

Autonomous and Connected Transportation Systems Modeling, Control, and Deployment

Mauro Salazar, Ramon Iglesias, Stephen Zoepef and Marco Pavone

Overview

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2. What will these new forms of mobility and transportation mean for **society**?

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1. How can we design **profitable** and **sustainable** mobility systems that leverage **autonomous vehicles**?
2. What will these new forms of mobility and transportation mean for **society**?
3. How can we ensure that such technologies benefit all members of society, improving **equity** rather than undermining it?

Goal of the Workshop

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2. Identify **modeling** and **control** methodologies to address them
3. **Share insights** from early deployments and turn such insights into an **actionable research roadmap**

Agenda - Morning

09:00-09:30	Mauro Salazar	Introduction Autonomous Mobility-on-Demand for Future Urban Mobility
09:30-10:00	Krishna Selvam	Ride-sharing Marketplace: Designing from Efficiency
10:00-10:30	Coffee Break	
10:30-11:00	Francesco Ciari	Planning Shared Automated Vehicle Fleets: Specific Modeling Requirements and Concepts to Address Them
11:00-11:30	Raphael Stern	Controlling Mixed Human and Autonomous Traffic
11:30-12:00	Salomon Wollenstein	How Many Smart Cars Does It Take to Make a Smart Traffic Network?
12:00-14:00	Lunch Break	

Agenda - Afternoon

13:30-14:00 Michael Levin Maximum-stability Dispatch Policy for Shared Autonomous Vehicles

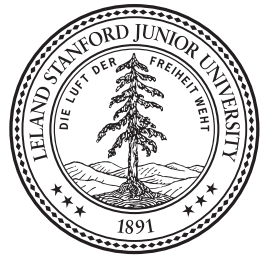
14:00-14:30 Michal Čáp Understanding the Fundamental Trade-offs in Large-scale Mobility-on-demand Systems

14:30-15:00 Javier Alonso-Mora Predictive Routing and Multi-objective Fleet Sizing for Shared Mobility-on-demand

15:00-15:30 Coffee Break

15:30-16:00 Emilio Frazzoli Autonomous Mobility-on-Demand: What is Known and What is Not Known

16:00-16:30 Feedback and Discussion on Future Directions



Stanford
University



Autonomous Mobility-on-Demand for Future Urban Mobility

Mauro Salazar and Marco Pavone

Facts about Mobility

Challenges



Facts about Mobility

Challenges

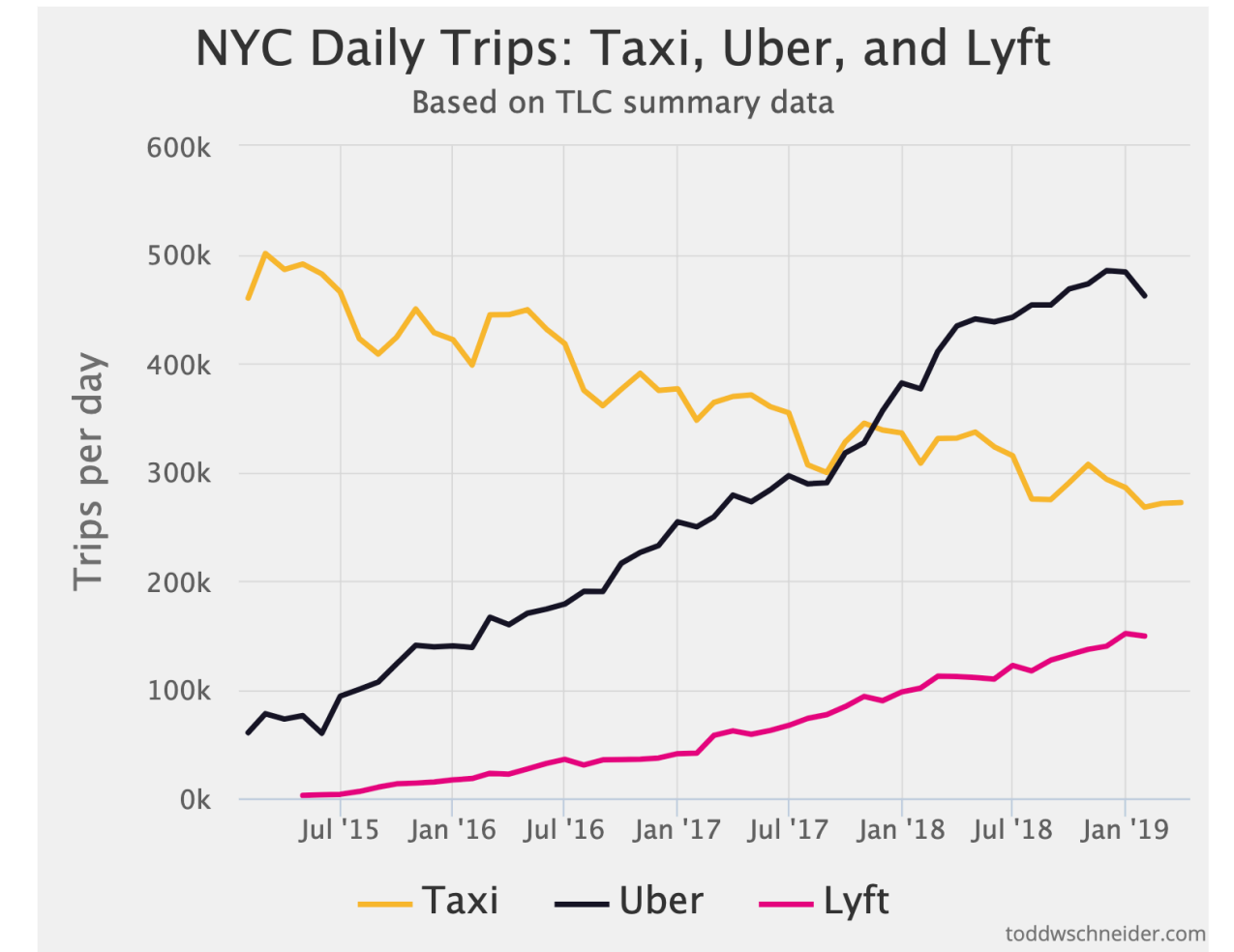


WSJ

TRANSIT

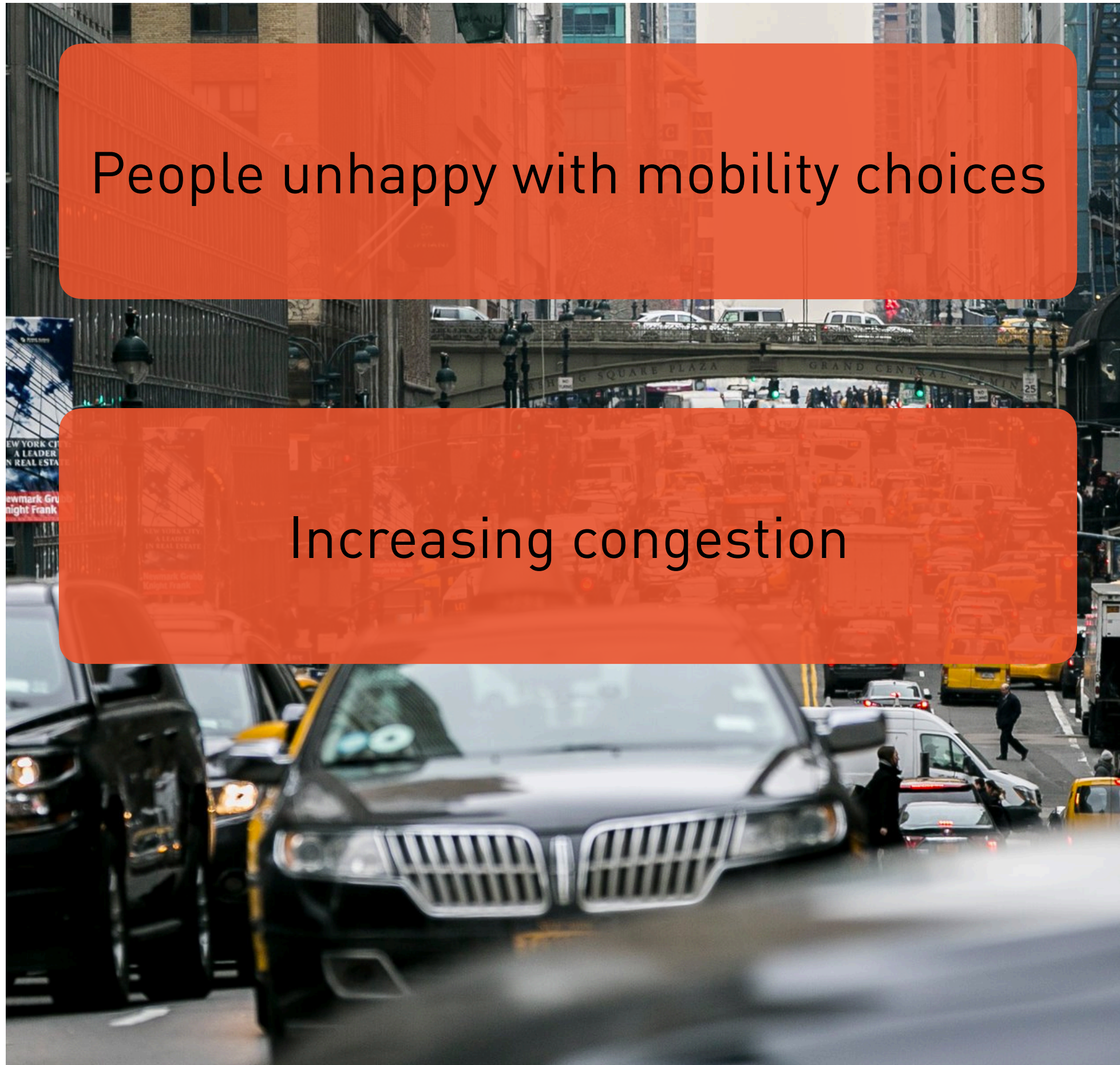
MTA Blames Uber for Decline in New York City Subway, Bus Ridership

Usage dips for mass transit coincided with taxi and ride-hailing trips, data shows



Facts about Mobility

Challenges

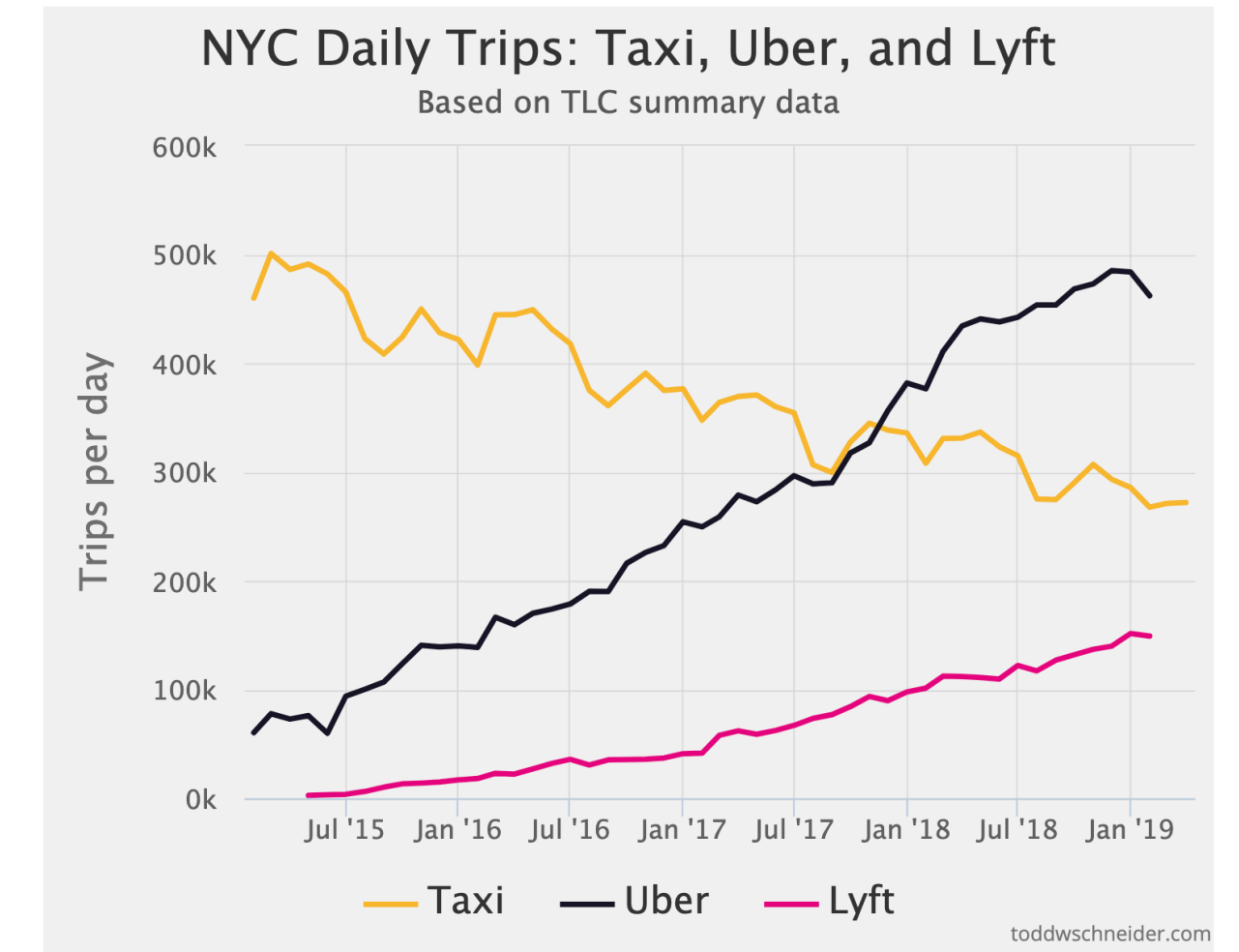


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The New York Times

***Over \$10 to Drive in Manhattan?
What We Know About the
Congestion Pricing Plan***

***Stuck and Stressed: The
Health Costs of Traffic***

The physical and psychological toll of brutal commutes can be considerable.

Facts about Mobility

Challenges

People unhappy with mobility choices

Increasing congestion

Environmental pollution

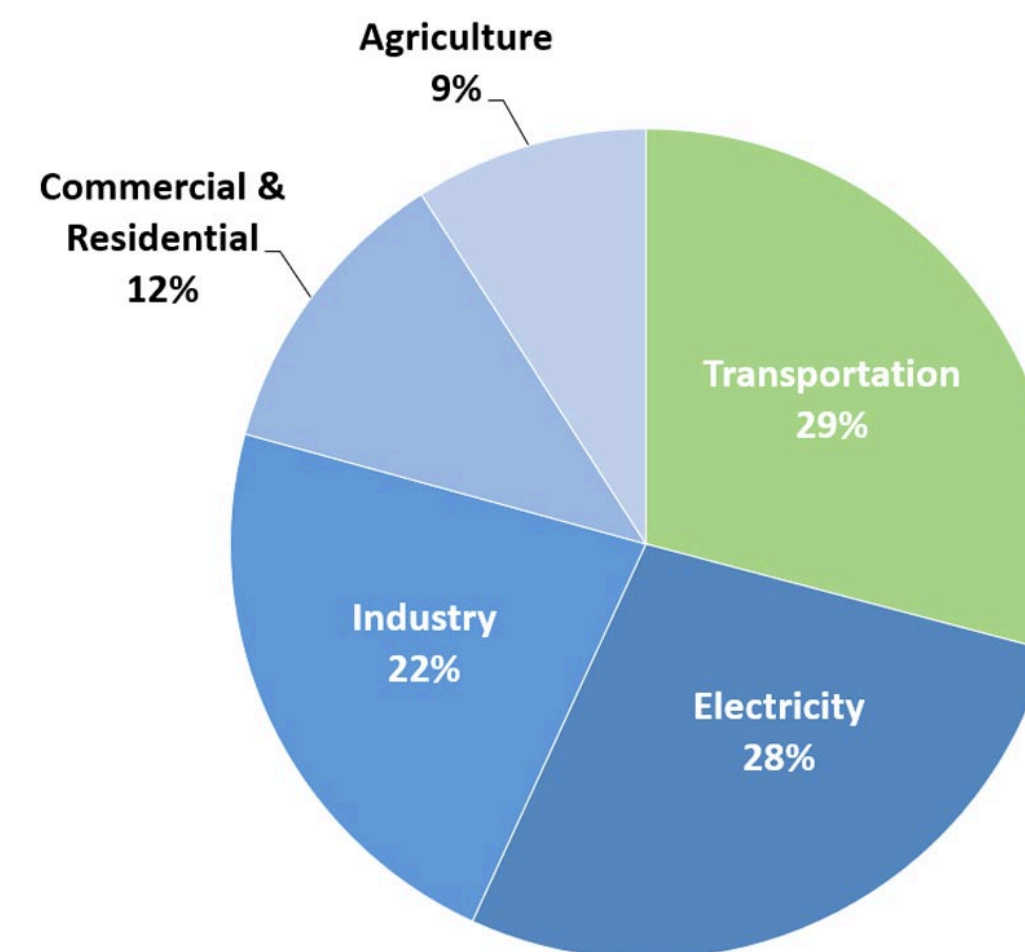
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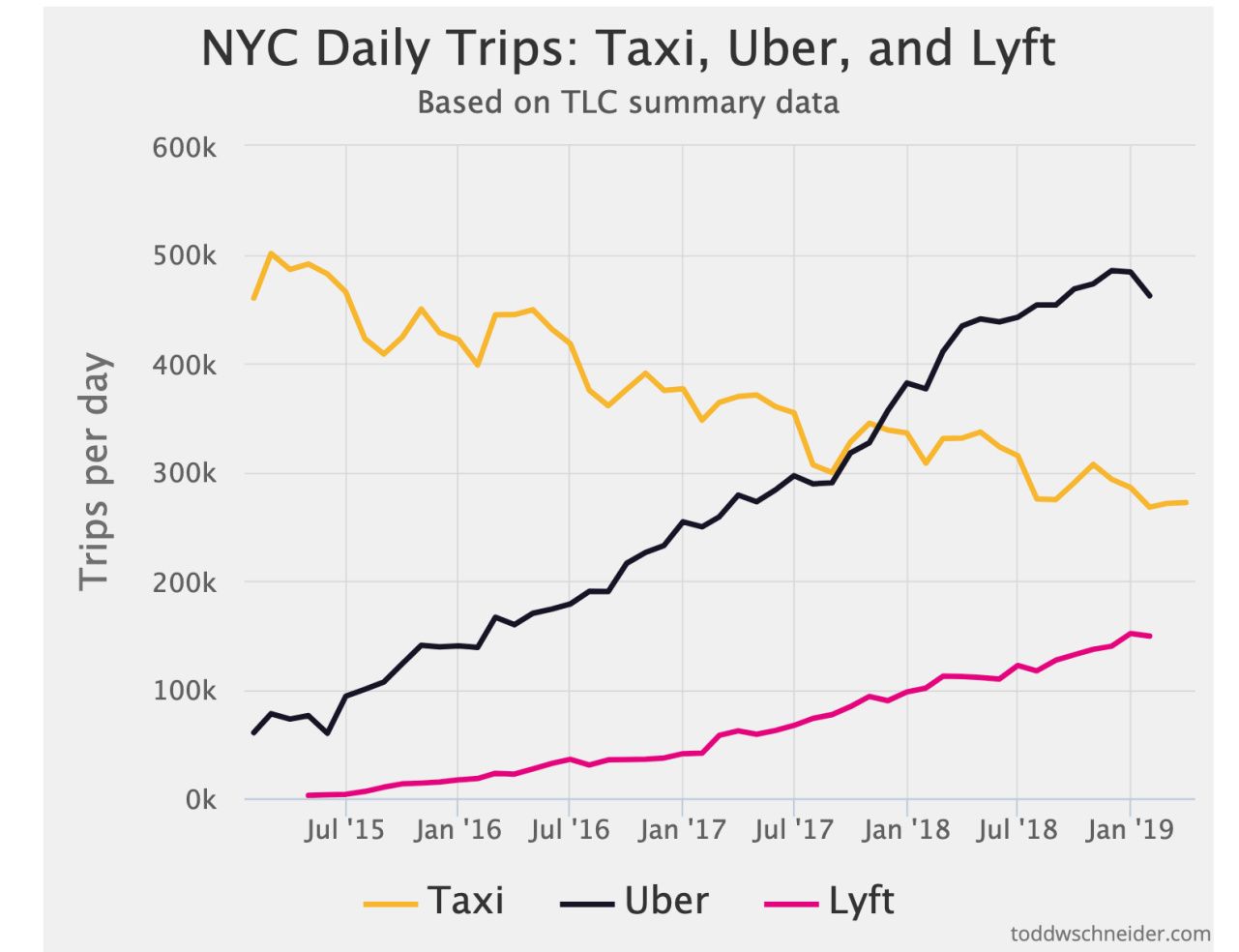
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Total U.S. Greenhouse Gas Emissions by Economic Sector in 2017



