Predictive routing and multi-objective fleet sizing for shared mobility-on-demand

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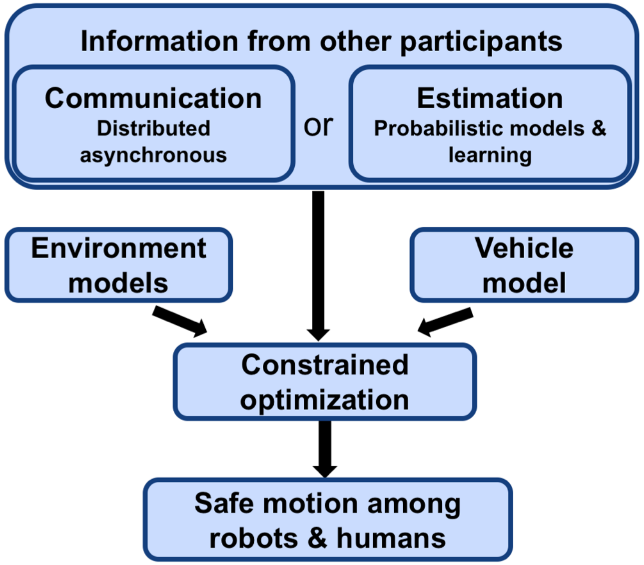
Autonomous cars will
make transport
reliable, safe, efficient,
comfortable and clean

Motion planning for autonomous vehicles



W. Schwarting et al., "**Safe Nonlinear Trajectory Generation for Parallel Autonomy With a Dynamic Vehicle Model**", T-ITS 2017
B. Zhou et al., " **Joint Multi-Policy Behavior Estimation and Receding-Horizon Trajectory Planning for Automated Urban Driving**", ICRA 2018
L. Ferranti et al., "**SafeVRU: A Research Platform for the Interaction of Self-Driving Vehicles with Vulnerable Road Users**", IV 2019


Autonomous cars will
solve all our problems!
Reliable, safe, efficient,
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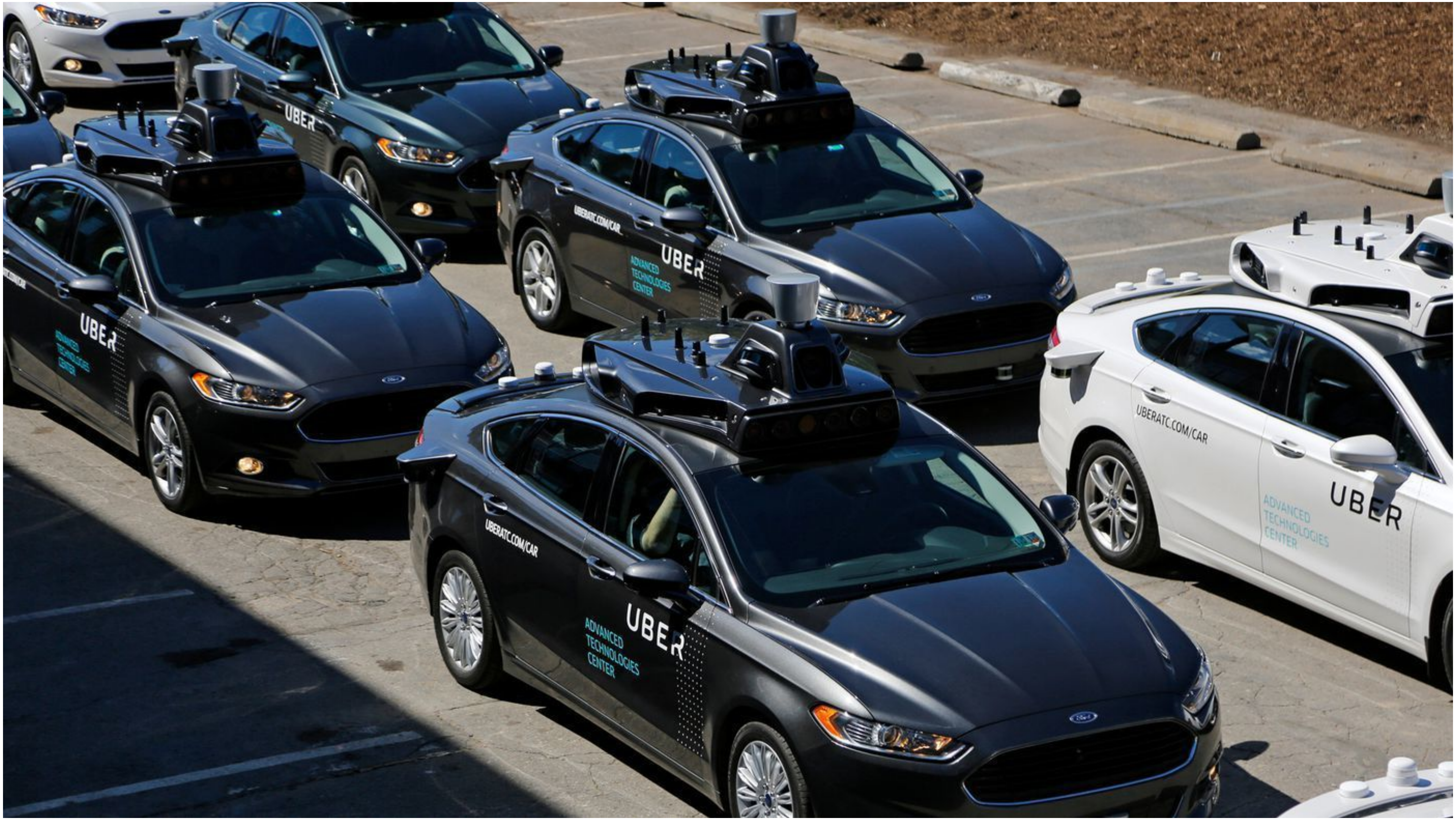
UBER
ADVANCED TECHNOLOGIES CENTER
UBERATC.COM/CAR


+40 %
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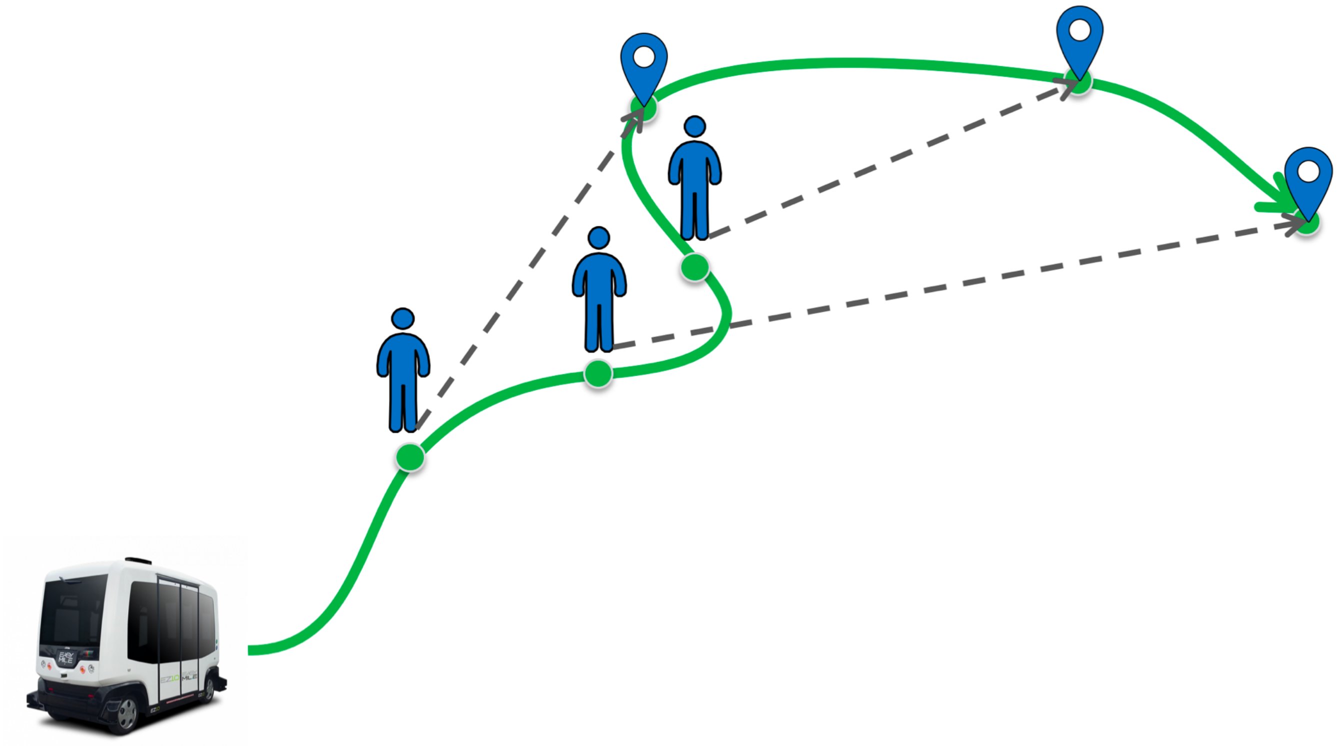
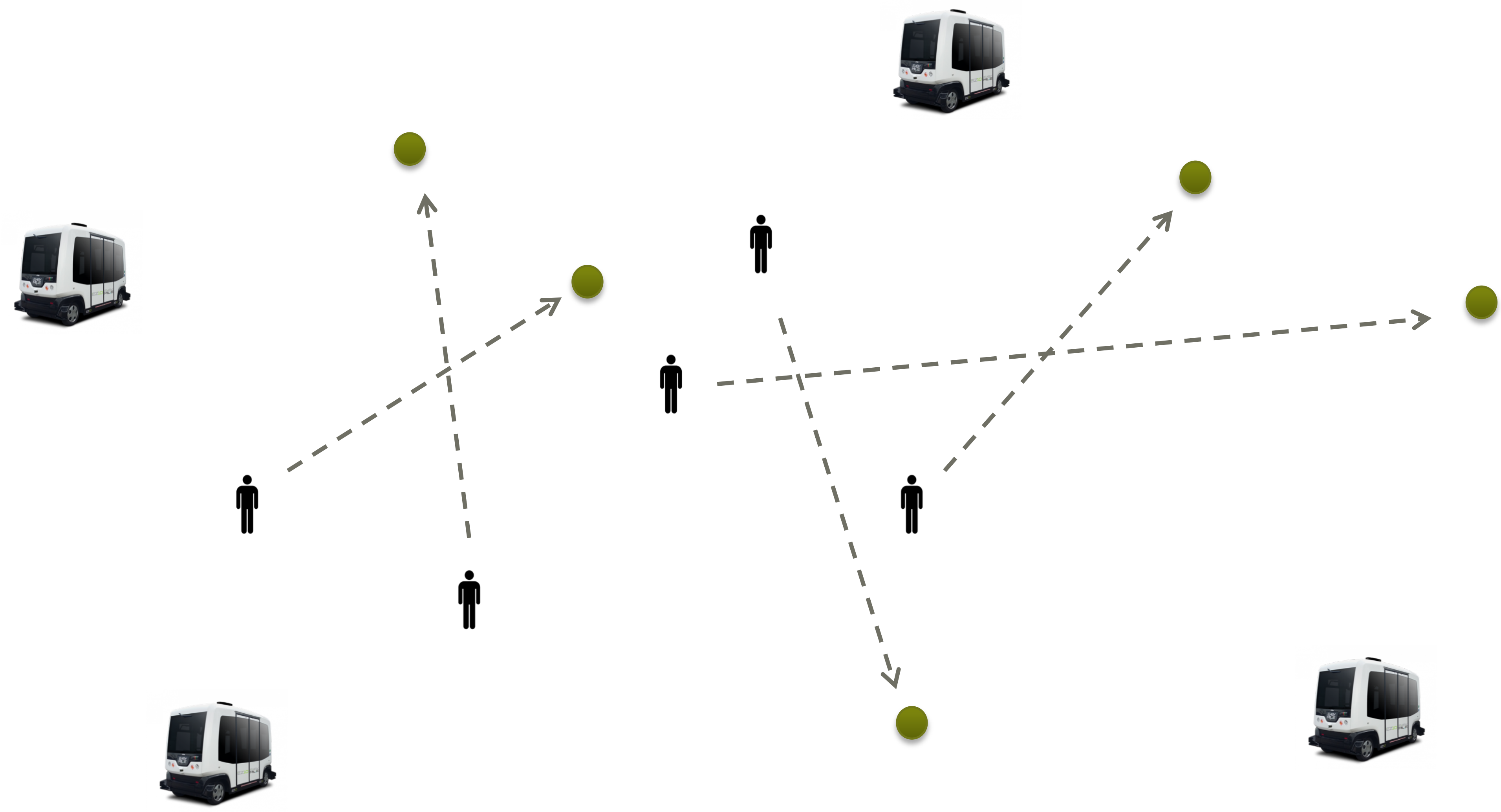
Ridesharing

