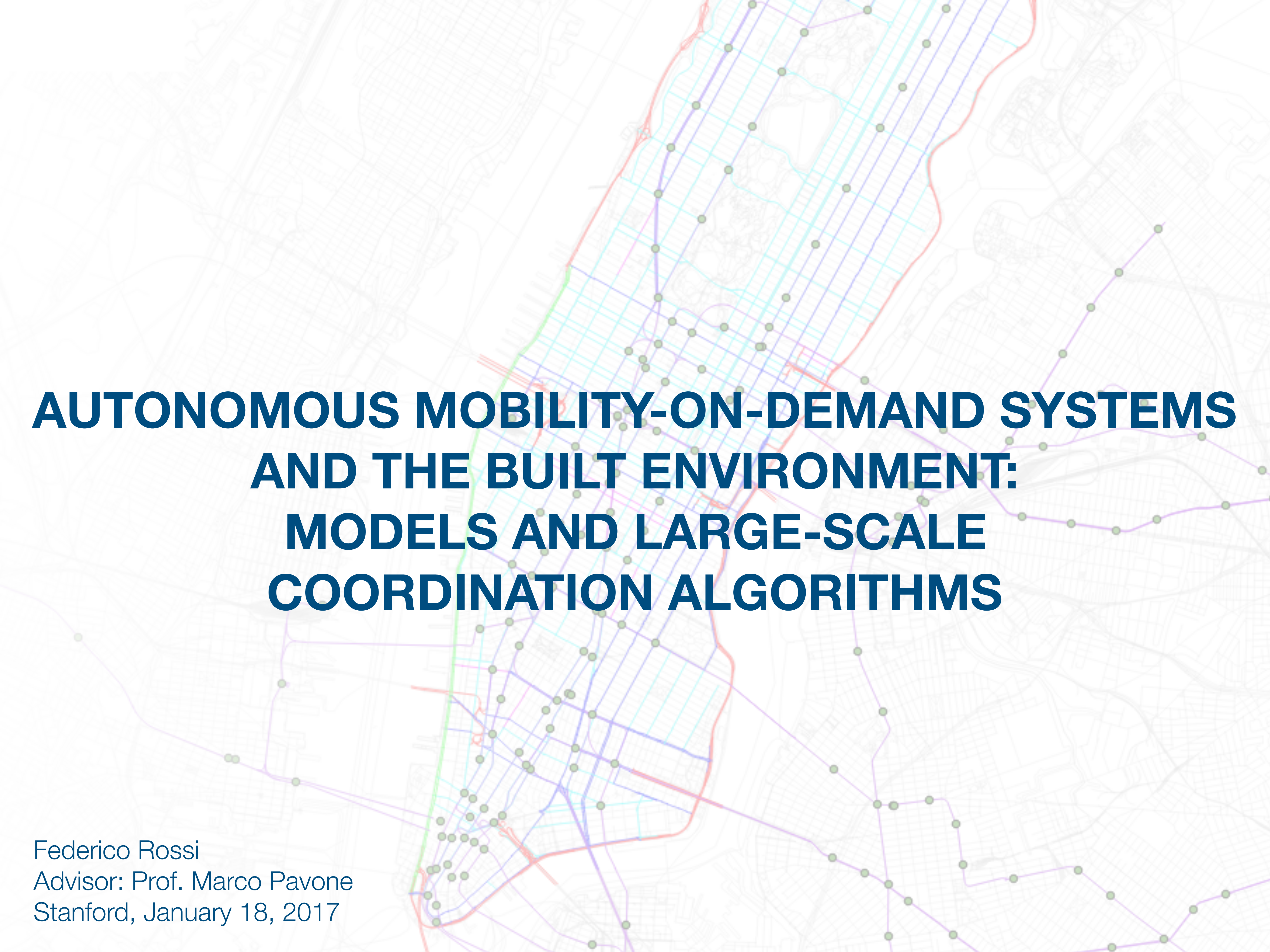


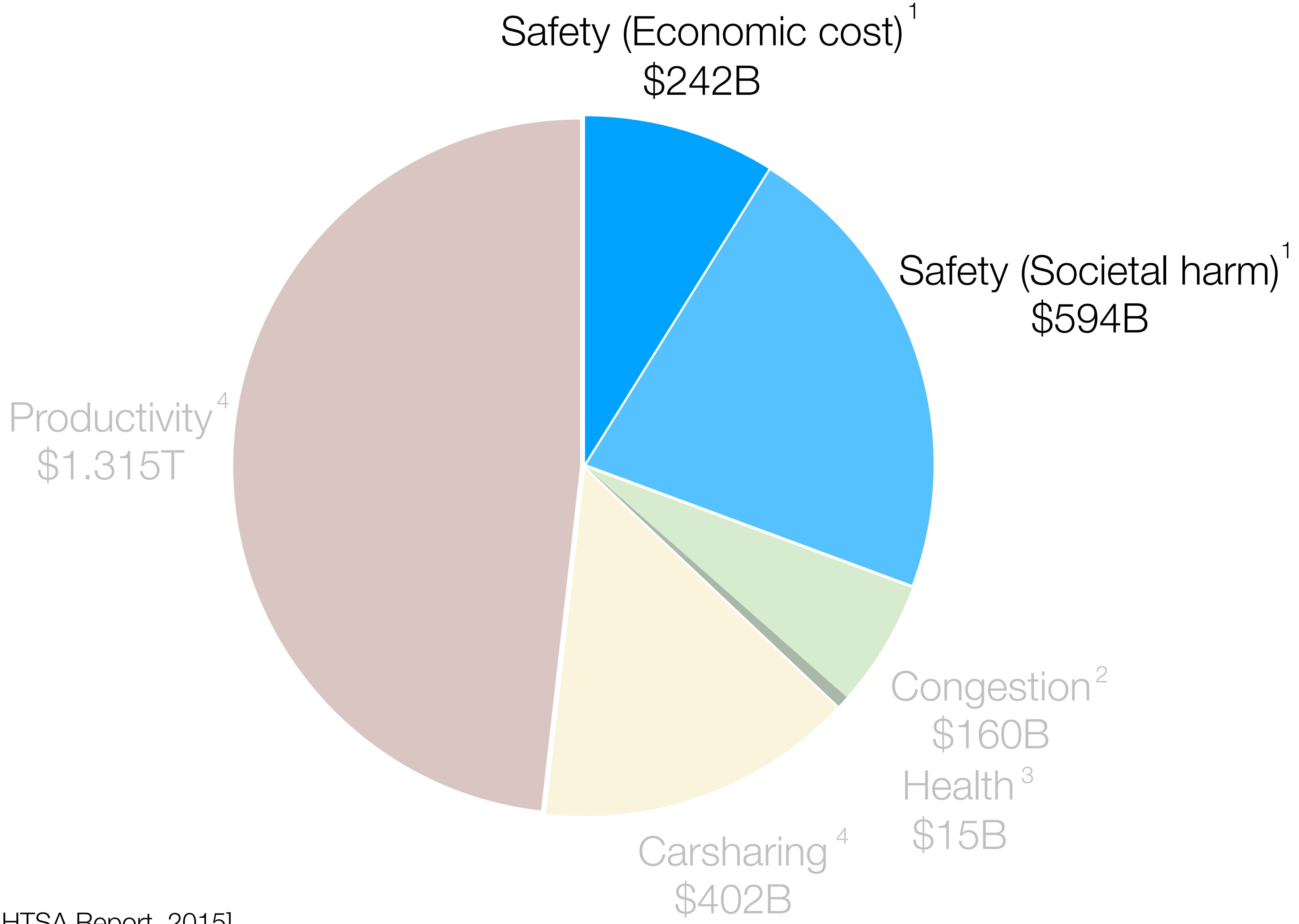
AUTONOMOUS MOBILITY-ON-DEMAND SYSTEMS AND THE BUILT ENVIRONMENT: MODELS AND LARGE-SCALE COORDINATION ALGORITHMS

Federico Rossi
Advisor: Prof. Marco Pavone
Stanford, January 18, 2017

Self-driving vehicles

2005 → **2017**

Self-driving vehicles



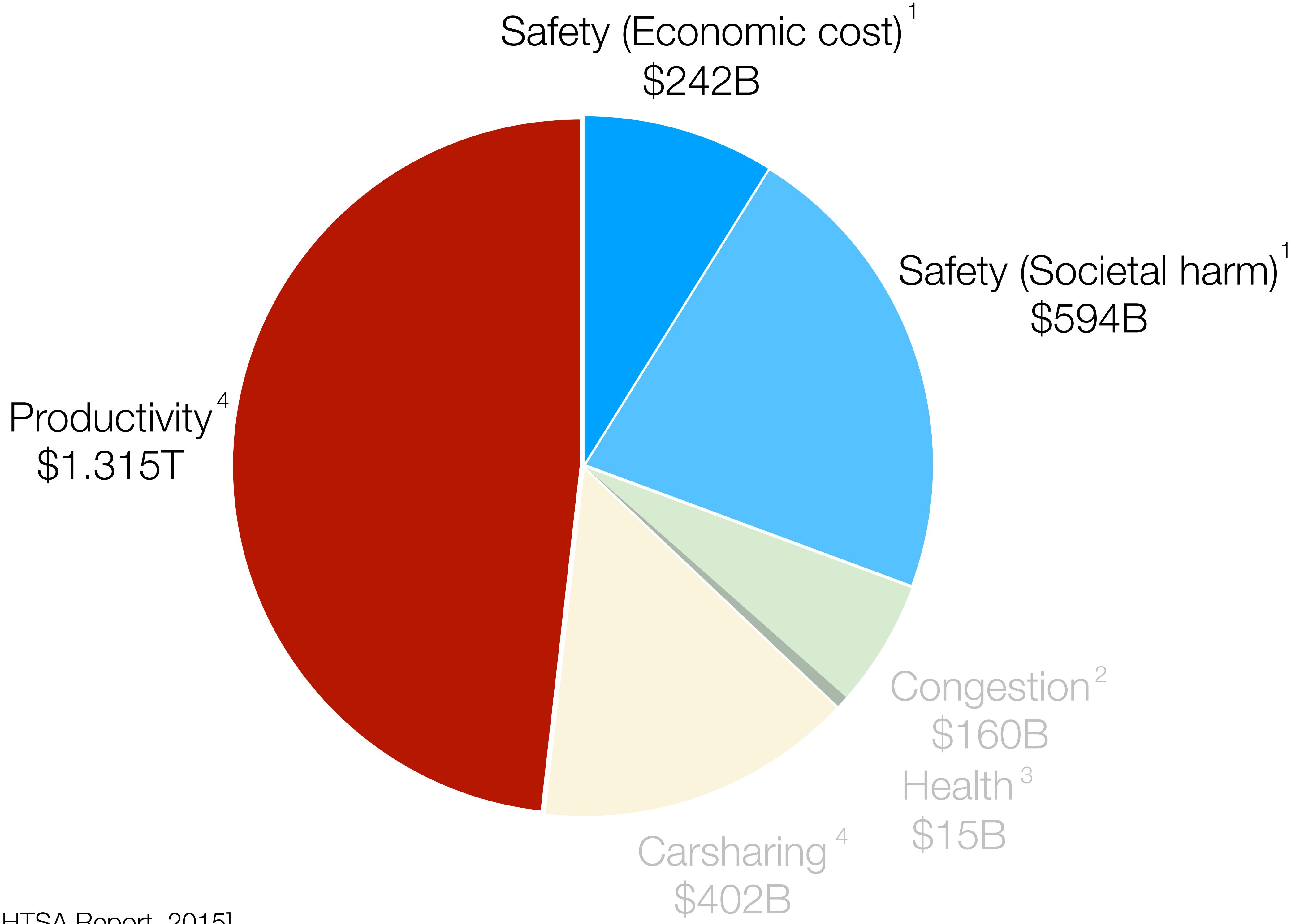
[1] [Blincoe et al., NHTSA Report, 2015]

[2] [Schrank et al., Texas A&M Transportation Institute, 2015]

[3] [Levy et al., Environmental Health, 2010]

[4] [Spieser, Treleaven, Zhang, Frazzoli, Morton, Pavone, Road Vehicle Automation, 2014]

Self-driving vehicles



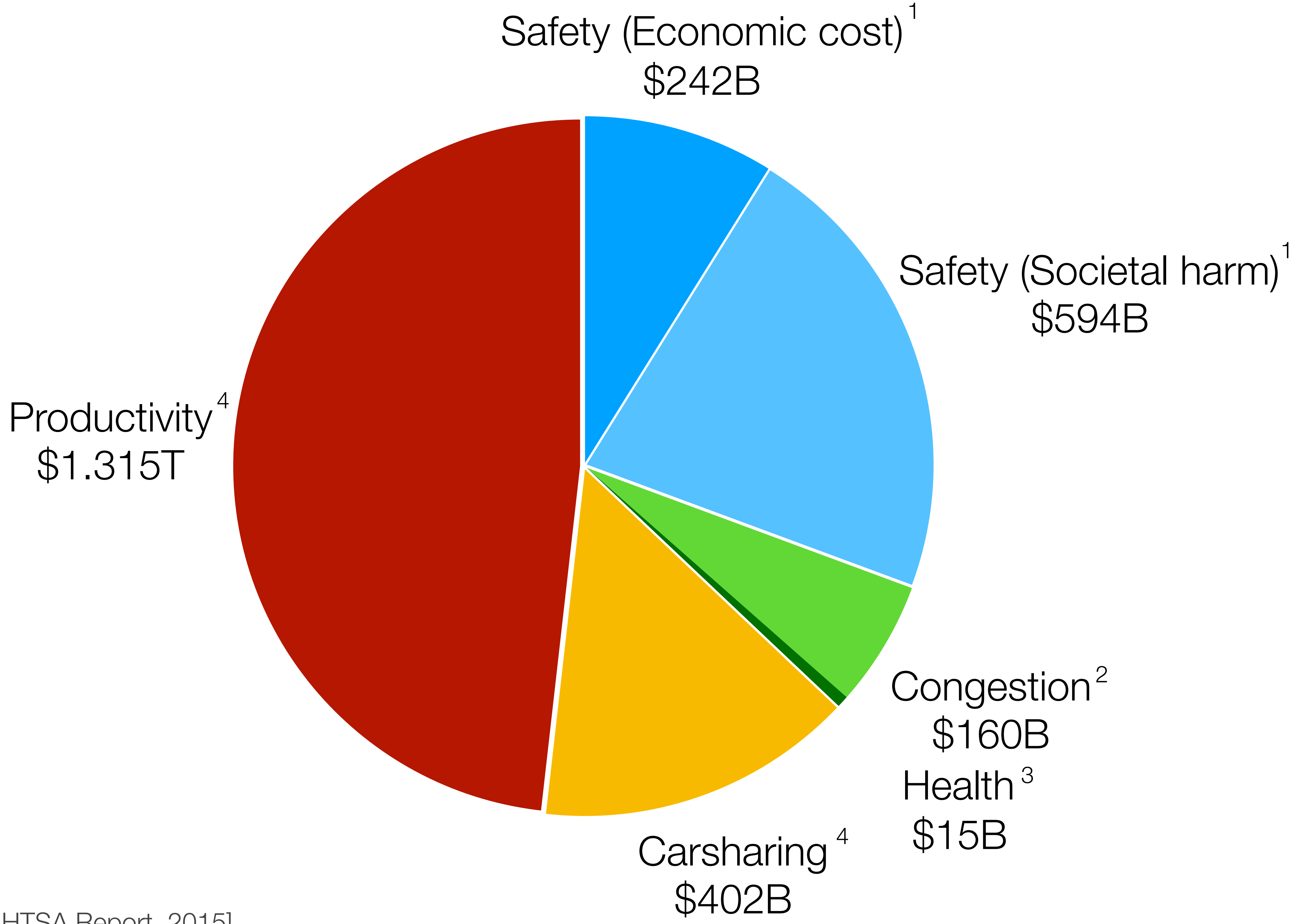
[1] [Blincoe et al., NHTSA Report, 2015]

[2] [Schrank et al., Texas A&M Transportation Institute, 2015]

[3] [Levy et al., Environmental Health, 2010]

[4] [Spieser, Treleaven, Zhang, Frazzoli, Morton, Pavone, Road Vehicle Automation, 2014]

Fleets of self-driving vehicles



[1] [Blincoe et al., NHTSA Report, 2015]

[2] [Schrank et al., Texas A&M Transportation Institute, 2015]

[3] [Levy et al., Environmental Health, 2010]

[4] [Spieser, Treleaven, Zhang, Frazzoli, Morton, Pavone, Road Vehicle Automation, 2014]

Autonomous Mobility-on-Demand

Vehicle Autonomy

+

Car Sharing

CAR
2GO

UBER

autolib'

Impact on the built environment?

AMoD systems and the built environment

- **Congestion**

"… the additional empty repositioning trips made by [shared autonomous vehicles] **increased congestion** and travel times and a significant number of [shared autonomous vehicles] were needed to provide effective service."
[Levin et al. 2016]

"Robocars present one risk of increased congestion, because they allow vehicles to move while empty. … Empty vehicles can **increase congestion**."
– Brad Templeton

- **The electric power network**

"Depending on the scenario, price may increase by only 1.2–2.7 percent (in WECC – RMP/ANM) or, for evening recharging at 6 kW, by as much as 141 percent (in FRCC), 196 percent (in WECC-CA) and 297 percent (in SERC). In contrast to what was suggested by other research, the model predicts **increases in electricity prices** for **almost all regions**."
[Hadley and Tsvetkova 2009]

"V2G could **stabilize large-scale** (one-half of US electricity) **wind power** with 3% of the fleet dedicated to regulation for wind, plus 8–38% of the fleet providing operating reserves or storage for wind."
[Kempton and Tomic 2005]

Problem statement

- Propose models that capture the the interaction between AMoD systems and the built environment, with particular attention to traffic congestion and the electric power network.
- Propose control algorithms that optimize the performance of such AMoD systems.
- Validate these algorithms with case studies with real-world data.

In the literature

Control of AMoD systems

- Queueing-theoretical models [Zhang et al. 2014; Zhang et al. 2015; Calafiore et al. 2017]
- Dynamic vehicle routing models [Psaraftis ’88; Berbeglia, Cordeau, Laporte ’10; Pavone ’10; Pavone et al. 2011; Treleaven, Pavone, Frazzoli ’13; Spieser et al. ’14]
- Fluidic models [Pavone et al. 2012; Levin 2017]

No interaction with the built environment

In the literature

Traffic congestion

No optimization

- Traffic modeling:
    - Static models [Wardrop 1952]
    - Simulation models [Treiber, Hennecke, Helbing, 2000; Maciejevski 2017; Fagnant et al. 2014, 2016]
    - Queueing models [Osorio, Bierlaire, 2009]

- Dynamic Traffic Assignment (DTA) and System-Optimal DTA [Janson 1991]

No rebalancing

In the literature

EVs and the power network

- Scheduling charging [Rotering and Ilic 2011; Turitsyn et al. 2010; Tushar et al. 2012]
- Location of charging stations [Goeke and Schneider 2015; Pourazarm et al. 2016]

No feedback

- Macroeconomic effect of EVs [Hadley and Tsvetkova 2009]
- Game-theoretical models [Sioshansi 2012; Wang et al. 2010]

No spatial model

- Joint routing, charging, and economic dispatch [Alizadeh et al. 2016; Khodayar et al. 2013]

Private vehicles

Contribution

- Will AMoD systems increase urban congestion?

  Not if properly routed [Zhang*, Rossi* and Pavone 2016a, Robotics: Science and Systems; Rossi et al. 2017, Autonomous Robots, in press.]

- Will fleets of electric vehicles help control the power network?

