WASEDA University
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Multifidelity urban computing: simulation and optimization

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Affiliation

- 2025.04- Lecturer (non-tenure) at Waseda University

Education

- 2019 Dr.Eng. Tokyo Tech
- 2016 M.Eng. Tokyo Tech
- 2014 B.Eng. Waseda University

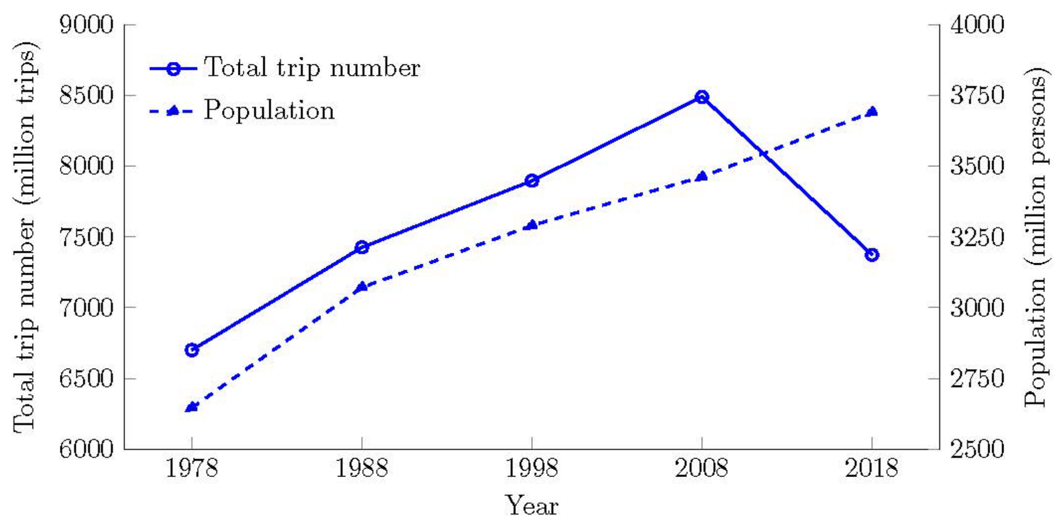
Experience

- 2019 – 2021 Postdoctoral Researcher, Tokyo Tech
- 2021 – 2022 Project Assistant Professor, Kanazawa University
- 2023 – 2024 Research Fellow, Monash University

Research Interests

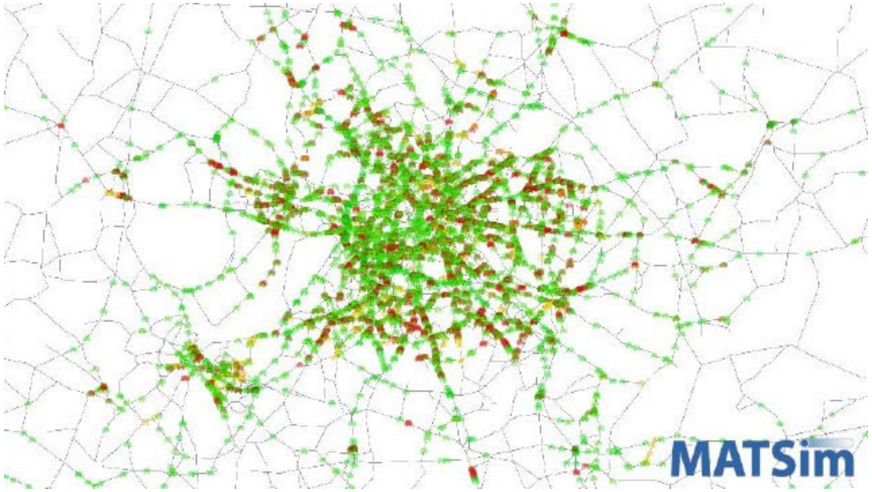
- Traffic flow theory; traffic control and management; transportation planning

- The 6th Tokyo Metropolitan Area Person Trip Survey (2018) revealed a turning point
  - Despite continued population growth, the total number of trips decreased for the first time
  - Travel behavior varies significantly across personal attributes (e.g., age, gender, employment status, household composition)
  - Understanding and incorporating detailed individual characteristics into policymaking is important
  - "***High-fidelity simulators***" are capable of integrating such detailed factors



High-fidelity simulator

- A modeling approach that aims to **reproduce real-world urban systems with very high-level of detail and realism**
  - Microscopic traffic simulation
  - Agent-based simulation
- Advantages
  - High realism, direct evaluation of real-world policies, and multimodal modelling..
- Disadvantages
  - Computationally expensive, difficult calibration, less tractable (a partial black-box)



High-fidelity simulator

- Some examples of high-fidelity simulators in transportation

- These simulators, *when properly calibrated*, are capable of highly detailed evaluations of policy measures

Data

Calibration/inference

comparison

Input
(e.g., travel demand)

Policy measure
(e.g., congestion pricing)

