# Multiple-Level Predictive Control of Mobile Cyber Physical Systems with Correlated Context

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# Goals of Project

- Thoroughly investigate mobile transportation and home health care systems with a model predictive feedback control approach based on spatiotemporal context
- Investigate human in the loop control
- Develop fundamental scientific solutions for mobile CPSs
- Driving applications are saving energy in workstations, home healthcare, and vehicular taxi systems

# Two Research Themes

- Fundamental CPS science
  - Systems of systems
  - Human-in-the-Loop
- Improve CPS applications
  - Taxi Systems
  - Save Energy on Workstations
  - Home Health Care
  - ICU

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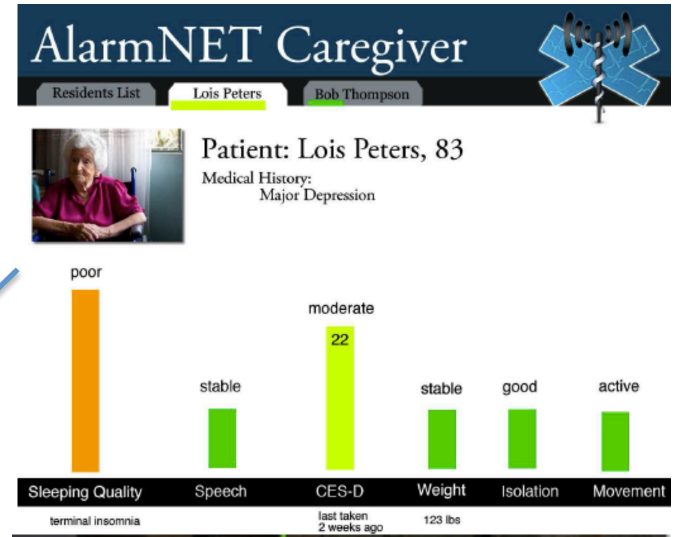
# Integration of CPSs in Smart Homes


Smart Thermostat

Home Health Care




$\int$

Security

Game

# Human-in-the-Loop CPS

Medication

Fluid Intake

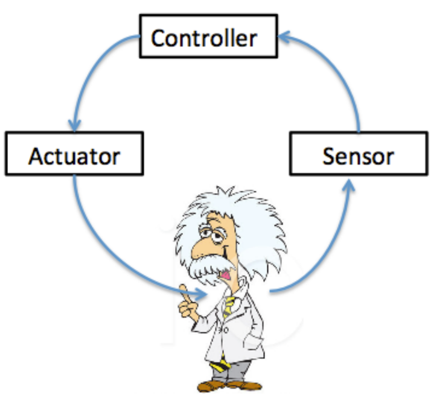
Exercise

Nutrition Control

# Detecting Primary and Secondary Conflicts in Mobile Medical Apps

- Motivation
  - There will be 2.03 billion smart phone users in 2015 worldwide
  - 500 million smart phone users will download healthcare apps by 2015


- Challenge
  - These medical apps are human-in-the-loop apps
  - They may conflict due to conflicting interventions:
    - Drug + Drug
    - Drug + Non-Drug (e.g., food/exercise)
    - Non-Drug + Non-Drug