  Yes, if properly coordinated [Rossi et al., in preparation for RSS 2018]

Other contributions

- Randomised algorithms for efficient routing in AMoD systems
- Model-predictive control of AMoD fleets with charging constraints [Zhang, Rossi and Pavone 2016b, ICRA]
- BMPC queuing-theoretical models of AMoD systems [Iglesias et al. 2016 WAFR; Iglesias et al. 2018, submitted to the International Journal of Robotics Research]
- Data-driven control of AMoD systems with LSTM estimation of customer demand [Iglesias et al. 2018, ICRA]

Network flow model

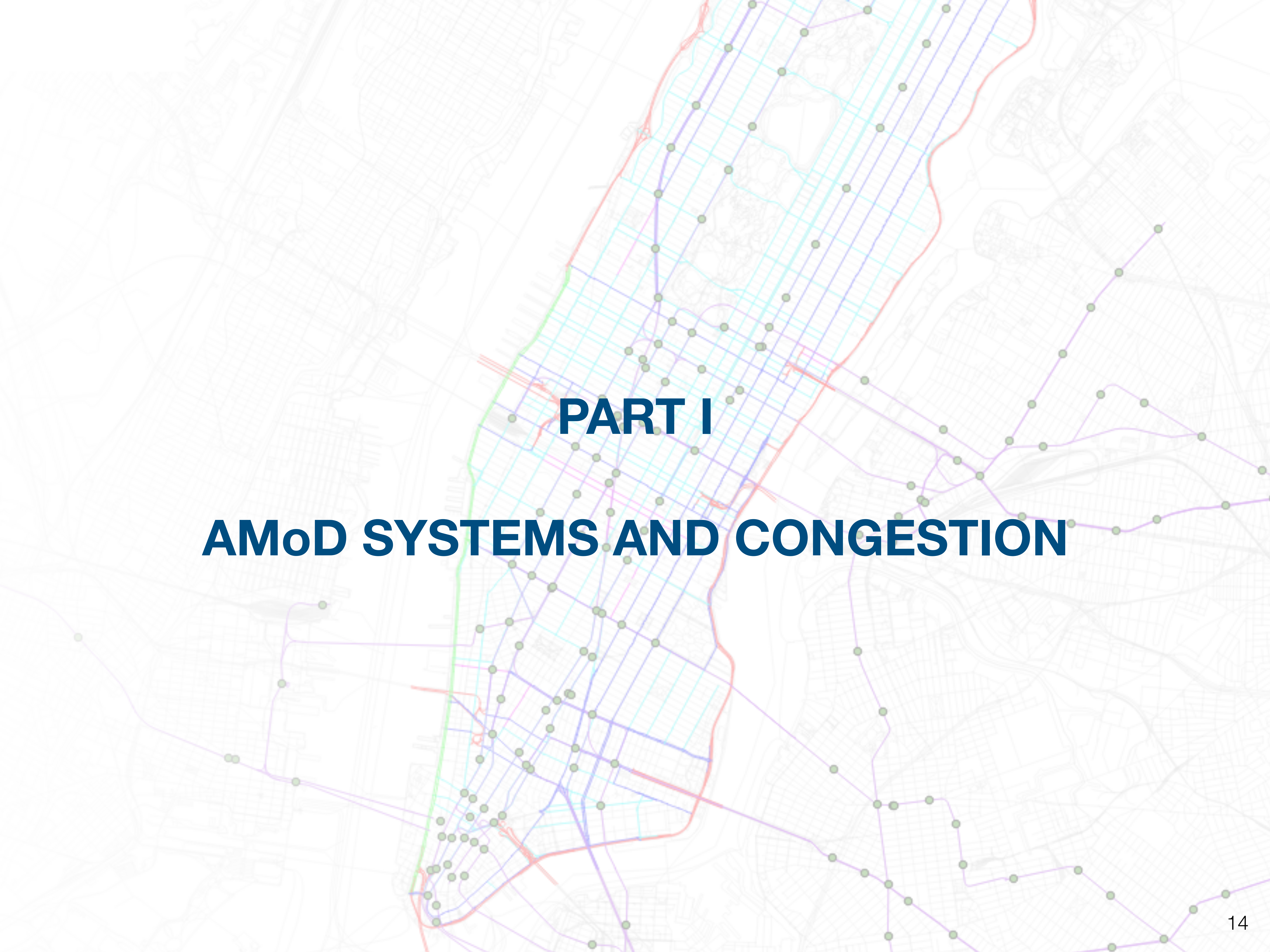
- Highly scalable (LP)
- Very expressive

- No stochasticity
- Continuum approximation

➡

Expectation of a stochastic process

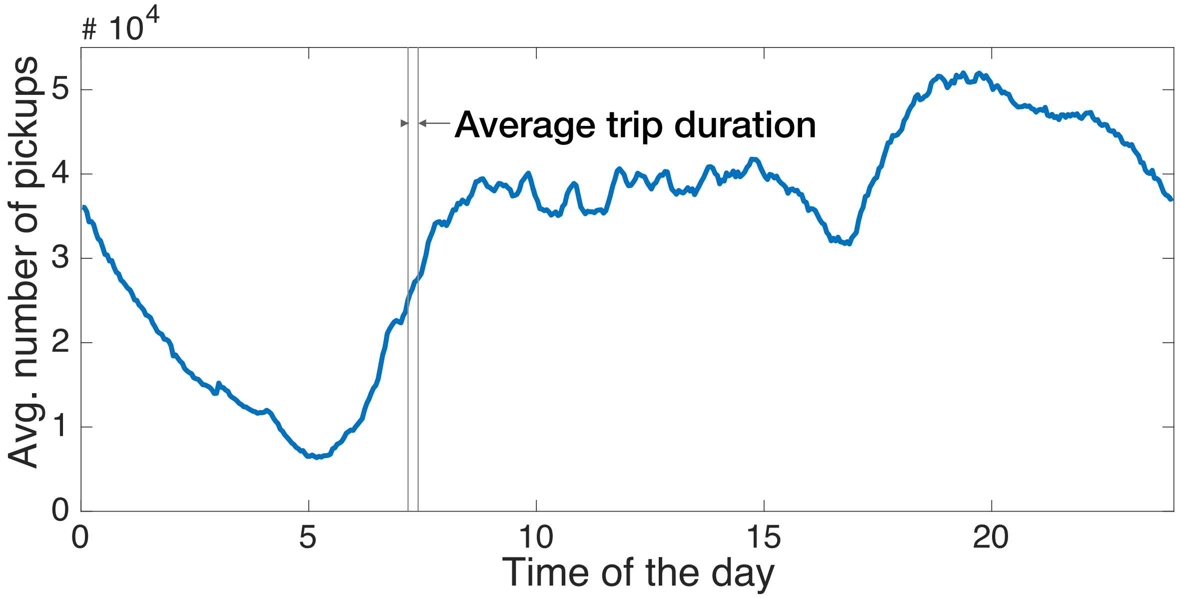
Flow decomposition and sampling



PART I

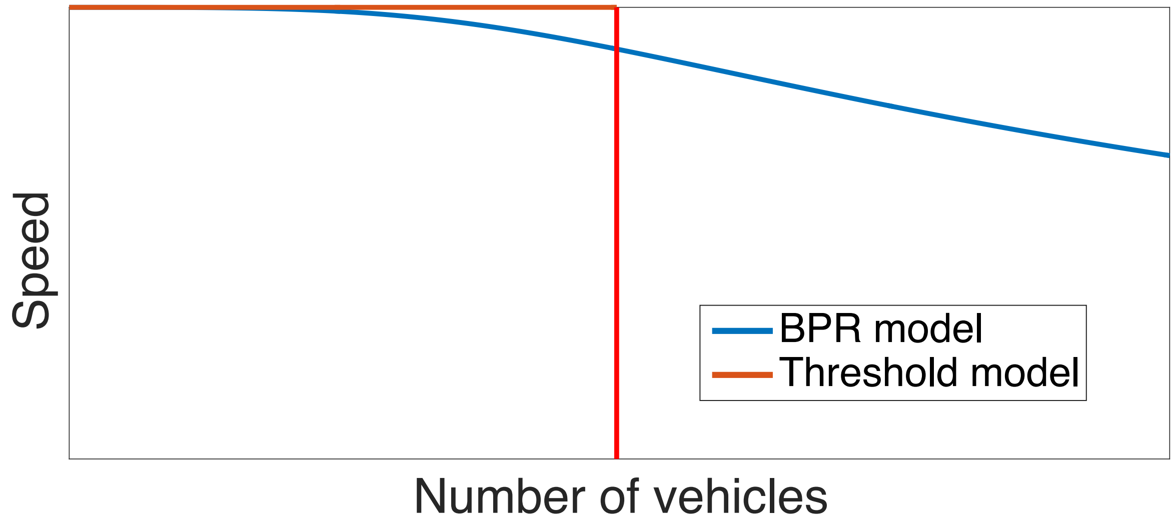
AMoD SYSTEMS AND CONGESTION

Our approach: assumptions



Customer demand is time-invariant

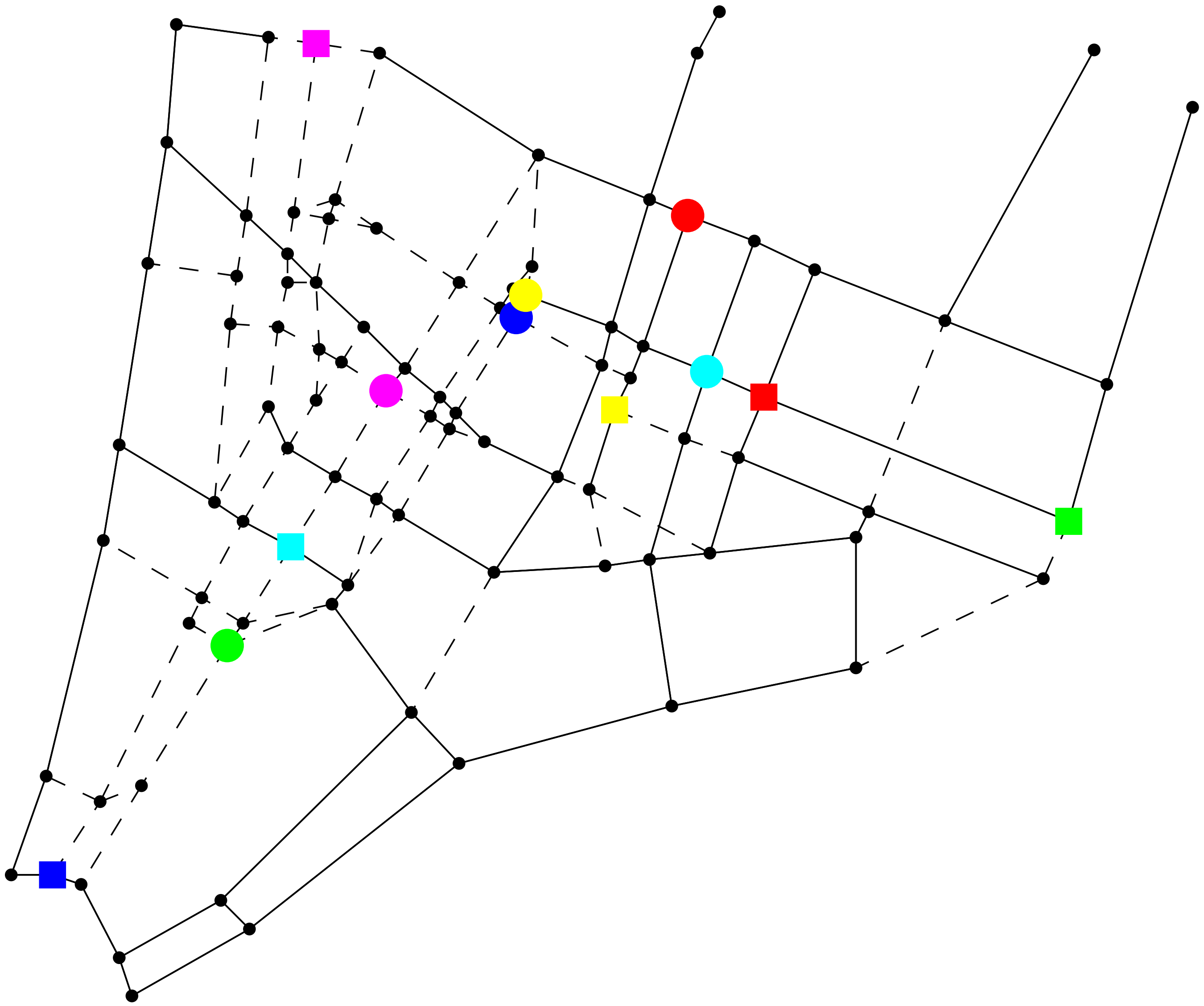
The road network is node-symmetric



Congestion is a threshold phenomenon

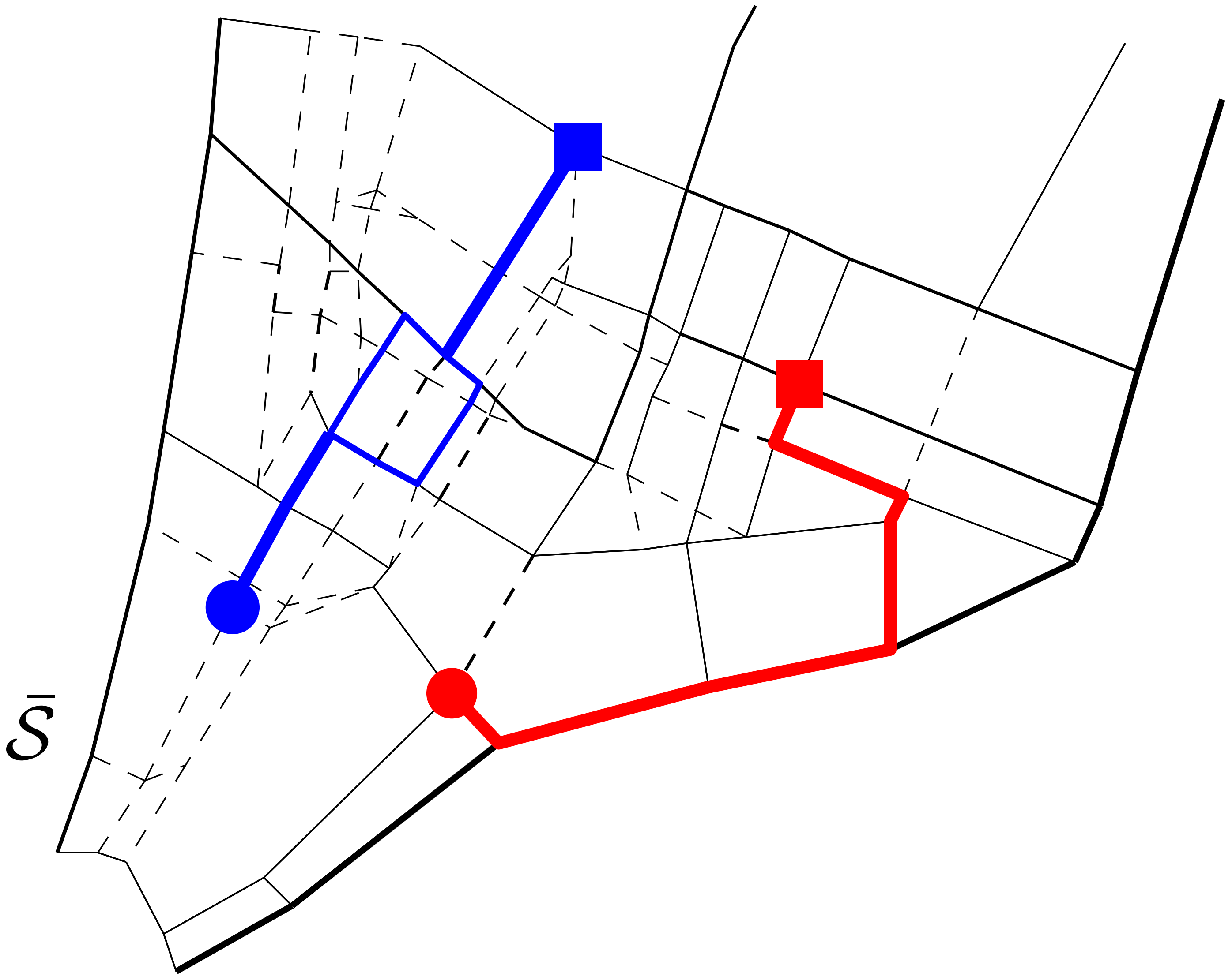
Customers and roads

- Transportation requests: origin, destination, rate of demand (customers/minute)
- Trips:
  - Customer trips service transportation requests
  - Rebalancing trips realign vehicles with requests
- Road network model:
  - Nodes: intersections
  - Directed, capacitated edges: roads



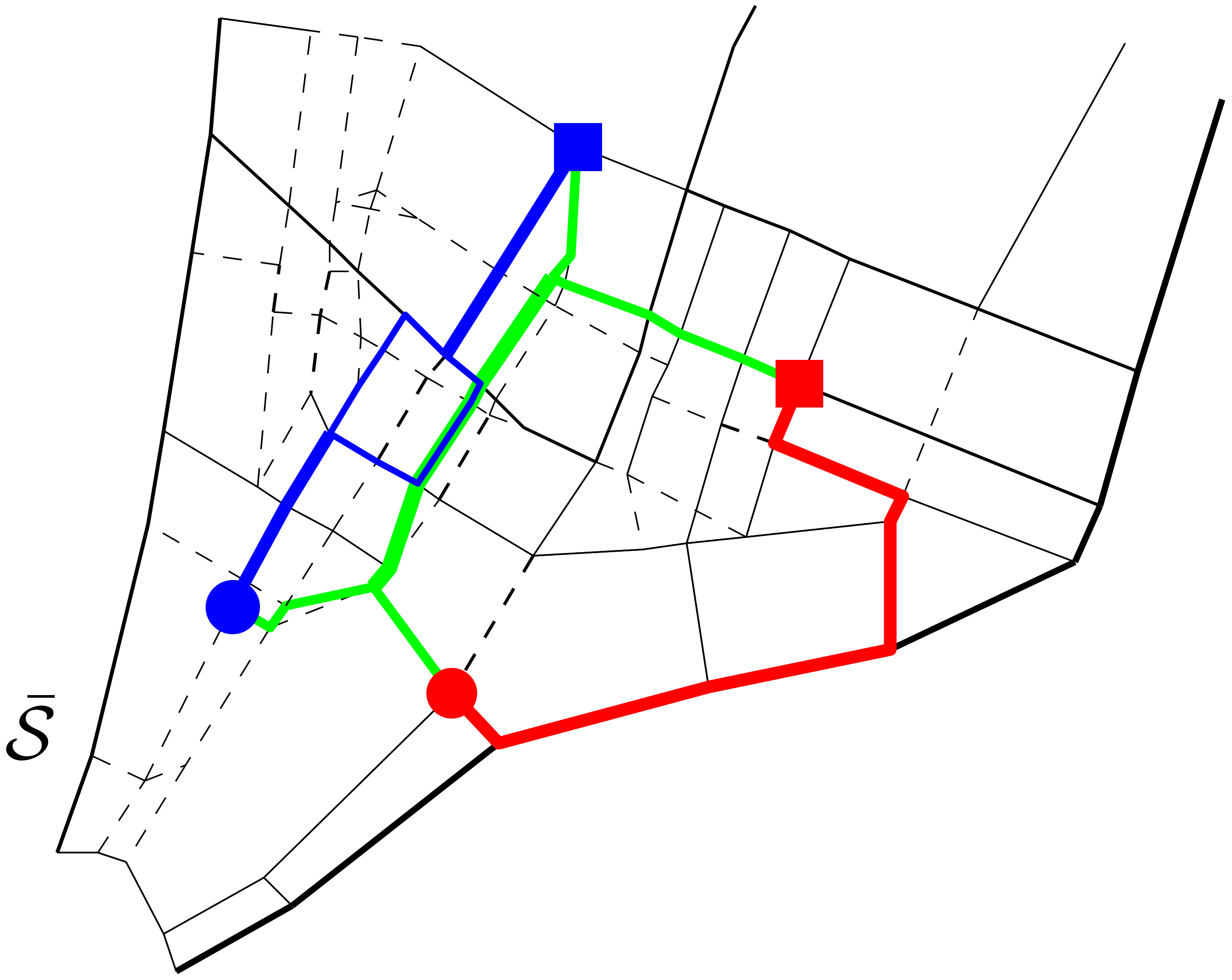
Road network and flows

- Customer **flows**
- Rebalancing flows
- Graph cut $(\mathcal{S}, \bar{\mathcal{S}})$
  - Edges separating $\mathcal{S}$ and $\bar{\mathcal{S}}$
  - Cut capacity $C_{\text{out}}, C_{\text{in}}$