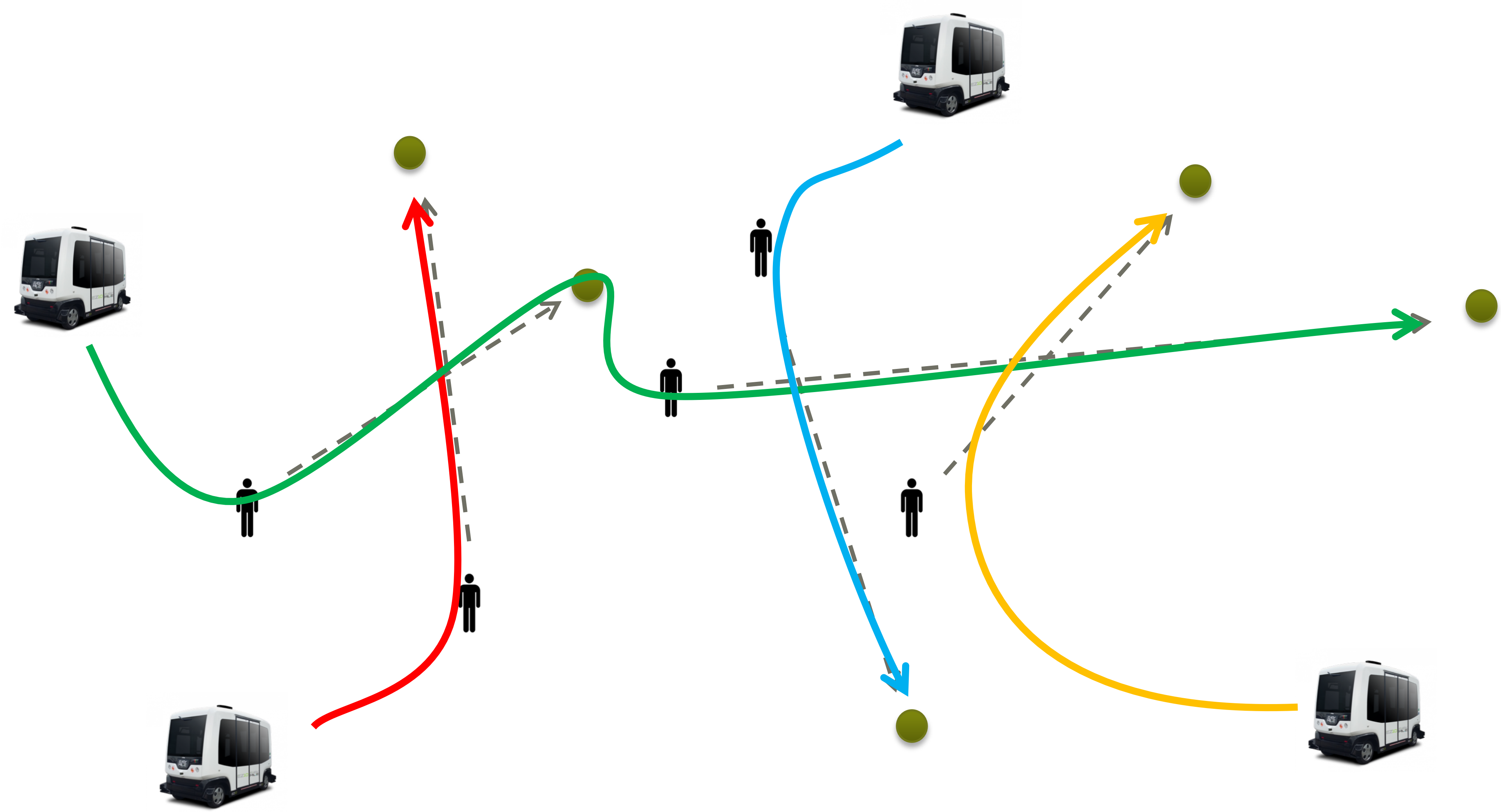
Ride sharing/pooling

Instead of one passenger per vehicle, we can have **shared rides**

- Several passengers in the same vehicle
- Higher efficiency
- Less cars on the roads

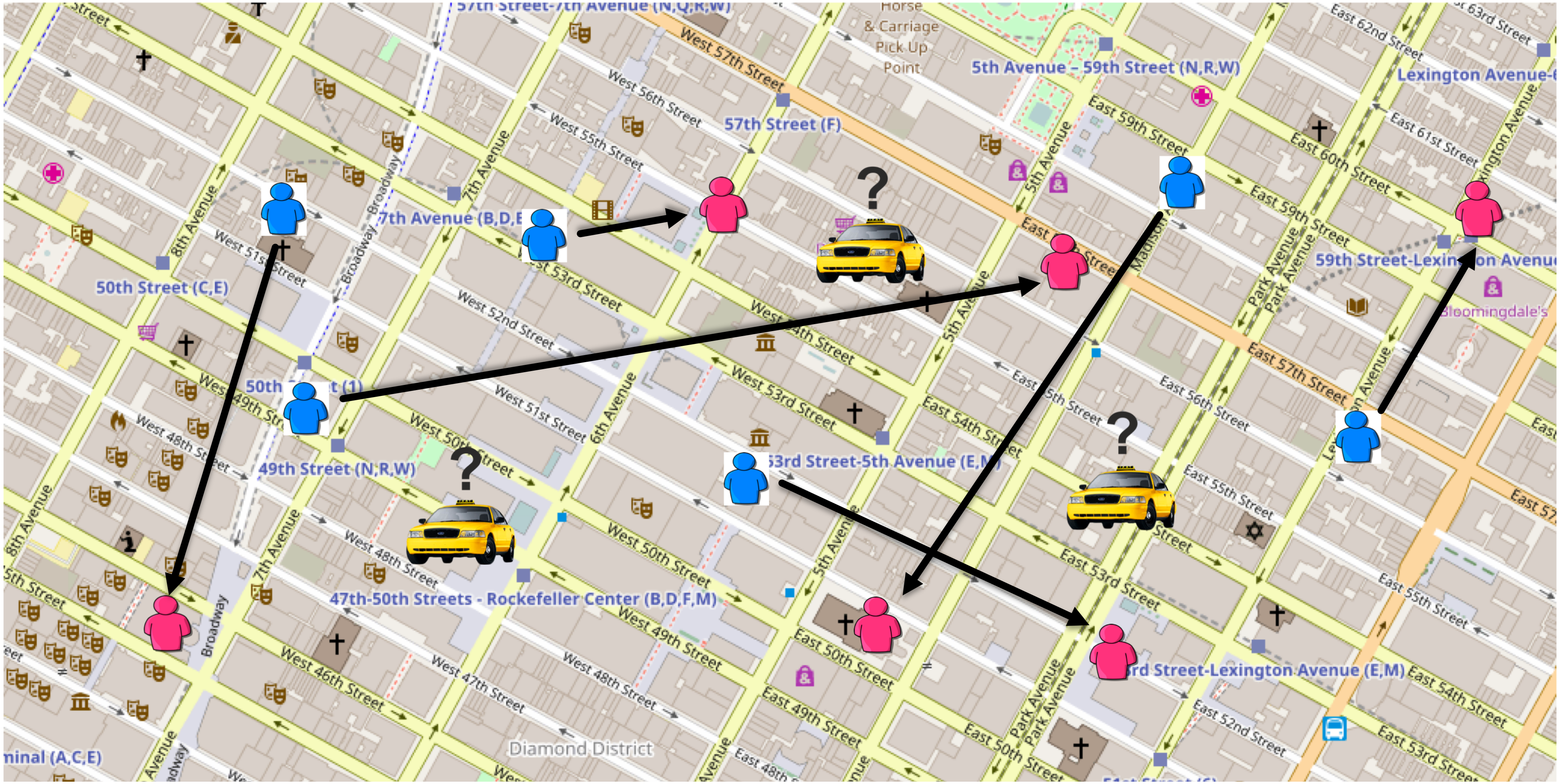






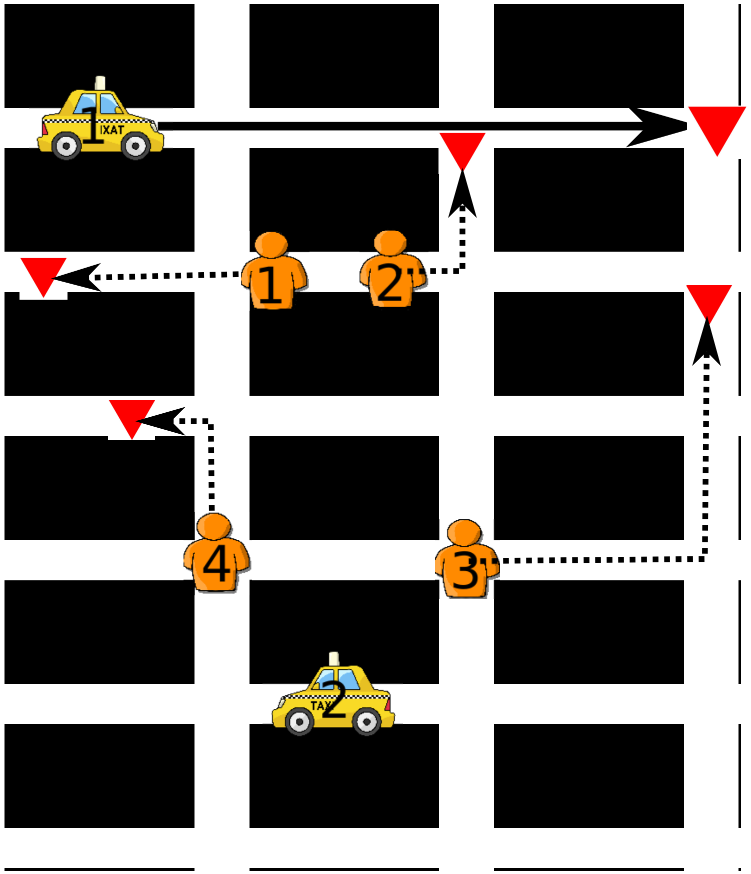
On-demand high-capacity ride-sharing

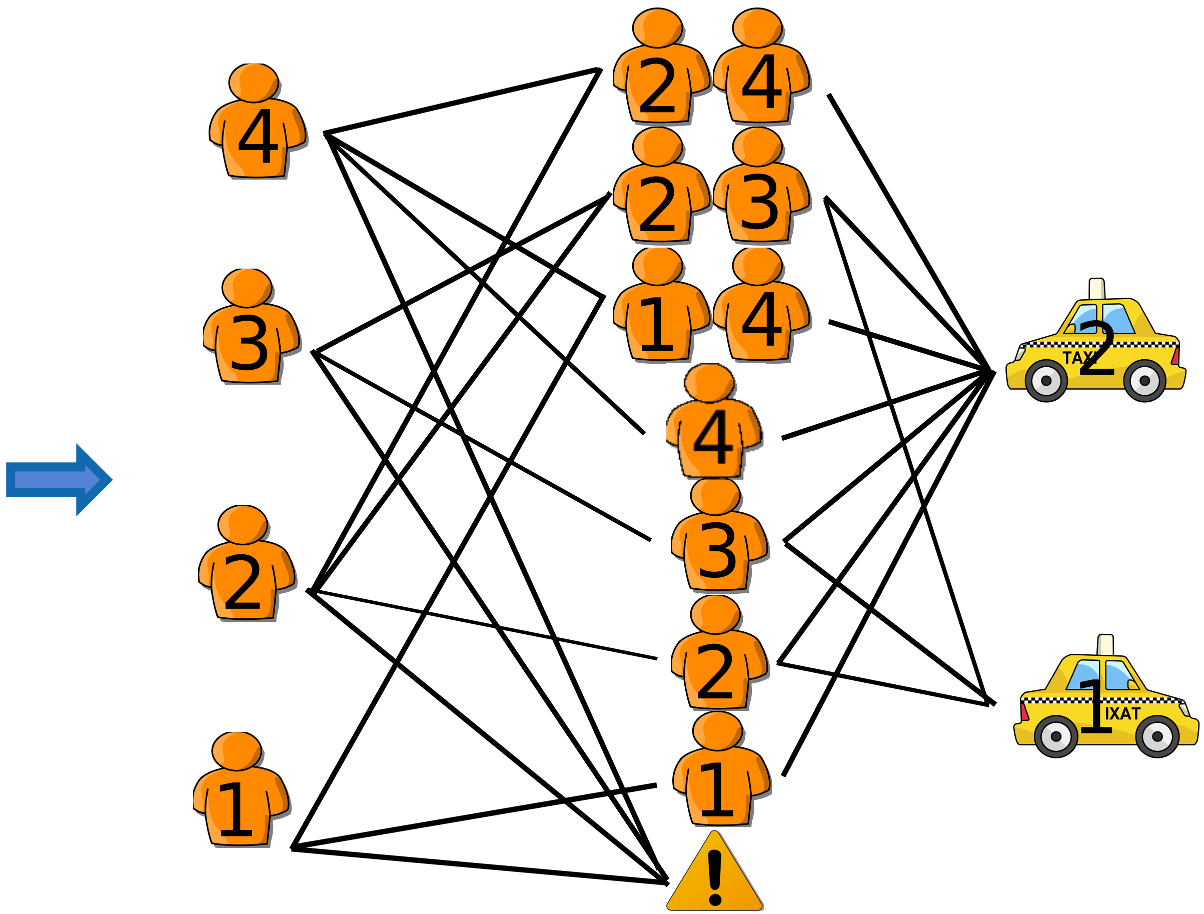
Large combinatorial complexity → Algorithm that is **scalable, online** and **anytime optimal**