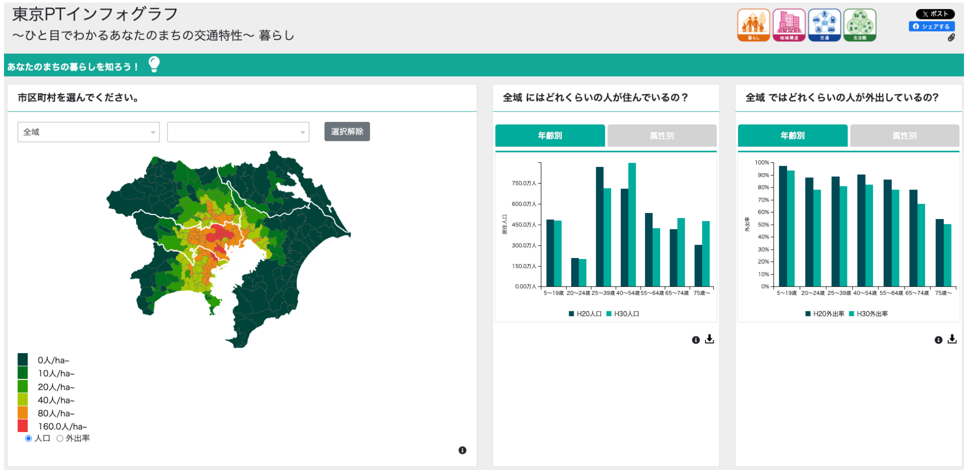
High-fidelity simulation

Output
(e.g., total travel time)

Output under policy

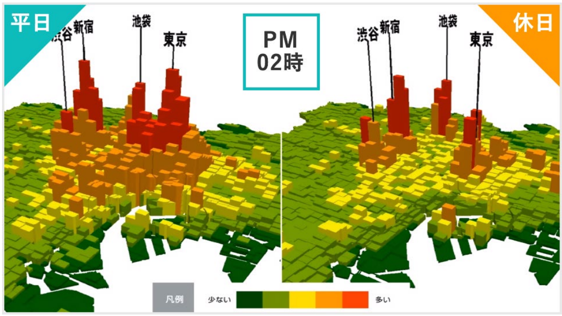
Data sources

Person trip survey



(source: Tokyo PT infograph)

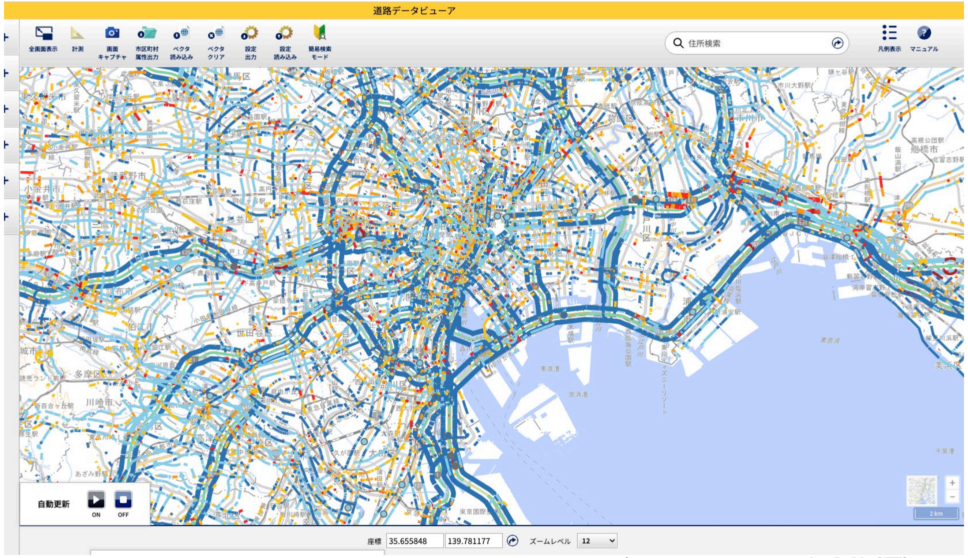
Mobile phone location data



(source: NTT Docomo)

Camera/radar detection data

Probe data



(source: xroad, MLIT)

Decision quality

- **High-fidelity simulation does not guarantee high-quality decisions**
  - When the data for calibration are not sufficiently representative of the policy task, a high-fidelity simulator can lead to low-quality decisions
  - High model fidelity × Low data fidelity → limited decision quality

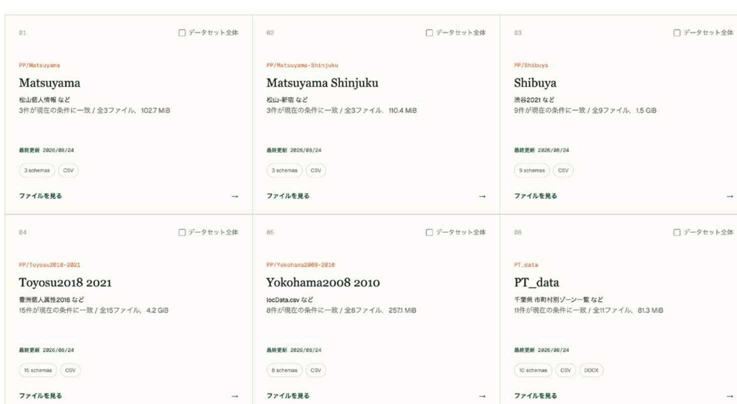
Urban decision quality = ƒ (model fidelity, data fidelity, task alignment)