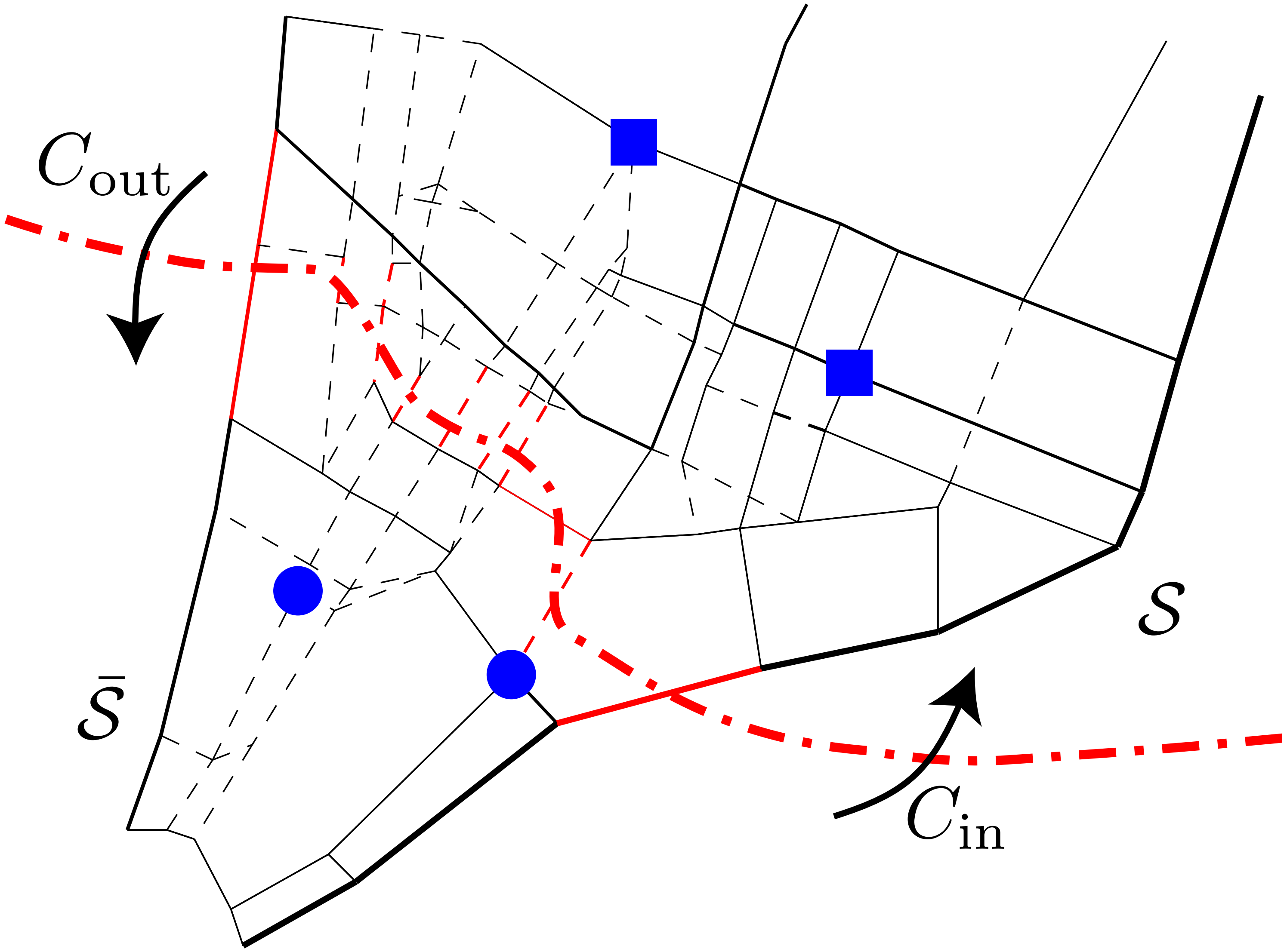
Road network and flows

- Customer flows
- **Rebalancing flows**
- Graph cut $(\mathcal{S}, \bar{\mathcal{S}})$
  - Edges separating $\mathcal{S}$ and $\bar{\mathcal{S}}$
  - Cut capacity $C_{\text{out}}, C_{\text{in}}$



Road network and flows

- Customer flows
- Rebalancing flows
- **Graph cut** $(\mathcal{S}, \bar{\mathcal{S}})$
  - Edges separating $\mathcal{S}$ and $\bar{\mathcal{S}}$
  - Cut capacity $C_{\text{out}}, C_{\text{in}}$



Linear model

$$\underset{f_m(\cdot,\cdot),f_R(\cdot,\cdot)}{\text{minimize}} \quad \sum_{m\in\mathcal{M}} \sum_{(u,v)\in\mathcal{E}} t(u,v) f_m(u,v) + \rho \sum_{(u,v)\in\mathcal{E}} t(u,v) f_R(u,v)$$

$$\text{subject to} \quad \sum_{u\in\mathcal{V}} f_m(u,s_m) + \lambda_m = \sum_{w\in\mathcal{V}} f_m(s_m,w) \qquad \forall m \in \mathcal{M}$$

$$\sum_{u\in\mathcal{V}} f_m(u,t_m) = \lambda_m + \sum_{w\in\mathcal{V}} f_m(t_m,w) \qquad \forall m \in \mathcal{M}$$

$$\sum_{u\in\mathcal{V}} f_m(u,v) = \sum_{w\in\mathcal{V}} f_m(v,w) \qquad \forall m \in \mathcal{M}, v \in \mathcal{V}\backslash\{s_m,t_m\}$$

$$\sum_{u\in\mathcal{V}} f_R(u,v) + \sum_{m\in\mathcal{M}} 1_{v=t_m}\lambda_m = \sum_{w\in\mathcal{V}} f_R(v,w) + \sum_{m\in\mathcal{M}} 1_{v=s_m}\lambda_m \qquad \forall v \in \mathcal{V}$$

$$f_R(u,v) + \sum_{m\in\mathcal{M}} f_m(u,v) \leqslant c(u,v) \qquad \forall (u,v) \in \mathcal{E}$$

Theoretical results

Sufficient condition for feasibility of rebalancing

Node-symmetric road graph
Feasible **customer** flows

⇒

Feasible **rebalancing** flows

1. In a node-symmetric road network **rebalancing does not increase congestion**

2. If goal is to maximize customer satisfaction, customer flows and rebalancing flows are **decoupled** and can be computed separately

Are road networks symmetric?

Urban center	Avg. frac. capacity disparity	Std. dev.
Chicago, IL	$1.2972 \cdot 10^{-4}$	$1.003 \cdot 10^{-4}$
New York, NY	$1.6556 \cdot 10^{-4}$	$1.304 \cdot 10^{-4}$
Colorado Springs, CO	$3.1772 \cdot 10^{-4}$	$2.308 \cdot 10^{-4}$
Los Angeles, CA	$0.9233 \cdot 10^{-4}$	$0.676 \cdot 10^{-4}$
Mobile, AL	$1.9368 \cdot 10^{-4}$	$1.452 \cdot 10^{-4}$
Portland, OR	$1.0769 \cdot 10^{-4}$	$0.778 \cdot 10^{-4}$

Very high degree of node-symmetry
(even with many one-way streets)

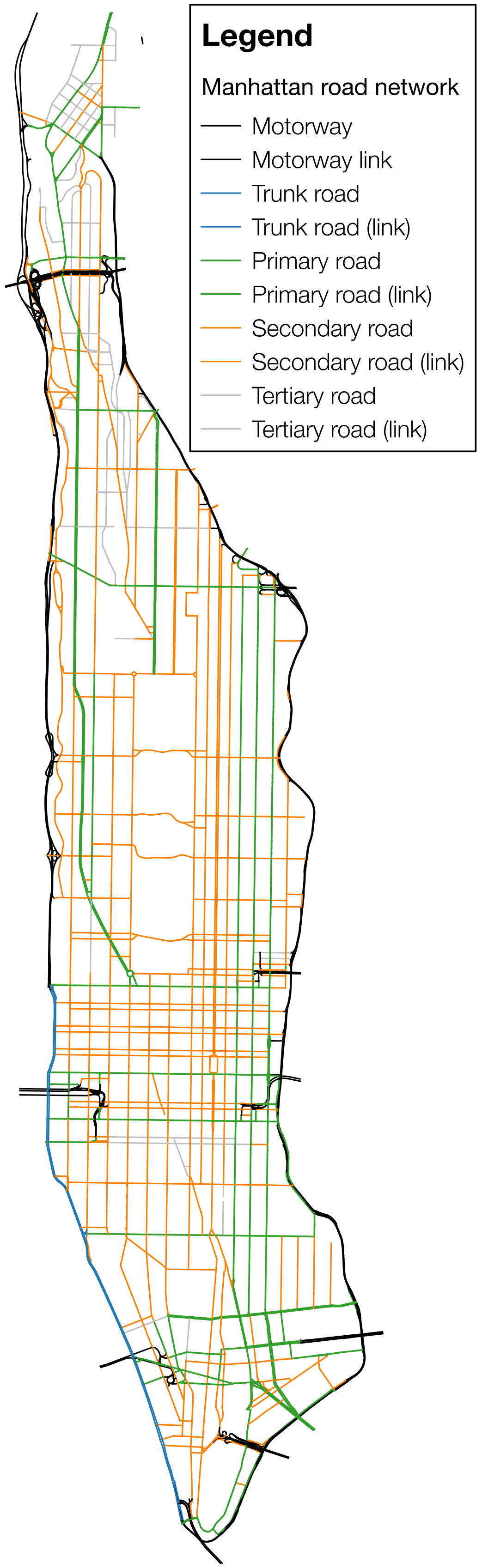
A real-time congestion-aware rebalancing algorithm

- Customers are routed on **fastest route** as soon as a vehicle is available

- Empty vehicles are rebalanced by a **batch algorithm**
  - Tries to match a given vehicle distribution
  - Minimum-cost **congestion-free** rebalancing flows
  - Computationally efficient (**totally unimodular**)

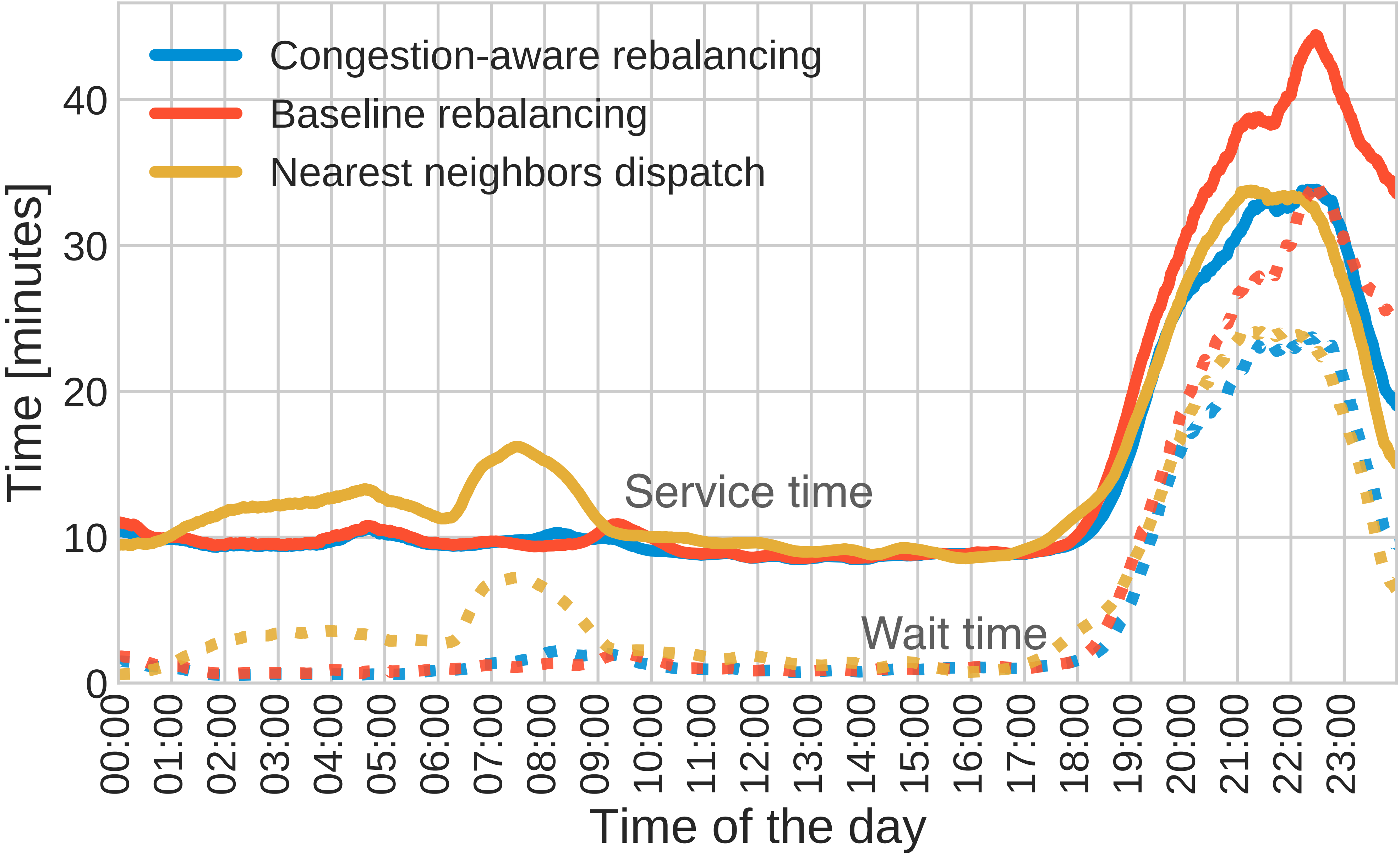
$$
\begin{aligned}
\underset{\substack{f_R(\cdot,\cdot),\\ \{ds_i\},\{dt_j\}}}{\text{minimize}} \quad & \sum_{(u,v)\in\mathcal{E}} t(u,v)\, f_R(u,v) \;+ \sum_{i\in S_R} C ds_i + \sum_{i\in T_R} C dt_i \\
\text{subject to} \quad & \sum_{u\in\mathcal{V}} f_R(u,v) + 1_{v\in S_R}(v_v^e(t) - v_v^d(t) - ds_v) \\
& \quad = \sum_{w\in V} f_R(v,w) + 1_{v\in T_R}(v_v^d(t) - v_v^e(t) - dt_v), \\
& \qquad\qquad\qquad\qquad\qquad\qquad \forall v \in \mathcal{V} \\
& f_R(u,v) \leqslant c_R(u,v), \qquad\qquad \forall (u,v) \in \mathcal{E}, \\
& f_R(u,v) \mathrlap{\in \mathbb{N}}{\geqslant 0}, \qquad\qquad \forall (u,v) \in \mathcal{E}, \\
& ds_i, dt_j \mathrlap{\in \mathbb{N}}{\geqslant 0}, \qquad\qquad \forall i \in S_R, j \in T_R.
\end{aligned}
$$

