MATSim
Multi-Agent Transport Simulation

Gradient Based Optimization of MATSim Using Iterative Backpropagation

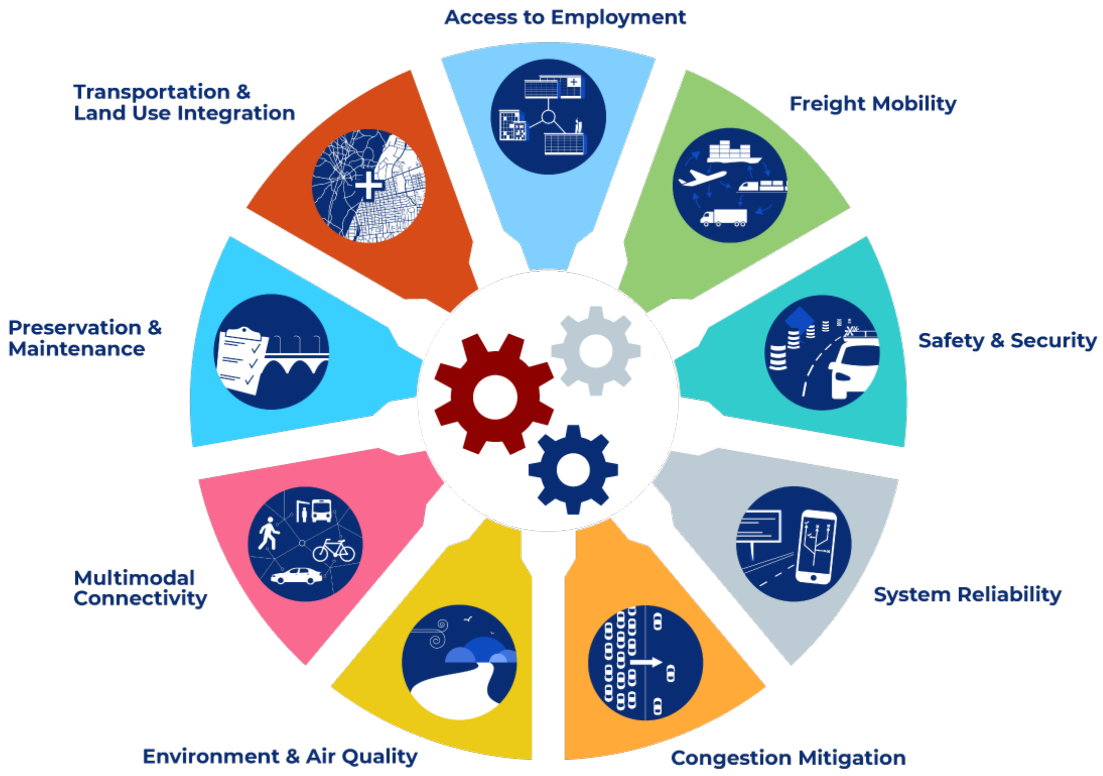
A.U.Z Patwary[1], Francesco Ciari[1], Enoch Lee[2] and Hong K. Lo[2]

