

Discovering Robust Urban Mobility Futures via Agent Based Simulation in Prototype Cities

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7th TRB Innovations in Travel Modeling Conference | Atlanta, GA. June 27, 2018

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Mobility of the future: motivation

Key question

How would

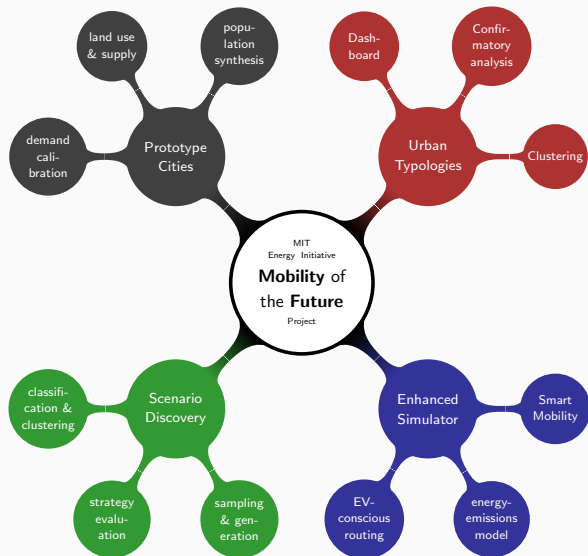
- Smart mobility/autonomous mobility on demand
- Vehicle and fuel technologies
- Energy and environmental policies

affect **future urban mobility**?

Approach

- Understand and replicate mobility and energy-related urban dynamics in worldwide prototypical metropolitan areas
- Build enhanced **urban** laboratory to simulate individual traveler reaction and transportation system performance
- Identify efficient policy intersections across various strategies under uncertainty futures

Research overview



Motivation for scenario discovery

Traditional scenario analysis

- Does not adequately address uncertainties in decision making
- Relies on overly narrow deterministic definition of a small number of scenarios

Scenario discovery

- Provides framework for sampling across space of multiple futures
- Allows for identification of clusters of cases where base strategy fails
- These give rise to robust scenarios

SCENARIO GENERATION

- identify & quantify uncertainties
- sample scenarios

SIMULATION

- run model for enumerated strategies across feasible scenarios
- obtain futures matrix

BENCHMARKING/CLASSIFICATION

- evaluate on performance metric(s)
- rank strategies based on minimum regret
- choose benchmark strategy
- classify success/failure outcomes on regret threshold

POLICY DECISIONS

- conditions under which chosen strategy would fail
- recommendation for alternative strategies
- policy insights based on robustness analysis
- further exploration of cases within critical regions identified

DISCOVERY

- identify high-interest regions where benchmark strategy fails (using PRIM algorithm)
- covering a large number of points
 - dense in number of failure cases
 - interpretable by parameter ranges

search/cluster

Prior work and significance of current contributions

Notable academic efforts and key milestones

- Foundations: exploratory modeling^{Bankes 1993}
- Development of Patient Rule Induction Method (PRIM) for high dimensional clustering^{Friedman and Fisher 1999}
- Formalization of scenario discovery/robust decision making^{Lempert et al. 2006}
- Demonstration of scenario discovery concept for robust urban planning^{Swartz and Zegras 2013}
- Climate change and resource management; Ethiopia^{Shortridge and Guikema 2016},
Global^{Rozenberg et al. 2014}, California^{Groves 2006}
- Extensions and improvements: data transformation^{Dalal et al. 2013}, heterogeneous types^{J. H. Kwakkel and Jaxa-Rozen 2016}, random bagging^{J. Kwakkel and Cunningham 2016}
- Software: exploratory modeling workbench^{J. H. Kwakkel 2017}, many-objective robust decision making^{Hadka et al. 2015}

Urban mobility arena

- Current work largely dominated by traditional scenario analysis and limited uncertainty analyses
- Bus lane strategy analyses in Marina Bay, Singapore^{Song 2013}
- Current: future urban mobility across global urban typologies

Case study: futures for autonomous mobility on demand (AMOD)

Scenarios (each a unique combination of discrete uncertainty factor outcomes)

