MIT Mobility Initiative

Dan & Eva Roos Thesis Prize

2021-23 Call
Winner Presentations

Mobility Initiative

About the Prize

- Thank Dan & Eva Roos for their generosity
- This is the 3rd edition of the Prize hosted by MMI
- The Thesis Prize is awarded to an outstanding MIT PhD dissertation in the field of transportation/mobility, submitted between Sep 2021 - Jun 2023
- Mobility is broadly defined and the thesis can be submitted to any department or PhD-granting program at MIT, and can address any aspect of transportation systems, such as:
  - research related to any mode of transport
  - passenger or freight transportation
  - theoretical or applied problems in transportation
  - technological, economic, planning or policy analysis in transportation and mobility
- https://www.mmi.mit.edu/roosaward

Previous Year Winners

Mobility Initiative

2021 Winner: Dr. Shenhao Wang, Deep Neural Networks for Choice Analysis

Honorary Mentions:

Dr. Arthur Delarue: Optimizing School Operations

Dr. Wilko Schwarting: Learning and Control for Interactions in Mixed Human-Robot Environments

Prize Selection Committee: Yossi Sheffi, Cindy Barnhart, Alexandre Jacquillat, Jinhua Zhao (Chair)

2018 Winner : Dr. Gabriel Kreindler “Essays on the Economics of Urban Transportation(Extended Abstract | Full Thesis

Prize Selection Committee: Ali Jadbabaie, CEE and IDSS, Yossi Sheffi, CTL and CEE , Hamsa Balakrishnan, Co-Chair, AeroAstro, Jinhua Zhao, Co-Chair, DUSP

2023 Prize

Selection Committee:

- Prof. Amedeo Odoni
- Prof. Alexandre Jacquillat
- Prof. Jinhua Zhao (Chair)

Shortlisted:

- Angela Acocella: Alternative Freight Contracts: Data-driven Design Under Uncertainty
- Hanzhang Qin: Stochastic Control Through a Modern Lens: Applications in Supply Chain Analytics and Logistical Systems
- Baichuan Mo -Toward a Resilient Public Transportation System: Effective Monitoring and Control under Service Disruptions
- Rounaq Basu - Planning sustainable cities: Coordinating accessibility improvements with housing policies
- Karthik Gopalakrishnan - Modeling and Control of Networked Systems: Applications to Air Transportation

2023 Prize

Winner:

- Baichuan Mo -Toward a Resilient Public Transportation System: Effective Monitoring and Control under Service Disruptions

Honorable Mentions

- Rounaq Basu - Planning sustainable cities: Coordinating accessibility improvements with housing policies
- Karthik Gopalakrishnan - Modeling and Control of Networked Systems: Applications to Air Transportation

Massachusetts Institute of Technology

Toward a Resilient Transportation System:

Applications to Public Transit

Baichuan Mo
Ph.D. @ MIT
Senior Research Scientist @ Lyft Inc.

Dec 08, 2023

A shift of transportation research paradigm

"Uncertainty is the only certainty there is."

——John Allen Paulos, Professor in Mathematics






- The world never works as expected. Various unpredictable incidents and disturbances happen everyday
- However, most of previous studies usually assume "normal situations" for prediction, planning, operation, and control in a transportation system

"Abnormal" is the "actual normal" of the world.

Shift of Research Paradigm: Certain, Normal → Uncertain, Abnormal

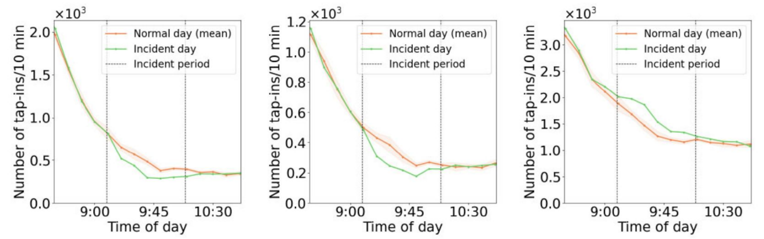
Resilience

- **Definition:** The ability of a system to cope with unplanned incidents and disruptions
- **Motivation:** Building a resilient transportation system is a way to embrace uncertainties and protect the system's functionality under these incidents.
- This dissertation focuses on two import tasks to develop a resilient public transit (PT) system: **Monitoring and Control.**

- 1) Understand the impact of unplanned incidents on PT systems (i.e., **Monitoring**)
- 2) Design mitigating strategies to relieve incident impacts (i.e., **Control**)

Understand the Impact: Long-term incidents

Empirical analysis



(a) Brown Line (blocked) (b) Purple Line (blocked) (c) Red Line (open)

(a) Demand changes of nearby bus stops and rail stations

Response inference

An example for inference illustration:

Passenger p

Observe that he/she transfers to a nearby bus using AFC data

Possible reason 1: he/she needs to transfer to a bus for normal commute

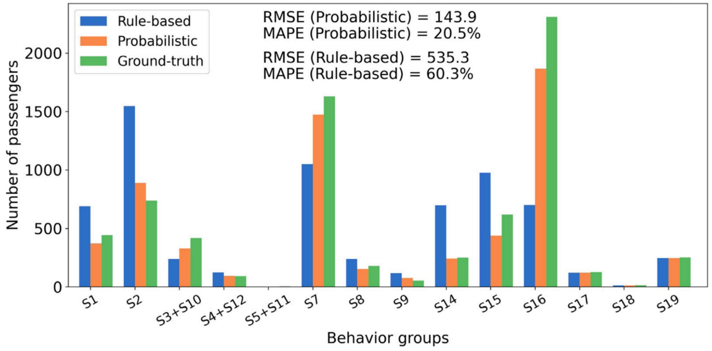
Possible reason 2: he/she transfers to an alternative route due to the incident