U.S. Environmental Protection Agency (2019). Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2017



The New York Times

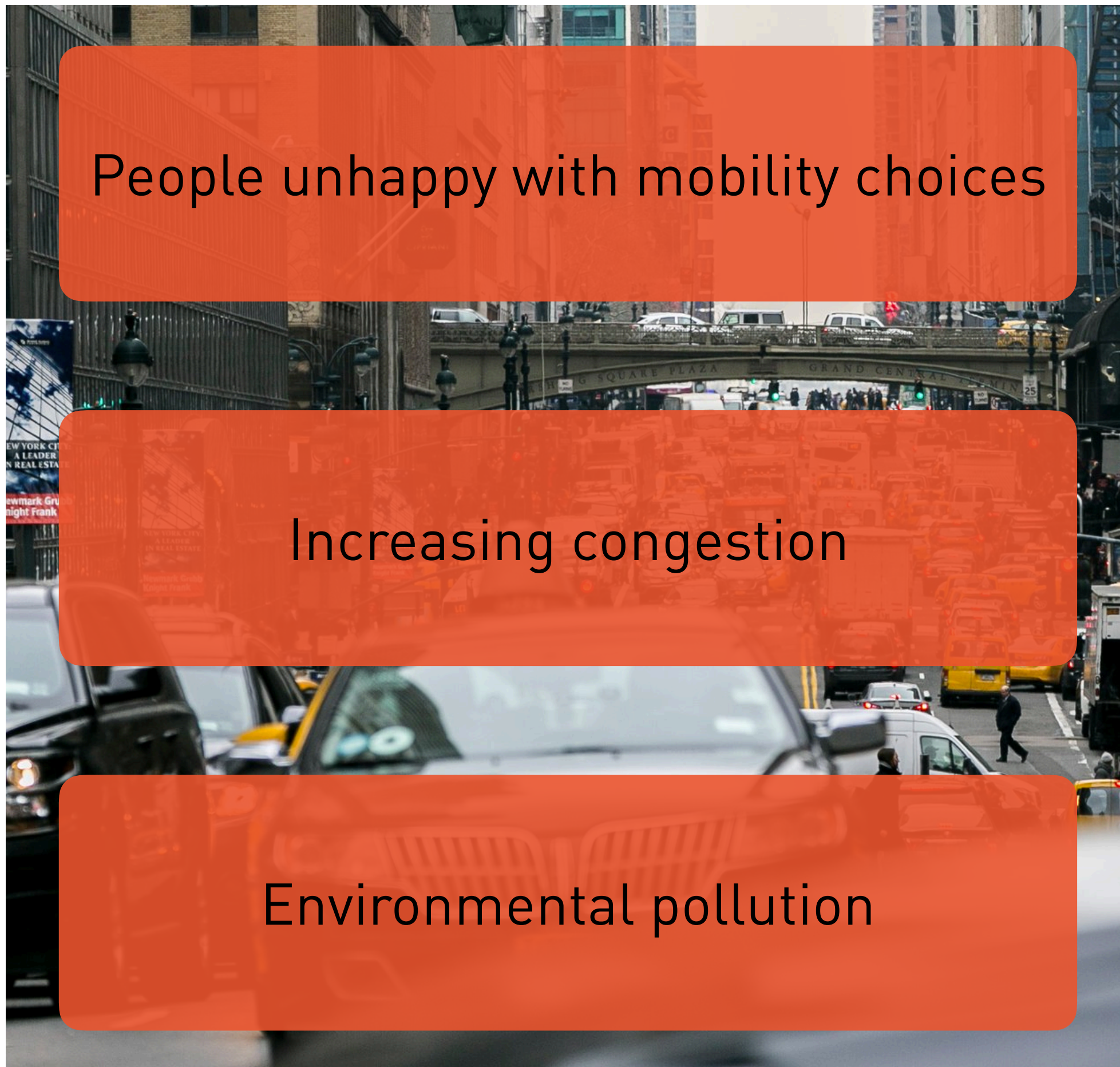
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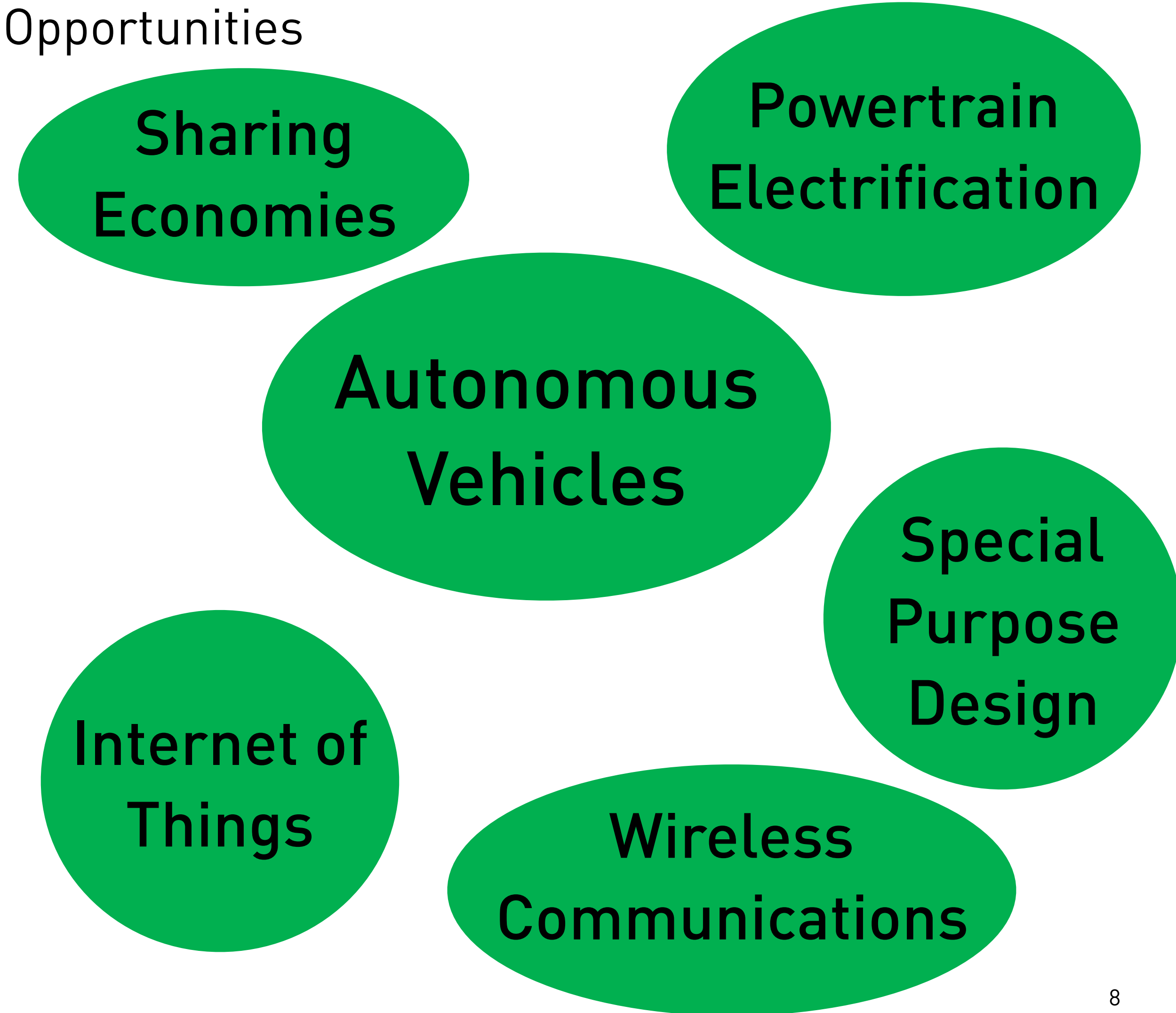
The physical and psychological toll of brutal commutes can be considerable.

Facts about Mobility

Challenges



Opportunities



Facts about Mobility

Challenges

People unhappy with mobility choices

Increasing congestion

Environmental pollution

Opportunities

Sharing Economies

Powertrain Electrification

Autonomous Vehicles

Special Purpose Design

Internet of Things

Wireless Communications

How can we fit all these opportunities together to address nowadays and future mobility issues?

Autonomous Mobility-on-Demand (AMoD)

Vehicle Autonomy



Car Sharing



+

Centrally controlled fleets of **self-driving cars** providing on-demand mobility

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Requirements: AMoD needs to be...

Economically-viable

Socially-inclusive

Environmentally-friendly

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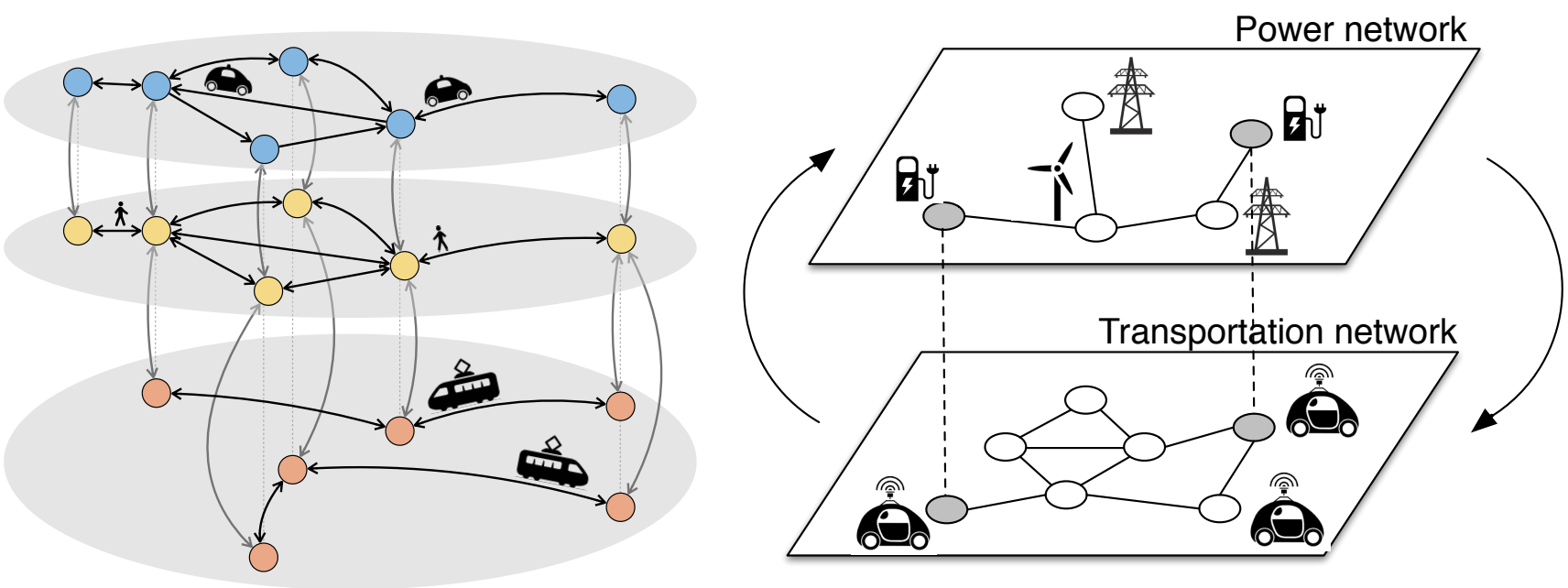
Economically-viable

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user-friendly

Autonomous Mobility-on-Demand

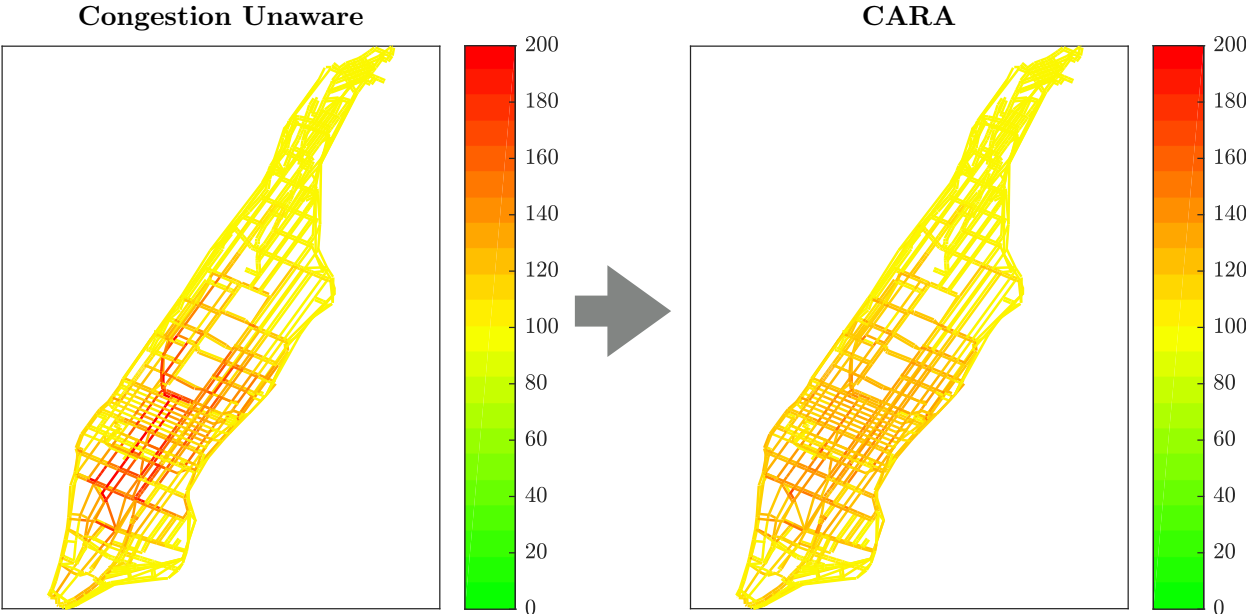
Interaction with Infrastructure



Salazar et al. ITSC18, T-ITS19
Zardini et al. TRB20

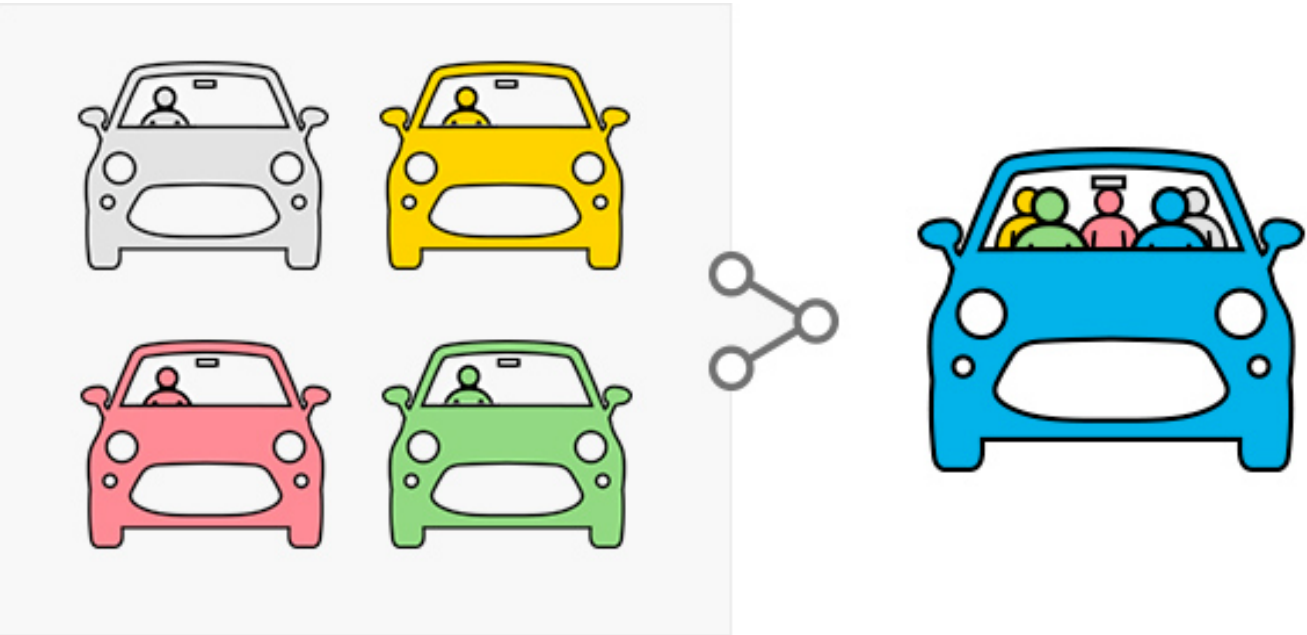
Rossi et al. RSS18,
Boewing et al. ACC20

Congestion-aware Routing



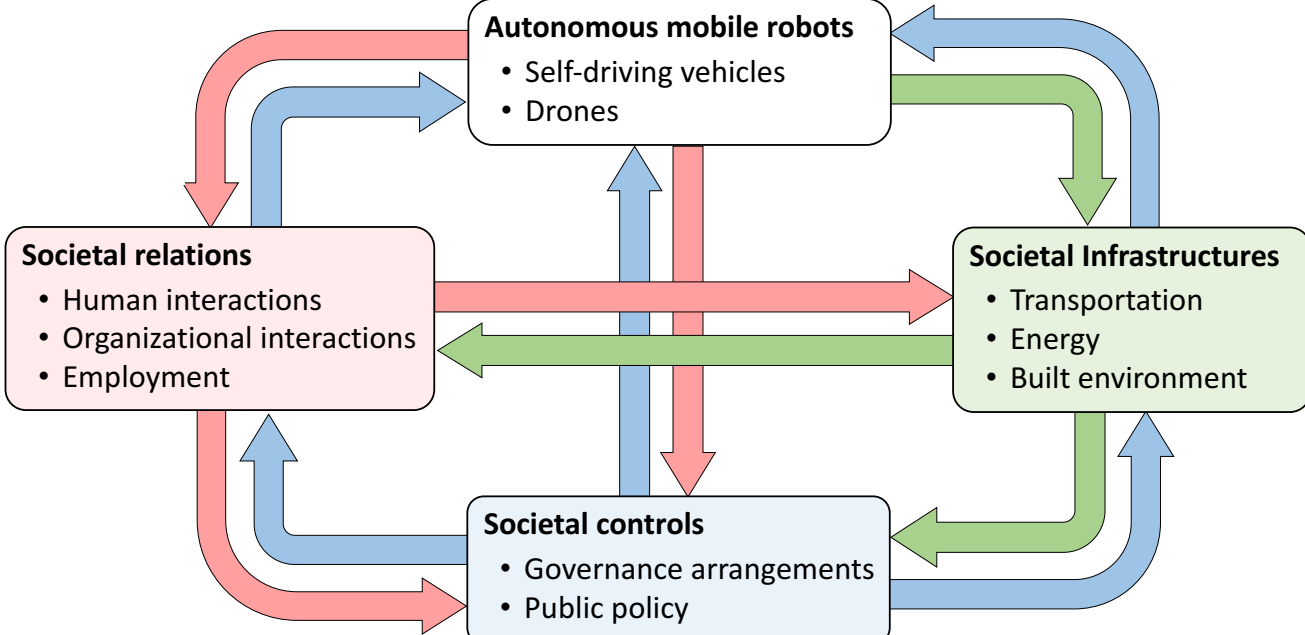
Salazar et al. ECC19, INFORMS18, Solovey et al. RSS19