Step 1: Compute feasible trips

Incremental search of feasible routes/schedules



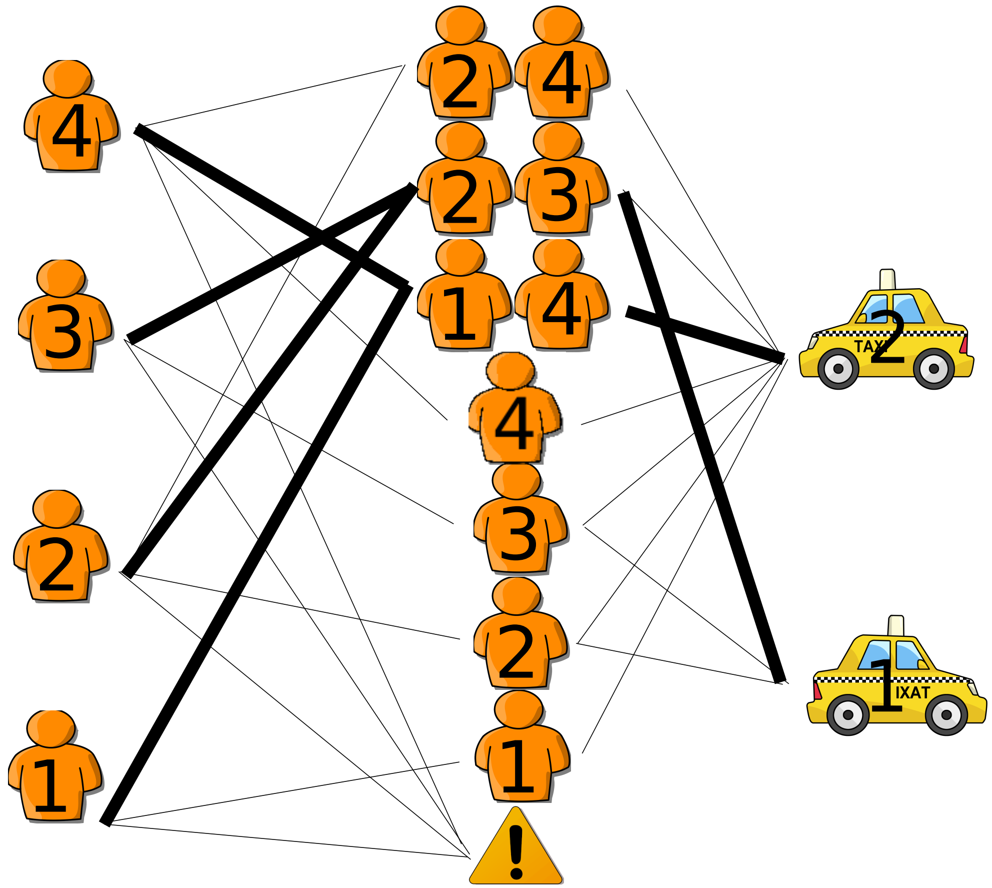


J. Alonso-Mora et al., **“On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment”,** PNAS 2017

Step 2: Assignment of vehicles to trips

Formulated as an Integer Linear Program

- Initialized from greedy assignment
- Optimized over time
- Minimize sum of delays



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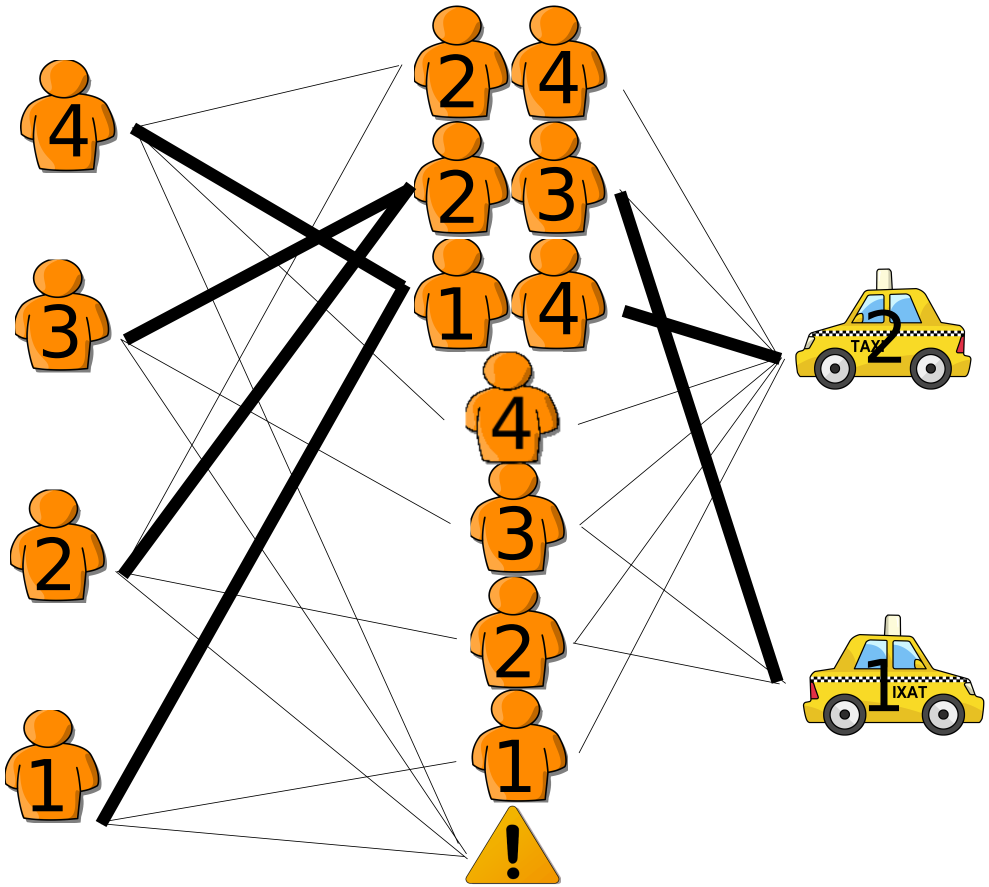


Algorithm 1. Optimal assignment

1: Initial guess: Σ_{greedy}

2: $\Sigma_{optim} := \arg\min_{\mathcal{X}} \sum_{i,j \in \mathcal{E}_{TV}} c_{i,j}\epsilon_{i,j} + \sum_{k \in \{1,\dots,n\}} c_{ko}\chi_k$

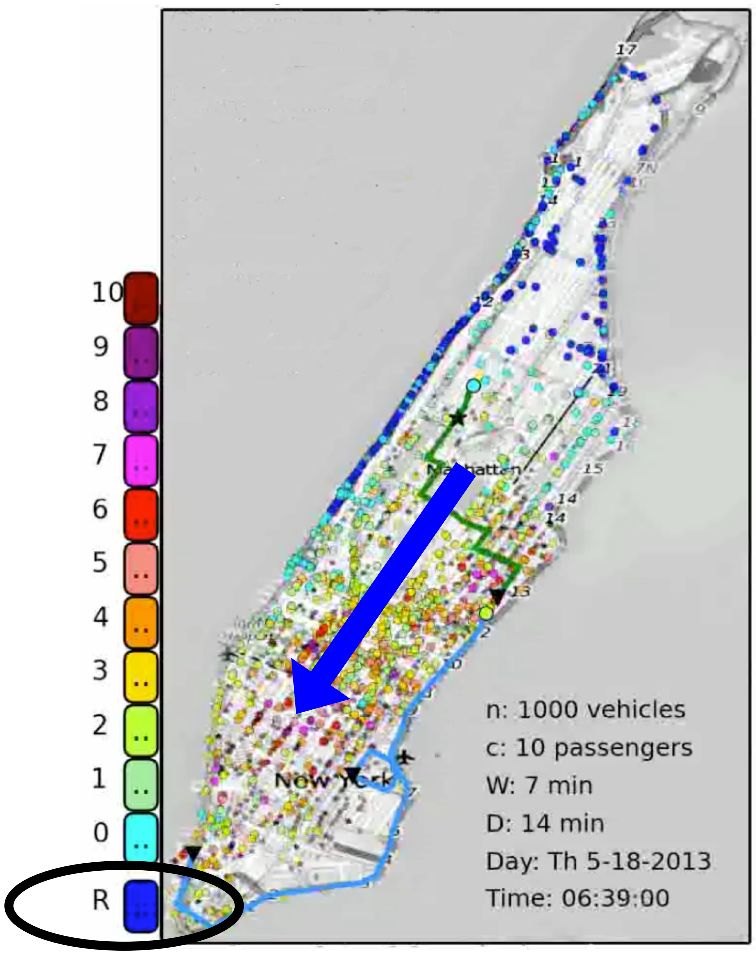
3: s.t. $\sum_{i \in \mathcal{I}^T_{V=j}} \epsilon_{i,j} \leq 1 \quad \forall v_j \in \mathcal{V}$

4: $\sum_{i \in \mathcal{I}^T_{R=k}} \sum_{j \in \mathcal{I}^V_{T=i}} \epsilon_{i,j} + \chi_k = 1 \quad \forall r_k \in \mathcal{R}$

J. Alonso-Mora et al., **"On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment",** PNAS 2017

Step 3: Rebalancing

Move idle vehicles towards areas of high demand (formulated as a Linear Program)