(Suppose S_i is the set of passengers who transfer to a bus stop due to incident, $N_i = |S_i|$)

$$\mathbb{P}(p \in S_i) = \mathbb{P}(\text{"Passenger } p\text{'s transfer is an atypical behavior"}) = \frac{\#\text{ days passenegr } p \text{ transfers to bus}}{\#\text{ days passenger } p \text{ with travel}}$$

$$\mathbb{E}(N_i) = \sum_p \mathbb{P}(p \in S_i) \quad \mathrm{Var}(N_i) = \sum_p (1 - \mathbb{P}(p \in S_i)) \times \mathbb{P}(p \in S_i)$$

(By def. of Bernoulli variable)

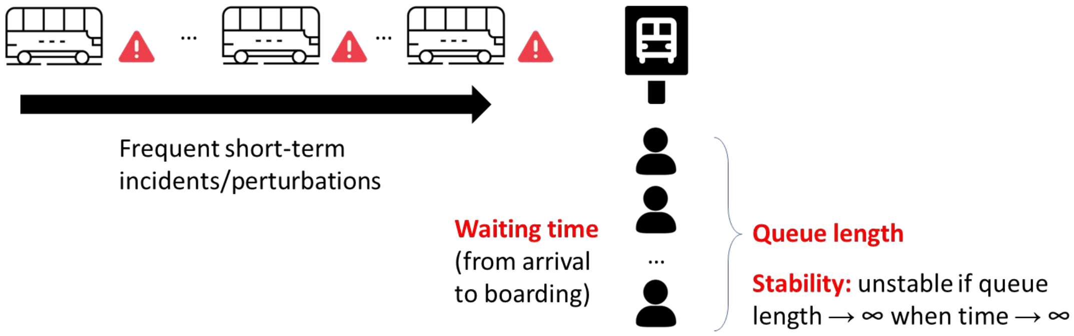


Impact of unplanned long-term service disruptions on urban public transit systems, B Mo et al., IEEE Open Journal of Intelligent Transportation Systems, 2022, 3, 551-569

Inferring Passenger Responses to Urban Rail Disruptions Using Smart Card Data: A Probabilistic Framework. B Mo et al.,. Transportation Research Part E: Logistics and Transportation Review, 2022, 159, 102628

Understand the Impact: Short-term incidents

Theoretical queuing analysis



Proposition 12. *Under the setting of this study, the bulk-service queuing system at station n is stable if and only if*

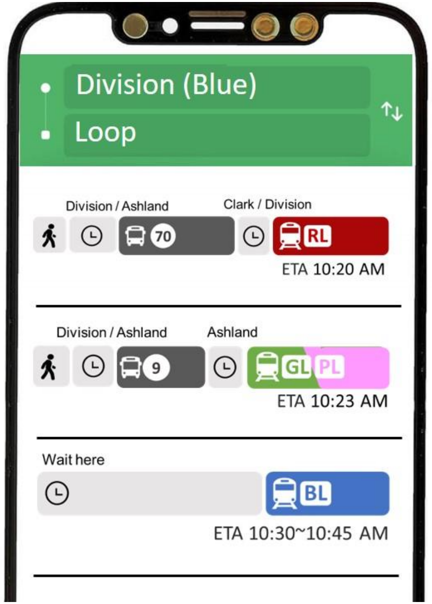
$$\rho^{(n)} = \frac{\bar{Y}^{(n)}}{\bar{S}^{(n)}} = \frac{\left(\mu \cdot \Phi\left(\frac{\mu}{\sigma}\right) + \sigma \cdot \phi\left(\frac{-\mu}{\sigma}\right)\right) \cdot \lambda^{(n)}}{\sum_{u=0}^{C} s_u^{(n)} u} = \frac{\lambda^{(n)} \cdot \mathbb{E}[\hat{H}^{(n)}_{Normal}]}{\sum_{u=0}^{C} s_u^{(n)} u} < 1 \qquad (2.59)$$

- higher rate of incidents (gamma) and higher duration of incidents (1/theta) make the system more likely to be unstable.
- The closed-form formulation can be used to calculate queue length and waiting time efficiently considering short-term perturbations.
- Public transit design diagnose (e.g., headways and vehicle capacity)

Evaluation of Public Transit Systems under Short Random Service Suspensions: A Bulk-Service Queuing Approach. B Mo et al., arXiv preprint arXiv:2301.00918

Control under disruptions: Path recommendation

Individual-based with behavior uncertainty



System recommendation (r')

User p choices (r)

	Path 1	Path 2	Path 3
Path 1	**0.7**	0.1	0.1
Path 2	0.2	**0.8**	0.3
Path 3	0.1	0.1	**0.6**

Matrix of $\pi^{r}_{p,r'}$

Control under disruptions: Path recommendation

New solving methods and with solution-quality bounds

- **Challenges**: Randomness in passenger behavior makes the decision variables (passenger flow) become random variables
- **Ideas**: Treat the passenger flow (decision variables) as realizations (deterministic), but add constraints to it (ε-feasibility and Γ-concentration)
- **Solution-quality bound**: The optimal system travel time (STT) in the new formulation is close to the expected STT without approximation (true system performance indicator) if ε and Γ are small enough.

$$\left|\mathbb{E}_{\boldsymbol{Q}|_{\boldsymbol{x}^*}}[STT(\boldsymbol{Q}|_{\boldsymbol{x}^*})] - SST(\boldsymbol{q}^*)\right| \leq 2L \cdot \|\boldsymbol{\epsilon}\|_1 + L \cdot \left(\|\mathbb{E}[\boldsymbol{Q}|_{\boldsymbol{x}^*}]\|_1 + \left\|\boldsymbol{q}^{Max}\right\|_1 + 2\,\|\boldsymbol{\epsilon}\|_1 \right) \cdot \|\boldsymbol{\Gamma}\|_2^2$$