Case study: NYC

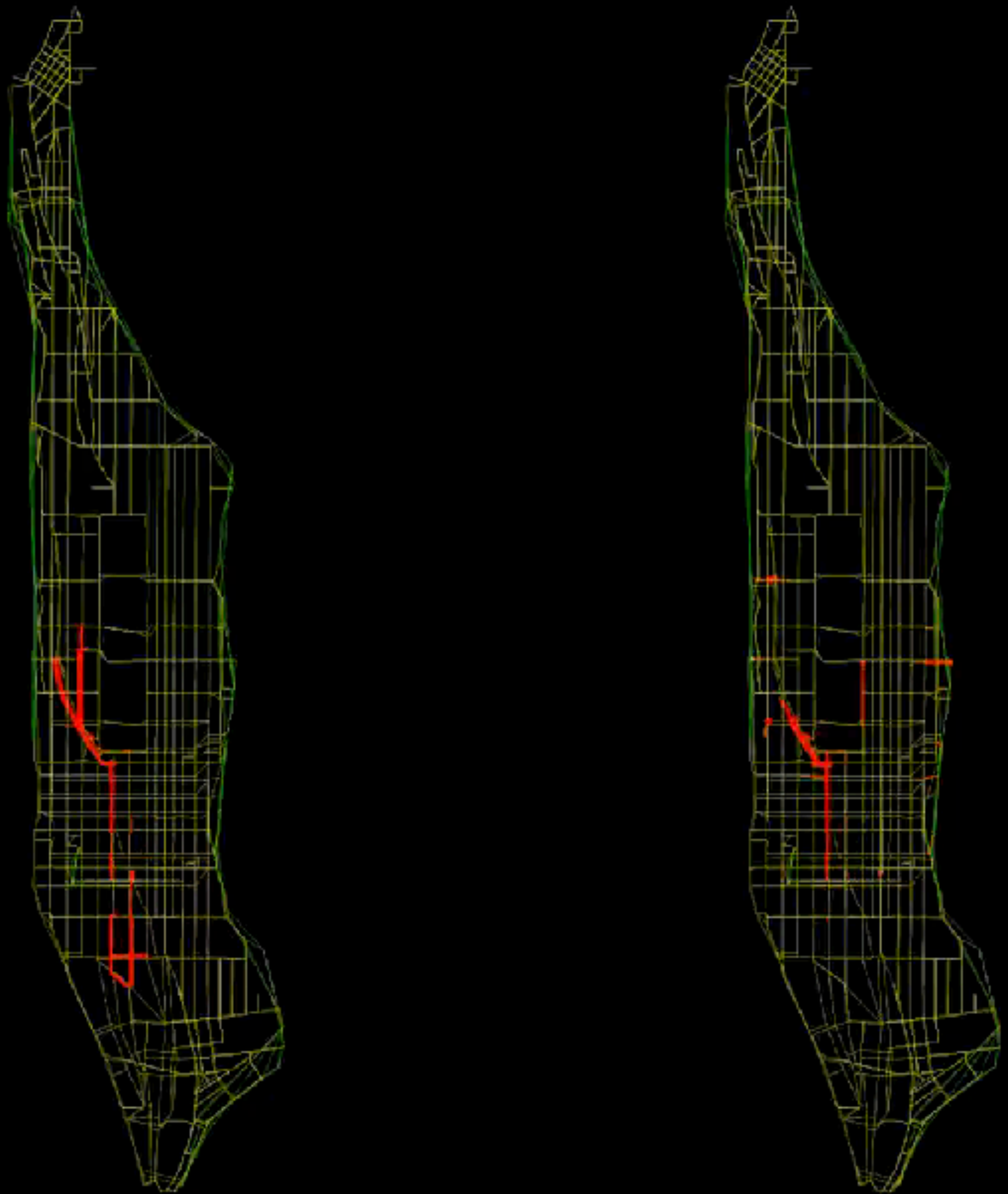


- 24-hour simulation
- NYC taxi data: 480000 customers
- 8000 vehicles

Medium congestion: road capacity reduced by 75%



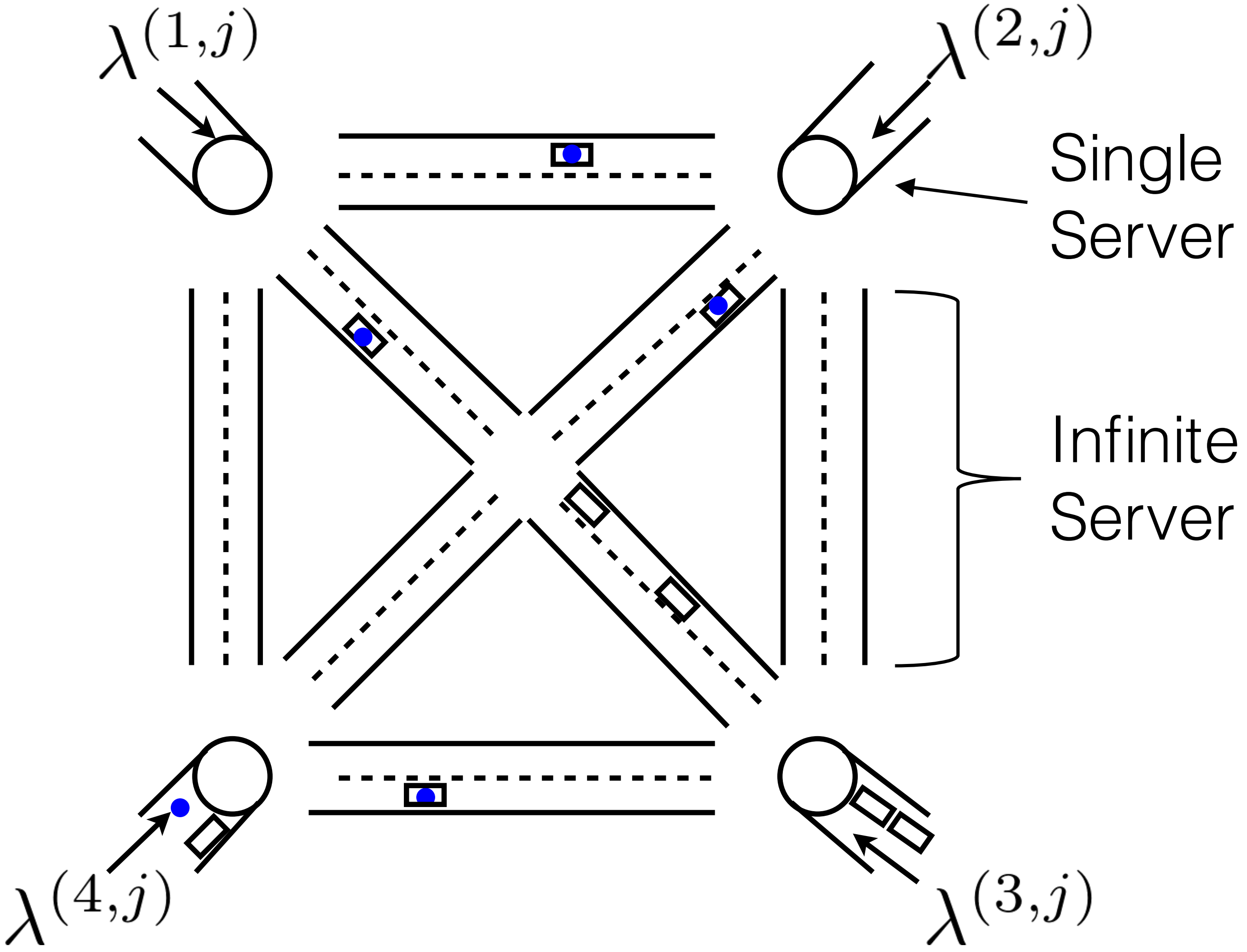
Experimental results



MATSim

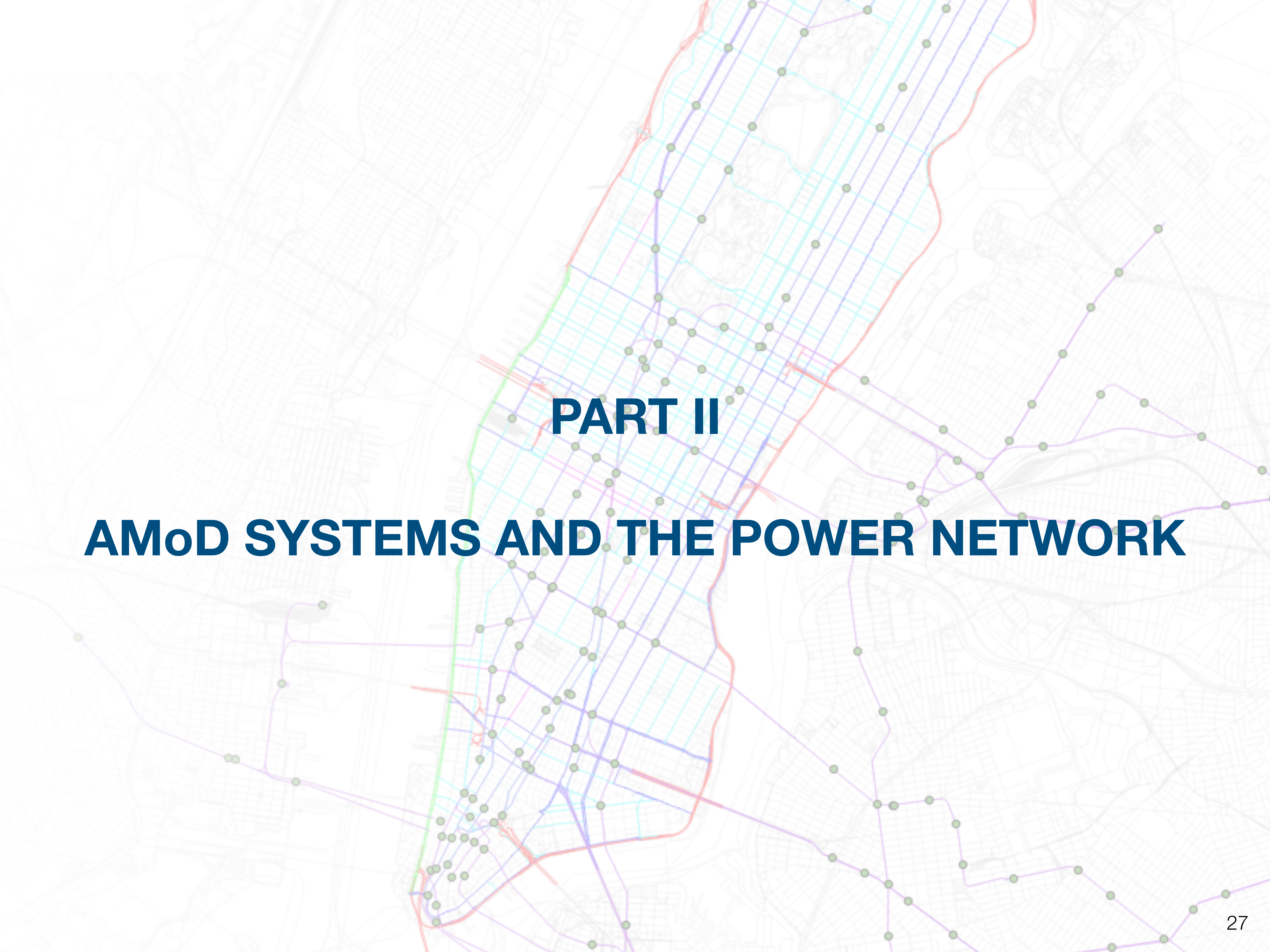
senozon

A BCMP queuing network model for congested AMoD systems



Network flow model is **equivalent** to a queuing-theoretical model for systems with **high availability**

[Iglesias, Rossi, Zhang and Pavone, 2016, 2017]

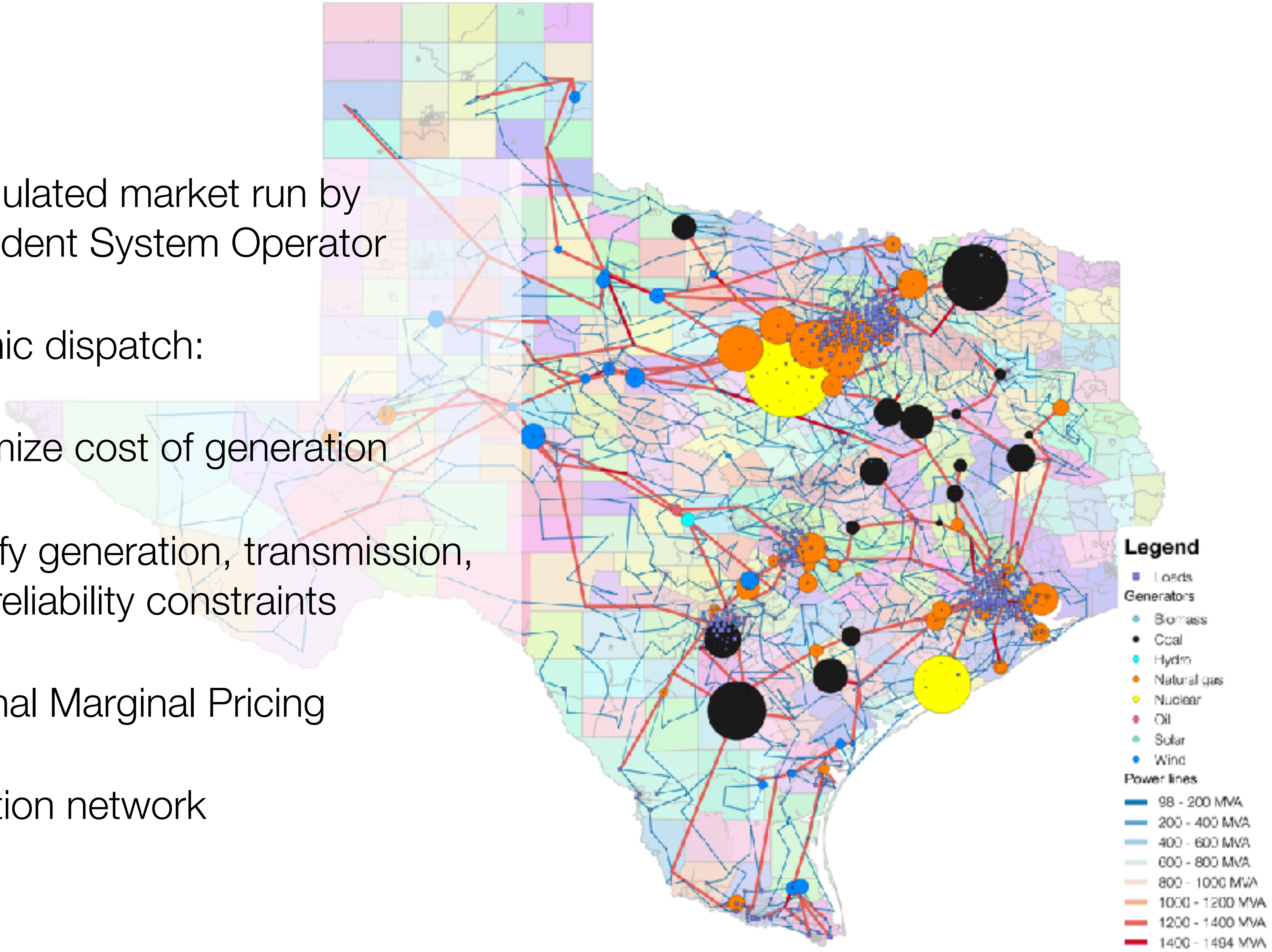


PART II

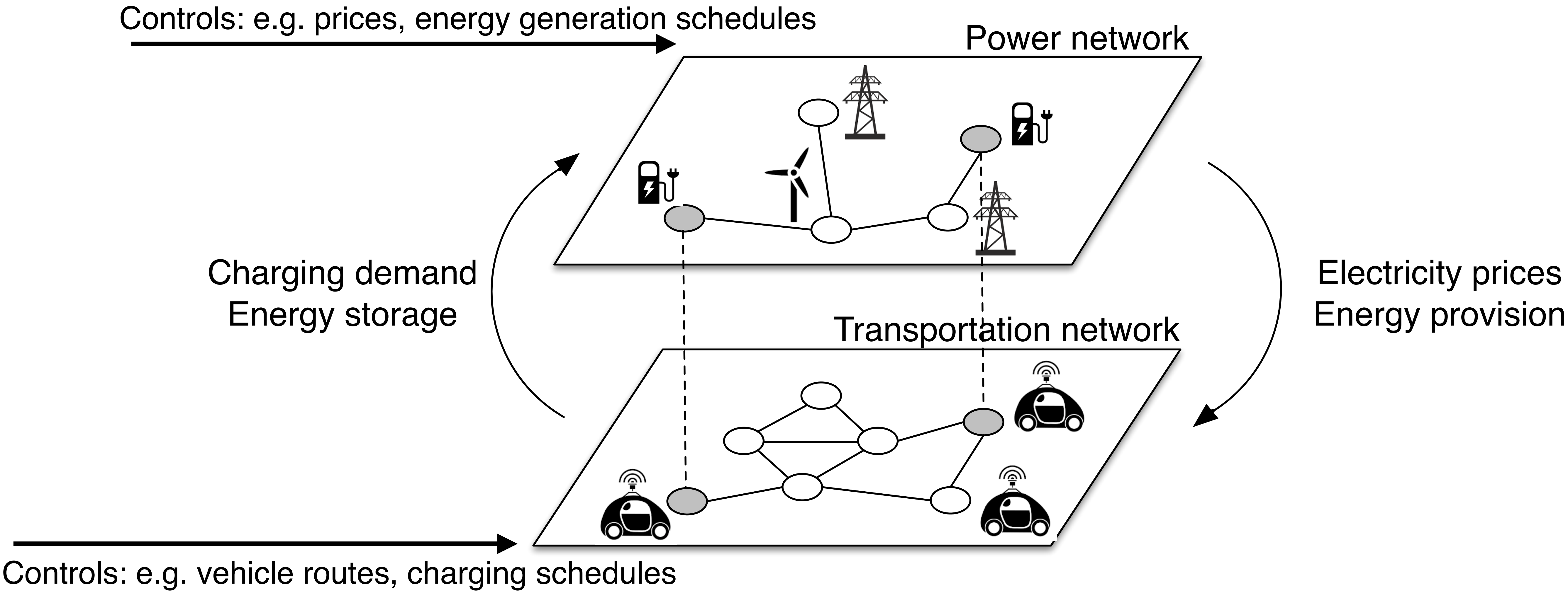
AMoD SYSTEMS AND THE POWER NETWORK

The electric power network

- Well-regulated market run by Independent System Operator
- Economic dispatch:
  - Minimize cost of generation
  - Satisfy generation, transmission, and reliability constraints
- Locational Marginal Pricing
- Distribution network



AMoD and the power network



Controls: e.g. prices, energy generation schedules

Power network

Charging demand
Energy storage

Electricity prices
Energy provision

Transportation network

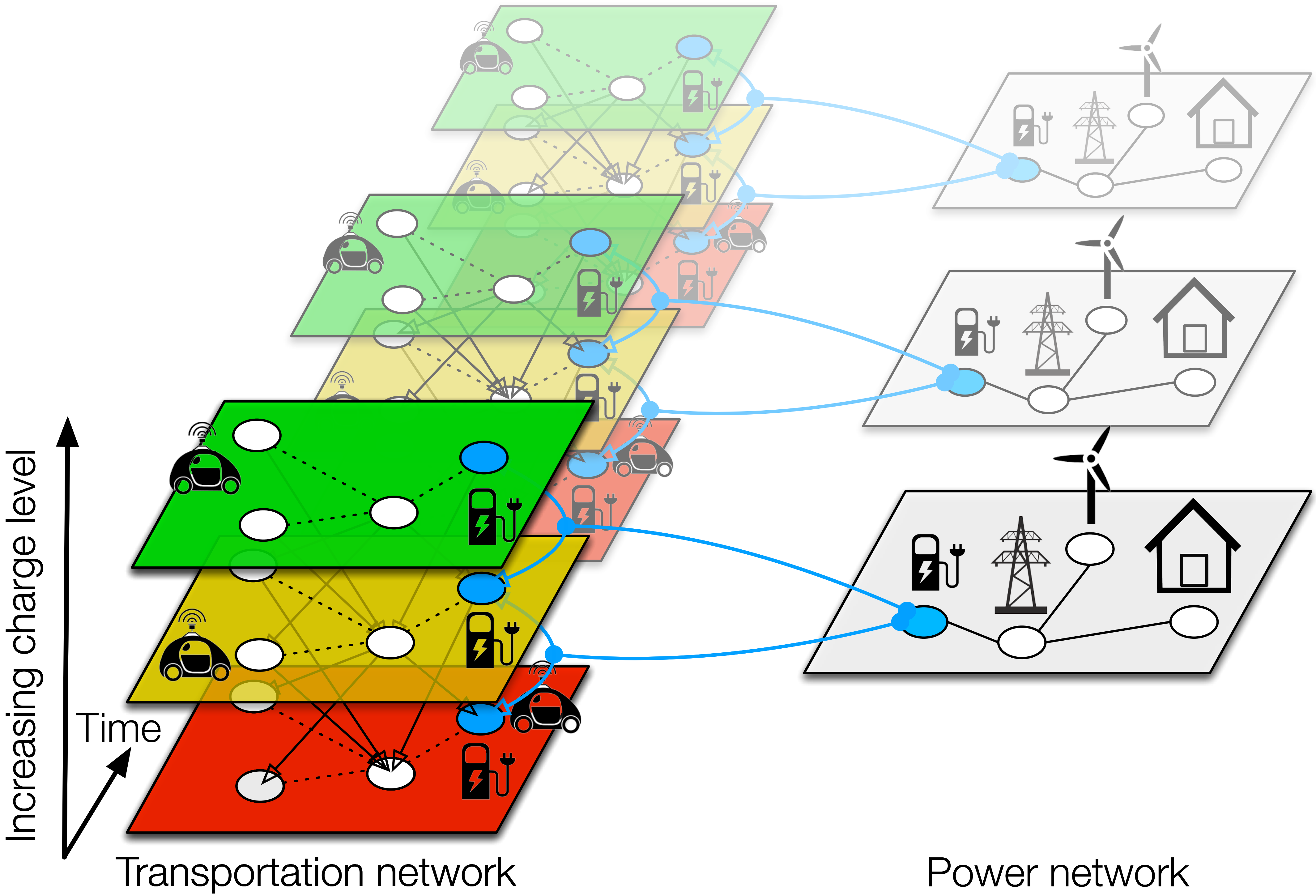
Controls: e.g. vehicle routes, charging schedules

Goal: **socially optimal** control policy for the AMoD system and the power network

Assumptions

- **Cooperation** between the transportation system operator and the power network's independent system operator
- Road network: **network flow** model
- Power transmission network: **DC** model
- Power distribution network: **thermal** constraints only
- Transportation system buys/sells electricity at **LMP** rate

Augmented AMoD network flow model



Linear model

$$\underset{f_m,\lambda_m^{c,\text{in}},\lambda_m^{c,t,\text{out}},N_F,\theta,p}{\text{minimize}} \; V_T\left(\sum_{(\mathbf{v},\mathbf{w})\in\mathcal{E}} t_{\mathbf{v},\mathbf{w}} \sum_{m=1}^{M} f_m(\mathbf{v},\mathbf{w})\right) + V_D\left(\sum_{(\mathbf{v},\mathbf{w})\in\mathcal{E}} d_{v_{\mathbf{v}},v_{\mathbf{w}}} \sum_{m=0}^{M} f_m(\mathbf{v},\mathbf{w})\right) + \sum_{t=1}^{T}\sum_{g\in\mathcal{G}} o_g(t)p(g,t)$$

subject to

$$\sum_{\mathbf{u}:(\mathbf{u},\mathbf{v})\in\mathcal{E}} f_m(\mathbf{u},\mathbf{v}) + 1_{v_{\mathbf{v}}=v_m} 1_{t_{\mathbf{v}}=t_m} \lambda_m^{c_{\mathbf{v}},\text{in}} = \sum_{\mathbf{w}:(\mathbf{v},\mathbf{w})\in\mathcal{E}} f_m(\mathbf{v},\mathbf{w}) + 1_{v_{\mathbf{v}}=w_m} \lambda_m^{t_{\mathbf{v}},c_{\mathbf{v}},\text{out}}, \quad \forall \mathbf{v}\in\mathcal{V}, m\in\{1,\dots,M\},$$

$$\sum_{c=1}^{C} \lambda_m^{c,\text{in}} = \lambda_m, \quad \forall m\in\{1,\dots,M\},$$

$$\sum_{t=1}^{T}\sum_{c=1}^{C} \lambda_m^{t,c,\text{out}} = \lambda_m, \quad \forall m\in\{1,\dots,M\},$$

$$\sum_{\mathbf{u}:(\mathbf{u},\mathbf{v})\in\mathcal{E}} f_0(\mathbf{u},\mathbf{v}) + \sum_{m=1}^{M} 1_{v_{\mathbf{v}}=w_m} \lambda_m^{t_{\mathbf{v}},c_{\mathbf{v}},\text{out}} + N_I(\mathbf{v})$$

$$= \sum_{\mathbf{w}:(\mathbf{v},\mathbf{w})\in\mathcal{E}} f_0(\mathbf{v},\mathbf{w}) + \sum_{m=1}^{M} 1_{v_{\mathbf{v}}=v_m} 1_{t_{\mathbf{v}}=t_m} \lambda_m^{c_{\mathbf{v}},\text{in}} + N_F(\mathbf{v}), \quad \forall \mathbf{v}\in\mathcal{V},$$

$$\sum_{c_{\mathbf{v}}=1}^{M}\left(\sum_{m=0}^{M} f_m(\mathbf{v},\mathbf{w})\right) \leqslant \overline{f}_{(v_{\mathbf{v}},v_{\mathbf{w}})}, \quad \forall (v_{\mathbf{v}},v_{\mathbf{w}})\in\mathcal{E}_R, \forall t_{\mathbf{v}}\in\{1\dots,T\},$$

$$\sum_{\substack{(v,w)\in\mathcal{E}_S:\\ v_{\mathbf{v}}=v_{\mathbf{w}}=s,\\ t_{\mathbf{v}}\leqslant t<t_{\mathbf{w}}}} \left(\sum_{m=0}^{M} f_m(\mathbf{v},\mathbf{w})\right) \leqslant \overline{S}_s, \quad \forall s\in\mathcal{S}, t\in\{1,\dots,T\},$$

$$\sum_{(u,v)\in\mathcal{E}_P} \frac{\theta(u,t)-\theta(v,t)}{x_{u,v}} + 1_{v\in\mathcal{G}}p(v,t) = 1_{v\in\mathcal{L}}d_v(t) + \sum_{(v,w)\in\mathcal{E}_P} \frac{\theta(v,t)-\theta(w,t)}{x_{v,w}}, \quad \forall v\in\mathcal{B}, t\in\{1,\dots,T\},$$

$$-\overline{p}_{b_1,b_2} \leqslant \frac{\theta(b_1,t)-\theta(b_2,t)}{x_{b_1,b_2}} \leqslant \overline{p}_{b_1,b_2}, \quad \forall (b_1,b_2)\in\mathcal{E}_P, t\in\{1,\dots,T\},$$

$$\underline{p}_g(t) \leqslant p(g,t) \leqslant \overline{p}_g(t), \quad \forall g\in\mathcal{G}, t\in\{1,\dots,T\},$$