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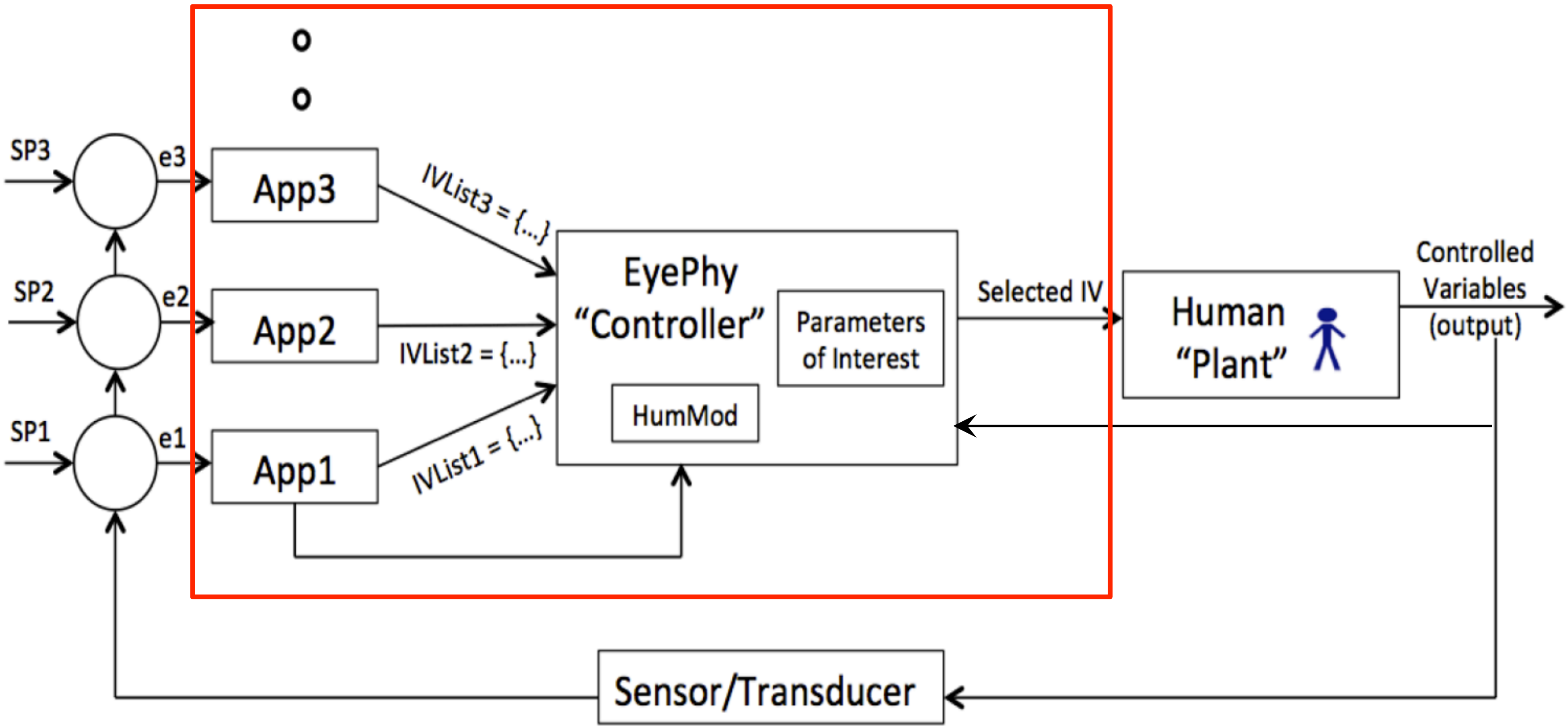
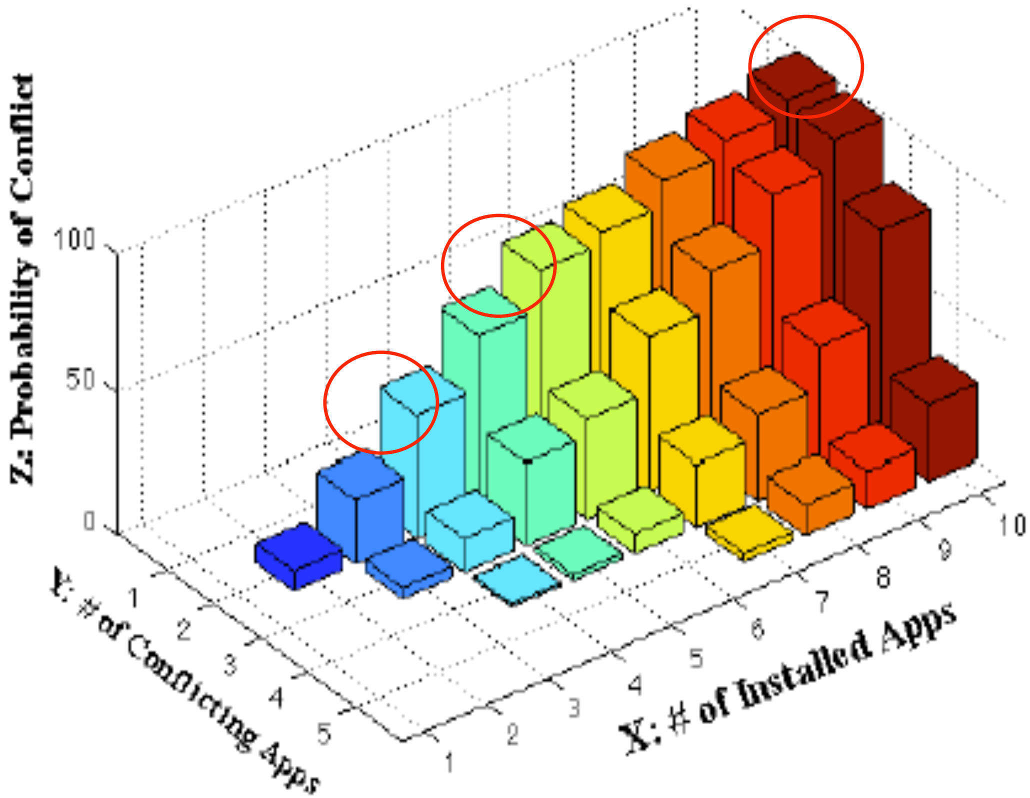
# Human-in-the Loop Architecture