Control under disruptions: Path recommendation

Chicago public transit case study

Table 2 Average travel time comparison for different models

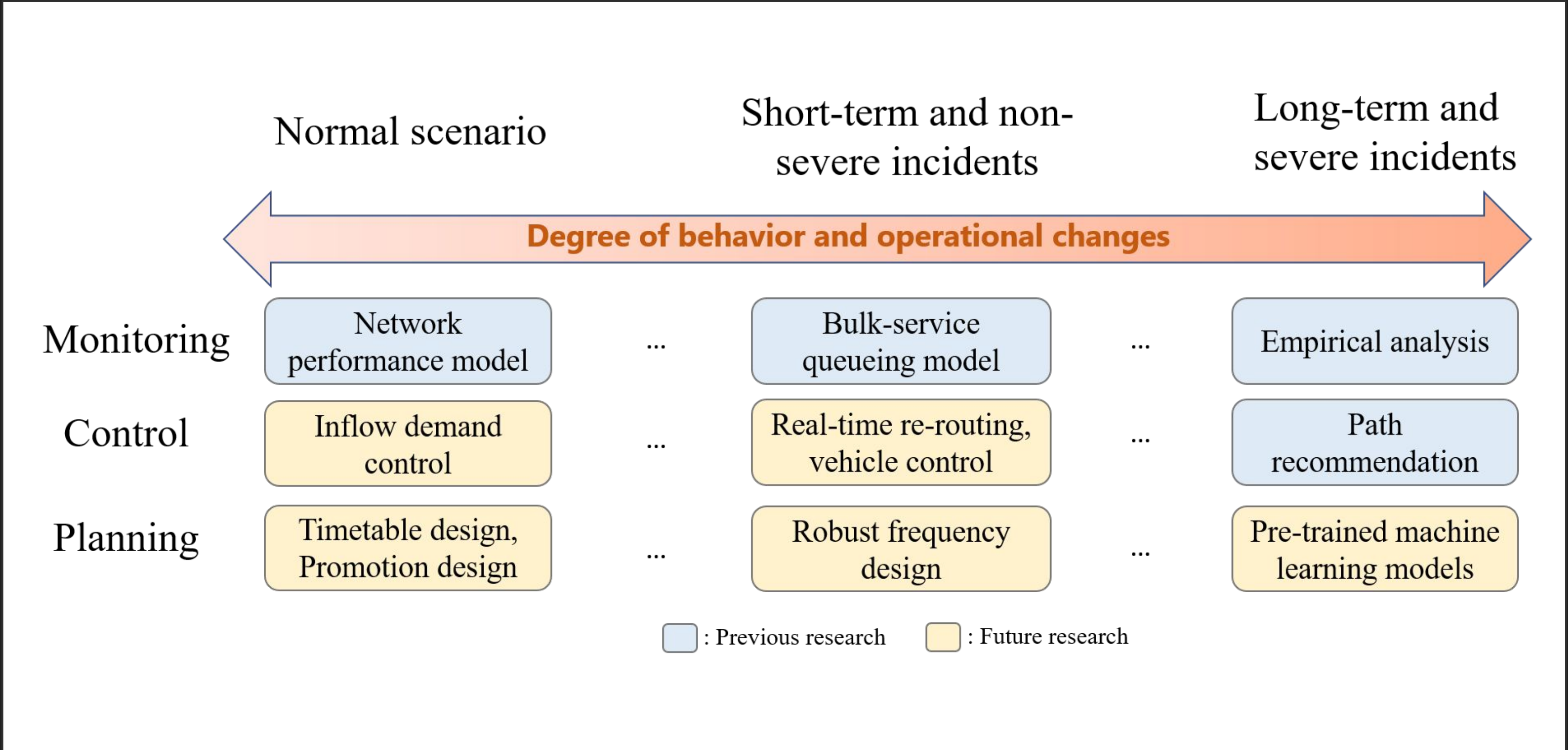
Models	Average travel time (all passengers)		Average travel time (incident line passengers)	
	Mean (min)	Std. (min)	Mean (min)	Std. (min)
Status quo	28.318	N.A.	40.255	N.A.
Capacity-based	27.609 (-2.5%)	0.033	33.848 (-15.9%)	0.165
IPR model	26.457 (-6.6%)	0.018	32.626 (-19.0%)	0.187

Numbers in parentheses represent percentage travel time reduction compared to the status quo

Implementation: Incident management system

Figure credit to Dingyi Zhuang

A unified framework and extensions



Massachusetts
Institute of
Technology

Planning sustainable cities

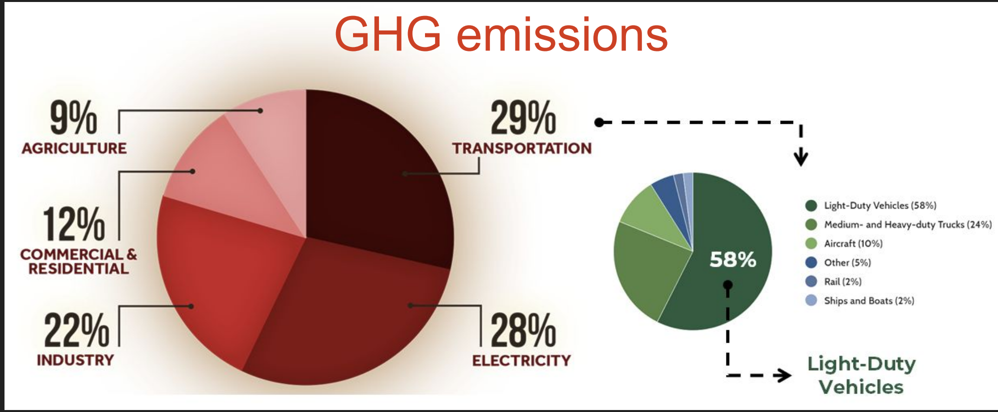
Coordinating accessibility improvements with housing policies