MPC Algorithms



Tsao et al. ICRA19, Zraggen et al. ITSC19

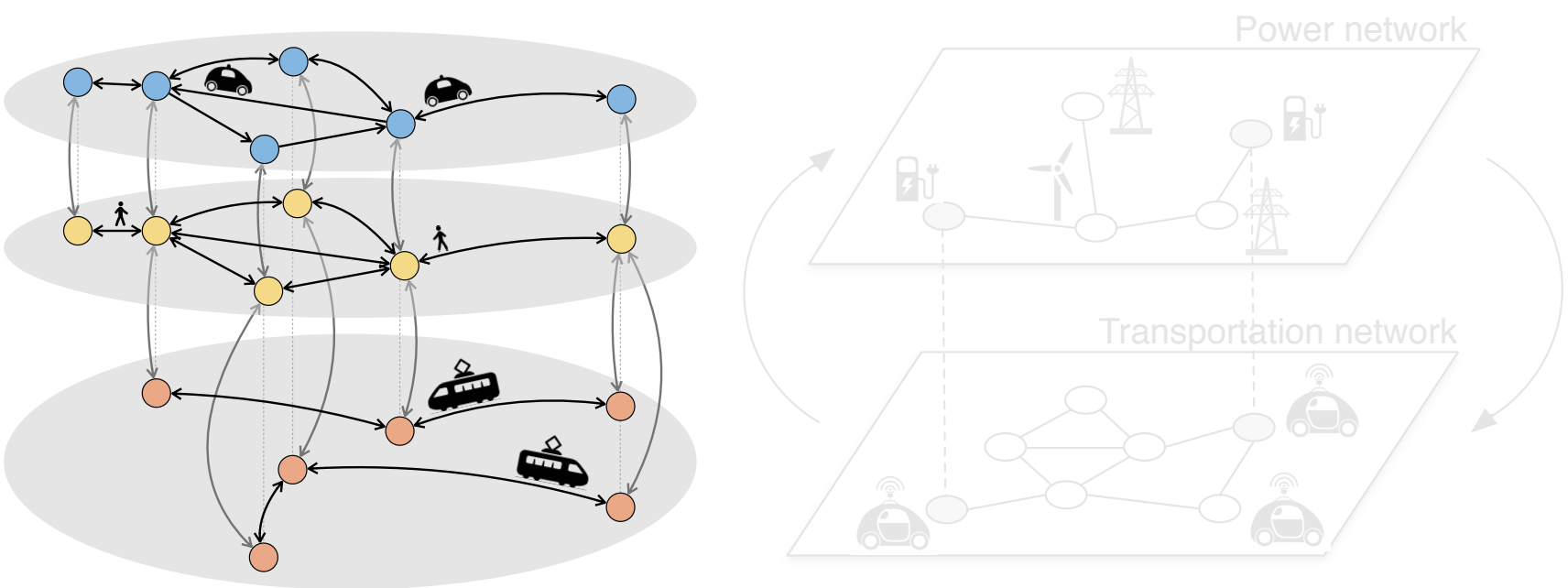
Societal Implications



Lanzetti et al. INFORMS19

Autonomous Mobility-on-Demand

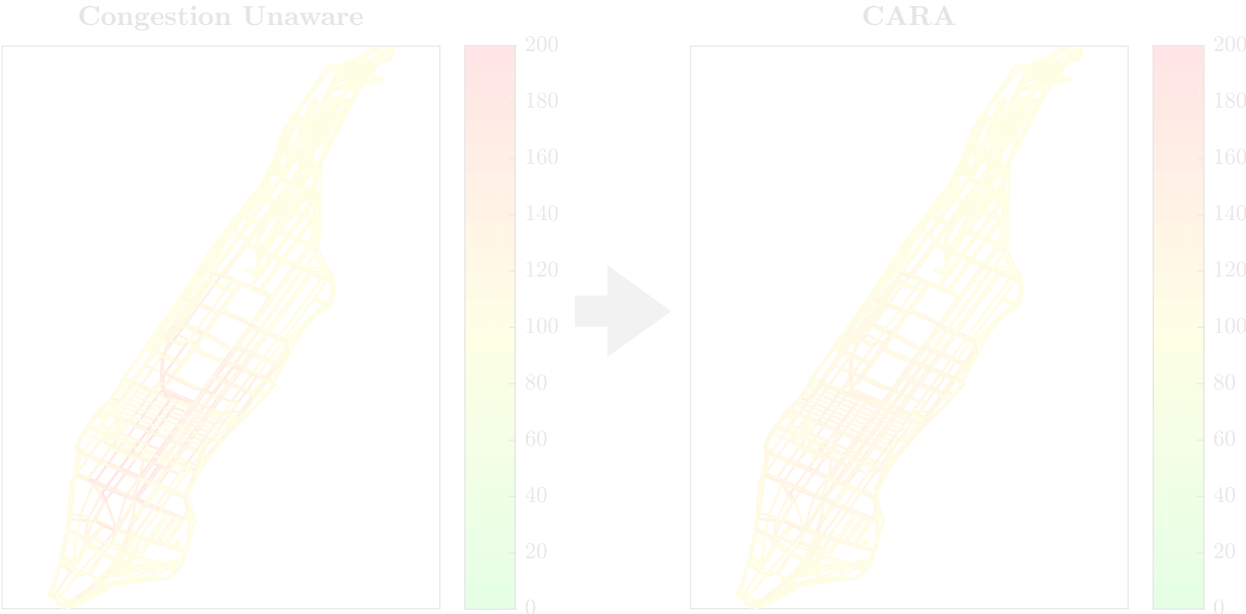
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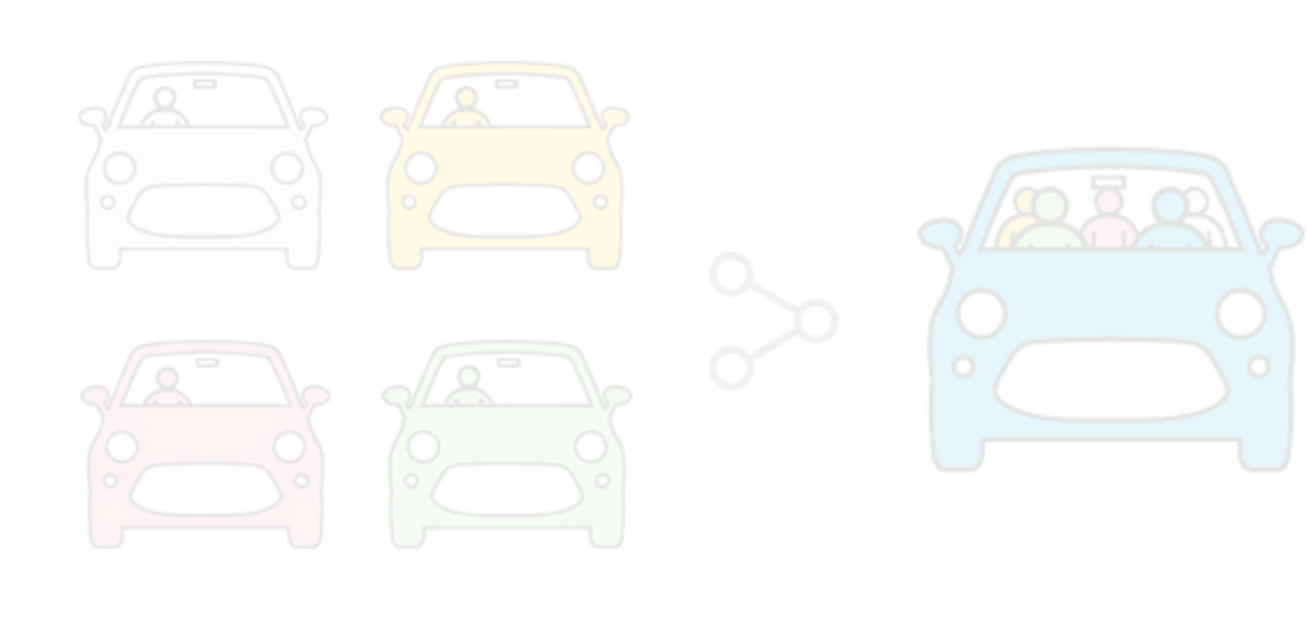
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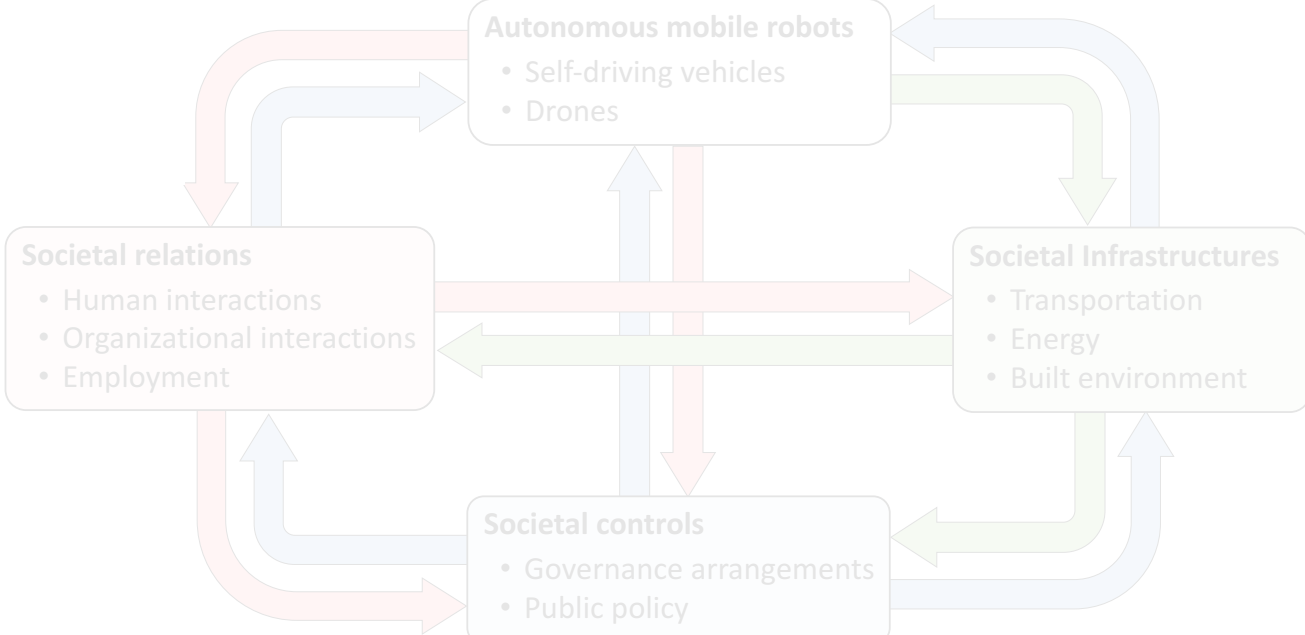
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Manhattan



Manhattan

The New York Times

Congestion Pricing

News about Congestion Pricing, including commentary and archival articles published in The New York Times.

Latest Search

Jan. 16, 2018

Cuomo's Congestion Pricing for New York City Begins to Take Shape

Jan. 19, 2018

Congestion Plan for Manhattan Gets Mixed Reviews

Jan. 22, 2018

In Protests, a Hint of the Fight to Come Over Congestion Pricing

WSJ

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Jan. 29, 2018

LETTER

Mobility Is a Mess in New York

March 31, 2018

Congestion Pricing Falters in New York, Again

April 9, 2018

Congestion Pricing Plan for Manhattan Ran Into Politics. Politics Won.

July 20, 2018

Pave Over the Subway? Cities Face Tough Bets on Driverless Cars

March 26

NEW YORK

Over \$10 to Drive in Manhattan? What We Know About the Congestion Pricing Plan

Will AMoD Save the Day?

Vehicle Autonomy



+

Car Sharing



Road Traffic Efficiency



Road Traffic Efficiency



Why Public Transit?



Why Public Transit?



Why Public Transit?



Optimal Operation of Intermodal AMoD Systems

Vehicle Autonomy



Car Sharing

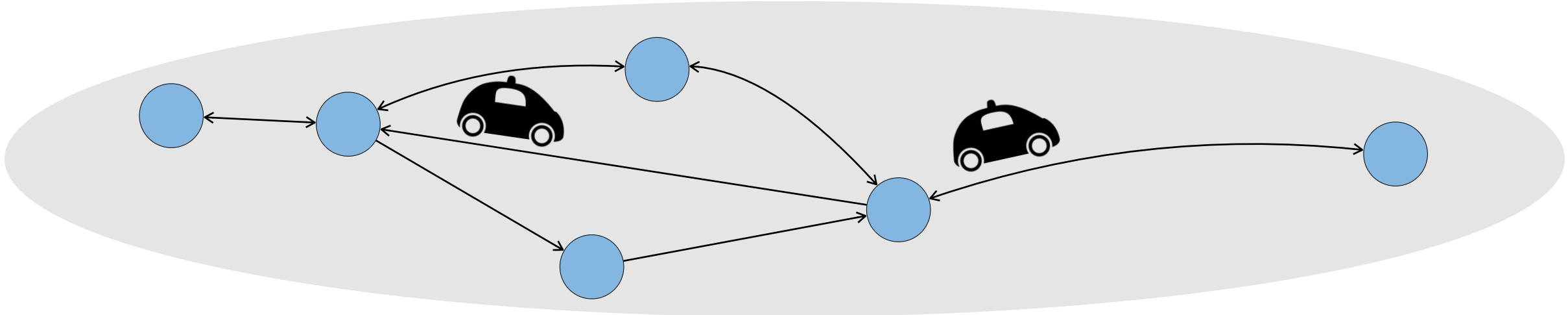


Public Transit

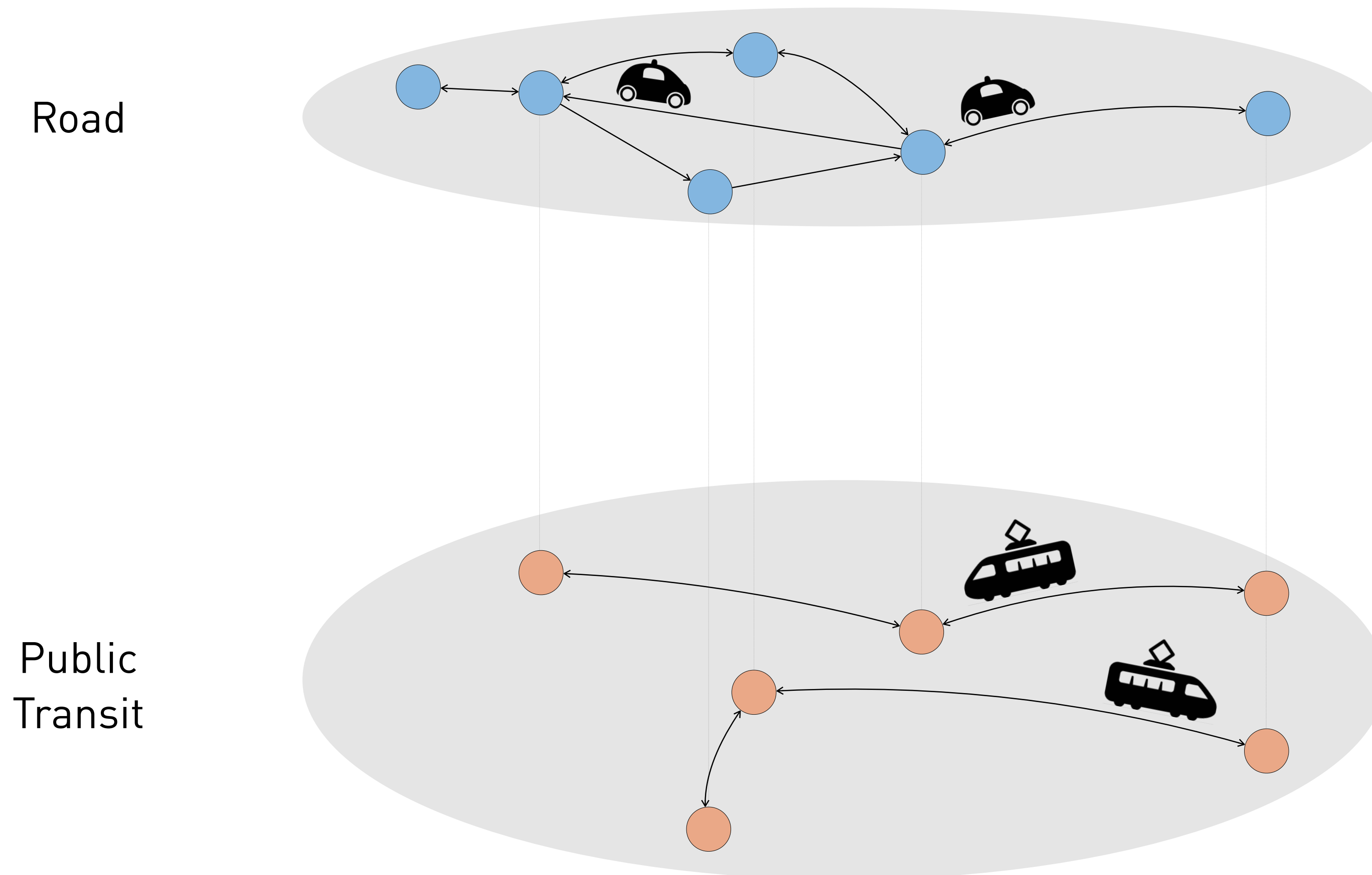


Intermodal Autonomous Mobility-on-Demand

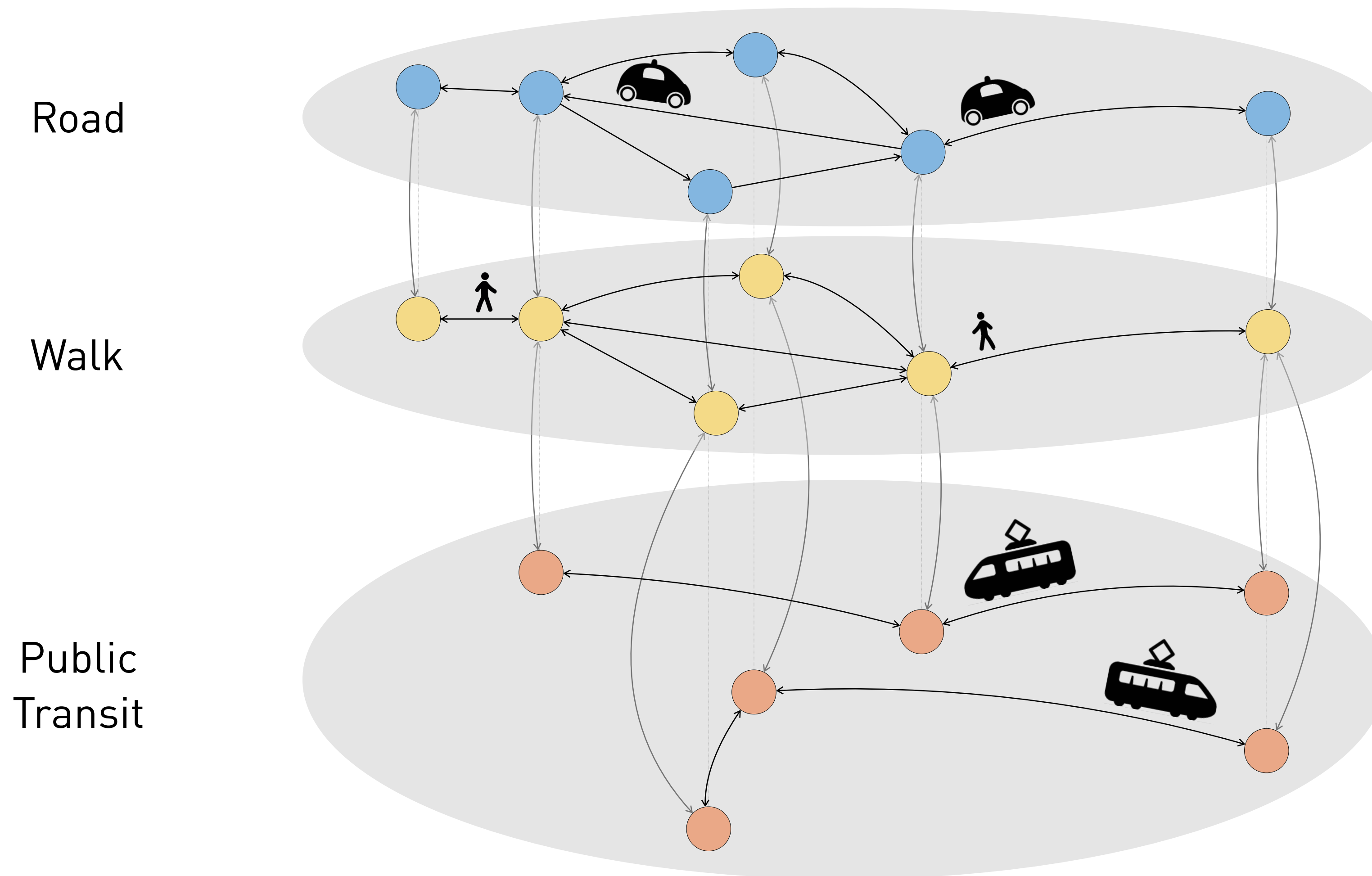
Road



Intermodal Autonomous Mobility-on-Demand



Intermodal Autonomous Mobility-on-Demand



Network Flow Model

Advantages

- Highly scalable (LP)
- Very expressive

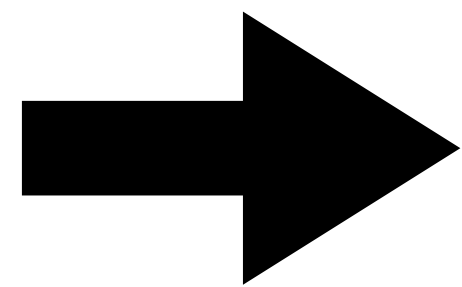
Network Flow Model

Advantages

- Highly scalable (LP)
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Assumptions

