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

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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

MIT Energy Initiative

Mobility of the Future

Prototype Cities
- land use & supply
- population synthesis
- demand calibration

Urban Typologies
- Dashboard
- Confirmatory analysis
- Clustering

Scenario Discovery
- classification & clustering
- strategy evaluation
- sampling & generation

Enhanced Simulator
- Smart Mobility
- EV-conscious routing
- energy-emissions model

Prototype Cities

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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
Prior work and significance of current contributions

### Notable academic efforts and key milestones

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

### Urban mobility arena

- **Current work largely dominated by traditional scenario analysis and limited uncertainty analyses**
- **Bus lane strategy analyses in Marina Bay, Singapore\(^{\text{Song 2013}}\)**
- **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)

<table>
<thead>
<tr>
<th>Uncertainty</th>
<th>Levels</th>
<th>Probabilities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Household level of motorization</td>
<td>−40%</td>
<td>0.1</td>
</tr>
<tr>
<td></td>
<td>−20%</td>
<td>0.3</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>+20%</td>
<td>0.1</td>
</tr>
<tr>
<td>ICEV proportion</td>
<td>25%</td>
<td>0.1</td>
</tr>
<tr>
<td></td>
<td>50%</td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td>75%</td>
<td>0.3</td>
</tr>
<tr>
<td></td>
<td>95%</td>
<td>0.4</td>
</tr>
<tr>
<td>Fuel price change</td>
<td>−50%</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>0.30</td>
</tr>
<tr>
<td></td>
<td>+50%</td>
<td>0.20</td>
</tr>
<tr>
<td></td>
<td>+100%</td>
<td>0.15</td>
</tr>
<tr>
<td></td>
<td>+150%</td>
<td>0.10</td>
</tr>
<tr>
<td>Smart mobility modeshare change</td>
<td>0</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td>+25%</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td>+50%</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td>+75%</td>
<td>0.25</td>
</tr>
</tbody>
</table>

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)

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

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

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

$$Z(s, f) = \text{median} (-ABA_n(f, s))$$ \hspace{1cm} (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 $\theta$
- 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 $\theta$
• 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:

<table>
<thead>
<tr>
<th>Uncertainty factor</th>
<th>min</th>
<th>max</th>
<th>qp values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Box 1 Fuel price</td>
<td>150.0</td>
<td>150.0</td>
<td>0.000741</td>
</tr>
<tr>
<td>Smart mobility preference</td>
<td>75.0</td>
<td>75.0</td>
<td>0.037253</td>
</tr>
<tr>
<td>Box 2 Vehicle Ownership</td>
<td>−20.0</td>
<td>−20.0</td>
<td>0.020650</td>
</tr>
<tr>
<td>ICE Proportion</td>
<td>75.0</td>
<td>95.0</td>
<td>0.175929</td>
</tr>
</tbody>
</table>

- 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 typologies:
  • 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 implementation