



A novel metamodel-based framework for large-scale dynamic origin-destination demand calibration

Takao Dantsuji

Institute of Science and Engineering, Kanazawa University

(Joint work with Nam H. Hoang, Nan Zheng and Hai L. Vu at Monash University)

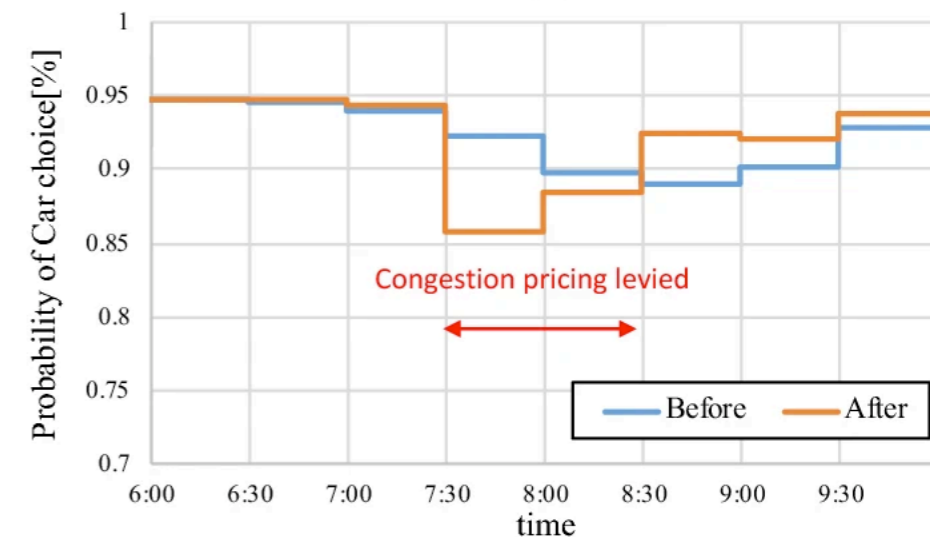
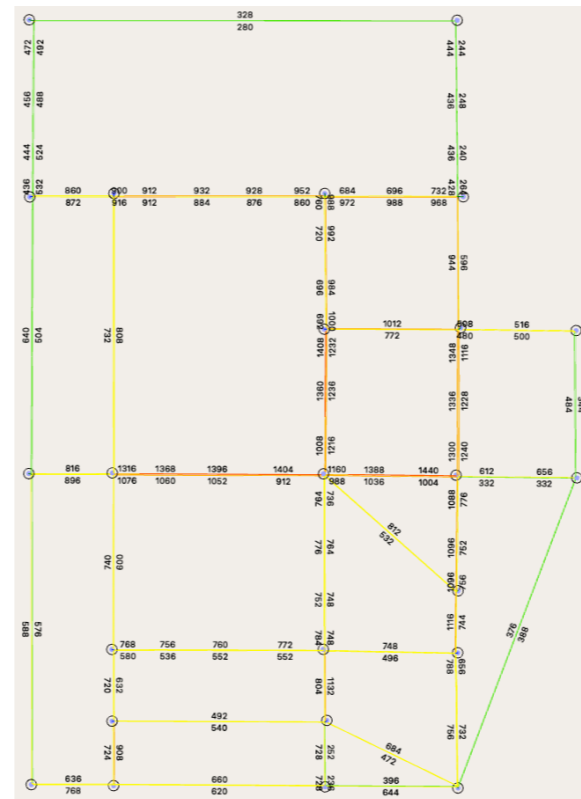
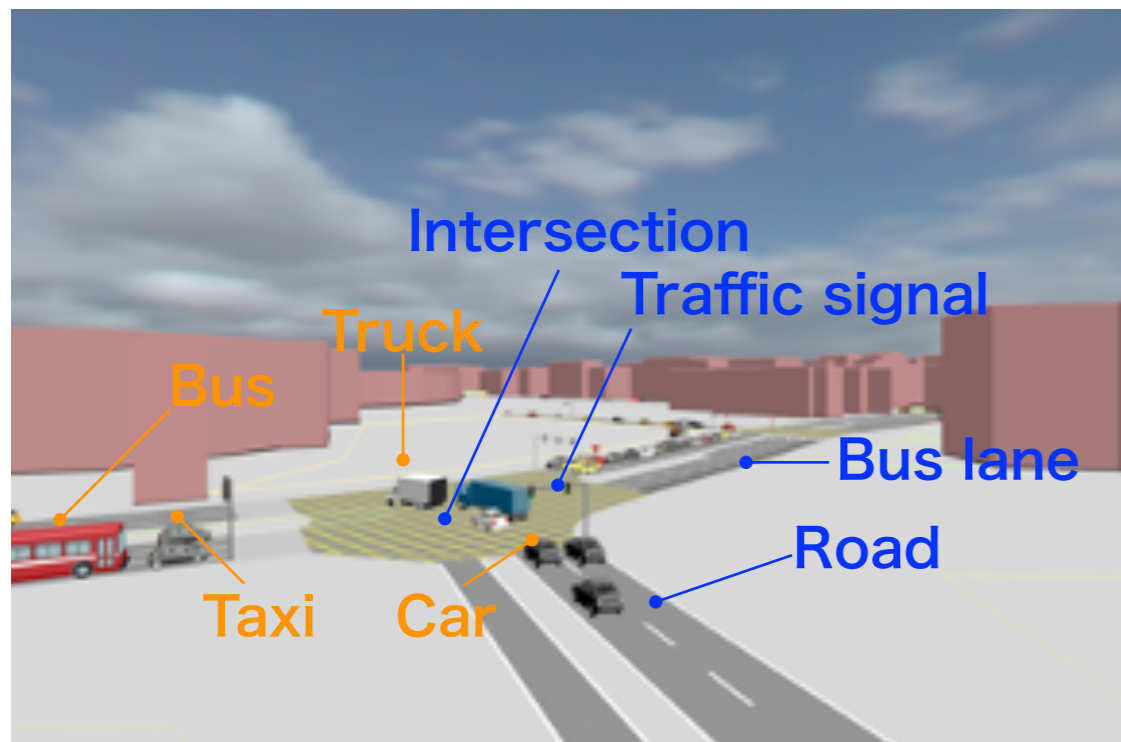
- OD demand estimation

 - Estimating general OD matrices for traffic planning and design

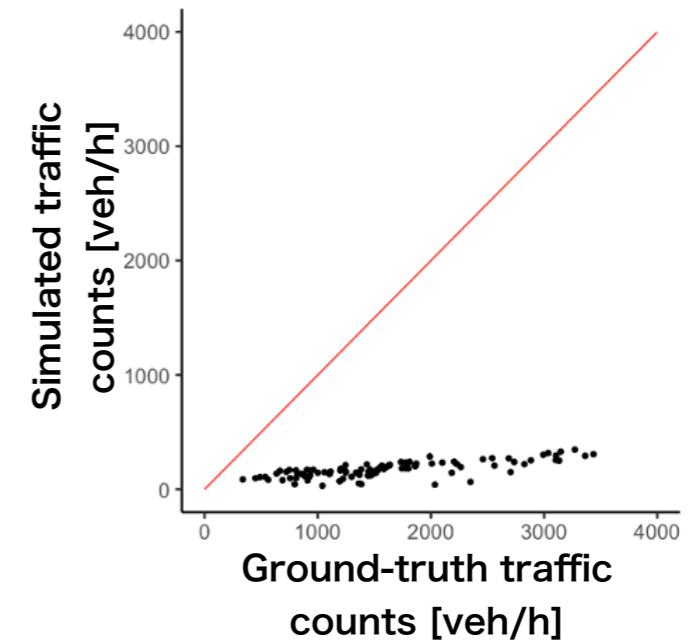
- OD demand calibration

 - Calibrating general OD matrices for a **stochastic traffic simulator**

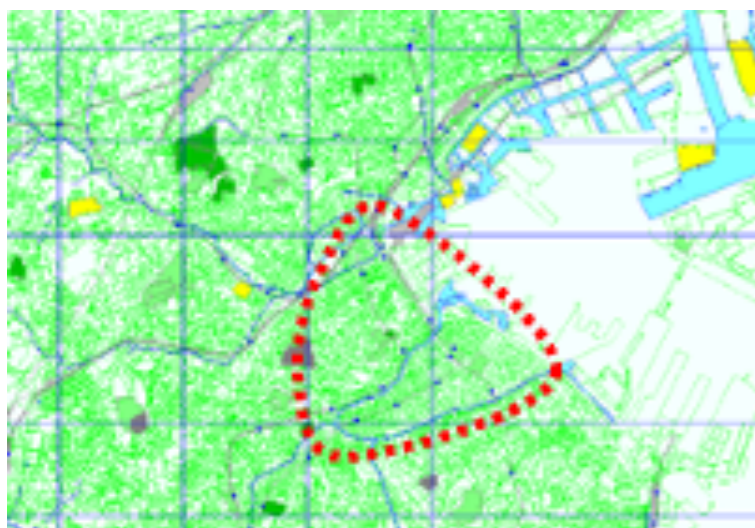
- A tool to describe the complex interactions of many traffic components of the demand and supply sides
- What is **likely** to occur quantitatively
- Useful for policy makers to investigate the performance of the pre-determined policies



