Simulation-Based Optimization of Highway Active Traffic Management Strategy Designs-Appendix

Zheng Li[abc], Jian Sun[a], Haoming Meng[c], and Ye Tian.[a*]

[a]College of Transportation, Tongji University, Shanghai, China

[b]Department of Civil and Environmental Engineering, University of Wisconsin-Madison, Madison, WI, USA

[c]Department of Computer Science, University of Wisconsin-Madison, Madison, WI, USA

[*]Corresponding author: Ye Tian; tianye@tongji.edu.cn

1 Overview of the proposed SBO method

The overviwe of the proposed SBO method is shown in Figure 1.

2 Pseudocode for CTM

The pseudocode for CTM is shown in Algorithm 1

Algorithm 1 Cell Transmission Model

For each time step $k \in K$:
  Compute mainline inlet flow $\phi_{0,k}$ via Equation (18).
  For each mainline cell $j \in J$:
    If $j = 1$ **and** $k = 1$, **then** compute density $\rho_{j,k}$ via Equation (20).
    Else if $k < j$, **then** compute density $\rho_{j,k}$ via Equation (21).
    Compute jam density $\rho^{\text{jam}}_{j,k}$, critical density $\rho^{\text{cri}}_{j,k}$, and capacity $q^{\text{cap}}_{j,k}$ via Equations (14)-(16).
  End for
  For each mainline cell $j \in J$:
    If $j \in J^*$, **then** compute mainline outflow $\phi^m_{j,k}$ via Equation (10).
    Else, compute mainline outflow $\phi^m_{j,k}$ via Equation (11).
  End for
  For each on-ramp $g \in G$:
    If $k = 1$, **then**
      Compute queue length $l_{g,k}$ via Equation (19).
      Compute on-ramp outflow $\phi^r_{g,k}$ via Equation (13).
    End if
    If $k \in K^*$, **then** compute queue length $l_{g,k+1}$ via Equation (12).
  End for
  For each mainline cell $j \in J$:
    If $k \in K^*$, **then** compute density $\rho_{j,k+1}$ via Equation (9).
  End for

3 Pseudocode for AHA sampling

The pseudocode for CTM is shown in Algorithm 2

4 Computation time analysis

We measured the runtime of our meta model-based SBO method in the Hang-Shao-Yong case on a personal laptop (Intel® Core™ i9-14900HX, 32 GB RAM). On average, each iteration's modules take:

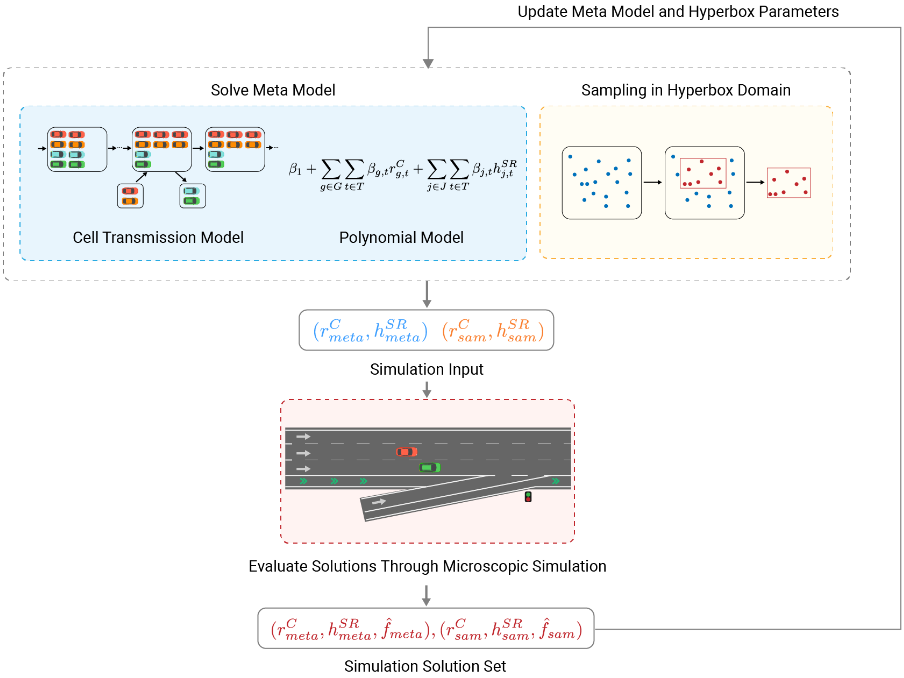

Figure 1: Overview of the SBO technique for determining the highway management strategies.