# Static Analysis (High Level Params)

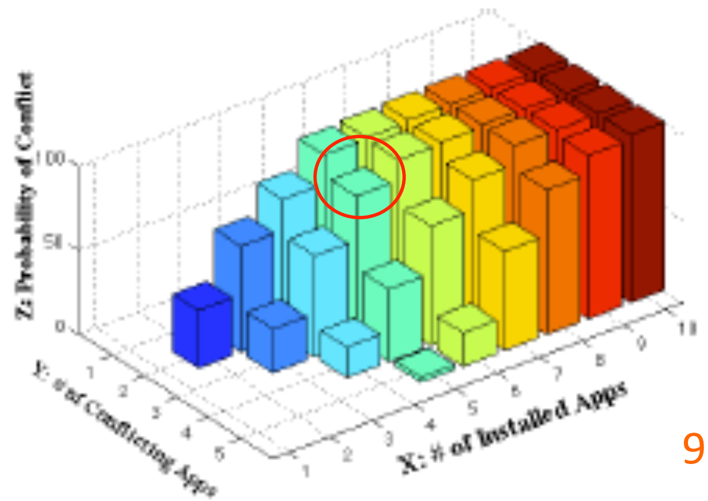



3 apps: 7%
5 apps: 62%
10 apps: 99%

**High Level Parameters**

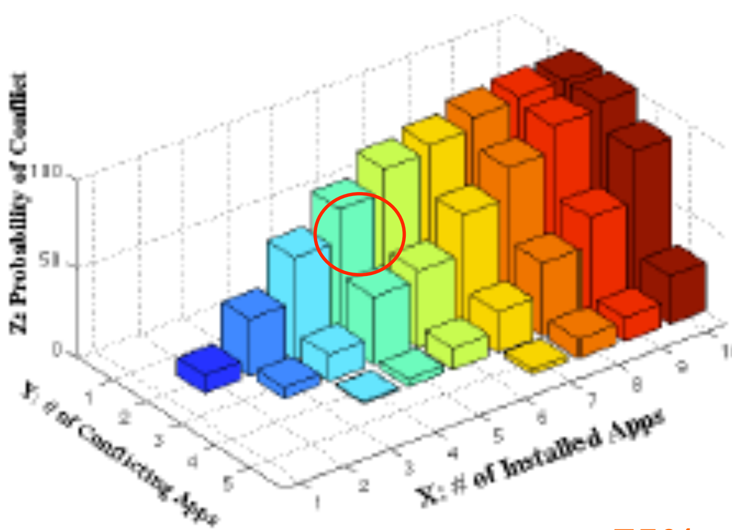
# Static Analysis (Low Level Params)