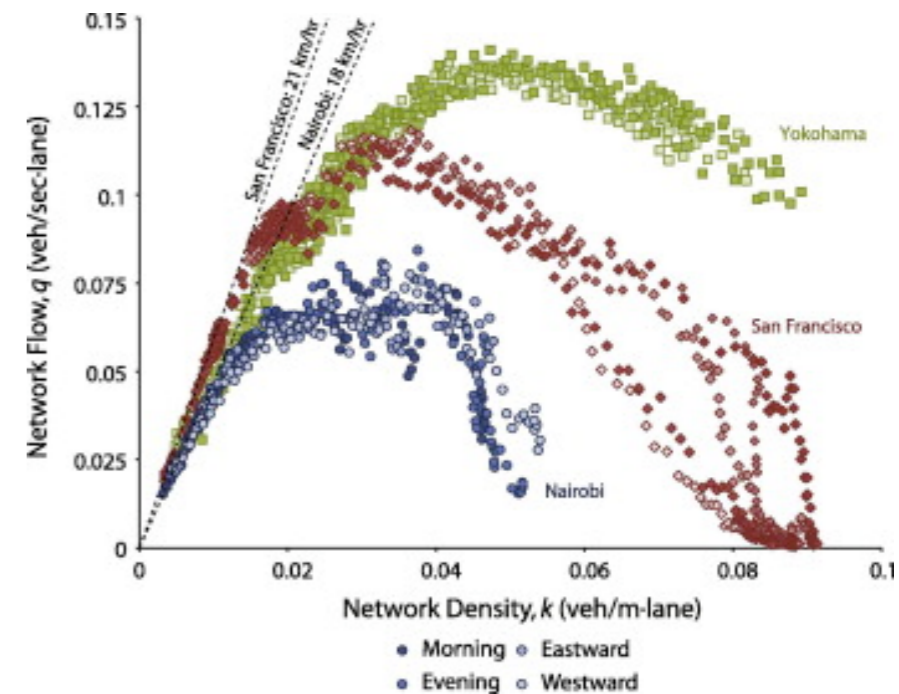
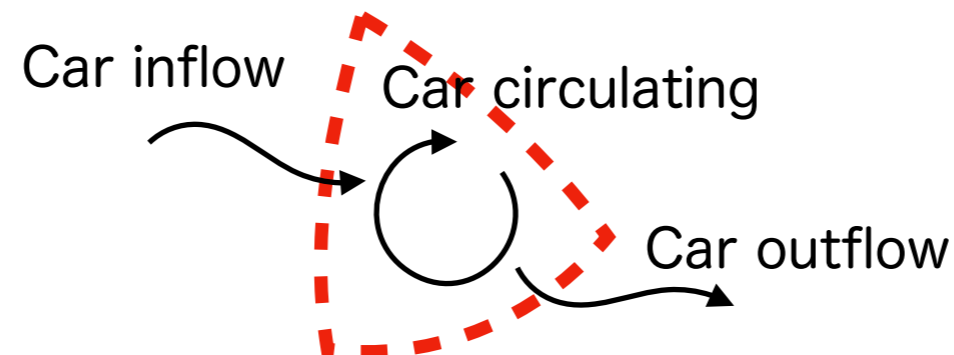
- The input for simulation (e.g., traffic demand) is a key component
 - Reliability of simulations
 - Calibration
- The general purpose algorithms (e.g., SPSA, GA, Kalman filter)
 - Applicable to a wide range of problems
 - The computational efficiency is not a priority
- Dynamic OD calibration for large-scale network is challenging
 - Computational efficiency
 - Scalability
- The lack of quantitatively methods to evaluate the calibration performance at large-scales
 - How to connect OD matrix with the complex traffic dynamics at aggregated levels



- A traffic model at the network level
- The MFD relates the network flow to the network density (Daganzo, 2007)
- Some requirements for the well-defined MFD (Geroliminis and Daganzo, 2008)
 - Homogeneous congestion pattern over space
 - Average trip length is constant over time



(Geroliminis and Daganzo, 2008)



(Gonzales et al., 2009)

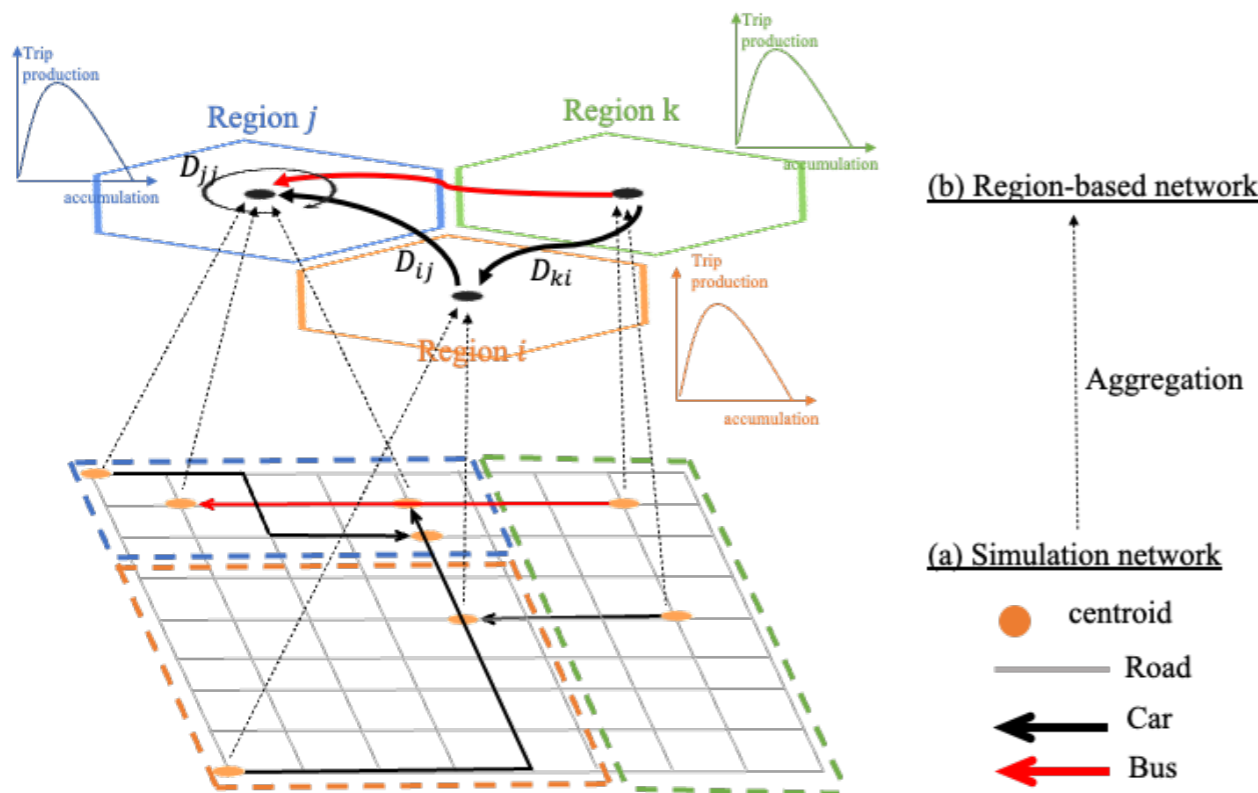
- Propose a novel OD matrix calibration framework for large-scaled networks
 - aggregated traffic flow dynamics
 - metamodel optimization approach
- Utilize multiple data sources for deriving the ground-truth values
- Demonstrate the scalability, accuracy and efficiency

