Calibrating Route Choice for Urban Rail System: A Comparative Analysis Using Simulation-Based Optimization Methods

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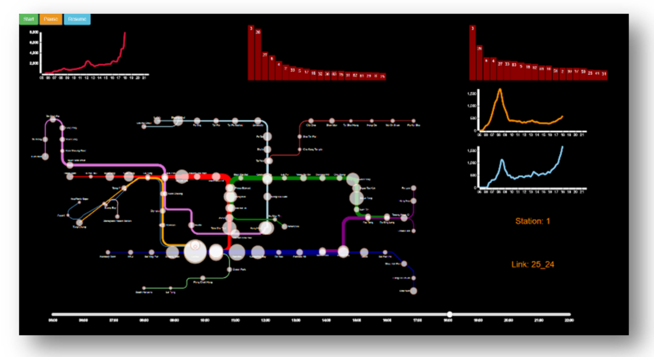
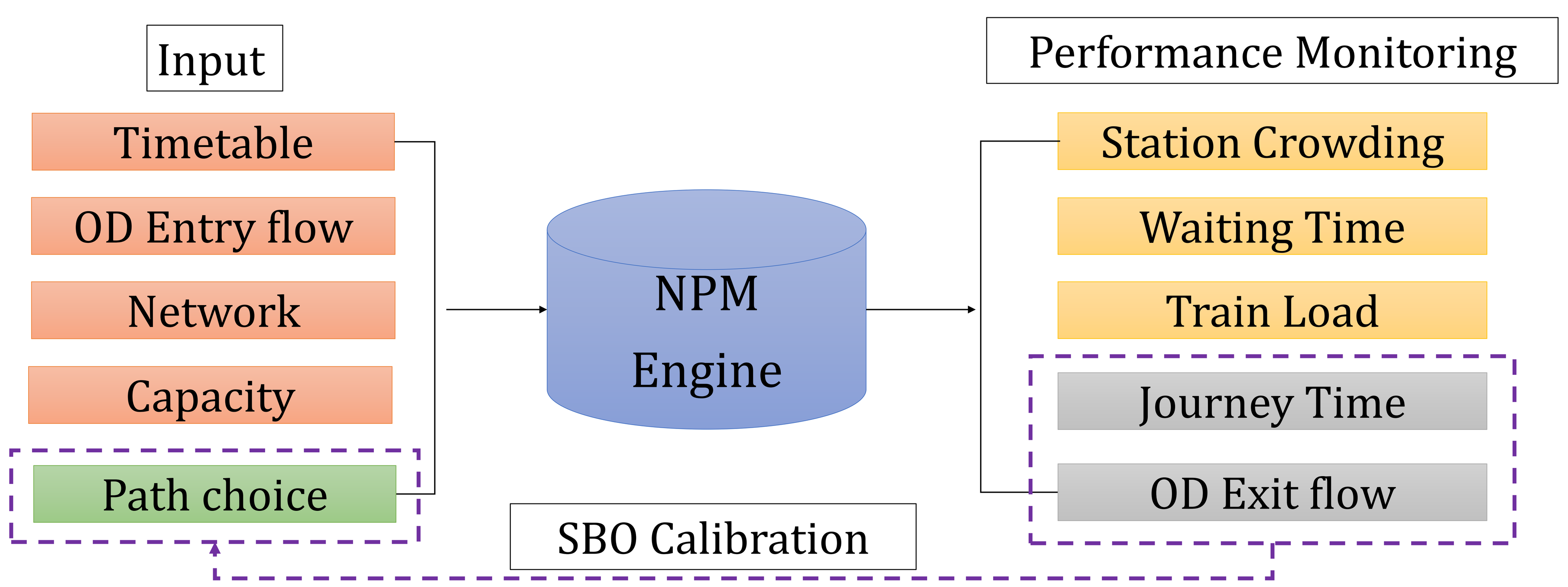
1 INTRODUCTION

- The Network Performance Model (NPM) provides performance monitoring and strategic decision support for urban railways
- Learning passengers' path choice behavior under station crowding (denied boarding) from automated fare collection (AFC) data is challenging
- Current path choice studies are formulated based on AFC journey times, assuming no crowding and independence of individual journey times
- The research addresses the path choice gaps by
  - Proposing a simulation-based optimization (SBO) framework to estimate route choice using AFC data
  - Comparing the performance of SBO optimizers