5 apps



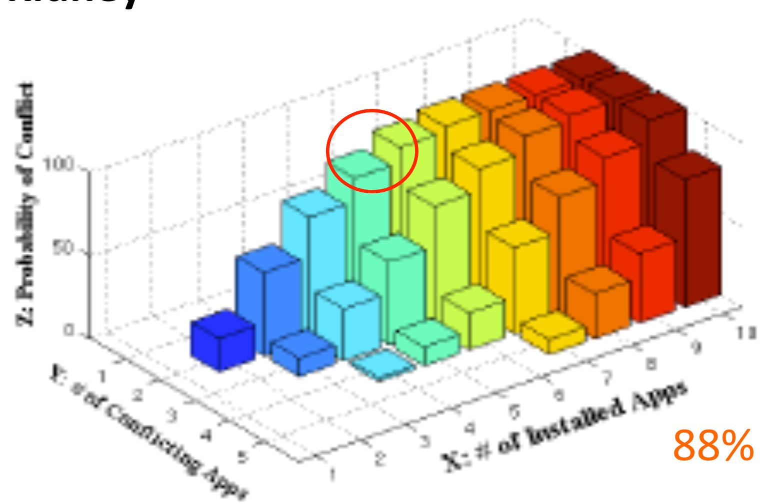

98%

Kidney




75%

Heart

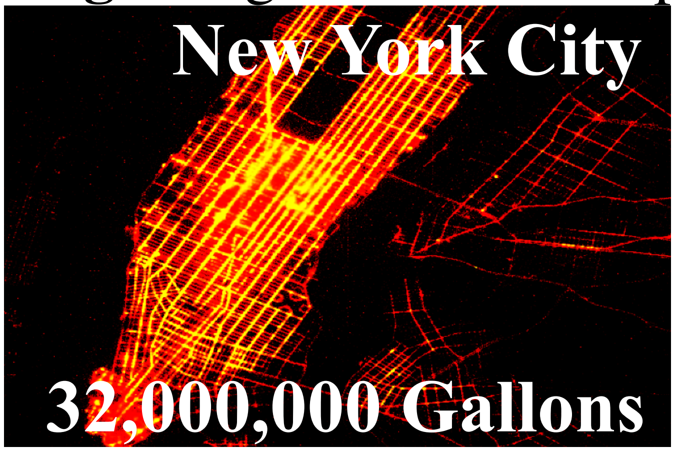



88%

Liver

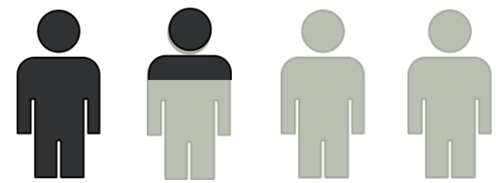
# Taxi Ridesharing

**Challenge:** High Gas Consumption




Reduce Mileage

**Opportunity:** Low Utilized Capacity



70% Wasted

1.3 Passengers/ride in NYC