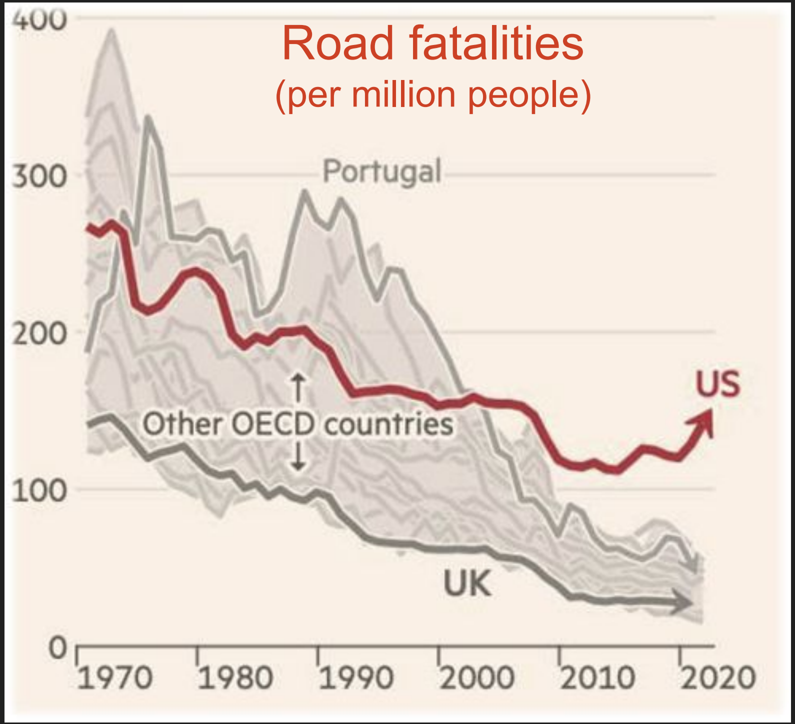
Rounaq Basu

Postdoctoral Associate, MIT
Manager of Multimodal Planning and Design, Boston Region MPO

December 8, 2023

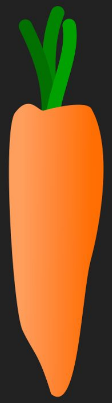
The challenges of auto-dependence





Car-lite programs

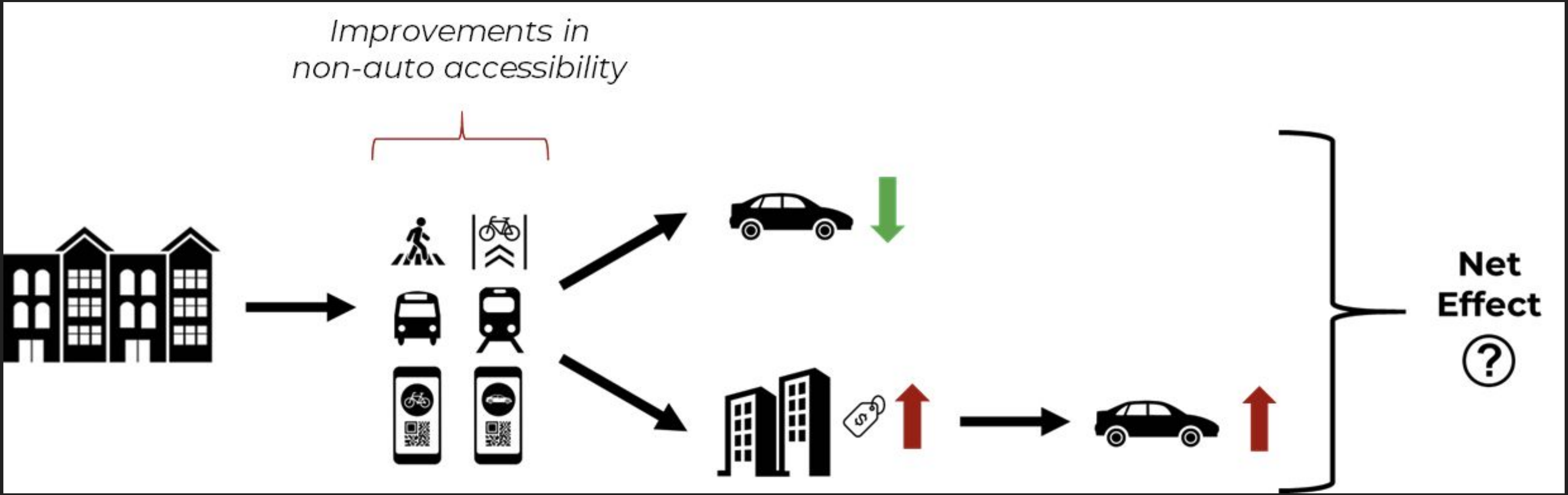
GOAL: Reduce private vehicle ownership, use, and emissions without reducing mobility and accessibility