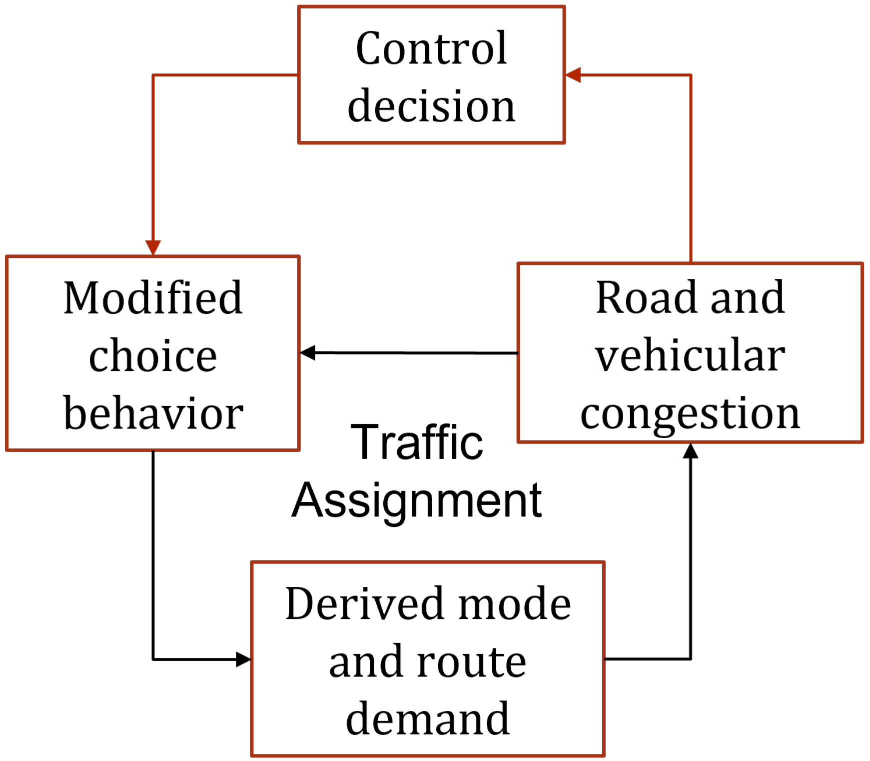
[1] Department of Civil, Geological and Mining Engineering, Polytechnique Montreal, Canada

[2] Department of Civil and Environmental Engineering, HKUST, China

POLYTECHNIQUE MONTRÉAL IVADO PRAISE HK Québec Ministère des Transports 香港科技大學 THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY

Introduction





Challenges

- **Mathematical Complexity**
  - No closed-form formulation
  - No analytical gradient

- **Computation Time**
  - 25 days for 100% HK scenario
  - 2 days for 10% Montreal scenario
  - Tight simulation budget (maximum 20)

- **High dimension problems**
  - OD estimation (49,000 variables for HK network)
  - Pricing optimization
  - Toll Optimization etc.

Solution Algorithms

- **Heuristics:**
  - **Genetic Algorithm** (Amirjamshidi and Roorda,2019; Chiappone et al., 2016; Spiliopoulou et al., 2015;Yu and Fan, 2017)
  - **Monte Carlo Sampling** (de Oliveira and Cunha, 2019;Henclewood et al., 2017)
  - **Artificial Bee Colony** (D. Huang et al., 2016b; Szeto and Jiang, 2012)
  - **SPSA** (Lee and Ozbay, 2009; Ma et al., 2007; Lu et al.,
  - 2015 and Oh et al.,2019)
- **Response surface:**
  - **Generic** (Polynomial, interpolation, etc.)
  - **Hybrid** (Generic + Traffic Model) (Osorio and Chong 2015, Zhang 2016, Osori 2019, Patwary et al. 2021)

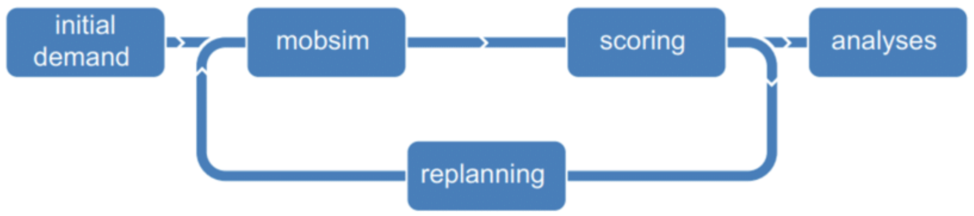
Gradient Based TA Optimization

Beneficial for **high dimensional** optimization. **Moving towards negative gradient** direction is **sufficient for minimization**.

Numerical (finite difference) gradient is **too costly to evaluate**.

(2d+1) function evaluation.

Cyclic dependencies (iterative loop) **prevents closed form gradient** formulation.