1.4 Passengers/ride in Shenzhen

***Sharing Capacity***

**State of the Art**

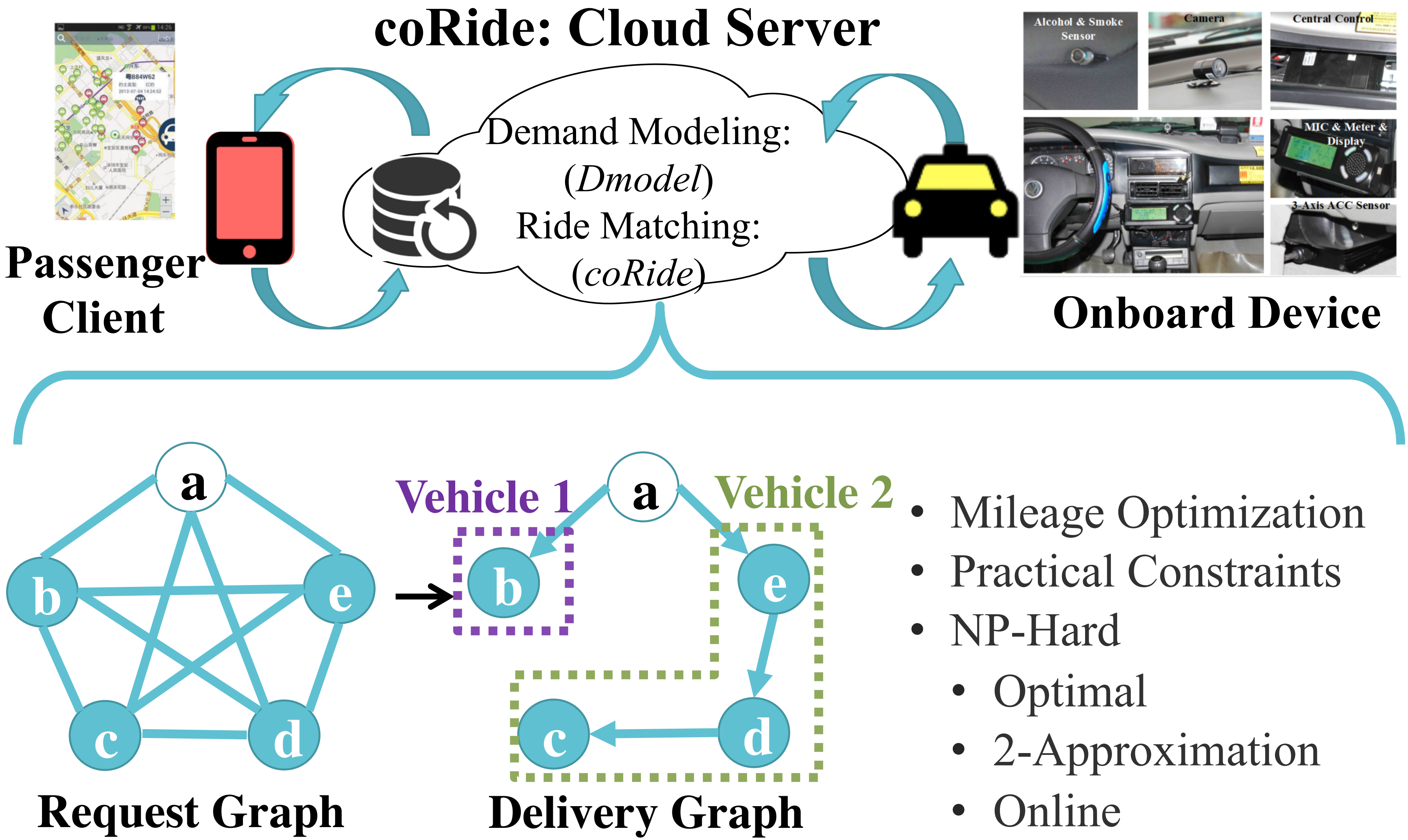
**ICDE 2013** **UberPool 2014**

- Ad Hoc Services
- Heuristic Matching
- Lacking Generalization

**Our Approach**

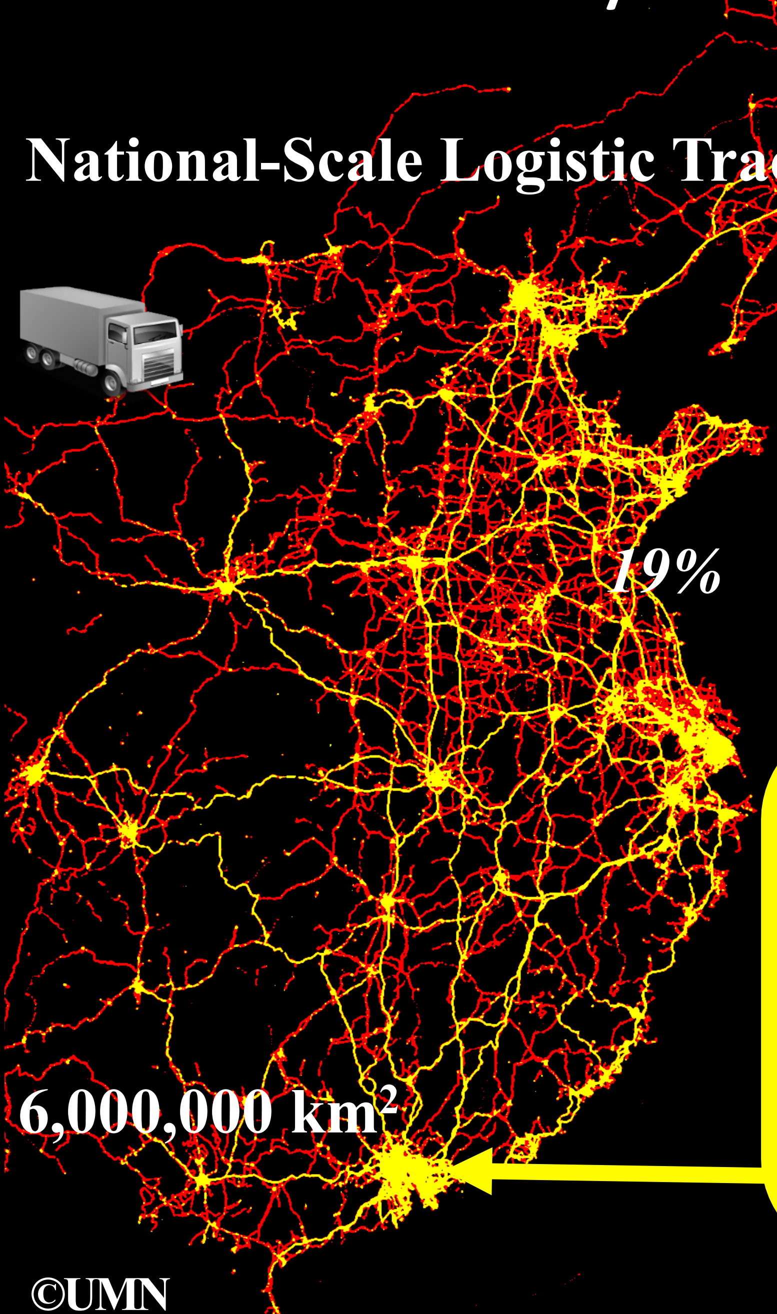
- Demand Modeling
- A Set of Optimizations
- Generalization to Other Logistics