- No stochasticity
- Continuum approximation
- One passenger per car



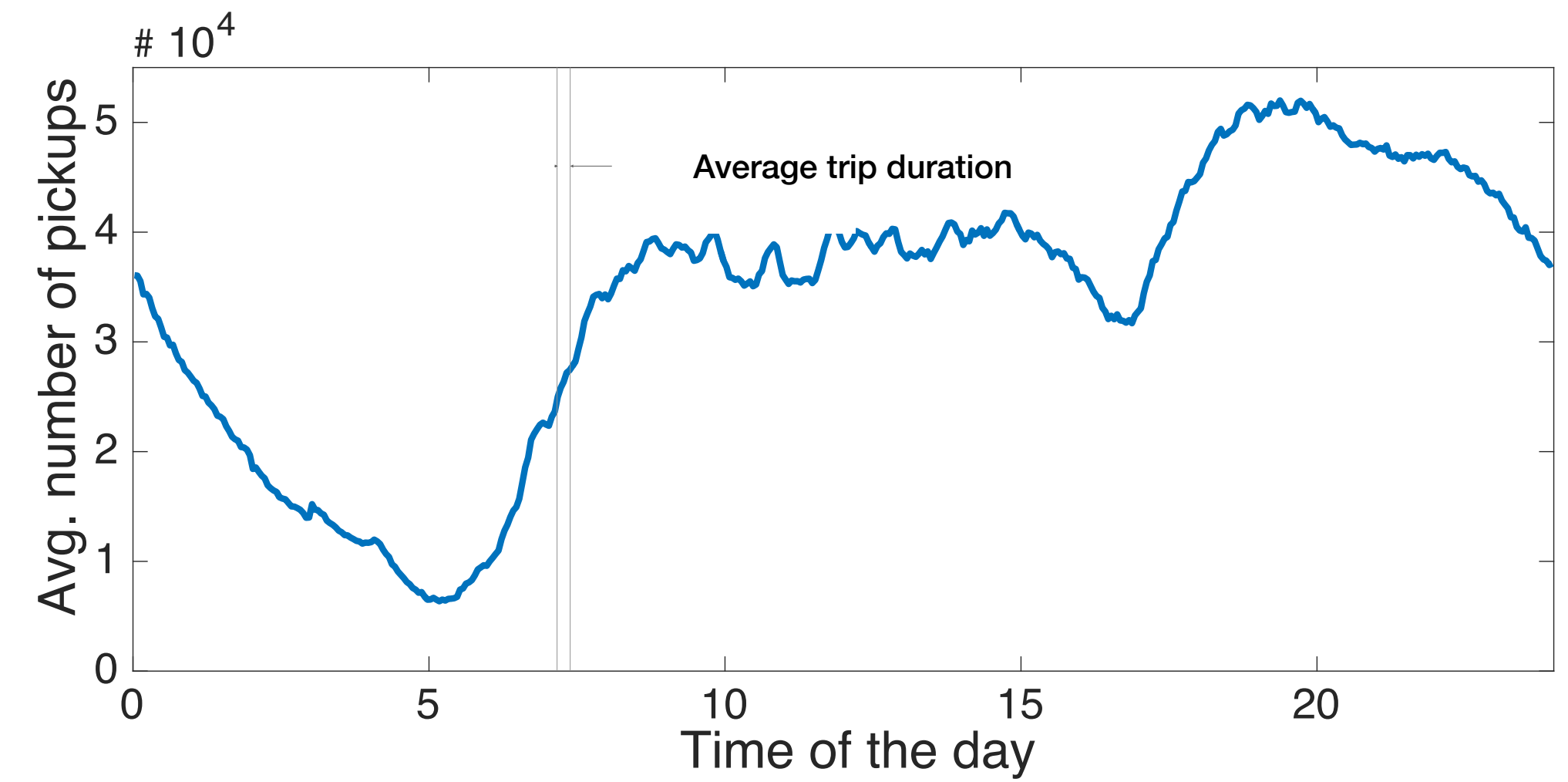
Stochastic process in expectation [Iglesias et al. 2018]

Flow decomposition and sampling

In line with current trends

Network Flow Model - Assumptions

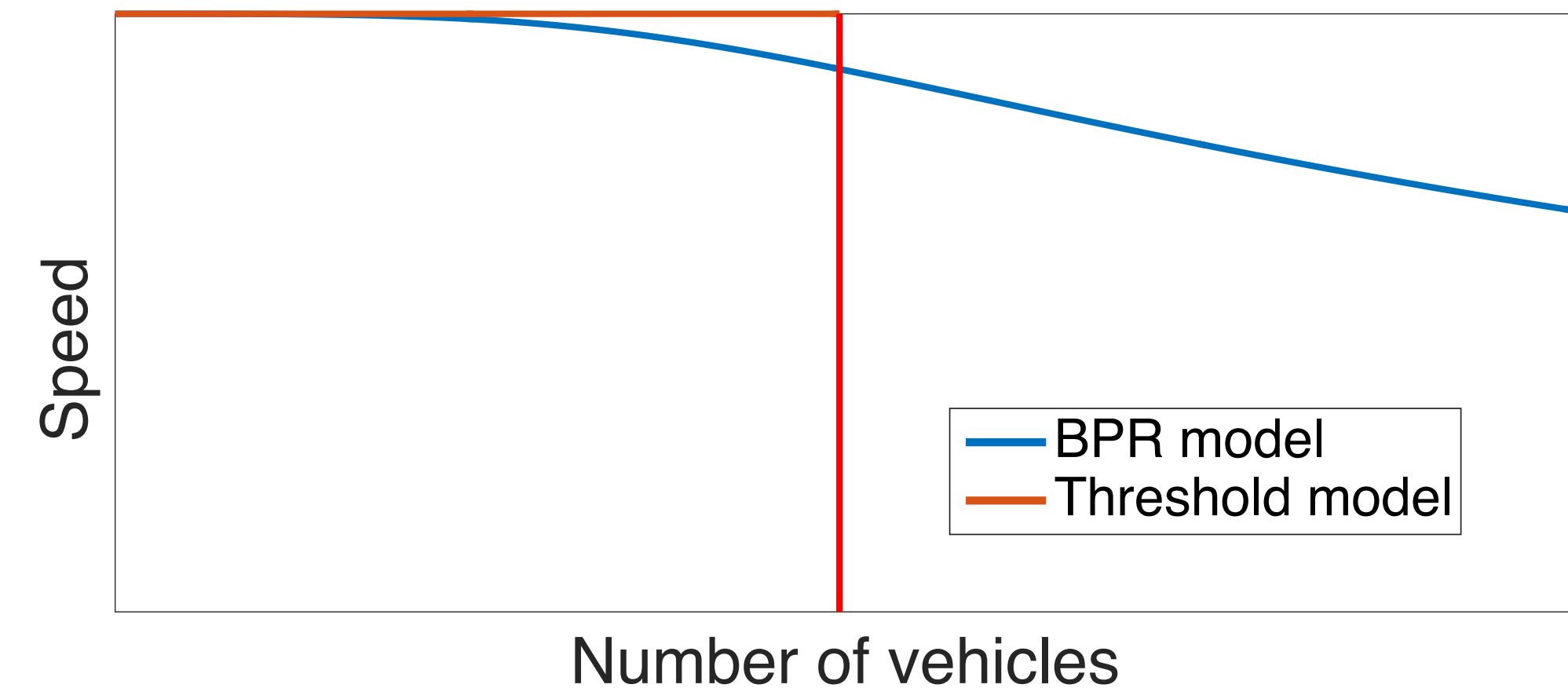
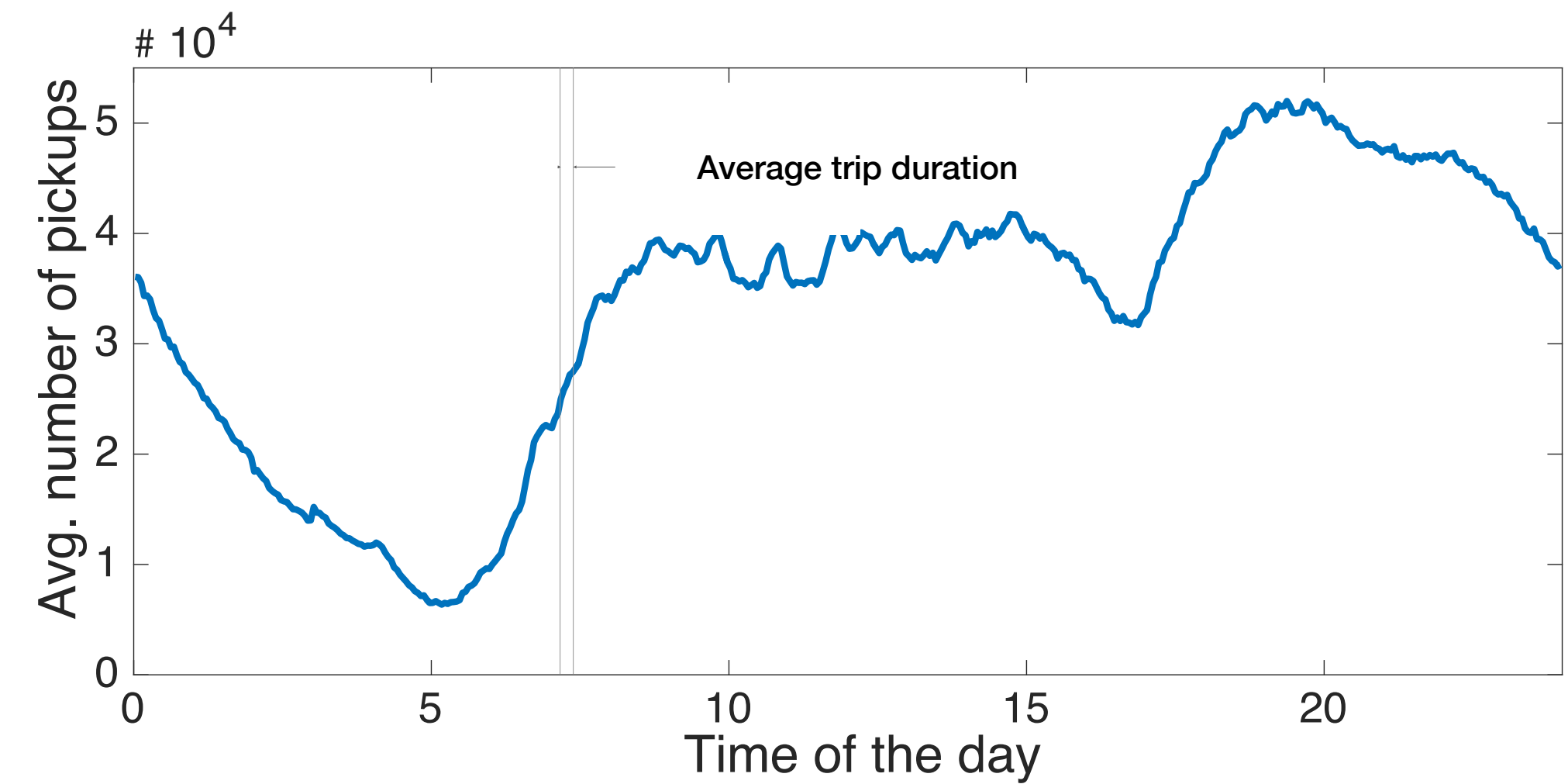
- Demand is time-invariant



Network Flow Model - Assumptions

- Demand is time-invariant

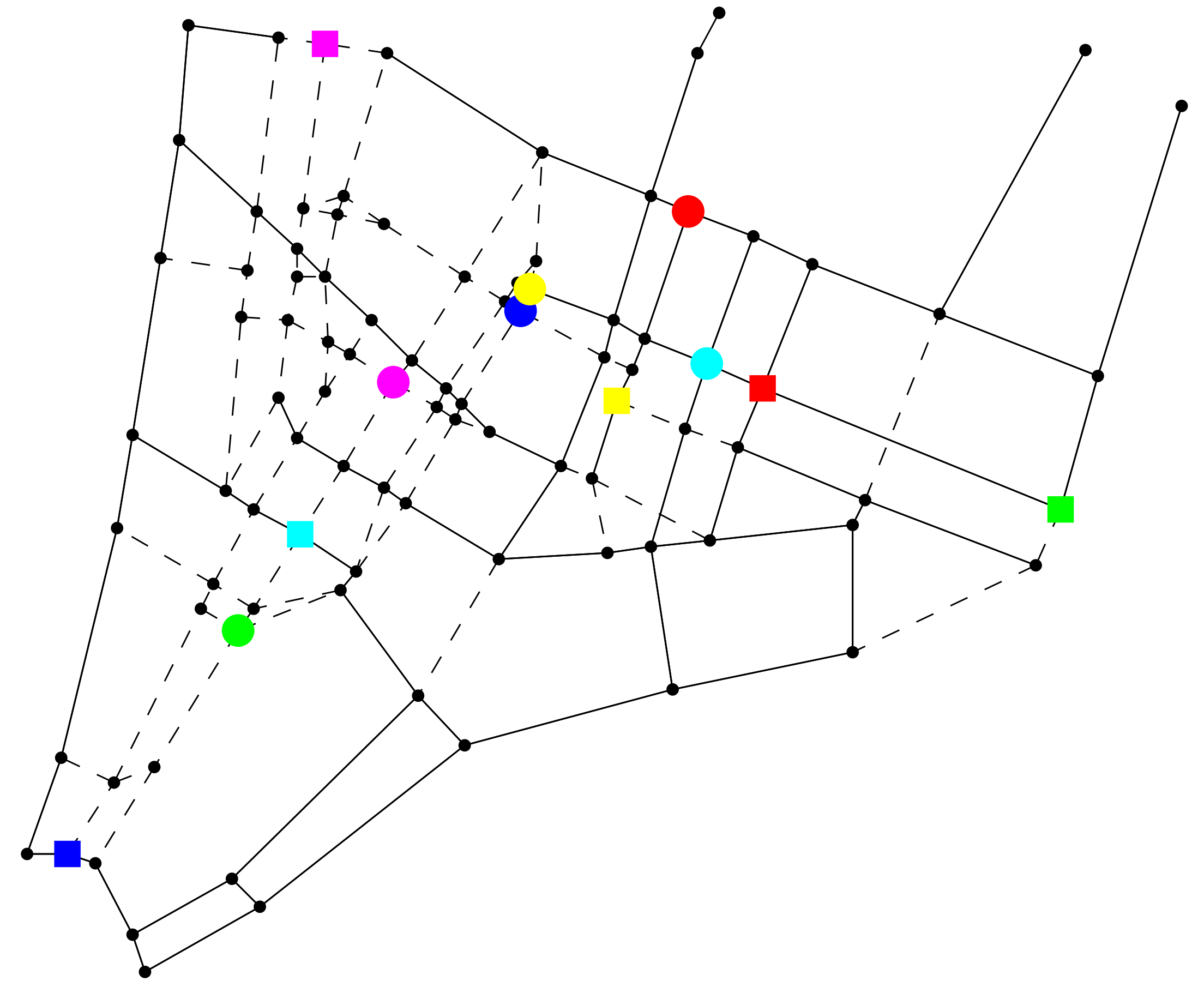
- Congestion as a threshold



Network Flow Model

Transportation requests

- Origin
- Destination
- Rate of demand (customers/minute)



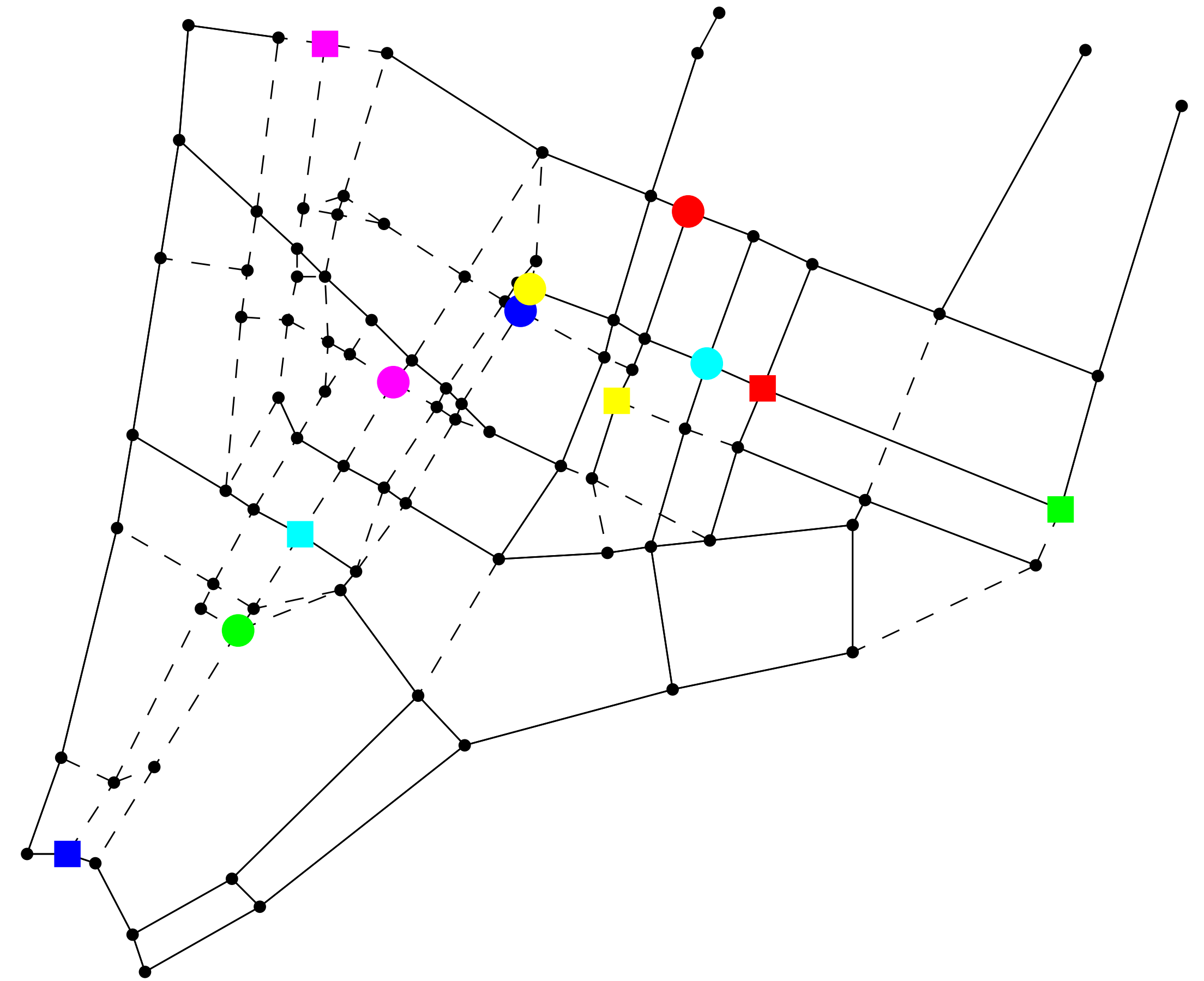
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Network model