~~"How high is the fidelity?"~~

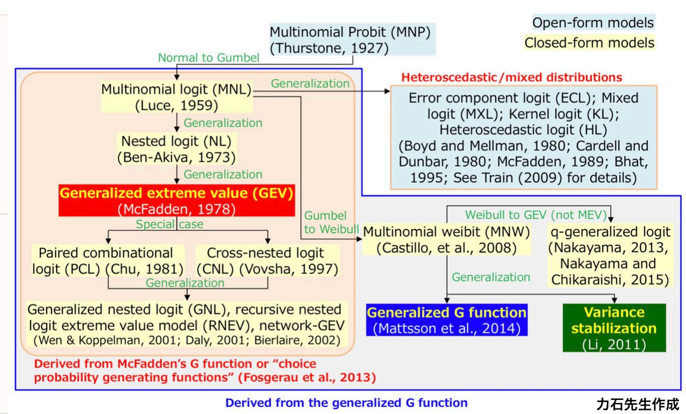
"Is the fidelity right for the decision?"

Your interest

Data



Model

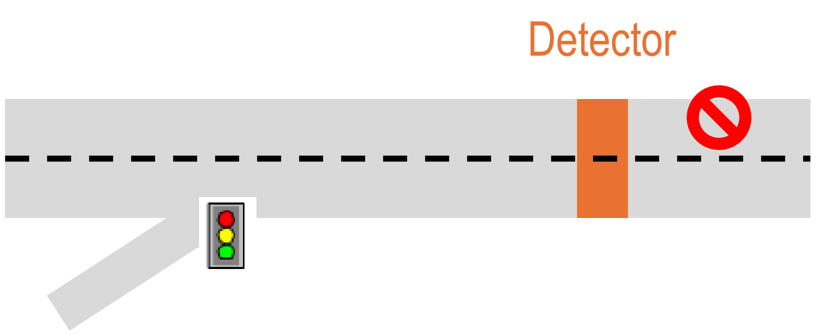


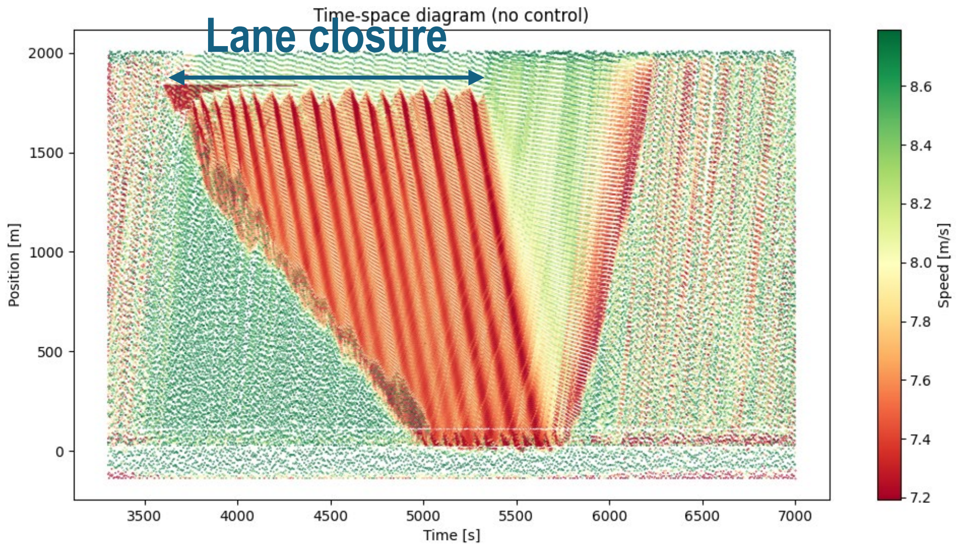
A simple example: the impact of ramp metering control

- Scenario: Lane closure due to an accident
  - Implement ramp metering control to prevent flow breakdown on the mainline
  - Apply an ALINEA-type control scheme (Papageorgiou et al., 1991)
    - $r(t+1) = \min\{0, r(t) - K_r(k_{target} - k(t))\}$

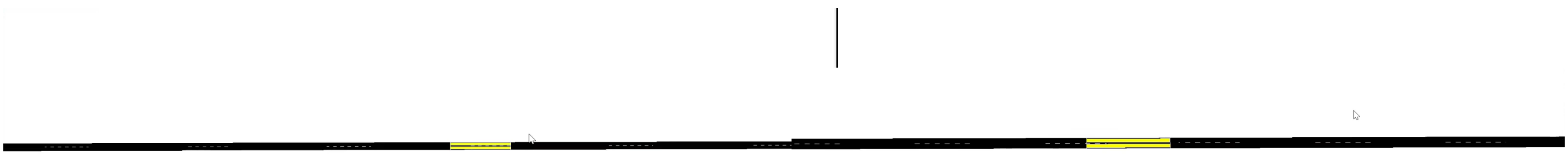
    $r(t)$: red phese duration of signal at time t, K_r: a constant regulator parameter,