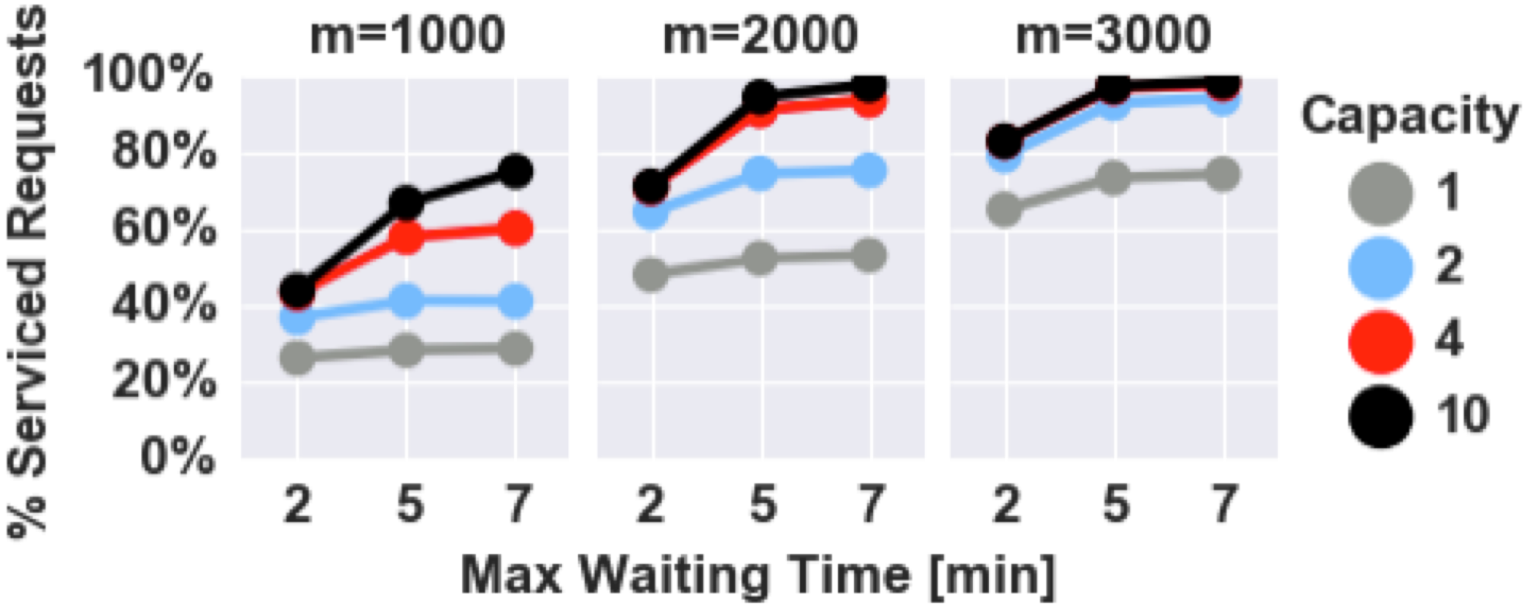


J. Alonso-Mora et al., **"On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment",** PNAS 2017

1000, 2000 and 3000 vehicles

Capacity Four

High service rate with less vehicles

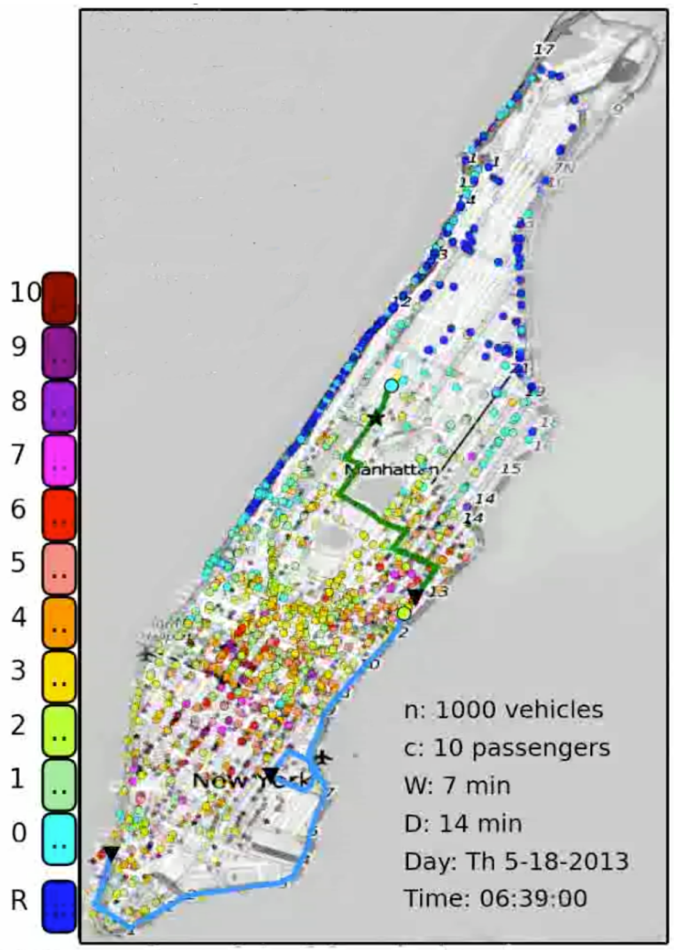


High service rate with <25% of taxis

J. Alonso-Mora et al., **"On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment", PNAS** 2017

Predictive routing

At peak times mismatch of vehicles & demand

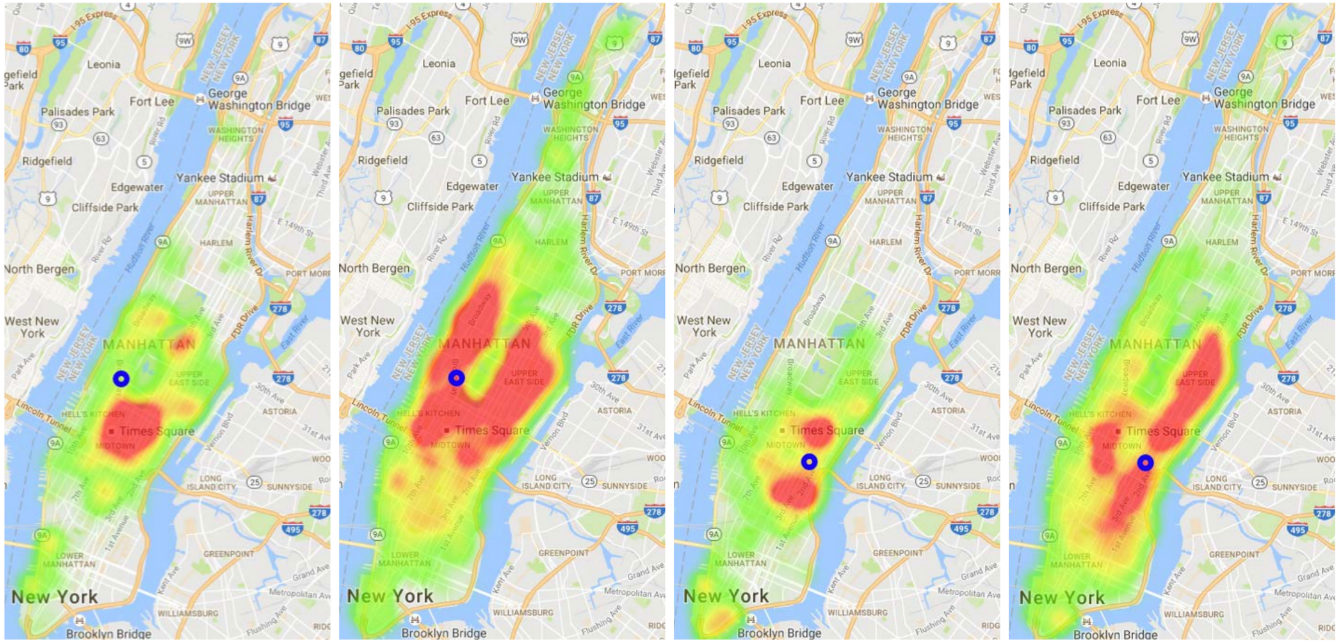


J. Alonso-Mora et al., “**Predictive Routing for Autonomous Mobility-on-Demand Systems with Ride-Sharing**”, IROS 2017

Predictive routing

At peak times mismatch of vehicles & demand

→ **Model of future demand** [from historical data] Pr(destination | origin, time)



(a) Westside, 7:30 – 8:00 (b) Westside, 21:30 – 22:00 (c) Eastside, 7:30 – 8:00 (d) Eastside, 21:30 – 22:00

J. Alonso-Mora et al., "**Predictive Routing for Autonomous Mobility-on-Demand Systems with Ride-Sharing**", IROS 2017

Predictive routing

At peak times mismatch of vehicles & demand

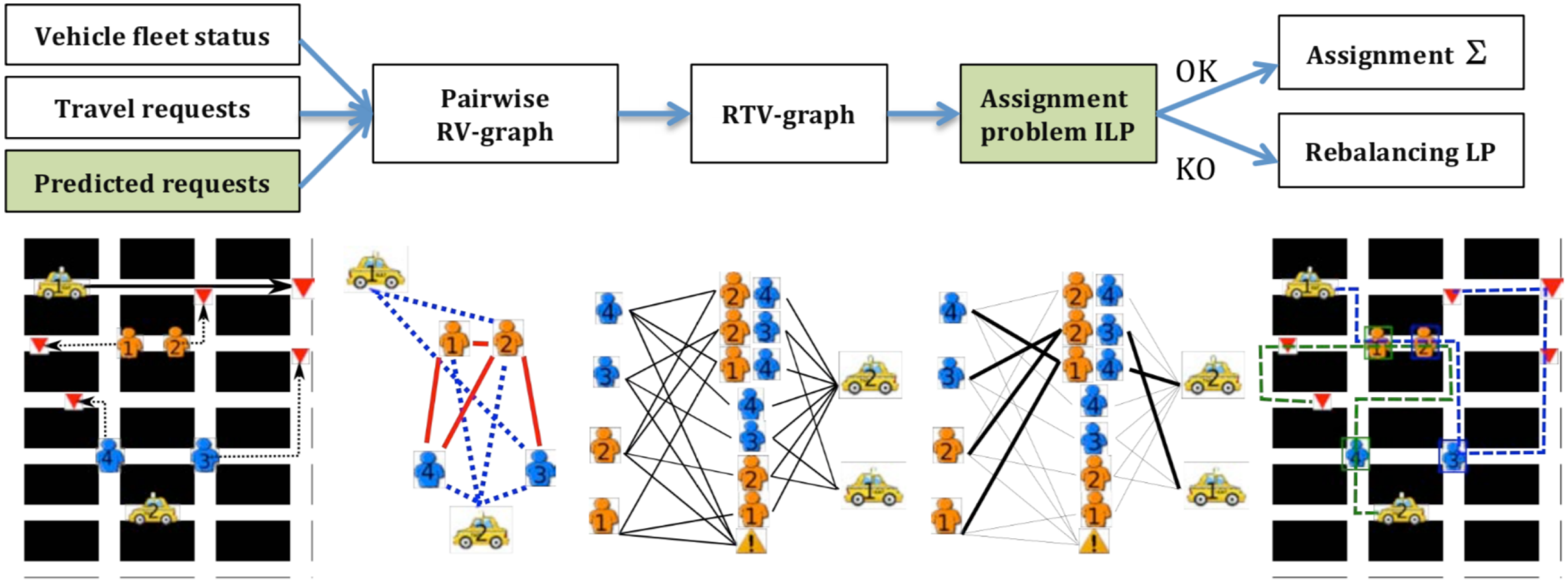
→ **Model of future demand** [from historical data]

Pr(destination | origin, time)

→ Better position the vehicles for the future, by **sampling expected requests**

$$C_{now}(\Sigma) + C_{future}(\Sigma)$$

→ Poor scalability

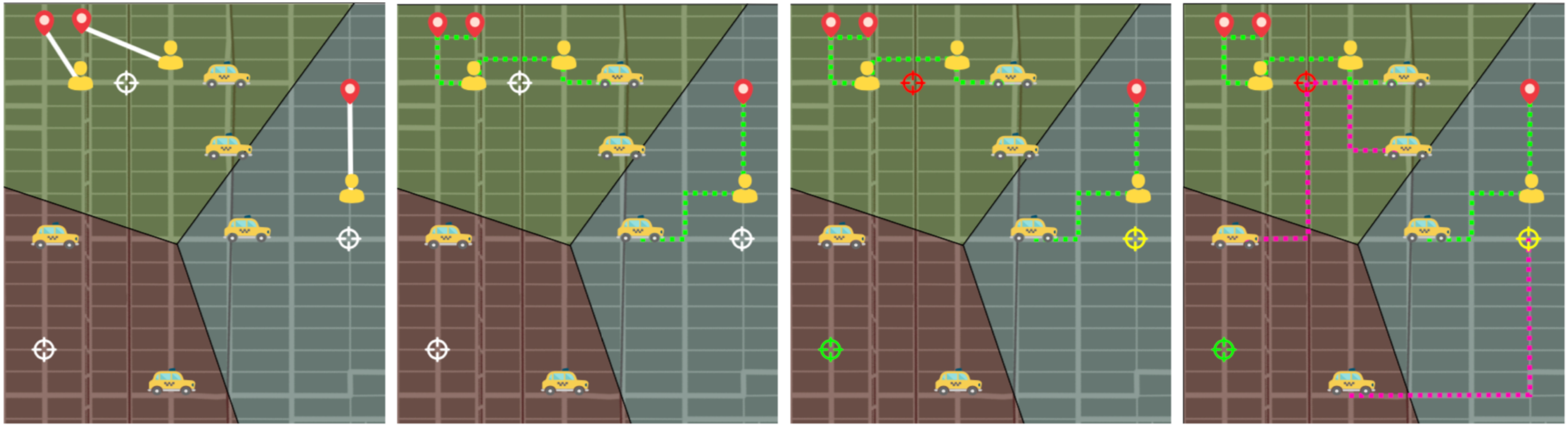


J. Alonso-Mora et al., "**Predictive Routing for Autonomous Mobility-on-Demand Systems with Ride-Sharing**", IROS 2017

Proactive rebalancing

Estimate vehicle demand per region, based on real-time data

Assign idle vehicles to rebalancing regions using the estimated demand



(a) Initial state (b) Schedule assignment (c) Demand estimation (d) Rebalancer assignment

A. Wallar et al., "**Vehicle Rebalancing for Mobility-on-Demand Systems with Ride-Sharing**", IROS 2018

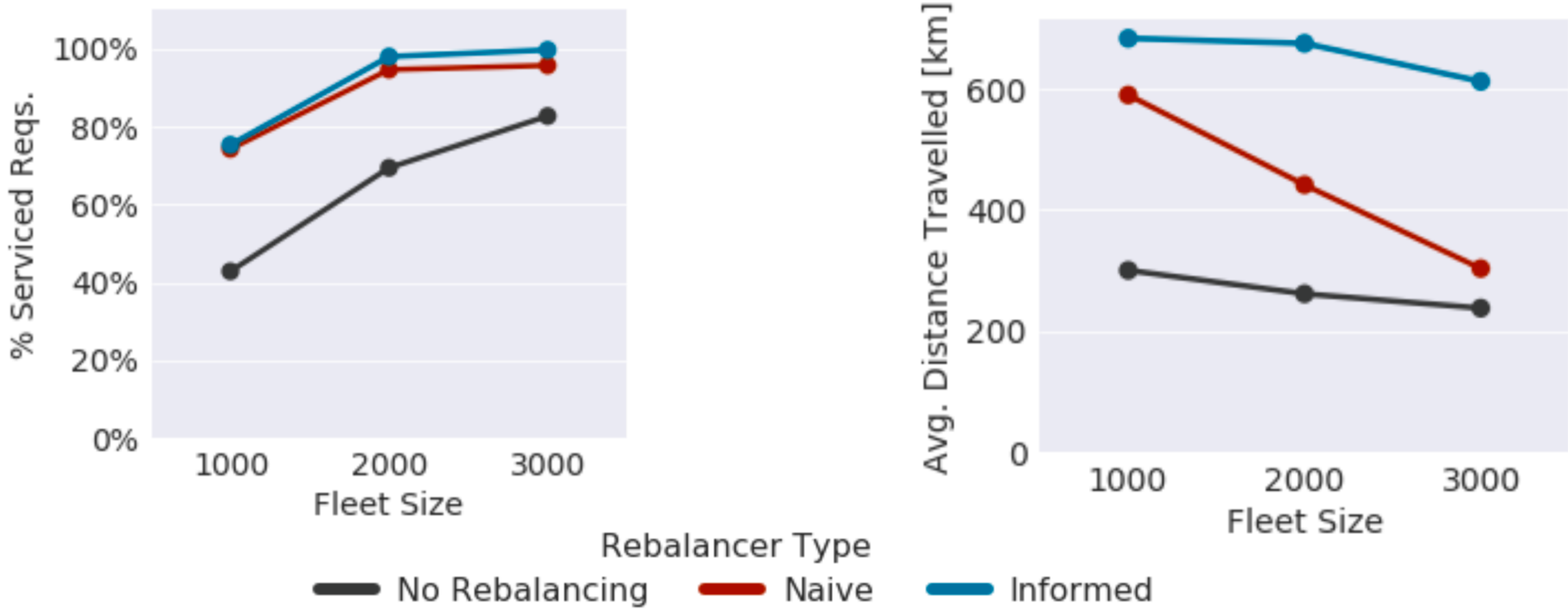
Proactive rebalancing

Estimate vehicle demand per region, based on real-time data

Assign idle vehicles to rebalancing regions using the estimated demand

→ Increase the service rate and reduce the waiting time

→ But, this might come at a cost of (much) **higher distance driven**!



