Modeling and Experimental Analysis of Mobility-on-Demand Systems

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Objectives

Enable sustainable urban personal mobility through autonomous driving and system-level coordination of autonomous vehicles

MIT CityCar. W.J. Mitchell et al., 2010

Motivation

Current model of urban mobility is unsustainable
- Over 3 trillion urban miles are driven annually in the U.S.
- Over 50% of the world population live in urban areas. This number will increase to 60% by 2030

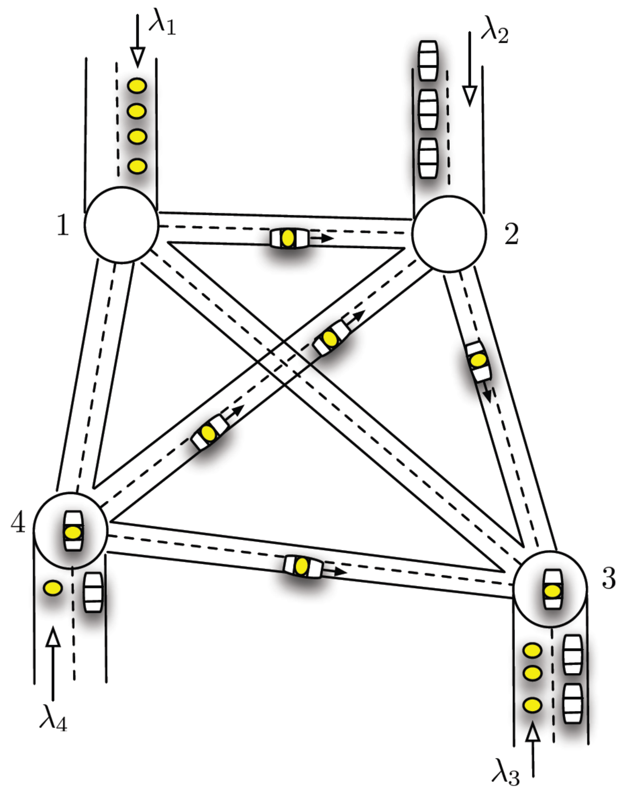
New models of urban mobility can benefit from system-level coordination and vehicle autonomy
- Car-sharing services are beginning to gain popularity
- Autonomous driving and system-level coordination can ensure quality of service for Mobility-on-Demand systems

Technical approach to studying Mobility-on-Demand Systems

Queuing models for MOD systems
1. Fully automated MOD systems
2. Hybrid human/automated MOD systems
3. Intermodal MOD systems

System-wide coordination architectures
- Dynamically route vehicles by taking into account safety, demand uncertainty, and charging constraints

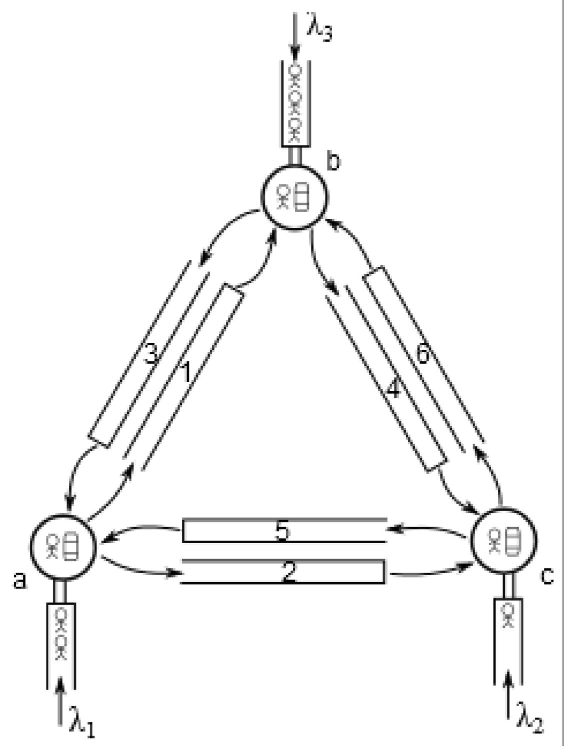
Validate results
- Simulations
- Experimental testbed of a mock urban environment with a fleet of vehicles
- Driverless shuttles providing MOD service on Stanford Campus



