Combining behavioral models and optimization to assess climate change actions

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EPFL

Outline

Transport and Mobility Laboratory, EPFL

Core competences

- Travel demand and choice modeling.
- Travel supply and optimization / operations research.
- Simulation of complex (transportation) systems.

Research identity

- Integration of demand and supply through a blend of choice models and optimization.

Travel demand and choice modeling

Specification and estimation of complex models

- Theory. [Bierlaire, 2006], [Fosgerau et al., 2013].
- Algorithms. [Bierlaire and Ortelli, 2022], [Lederrey et al., 2021].
- Software (Biogeme) [Bierlaire, 2003], [Bierlaire, 2023].

Activity-based models

- Synthetic populations. [Farooq et al., 2013], [Kukic et al., 2023].
- Optimization-based models. [Pougala et al., 2022], [Pougala et al., 2023].
- Households interactions. [Rezvany et al., 2023].

Travel supply and optimization / operations research

Vehicle routing problems

- Waste collection. [Markov et al., 2020].
- School bus. [Spada et al., 2005].

Trains timetabling

- Rescheduling. [Binder et al., 2021].
- Elastic demand. [Robenek et al., 2018].
- Cyclicity. [Robenek et al., 2017].

Port operations

- Scheduling. [Abou Kasm et al., 2021].
- Berth allocation. [Umang et al., 2013].
- Quay crane assignment and scheduling. [Vacca et al., 2013], [Chen and Bierlaire, 2017].
- Yard assignment. [Robenek et al., 2014].

Simulation of complex (transportation) systems

Pedestrian flows

- Control strategies. [Molyneaux et al., 2021].
- Network loading. [Hänseler et al., 2017].

Supply-demand equilibrium

- Disaggregate demand. [Bortolomiol et al., 2021].
- Railways. [Binder et al., 2021].
- Housing market. [Hurtubia et al., 2019].

Outline

The team

Michel Bierlaire

- 1996: PhD in Mathematics, University of Namur, Belgium. [Dpt Math.]
- 1996–1998: postdoc, MIT. [Dpt Civil Eng.]
- 1998–2006: senior scientist, EPFL. [Dpt Math.]
- 2006–2012: associate professor, EPFL. [Dpt Civil Eng.]
- 2012–now: full professor, EPFL. [Dpt Civil Eng.]

The team

PhD students

- Barbara Tormachio: optimization.
- Tom Haering: choice-based optimization.
- Marija Kukic: simulation.
- Negar Rezvany: optimization-based travel demand.
- Cloe Cortes Balcells: simulation-based policy analysis.
- Nicola Ortelli: optimization for choice models.

The team

Postdocs

- Léa Ricard: data-driven optimization under uncertainties.
- Fabian Torres: vehicle routing and crowd-shipping.
- Evangelos Paschalidis: driving behavior models.
- Pavel Ilinov: endogenous information acquisition in economics.

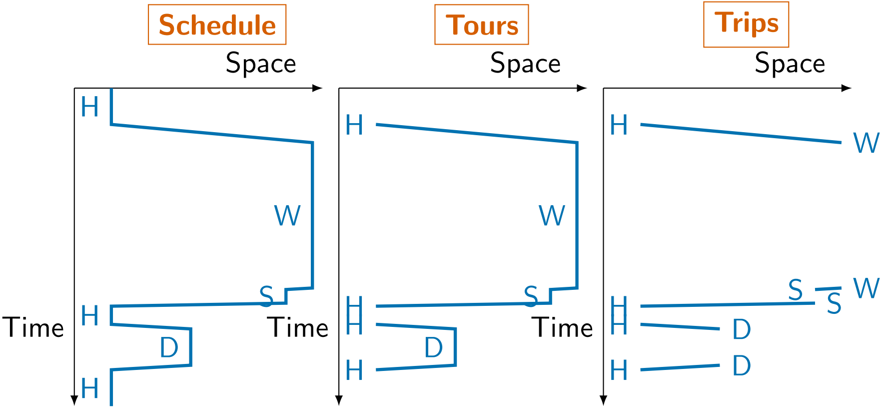
Outline

Introduction

- Travel demand is derived from activity demand.
- Activity demand is influenced by socio-economic characteristics, social interactions, cultural norms, basic needs, etc. [Chapin, 1974]
- Activity demand is constrained in space and time [Hägerstraand, 1970].