Improve accessibility from non-auto modes

Make owning and using a car less attractive

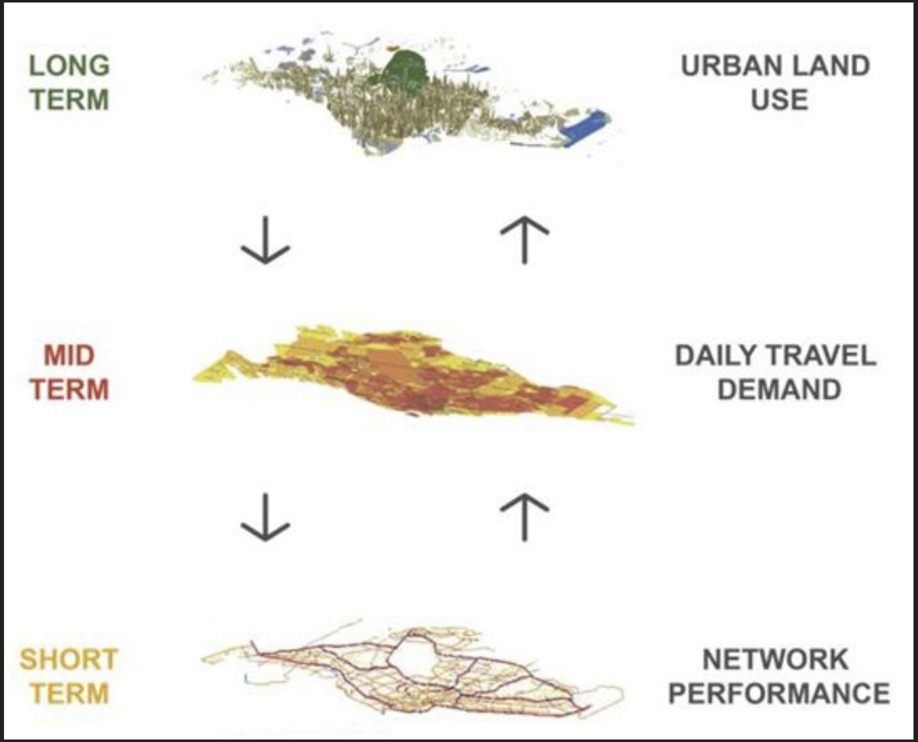
Neighborhood change



Car-lite policy scenarios

- Blanket ban on private vehicles
- Non-auto accessibility improvements
    - Non-auto accessibility = Auto accessibility *(on average)*
- Non-auto accessibility improvements + Housing policies
    - Upzoning *(Increased housing supply)*
    - Parking minimum reductions *(Reduced vehicle ownership opportunities in new housing supply)*

Integrated Urban Modeling



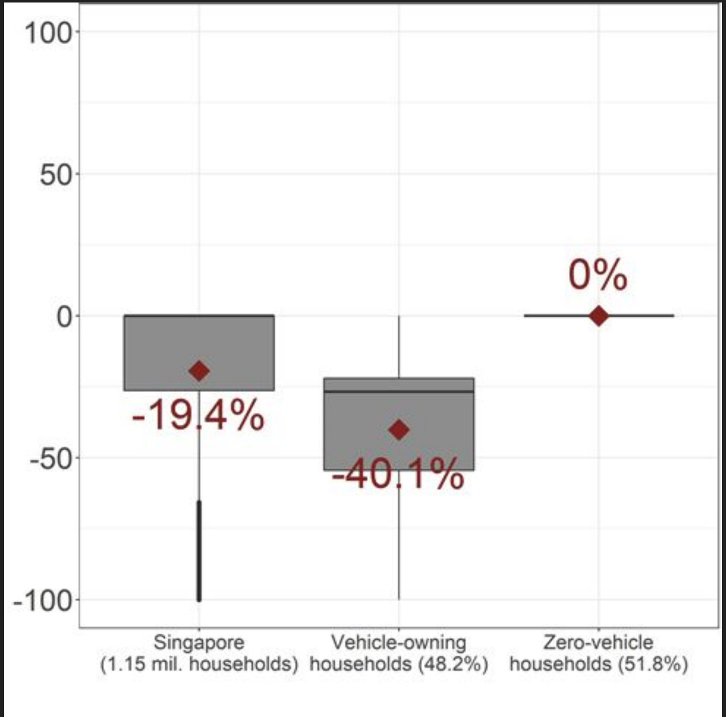
SimMobility

A land use-transport interaction (LUTI) model

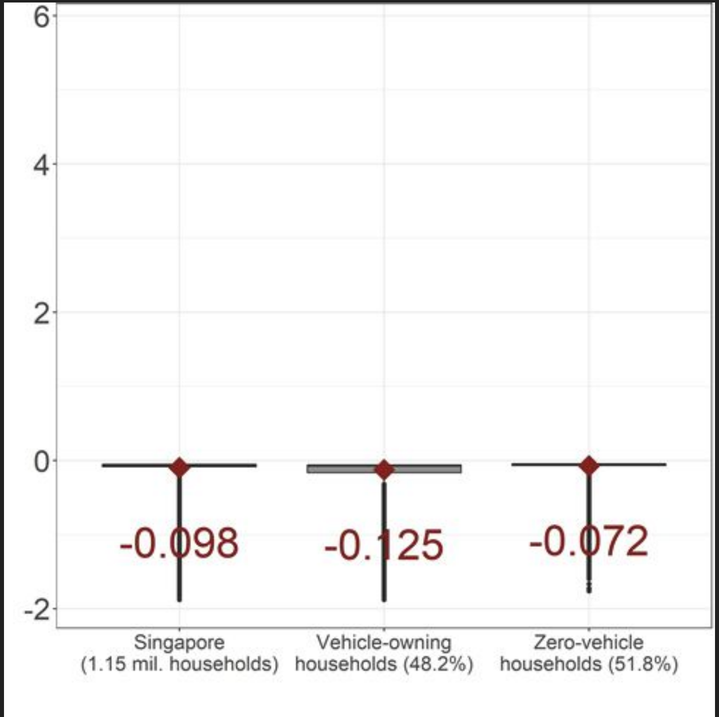
SMART
Singapore-MIT Alliance for Research and Technology

Blanket ban on private vehicles

Change in accessibility (%)

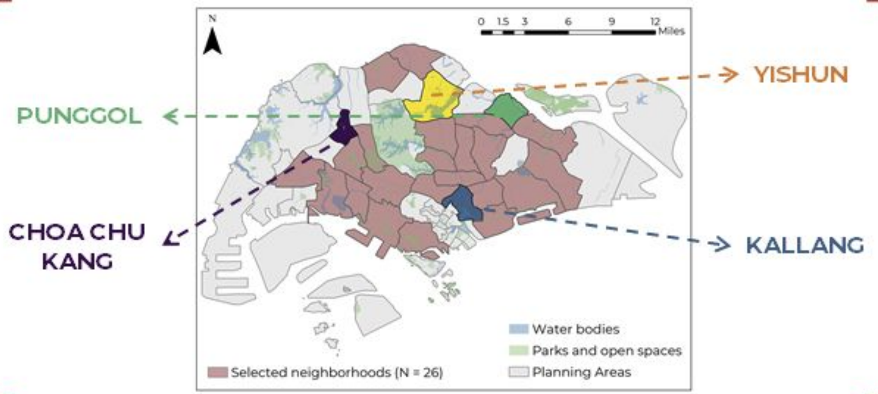


Change in consumer surplus
(million SGD)