Modeling MOD systems as queuing networks

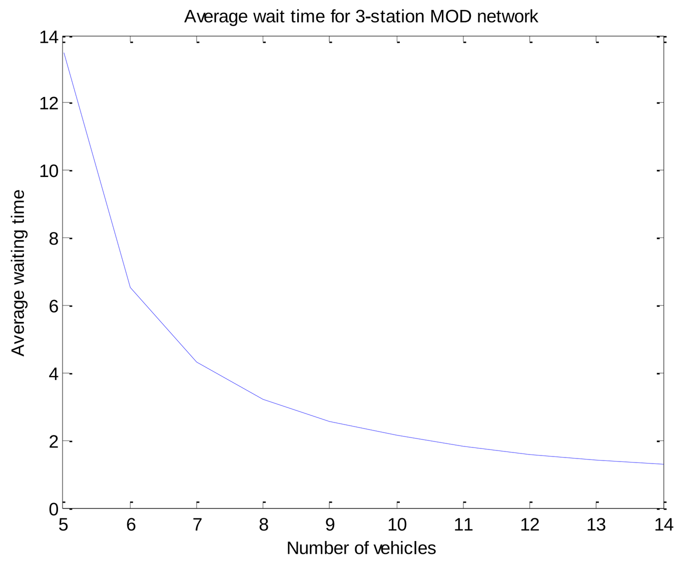
Approaches to modeling MOD systems
- Fluidic model
- Dynamic vehicle routing
- **Jackson network model**

Vehicles form a closed Jackson network
- Roads between pairs of stations form infinite server queues
- Congestion effects are not taken into account



Key Quantities:
- α_{jk} = rate of empty vehicles + rate of customer carrying vehicles
- ρ_i = Throughput of station i
- λ_{ci} = Arrival rate of customers to station i
- $\bar{Q}_i$ = Probability station i is empty

Solving for customer wait time
- ρ_i represents an effective customer service rate
- Stable if $\lambda_{ci} < \rho_i$
- Waiting time at station i is $\frac{1}{\rho_i - \lambda_{ci}}$
- $\bar{Q}_i = 1 - \frac{\lambda_{ci}}{\rho_i}$
- α_{jk} depends on $\bar{Q}_i$. If we knew $\bar{Q}_i$, we can solve for the waiting time

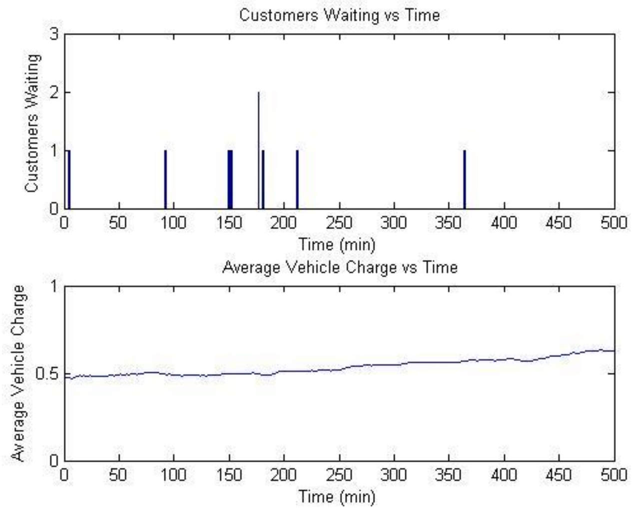


For a given system, we can determine the number of vehicles required to achieve a desired wait time

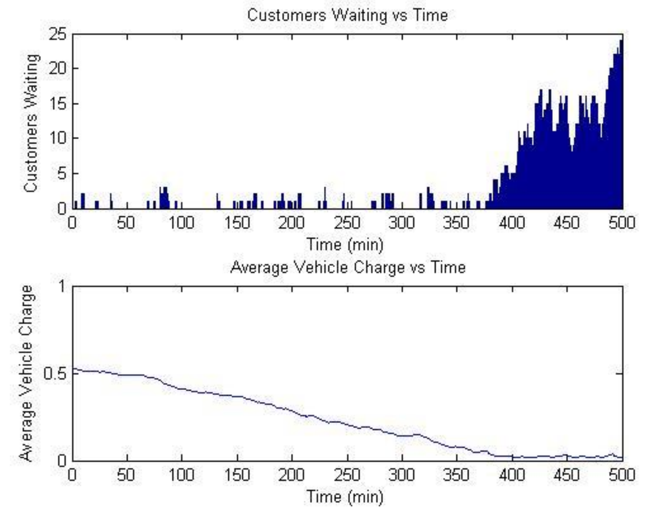
An iterative procedure to solve for $\bar{Q}_i$
1. Make an initial guess for $\bar{Q}_i^0$
2. Solve the closed Jackson network to find throughput ρ
3. Use Little's theorem to determine $\bar{Q}_i^1$
4. Iterate until convergence
5. Solve for the waiting time at each station