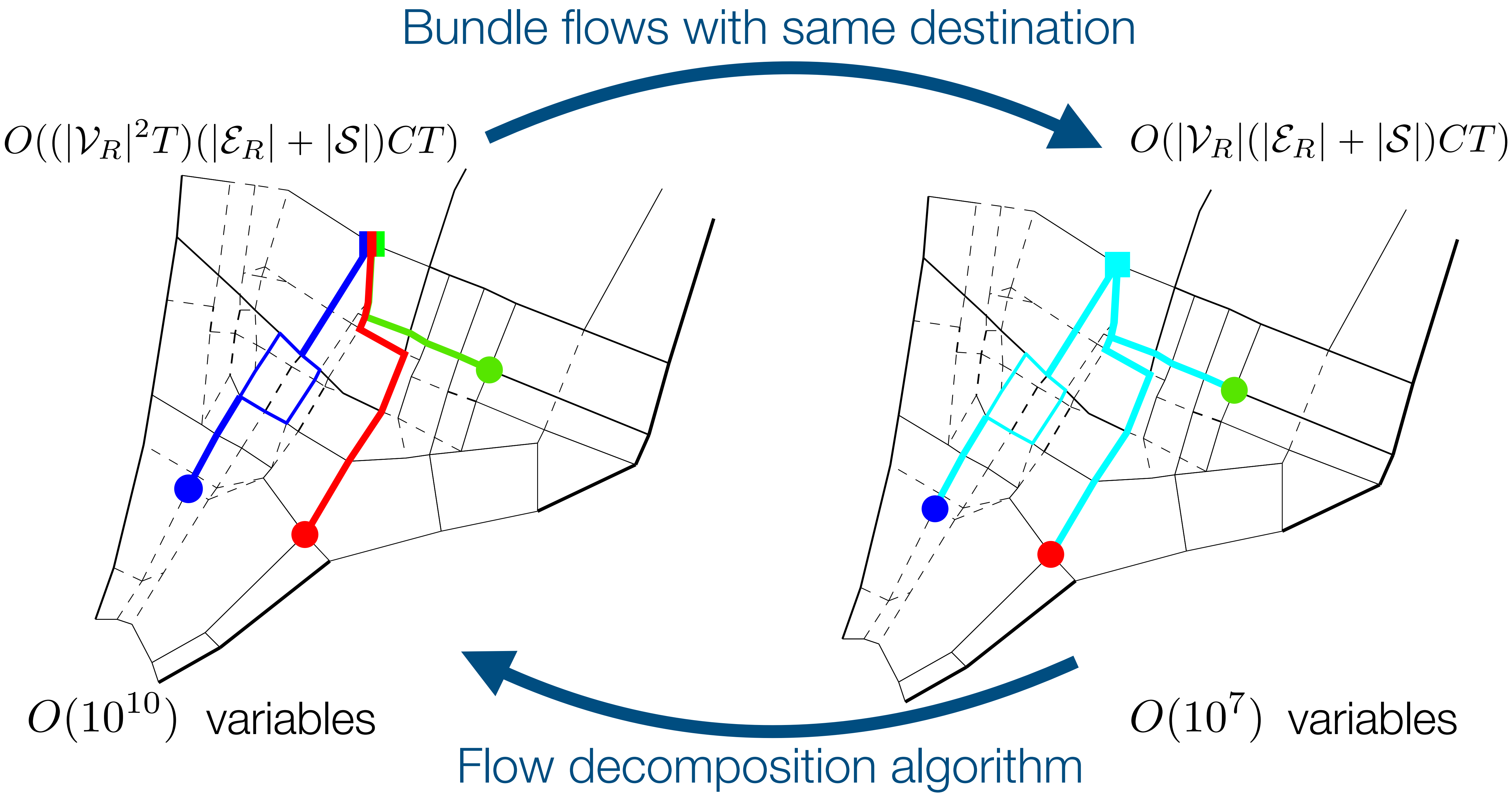
$$-p_g^-(t) \leqslant p(g,t+1)-p(g,t) \leqslant p_g^+(t), \quad \forall g\in\mathcal{G}, t\in\{1,\dots,T-1\},$$

$$d_l(t)(t) \leqslant \overline{d}_l(t), \quad \forall l\in\mathcal{L}, t\in\{1,\dots,T\},$$

$$d_l(t) = d_{l,e}(t) + J_C\delta c^+_{\mathcal{M}_{\text{P,R}}(l)} \sum_{(\mathbf{v},\mathbf{w})\in M^+_{P,G}(l,t)} \sum_{m=0}^{M} f_m(\mathbf{v},\mathbf{w})$$

$$+ J_C\delta c^-_{\mathcal{M}_{\text{P,R}}(l)} \sum_{(\mathbf{v},\mathbf{w})\in M^-_{P,G}(l,t)} \sum_{m=1}^{M} f_m(\mathbf{v},\mathbf{w}), \quad \forall l\in\mathcal{L}, t\in\{1,\dots,T\}.$$

Flow bundling



Bundle flows with same destination

$O((|\mathcal{V}_R|^2 T)(|\mathcal{E}_R| + |\mathcal{S}|)CT)$

$O(|\mathcal{V}_R|(|\mathcal{E}_R| + |\mathcal{S}|)CT)$

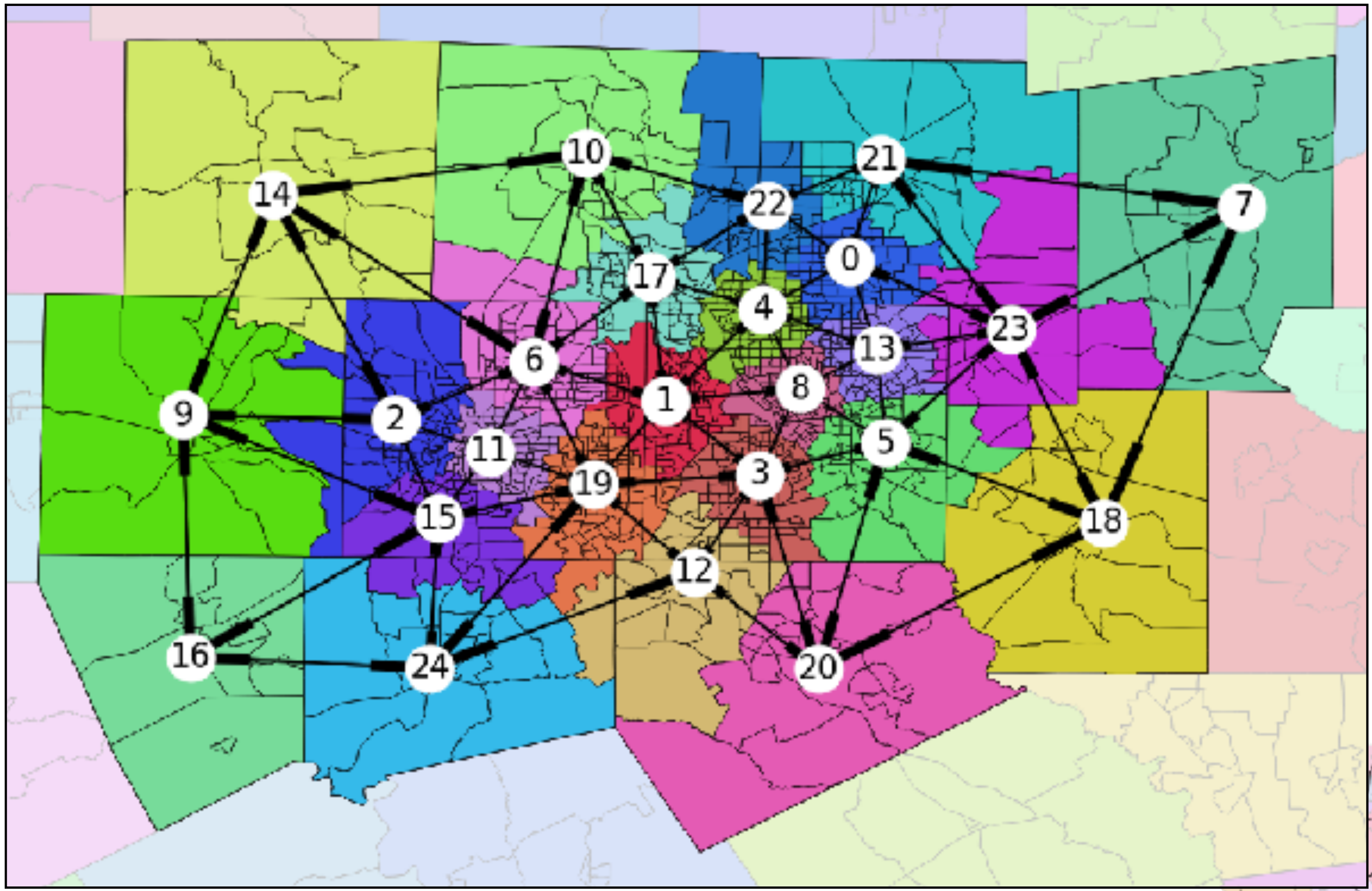
$O(10^{10})$ variables

$O(10^7)$ variables

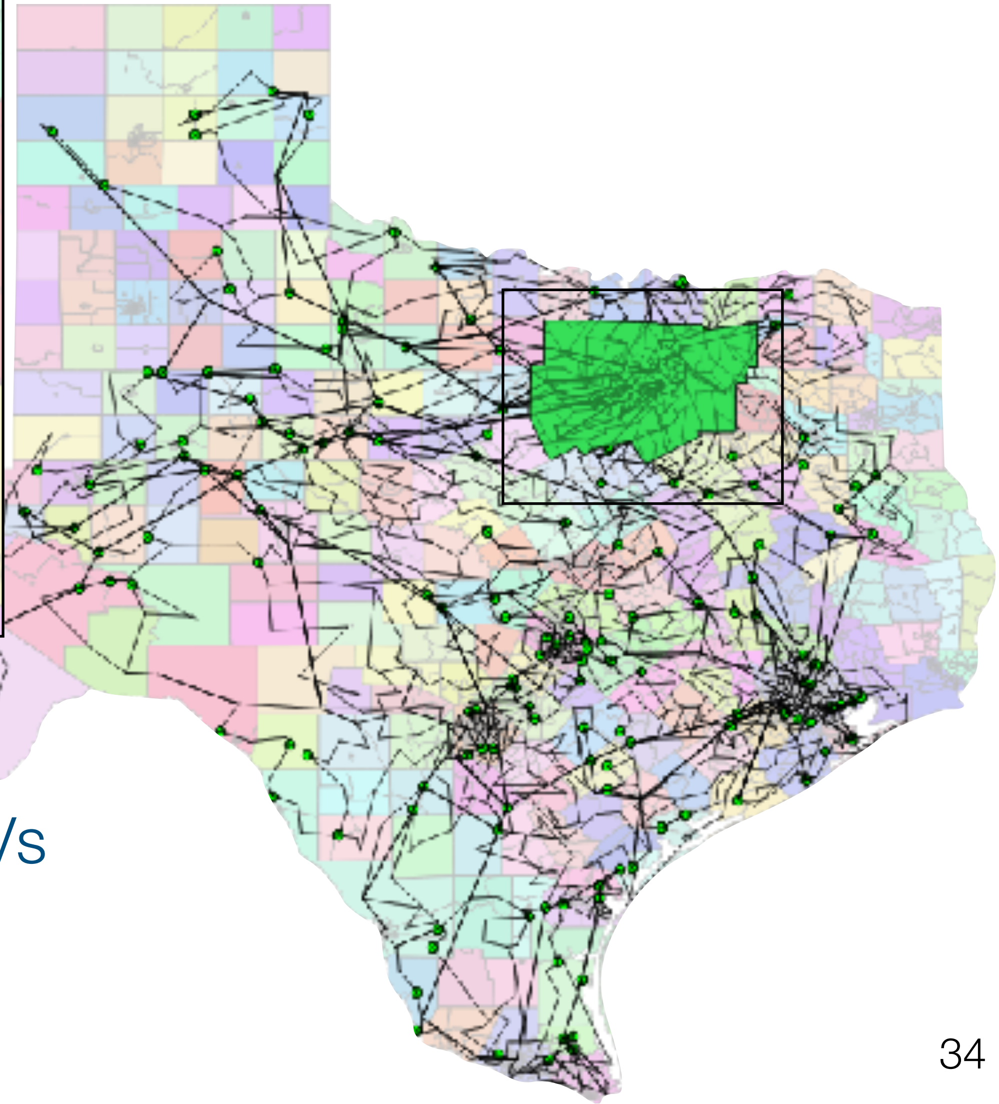
Flow decomposition algorithm

Theorem: flow bundling is lossless

Case study: Dallas-Fort Worth



Power network
282 generators
2007 buses
2481 transmission lines

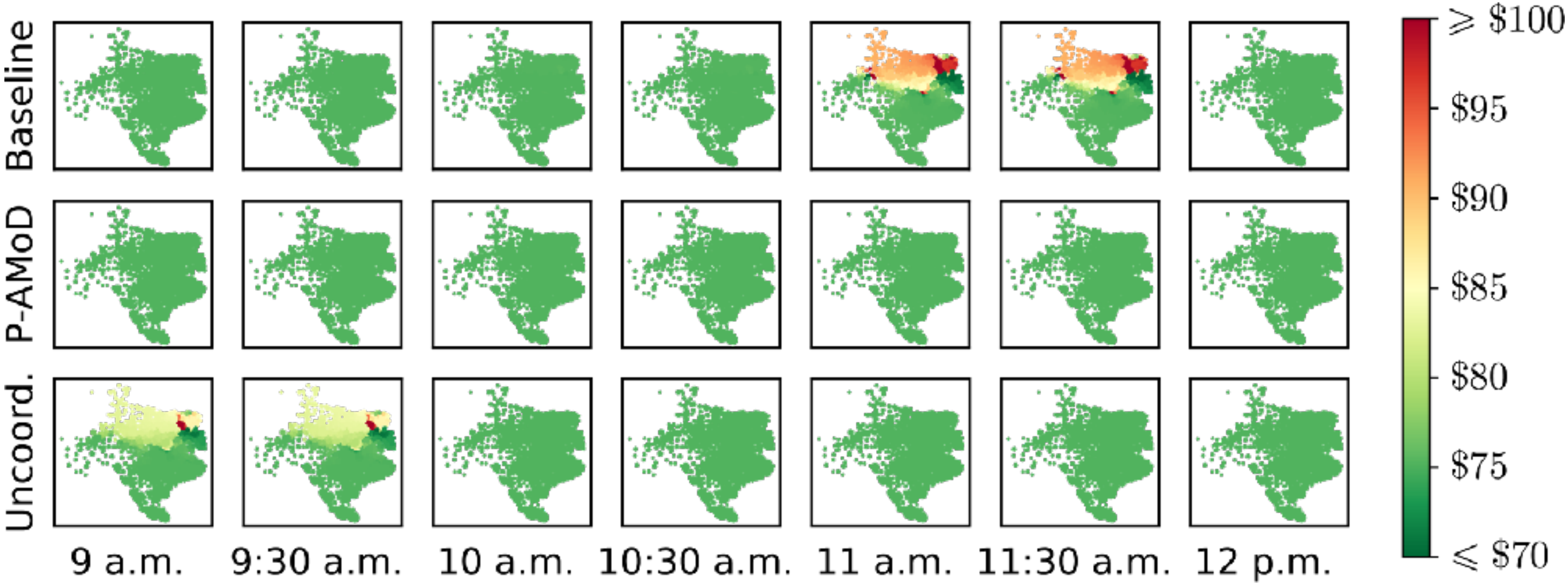


Road network
25 nodes
173 road links
30 charge levels

Trips
10 hours
6250 O-D-T pairs
400,000 customers

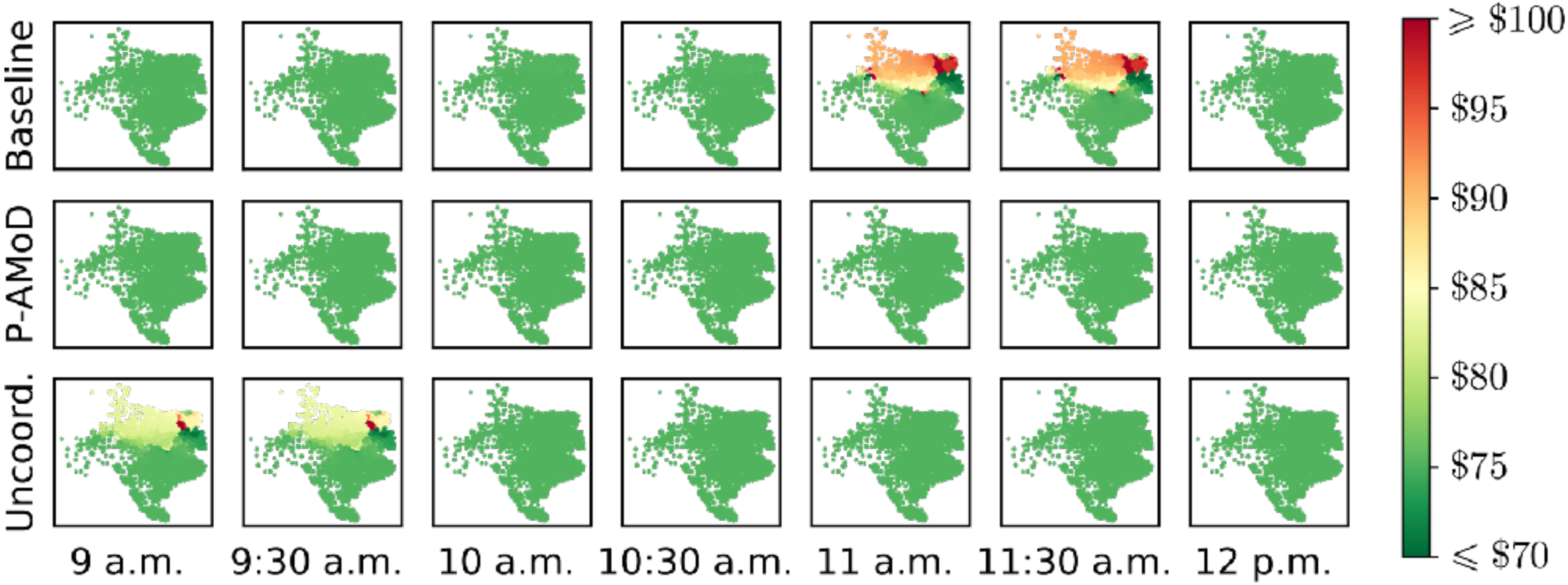
EV fleet
150,000 EVs

Experimental results



	No cars	P-AMoD	Uncoordinated
Avg. passenger travel time	-	1h15m11s	1h15m11s
Tot. energy demand [GWh]	517.498	520.541	520.979
Tot. electricity expenditure [k$]	39,604.71	39,264.84	39,629.50
w.r.t. no cars [k$]	-	**-339.87**	+24.79
Avg. power price in DFW [$/MWh]	78.68	**75.79**	77.47
TSO tot. elec. expenditure [k$]	-	**227.98**	296.82

Experimental results



Coordination **does not affect** passenger **travel times**

Coordination **reduces** the total price of electricity w.r.t. baseline, despite extra demand!