A. Wallar et al., "**Vehicle Rebalancing for Mobility-on-Demand Systems with Ride-Sharing**", IROS 2018

Competing objectives

Quality of Service

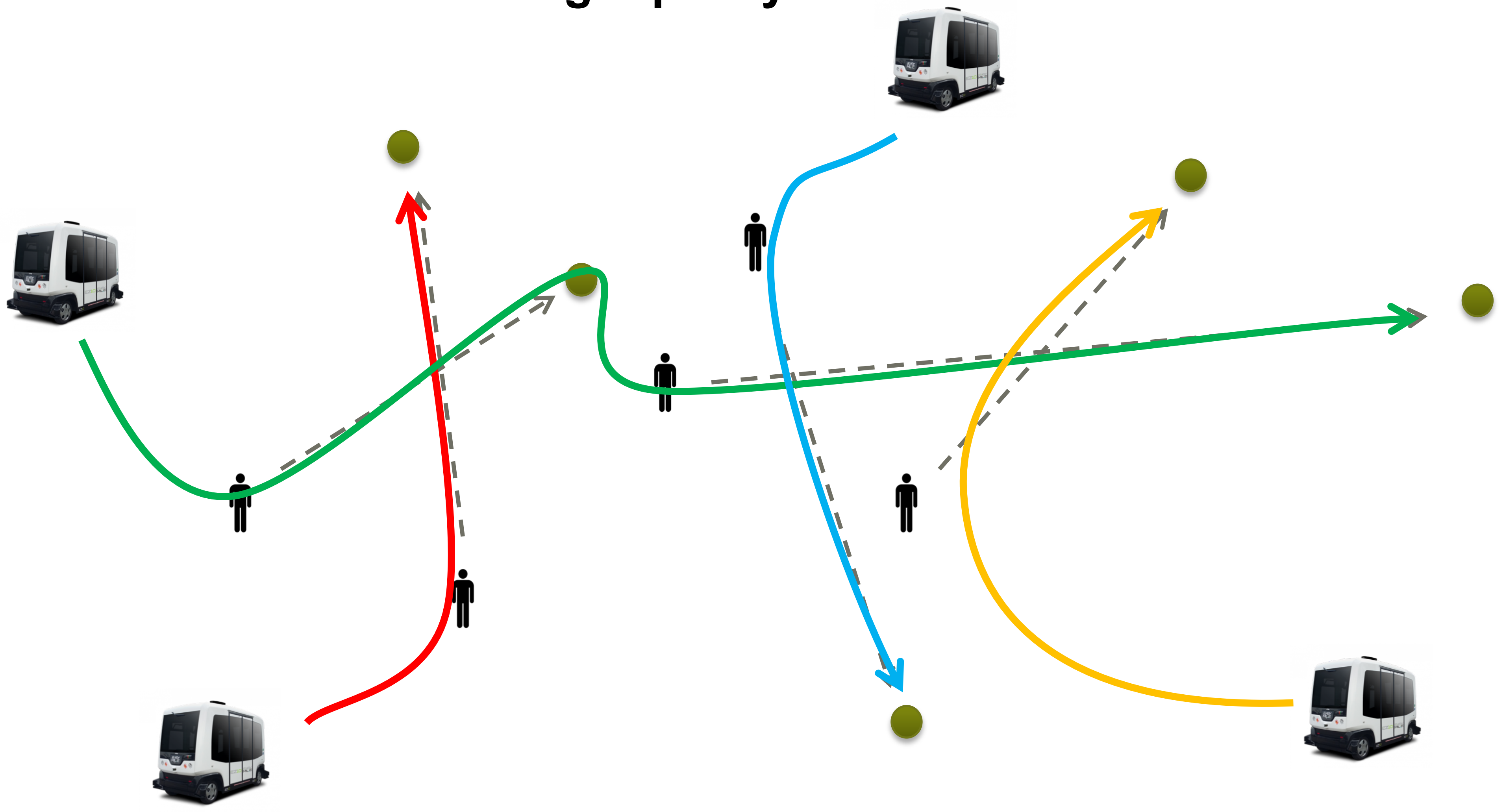
C_{QoS} := Avg. Passenger Travel Delay

Operation Cost

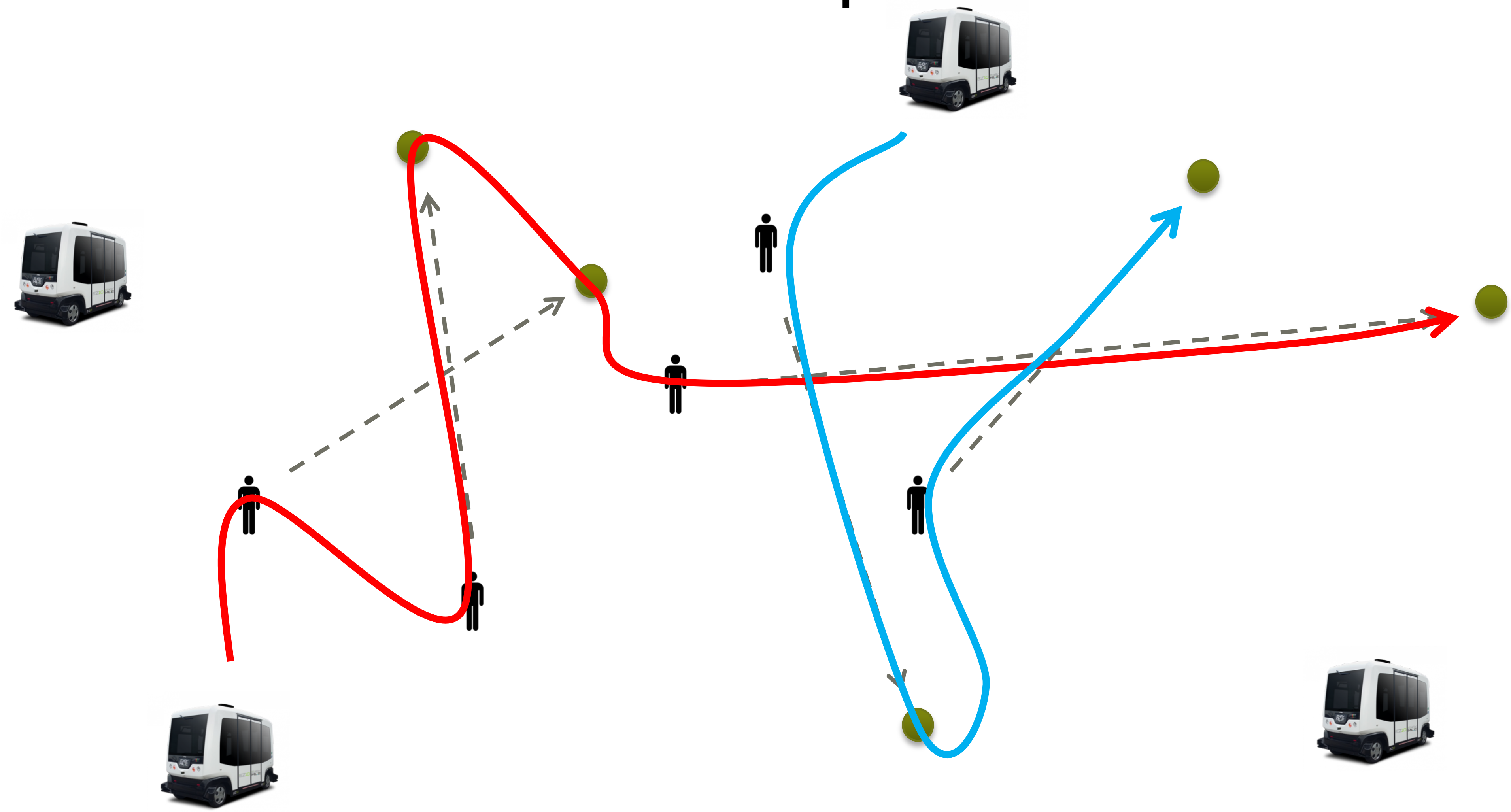
C_{OC} := Total Vehicle Distance Driven

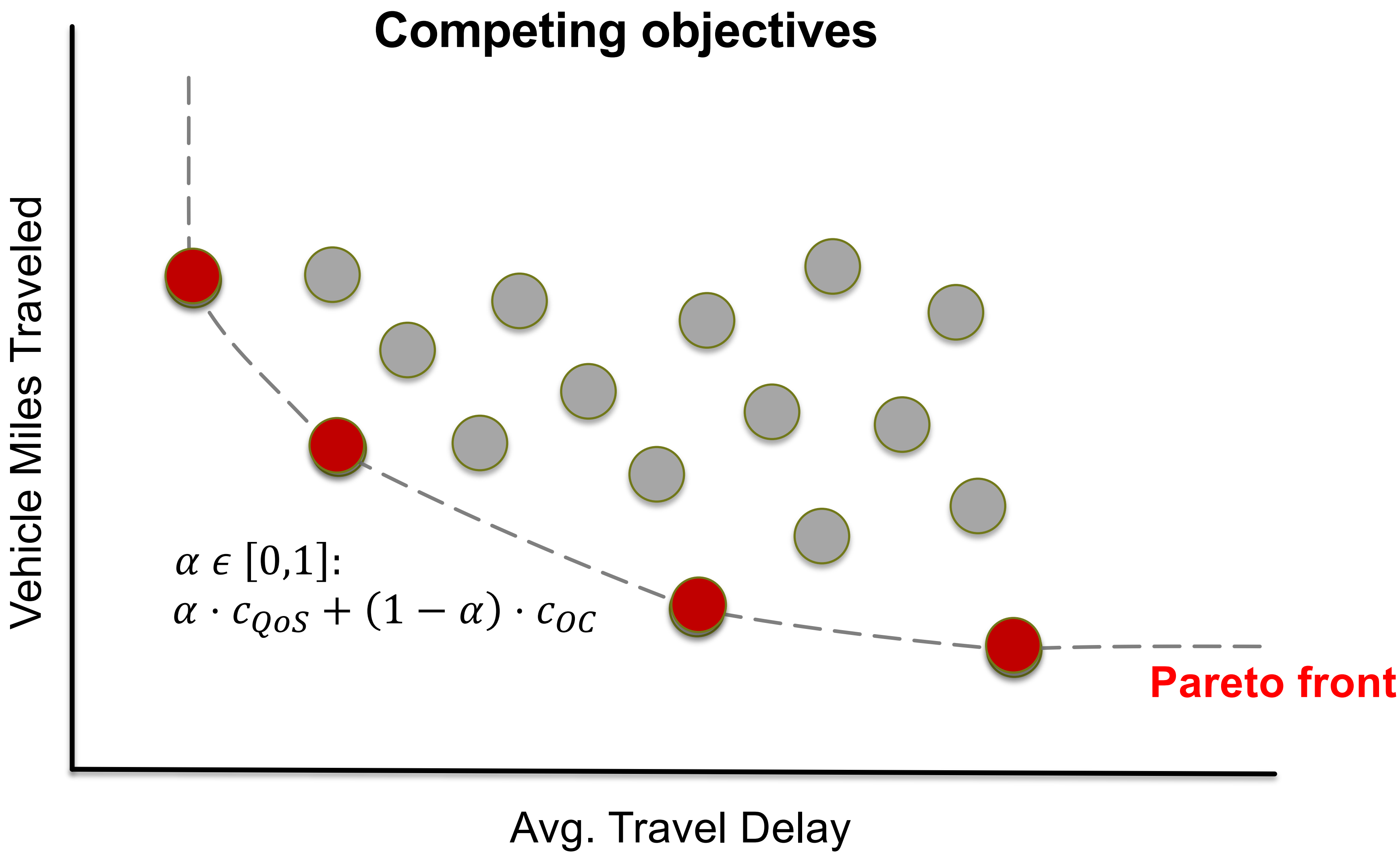
M. Cap and J. Alonso-Mora, “**Multi-Objective Analysis of Ridesharing in Automated Mobility-on-Demand**”, RSS 2018