Uncertainty	Levels / Probabilities				
Household level of motorization	-40%	-20%	0	+20%	
	0.1	0.3	0.5	0.1	
ICEV proportion	25%	50%	75%	95%	
	0.1	0.2	0.3	0.4	
Fuel price change	-50%	0	+50%	+100%	+150%
	0.25	0.30	0.20	0.15	0.10
Smart mobility modeshare change	0	+25%	+50%	+75%	
	0.25	0.25	0.25	0.25	

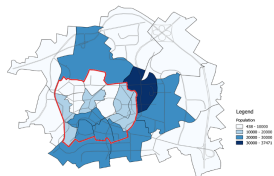
Prototype city testbed: dense public transit-oriented network; 2 rail lines, 5 bus lines, 99 nodes, 127 bidirectional links



Strategies (each corresponds to a fixed policy implementation)

- **CBD_Restriction:** restriction of AMOD to CBD; Mass Transit included, private cars excluded
- **Do_Nothing:** no AMOD, current on-demand levels
- **Full_AMOD:** full AMOD deployment including first/last mile
- **MOD_PT_Complement:** MOD as Public Transportation Complement (first/last mile)
- **No_PT_AMOD_Substitution:** AMOD as Mass Transit substitute
- **PT_Enhancement** Public Transportation Enhancement (doubling of frequency; first/last mile)

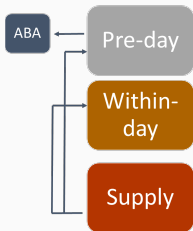
24 zones, population 350 000; CBD encircled in red; darker shades indicate greater population density



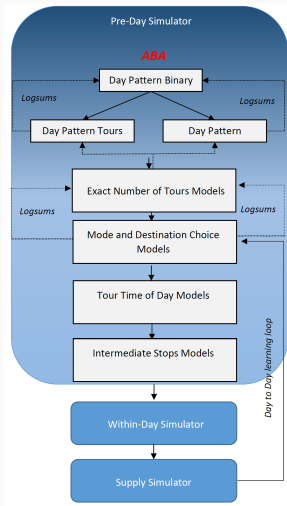
Case study: Simulation and evaluation framework

Simulation laboratory:
SimMobility Mid-Term

Components:



- Integrated agent-based simulator with full feedback loops
- Initial exploration conducted for activity-based model (pre-day component)
- **126 scenarios** generated
- Run across 6 strategies



- The regret is computed for all scenarios based on the benchmark strategy specified

Regret

For benchmark strategy $s^b \in S$ and a scenario $f \in F$, the regret r is

$$r(f) = Z(s^b, f) - \min_{s \in S} Z(s, f) \quad (1)$$

- Futures are evaluated using the median activity-based accessibility (ABA) measure in terms of time (minutes).

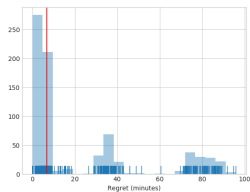
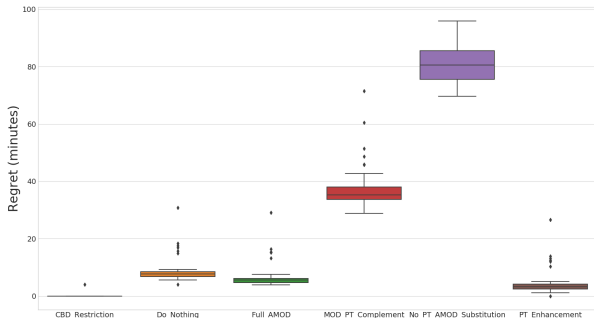
Performance

We define cost function $Z(s, f)$ as

$$Z(s, f) = \text{median}(-ABA_n(f, s)) \quad (2)$$

where ABA_n is the activity-based accessibility for each individual n and N is the population.