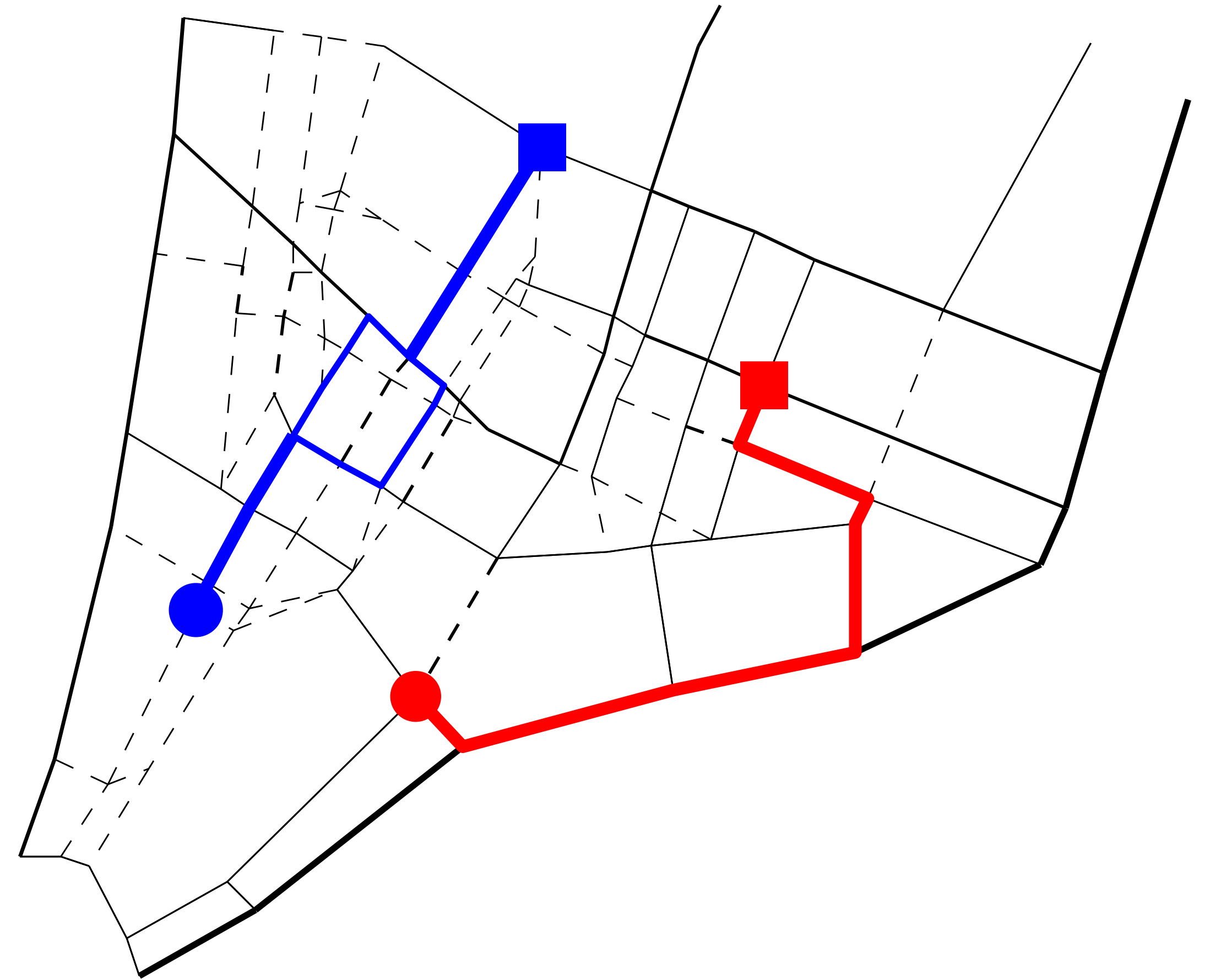
- Nodes: intersections and stops
- Capacitated arcs: roads, walk, switch and public transit



Network Flow Model

Flows

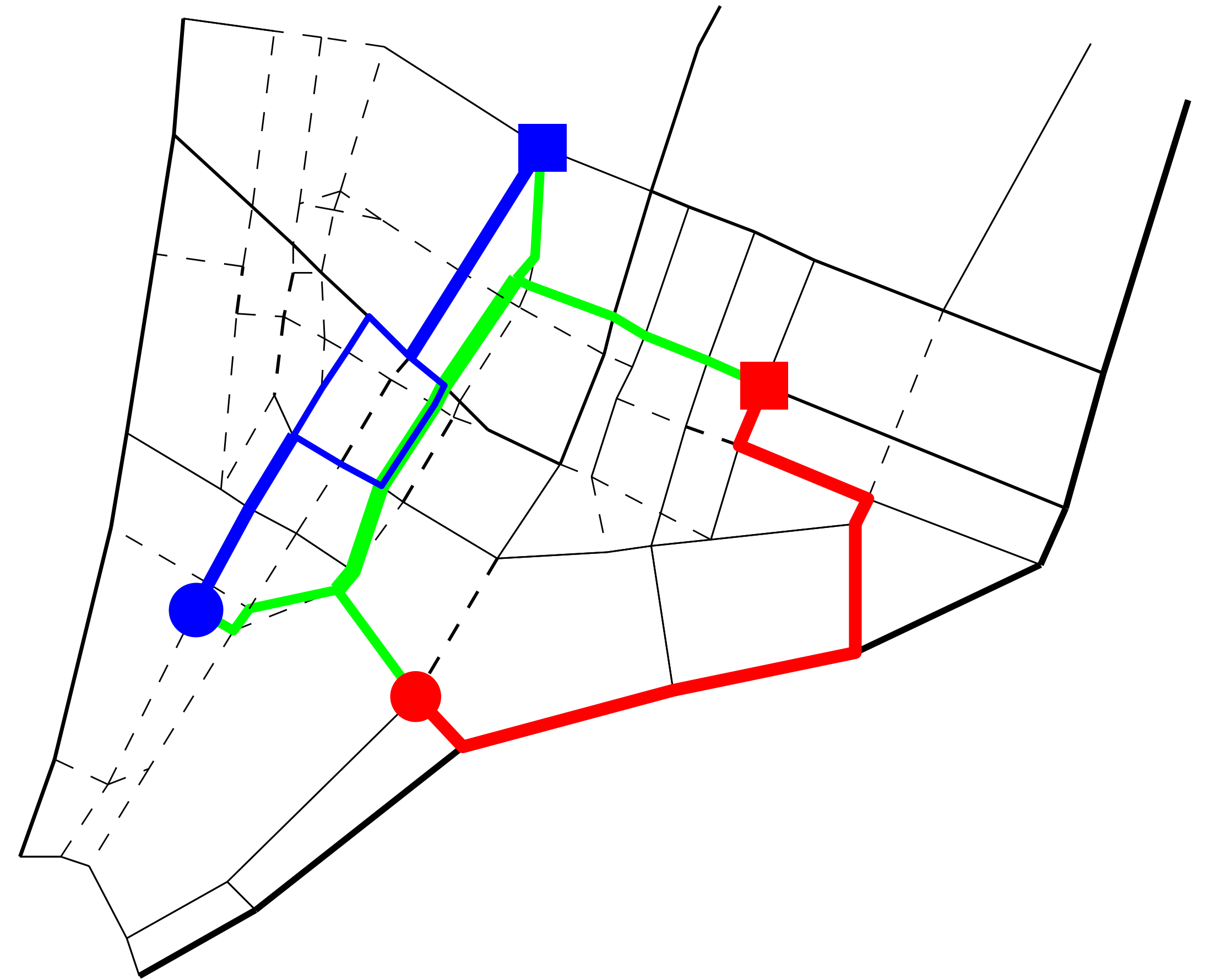
- Customer flows $f_m(i, j)$
- Rebalancing flows



Network Flow Model

Flows

- Customer flows
- Rebalancing flows $f_0(i, j)$



Network Flow Model

Extended Graph

$$G = (\mathcal{V}, \mathcal{A}), \quad \mathcal{V} = \mathcal{V}_R \cup \mathcal{V}_P \cup \mathcal{V}_W, \quad \mathcal{A} = \mathcal{A}_R \cup \mathcal{A}_P \cup \mathcal{A}_W \cup \mathcal{A}_{RW} \cup \mathcal{A}_{PW}$$

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Conservation of Customers

$$\sum_{i \in \mathcal{V}} f_m(i, j) + \mathbf{1}_{j=o_m} \cdot \alpha_m = \sum_{k \in \mathcal{V}} f_m(j, k) + \mathbf{1}_{j=d_m} \cdot \alpha_m \quad \forall m \in \mathcal{M}, \forall j \in \mathcal{V}$$

Network Flow Model

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Conservation of Vehicles

$$\sum_{i \in \mathcal{V}_R} \left(f_0(i, j) + \sum_{m \in \mathcal{M}} f_m(i, j) \right) = \sum_{k \in \mathcal{V}_R} \left(f_0(j, k) + \sum_{m \in \mathcal{M}} f_m(j, k) \right) \quad \forall j \in \mathcal{V}_R$$

Network Flow Model

Capacity of Road and Public Transportation

$$f_0(i, j) + \sum_{m \in \mathcal{M}} f_m(i, j) \leq c_R(i, j), \quad \forall (i, j) \in \mathcal{A}_R$$

$$\sum_{m \in \mathcal{M}} f_m(i, j) \leq c_P(i, j), \quad \forall (i, j) \in \mathcal{A}_P$$

Network Flow Model

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Objective Social Welfare: **time, operational costs and energy**

$$\begin{aligned} \min_{\{f_m(\cdot, \cdot)\}_m, f_0(\cdot, \cdot)} & \sum_{(i, j) \in \mathcal{A}} \sum_{m \in \mathcal{M}} V_T \cdot t_{ij} \cdot f_m(i, j) \\ & + \sum_{(i, j) \in \mathcal{A}_R} (V_{D,R} \cdot s_{ij} + V_E \cdot e_{R,ij}) \cdot \left(f_0(i, j) + \sum_{m \in \mathcal{M}} f_m(i, j) \right) \\ & + \sum_{(i, j) \in \mathcal{A}_P} V_{D,P} \cdot s_{ij} \cdot \sum_{m \in \mathcal{M}} f_m(i, j) \end{aligned}$$

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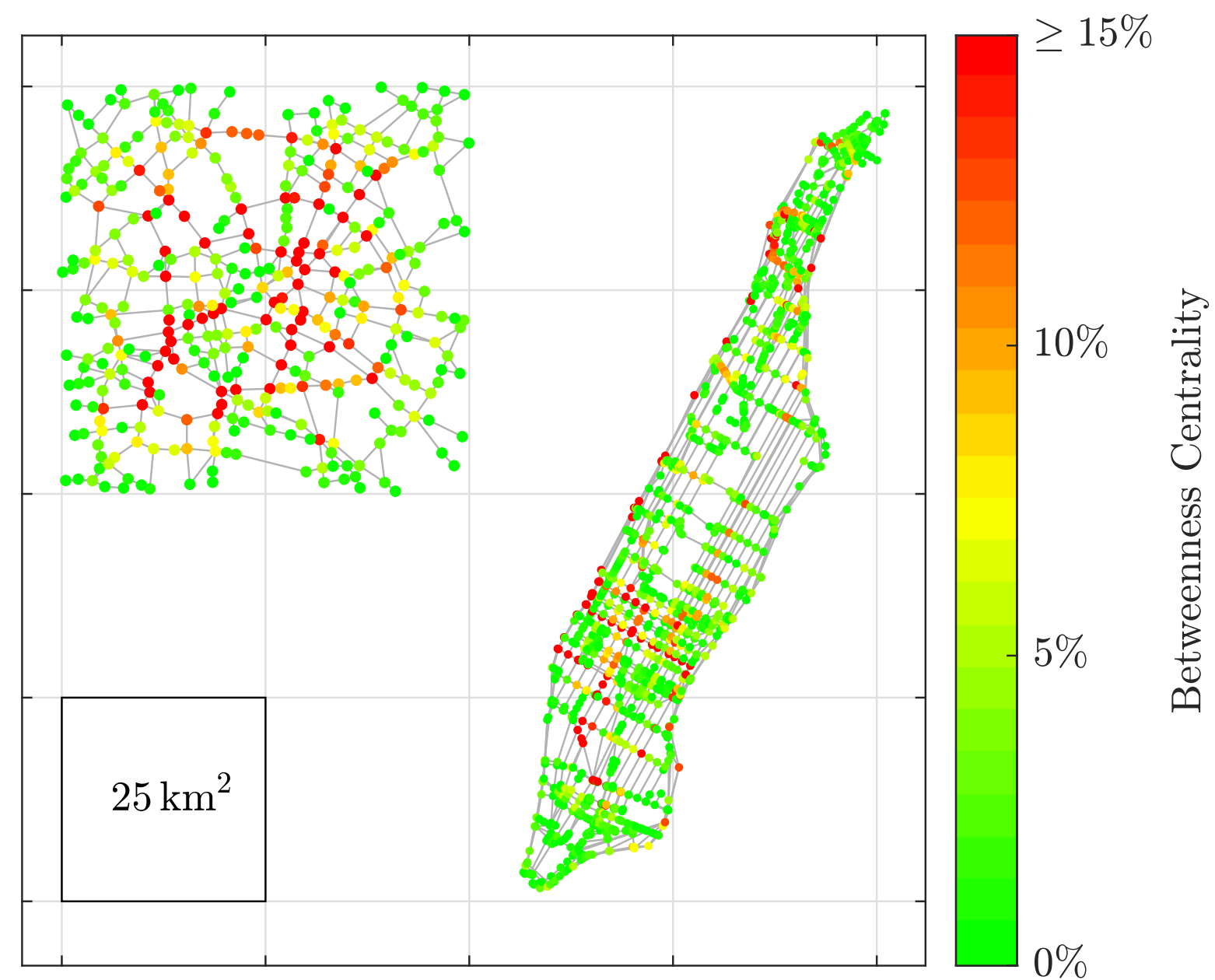
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Let us now consider a case study...

Intermodal AMoD - Berlin and NYC

REQUESTS IN BERLIN AND NYC.

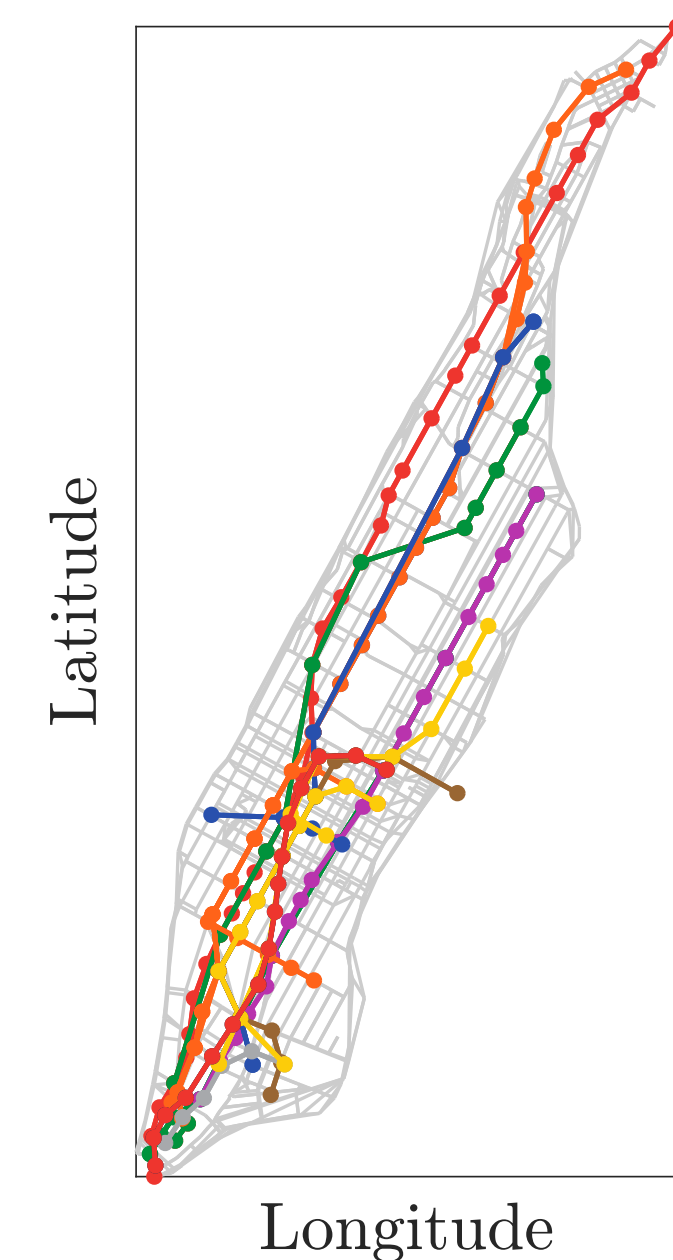
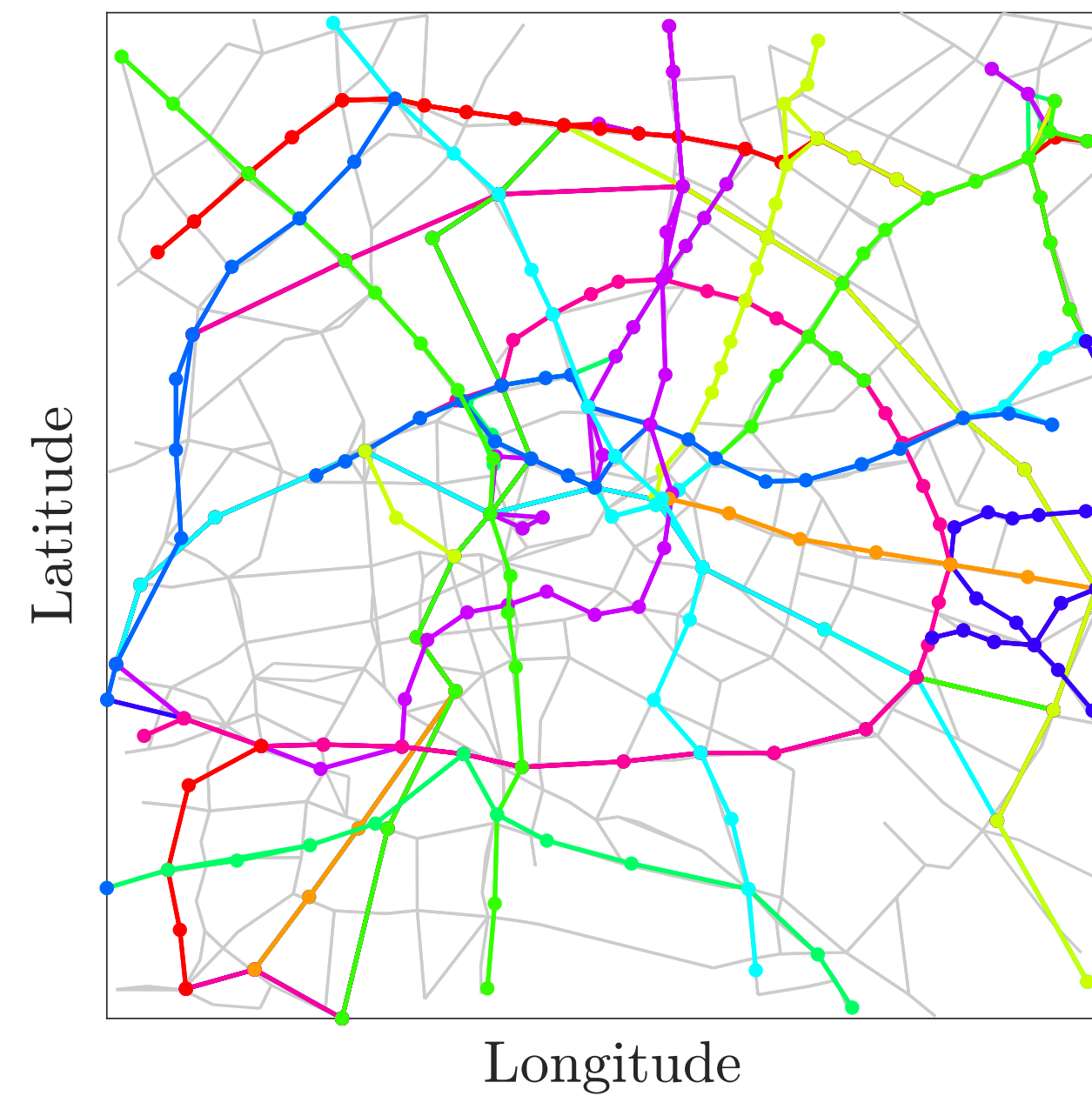
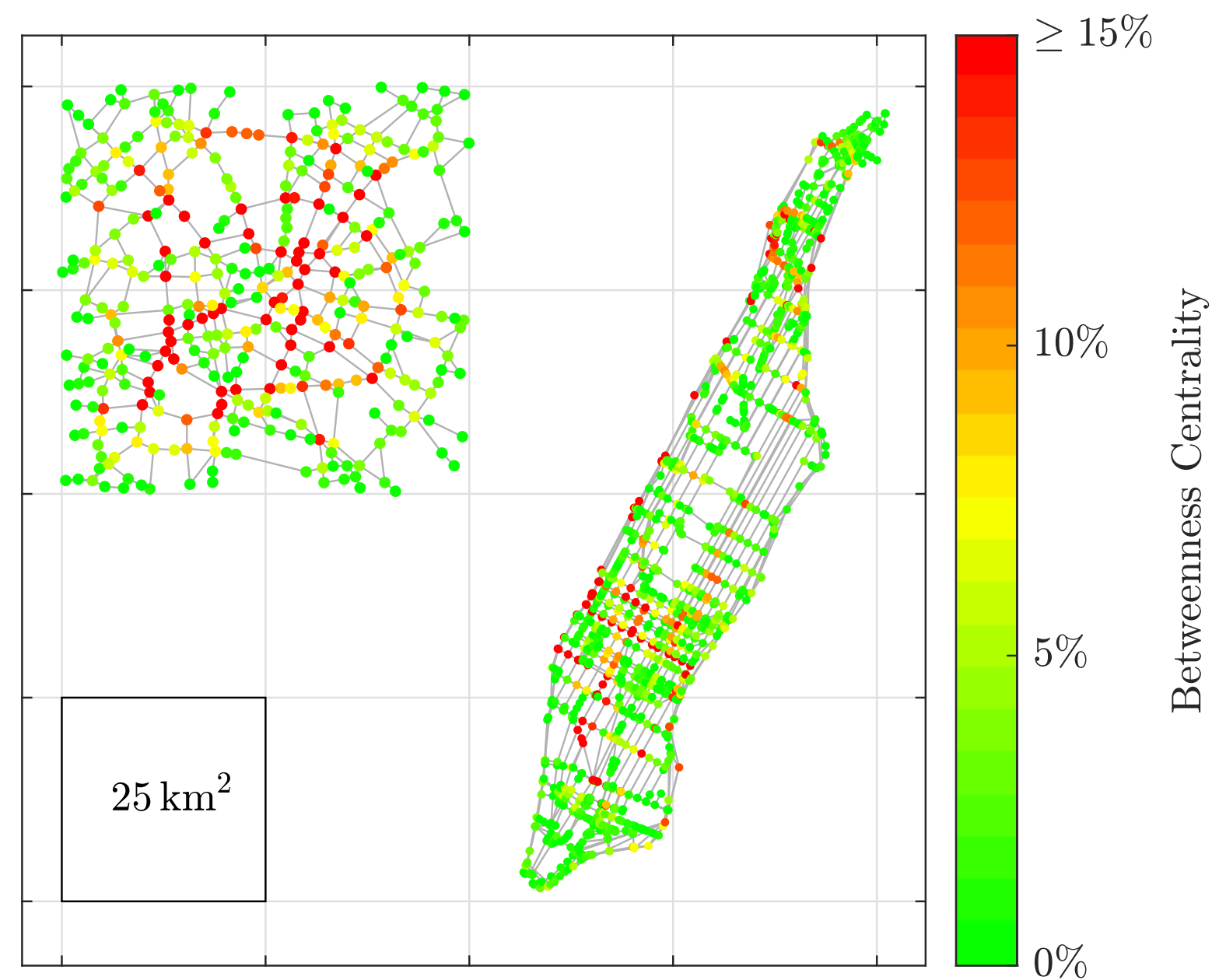
	NYC	Berlin
M	8,658	2,646
$\sum_{m \in \mathcal{M}} \alpha_m$	44.943 1/s	3.771 1/s
$\sum_{m \in \mathcal{M}} \alpha_m \ o_m - d_m\ _2 / \sum_{m \in \mathcal{M}} \alpha_m$	2.4 km	4.0 km