High quality of service



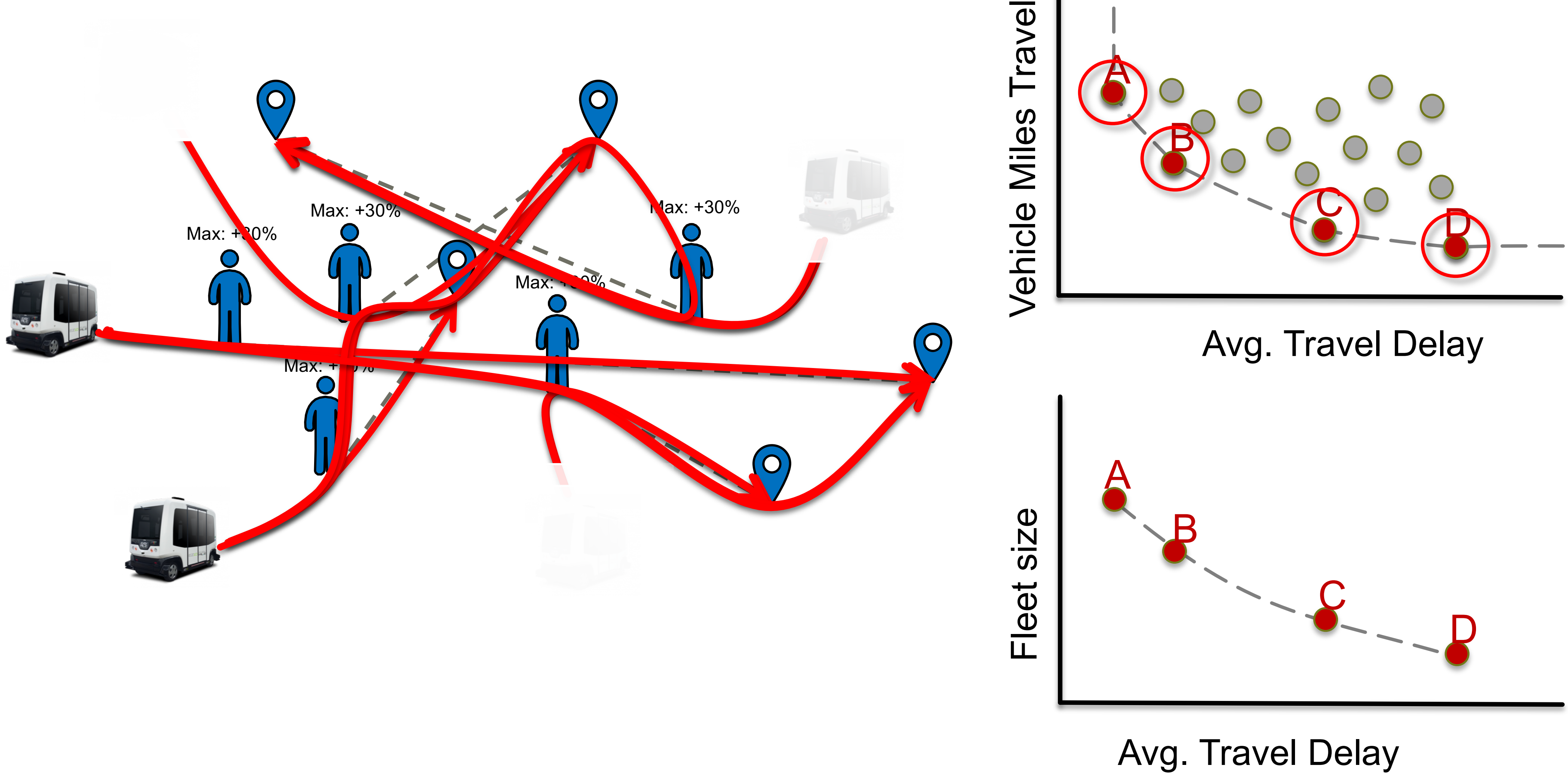
Low cost of operation





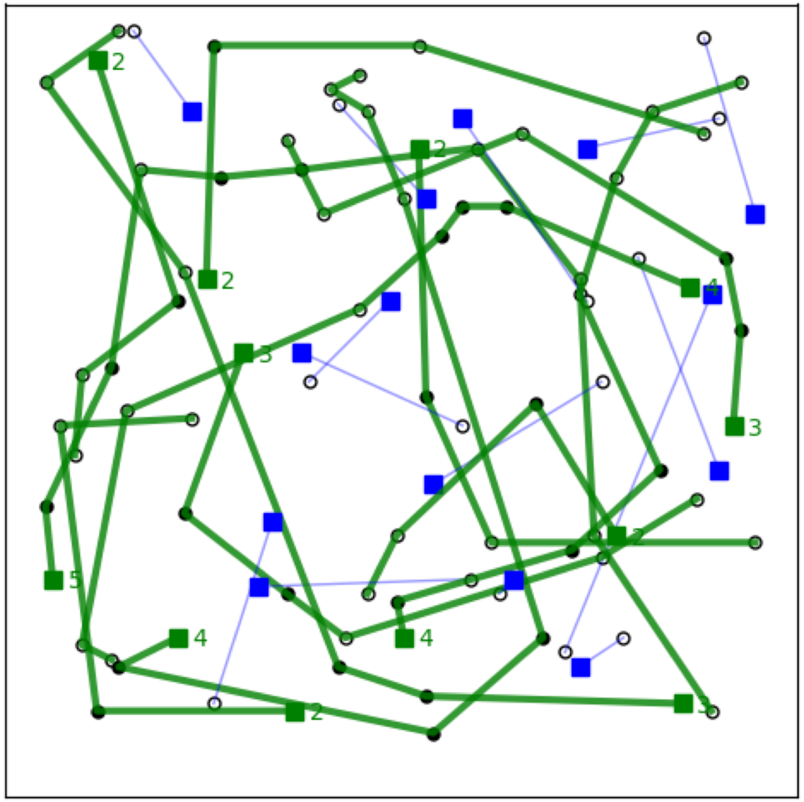
M. Cap and J. Alonso-Mora, "**Multi-Objective Analysis of Ridesharing in Automated Mobility-on-Demand**", RSS 2018

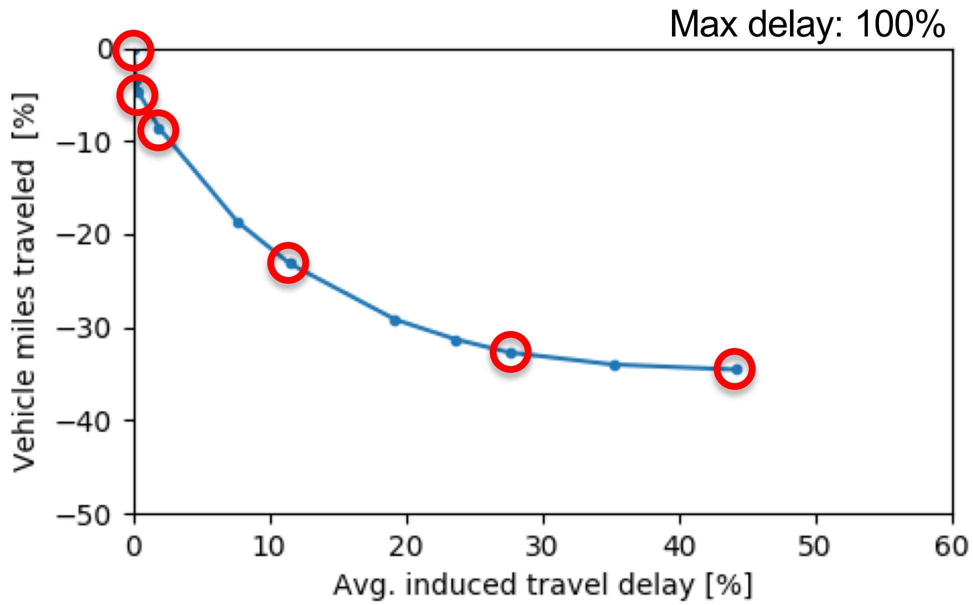
Pareto front



M. Cap and J. Alonso-Mora, "**Multi-Objective Analysis of Ridesharing in Automated Mobility-on-Demand**", RSS 2018

Illustration:
Synthetic travel demand
(50 requests)





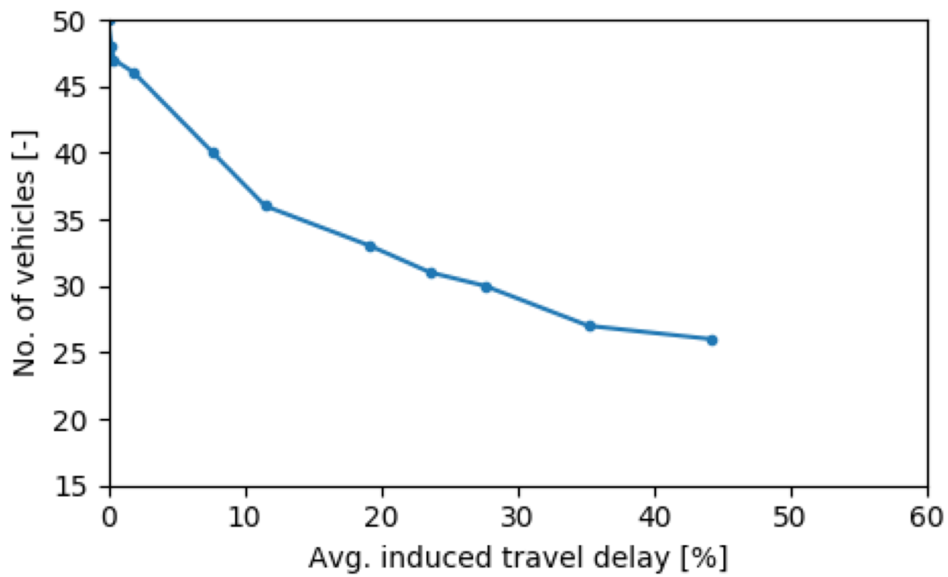


Illustration:
Synthetic travel demand
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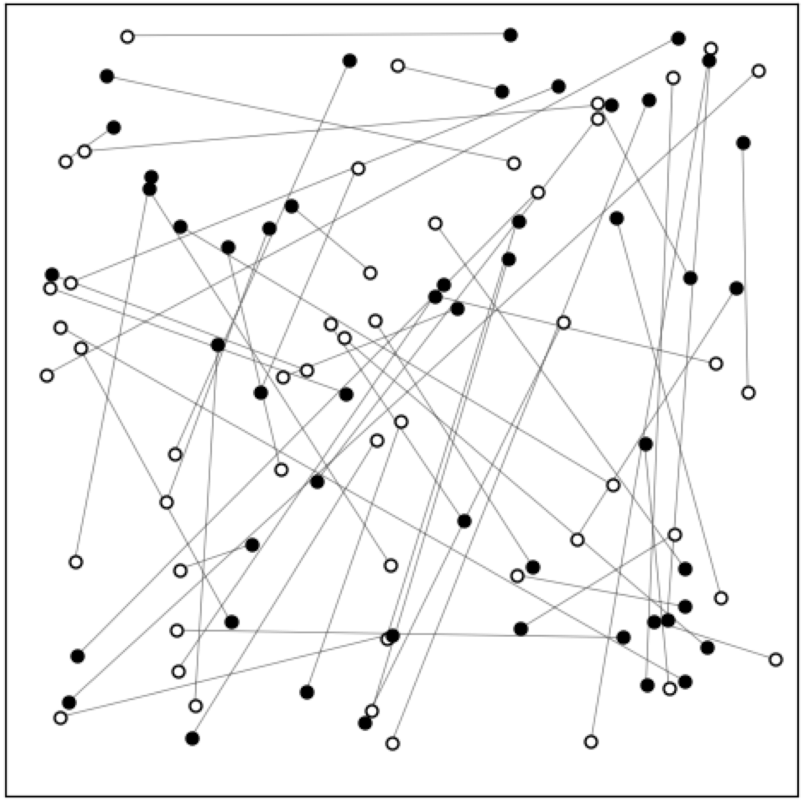