- A simulation network is divided into N regions (e.g., Ji and Geroliminis, 2012)
- Traffic demand from centroids are aggregated to representative regional centroids
- Optimization problem for OD demand calibration

$$\min_{\mathbf{D}} \underbrace{\sum_{i \in I} \sum_{j \in I} \left(N_{i,t} - E[n_{i,t}^c(\mathbf{D}) + n_{i,t}^b(\mathbf{D})] \right)^2}_{\text{MSE in the total accumulations}} + \delta_1 \underbrace{\sum_{i \in I} \sum_{j \in I} (D_{i,j}^0(t) - D_{i,j}(t))^2}_{\text{Distance between initial and optimized demands}}$$

MSE in the total accumulations

Distance between initial and optimized demands



\mathbf{D} : vector of the regional car OD matrix

$N_{i,t}$: ground truth total accumulation in region i at time t

$n_{i,t}^c(\mathbf{D})$: Car accumulation in region i at time t from simulation with demand \mathbf{D}

$n_{i,t}^b(\mathbf{D})$: Bus accumulation in region i at time t from simulation with demand \mathbf{D}

$D_{i,j}^0(t)$: Initial demand generated in region i with final destination j at time t

$D_{i,j}(t)$: demand generated in region i with final destination j at time t

δ_1 : weight factor

- Dimension as the size of the problem is $I \times I \times T$
 - I, T : number of regions, time steps
- Even for a small-scale network (e.g. 3 regions, 15 time steps), the dimension is 135
- Calibration of the aggregated OD matrices is still high-dimensional problem
- Running multiple replications of the simulation is expensive
- An efficient algorithm that require **a few iterations** has to be developed

- A model of the models : simpler deterministic approximating function
- The proposed metamodel optimization

Simulation-based optimization $\min_{\mathbf{D}} \sum_{i \in I} \sum_{j \in I} \left(N_{i,t} - E[n_{i,t}^c(\mathbf{D}) + n_{i,t}^b(\mathbf{D})] \right)^2 + \delta_1 \sum_{i \in I} \sum_{j \in I} (D_{i,j}^0(t) - D_{i,j}(t))^2$

Metamodel optimization $\min_{\mathbf{D}} \underbrace{f_1(\mathbf{D}; \beta)}_{\text{analytical model}} + \delta_1 \sum_{i \in I} \sum_{j \in I} (D_{i,j}^0(t) - D_{i,j}(t))^2$

↖ Metamodel parameter
↓

- The objective function estimate is produced with low computational burden

- Analytical macroscopic traffic flow model (Zheng and Geroliminis, 2013; Yildirimoglu et al., 2015)

$$f_1(\mathbf{D}; \beta) = \sum_{i \in I} \sum_{t \in T} \left(N_{i,t} - (n_i^c(t) + n_i^b(t)) \right)^2$$

$$n_i^c(t) = \beta_{i,t} \sum_{j \in J} n_{i,j}^c(t)$$

$$n_{i,j}^c(t+1) = \begin{cases} n_{i,i}^c(t) + D_{i,i}(t) + \sum_{k \in V_i} \hat{M}_{k,i}^i(t) - O_{i,i}(t) & \text{if } i = j \\ n_{i,j}^c(t) + D_{i,j}(t) + \sum_{k \in V_i} \hat{M}_{k,j}^i(t) - \sum_{k \in V_k} \hat{M}_{i,j}^k(t) & \text{if } i \neq j \end{cases}$$

$$\hat{M}_{i,j}^k(t) = \min[M_{i,j}^k(t), C_{i,k}(n_k^c(t), n_k^b(t))]$$

$$M_{i,j}^k(t) = \sum_{r \in R} P_r(t) O_{i,j}(t)$$

$$O_{i,j}(t) = \frac{n_{i,j}^c(t) v_i(t)}{L_i}$$

$$P_r(t) = \frac{e^{\theta TT_r(t)}}{\sum_{l \in L} e^{\theta TT_l(t)}}$$

$$TT_i(t) = \frac{L_i}{v_i(t)}$$

$$v_i(t) = a_i + a_i^c n_i^c(t) + a_i^b n_i^b(t)$$

Number of vehicles

Conservation law

Capacitated inflow

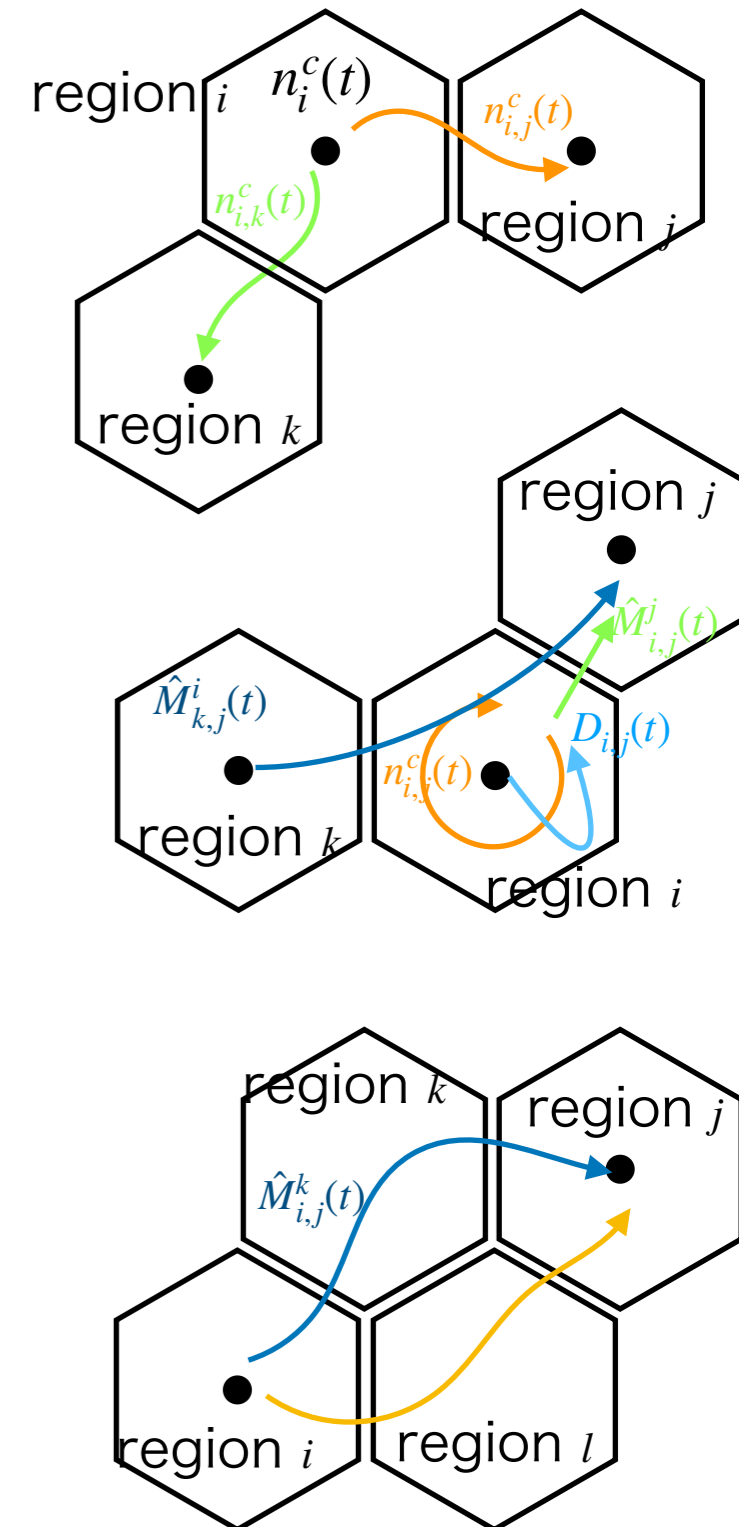
Inflow

Outflow

Regional choices probability

Average travel time

Average travel speed



- The heterogeneity exists in the trip lengths or congestion patterns over spaces
(Buisson and Ladier, 2009; Mazloumian et al., 2010; Sun and Geroliminis, 2011)

