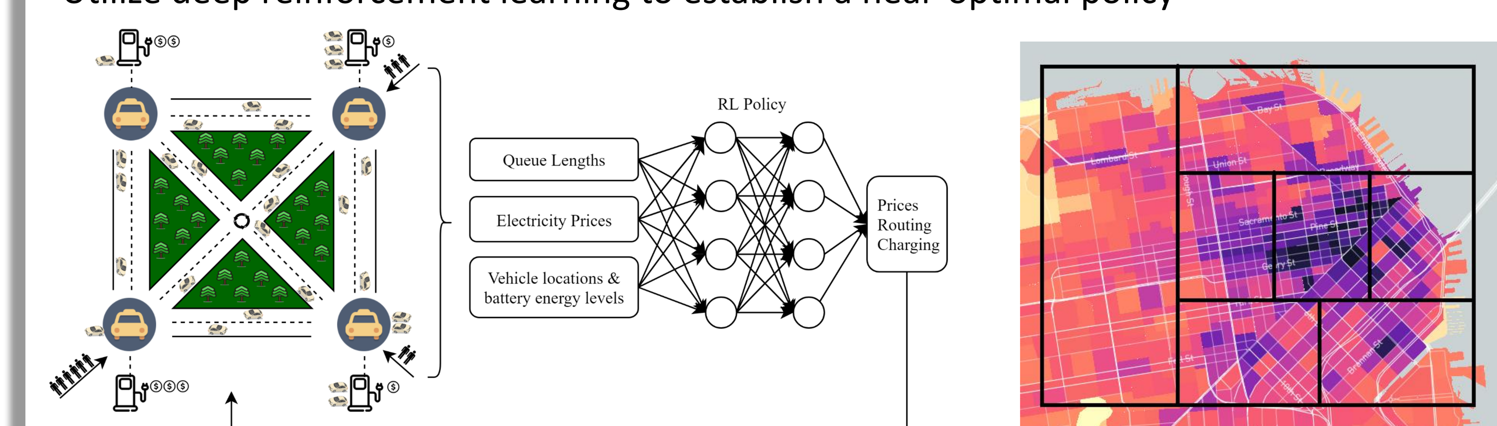
- **Offline analysis:** optimizing P-AMoD and 3-phase power distribution networks in Orange County; joint optimization of electric AMoD and station siting in San Francisco
- **Online control:** deep RL model for real-time control in Bay Area and Manhattan
- **Competition:** study monopoly vs duopoly equilibria of electric AMoD systems

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

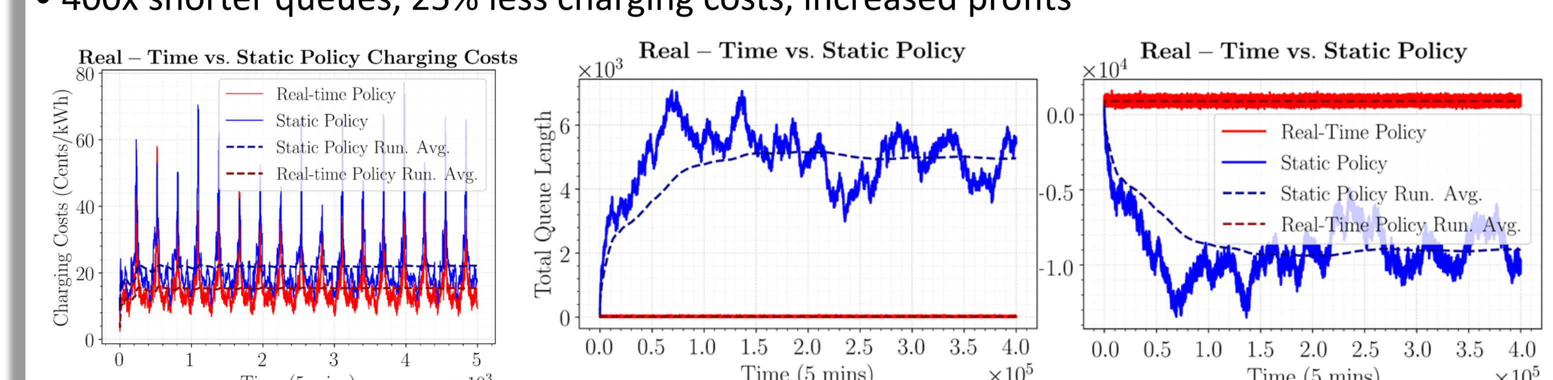


- A real-time control policy can perform better in the stochastic environment
- Due to the curse of dimensionality, intractable to solve for the optimal policy
- Utilize deep reinforcement learning to establish a near-optimal policy



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

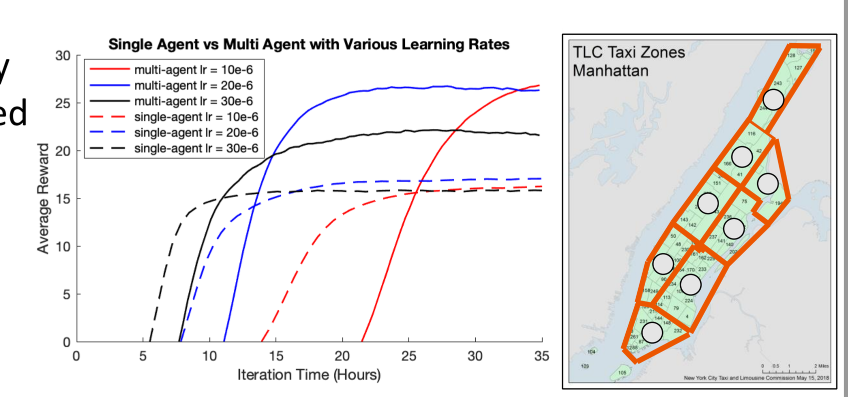


Improvements with Multi-agent RL

- Reinforcement Learning network has good performance, but it's increasingly difficult to train when applied to larger maps, as both the state and action spaces are of dimension $O(n^2)$
- Multi-Agent RL exploits the locality of the process, accelerates training by significantly reducing the number of parameters required