Non-auto accessibility improvements

- *Initial characteristics*
  - Higher-income
  - Less car-free
- *Policy outcome*
  - Less gentrification



- *Initial characteristics*
  - Lower-income
  - More car-free
- *Policy outcome*
  - More gentrification

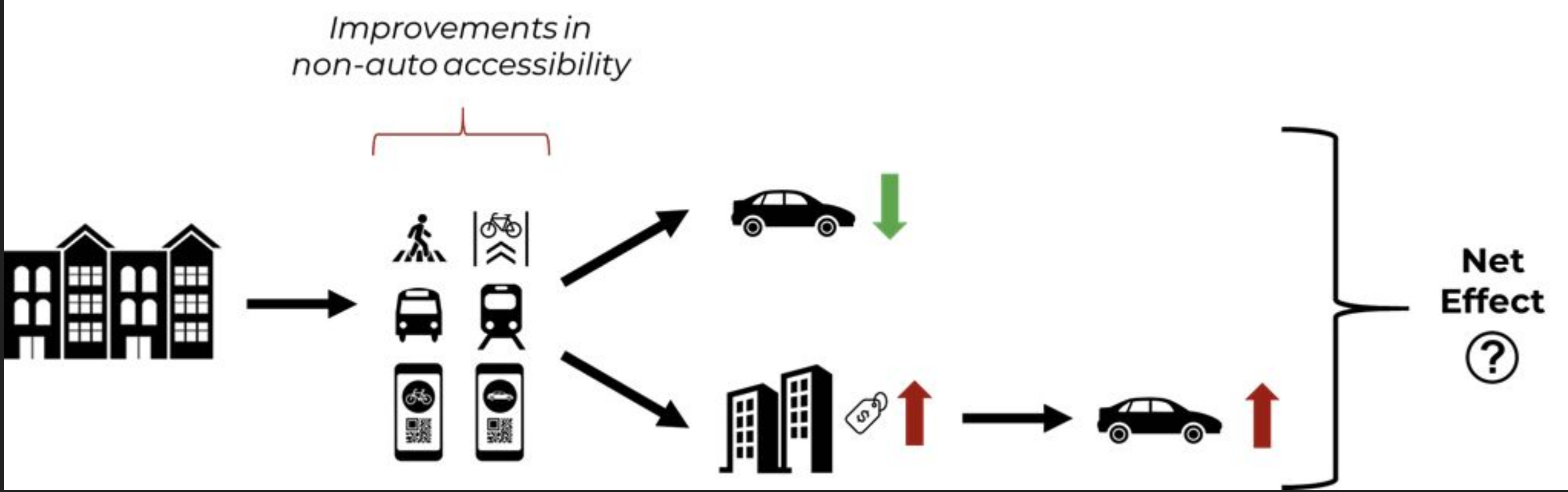
Lower-income and more vehicle-free neighborhoods are ***more*** susceptible to accessibility-induced gentrification (**!**)

Coordinated housing-mobility policies

GOAL: Mitigating undesired consequences while maximizing benefits of accessibility improvements

- No ‘one size fits all’ housing policy!
- Certain policy combinations can result in worse outcomes compared to ‘baseline’ or ‘no-coordination’ scenarios

Key takeaways (1)



Planning sustainable cities requires careful attention to *both transportation and housing* impacts of accessibility improvements

Key takeaways (2)

How can we accelerate sustainable mobility outcomes?

Improve accessibility from non-auto modes

+

Make owning and using a car less attractive

Massachusetts Institute of Technology

Modeling and Control of Networked Systems

Applications to Air Transportation

Karthik Gopalakrishnan
Systems Engineer at Tesla

PhD in Aeronautics and Astronautics, 2021
Advisor: Prof. Hamsa Balakrishnan

Air travel connects the world…

4.5 billion pax, $6.7 trillion worth goods, 22k city pairs, 39 million scheduled flights

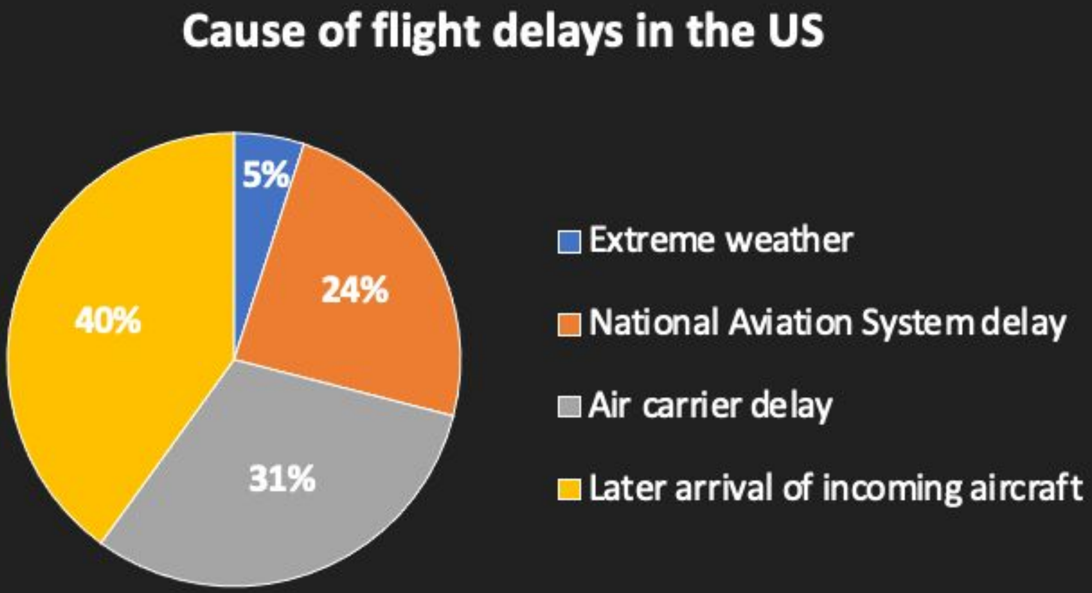
[Image: Wikipedia]

..but the system is far from perfect

In the US, almost 20% of flights are delayed and 2% of flights are cancelled
This costs $30-40 billion a year (approx $300 / min of delay / flight)

[Image: Getty]

What causes flight delays?