2 METHODOLOGY

Framework



Problem formulation

Minimize the difference (between estimated and observed) of OD exit flows and journey time distribution

$$\begin{aligned}\min_{\beta} \quad & w_1 \sum_{i,j_n} (q^{i,j_n} - \tilde{q}^{i,j_n})^2 + w_2 \sum_{i,j_n \in \mathscr{D}} D_{\mathrm{KL}}(p_{i,j_n}(x) \| \tilde{p}_{i,j_n}(x)) \\ \text{s.t.} \quad & q^{i,j_n} = \mathrm{NPM}(\beta, q^{i_m,j}, \theta) \qquad \forall i, j_n, \\ & p_{i,j_n}(x) = \mathrm{NPM}(\beta, q^{i_m,j}, \theta) \qquad \forall i, j_n \in \mathscr{D}, \\ & L_\beta \leq \beta \leq U_\beta\end{aligned}$$

$q^{i_m,j}$: Number of passengers entering station i during time interval m and exiting at station j
q^{i,j_n} : Number of passengers exiting at station i during time interval n with origin i
p_{i,j_n} : Journey time distribution for passengers with origin i, destination j, and exit at time interval n
β : Path choice parameters of a C-logit model
L_β: Lower bound of β.
U_β: Upper bound of β.
θ : External inputs to the NPM model, including time table and transit network typology.

Model assumption

- The route choice fractions are estimated using a C-logit model. CF is the commonality factor.

$$p_r^{i_m,j} = \frac{\exp(\beta_X \cdot X_{r,m} + \beta_{CF} \cdot CF_r)}{\sum_{r'} \exp(\beta_X \cdot X_{r',m} + + \beta_{CF} \cdot CF_{r'})}$$

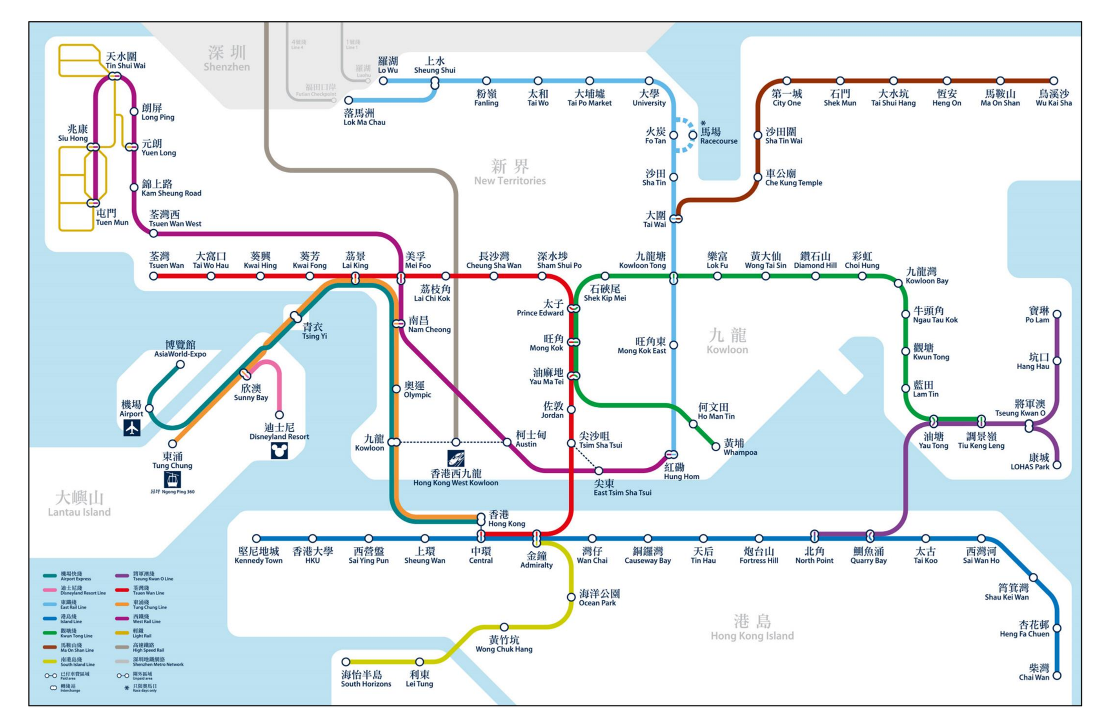
3 SIMULATION-BASED OPTIMIZATION ALGORITHMS