Intermodal AMoD - Berlin and NYC

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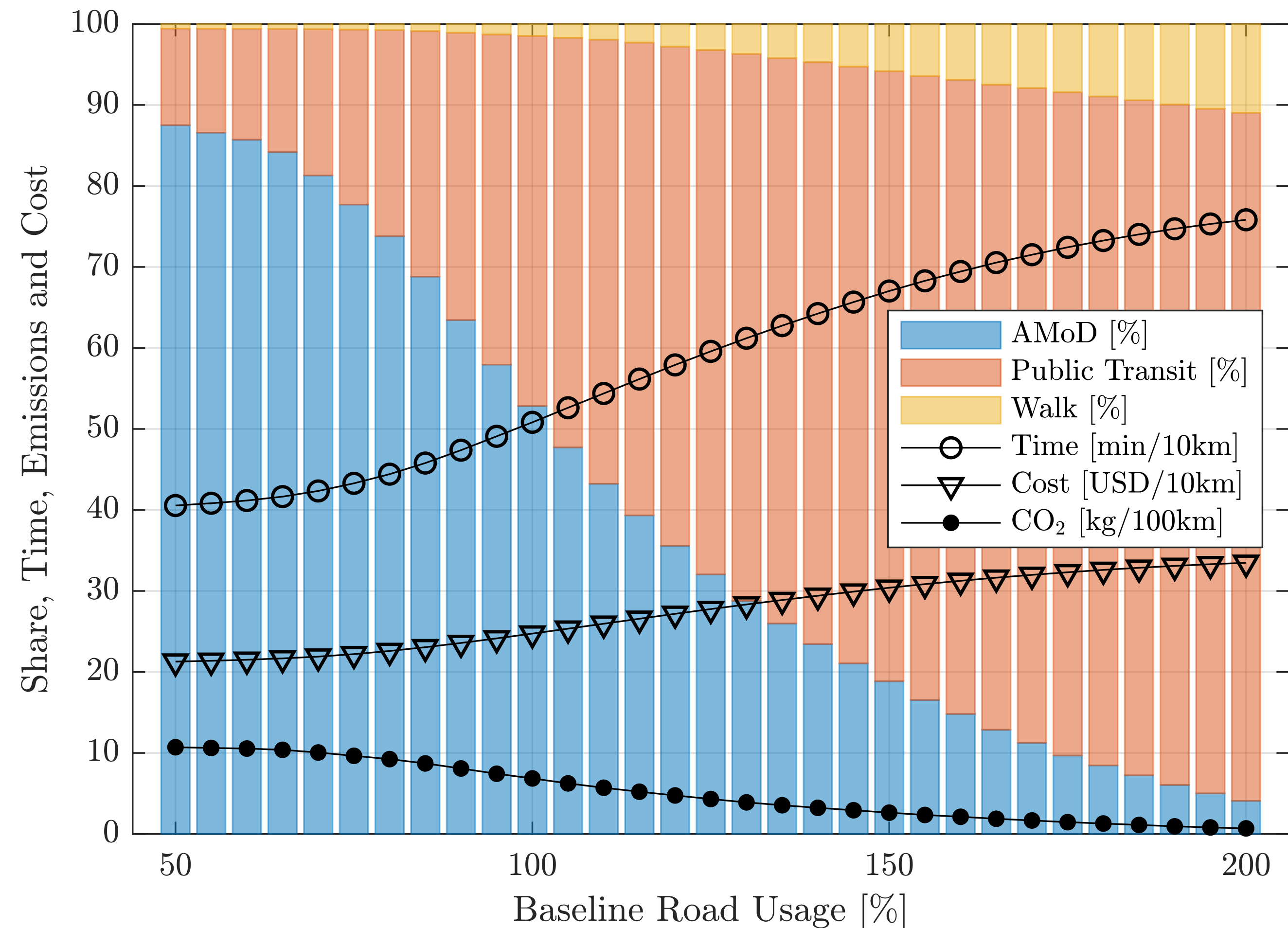


Case Study - Berlin

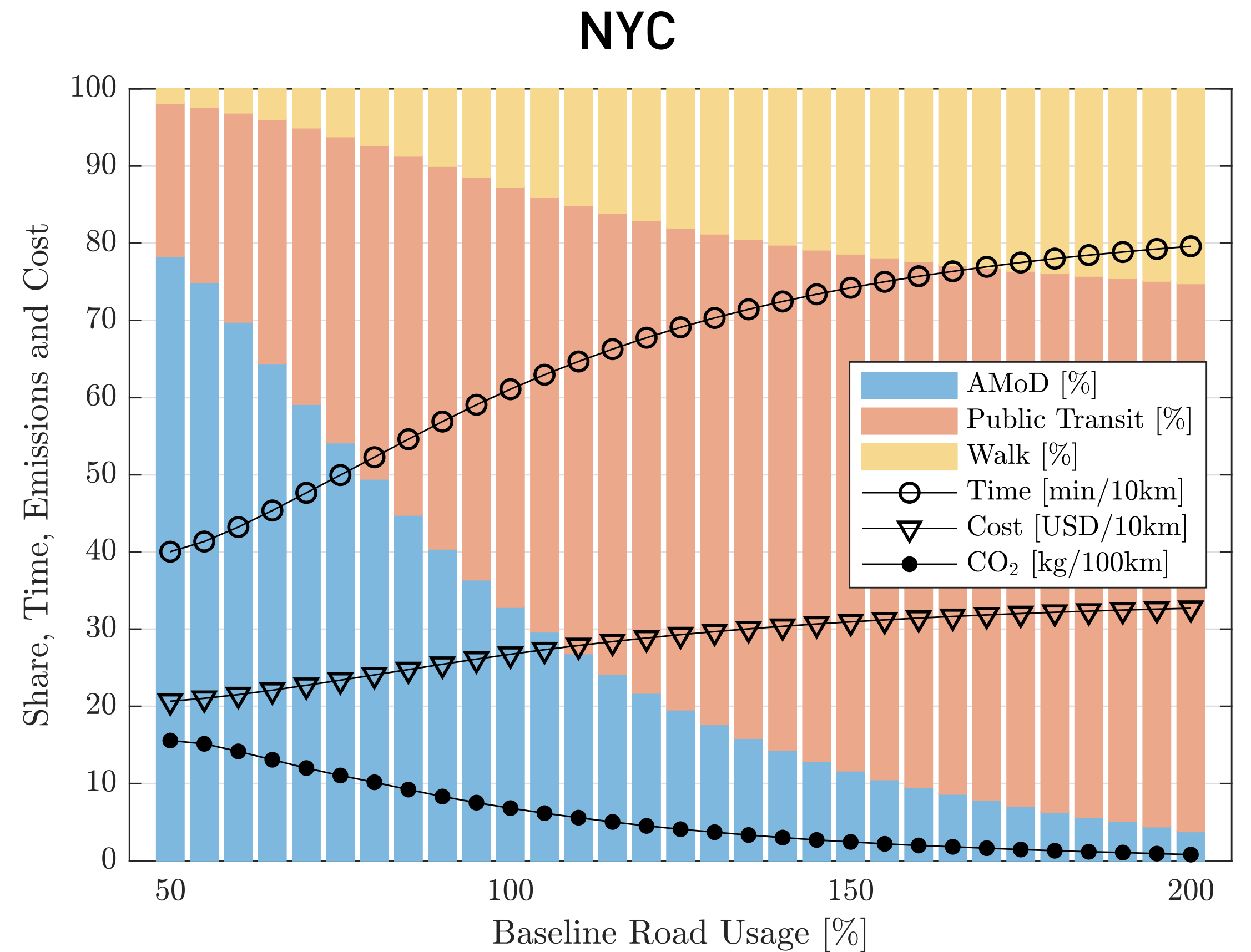
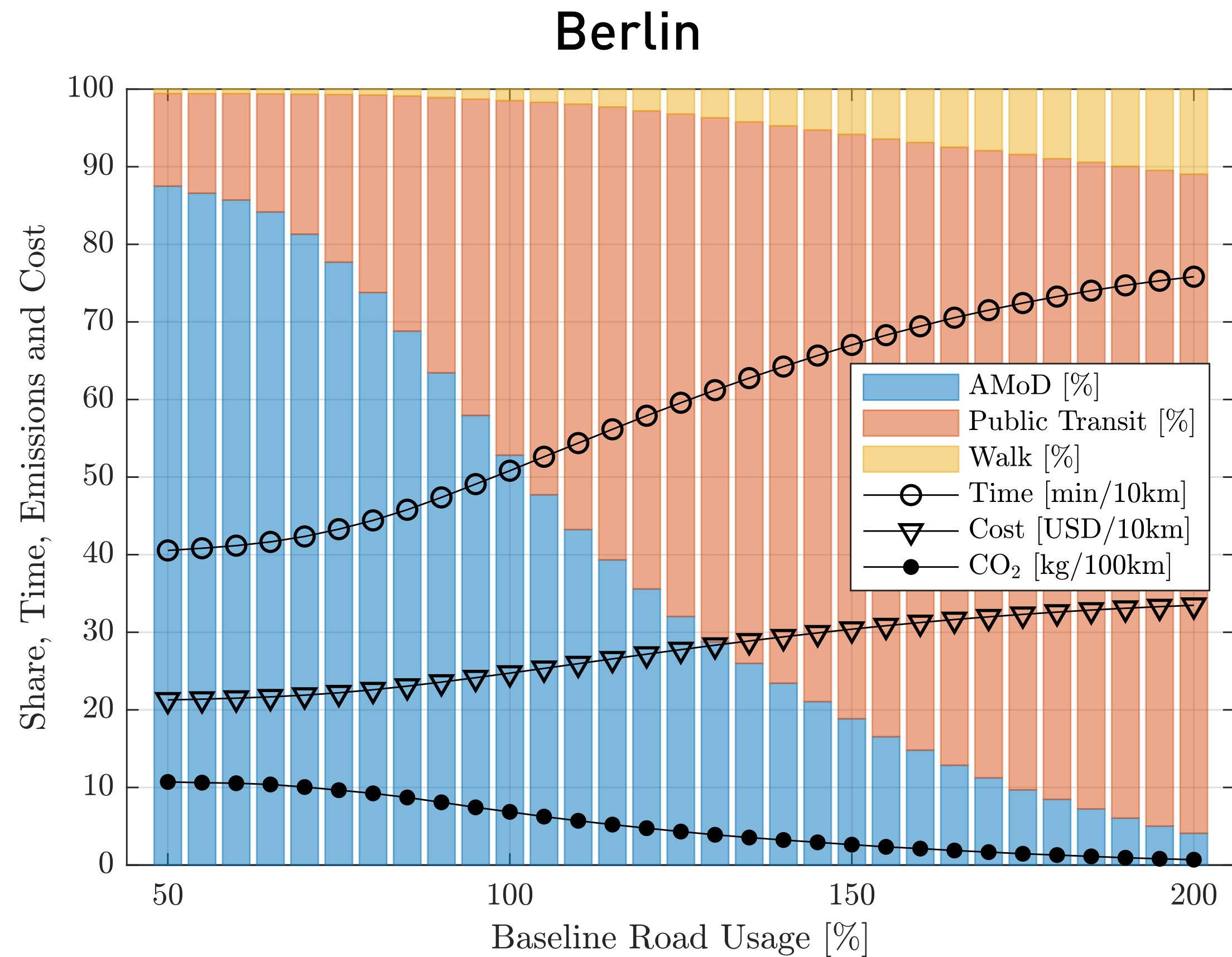
I-AMoD - Scan in Exogenous Traffic

Case Study - Berlin

I-AMoD - Scan in Exogenous Traffic



Case Study - Berlin VS NYC

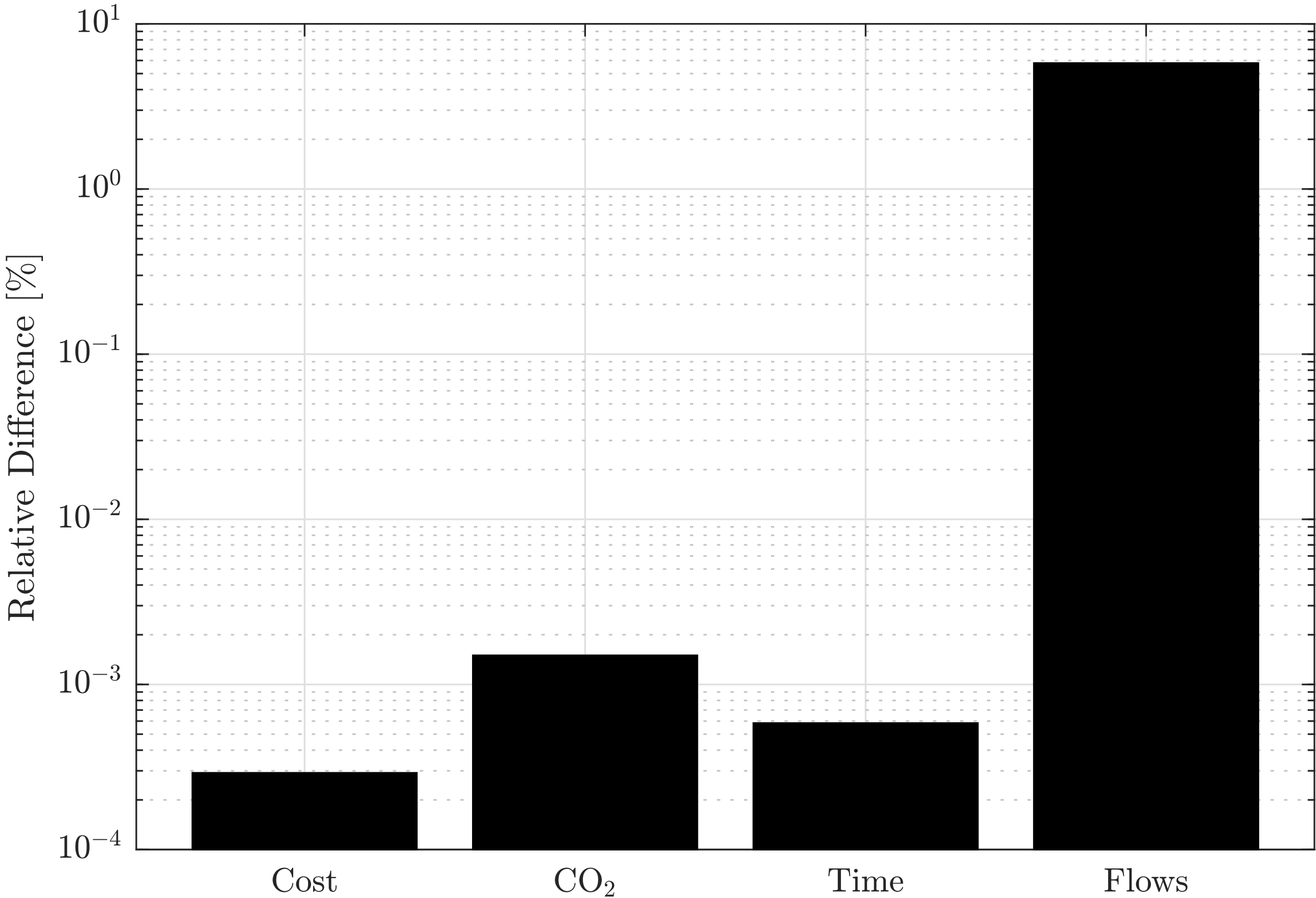


Case Study - NYC

I-AMoD - Fractional VS Integer Solution, what are the differences?

Case Study - NYC

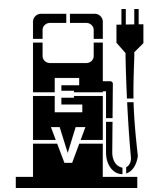
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[Salazar, Rossi, Schiffer, Onder, Pavone, ITSC18; Salazar, Lanzetti, Rossi, Schiffer, Pavone, T-ITS19]

Case Study - NYC

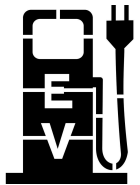
What is the impact of the vehicle size and powertrain type?



Lightweight
Battery Electric

Case Study - NYC

What is the impact of the vehicle size and powertrain type?



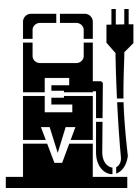
Lightweight
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Lightweight
IC Engine

Case Study - NYC

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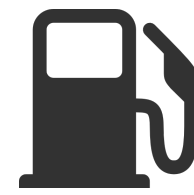
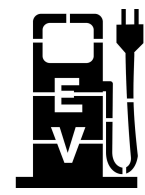


Sport Utility
Battery Electric

Sport Utility
IC Engine

Case Study - NYC

What is the impact of the vehicle size and powertrain type?