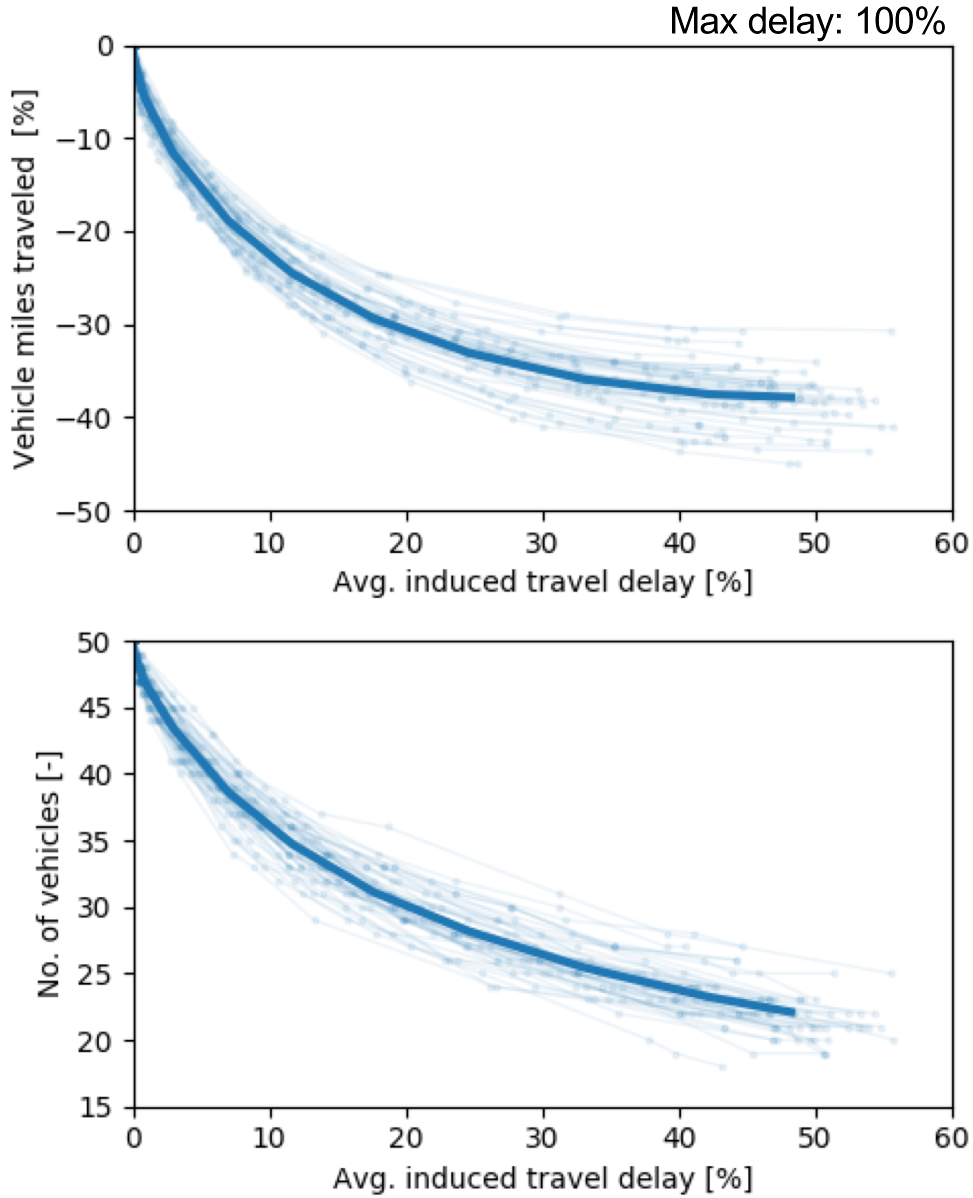
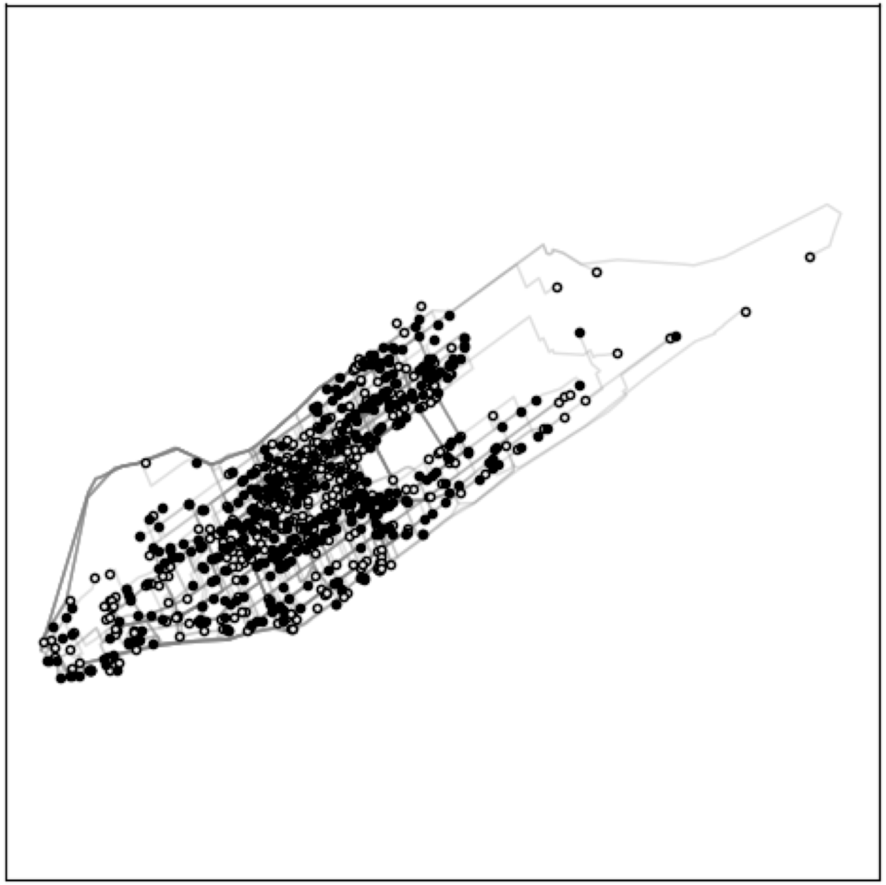
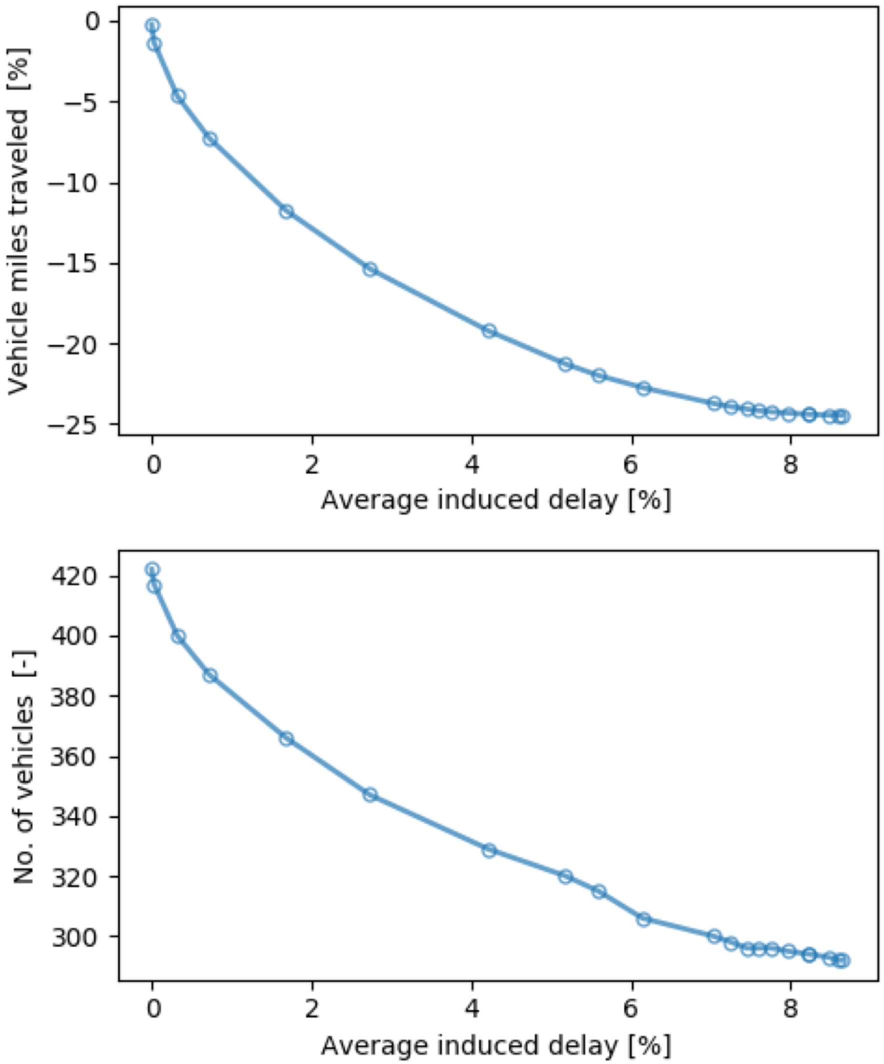


Illustration:
1 minute of Manhattan Taxi Requests
(427 requests)



Max delay: 25%



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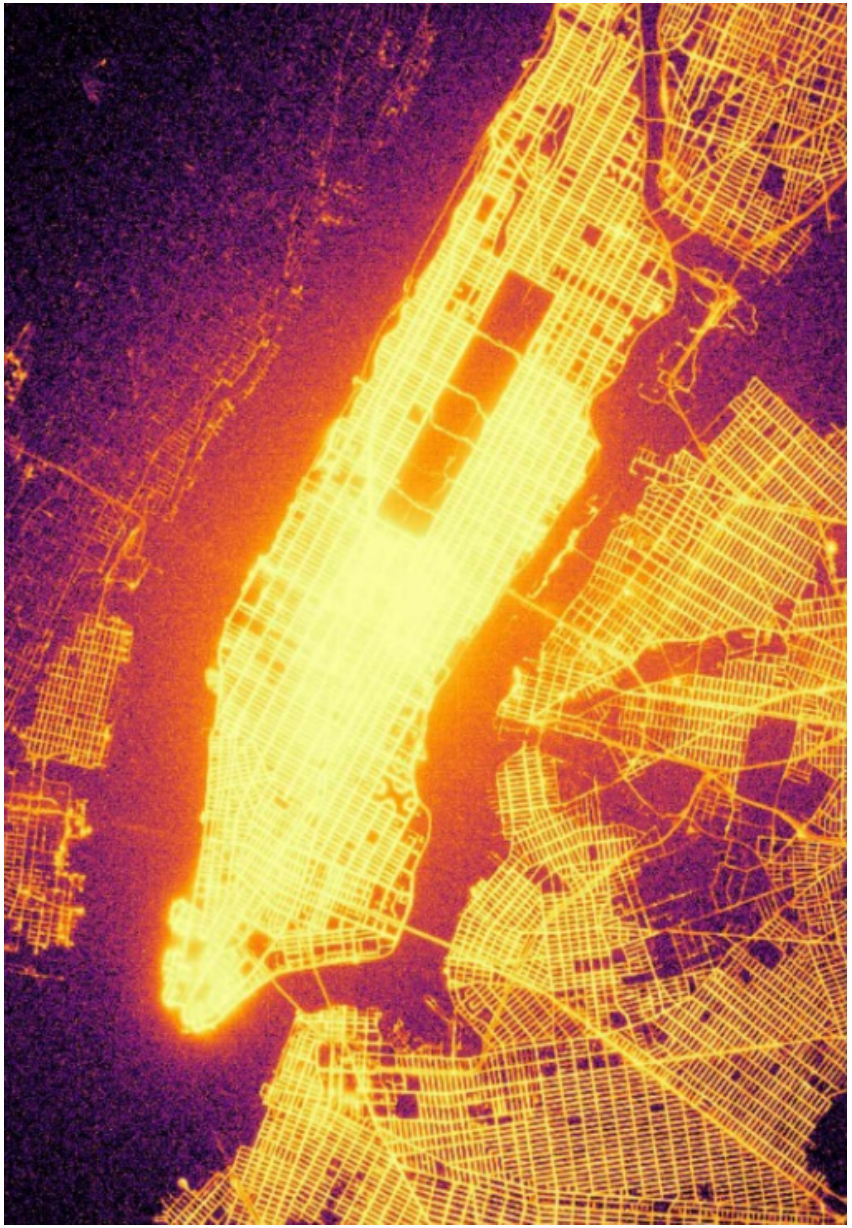


Number of vehicles

Fleet size and composition

From historical data we can compute the fleet size and composition required for a given day

→ Constraints: service all requests, maximum waiting time and delay

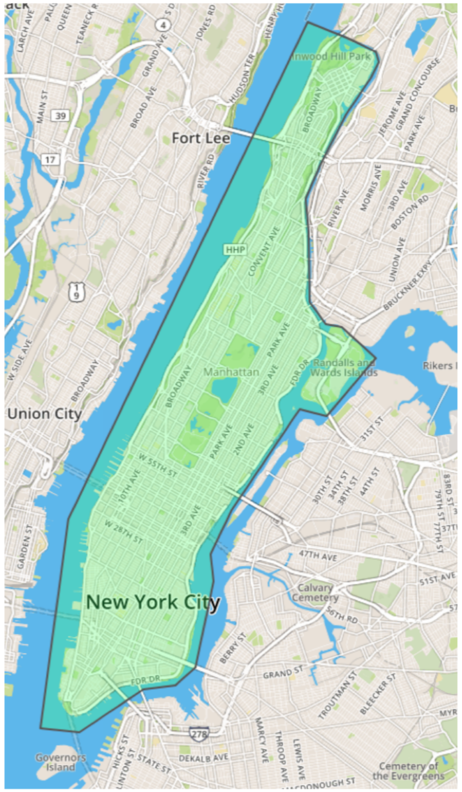
1. Compute a set of deposits, e.g., distance from any point to closest deposit < 1 min
2. In small batches, e.g., 1 h, compute feasible and locally optimal schedules [Similar to RTV]
3. Long term rebalancing (chain schedules from multiple batches) [Max. matching ILP]