Algorithm 2 AHA sampling

Initialization:

Set iteration steps $u = 0$.

Set hyperbox parameters for on-ramp in-merge rates $\mathcal{H}_u^{RC} = \{0.15 \leq r^c_{g,t} \leq 1, \forall g \in G, \forall t \in T\}$.

Set hyperbox parameters for shoulder lane states $\mathcal{H}_u^{HSR} = \{h^{SR}_{g,t} \in \{0, 1\}, \forall g \in G, \forall t \in T\}$.

Step 1: Sampling

Uniformly sample within the hyperbox domain defined by Equations 43-44 to obtain ω solutions:

$$(\mathbf{r}^c_{sam,1,u}, \mathbf{h}^{SR}_{sam,1,u}), \ldots, (\mathbf{r}^c_{sam,\omega,u}, \mathbf{h}^{SR}_{sam,\omega,u}).$$

Step 2: Simulation

Evaluate $(\mathbf{r}^c_{sam,1,u}, \mathbf{h}^{SR}_{sam,1,u}), \ldots, (\mathbf{r}^c_{sam,\omega,u}, \mathbf{h}^{SR}_{sam,\omega,u})$ through microscopic simulations to obtain delays:

$$\hat{f}_{sam,1,u}, \ldots, \hat{f}_{sam,\omega,u}.$$

Update simulation solution sets through Equations 38 and 42.

Step 3: Updating hyperbox parameters

Update hyperbox parameters through Equations 43-44.

Update iteration step $u = u + 1$.

Return to Step 1.

hyperbox sampling: 0.0014 s; Gurobi optimization of the meta model: 0.1018 s; hyperbox parameter update: 0.0036 s; meta model parameter update: 0.1686 s.

By far the dominant cost is the TESS NG microscopic simulation: a one-hour run takes 21.14 min, so one SBO iteration is around 21 min while non-simulation steps are negligible; since Figure 7 in the manuscript shows that designing a one-hour ATM strategy needs about 5–10 simulations, total runtime on our laptop is around 100 min. Most prior transportation SBO studies target offline problems (e.g., network design, pre-timed signals), so our offline, pre-scheduled highway ATM optimization over 30–60 min horizons is a substantial contribution under a tight simulation budget. Nevertheless, the approach is also viable in real time: (1) all modules except simulation are trivial in cost; (2) we used a non-latest TESS NG, whereas newer releases speed offline simulation by 8–10× (a 60-min scenario in around 6–7 min), making our HSY case solvable in 30 min; and (3) cloud deployment enables parallel, high-performance runs and seamless live-data integration, reducing runtimes to mere minutes and supporting fully automated, adaptive ATM control.

5 Comparisons between Macroscopic and Microscopic Model-Based Optimization Methods in Terms of Parameter Calibration

Macroscopic and microscopic models differ significantly in calibration complexity. Microscopic models require numerous parameters (e.g., for car-following and lane-changing behaviors), making them harder to calibrate—especially in data-scarce environments. Macroscopic models, by contrast, are simpler and more robust due to fewer parameters and are thus more practical for real-time control with limited data.

In this study, we focus on offline, pre-scheduled ATM optimization, where microscopic models can be carefully calibrated and provide high-fidelity results. In such settings, the detailed behavioral dynamics of microscopic models become an advantage.

For real-time or multi-region deployments, parameter variability poses a challenge. Microscopic models are less adaptable in real-time due to calibration complexity. However, their limitations can be mitigated by: (1) using time-of-day calibrated parameters; and (2) leveraging empirical mappings from observable macroscopic indicators (e.g., speed, flow) to estimate microscopic parameters (Treiber, Hennecke, and Helbing (2000)).

In summary, macroscopic models are more robust under uncertainty, while microscopic models offer greater accuracy when calibrated properly. With appropriate strategies, microscopic models can also support adaptive control in near real-time contexts.

References

Treiber, M., Hennecke, A., & Helbing, D. (2000). Congested traffic states in empirical observations and microscopic simulations. *Physical review E*, *62*(2), 1805.