# System Design and Optimization



# Field Study and Trace-driven Evaluation

***Reduced Mileage (%)***



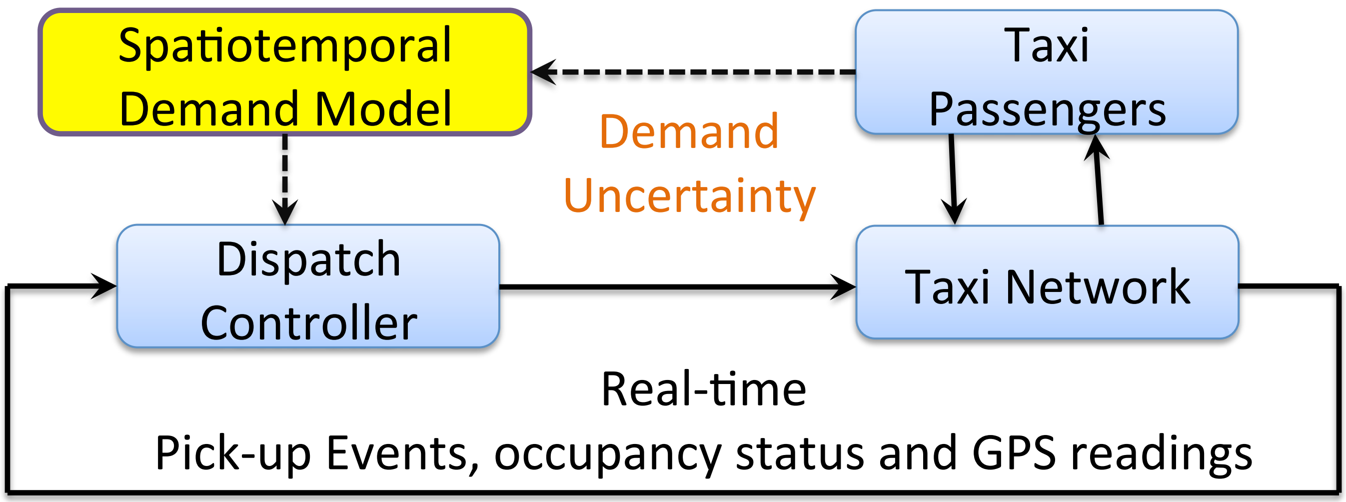


# MPC Approach to Taxi Dispatching

- Input: estimated passenger demand in each region, a supply model, a trip model.
- Output: the region to which every unoccupied taxi should go at each step.
- Cost measures: idle cruising distance, mismatch of supply/demand ratio
- Control requirement: process passenger requests as much as possible, with minimal idle distance.
- Approach: a multi-objective optimization problem formulation, applying the Model Predictive Control idea that utilizes both historical and real-time GPS information, consider both current and future costs.

# Data-Driven Robust Taxi Dispatch

- Motivation
  - predicted future demand helps balance supply and demand, reducing idle driving distance
  - but demand uncertainties based on real data affect result
- Goal
  - a dispatch approach considers model uncertainties when making dispatch decisions
- Challenge
  - NP-hard robust optimization →convex optimization