Activity-based models

Travel demand models



H: Home, W: Work, S: Shop, D: Dining out [Source: M. Ben-Akiva]

How to have the cake and eat it too?

	Econometric	Rule-based
Micro-economic theory	X	—
Parameter inference	X	—
Testing/validation	X	—
Joint decisions	—	X
Complex rules	—	X
Complex constraints	—	X

Integrated approach

Main philosophy

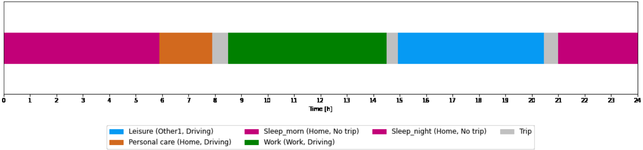
- Choices are driven both by constraints than by preferences.
- Choice set cannot be enumerated.
- Instead, it is represented by the constraints.
- They can capture the complex interactions and rules.

Methodology: mathematical programming

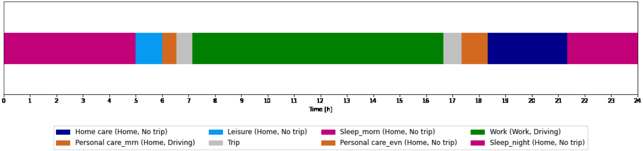
- Individuals are solving an optimization problem.
- Decisions: activity participation and scheduling.
- Objective function: utilities.
- Constraints: complex rules.

Simulation: From isolated individuals...

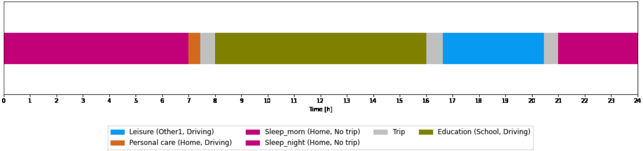
Sara



David

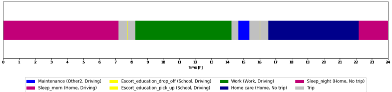


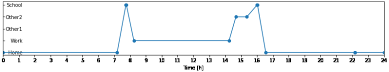
Alice



Simulation: To family of 3; 2 adults and 1 child. . .

Sara





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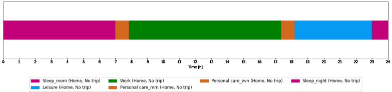

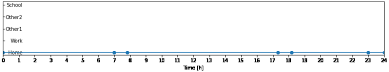

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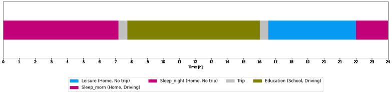
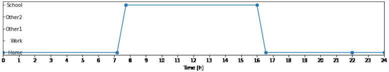
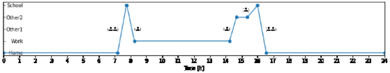




Car



Simulation: Family of 3; 2 adults and 1 child

Table: Car location sequence and occupancy in the example of family of 3

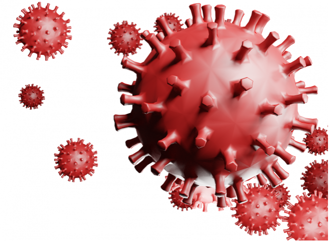
Location	Start time (hh:mm)	End time (hh:mm)	Duration (hh:mm)	Person using	Parked_out indicator	Car occupancy
Home	00:00	7:12	7:12	-	0	0
On the road	7:12	7:45	0:33	1&3	0	2
School	7:45	7:47	0:02	1	0	1
On the road	7:47	8:15	0:28	1	0	1
Work	8:15	14:15	6:00	1	1	0
On the road	14:15	14:40	0:25	1	0	1
Other2	14:40	15:22	0:42	1	1	0
On the road	15:22	16:00	0:38	1	0	1
School	16:00	16:02	0:02	1	0	1
On the road	16:02	16:33	0:31	1&3	0	2
Home	16:33	24:00	7:27	-	0	0