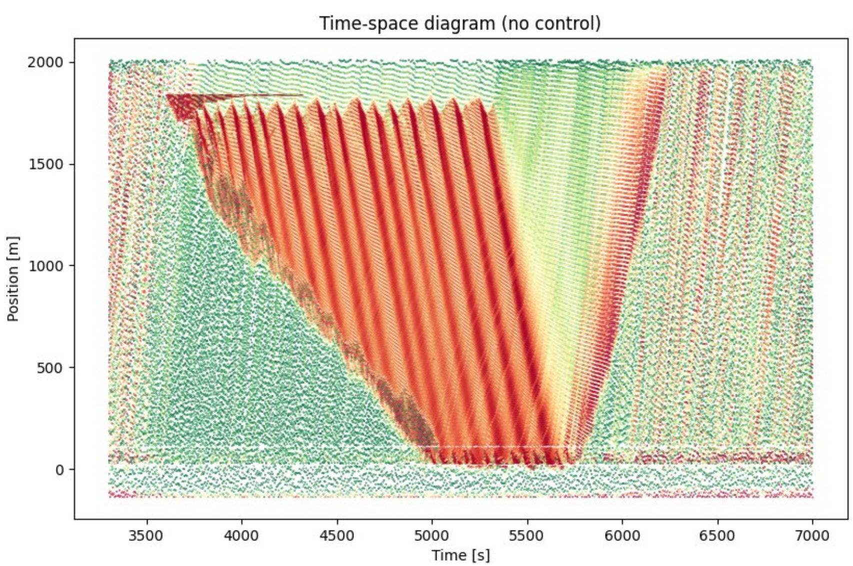
    $k(t)$: downstream density measurement at time t, k_{target}: desired downsream density

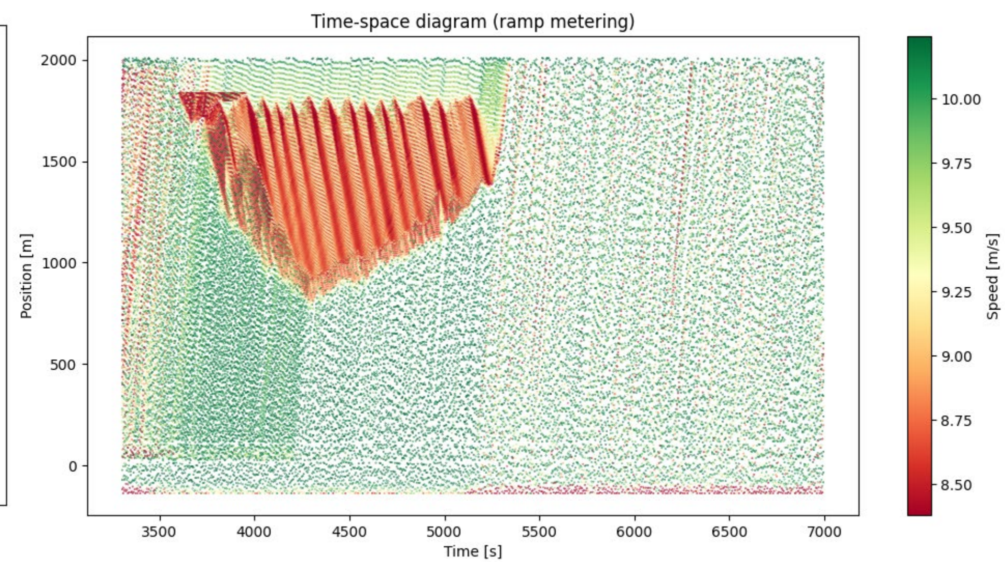




A simple example: the impact of ramp metering control







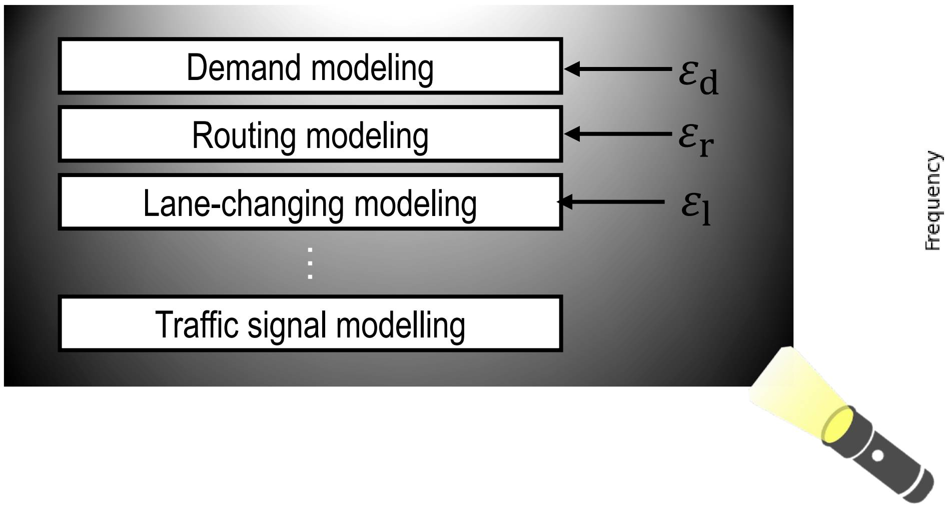
Ave. Travel time. 191.7 sec/veh → 172.6 sec/veh