TSO: **23.5% lower** electricity bill **($35M/year)**

Local power network customers: **2.2% lower** electricity bill **($122M/year)**

Self-interested actors

Why would a **self-interested** transportation system operator (TSO) optimize for **social welfare**?

Theorem: the social optimum is a Nash equilibrium

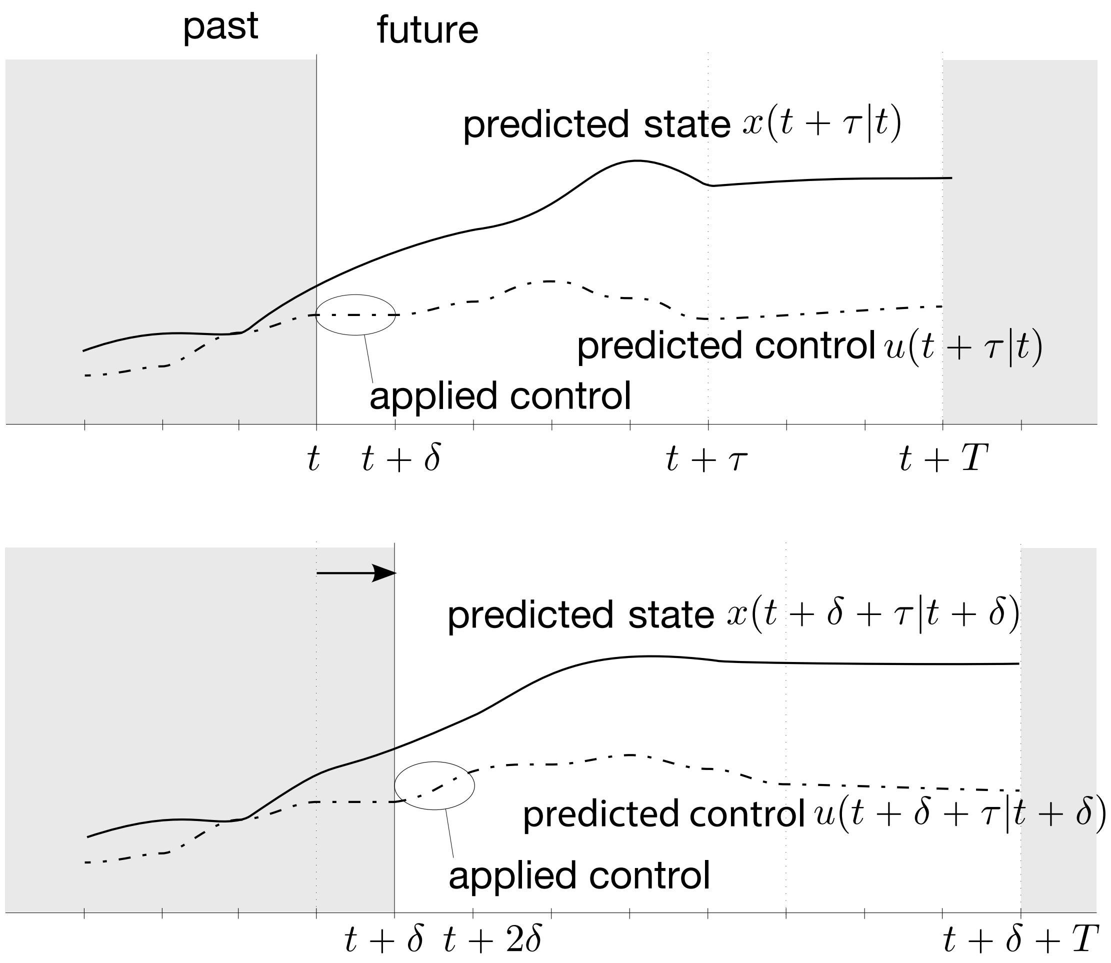
For TSO, optimal charging schedule is the **best response** to given electricity prices (and vice versa).

Theorem: the equilibrium can be computed without sharing private information

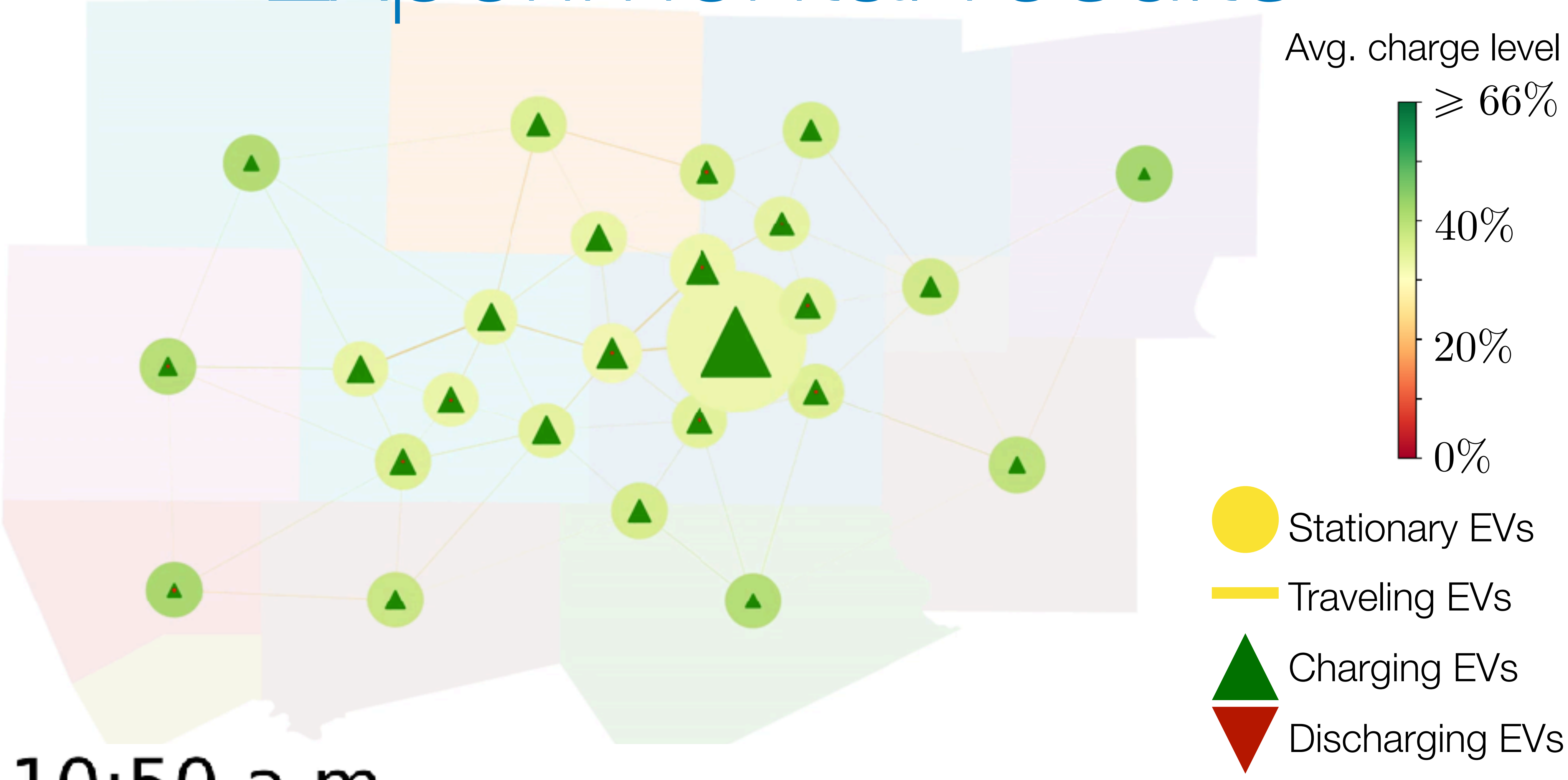
TSO and ISO can compute the optimum with a **dual decomposition** algorithm. Only **public information** (price of electricity and charging schedule) is shared.

A real-time P-AMoD algorithm

- **Assumption**: customer-carrying vehicles always follow **shortest route**; **no charging** when customers on board
- **Suboptimal**, but **fast** (1h→ 1m)
- **Receding-horizon** implementation
- Fractional output is **sampled**



Experimental results



10:50 a.m.

TSO: **13.9% lower** electricity bill **($16M/year)**
Total electricity expenditure **reduced** by **75M/year** w.r.t. greedy
Local power network customers: **0.88% lower** electricity bill

Conclusions

AMoD systems do not increase congestion if properly routed

- Capacitated network flow model with theoretical guarantees
- Model-predictive control algorithm
- 22% reduction in customer wait times compared to baseline algorithm (NYC)

AMoD systems can act as mobile storage units in the power network

- Joint model for AMoD systems and power network
- Control algorithm: efficient *socially optimal* solution with bundling
- Socially optimal solution is a Nash equilibrium, can be computed with no private information
- Cooperation reduces in 23% lower electricity price for TSO, $120M in savings for power network customers (DFW)

Future research directions

- Customer demand **prediction**
- **Stochastic control** of AMoD systems
- How should AMoD systems interact with **public transportation**?
- Will AMoD systems foster adoption of **renewable** energy sources?
- What will the effect of AMoD systems on **pollution** be?

Acknowledgements

This research was supported by the National Science Foundation under CAREER Award CMMI-1454737, by the Toyota Research Institute (TRI), and by the Office of Naval Research (ONR).

Acknowledgements

Thanks!

Contact: hello@federico.io

Thanks!

Contact: hello@federico.io

Thanks!

Contact: hello@federico.io

References

[Ahuja et al., 1993] Ahuja, R. K., Magnanti, T. L., and Orlin, J. B. (1993). *Network Flows: Theory, Algorithms and Applications*. Prentice Hall.

[Alizadeh et al., 2016] Alizadeh, M., Wai, H.-T., Chowdhury, M., Goldsmith, A., Scaglione, A., and Javidi, T. (2016). Joint management of electric vehicles in coupled power and transportation networks. *IEEE Transactions on Control of Network Systems*. In press.

[Alizadeh et al., 2014] Alizadeh, M., Wai, H.-T., Scaglione, A., Goldsmith, A., Fan, Y. Y., and Javidi, T. (2014). Optimized path planning for electric vehicle routing and charging. In *Allerton Conf. on Communications, Control and Computing*.

[Balmer et al., 2009] Balmer, M., Rieser, M., Meister, K., Charypar, D., Lefebvre, N., and Nagel, K. (2009). MATSim-t: Architecture and simulation times. In *Multi-Agent Systems for Traffic and Transportation Engineering*, chapter 3.

[Barnard, 2016] Barnard, M. (2016). Autonomous cars likely to increase congestion. Available at `http://cleantechnica.com/2016/01/17/autonomous-cars-likely-increase-congestion`.

[Barth and Todd, 1999] Barth, M. and Todd, M. (1999). Simulation model performance analysis of a multiple station shared vehicle system. *Transportation Research Part C: Emerging Technologies*, 7(4):237–259.

[Berbeglia et al., 2010] Berbeglia, G., Cordeau, J.-F., and Laporte, G. (2010). Dynamic pickup and delivery problems. *European Journal of Operational Research*, 202(1):8–15.

[Bertsekas, 1999] Bertsekas, D. (1999). *Nonlinear programming*. Athena Scientific, 2 edition. [Boeing, 2017] Boeing, G. (2017). OSMnx: New methods for acquiring, constructing, analyzing, and visualizing complex street networks. *Computers, Environment and Urban Systems*. Forthcoming. [Bureau of Public Roads, 1964] Bureau of Public Roads (1964). Traffic assignment manual. Technical report, U.S. Department of Commerce, Urban Planning Division.

[Bureau of Transportation Statistics, 2016] Bureau of Transportation Statistics (2016). National transportation statistics. Technical report, U.S. Department of Transportation.

[Chevrolet, 2017] Chevrolet (2017). Bolt EV. Available at `http://www.chevrolet.com/ bolt-ev-electric-vehicle`.

[Daganzo, 1994] Daganzo, C. F. (1994). The cell transmission model: A dynamic representation of highway traffic consistent with the hydrodynamic theory. *Transportation Research Part B: Methodological*, 28(4):269–287.

[Dubhashi and Ranjan, 1996] Dubhashi, D. P. and Ranjan, D. (1996). Balls and bins: A study in negative dependence. *BRICS Report Series*, 3(25):1–27.

[EIA, 2017] EIA (2017). Levelized cost and levelized avoided cost of new generation resources in the annual energy outlook 2017. Technical report, U.S. Energy Information Administration.

[Electric Reliability Council of Texas (ERCOT), 2017] Electric Reliability Council of Texas (ER- COT) (2017). Grid information. Available at `http://www.ercot.com/gridinfo/`.

[Evarts, 2013] Evarts, E. (2013). Many americans are just a plug away from owning an electric car. `https://www.yahoo.com/news/many-americans-just-plug-away-owning-electric-car-160000286.html`.

[Even et al., 1976] Even, S., Itai, A., and Shamir, A. (1976). On the complexity of timetable and multicommodity flow problems. *SIAM Journal on Computing*, 5(4):691–703.

[Fagnant and Kockelman, 2014] Fagnant, D. J. and Kockelman, K. M. (2014). The travel and envi- ronmental implications of shared autonomous vehicles, using agent-based model scenarios. *Trans- portation Research Part C: Emerging Technologies*, 40:1–13.

[Federal Highway Administration, 2014] Federal Highway Administration (2014). Census Trans- portation Planning Products (CTTP) 2006-2010 Census Tract Flows. Technical report, U.S. Department of Transportation.

[Ford and Fulkerson, 1962] Ford, L. R. and Fulkerson, D. R. (1962). *Flows in Networks*. Princeton University Press.

[Glover et al., 2011] Glover, J., Sarma, M., and Overbye, T. (2011). *Power System Analysis and Design*. Cengage Learning, fifth edition.

[Goeke and Schneider, 2015] Goeke, D. and Schneider, M. (2015). Routing a mixed fleet of electric and conventional vehicles. *European Journal of Operational Research*, 245(1):81–99.

[Khodayar et al., 2013] Khodayar, M. E., Wu, L., and Li, Z. (2013). Electric vehicle mobility in transmission-constrained hourly power generation scheduling. *IEEE Transactions on Smart Grid*, 4(2):779–788.

[Kirschen and Strbac, 2004] Kirschen, D. S. and Strbac, G. (2004). *Fundamentals of Power System Economics*. John Wiley & Sons, first edition.

[Le et al., 2015] Le, T., Kov´acs, P., Walton, N., Vu, H. L., Andrew, L. L. H., and Hoogendoorn, S. S. P. (2015). Decentralized signal control for urban road networks. *Transportation Research Part C: Emerging Technologies*, 58:431–

References

[Leighton et al., 1995] Leighton, T., Makedon, F., Plotkin, S., Stein, C., Tardos, É., and Tragoudas, S. (1995). Fast approximation algorithms for multicommodity flow problems. *Journal of Computer and System Sciences*, 50(2):228–243.

[Levin et al., 2017] Levin, M. W., Kockelman, K. M., Boyles, S. D., and Li, T. (2017). A general framework for modeling shared autonomous vehicles with dynamic network-loading and dynamic ride-sharing application. *Computers, Environment and Urban Systems*, 64:373 – 383.

[Levin et al., 2016] Levin, M. W., Li, T., Boyles, S. D., and Kockelman, K. M. (2016). A general framework for modeling shared autonomous vehicles. In *95th Annual Meeting of the Transportation Research Board.*

[Lighthill and Whitham, 1955] Lighthill, M. J. and Whitham, G. B. (1955). On kinematic waves. II. a theory of traffic flow on long crowded roads. *Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, 229(1178):317–345.

[Liu et al., 2009] Liu, H., Tesfatsion, L., and A., C. A. (2009). Derivation of locational marginal prices for restructured wholesale power markets. *Journal of Energy Markets*, 2(1):3–27.

[Maciejewski and Bischoff, 2017] Maciejewski, M. and Bischoff, J. (2017). Congestion effects of autonomous taxi fleets. *Transport.* (submitted).

[Maciejewski et al., 2017] Maciejewski, M., Bischoff, J., Hrl, S., and Nagel, K. (2017). Towards a testbed for dynamic vehicle routing algorithms. In *International Conference on Practical Appli- cations of Agents and Multi-Agent Systems - Workshop on the application of agents to passenger transport (PAAMS-TAAPS).* Submitted.

[Mitchell et al., 2010] Mitchell, W. J., Borroni-Bird, C. E., and Burns, L. D. (2010). *Reinventing the automobile: Personal urban mobility for the 21st century.* MIT Press.

[Mittelmann, 2016] Mittelmann, H. D. (2016). Decision tree for optimization software.

[Mitzenmacher and Upfal, 2005] Mitzenmacher, M. and Upfal, E. (2005). *Probability and computing: Randomized algorithms and probabilistic analysis.* Cambridge University Press.

[Neuburger, 1971] Neuburger, H. (1971). The economics of heavily congested roads. *Transportation Research*, 5(4):283–293.

[OECD, 2014] OECD (2014). The cost of air pollution - health impacts of road transport. Technical report, Organisation for Economic Co-operation and Development (OECD).

[O'Neill et al., 2011] O'Neill, R. P., Dautel, T., and Krall, E. (2011). Recent ISO software enhance- ments and future software and modeling plans. Technical report, Federal Energy Regulatory Commission.

[Osorio and Bierlaire, 2009] Osorio, C. and Bierlaire, M. (2009). An analytic finite capacity queue- ing network model capturing the propagation of congestion and blocking. *European Journal of Operational Research*, 196(3): 996–1007.

[Overbye et al., 2004] Overbye, T. J., Cheng, X., and Sun, Y. (2004). A comparison of the AC and DC power flow models for LMP calculations. In *Hawaii International Conference on System Sciences.*

[Papageorgiou et al., 1991] Papageorgiou, M., Hadj-Salem, H., and Blosseville, J.-M. (1991). ALINEA: A local feedback control law for on-ramp metering. *Transportation Research Record: Journal of the Transportation Research Board*, (1320):58–64.

[Pavone et al., 2011] Pavone, M., Smith, S. L., Frazzoli, E., and Rus, D. (2011). Load balancing for Mobility-on-Demand systems. In *Robotics: Science and Systems.*

[Pavone et al., 2012] Pavone, M., Smith, S. L., Frazzoli, E., and Rus, D. (2012). Robotic load balancing for Mobility-on-Demand systems. *Int. Journal of Robotics Research*, 31(7):839–854.

[Peeta and Mahmassani, 1995] Peeta, S. and Mahmassani, H. S. (1995). System optimal and user equilibrium time-dependent traffic assignment in congested networks. *Annals of Operations Re- search*, 60(1):81–113.

[Pérez et al., 2010] Pérez, J., Seco, F., Milanés, V., Jiménez, A., Díaz, J. C., and De Pedro, T. (2010). An RFID-based intelligent vehicle speed controller using active traffic signals. *Sensors*, 10(6):5872–5887.

[Pourazarm et al., 2016] Pourazarm, S., Cassandras, C. G., and Wang, T. (2016). Optimal routing and charging of energy-limited vehicles in traffic networks. *Int. Journal of Robust and Nonlinear Control*, 26(6):1325–1350.

[Raghavan and Tompson, 1987] Raghavan, P. and Tompson, C. D. (1987). Randomized rounding: A technique for provably good algorithms and algorithmic proofs. *Combinatorica*, 7(4):365–374.

References

[Rossi et al., 2017a] Rossi, F., Iglesias, R., Zhang, R., and Pavone, M. (2017a). Congestion- aware randomized routing in autonomous mobility-on-demand systems. Extended version available at `https://asl.stanford.edu/wp-content/papercite-data/pdf/Rossi.Iglesias. Zhang.Pavone.CDC17.pdf`.

[Rossi et al., 2017b] Rossi, F., Zhang, R., Hindy, Y., and Pavone, M. (2017b). Routing autonomous vehicles in congested transportation networks: structural properties and coordination algorithms. *Autonomous Robots*. Submitted.