Outline

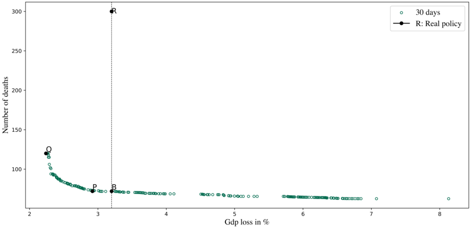
Motivation

Challenges

- Accounting for individual behaviour through an epidemic outbreak by using **large scale models**.
- Difficulty of finding **disaggregated data** to **validate** the model.
- Capturing **spread of the disease** through **daily activities**.
- Allows to **assess the impact** that a certain policy has on **different segments of the population**.



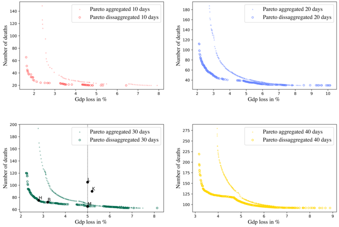
Analysis of Policy Scenarios and Their Impacts



Analysis of Policy Scenarios and Their Impacts [1]

[1] **Policy S (Health-focused)Group 1:** Full opening for work and shopping; no leisure and education.**Group 2:** Total closure in leisure and work; shopping reduced to 40%.**Group 3:** Total closure in education.**Policy P (Economic-focused)Group 1:** Full operations for work and shopping.**Group 2:** Leisure activities at 15%; education at 45%.**Policy Q (Balanced approach)Group 1:** Education allowed up to 60%, emphasizing the importance of education alongside health.

Pareto Fronts for Aggregated and Disaggregated Policies



Analysis

- **Customization Benefits:** Disaggregated policies allow for tailored strategies that can be more effective than one-size-fits-all approaches.
- **Efficiency in Policy M:** In a 30-day scenario at 5% GDP loss, Policy M significantly reduces deaths compared to Policy L—saving an estimated 5 lives per 100,000 people.
- **Optimal Outcomes:** Policy H in the disaggregated case optimizes outcomes with only a 2.8% GDP loss while maintaining lower death rates, outperforming the aggregated Policy K which results in higher deaths (90) and a 5.2% GDP loss.

Contributions

The most significant contributions are:

- We develop a tool that analyzes community readiness for policy changes, focusing on activity-restriction impacts.
- Our tool uses multiobjective optimization to balance health impacts against economic considerations, optimizing policy designs for diverse community needs.
- We demonstrate the tool's effectiveness and scalability through its capacity to process large datasets, offering a major advancement in policy management technology.

Outline

What about Climate Change?

Main ideas

- The level of granularity of activity-based models is appropriate for this context.
- Simulation tools can be used to assess the effect of policies.
- Multi-objective optimization can be used to identify a set of efficient policies.

Transportation

Examples of policies

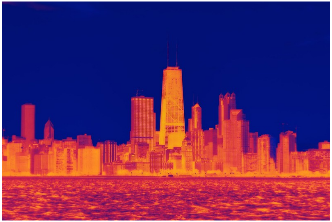
- Congestion pricing.
- Adoption of electric vehicles.
- Flexible work and telecommuting policies.
- Bike-sharing and micromobility programs.

Energy

Examples of policies

- Subsidies for renewable energy.
- Dynamic pricing and demand response programs.
- Personalized energy efficiency recommendations.
- Smart charging.

Land use and urban planning



Examples of policies

- Transit-oriented development.
- Urban heat island mitigation.
- Disaster resilience and climate adaptation planning.
- Affordable Housing and Social Equity

Consumer Behavior and Sustainable Consumption

Examples of policies

- Waste reduction and recycling programs.
- Shared economy and product-as-a-service models.
- Nudging and behavioral interventions.
- Dynamic pricing for resource conservation.

Conclusion

Main philosophy

Behaviorally driven research.

Methodological approach

Combine advanced econometric models with optimization.

Scope for applications

- Currently: disagreggate travel demand models.
- High potential for many other fields.

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