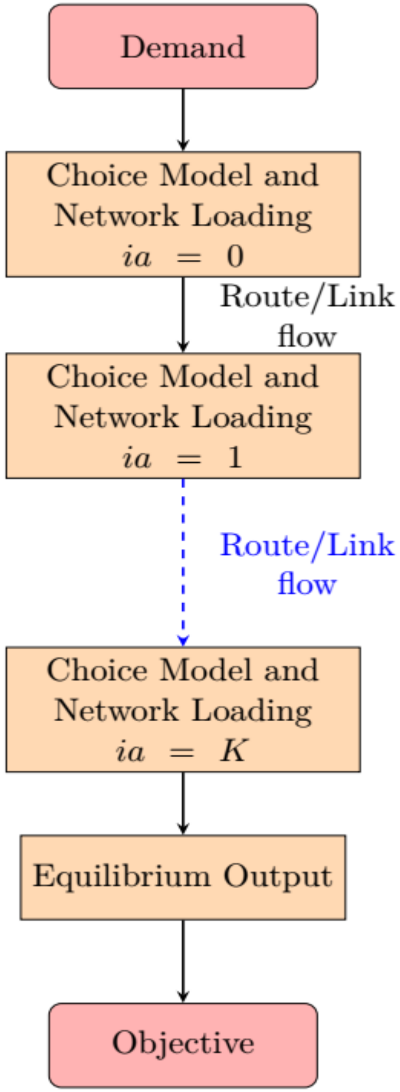


IB Gradient Estimation

TA solution procedures operates in **two steps**:

Auxiliary Flow Computation: Calculates the **choice model (scoring and choice strategy)** and **network loading model (Mobsim)**, generating subsequent flow as a function of the flow and cost of previous iteration.

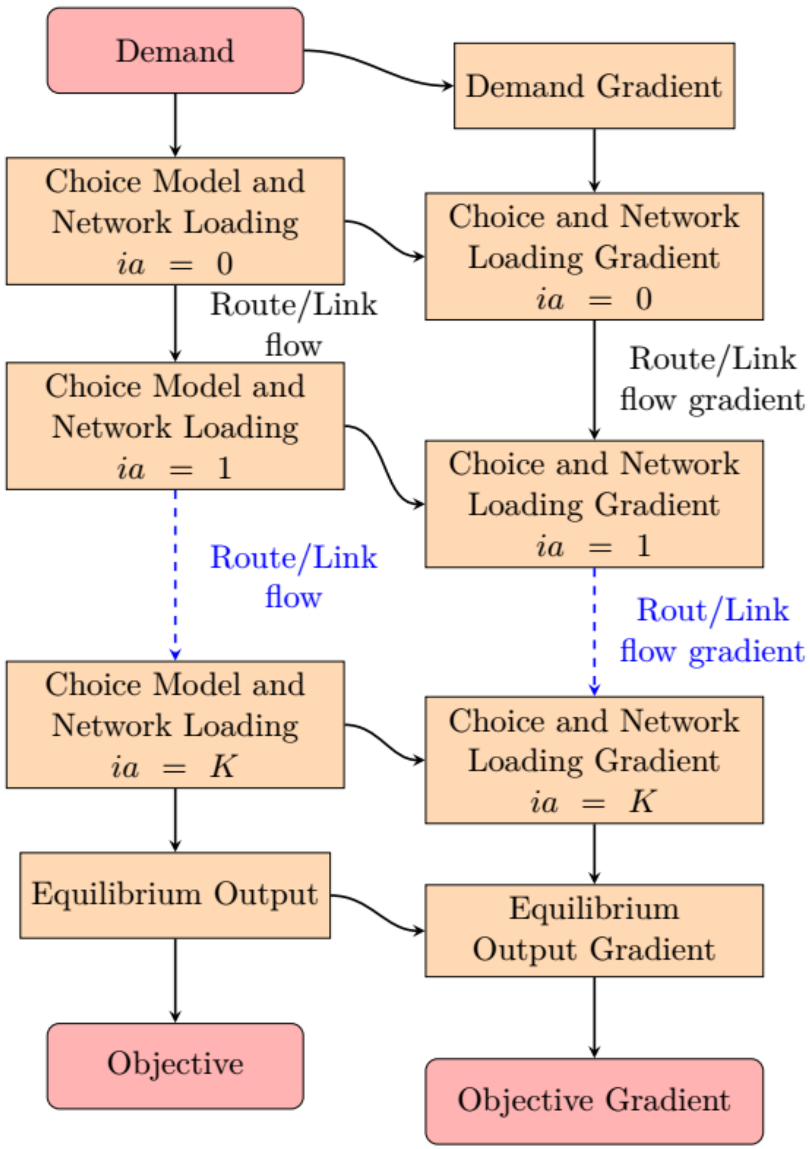
Flow Update: Updates the flow by merging previous iteration's flow and newly calculated flow with a decaying merge rule. **(MSA in MATSim)**



IB Gradient Estimation

IB introduces a '**gradient backpropagation**' step along with the network loading step.