[Rotering and Ilic, 2011] Rotering, N. and Ilic, M. (2011). Optimal charge control of plug-in hy- brid electric vehicles in deregulated electricity markets. *IEEE Transactions on Power Systems*, 26(3):1021–1029.

[Seow et al., 2010] Seow, K. T., Dang, N. H., and Lee, D. H. (2010). A collaborative multiagent taxi-dispatch system. *IEEE Transactions on Automation Sciences and Engineering*, 7(3):607–616.

[Sioshansi, 2012] Sioshansi, R. (2012). OR Forum—modeling the impacts of electricity tariffs on plug-in hybrid electric vehicle charging, costs, and emissions. *Operations Research*, 60(3):506- 516.

[Smith et al., 2013] Smith, S. L., Pavone, M., Schwager, M., Frazzoli, E., and Rus, D. (2013). Rebal- ancing the rebalancers: Optimally routing vehicles and drivers in Mobility-on-Demand systems. In *American Control Conference*.

[Spieser et al., 2014] Spieser, K., Treleaven, K., Zhang, R., Frazzoli, E., Morton, D., and Pavone, M. (2014). Toward a systematic approach to the design and evaluation of Autonomous Mobility- on-Demand systems: A case study in Singapore. In *Road Vehicle Automation*. Springer.

[Srinivasan, 1999] Srinivasan, A. (1999). A survey of the role of multicommodity flow and random- ization in network design and routing. In *Randomization Methods in Algorithm Design*.

[Stott et al., 2009] Stott, B., Jardim, J., and Alsa¸c, O. (2009). DC power flow revisited. *IEEE Transactions on Power Systems*, 24(3):1290–1300.

[Templeton, 2010] Templeton, B. (2010). Traffic congestion & capacity. Available at `http://www. templetons.com/brad/robocars/congestion.html`.

[Treiber et al., 2000] Treiber, M., Hennecke, A., and Helbing, D. (2000). Microscopic simulation of congested traffic. In *Traffic and Granular Flow '99*. Springer Berlin Heidelberg.

Treleaven et al., 2011] Treleaven, K., Pavone, M., and Frazzoli, E. (2011). An asymptotically opti- mal algorithm for pickup and delivery problems. In *Proc. IEEE Conf. on Decision and Control*.

[Treleaven et al., 2012] Treleaven, K., Pavone, M., and Frazzoli, E. (2012). Models and efficient algorithms for pickup and delivery problems on roadmaps. In *Proc. IEEE Conf. on Decision and Control*.

[Treleaven et al., 2013] Treleaven, K., Pavone, M., and Frazzoli, E. (2013). Asymptotically opti- mal algorithms for one-to-one pickup and delivery problems with applications to transportation systems. *IEEE Transactions on Automatic Control*, 58(9):2261–2276.

[Turitsyn et al., 2010] Turitsyn, K., Sinitsyn, N., Backhaus, S., and Chertkov, M. (2010). Robust broadcast-communication control of electric vehicle charging. In *IEEE International Conference on Smart Grid Communications (SmartGridComm)*.

[Tushar et al., 2012] Tushar, W., Saad, W., Poor, H. V., and Smith, D. B. (2012). Economics of electric vehicle charging: A game theoretic approach. *IEEE Transactions on Power Systems*, 3(4):1767–1778.

[United States Census Bureau, 2017] United States Census Bureau (2017). American Community Survey. Commuting in the United States: 2009. Supplemental Table B: Time of Departure. Avail- able at `https://www.census.gov/hhes/commuting/data/commuting.html`.

[Urmson, 2014] Urmson, C. (2014). Just press go: Designing a self-driving vehicle. Available at `http://googleblog.blogspot.com/2014/05/just-press-go-designing-self-driving. html`.

[U.S. Department of Transportation, 2015] U.S. Department of Transportation (2015). Revised de- partmental guidance on valuation of travel time in economic analysis. Technical report.

[Wang et al., 2010] Wang, L., Lin, A., and Chen, Y. (2010). Potential impact of recharging plug-in hybrid electric vehicles on locational marginal prices. *Naval Research Logistics*, 57(8):686–700.

[Wardrop, 1952] Wardrop, J. G. (1952). Some theoretical aspects of road traffic research. *Proceedings of the Institution of Civil Engineers*, 1(3):325–362.

[Wilkie et al., 2014] Wilkie, D., Baykal, C., and Lin, M. C. (2014). Participatory route planning. In *ACM SIGSPATIAL*.

[Wilkie et al., 2011] Wilkie, D., van den Berg, J. P., Lin, M. C., and Manocha, D. (2011). Self-aware traffic route planning. In *Proc. AAAI Conf. on Artificial Intelligence*.

[World Health Organization (WHO), 2014] World Health Organization (WHO) (2014). 7 million premature deaths annually linked to air pollution. `http://www.who.int/mediacentre/news/ releases/2014/air-pollution/en/`.

References

[Xiao et al., 2015] Xiao, N., Frazzoli, E., Luo, Y., Li, Y., Wang, Y., and Wang, D. (2015). Through- put optimality of extended back-pressure traffic signal control algorithm. In *Mediterranean Conf. on Control and Automation*.

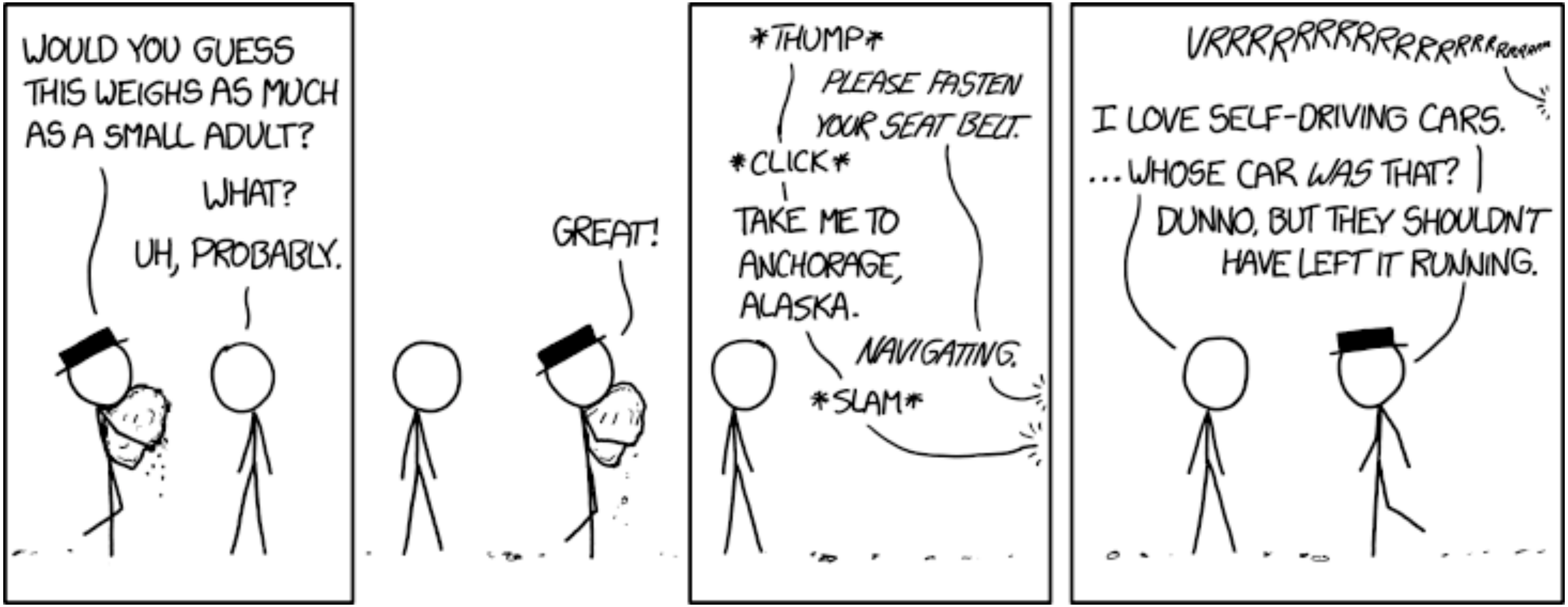
[Yang and Koutsopoulos, 1996] Yang, Q. and Koutsopoulos, H. N. (1996). A microscopic traffic simulator for evaluation of dynamic traffic management systems. *Transportation Research Part C: Emerging Technologies*, 4(3):113–129.

[Zhang and Pavone, 2015] Zhang, R. and Pavone, M. (2015). A queueing network approach to the analysis and control of Mobility-on-Demand systems. In *American Control Conference*.

[Zhang and Pavone, 2016] Zhang, R. and Pavone, M. (2016). Control of robotic Mobility-on- Demand systems: A queueing-theoretical perspective. *Int. Journal of Robotics Research*, 35(1- 3):186–203.

[Zhang et al., 2016a] Zhang, R., Rossi, F., and Pavone, M. (2016a). Model predictive control of Autonomous Mobility-on-Demand systems. In *Proc. IEEE Conf. on Robotics and Automation*.

[Zhang et al., 2016b] Zhang, R., Rossi, F., and Pavone, M. (2016b). Routing autonomous vehicles in congested transportation networks: Structural properties and coordination algorithms. In *Robotics: Science and Systems*.



xkcd.com/1559

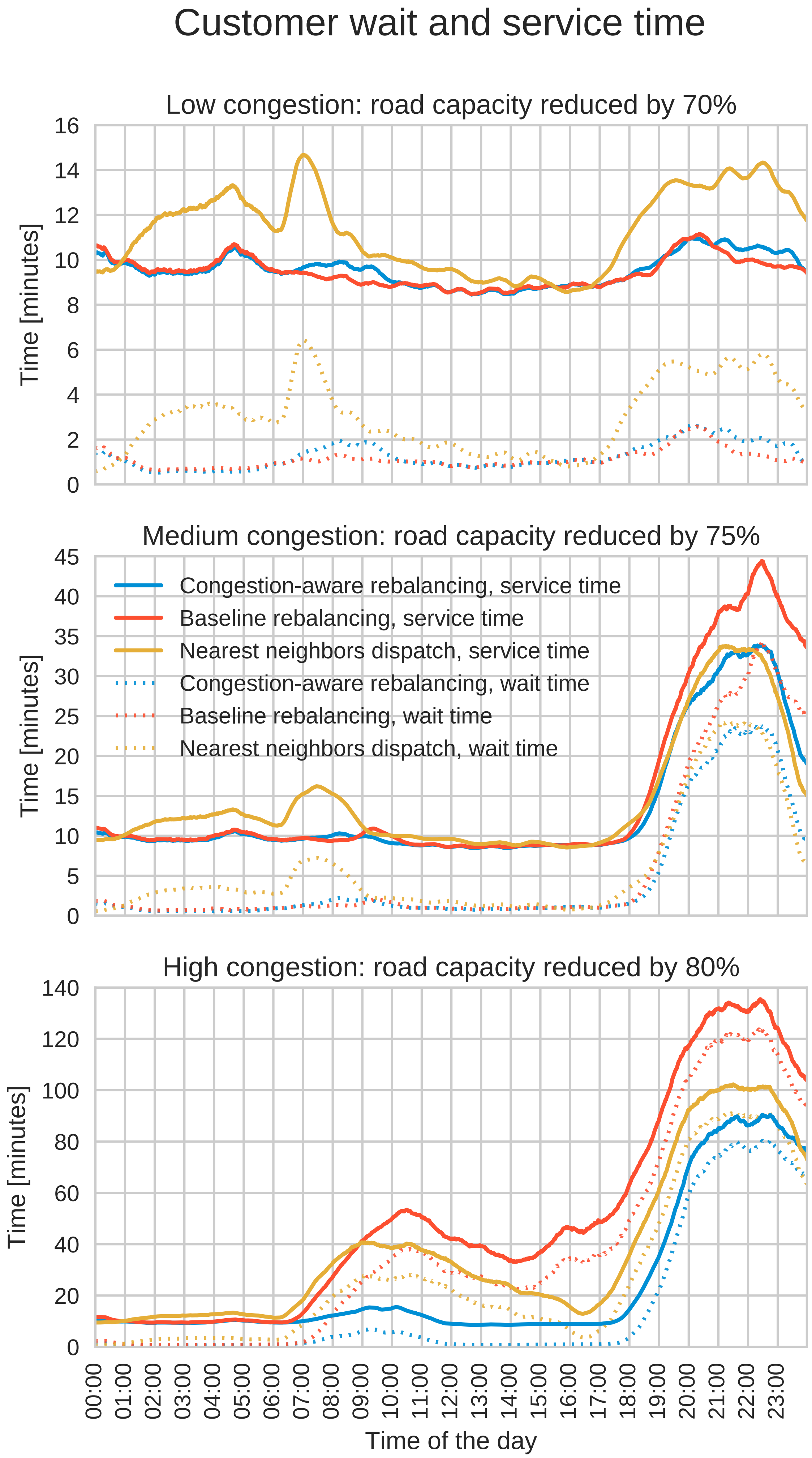
UPCOMING AND RECENTLY-ACHIEVED

SELF-DRIVING CAR MILESTONES

- AUTOMATIC EMERGENCY BRAKING
- HIGHWAY LANE-KEEPING
- SELF-PARKING
- FULL HIGHWAY AUTONOMY
- FIRST SEX IN A SELF-DRIVING CAR
- FULL TRIPS WITH NO INPUT FROM DRIVER
- FULL TRIPS BY EMPTY CARS
- SELF-REFUELING OF EMPTY CARS
- AN EMPTY CAR WANDERING THE HIGHWAYS FOR MONTHS OR YEARS UNTIL SOMEONE NOTICES THE CREDIT CARD FUEL CHARGES
- CARS THAT READ OTHER CARS' BUMPER STICKERS BEFORE DECIDING WHETHER TO CUT THEM OFF
- AUTONOMOUS ENGINE REVVING AT RED LIGHTS
- SELF-LOATHING CARS
- AUTONOMOUS CANYON JUMPING
- CARS CAPABLE OF ARGUING ABOUT THE TROLLEY PROBLEM ON FACEBOOK

xkcd.com/1925

More results on congestion



P-AMoD: full results

```
Price paid by the TSO
   coordinated:  227977.072133
 uncoordinated:  296817.428591
Unit price paid by the TSO
   coordinated:  7491.27746558
 uncoordinated:  8526.40186212
Price paid by all
      ISO only:  39604707.8459
   coordinated:  39264836.8294
 uncoordinated:  39629497.7003
Price paid by all per 100 KW
      ISO only:  7653.10996073
   coordinated:  7543.07587502
 uncoordinated:  7606.73059846
Price paid by everyone else
      ISO only:  39604707.8459
   coordinated:  39036859.7572
 uncoordinated:  39332680.2717
Price per hundred KW paid by everyone else
      ISO only:  7653.10996073
   coordinated:  7543.3804841
 uncoordinated:  7600.54406513


Cost of generation
     ISO only:  40529884.5782
  coordinated:  40756002.7821
uncoordinated:  40917155.1849
Cost of generation per hundred KW
     ISO only:  7831.88868807
  coordinated:  7829.54027502
uncoordinated:  7853.89153051


Price paid by all in Dallas
      ISO only:  12832491.2268
   coordinated:  12591742.8793
 uncoordinated:  12905202.0542
Price per hundred KW paid by all in Dallas
      ISO only:  7868.57561461
   coordinated:  7579.51783894
 uncoordinated:  7747.77901222
Price paid by everyone else in Dallas
      ISO only:  12832491.2268
   coordinated:  12363765.8072
 uncoordinated:  12608384.6256
Price per hundred KW paid by everyone else in Dallas
      ISO only:  7868.57561461
   coordinated:  7581.16443766
 uncoordinated:  7731.15882576
Price paid by everyone else NOT in Dallas
      ISO only:  26772216.6191
   coordinated:  26673093.95
 uncoordinated:  26724295.6461
Price per hundred KW paid by everyone else NOT in Dallas
      ISO only:  7553.96209363
   coordinated:  7525.99396176
 uncoordinated:  7540.44086681
Price paid by all at charging nodes
      ISO only:  2243271.04358
   coordinated:  2390693.73131
 uncoordinated:  2501941.65175
Price per hundred KW paid by all at charging nodes
      ISO only:  7862.43259969
   coordinated:  7571.53715428
 uncoordinated:  7815.47304232
Price paid by everyone else at charging nodes
      ISO only:  2243271.04358
   coordinated:  2162716.65918
 uncoordinated:  2205124.22316
Price per 100 KW paid by everyone else at charging nodes
      ISO only:  7862.43259969
   coordinated:  7580.09782801
 uncoordinated:  7728.73194622
```

https://phobos.stanford.edu:8899/notebooks/AMoD-power/atx/DFW_scenario_prep_Federico.ipynb

SuboptimalLinear model

$$\underset{f_m,\lambda_m^{c,\mathrm{in}},\lambda_m^{c,t,\mathrm{out}},N_F,\theta,p}{\text{minimize}} \quad V_D\left(\sum_{(\mathbf{v},\mathbf{w})\in\mathcal{E}} d_{v_\mathbf{v},v_\mathbf{w}} \sum_{m=0}^{M} f_m(\mathbf{v},\mathbf{w})\right) + \sum_{t=1}^{T}\sum_{g\in\mathcal{G}} o_g(t)p(g,t)$$

subject to

$$\lambda_m^{t,c,\mathrm{out}} = \begin{cases} \lambda_m^{c+c_{v_m\to w_m},\mathrm{in}} & \text{if } t_m = t - t_{v_m\to w_m} \\ 0 & \text{otherwise} \end{cases}$$

$$\forall t\in\{1,\dots,T\}, c\in\{1,\dots,C\}, m\in\{1,\dots,M\},$$

$$\sum_{c=1}^{C}\lambda_m^{c,\mathrm{in}} = \lambda_m, \qquad \forall m\in\{1,\dots,M\},$$

$$\sum_{t=1}^{T}\sum_{c=1}^{C}\lambda_m^{t,c,\mathrm{out}} = \lambda_m, \qquad \forall m\in\{1,\dots,M\},$$

$$\sum_{\mathbf{u}:(\mathbf{u},\mathbf{v})\in\mathcal{E}} f_0(\mathbf{u},\mathbf{v}) + \sum_{m=1}^{M} 1_{v_\mathbf{v}=w_m}\lambda_m^{t_\mathbf{v},c_\mathbf{v},\mathrm{out}} + N_I(\mathbf{v})$$

$$= \sum_{\mathbf{w}:(\mathbf{v},\mathbf{w})\in\mathcal{E}} f_0(\mathbf{v},\mathbf{w}) + \sum_{m=1}^{M} 1_{v_\mathbf{v}=v_m}1_{t_\mathbf{v}=t_m}\lambda_m^{c_\mathbf{v},\mathrm{in}} + N_F(\mathbf{v}), \qquad \forall\mathbf{v}\in\mathcal{V},$$

$$\sum_{c_\mathbf{v}=1}^{M}\left(\sum_{m=0}^{M} f_m(\mathbf{v},\mathbf{w})\right) \leqslant \overline{f}_{(v_\mathbf{v},v_\mathbf{w})}, \qquad \forall(v_\mathbf{v},v_\mathbf{w})\in\mathcal{E}_R, \forall t_\mathbf{v}\in\{1\dots,T\},$$

$$\sum_{\substack{(v,w)\in\mathcal{E}_S:\\ v_\mathbf{v}=v_\mathbf{w}=s,\\ t_\mathbf{v}\leqslant t<t_\mathbf{w}}}\left(\sum_{m=0}^{M} f_m(\mathbf{v},\mathbf{w})\right) \leqslant \overline{S}_s, \qquad \forall s\in\mathcal{S}, t\in\{1,\dots,T\},$$

$$\sum_{(u,v)\in\mathcal{E}_P}\frac{\theta(u,t)-\theta(v,t)}{x_{u,v}} + 1_{v\in\mathcal{G}}p(v,t) = \quad 1_{v\in\mathcal{L}}d_v(t) + \sum_{(v,w)\in\mathcal{E}_P}\frac{\theta(v,t)-\theta(w,t)}{x_{v,w}},$$

$$\forall v\in\mathcal{B}, t\in\{1,\dots,T\},$$

$$-\overline{p}_{b_1,b_2} \leqslant \frac{\theta(b_1,t)-\theta(b_2,t)}{x_{b_1,b_2}} \leqslant \overline{p}_{b_1,b_2}, \qquad \forall(b_1,b_2)\in\mathcal{E}_P, t\in\{1,\dots,T\},$$

$$\underline{p}_g(t) \leqslant p(g,t) \leqslant \overline{p}_g(t), \qquad \forall g\in\mathcal{G}, t\in\{1,\dots,T\},$$

$$-p_g^-(t) \leqslant p(g,t+1) - p(g,t) \leqslant p_g^+(t), \qquad \forall g\in\mathcal{G}, t\in\{1,\dots,T-1\},$$

$$d_l(t)(t) \leqslant \overline{d}_l(t), \qquad \forall l\in\mathcal{L}, t\in\{1,\dots,T\},$$

$$d_l(t) = d_{l,e}(t) + J_C\delta c^+_{\mathcal{M}_{\mathrm{P,R}}(l)} \sum_{(\mathbf{v},\mathbf{w})\in M^+_{P,G}(l,t)}\sum_{m=0}^{M} f_m(\mathbf{v},\mathbf{w})$$

