# Data-Driven Network Performance Model (NPM) for Urban Rail Systems 

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Jan, 2020

## Motivation

- Monitoring network performance (online/offline) is crucial
- Understand system
- Improve service attractiveness
- Assist planning and operations
- Objective
- Develop a self-calibrated data-driven monitoring \& decision support platform
- Performance monitoring
- Operations planning


## Network Performance Model (NPM)



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Self-calibration/Optimization

## NPM Engine

- Event-based simulation:
- First-come-first-serve
- Strick capacity constraints

- Train arrival:
- Offload passengers
- Train departure:
- Load passengers
- Update states of train and platform


## Train Capacity

## - Effective train capacity:

- Number of passengers in the train when it departures while there are leftbehind passengers on the platform.
- Train capacity may vary by station and crowding levels
- Platform geometry and access impact passenger distribution along the platform, and hence, load distribution on trains.
- Different crowding levels affect passenger willingness to board
- Expectation:
- High train load $\rightarrow$ high effective capacity [Liu et al. 2018]
- High crowding on the platform $\rightarrow$ high effective capacity


## Effective Capacity Model

- Effective capacity of a train at platform $i\left(E C_{i}\right)$ is:

$$
E C_{i}= \begin{cases}C+\beta_{1} L_{i}+\beta_{2} Q_{i} & \text { if platform } i \text { is in the list of congested stations } \\ C & \text { otherwise }\end{cases}
$$

where $C_{i}$ : base capacity
$L_{i}$ : train load and
$Q_{i}$ : number of passengers waiting at platform

## Estimation of Capacity Model Parameters

- Simulation-Based Optimization
- Minimize the error between
- observed OD exit flow and model-derived OD exit flow
- observed journey time distribution (JTD) and model-derived JTD

$$
\begin{array}{cl}
\min _{\beta_{1}, \beta_{2}} & \left.w_{1} \sqrt{\sum_{i, j, t}\left(q^{i, j_{t}}-\tilde{q}^{i}, j_{t}\right.}\right)^{2}+w_{2} 2 \sum_{i, j, t} D_{\mathrm{KL}}\left(p_{i, j_{t}}(x) \| \tilde{p}_{i, j_{t}}(x)\right) \\
\text { s.t. } & q^{i, j_{t}}, p_{i, j_{t}}(x)=\operatorname{NPM}\left(\beta_{1}, \beta_{2}\right) \quad \forall i, j, t \\
& D_{\mathrm{KL}}\left(p_{i, j_{t}}(x) \| \tilde{p}_{i, j_{t}}(x)\right)=\int_{x} p_{i, j_{t}}(x) \cdot \log \frac{p_{i, j_{j}}(x)}{\tilde{p}_{i, j_{t}}(x)} \mathrm{d} x .
\end{array}
$$

## Applications

- Hong Kong MTR network
- Demand on March $16^{\text {th }}$, 2017. Evening Peak
- Path choice from survey
- Validation
- OD exit flow by time
- Left behind survey at key stations



## Path Choice

- Path choices are modeled using a C-logit model from survey data

$$
p_{r}^{i_{m}, j}=\frac{\exp \left(\beta_{X} \cdot X_{r, m}+\beta_{C F} \cdot C F_{r}\right)}{\sum_{r^{\prime} \in \mathscr{R}(i, j)} \exp \left(\beta_{X} \cdot X_{r^{\prime}, m}++\beta_{C F} \cdot C F_{r^{\prime}}\right)}
$$

TABLE 3: Route Choice Model Estimation Results

|  | Estimate | Std. Error | t-value |  |
| :--- | :--- | :--- | :--- | :--- |
| In-vehicle time | -0.147 | 0.011 | -13.64 | $* * *$ |
| Relative walking time | -1.271 | 0.278 | -4.56 | $* * *$ |
| Number of transfers | -0.573 | 0.084 | -6.18 | $*^{* *}$ |
| CF | -3.679 | 1.273 | -2.89 | $*^{*}$ |
| $\rho^{2}=0.54$ |  |  |  |  |
| $* * *: \mathrm{p}<0.01 ;{ }^{* *}: \mathrm{p}<0.05$. |  |  |  |  |

- AFC-data based path choice estimation [Poster session A139]


## Results: Effective Capacity

- Parameter estimation (Bayesian Optimization Algorithm)


$$
E C_{i}=\left\{\begin{array}{l}
C+\beta_{1} L_{i}+\beta_{2} Q_{i} \\
C
\end{array}\right.
$$

$$
C=230 \mathrm{pax} / \mathrm{car} \times \mathrm{Num}
$$ of cars in a train (fixed)

Optimal Solution:

$$
\begin{aligned}
& \beta_{1}=0.0904 \\
& \beta_{2}=0.0718
\end{aligned}
$$

## Results: Effective Capacity

- Train load (pax/train) at Admiralty station

Peak period


## Validation: OD Exit Flow Estimates



## Validation: Left Behind Estimates



## Applications

- [History] Monitor crowding patterns: train load, left behind, waiting time, ...
- [History] Diagnose crowding sources: where does the congestion come from?
- [History] Evaluate network resilience: how does system change if link disruption happens?
- [Future] Operations planning: time table evaluation, dispatching strategies, ...



## Dispatching strategies evaluation

- Impact of dispatching an empty train from upstream to relieve the crowding in the platform at Admiralty station



## Interactive Visualization



- What is happening?
- What is the problem?
- Why it happens?
- What will happen
- if nothing change?
- if things change?
- if actions taken?


## Conclusion

- Data-driven NPM platform:
- Performance monitoring (what was/is...)
- Operations control and strategic planning (what if...)
- Effective train capacity formulation
- Effective train calibration using AFC data
- Future work
- Simultaneous calibration of route choice and train capacity


## Thanks

Q\&A