Gradient Backpropagation: It uses information from the network loading step to **calculate the flow gradient of the current iteration as a function of the flow gradient of the previous iteration**.



Pros and Cons of IB

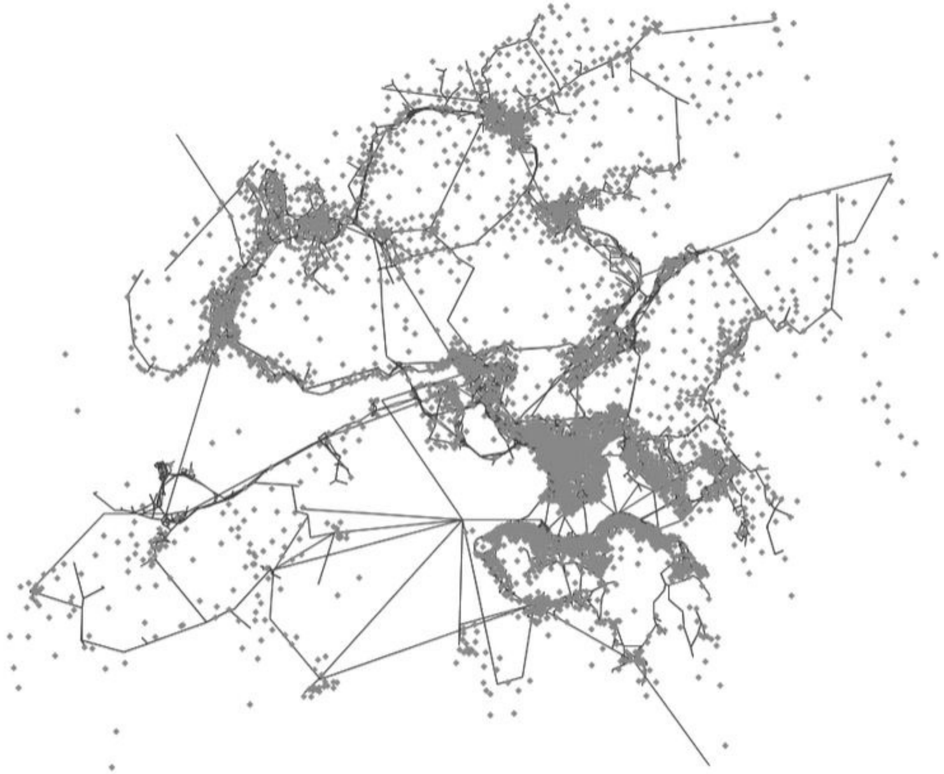
Pros:

- Requires **one function evaluation** to obtain **high-dimensional**, **accurate analytical gradient**.
- **Efficient** in computation, **can run parallelly on GPU**.
- Works well with **large-scale, multi-modal** network.

Cons:

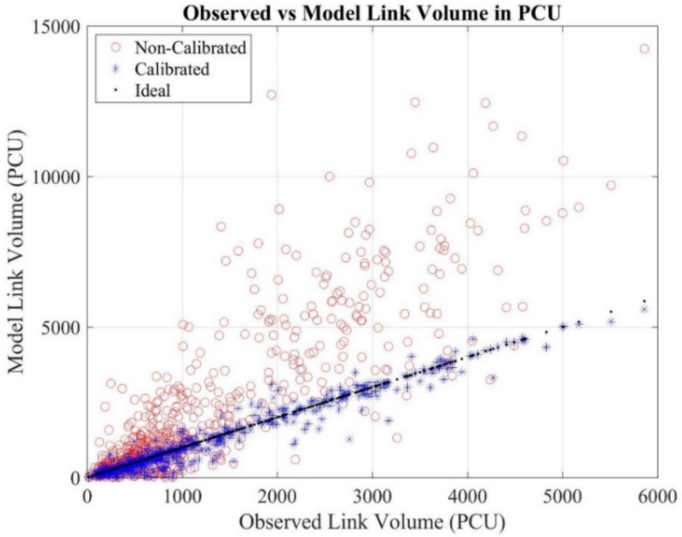
- Requires **formulation** through the **choice and network loading model**.
- Only **implemented in static setting** for now.