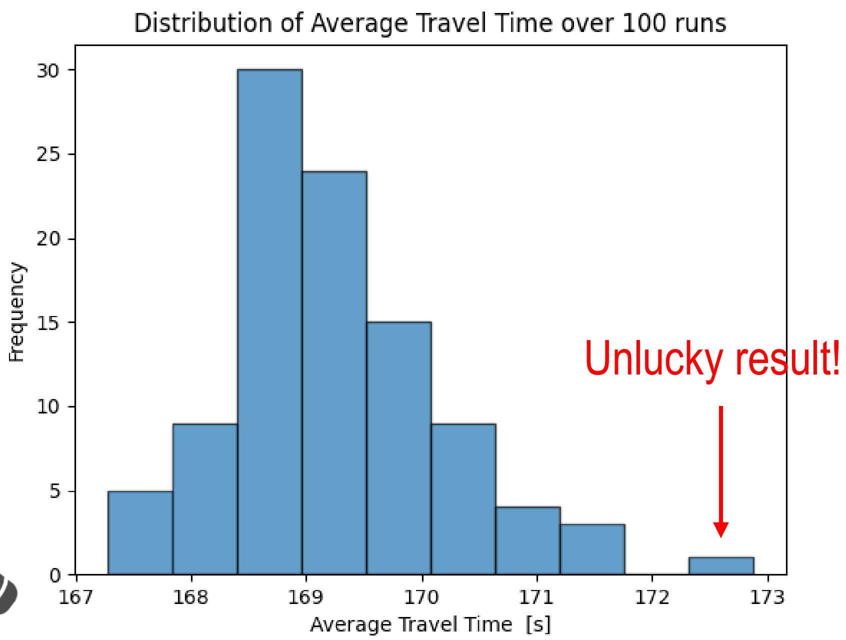
Do not trust a single-run result

Stochasticity and random seeds

- Many high-fidelity transportation and traffic simulations include random processes: vehicle departures, route choices, driving behavior, etc.
- A single run with one random seed may give a result that is lucky or unlucky

Black-box simulation (e.g., SUMO)





How many replications are enough?

- The sample mean from k replications is an approximator of the mean of the random variable ***if k is sufficiently large***

$$\mathbb{E}[\mathrm{Z}] \approx \frac{1}{\mathrm{k}} \sum_{i=1}^{k} \mathrm{Z}_i$$

Z is the performance measure, Z_i is the performance measure from ith replication, k is the sample size

- When to stop generating new data (Section 8.1 in Ross, 2013)
  - Set a threshold d for the standard deviation of the estimator
  - Run at least 100 replications
  - Stop generating new data if $\frac{s}{\sqrt{k}} < d$ where s is the sampled standard deviation based on k replications, otherwise continue to run simulations
  - The estimate of the performance (e.g., averag travel time) is given by $\bar{\mathrm{Z}} = \frac{\sum_{i=1}^{k} \mathrm{Z}_i}{k}$

Simulation-based optimization

Beyond pre-determined scenarios

- We can now evaluate the impacts of given policy measures
- The next question is: ***what is the optimal policy measure?***

A general simulation-based optimization problem

$$\min_{u} \mathbb{E}_{\varepsilon}[f(x,\varepsilon)]$$

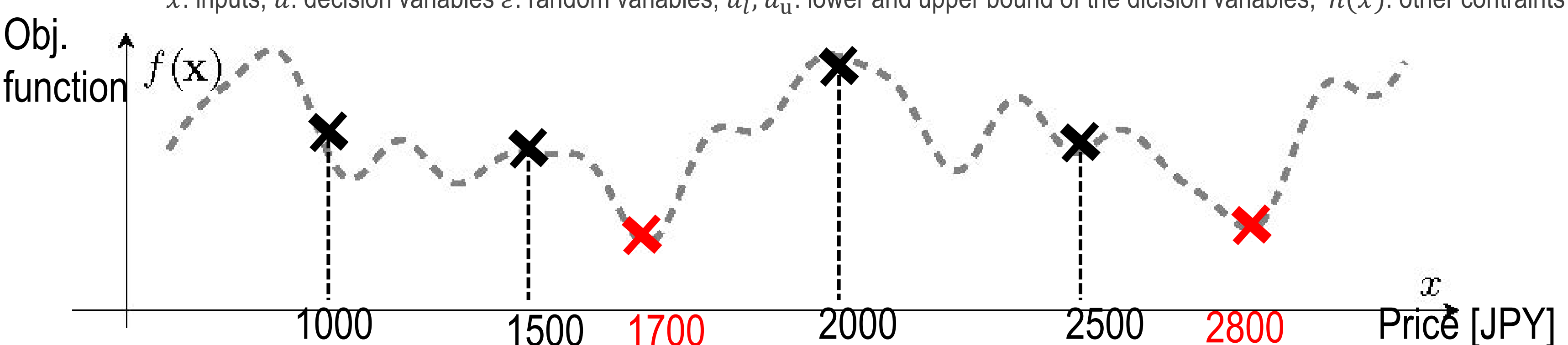
s.t.