- Gaps between the simulated and the analytical accumulations

- To fill the gaps, the metamodel parameters are adjusted

adjusting parameter at iteration h

$$\min_{\eta^h} \sum_{s \in S} w_h(\mathbf{D}_s) \sum_{i \in I} \sum_{t \in T} \left(\eta_{i,t}^h \beta_{i,t}^{h-1} n_{i,s}^c(t) - E[n_{i,t}^c(\mathbf{D}_s)] \right)^2 + w_0 \sum_{i \in I} \sum_{t \in T} (\eta_{i,t}^h - 1)^2$$

a set of samples metamodel parameter at iteration $h-1$ analytical accumulation of sample s simulated accumulation of sample s

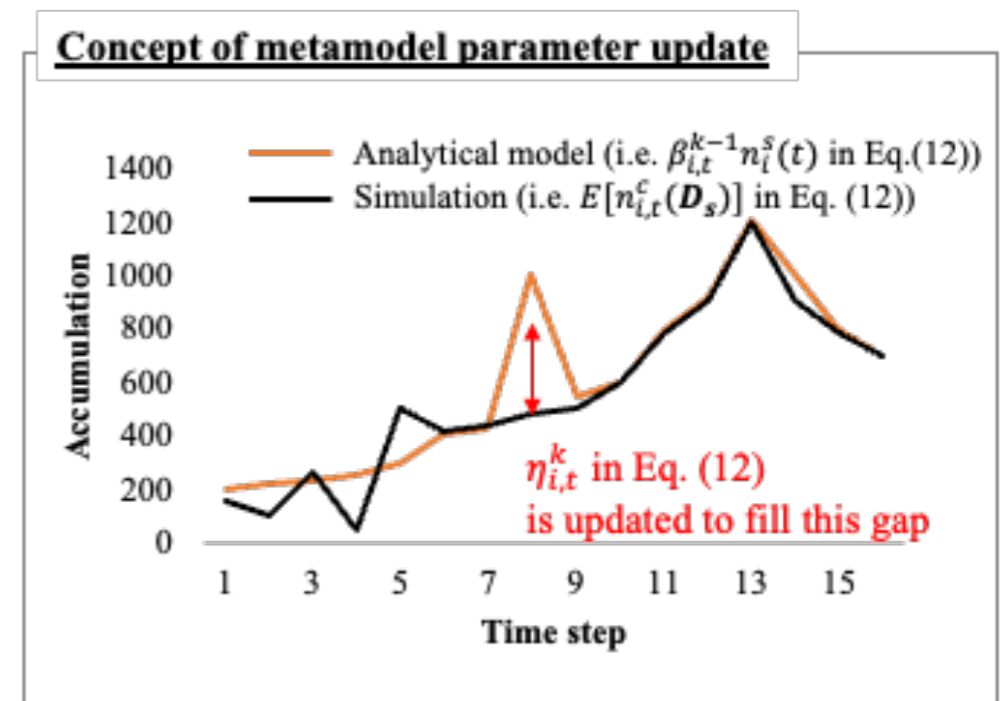
Subject to

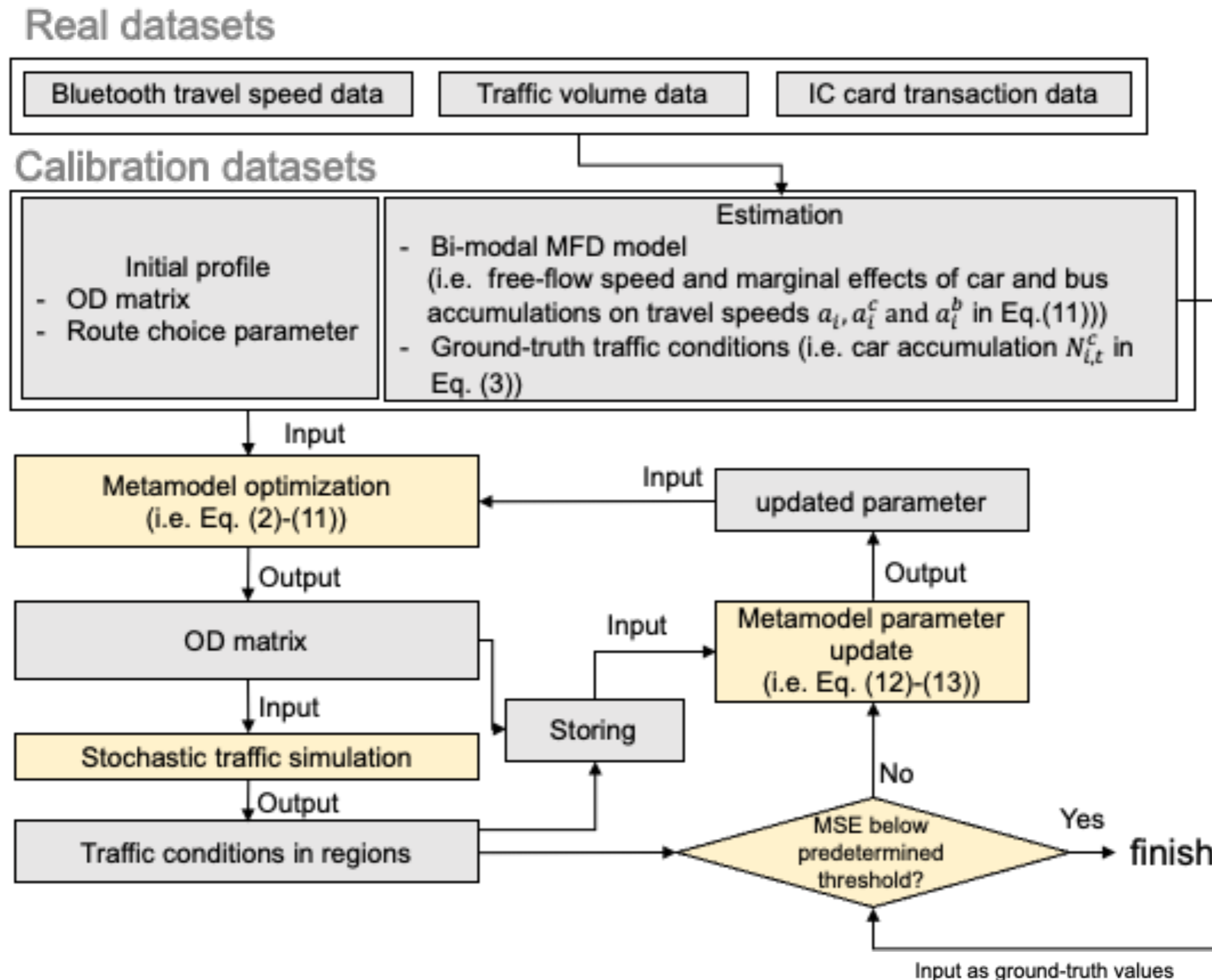
$$\beta_{i,t}^l \leq \eta_{i,t}^h \beta_{i,t}^{h-1} \leq \beta_{i,t}^u$$