Algorithms Summary

Type	Algorithm	Source
Direct search	Nelder-Mead Simplex Algorithm (NMSA)	Gao and Han (*31*)
	Mesh Adaptive Direct Search (MADS)	Abramson et al. (*32*)
Gradient-based	Simultaneous Perturbation Stochastic Approximation (SPSA)	Spall et al. (*33*)
Response surface	Bayesian Optimization (BYO)	Snoek et al. (*34*)
	Constrained Optimization using Response Surfaces (CORS)	Regis and Shoemaker (*35*)

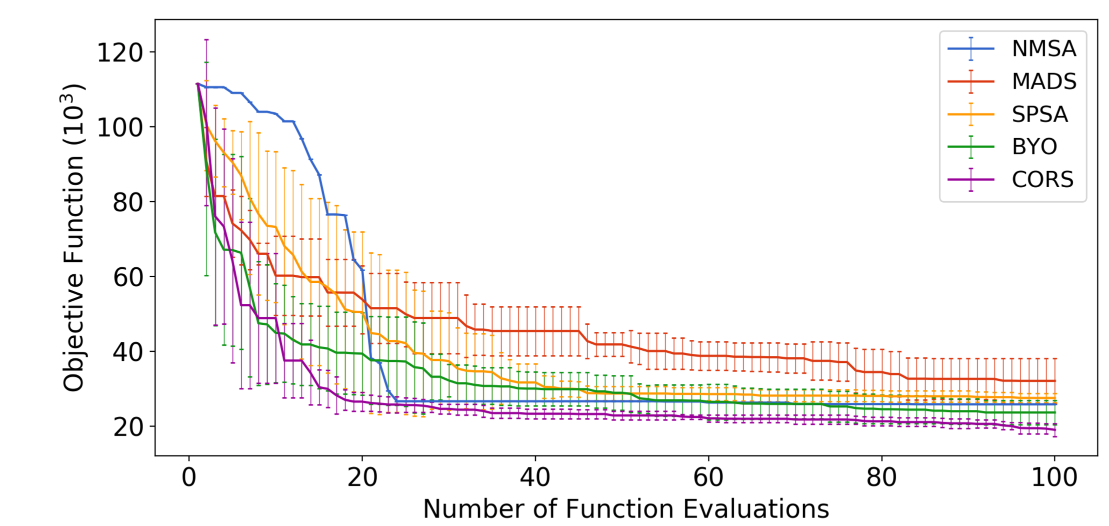
4 RESULTS

Case study



- Synthetic data using Hong Kong MTR System
  - Generate transaction tap-out times given a 'true' path choice model and tap-in times

Model convergence and estimation results



Variable Name	"True"	Estimated Parameters of C-logit Model				
		NMSA	MADS	SPSA	BYO	CORS
In-vehicle time	-0.0663	-0.0656	-0.0542	-0.0693	-0.0623	-0.0645
Number of transfers	-0.4380	-0.4295	-0.3100	-0.3015	-0.4641	-0.4450
Transfer walking time	-0.1830	-0.1430	-0.1800	-0.2132	-0.1698	-0.1840
Map distance	-0.0767	-0.0639	-0.1000	-0.0946	-0.0792	-0.0739
Commonality factor	-0.9410	-0.6757	-0.9000	-0.6764	-0.9476	-0.9690
Objective function	0	25795.9	24447.2	25092.2	17551.5	16300.0

5 CONCLUSION

- All algorithms converge to a small objective value with a limited number of function evaluations.
- The response surface methods (BYO and CORS) perform best in terms of the convergence speed, objective values and parameter estimates (compared to the 'true' choice model parameters).
- Despite a similar objective function value, algorithms may give different β estiamtes. For example, NMSA results in good value for the coefficients of in-vehicle time and number of transfers, but less accurate results for the commonality factors. SPSA shows similar properties.

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