$$\mathbb{E}_{\varepsilon}[g(x,\varepsilon)] \leq 0$$

$$h(x) \leq 0$$

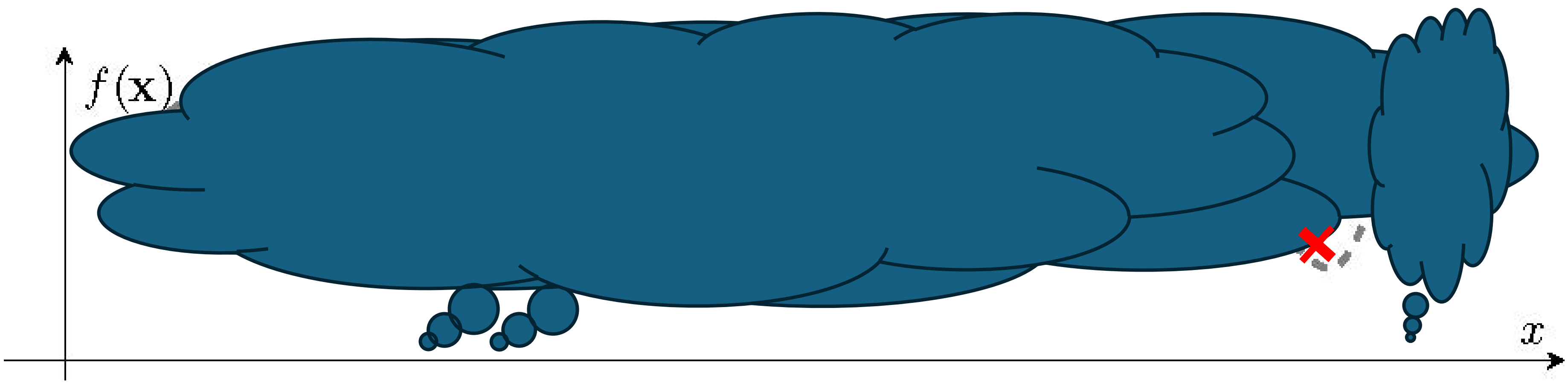
$$u_l \leq u \leq u_u$$

x: inputs, u: decision variables ε: random variables, u_l, u_{u}: lower and upper bound of the dicision variables, $h(x)$: other contraints

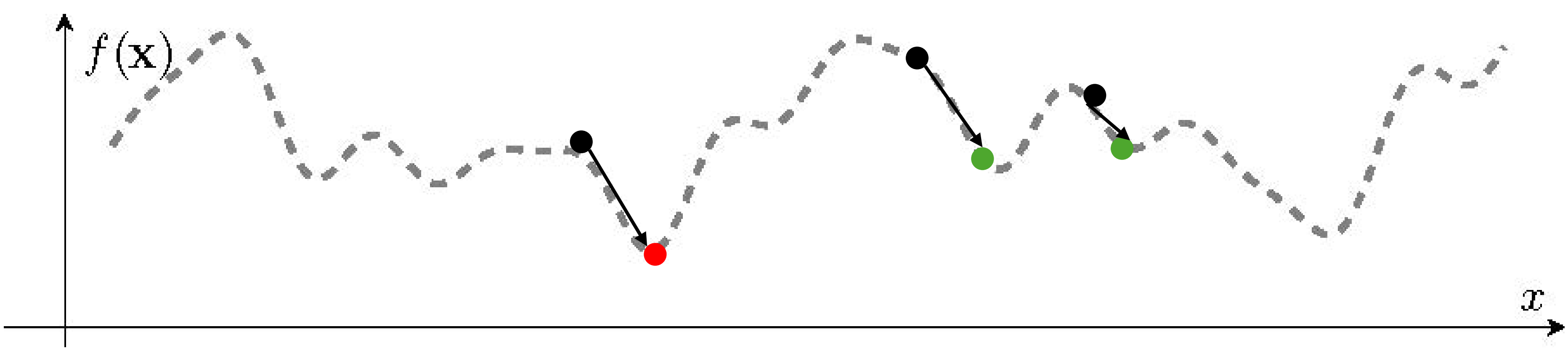


Challenges of simulation-based optimization

- **Analytically intractable**
  - True objective function is not explicitly available
  - The objective function cannot be evaluated exactly due to stochastic noise
- **High computational cost**
  - Ideally, simulating all possible parameter combinations would yields the best solution
  - However, the simulation itself is computationally expensive

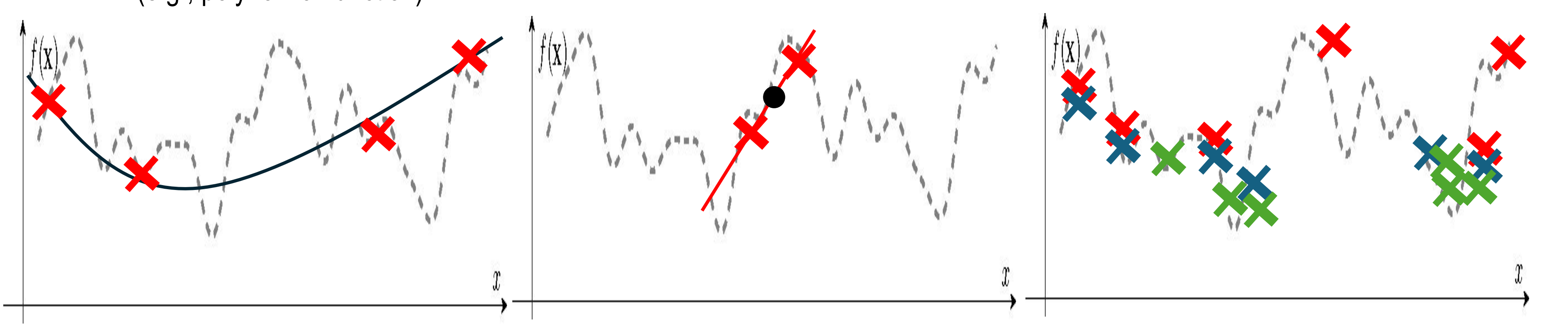


- **Local and global optima**
  - Local optimum: a point at which no nearby improvement can be found
  - Global optimum: the true minimum (or maximum) over the entire parameter space
  - Simulation-based optimization algorithms can generally guarantee only convergence to a local optimum
    - A common strategy is to try different initial points to increase the chance of finding the global optimum.