metamodel parameter at next iteration

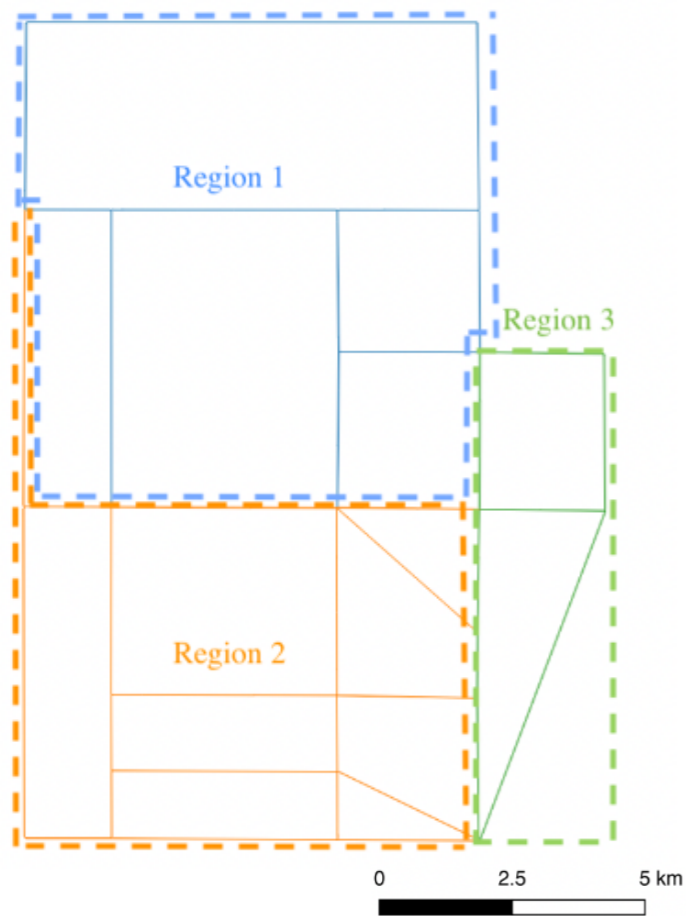
- Weight $w_h(\mathbf{D}_s)$

$$w_h(\mathbf{D}_s) = \frac{1}{1 + c ||\mathbf{D}_s - \mathbf{D}_h||}$$

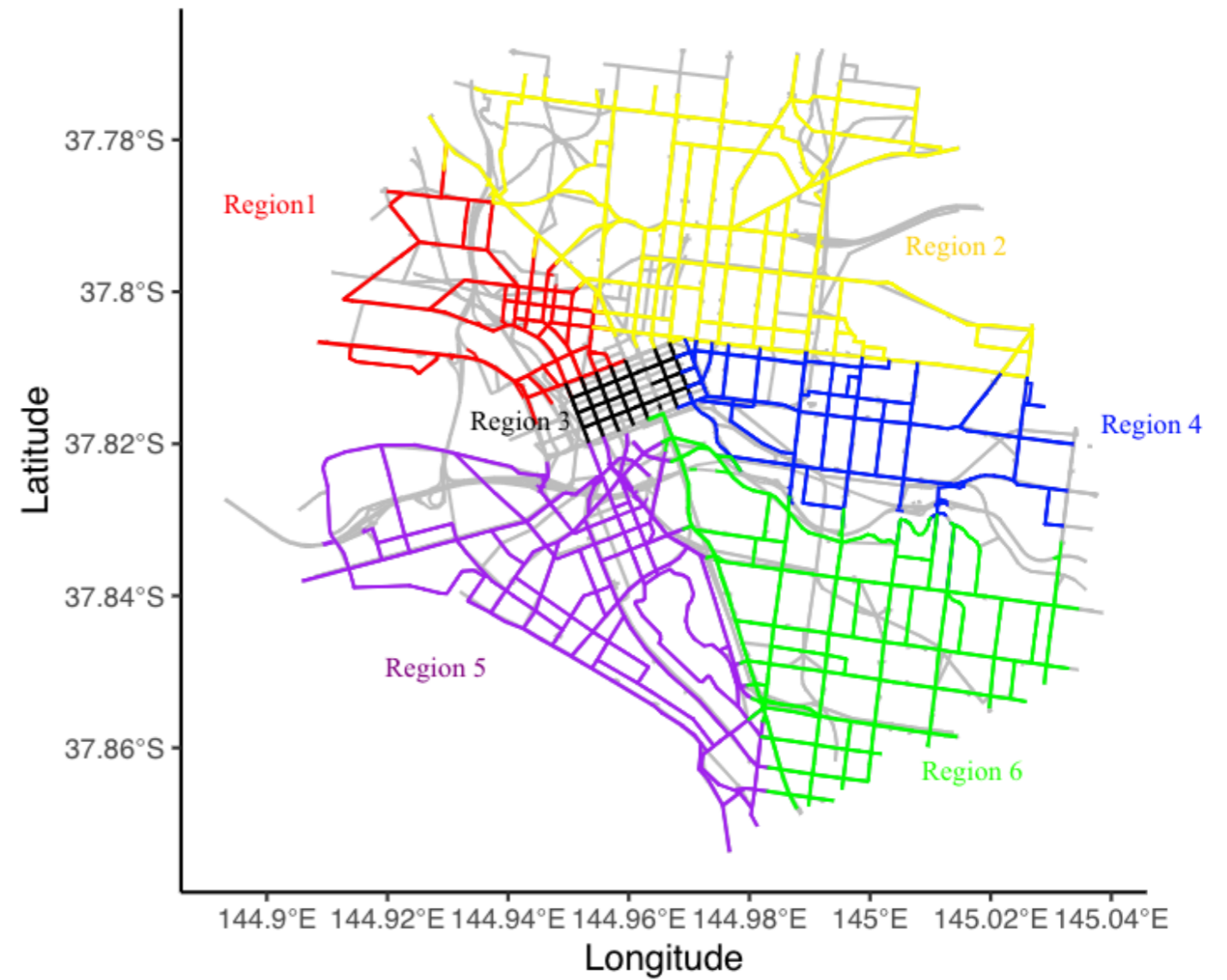




Sioux-falls (SF) network

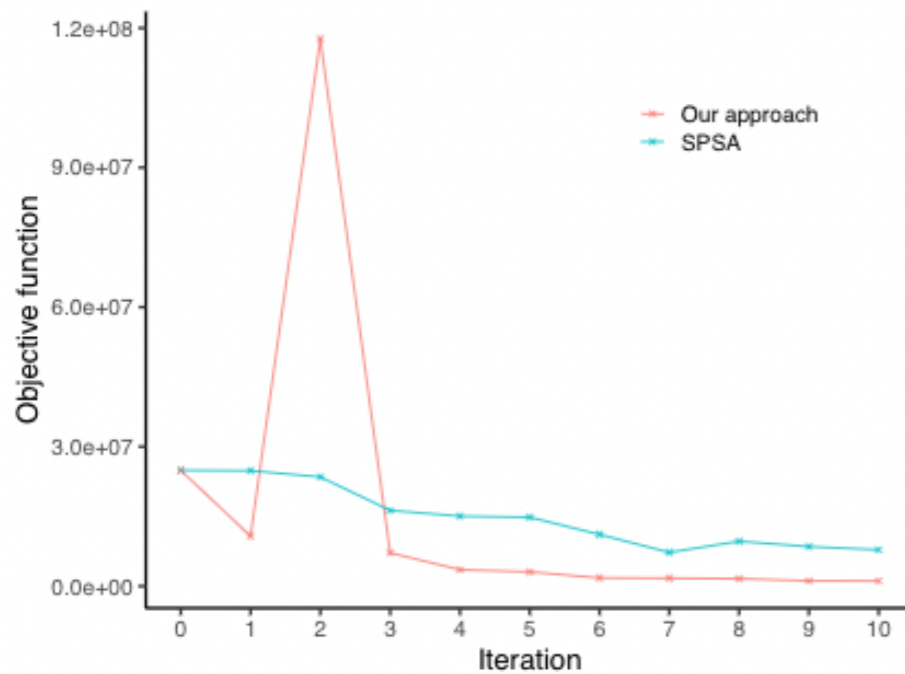


Melbourne CBD network

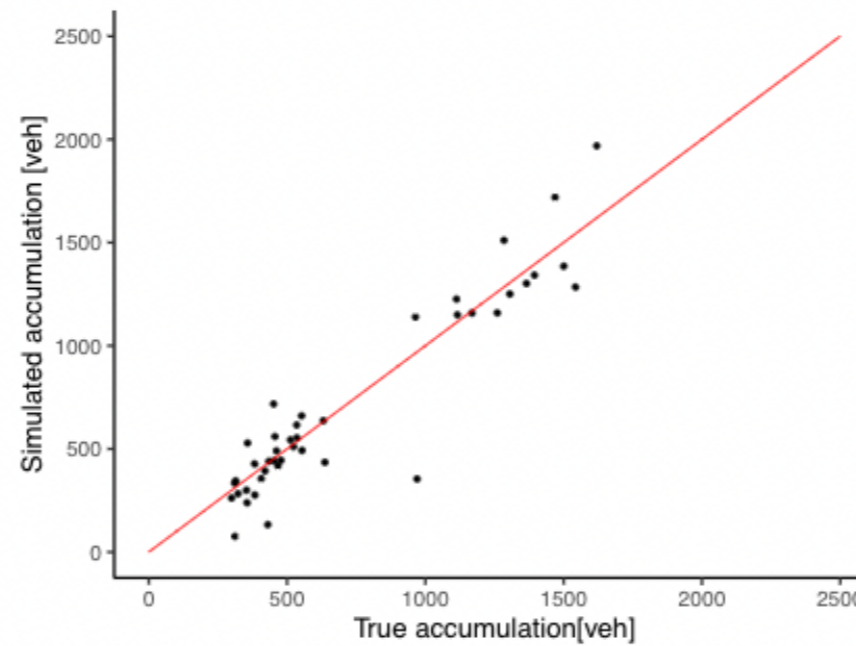


- The performance of the proposed approach and SPSA
 - A few iterations are needed to understand the direction of parameters' adjustment
 - After 5th iteration, the objective function estimated becomes stable over iterations