Charging problem for electric vehicles

Current battery technology takes longer to charge than to discharge
- One of the main issues of current car-sharing services
- Developing real-time rebalancing algorithms for electric vehicles
- Can only rebalance vehicles with sufficient charge
- Adding a "safety threshold" on the amount of charge required significantly increases wait time



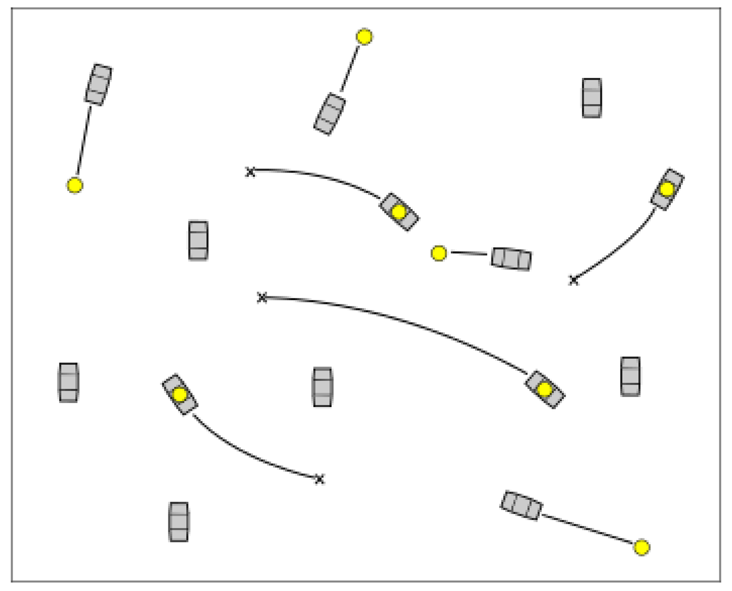
Stable system



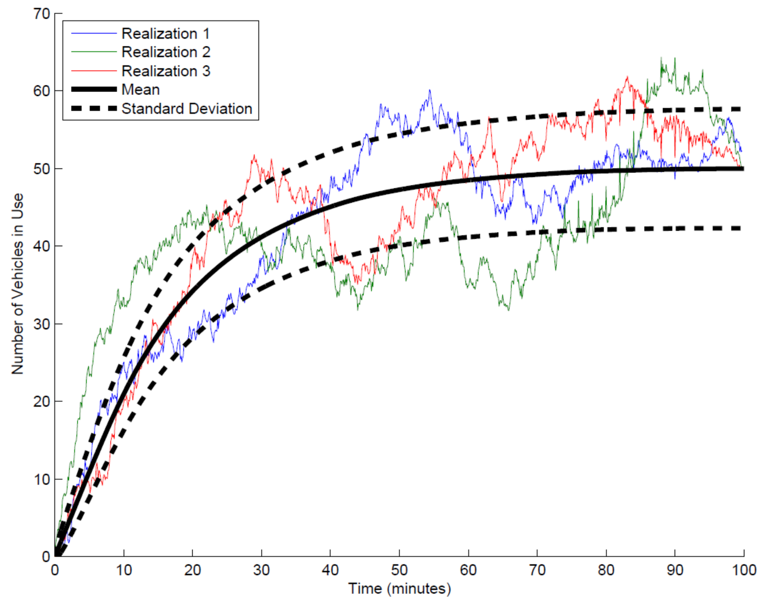
Instability due to charge. System load too high for vehicles to stop and charge

Routing algorithms with provable performance guarantees

Large fleets of autonomous "taxis" could revolutionize urban transit, but optimal routing of vehicles to customers is NP hard
- Service time for customers depend on many **geographically distributed components**, which are statistically dependent
- With many vehicles and many customers, the **spatial** element of the queue becomes **less important**
- Tractable algorithms can be given which are **asymptotically optimal** for systems with **many customers and many vehicles**