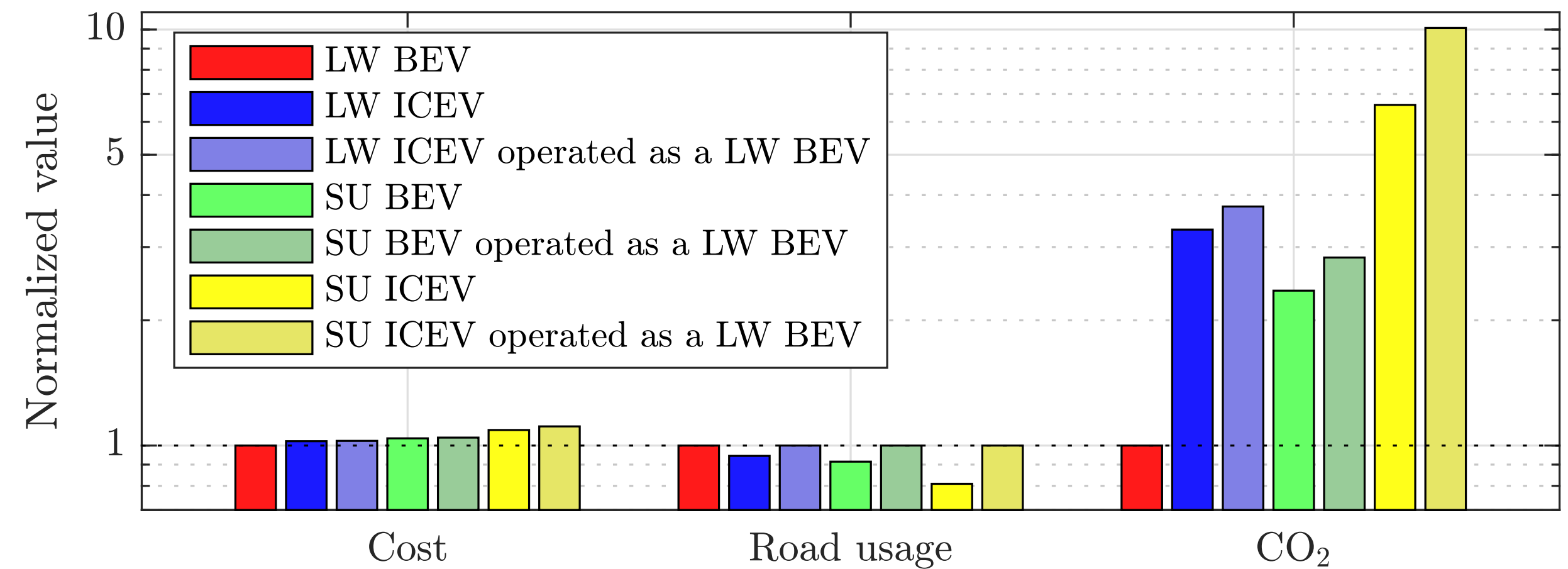
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Sport Utility
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Sport Utility
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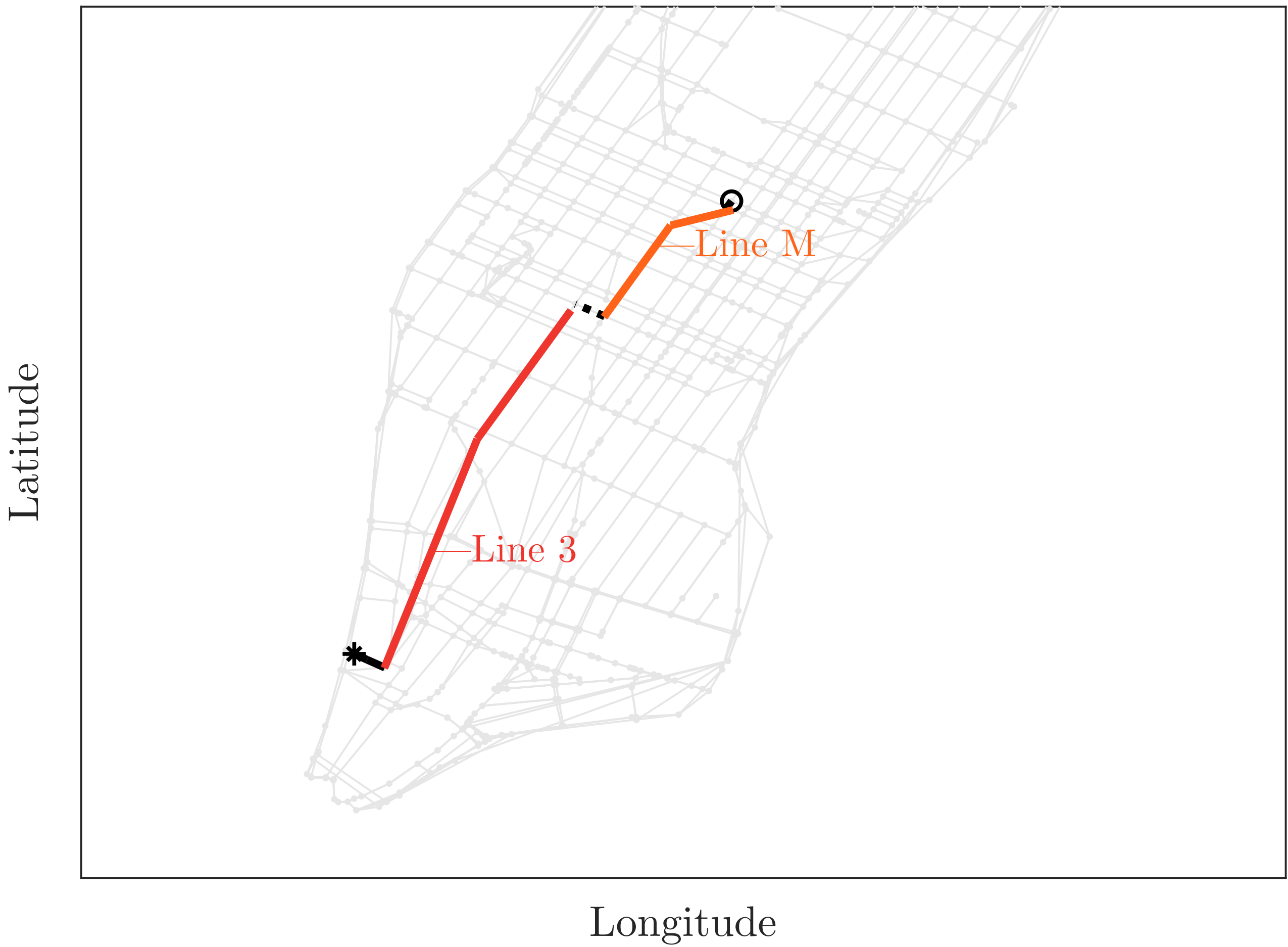


Case Study - NYC

I-AMoD - Sample optimal path

Case Study - NYC

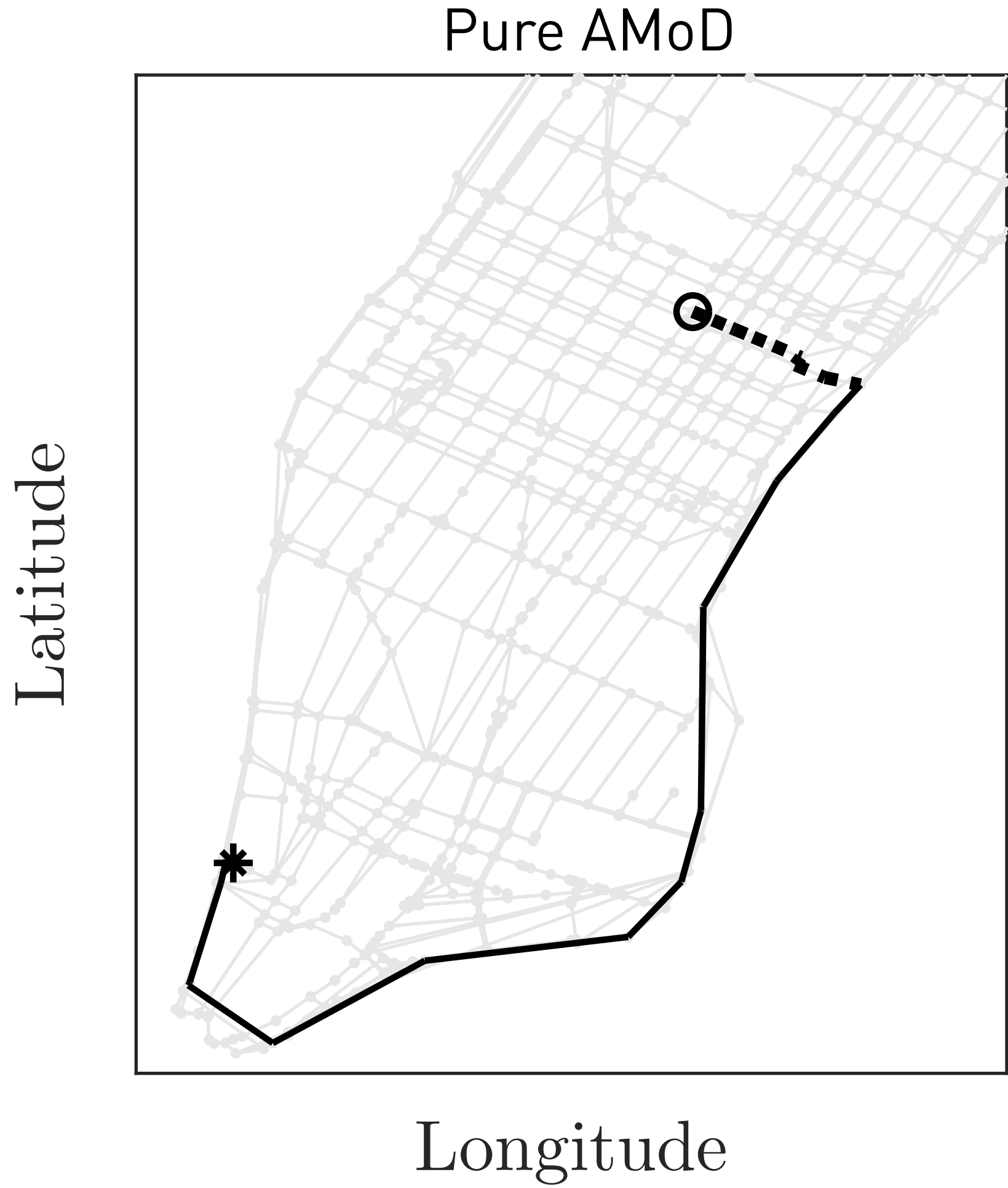
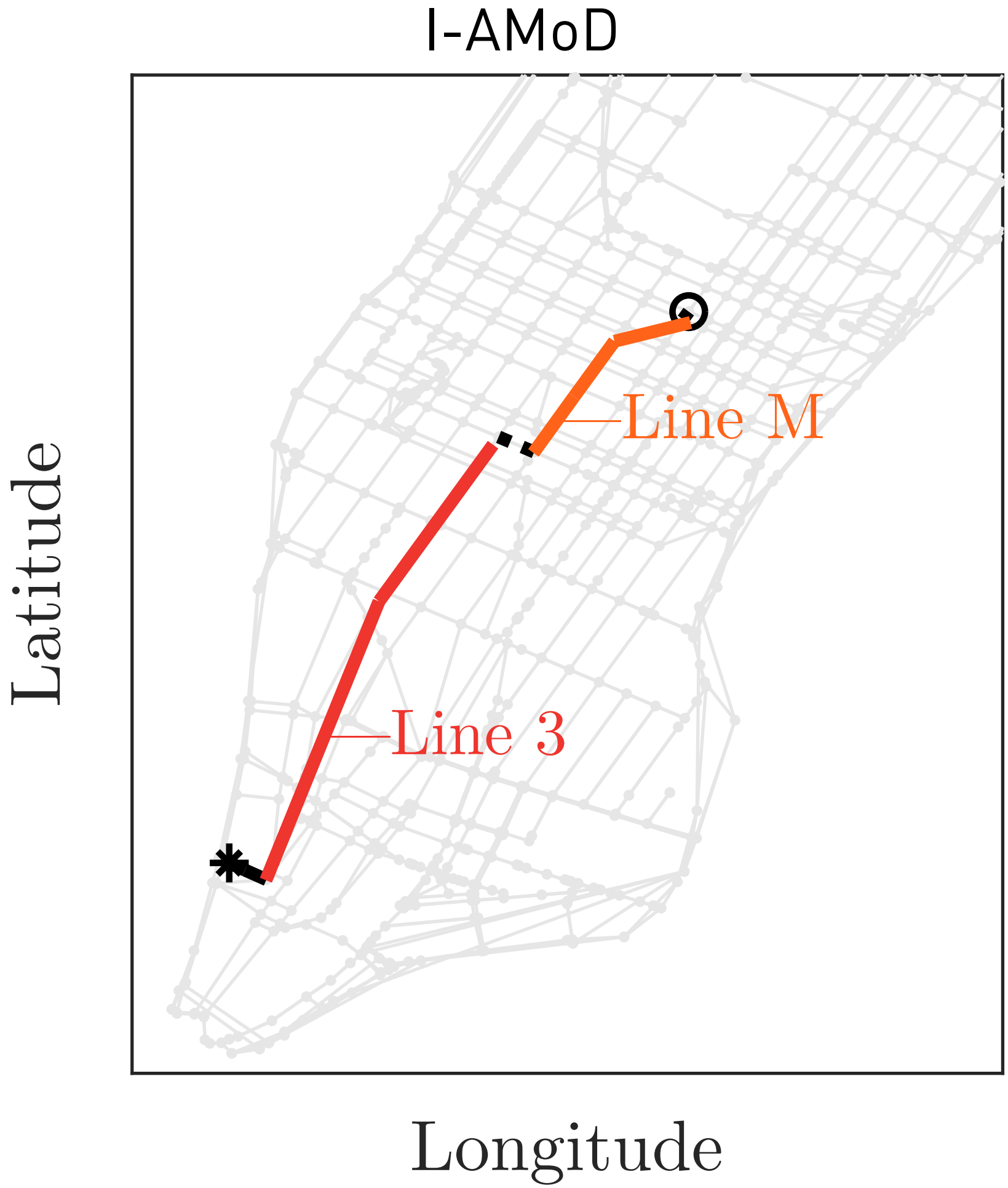
I-AMoD - Sample optimal path



[Salazar, Rossi, Schiffer, Onder, Pavone, ITSC18]

Case Study - NYC

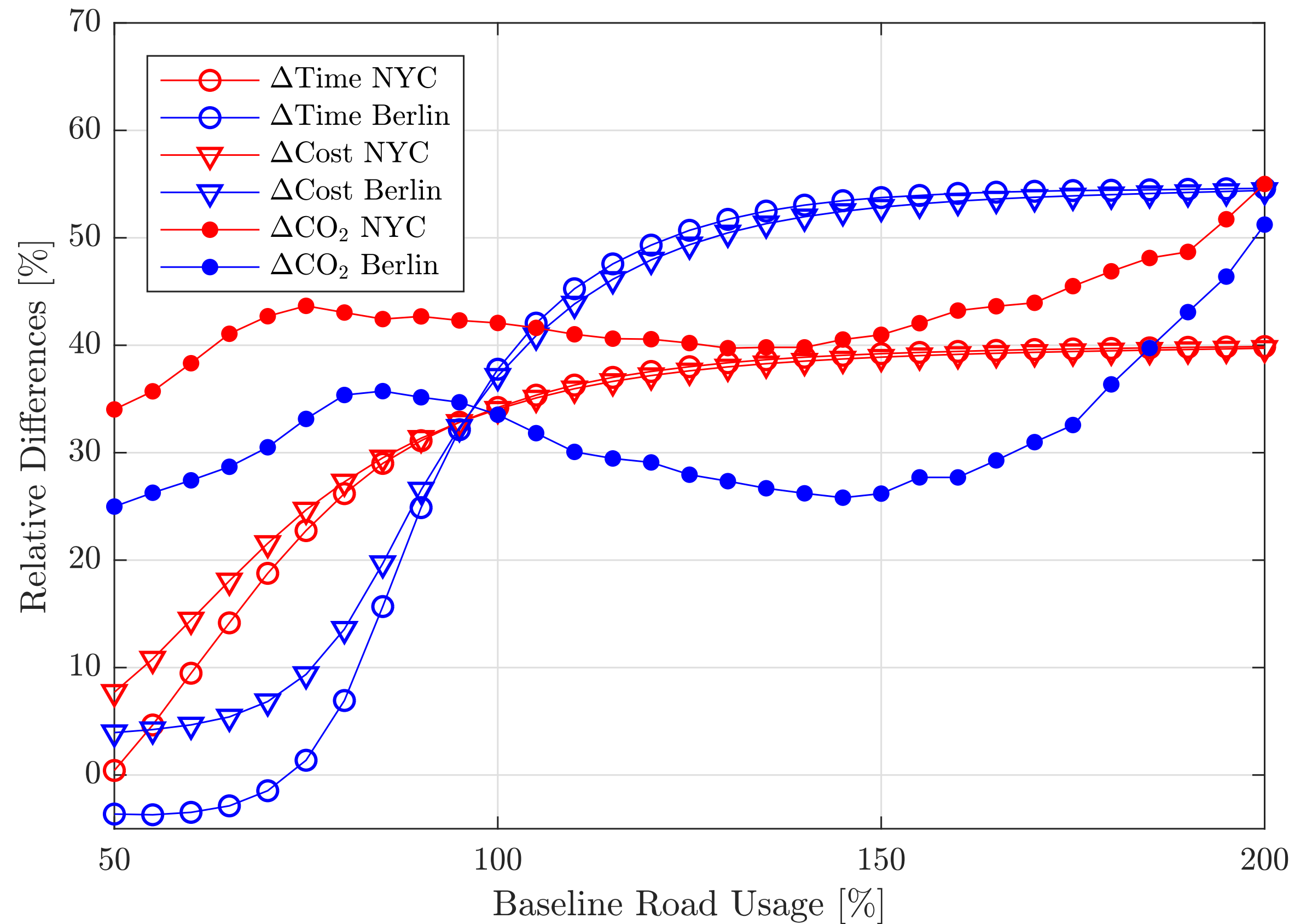
Sample optimal paths



[Salazar, Rossi, Schiffer, Onder, Pavone, ITSC18]

Case Study - NYC and Berlin

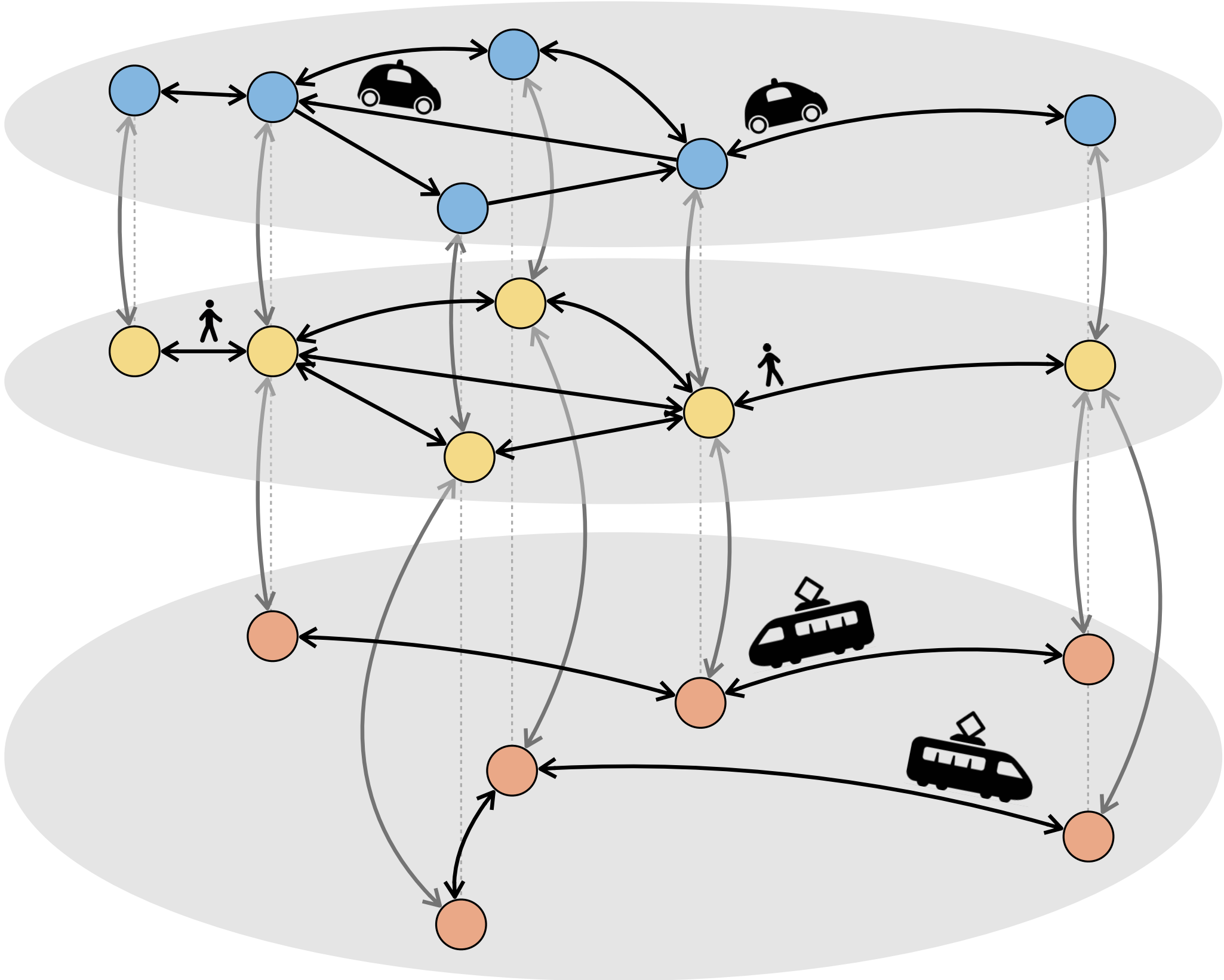
Pure AMoD VS I-AMoD - Relative Difference