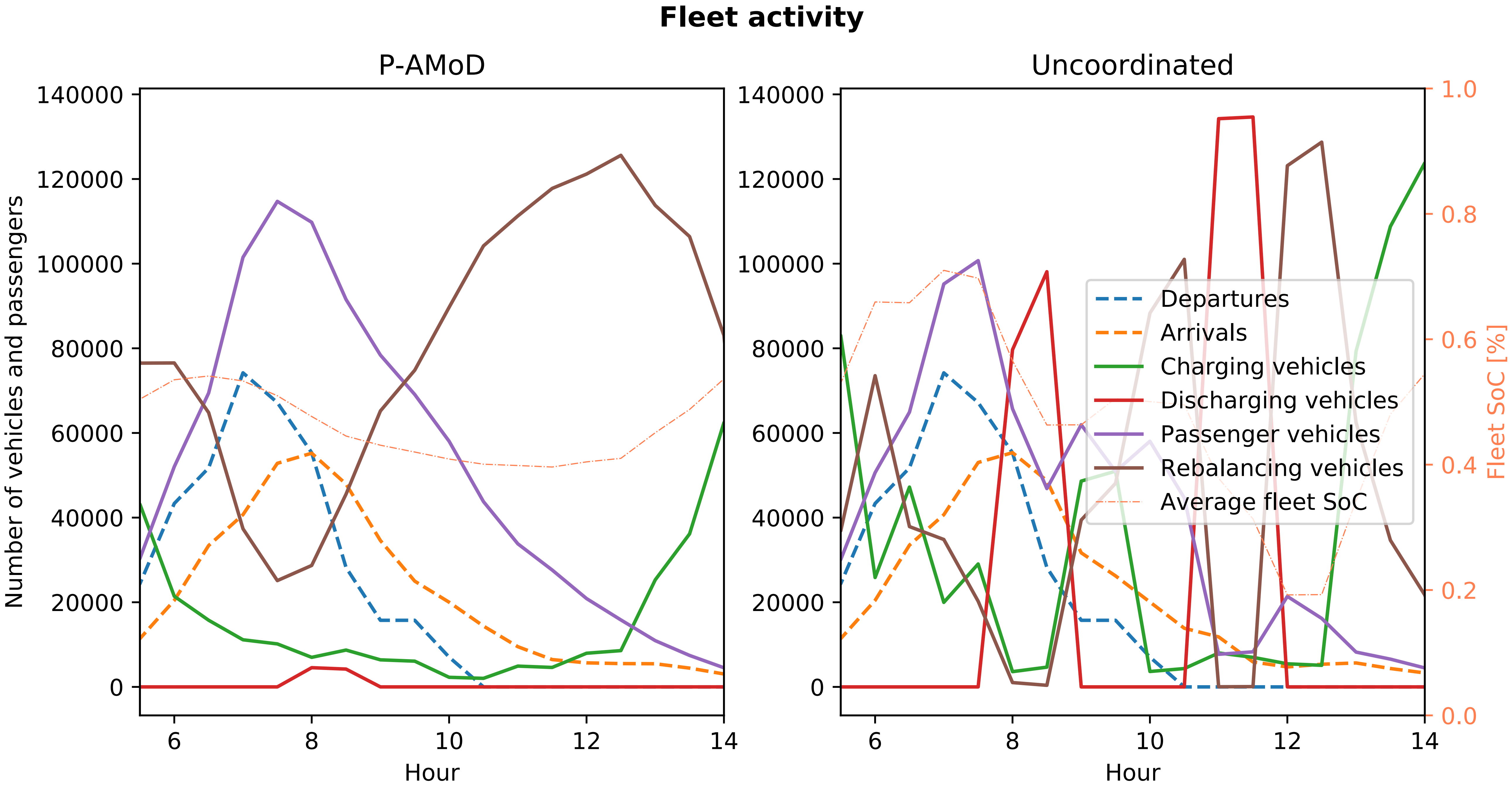
$$+ J_C\delta c^-_{\mathcal{M}_{\mathrm{P,R}}(l)} \sum_{(\mathbf{v},\mathbf{w})\in M^-_{P,G}(l,t)}\sum_{m=1}^{M} f_m(\mathbf{v},\mathbf{w}), \qquad \forall l\in\mathcal{L}, t\in\{1,\dots,T\}.$$

Dual decomposition algorithm

Algorithm 1 Dual decomposition distributed algorithm for the P-AMoD problem

```
$k \leftarrow 1$
ISO sets $\lambda_{\text{ISO}}^{\text{eq},k} \leftarrow$ dual solution to Economic Dispatch problem with $\{d_l\} = \{d_{l,e}\}$.
repeat
    ISO informs TSO of $\lambda_{\text{ISO}}^{\text{eq},k}$
    TSO sets $\{f_m^k, \lambda_m^{c,\text{in},k}, \lambda_m^{t,c,\text{out},k}, N_F^k\} \leftarrow$solution to VRCP Problem with $p_{(\mathbf{v},\mathbf{w})} = \lambda_{\text{ISO}}^{\text{eq},k}$
    ISO sets $\{\theta^k, p^k\} \leftarrow$ solution to Lagrangian relaxation of Economic Dispatch Problem
    TSO informs ISO of proposed charging schedule $f_m^k$.
    ISO updates $\lambda_{\text{ISO}}^{\text{eq},k+1} \leftarrow \lambda_{\text{ISO}}^{\text{eq},k} + \alpha_k f_{\text{ISO}}^{\text{eq}}(f_m^k, \theta^k, p^k)$
    $k \leftarrow k + 1$
until $\|\lambda_{\text{ISO}}^{\text{eq},k+1} - \lambda_{\text{ISO}}^{\text{eq},k}\| \leqslant \varepsilon$
```

Fleet activity: P-AMoD vs uncoordinated



Sensitivity to node-symmetry

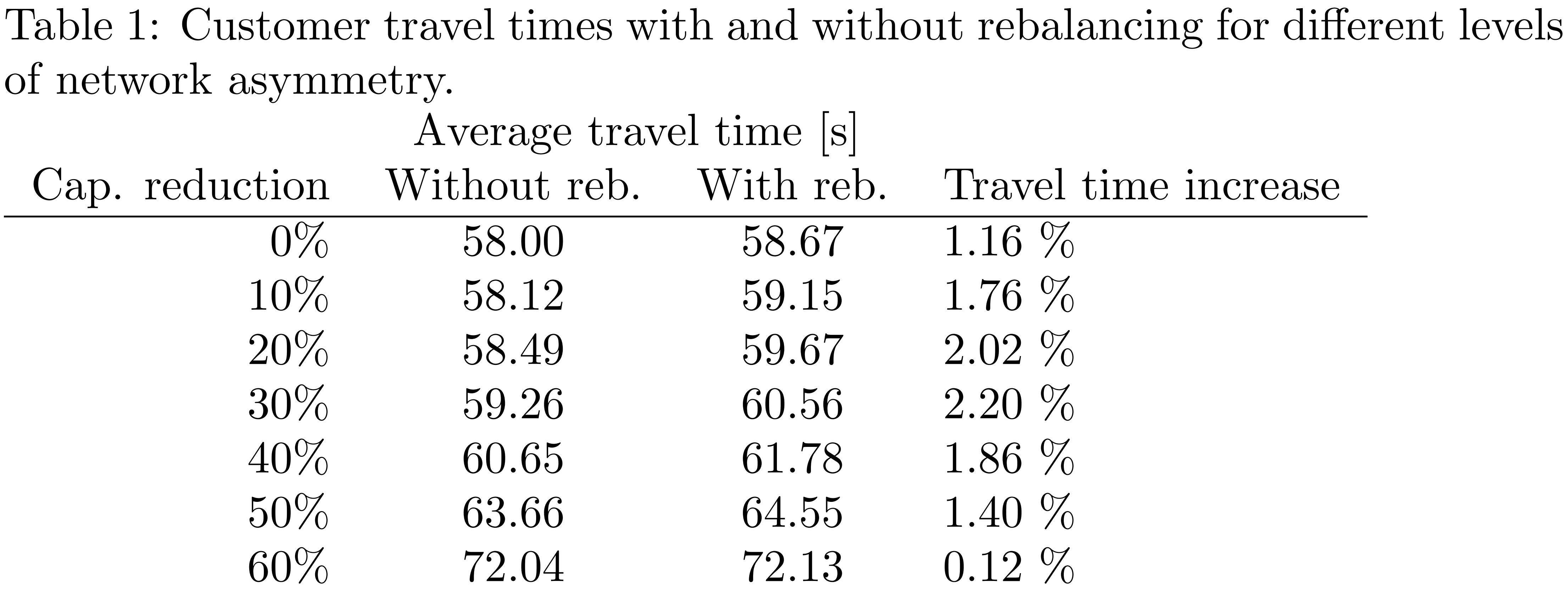
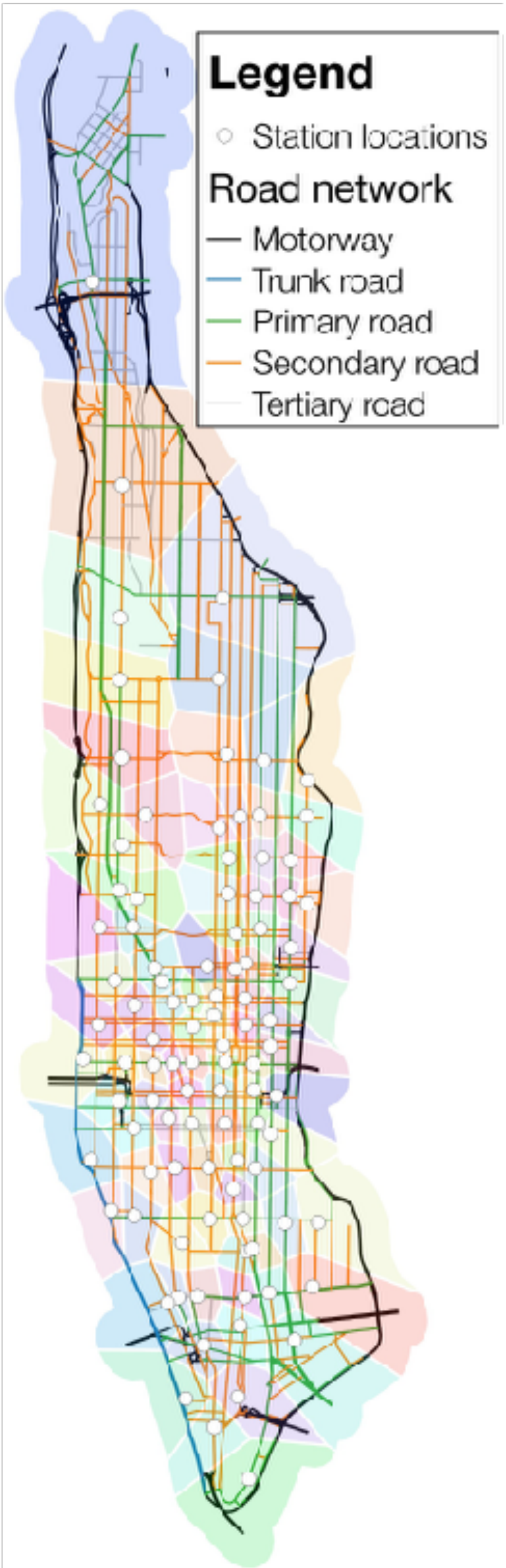


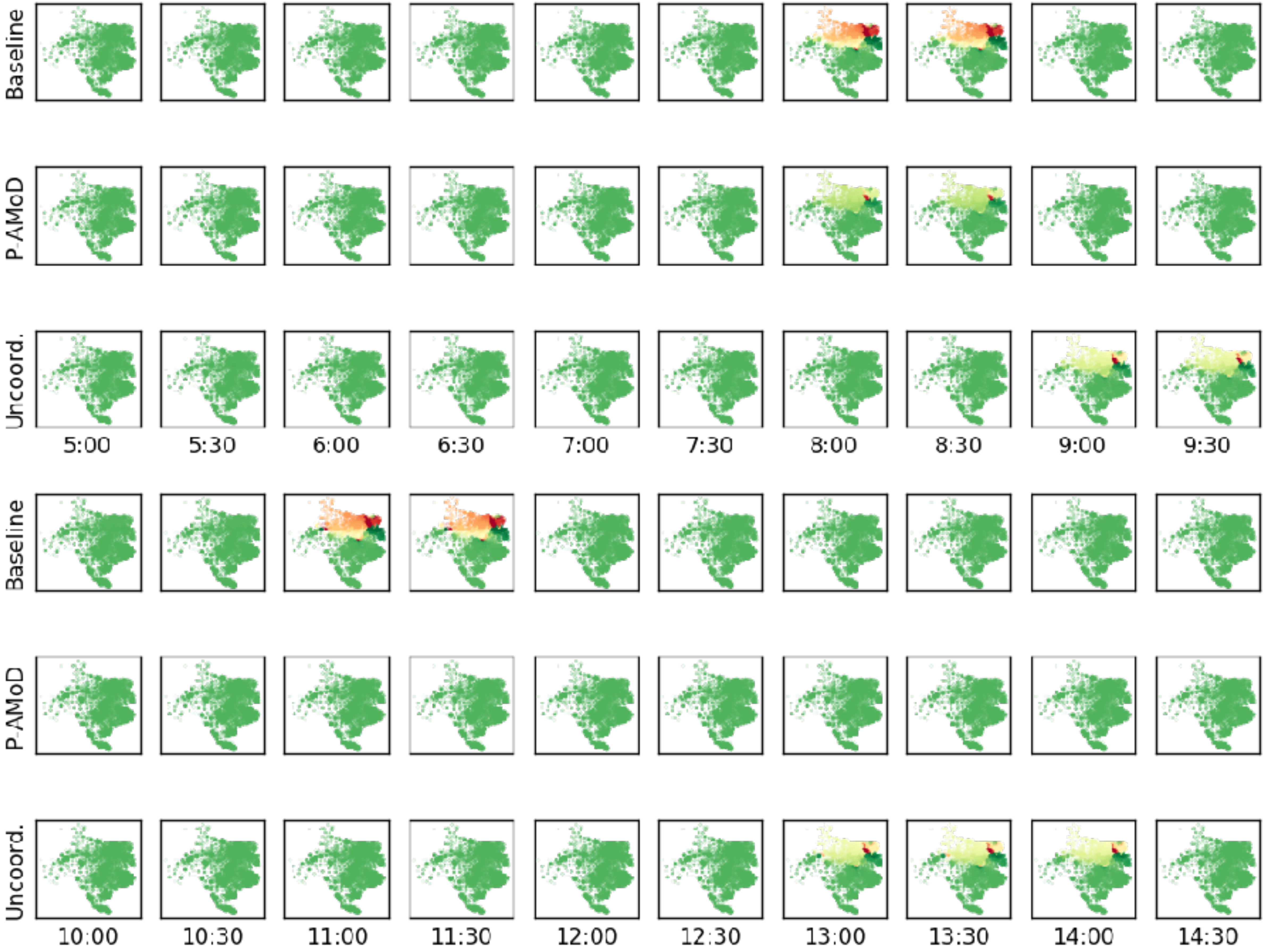
Table 1: Customer travel times with and without rebalancing for different levels of network asymmetry.

	Average travel time [s]		
Cap. reduction	Without reb.	With reb.	Travel time increase
0%	58.00	58.67	1.16 %
10%	58.12	59.15	1.76 %
20%	58.49	59.67	2.02 %
30%	59.26	60.56	2.20 %
40%	60.65	61.78	1.86 %
50%	63.66	64.55	1.40 %
60%	72.04	72.13	0.12 %

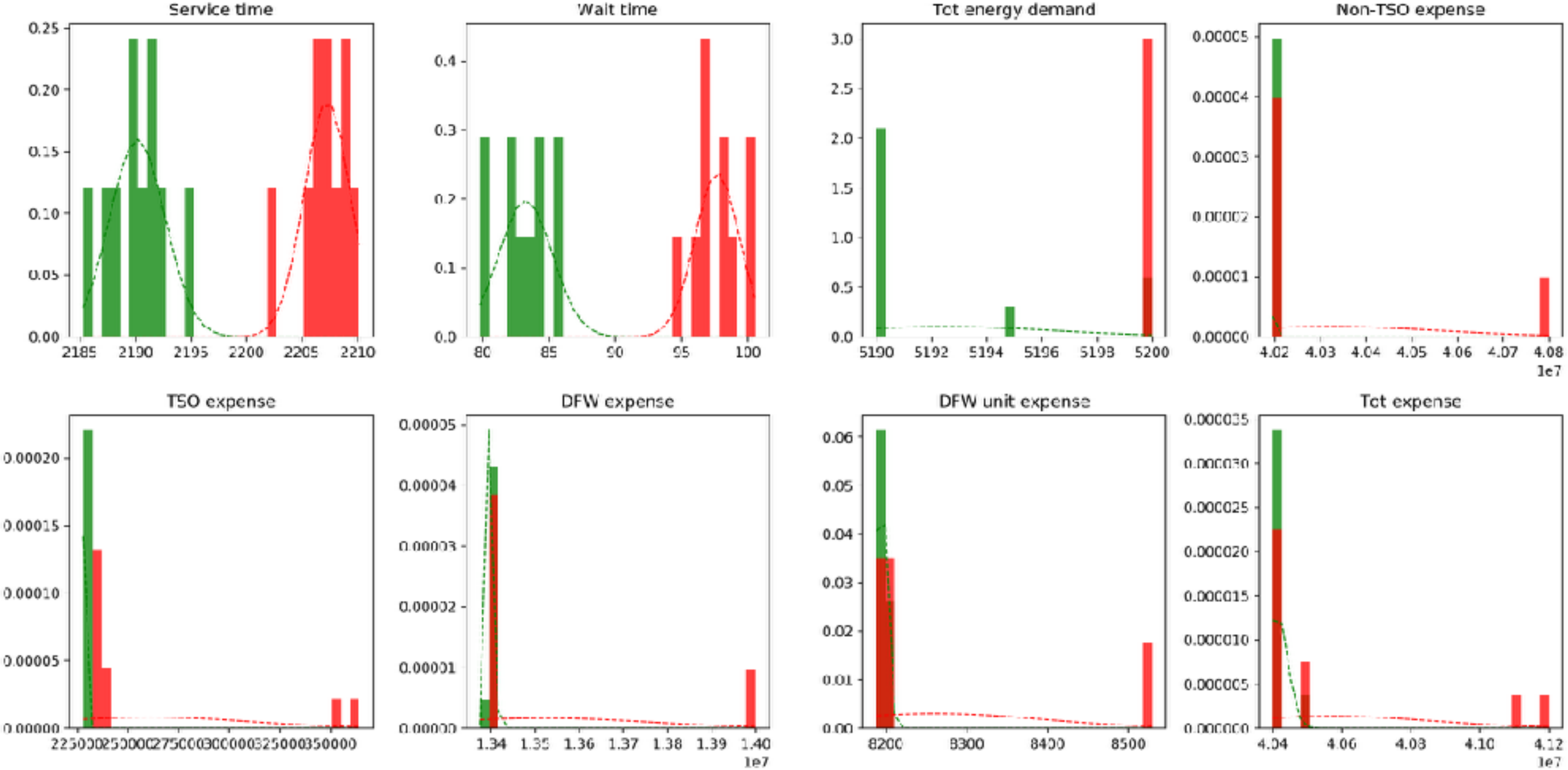
A map of New York



Full P-AMoD results



Receding-horizon P-AMoD



Receding-horizon P-AMoD