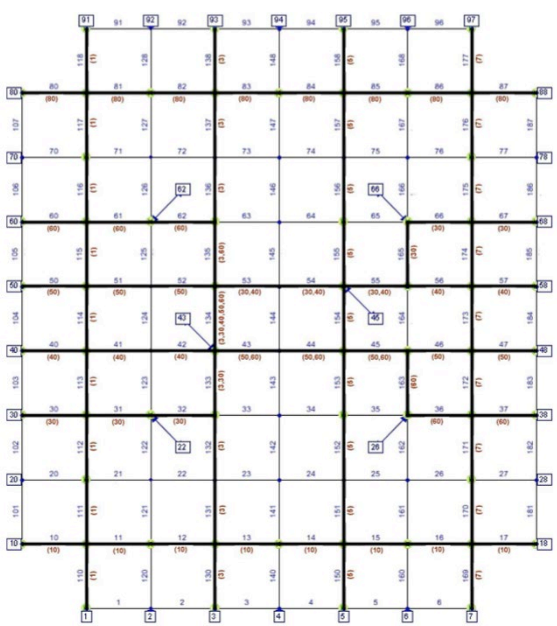
- general-purpose simulation-based optimization algorithms
  - Algorithms that do not rely on problem specific structures and can be applied across a wide range of problems as long as the objective function can be evaluated through simulation
- Some examples (more comprehensive review see e.g., Gosavi 2015; Amaran et al., 2016;)
  - Response surface methodology
  - Gradient-based method (e.g., Simultaneous Perturbation Stochastic Approximation, SPSA)
  - Random search method (e.g., Genetic algorithm, GA)

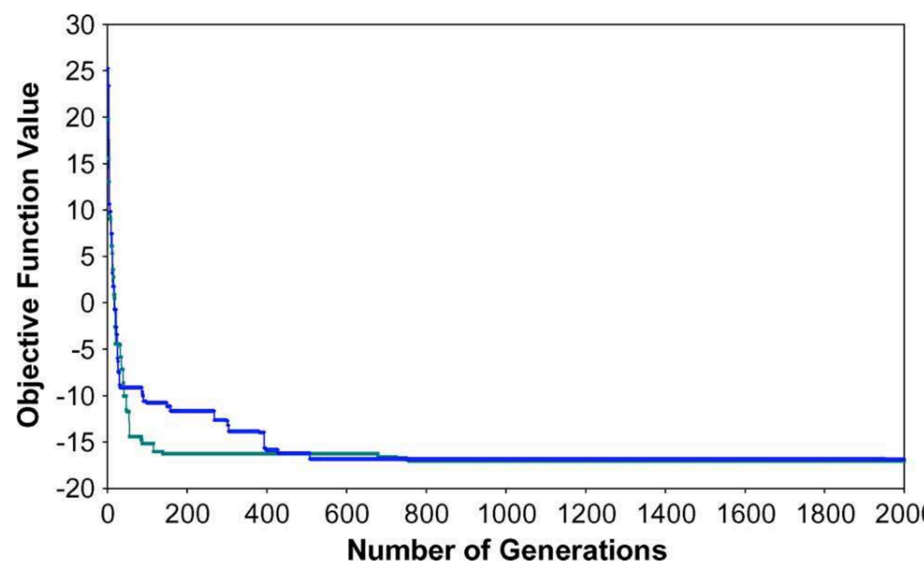
Response surface methodology (e.g., polynomial function) | SPSA | GA



Is the computational efficiency sufficient?

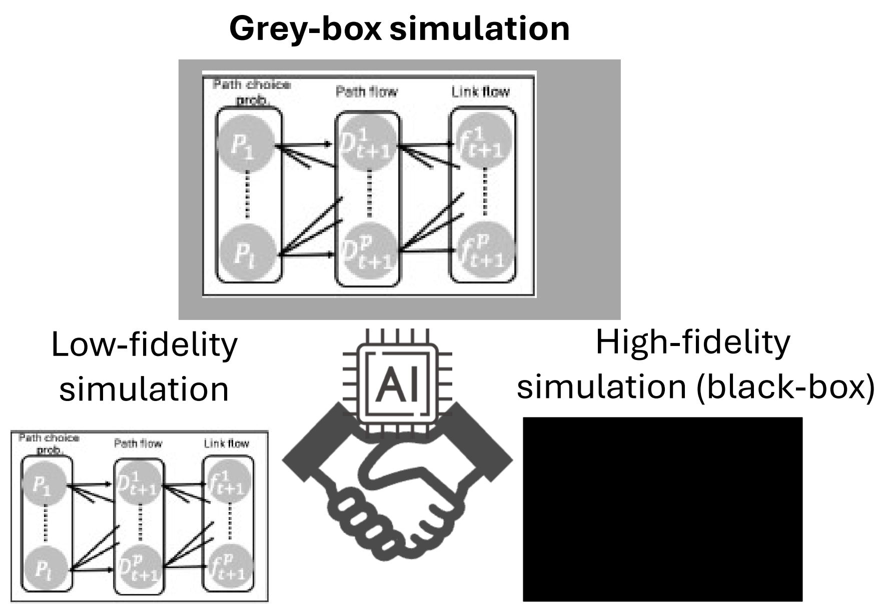
- Optimizing transit priory using a Genetic Algorithm (Mesbah et al., 2011, IEEE on ITS)
  - the network size: 120 links
  - “…, the objective functions did not improve after 800 generations”
  - ”.., a population size of 30-40 chromosomes is recommended for this network”
  - 24,000 – 32,000 simulations in total,
  - if each simulation requires 1 hour, it takes 2.7 – 3.7 years!