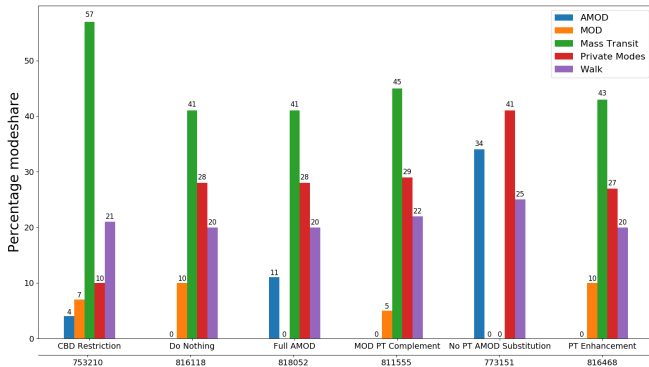
Preliminary results: regret distribution and thresholding



- Median regret across all strategy benchmarks: 6.6 minutes
- Chosen as failure threshold θ
- Strategy used as benchmark for PRIM analyses: **Full_AMOD**
- Number of failure cases: 16/126
- A given scenario is classified a failure if regret is greater than θ

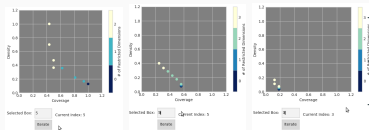
Modeshare across strategies

- Initially simulate demand for base scenario (no change in any of uncertainty factors) across all six strategies
- Second x axis indicates total number of trips



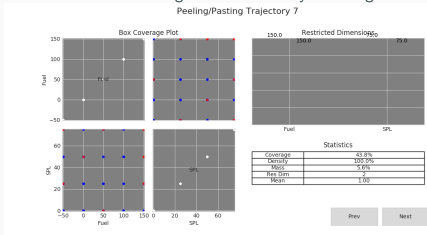
Preliminary results: PRIM outcomes

Box-finding sequence and limits:



Uncertainty factor		min	max	qp values
Box 1	Fuel price	150.0	150.0	0.000741
	Smart mobility preference	75.0	75.0	0.037253
Box 2	Vehicle Ownership	-20.0	-20.0	0.020650
	ICE Proportion	75.0	95.0	0.175929

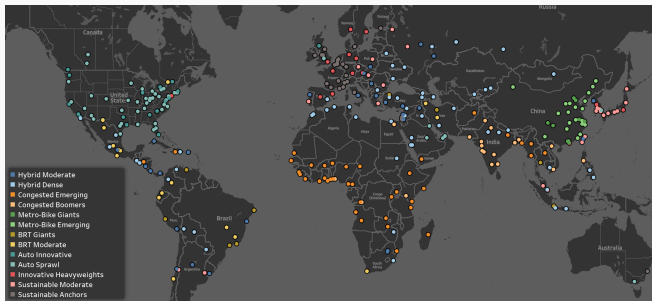
- First box has 50% coverage and 47% density and 1 significant constrained dimension



- Subsequent boxes discovered do not have significant bounds
- “Full_AMOD” strategy is vulnerable under highest fuel price
- Indicates that proper planning must be done to ensure demand is met without lowering performance
- Further exploration required to measure modal shifts and levels of service based on network effects to properly measure impacts of other uncertainty factors

Outlook

- Current case study performed for only activity-based accessibility outcomes
- Supply to be simulated for energy, network performance outcomes, feedback for ABA iterations
- Further experimental design for discovery across 4 distinct prototype cities representing key urban typologies¹:
 - **Auto-Sprawl** • **Auto-Innovative** • **Innovative-Heavyweight** • **Sustainable Anchor**
- Key expected result: policy recommendations for robust strategies and efficient outcomes given the urban typology with focus on AMOD implementation²



¹Yafei Han et al. (2018). "Global Urban Typology Discovery with a Latent Class Choice Model". In: Transportation Research Board 97th Annual Meeting. Washington DC, United States.

²Rounaq Basu et al. (2018). "Automated Mobility-on-Demand vs. Mass Transit: A Multi-Modal Activity-Driven Agent-Based Simulation Approach". In: *Transportation Research Record* 0.0, p. 0361198118758630. DOI: [10.1177/0361198118758630](https://doi.org/10.1177/0361198118758630).