Coordination with public transit significantly reduces **travel times, number of vehicles, emissions and cost!**

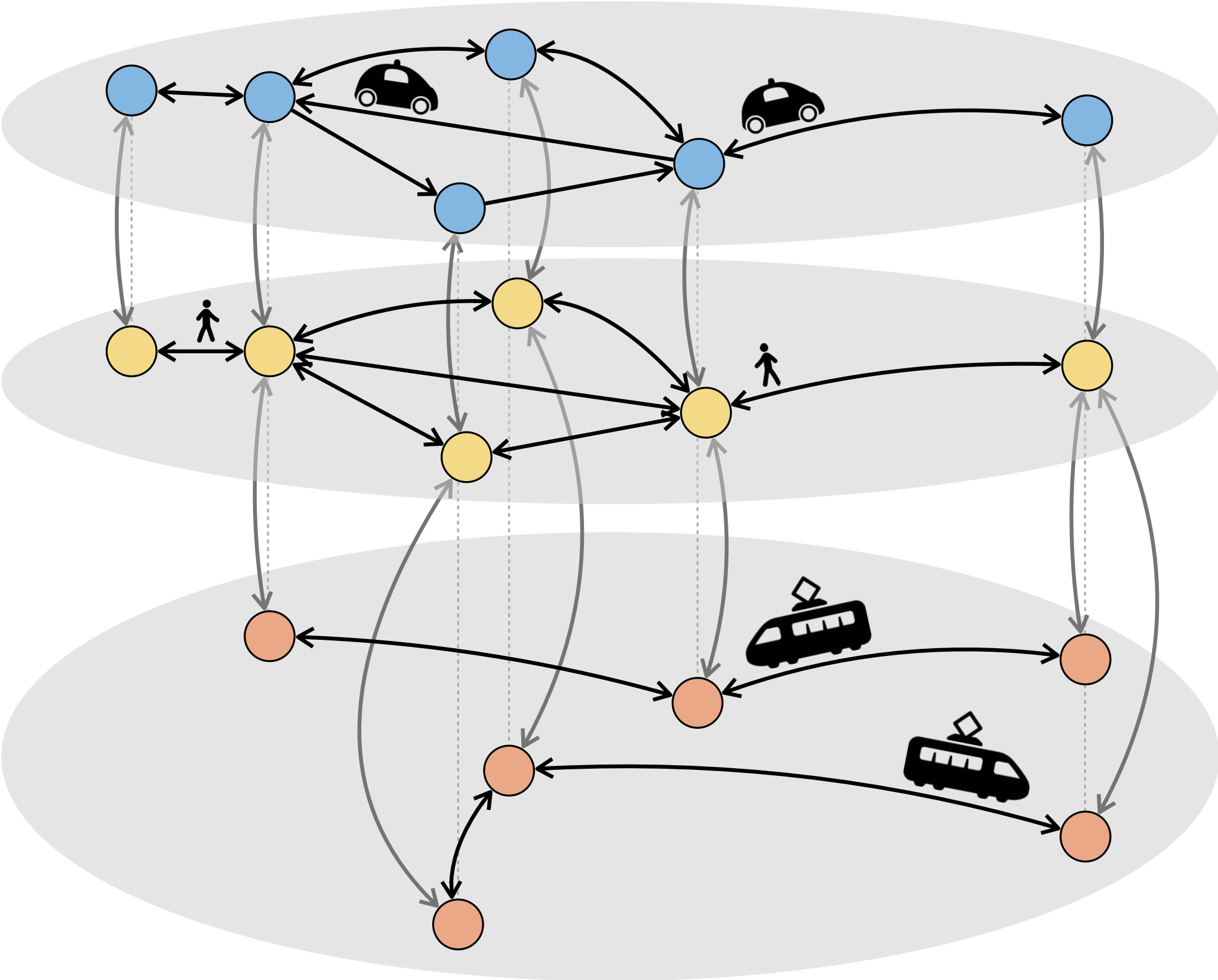
Intermodal Autonomous Mobility-on-Demand

Time-invariant Model for Analysis and Planning



Intermodal Autonomous Mobility-on-Demand

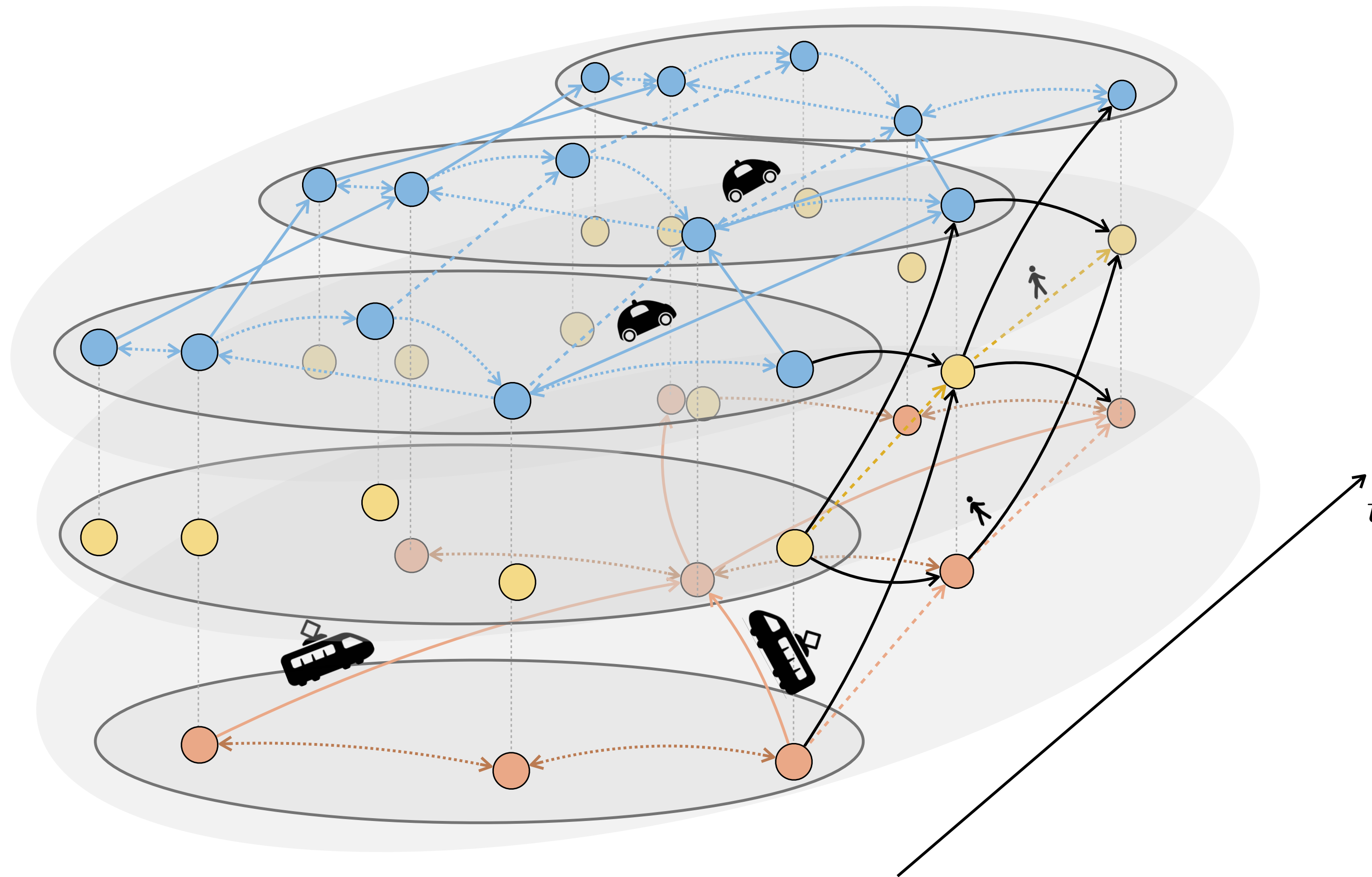
Time-invariant Model for Analysis and Planning



Where do we go from here?

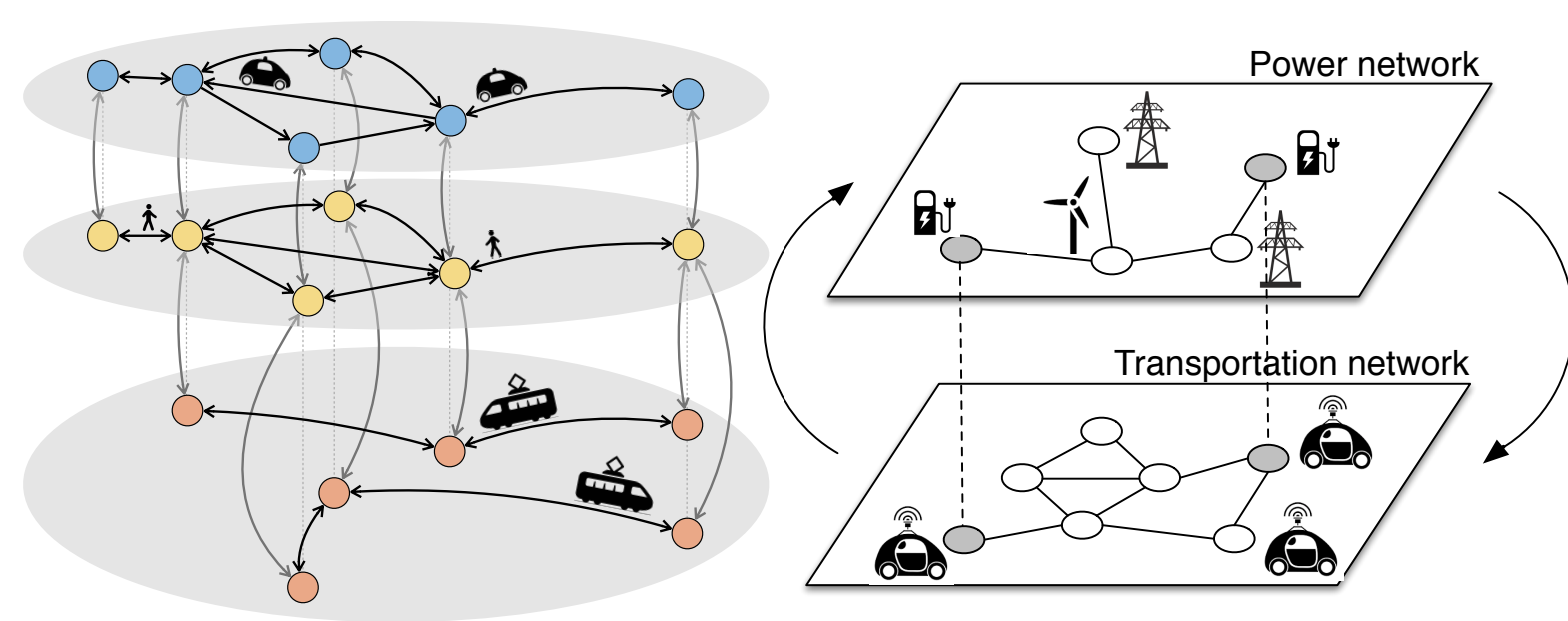
Intermodal Autonomous Mobility-on-Demand

Time-variant Model for Control and Operation: MPC for Intermodal Routing

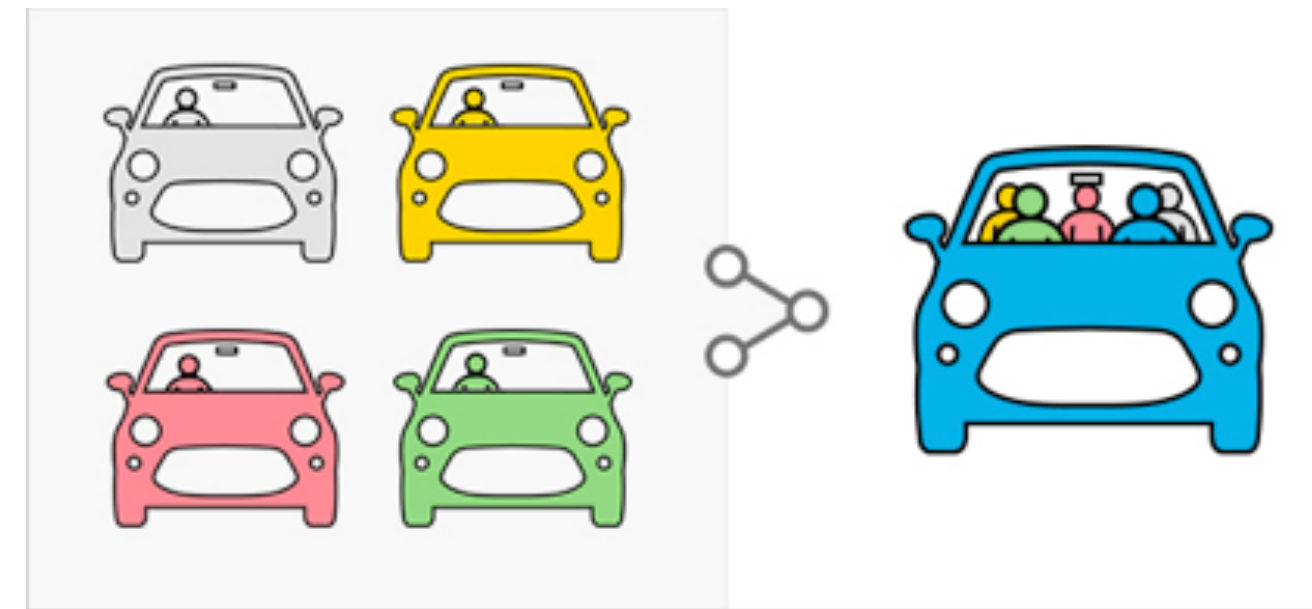


Opportunities in AMoD

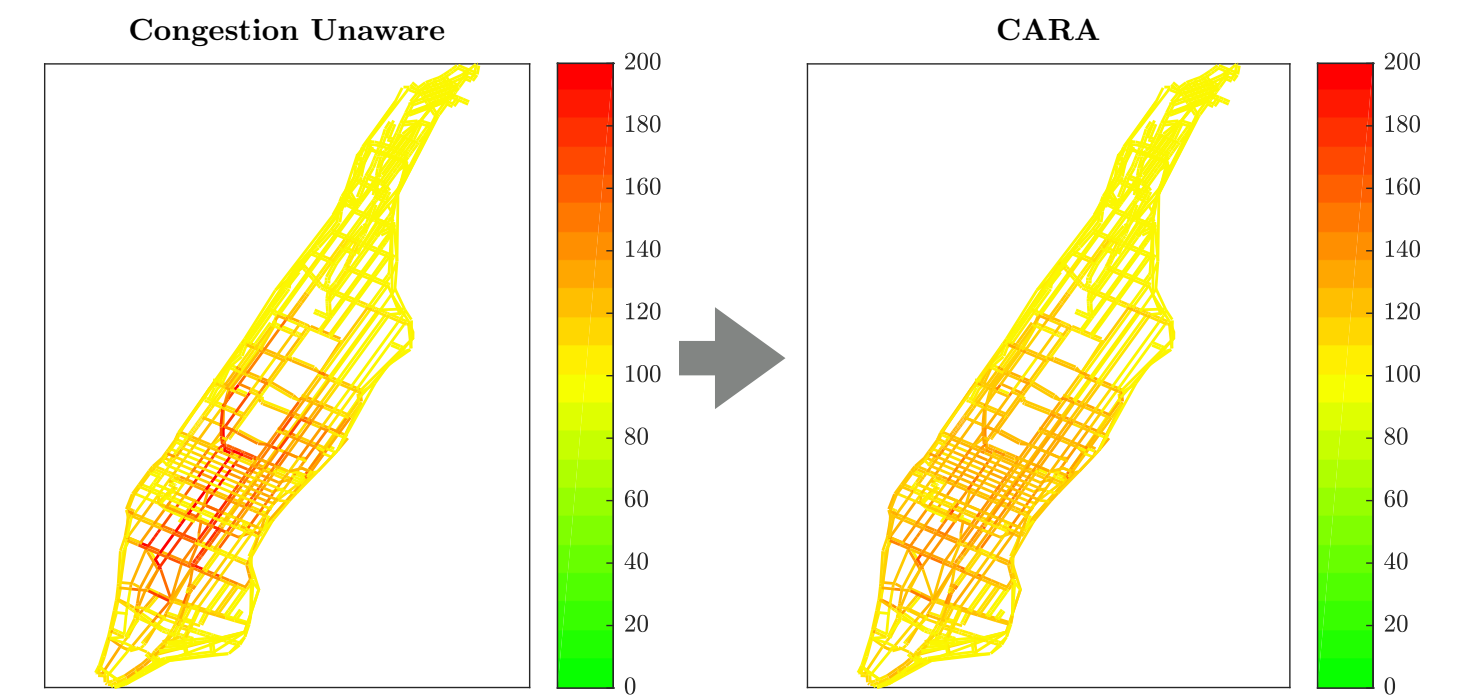
Interaction with Infrastructure



Ride-sharing



Real-time Routing Algorithms



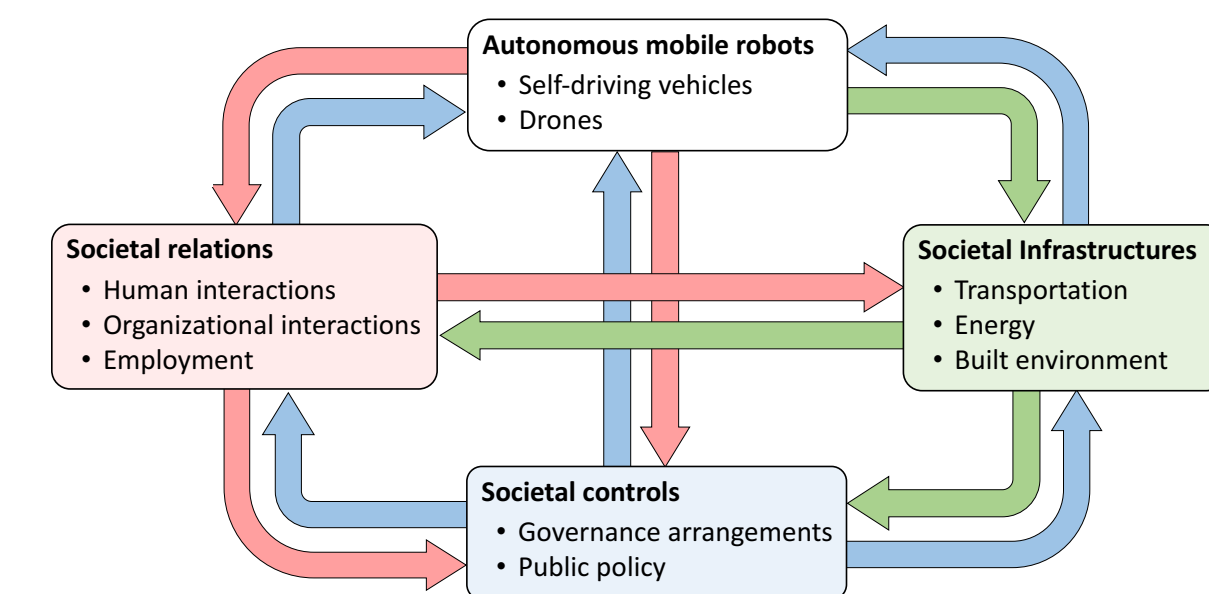
Real-world Case Studies



Technology Infusion



Societal Implications

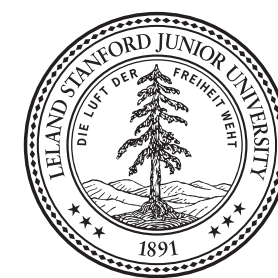


Conclusion

- Autonomous driving might lead to a **transformational** paradigm for personal urban mobility
- Integration of autonomous driving with the urban infrastructure gives rise to an entirely new class of problems (and opportunities)
- Solutions to these problems are key to enable AMoD and to carefully evaluate their value proposition

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