Case Study in Manhattan Area

- Using real network and demand data, develop multi-agent RL policy
- 80% increase in profits

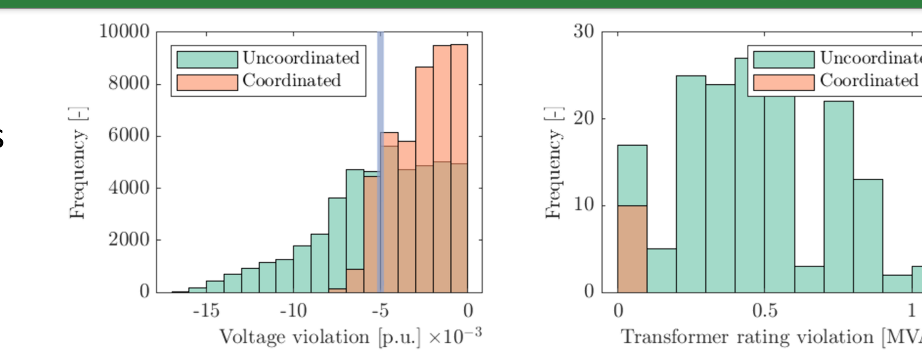


[1] B. Turan, R. Pedarsani, and M. Alizadeh, "Dynamic pricing and fleet management for electric autonomous mobility on demand systems," *Transportation Research Part C: Emerging Technologies*, vol. 121, p. 102829, 2020.

[2] A. Wang, B. Turan, and M. Alizadeh, "Multi-agent Reinforcement Learning for Dynamic Pricing and Fleet Management In autonomous mobility-on-demand systems," *International Telemetering Conference*, 2022.

Results: Power-in-the-loop AMoD (P-AMoD) in Orange County, CA

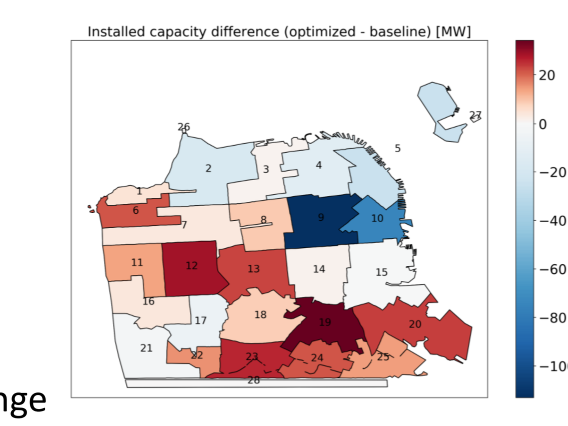
- Uncoordinated electric AMoD causes substation overloads (7.98MVAh) and voltage violations (24.04 p.u.-h) across 14 PDNs over an 8-hr commute cycle
- Coordination reduces substation overloads by 99.71% and voltage violations by 50.28%, while operating costs increase by only 3.13% (3300 USD)



[3] 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: Electric AMoD Systems with Charging Station Siting

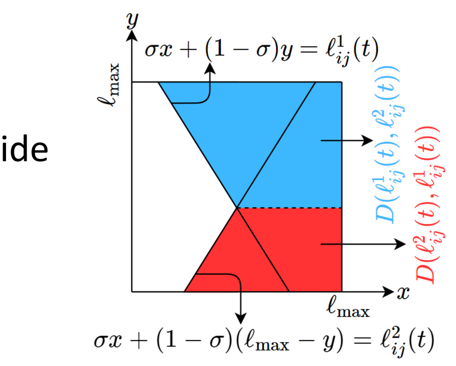
- Planning and operations optimized jointly: station siting, heterogeneous fleet sizing, charging, routing, and rebalancing solved using LP network flow model
- Case Study in San Francisco, CA: joint siting of stations reduces vehicle deadhead travel, peak charging demand, and total fleet costs by 10% compared to scaled-up present-day siting baseline
- Stations are more spatially distributed than present-day siting
- Low-cost, efficient EVs are more cost-effective despite short range
- Mid-power charging (20-30kW) is sufficient; reduction in installed ≥50kW DC fast charging capacity



[4] J. Luke, M. Salazar, R. Rajagopal, and M. Pavone, "Joint optimization of autonomous electric vehicle fleet operations and charging station siting," *2021 IEEE International Intelligent Transportation Systems Conference (ITSC)*, pp. 3340–334, 2021.

Results: Competition in Electric 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

[5] B. Turan and M. Alizadeh, "Competition in electric autonomous mobility on demand systems," *IEEE Transactions on Control of Network Systems*, vol. 9, no. 1, pp. 295-307, 2022.

Conclusions

Electric 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 (Orange County, CA case study)
- Reinforcement learning model controls pricing and fleet operations in a stochastic real-time environment with reduced queues and charging costs
- *Joint* optimization of E-AMoD systems with charging station siting reduces total costs, vehicle deadhead, peak charging, and fast charging capacity (San Francisco, CA case study)

Award ID#: 1837135