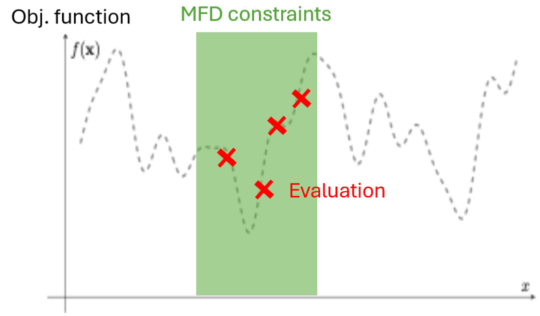
Low-fidelity and multi-fidelity simulators

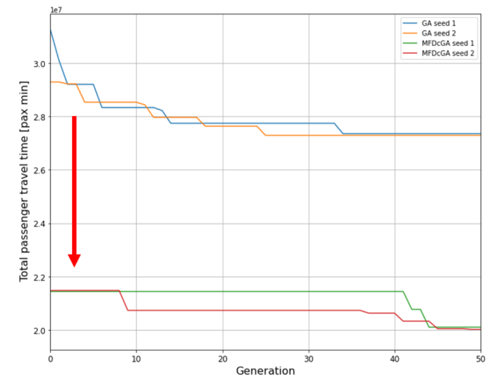
- Low-fidelity simulators: simplified modeling frameworks
  - Static traffic assignment (timeless)
  - Macroscopic Fundamental Diagram, MFD (spaceless)
  - Aggregate behavioral modelling (individual-less)
- Advantages
  - Run extremely fast, low calibration difficulty, tractable(white-box)
- Multi-fidelity simulation-based frameworks (grey-box simulation)



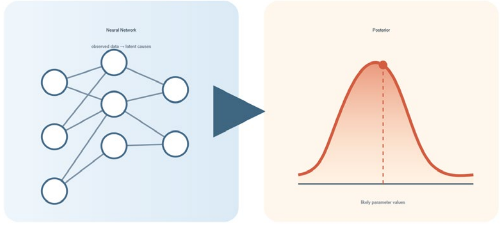
Multi-fidelity simulation-based frameworks

A bimodal MFD-constrained genetic algorithm for dynamic bus lane design (Dantsuji, 2025)

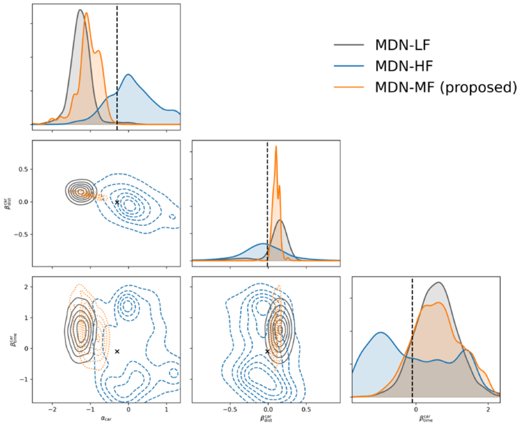


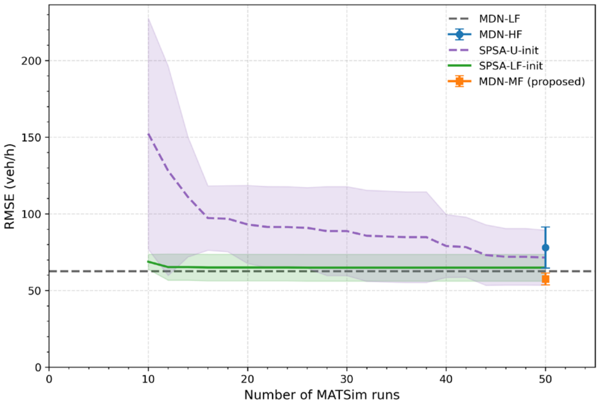


Efficient calibration of agent-based transport models via multi-fidelity simulation-based inference (Mayuzumi and Dantsuji, IEEE ITSC 2026)



<Low-fidelity> Combined modal split and static traffic assignment model	<High-fidelity> MATSim





List of the other my multi-fidelity simulation-based framework works

- Mixed-granularity physics-informed deep learning for traffic state estimation (Xue et al., under review)
- A hybrid neural network for real-time OD demand calibration under disruption (Dantsuji et al., under revision)
- A new framework for vehicle trajectory prediction based on physics-informed deep learning models (Xue et al., TR-C, 2026)
- A novel metamodel-based framework for large-scale dynamic origin-destination demand calibration (Dantsuji et al., TR-C, 2022)

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Feedback