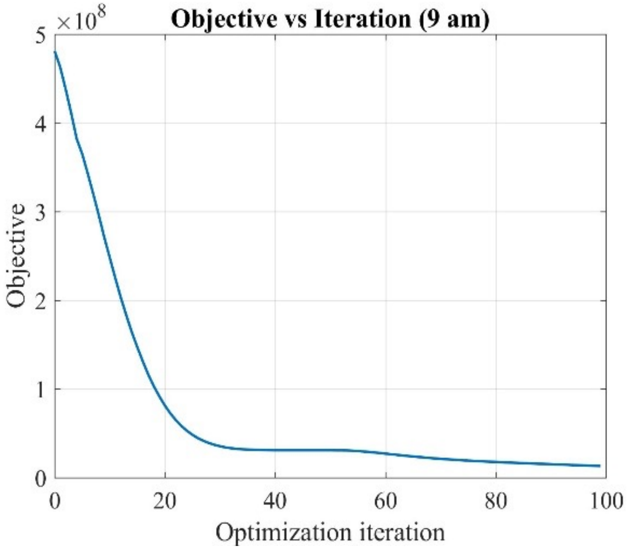
Application of IB in static HK Network

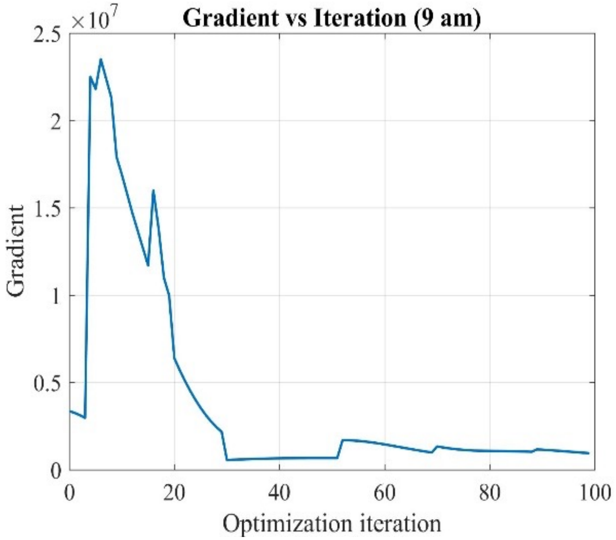


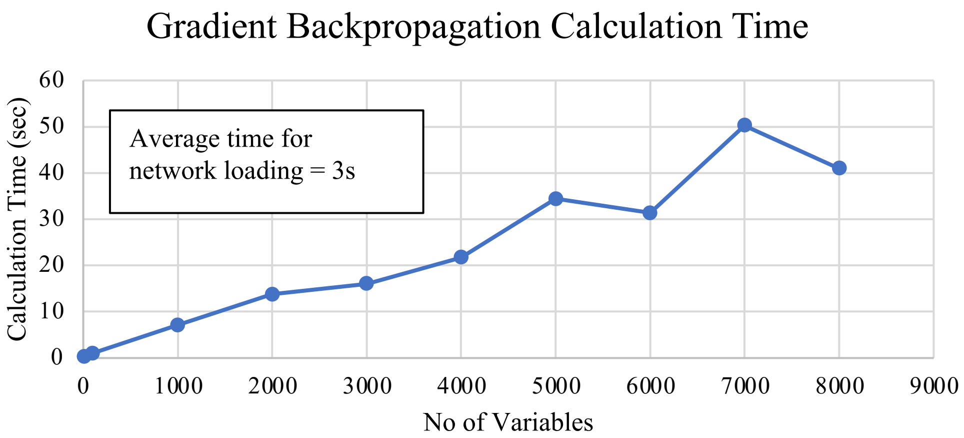
- The network contains **8,797 nodes**, **18,207 physical links**, **1,446 transit lines**, and **2,684 transit routes** with **9,222 stops** or stations.
- The number of time-specific **transit** direct and transfer **links is 433,812.**
- Transit hyper path is extracted from MATSim. The total number of **transit hyper paths are 603,628** and **auto routes are 56,676**.
- **591 peak hour** measurements from ATC 2016 are used for calibration.
- The total number of **origin-destination pairs** in the model is **165,509.**
- The model is **static**, and the calibration is performed **per time step** for origin and destination multiplier, i.e., $\boldsymbol{\theta} \in \{\boldsymbol{\theta_{O,t}}, \boldsymbol{\theta_{D,t}}\}$ to save memory.
- **Variable size is 8,301**. Max memory consumption is **130 GB**.