"Your flight is delayed because the incoming flight is delayed"

How do we model, predict, and reduce the spread of flight delays?

- Data-driven methods: Accurate but not interpretable
- Network model: Interpretable but not accurate

[Data: FAA]

Features of our new delay propagation model

Airport delays don't change abruptly

Airport delays experience network effects

$$d_{in}^{i}(t+1) = \alpha_{in}^{i} \; d_{in}^{i}(t) + \sum_{j} \underbrace{\beta_{in}^{ji} \; a_{ji}(t) \; d_{out}^{j}(t)}$$

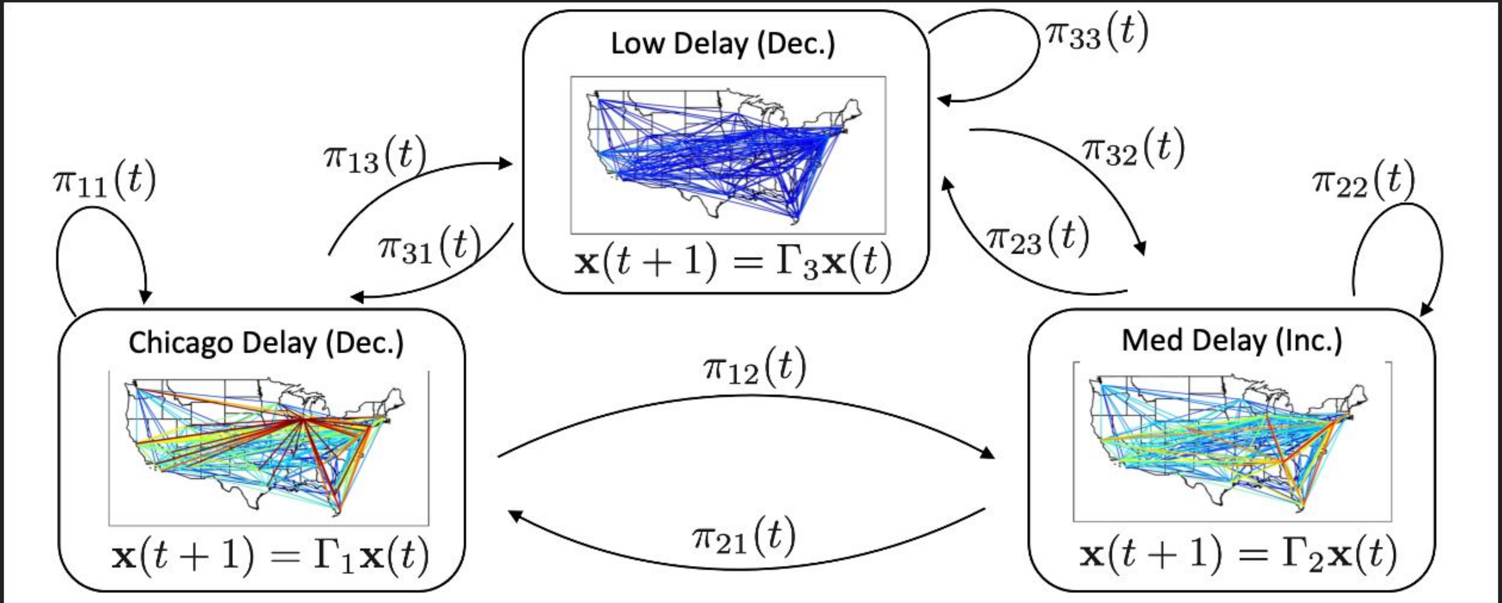
Time-varying network topology

α: Persistence coefficient

β: Network-effect coefficient

[Images: SITA, Wikipedia]