A spatially constrained MOD system with many customers and many vehicles

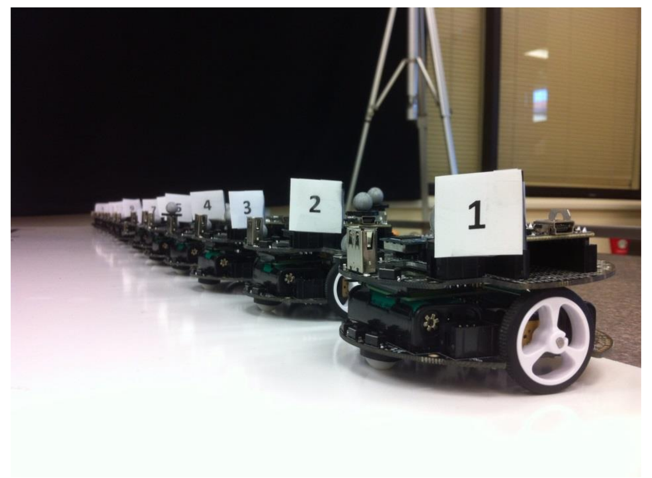


For large systems, we can approximate the number of vehicles in use at any time

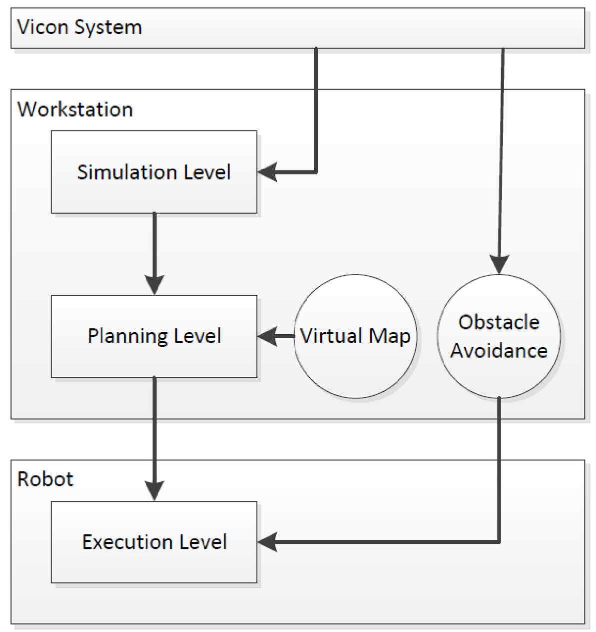
Experimental testbed

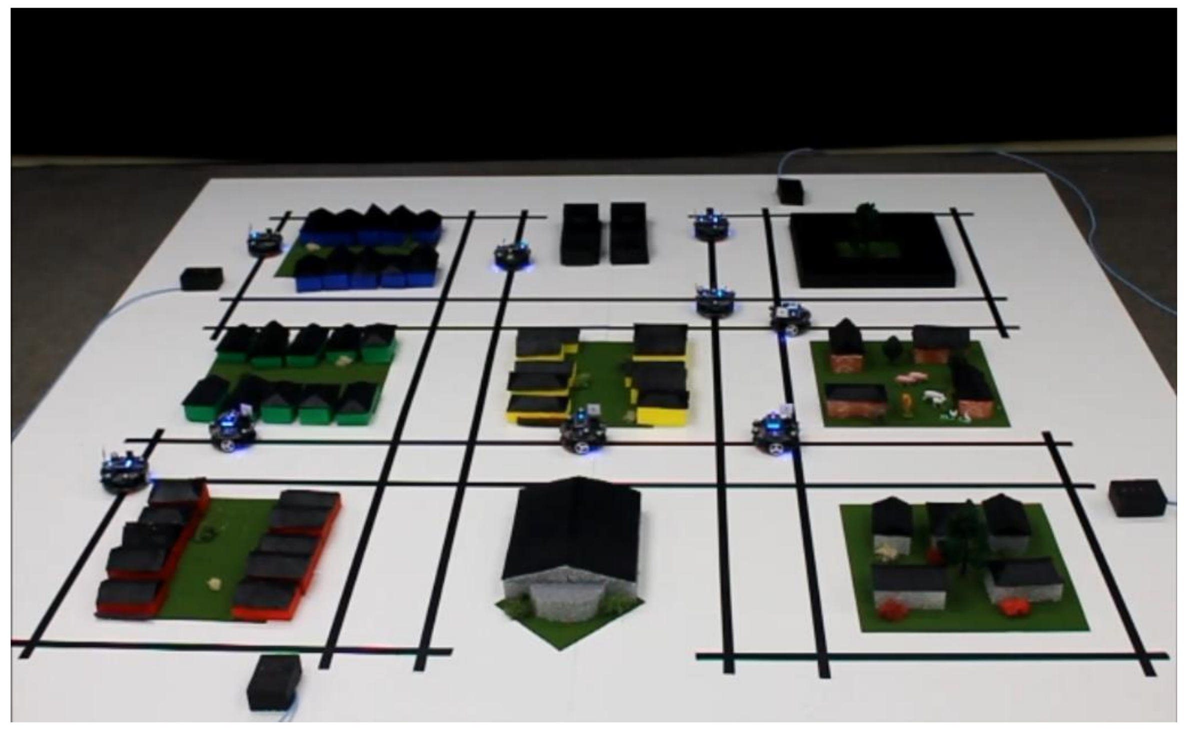
Experimentally evaluate rebalancing policies for MOD systems

Hardware
- 18 Pololu m3pi Robots
- Vicon Motion Capture System



Software





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