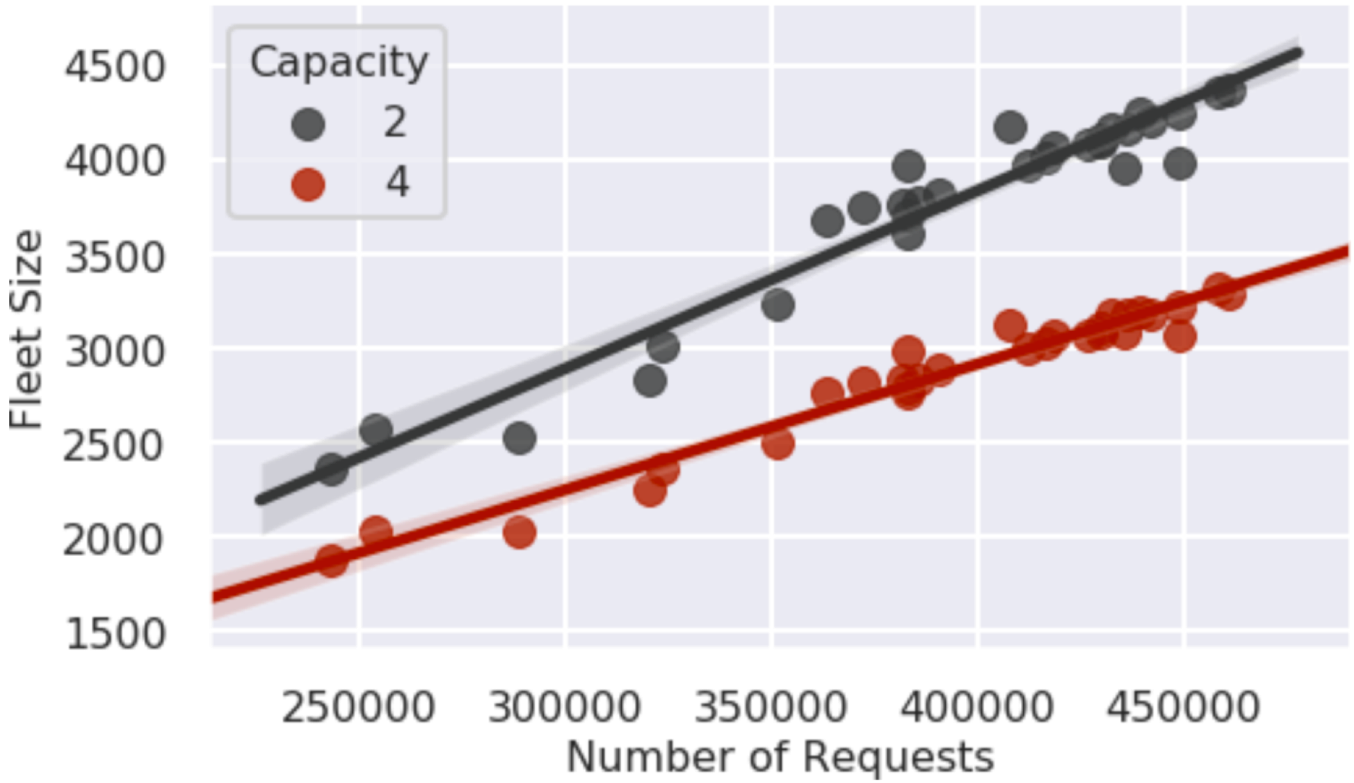
A. Wallar, J. Alonso-Mora and D. Rus, "**Optimizing Vehicle Distributions and Fleet Sizes for Shared Mobility-on-Demand**", ICRA 2019
A. Wallar et al., **"Optimizing Multi-class Fleet Compositions for Shared Mobility-as-a-Service**", ITSC 2019

Fleet size and composition

From historical data we can compute the fleet size and composition required for a given day

→ Constraints: service all requests, maximum waiting time (3 min) and delay (6 min)



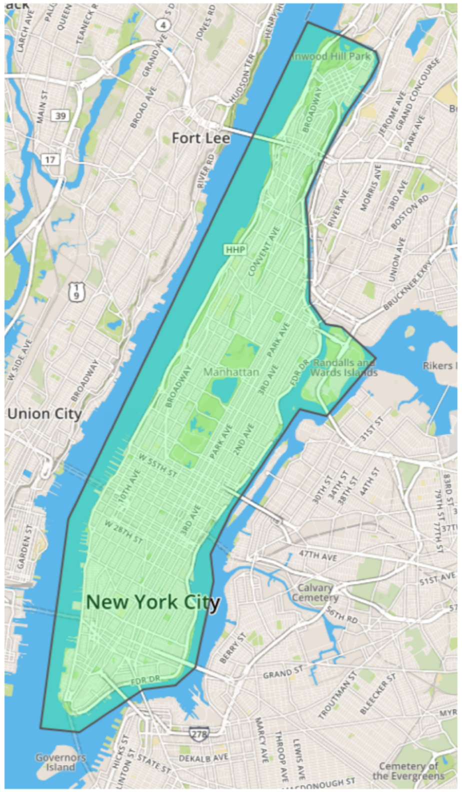


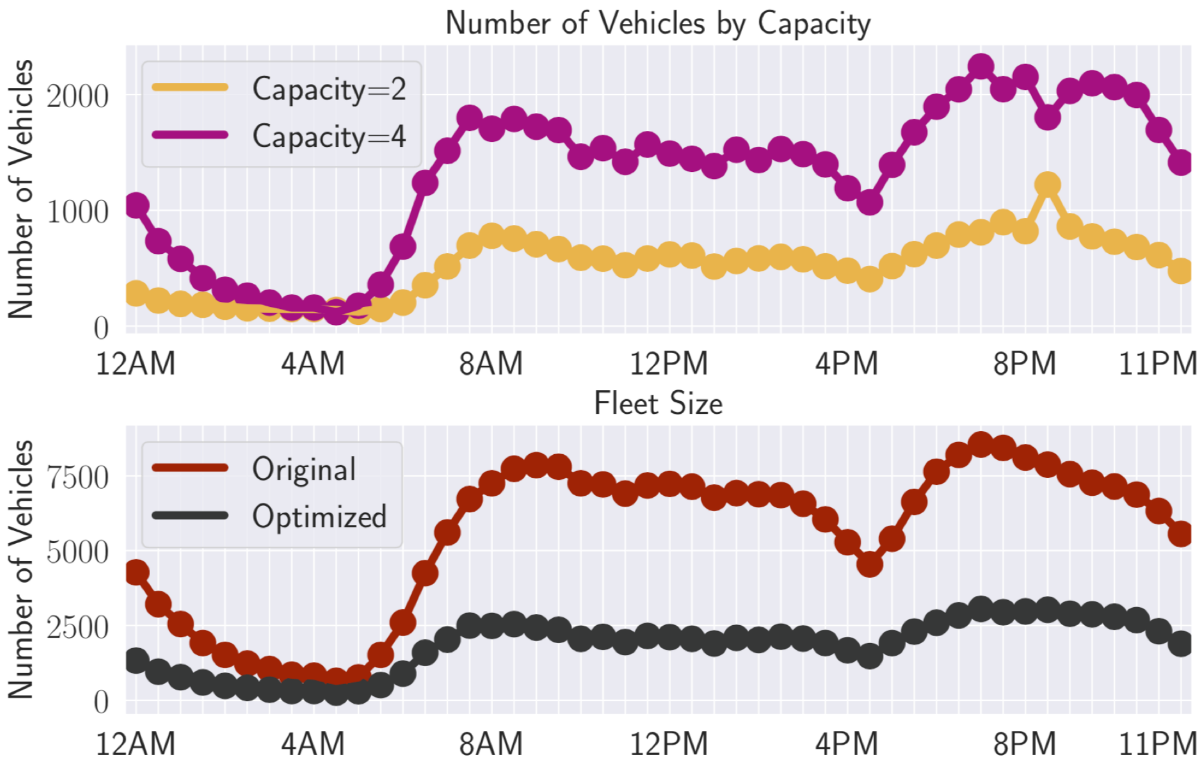
A. Wallar, J. Alonso-Mora and D. Rus, "**Optimizing Vehicle Distributions and Fleet Sizes for Shared Mobility-on-Demand**", ICRA 2019
A. Wallar et al., **"Optimizing Multi-class Fleet Compositions for Shared Mobility-as-a-Service**", ITSC 2019

Fleet size and composition [mixed fleet]

From historical data we can compute the fleet size and composition required for a given day

→ Constraints: service all requests, maximum waiting time (3 min) and delay (6 min)





A. Wallar, J. Alonso-Mora and D. Rus, "**Optimizing Vehicle Distributions and Fleet Sizes for Shared Mobility-on-Demand**", ICRA 2019
A. Wallar et al., **"Optimizing Multi-class Fleet Compositions for Shared Mobility-as-a-Service**", ITSC 2019

Fleet size and composition

From historical data we can compute the fleet size and composition required for a given day

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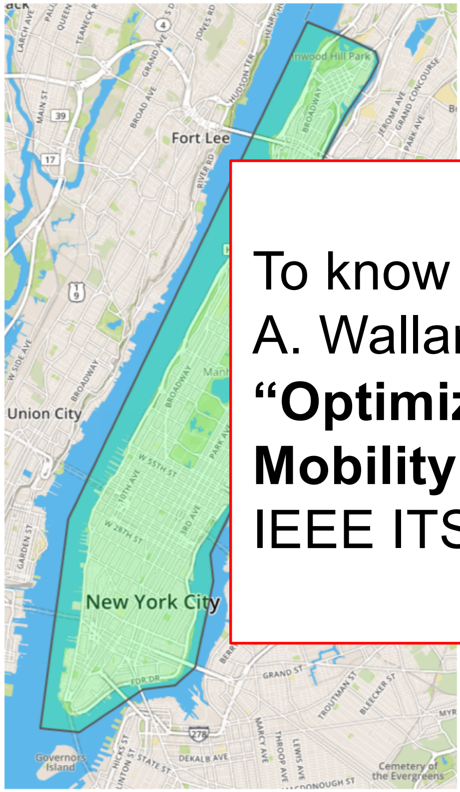

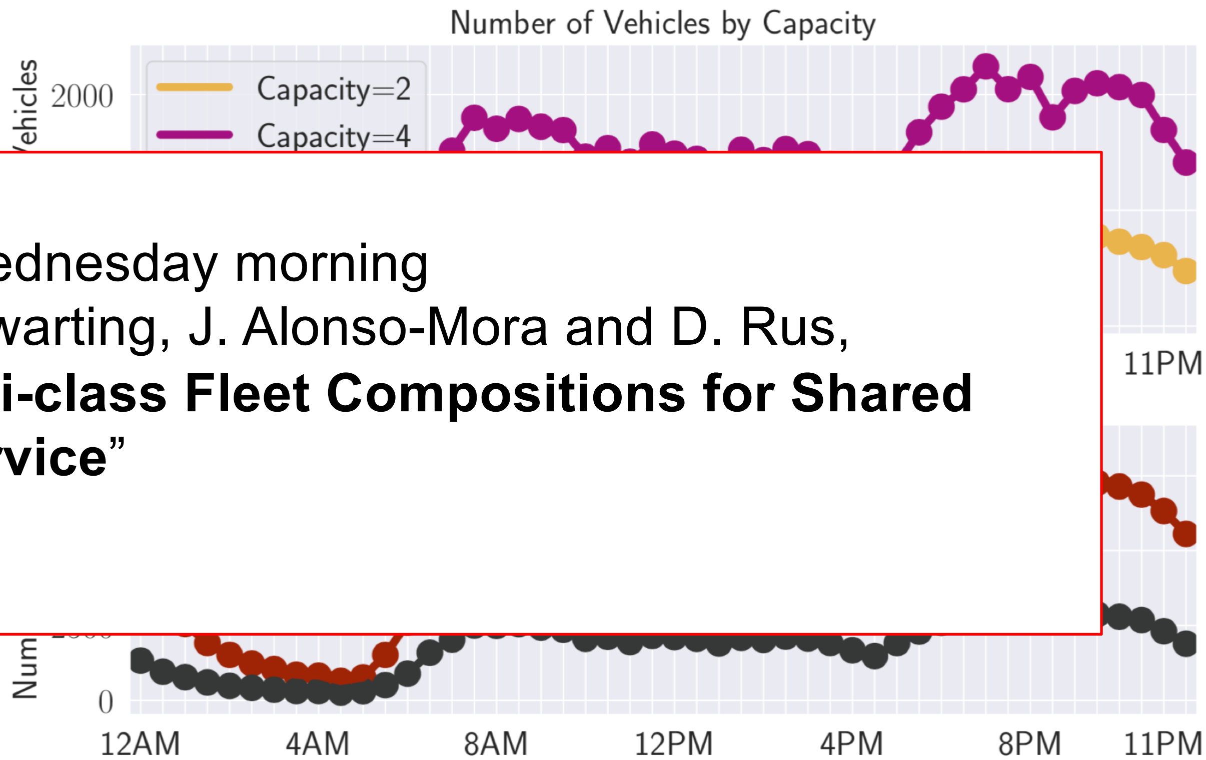

To know more: Wednesday morning
A. Wallar, W. Schwarting, J. Alonso-Mora and D. Rus, **“Optimizing Multi-class Fleet Compositions for Shared Mobility-as-a-Service”**
IEEE ITSC 2019

A. Wallar, J. Alonso-Mora and D. Rus, “**Optimizing Vehicle Distributions and Fleet Sizes for Shared Mobility-on-Demand**”, ICRA 2019
A. Wallar et al., **“Optimizing Multi-class Fleet Compositions for Shared Mobility-as-a-Service**”, ITSC 2019

Summary

Automated Mobility on Demand with Ride-Sharing

- Online method for high-capacity ride-sharing
- Predictive routing
- Multi-objective analysis
- Fleet sizing

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Funding:

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NWO Applied and Engineering Sciences

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