HK OD Multiplier Calibration Result





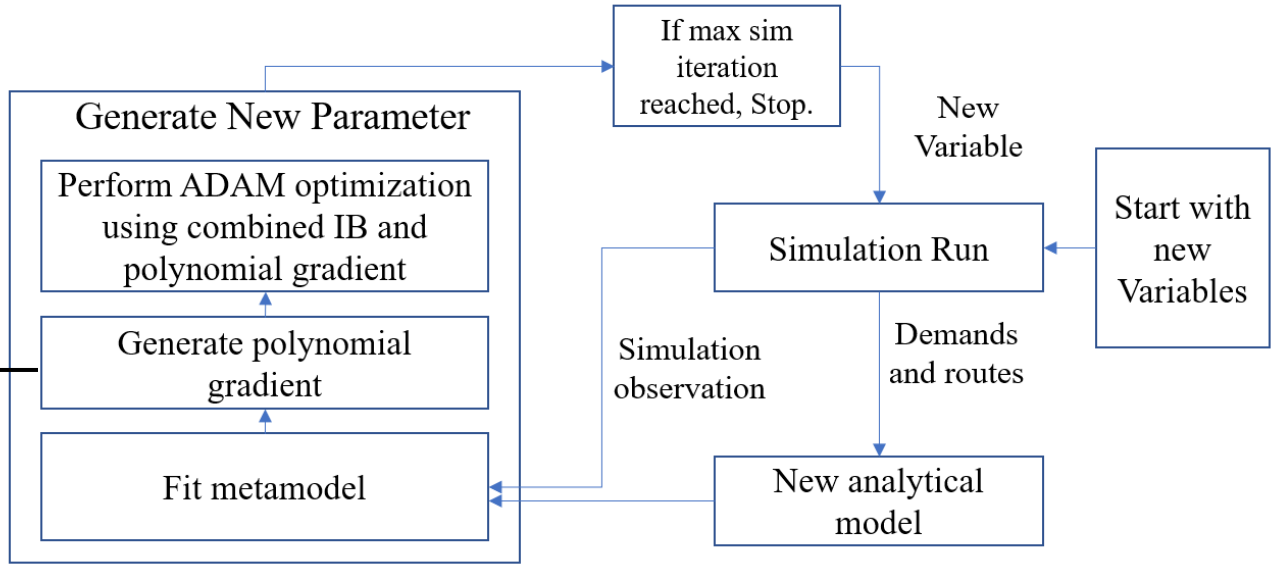




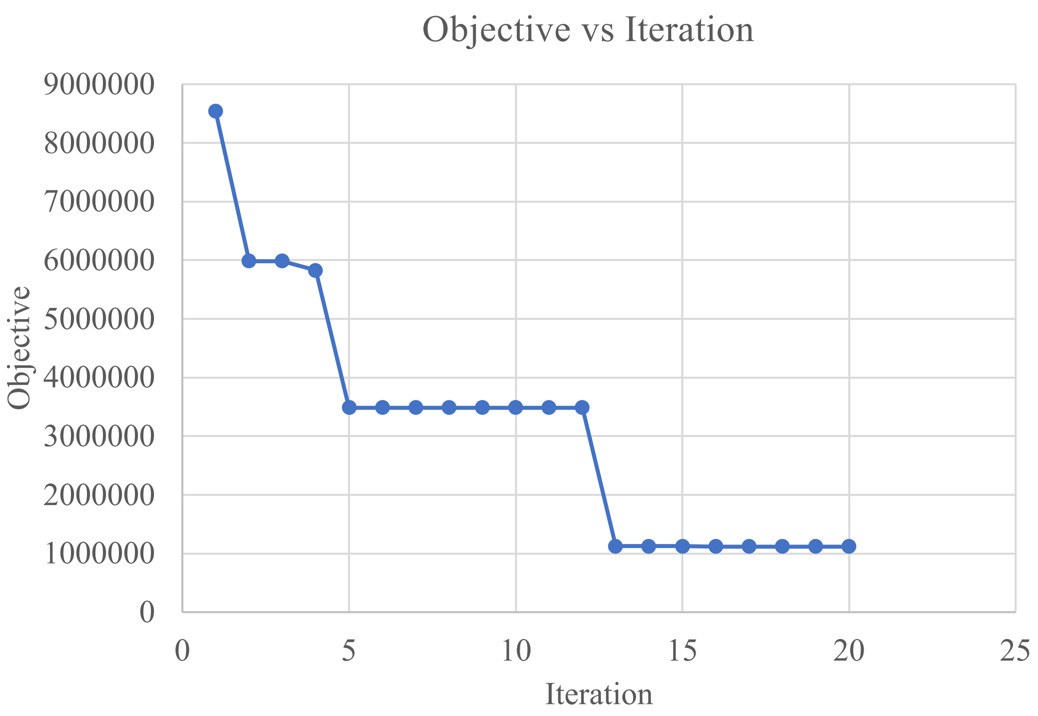
- Objective Reduction: 98.27%
- Initial vs Final MAPE: 95.29 vs 21.23%
- Initial vs Calibrated Mean GEH: 24.18 vs 6.09
- We have used ADAM (King Ma and Ba 2015) as gradient based optimizer.

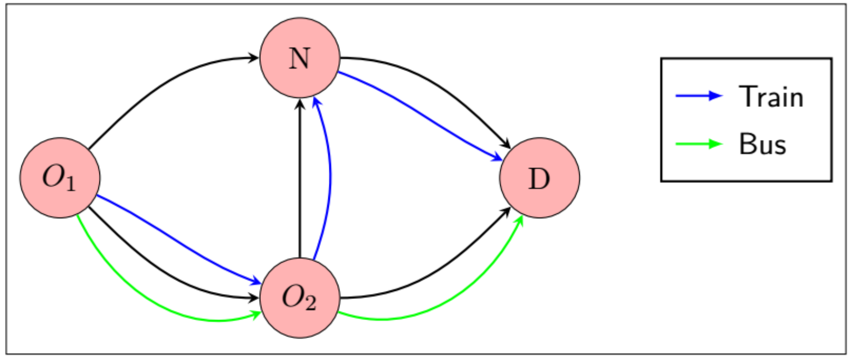
Using static IB for MATSim optimization

The **polynomial/generic model gradient** works as a **gradient corrector**. For a “**close enough”** model we can drop this bridging layer.



Results from a Toy Network (MATSim)





No Polynomial Function Used

Variables: origin destination demand multipliers (O1,O2,D)
OD: O1-D, O2-D
Known: Link Counts, Train and bus passenger counts.

Insight:
Gradient of the fitted underdetermined polynomial worsen the convergence. Alternative metamodel should be used. (Suggestions?)

Dynamic Extension of IB

Key insight:

The **travel time gradient** of a route in dynamic setting **is inverse to the route output flow rate**.

Can be calculated in two ways:

1. **Finite difference** on a **fixed time step DNL model**.
2. **Flow the gradients through the network**.

We have picked Link transmission model (LTM) for its simple link and node model formulation. The insight from LTM will help push the algorithm towards event-based algorithms, i.e., Mobsim in MATSim.

Conclusion

- A metamodel corrected gradient based optimization of MATSim is explored.
- As future work, **IB** is extended for Link Transmission Model (LTM) and preferably to MATSim directly.

Thanks for your attention.

Questions?

ashraf-uz-zaman.patwary@polymtl.ca