Improving predictions of the impact of disturbances on public transport usage based on smartcard data

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Introduction

- Many (un)planned disturbances in public transport (e.g. track maintenance, incidents)
- Important to quantify passenger impact (e.g. extra transfers and travel time) and operator impact (e.g. loss of passenger revenues) of these disturbances
- Availability of AFC data led to development of smartcard data driven models for PT ridership predictions recent years
- Extend these models to predict PT ridership during track closures

Study objectives

- Improve accuracy of PT ridership prediction models in case of planned, temporary disturbances
- Calibrate and validate model parameter set based on revealed passenger behavior (AFC data)
- Based on 4 large disturbances occurred on HTM transit network in The Netherlands

Experimental design: systematic evaluation of different parameter sets

Parameters	Elasticity E_δ	Waiting time WTT^R	In-vehicle time IVT^R	Frequency
Parameter values	*{-0.7, -1.1, -1.5}*	*{1.5, 2.0}*	*{1.0, 1.25}*	*$\{f^R, f^T\}$*
Scenario 1 (default)	-1.1	1.5	1.0	f^R
Scenario 2	-1.1	1.5	1.0	MIN(f^R;f^T)
Scenario 3	-1.1	1.5	1.25	f^R
Scenario 4	-1.1	1.5	1.25	MIN(f^R;f^T)
Scenario 5	-1.1	2.0	1.0	f^R
Scenario 6	-1.1	2.0	1.0	MIN(f^R;f^T)
Scenario 7	-1.1	2.0	1.25	f^R
Scenario 8	-1.1	2.0	1.25	MIN(f^R;f^T)
Scenario 9	-0.7	1.5	1.0	f^R
Scenario 10	-0.7	1.5	1.0	MIN(f^R;f^T)
Scenario 11	-0.7	1.5	1.25	f^R
Scenario 12	-0.7	1.5	1.25	MIN(f^R;f^T)
Scenario 13	-0.7	2.0	1.0	f^R
Scenario 14	-0.7	2.0	1.0	MIN(f^R;f^T)
Scenario 15	-0.7	2.0	1.25	f^R
Scenario 16	-0.7	2.0	1.25	MIN(f^R;f^T)
Scenario 17	-1.5	1.5	1.0	f^R
Scenario 18	-1.5	1.5	1.0	MIN(f^R;f^T)
Scenario 19	-1.5	1.5	1.25	f^R
Scenario 20	-1.5	1.5	1.25	MIN(f^R;f^T)
Scenario 21	-1.5	2.0	1.0	f^R
Scenario 22	-1.5	2.0	1.0	MIN(f^R;f^T)
Scenario 23	-1.5	2.0	1.25	f^R
Scenario 24	-1.5	2.0	1.25	MIN(f^R;f^T)

Evaluation framework

$$\Delta P = \left(\left(\frac{P_{\delta,p} - P_{\delta_0,p}}{P_{\delta_0,p}} \right) - \left(\frac{P_{\delta,r} - P_{\delta_0,r}}{P_{\delta_0,r}} \right) \right) * 100 \quad \forall\, l \in L \;\; \forall\, t$$

$$\Delta PK = \left(\left(\frac{PK_{\delta,p} - PK_{\delta_0,p}}{PK_{\delta_0,p}} \right) - \left(\frac{PK_{\delta,r} - PK_{\delta_0,r}}{PK_{\delta_0,r}} \right) \right) * 100 \quad \forall\, l \in L \;\; \forall\, t$$

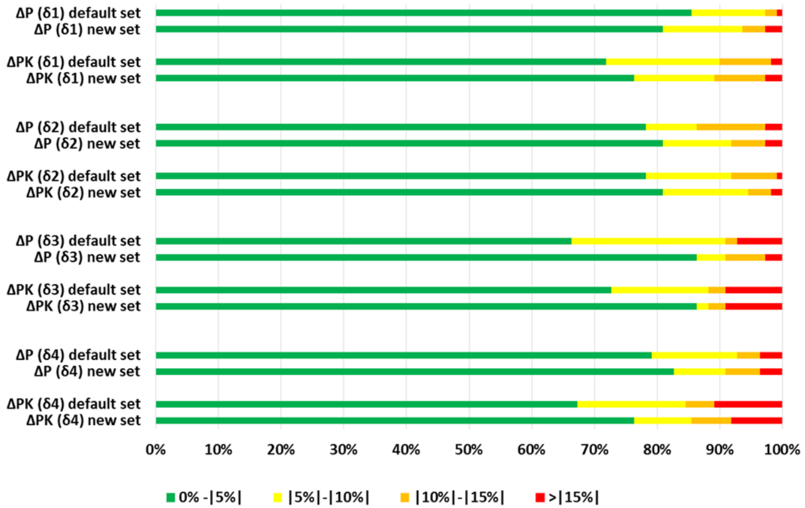
P	*# of passengers*
PK	*# of pass-km*
δ	*disruption scenario*
δ_0	*base scenario*
r	*realized ridership*
p	*predicted ridership*
l	*transit line*
t	*time period*

Case studies Netherlands: 2 disturbances for calibration + 2 disturbances for validation

Results: new parameter set + improved prediction accuracy during disturbances

Parameter	Default parameter values	New parameter values
Elasticity E_δ	-1.1	-0.7
Waiting time coefficient for rail-replacement bus	1.5	1.5
In-vehicle time coefficient for rail-replacement bus	1.0	1.11
Frequency f^R of rail-replacement bus	f^R	MIN(f^R; f^T)

Prediction accuracy results



Conclusions

- In-vehicle time perception rail-replacement busses is 1.1 times higher than in initial tram line
- The higher frequency of rail-replacement busses than the initial tram line is not perceived
- Further research: segmentation of parameter set to disruption location, duration and purpose

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