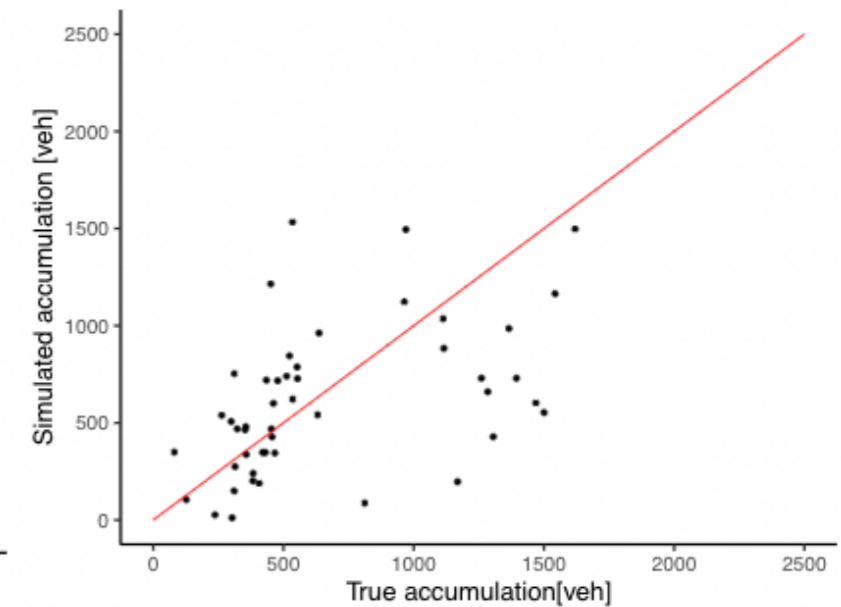
Obj. function estimated



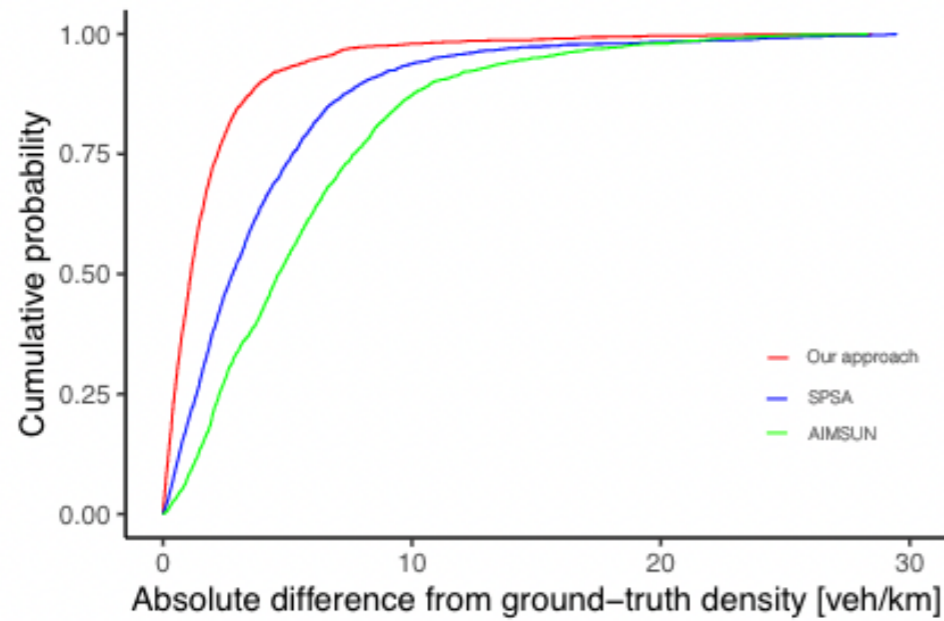
The proposed approach



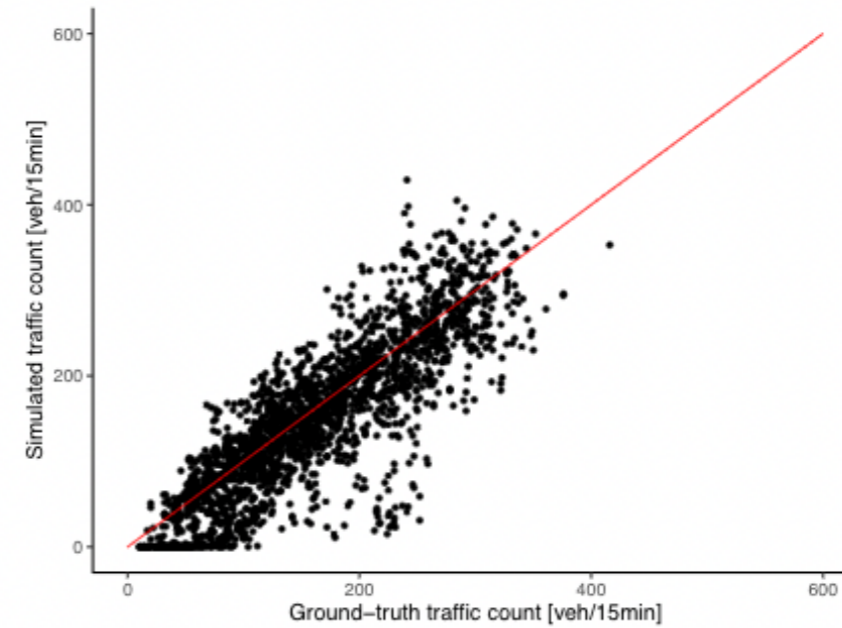
SPSA



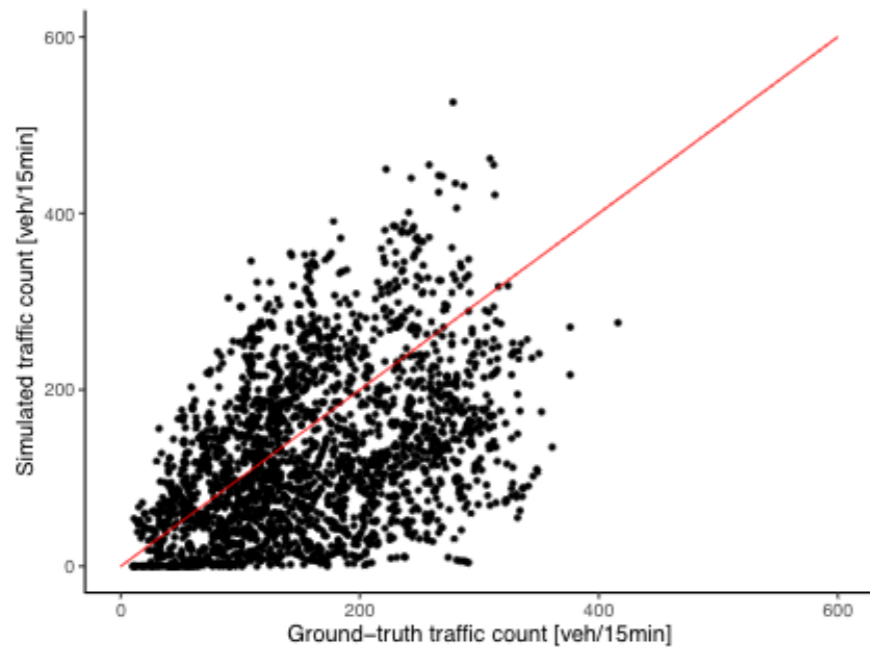
Comparison at 10 iteration



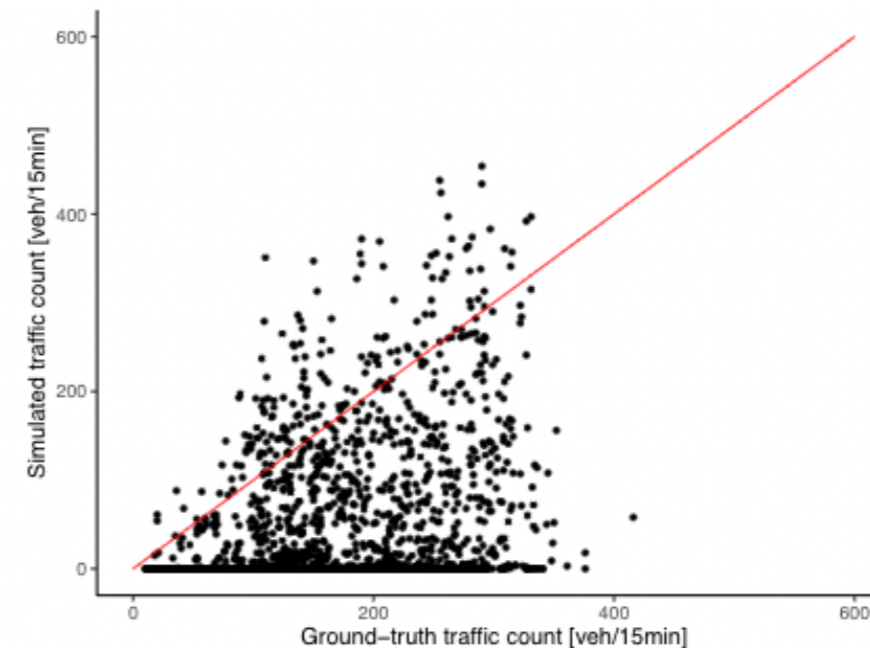
The proposed approach at 10th iteration



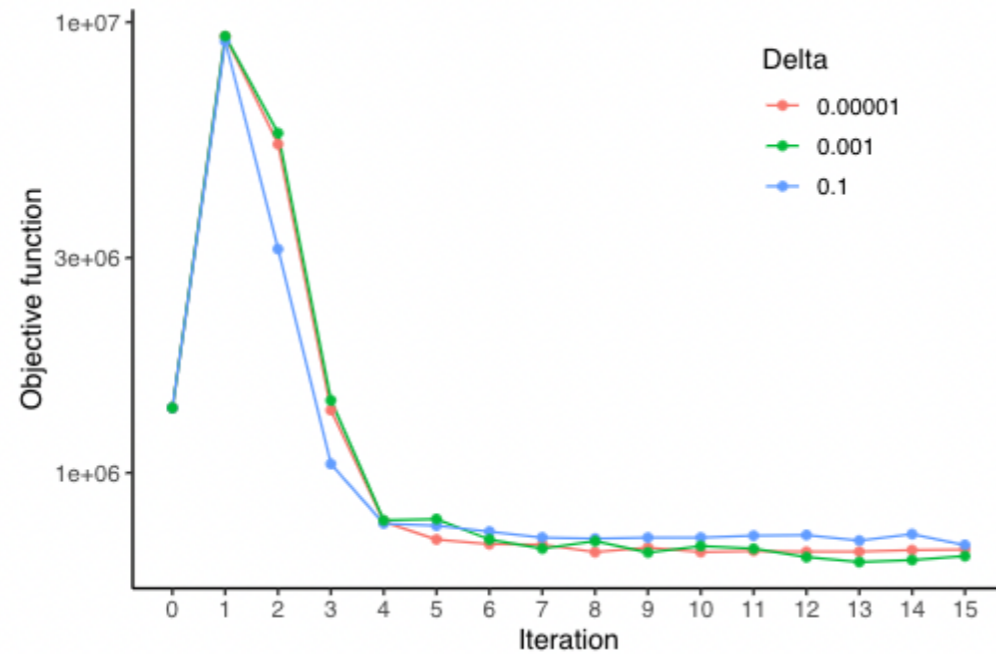
SPSA at 10th iteration



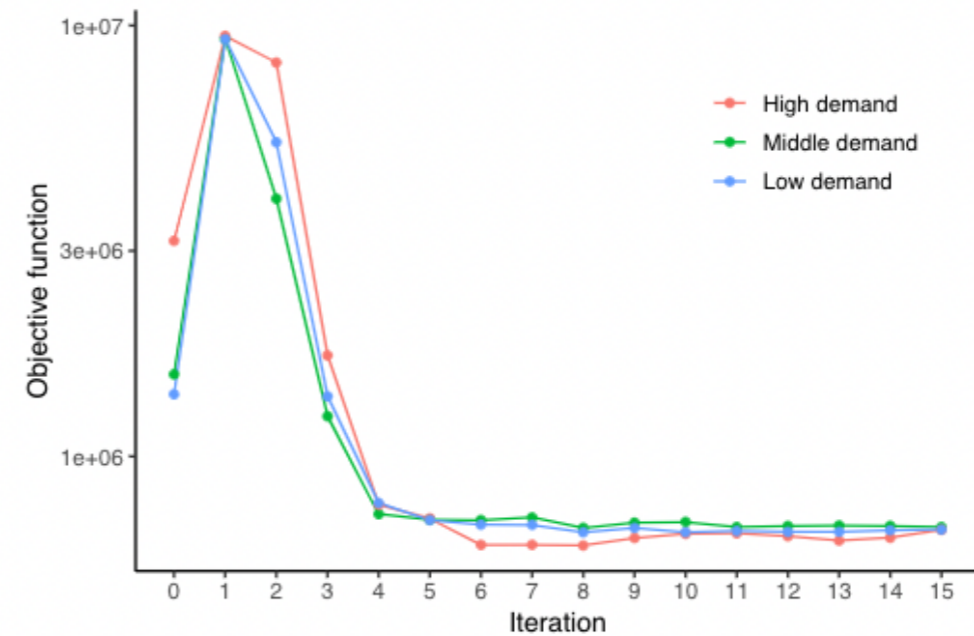
Aimsun at 10th iteration



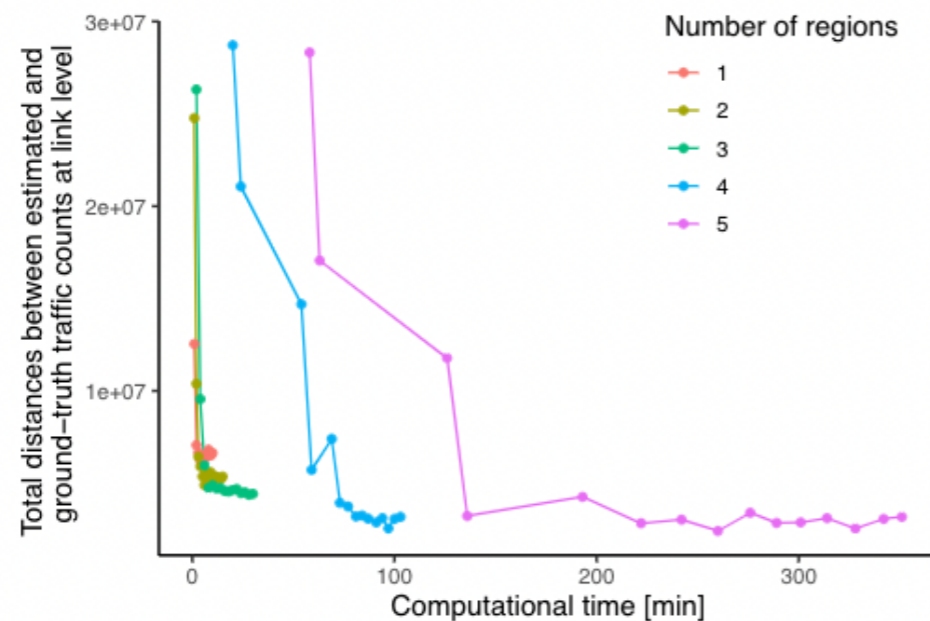
Sensitivity analysis on weight factor



Sensitivity analysis on initial demand

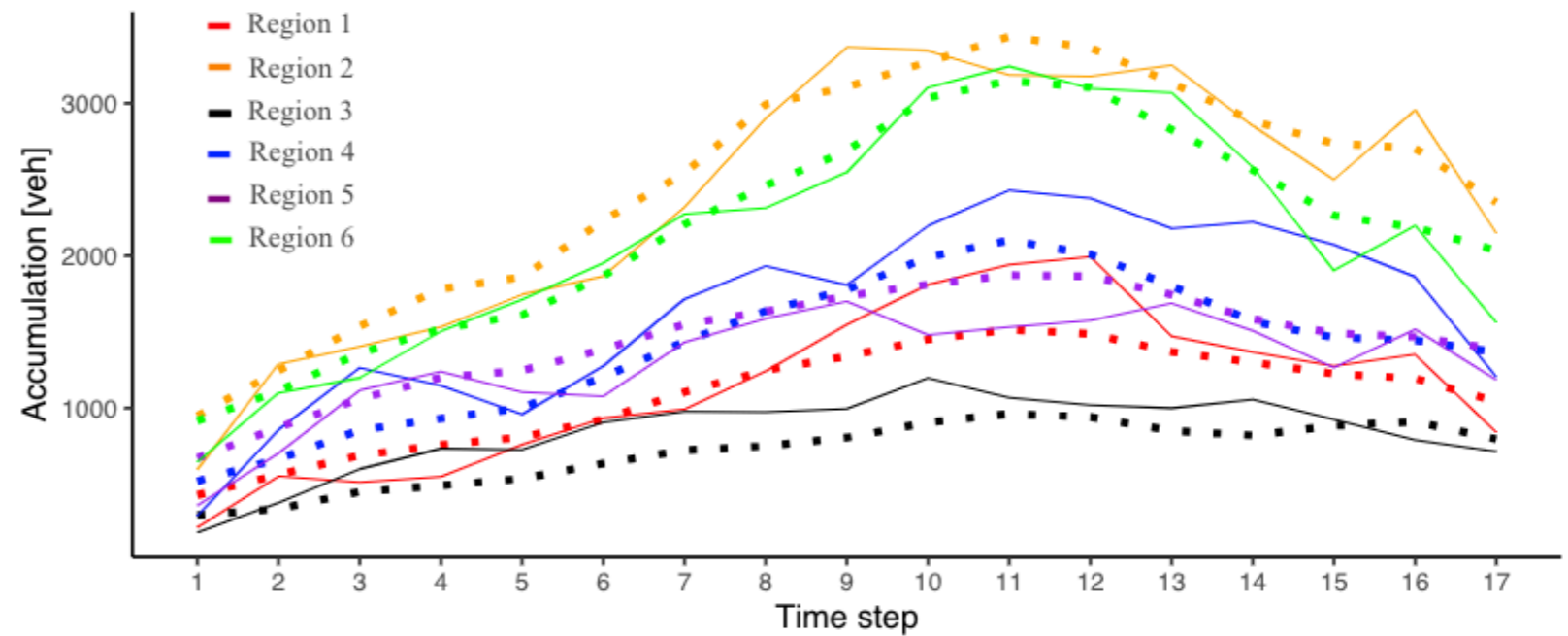


Sensitivity analysis on number of regions



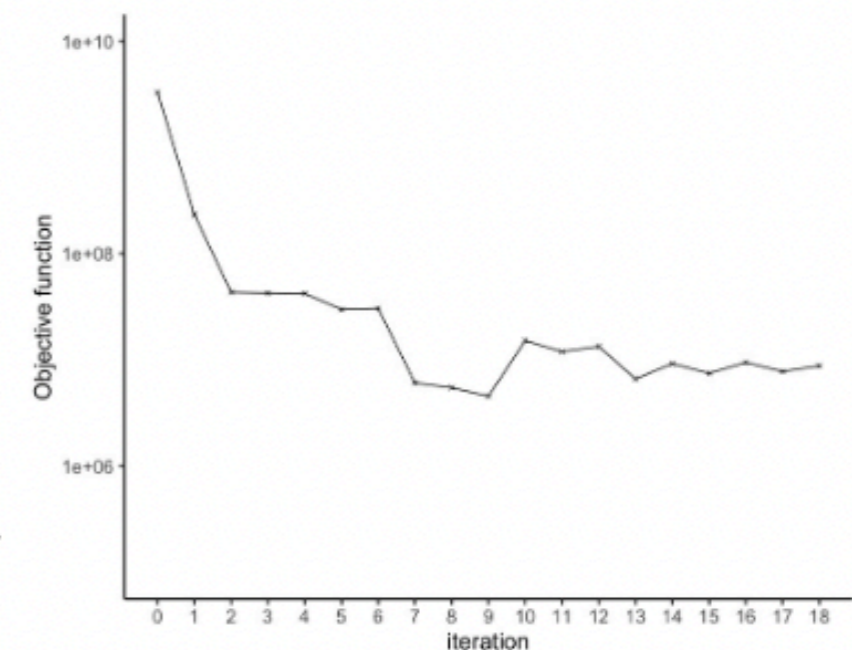
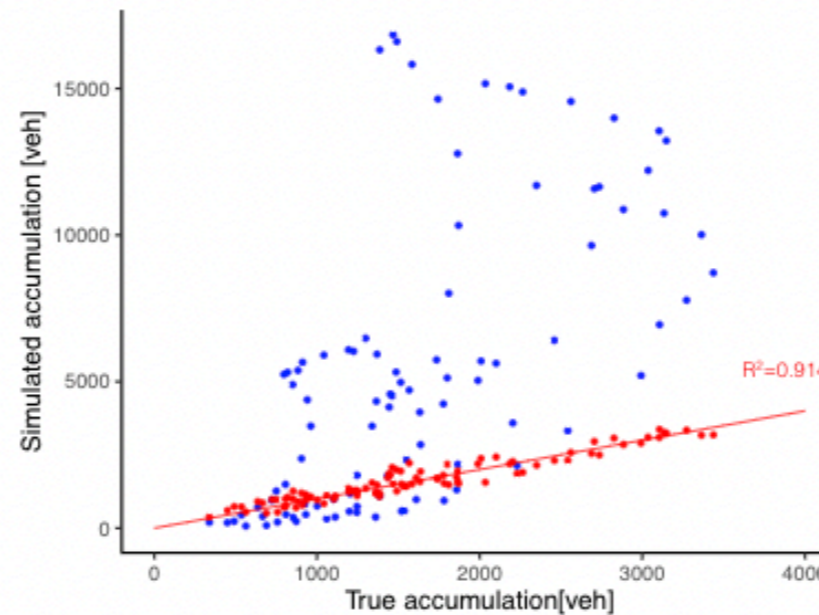
Ground-truth (dotted) and simulated (solid) accumulations

- Data for grand-truth values
 - SCATS data
 - Bluetooth travel time
 - IC smart card (Myki data)



Initial (blue) & simulated (red)

Obj. function estimated



Conclusions

- Developed a computationally efficient metamodel optimization framework for the OD demand calibration of large-scaled networks