# Data-Driven Robust Taxi Dispatch

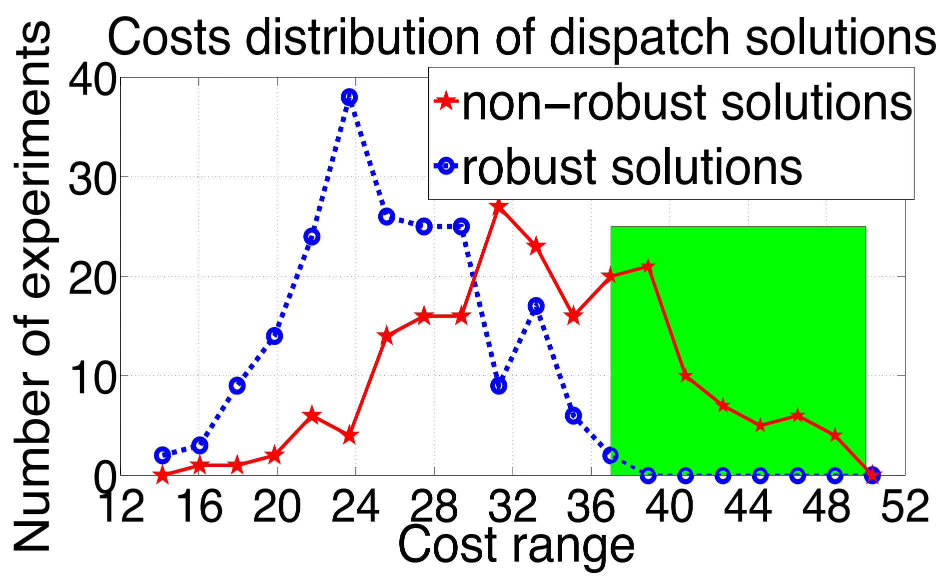
- **Solution:**
  robust optimization with demand model as uncertain parameters
- **Objectives:**
  balance supply demand ratio and reduce idle mileage
- **Algorithm:** proved equivalent form of standard convex optimization, solvable in polynomial time

$$\min_{X^1} \max_{r^1\in\Delta} \min_{X^2,L^2} \max_{r^2\in\Delta} \dots \min_{X^\tau,L^\tau} \max_{r^\tau\in\Delta}$$

$$J = \sum_{k=1}^{\tau} (J_D(X^k) + \beta J_E(X^k, r^k))$$

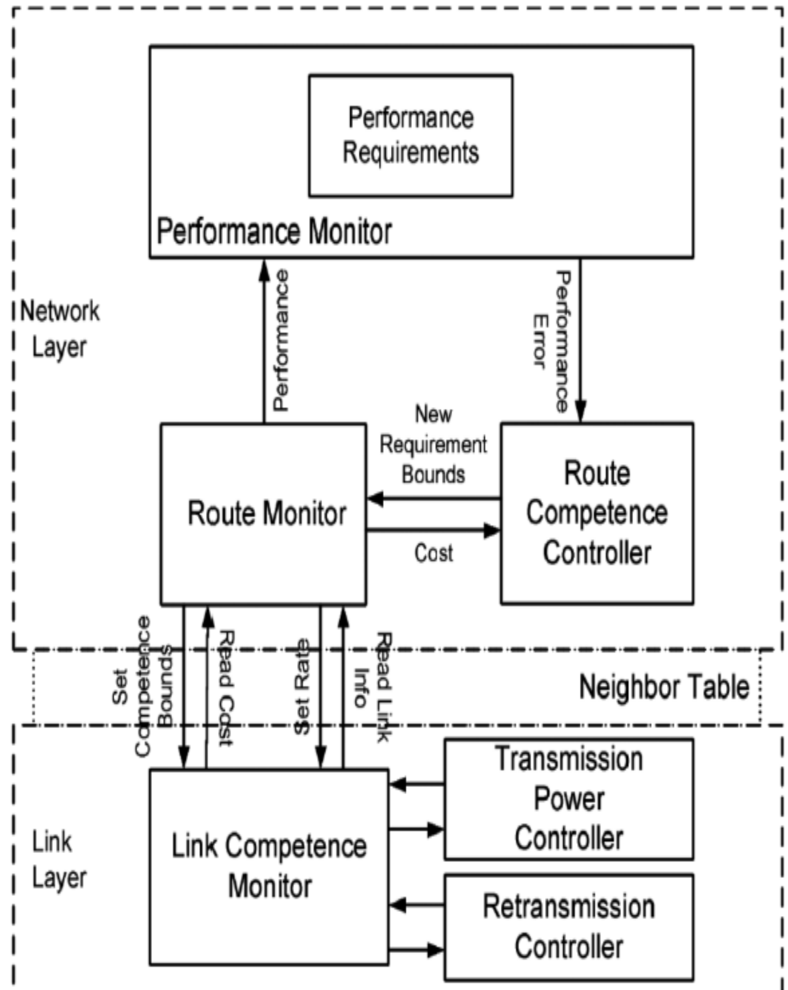
$$= \sum_{k=1}^{\tau} \sum_i \left( \sum_j X_{ij}^k W_{ij} + \frac{\beta r_i^k}{(\mathbf{1}_n^T X_{\cdot i}^k - X_{i\cdot}^k \mathbf{1}_n + L_i^k)^\alpha} \right)$$

