Models, Algorithms, and Evaluation for Autonomous Mobility-On-Demand Systems

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Potential Benefits of Self-Driving Cars (US Market)

- **Safety**\(^1\):
  - Value of a statistical life = $9.1M
  - Economic cost of traffic accidents = $242B
  - Societal harm of traffic accidents (loss in lifetime productivity) = $594B

- **Value of time**:
  - \((\text{productivity/leisure})^4 = \$1.3T\)

- **Throughput**:
  - Economic cost of congestion (time/fuel wasted)\(^2 = \$160B\)
  - Health cost of congestion (pollution)\(^3 = \$15B\)

- **Enabling carsharing on a massive scale**\(^4 = \$402B\)

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1 [Blincoe et al., NHTSA Report, ‘15]
2 [Schrank et al., Texas A&M Transportation Institute, ‘15]
3 [Levy et al., Environmental Health, ‘10]
4 [Spieser, Treleaven, Zhang, Frazzoli, Morton, Pavone, Road Vehicle Automation, ‘14]
Autonomous Mobility-on-Demand (AMoD)

Research Objectives:

1. **Modeling**: stochastic models for tractable analyses
2. **Control**: real-time routing of autonomous vehicles at a city-wide scale
3. **Applications**: case studies and technology infusion
How to Control a Fleet of Autonomous Vehicles?

Problem:

- **Problem data/model:** travel demand, road network
- **Control inputs:** vehicle routing, passenger loading/unloading
- **Outputs:** customer service times, availability, traffic, etc.

Previous work:

- **Traffic modeling:** Focuses on analysis rather than control
- **Dynamic Traffic Assignment:** Does not address some operational constraints, e.g. rebalancing
- **Dynamic Vehicle Routing:** Results only available for light-load or heavy-load situations, difficult to assess quality of service
Approach: Flow Models

- Customers and rebalancing vehicles: **network flows**

- **Equal availability**: Flow In = Flow Out

- **Node-symmetric** \(\rightarrow\) rebalancing flow exists

- **Can include stochasticity** via Queueing Theory

- Finding customer and rebalancing flows: \textbf{LP}
Approach: Receding Horizon Control

- Past state: $x(t + \tau | t)$
- Future state: $x(t + \delta + \tau | t + \delta)$
- Predicted control: $u(t + \tau | t)$
- Applied control: $u(t + \delta + \tau | t + \delta)$

Diagram showing the receding horizon control process with time intervals $t$, $t + \delta$, $t + \tau$, $t + T$, and $t + \delta + T$.
Manhattan Case Study: Steady State Analysis

- 1007 road links
- 50 stations
- Travel demand from **NYC TLC dataset**
- **90% availability** with ~2,400 vehicles; ~1500 serving customers, ~400 rebalancing, ~500 idle
Manhattan Case Study: Real Time Control

Service Time

- Low congestion: road capacity reduced by 70%
- High congestion: road capacity reduced by 80%

Naïve (no congestion)
- Nearest-Neighbor (no rebalancing)
- Congestion-aware

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Conclusions

Future Directions

- Vehicle-to-Grid
- Intermodal Systems
- Societal Impacts

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