- Utilized the region-based traffic dynamics as an analytical model of the metamodel
- Tested the proposed approach with two case studies

Future directions

- Extend to other optimization problems such as dynamic congestion pricing

References

- Zheng, N., Dantsuji, T., Wang, P., & Geroliminis, N. (2017). Macroscopic approach for optimizing road space allocation of bus lanes in multimodal urban networks through simulation analysis. *Transportation Research Record*, 2651(1), 42-51.
- Dantsuji, T., Fukuda, D., & Zheng, N. (2021). Simulation-based joint optimization framework for congestion mitigation in multimodal urban network: a macroscopic approach. *Transportation*, 48(2), 673-697.
- Geroliminis, N., & Daganzo, C. F. (2008). Existence of urban-scale macroscopic fundamental diagrams: Some experimental findings. *Transportation Research Part B: Methodological*, 42(9), 759-770.
- Daganzo, C. F. (2007). Urban gridlock: Macroscopic modeling and mitigation approaches. *Transportation Research Part B: Methodological*, 41(1), 49-62.
- Gonzales, E. J., Chavis, C., Li, Y., & Daganzo, C. F. (2009). Multimodal transport modeling for Nairobi, Kenya: insights and recommendations with an evidence-based model.
- Ji, Y., & Geroliminis, N. (2012). On the spatial partitioning of urban transportation networks. *Transportation Research Part B: Methodological*, 46(10), 1639-1656.
- Yildirimoglu, M., Ramezani, M., & Geroliminis, N. (2015). Equilibrium analysis and route guidance in large-scale networks with MFD dynamics. *Transportation Research Part C*, (59), 404-420.
- Zheng, N., & Geroliminis, N. (2013). On the distribution of urban road space for multimodal congested networks. *Procedia-Social and Behavioral Sciences*, 80, 119-138.
- Buisson, C., & Ladier, C. (2009). Exploring the impact of homogeneity of traffic measurements on the existence of macroscopic fundamental diagrams. *Transportation Research Record*, 2124(1), 127-136.
- Mazloumian, A., Geroliminis, N., & Helbing, D. (2010). The spatial variability of vehicle densities as determinant of urban network capacity. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 368(1928), 4627-4647.
- Geroliminis, N., & Sun, J. (2011). Properties of a well-defined macroscopic fundamental diagram for urban traffic. *Transportation Research Part B: Methodological*, 45(3), 605-617.