$$\begin{aligned}
\text{s.t.} \quad & (L^{k+1})^T = (\mathbf{1}_n^T X^k - X^k \mathbf{1}_n + (L^k)^T) P^k, \\
& \mathbf{1}_n^T X^k - X^k \mathbf{1}_n + (L^k)^T > 0, \\
& X_{ij}^k W_{ij} \le m X_{ij}^k, \\
& X_{ij}^k \ge 0, \quad i, j \in \{1, 2, \dots, n\}.
\end{aligned}$$



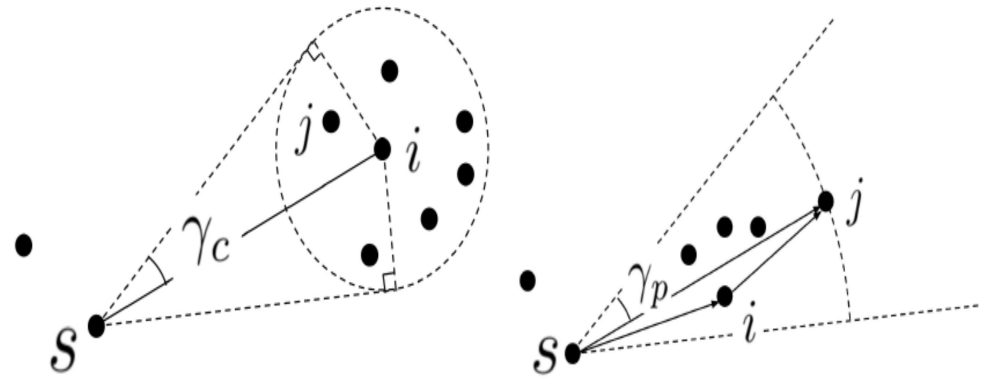
# Wireless Network Research for Mobile CPS

- Wireless Network Control for Stable Performance
  - Long term estimation for performance stability
  - Stabilize Reliability and Latency
  - Global coordination + local control
  - Adaptive Control Analysis

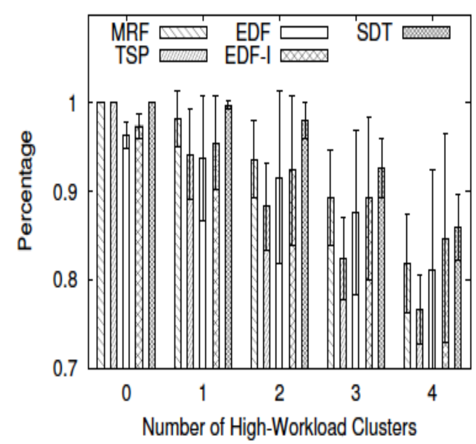


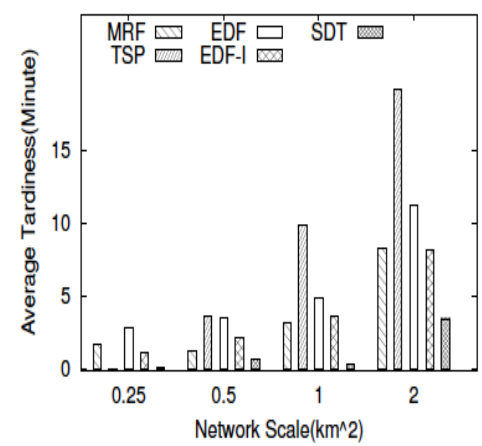
# Mobility Scheduling

- Energy Charging
  - Maximize task coverage under real-time constraints
  - Cluster tasks based on their location and urgency
  - Cluster tasks along the traveling path
  - Outperform existing solutions by 10% in coverage, and by 85% in tardiness
- Time-constrained Data Collection using Data Mule
  - Optimize the path of data mule for data collection within a specified time duration
  - Provide analytical bound
  - Design a PTAS algorithm with a constant-factor approximation




(a) Cluster Dependency (b) Path Dependency



# Future Work

- Robust control under uncertainty
- Fundamentals of modeling and control for humans in the loop

- Supported by NSF CNS1239483