The Markov Jump Linear System (MJLS) model

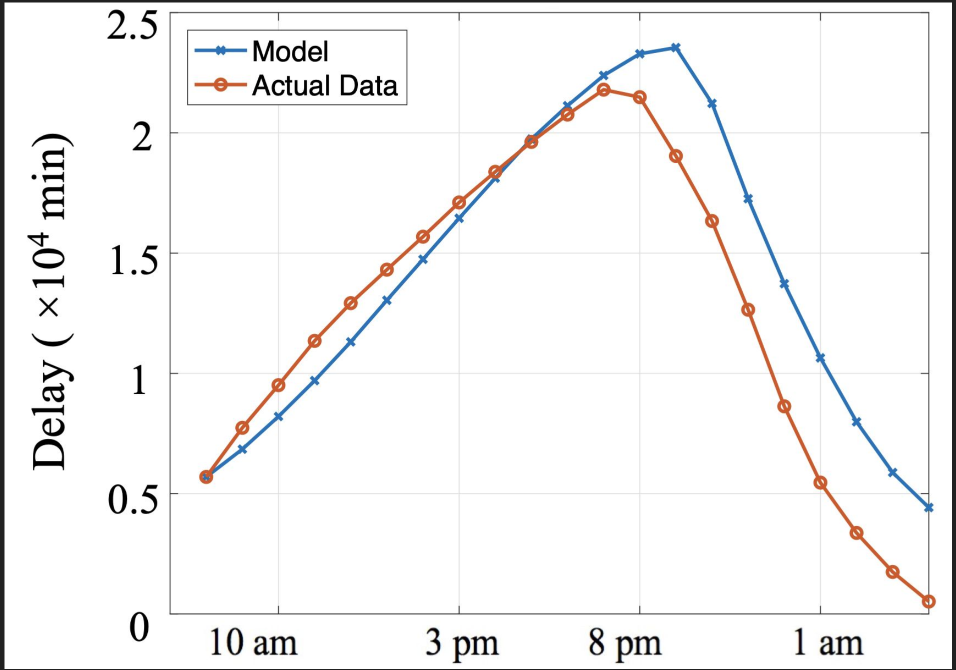


The model combines interpretability and accuracy

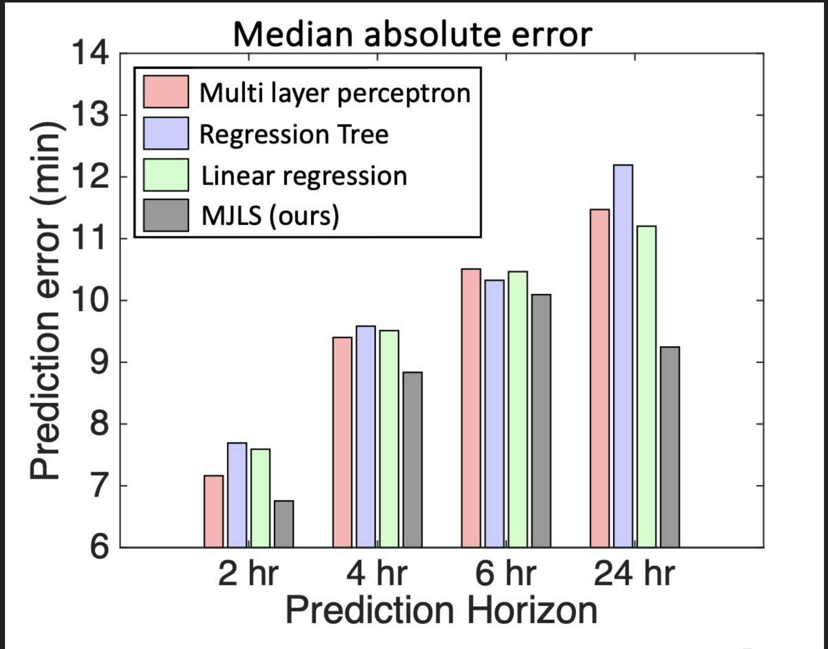
- Network modes and their transitions are interpretable
- Network modes, model coefficients, and transition probabilities are learnt from data

The MJLS model performs well..

… qualitatively



and quantitatively

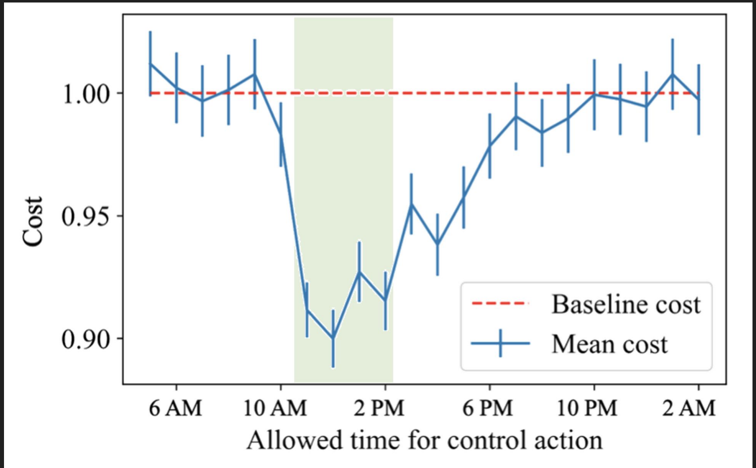


The model suggest strategies to minimize delays

We solve an optimal control problem to identify the ideal airports and network modes that can help minimize the spread of delays in the entire country

Target airports to reduce delays:
Atlanta, Chicago, San Francisco, Los Angeles

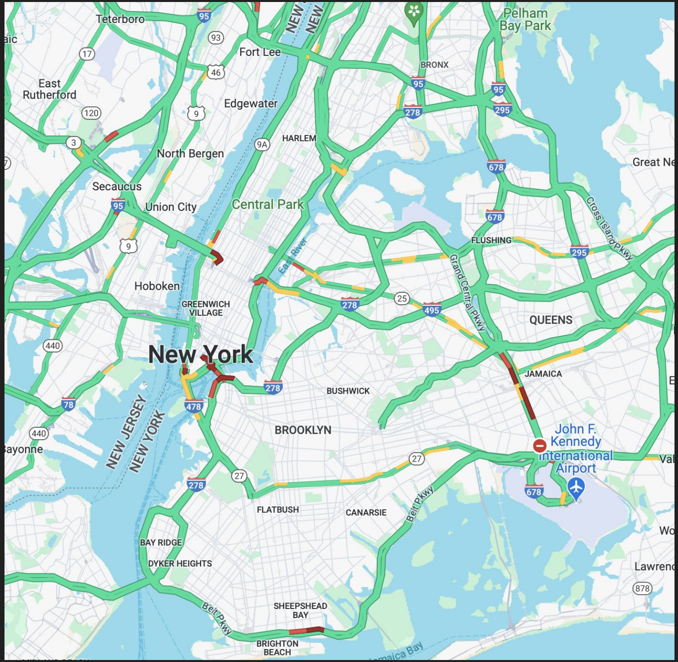
Ideal time to reduce delays:
10 AM to 2 PM Eastern



Data-driven network models offer a powerful paradigm to study large-scale transportation systems

UAM/AAM traffic management

Road traffic prediction & control



[Images: NASA, Google]

Q&A