IMPROVING PREDICTIONS OF THE IMPACT OF DISTURBANCES ON PUBLIC TRANSPORT USAGE BASED ON SMART CARD DATA

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ABSTRACT

The availability of smart card data from public transport travelling the last decades allows analyzing current and predicting future public transport usage. Public transport models are commonly applied to predict ridership due to structural network changes, using a calibrated parameter set. Predicting the impact of planned disturbances, like temporary track closures, on public transport ridership is however an unexplored area. In the Netherlands, this area becomes increasingly important, given the many track closures operators are confronted with the last and upcoming years. We investigated the passenger impact of four planned disturbances on the public transport network of Den Haag, the Netherlands, by comparing predicted and realized public transport ridership using smart card data. A two-step search procedure is applied to find a parameter set resulting in higher prediction accuracy. We found that in-vehicle time in rail-replacing bus services is perceived $\approx$1.1 times more negatively compared to in-vehicle time perception in the initial tram line. Besides, passengers do not seem to perceive the theoretical benefit of the usually higher frequency of rail-replacement bus services compared to the frequency of the replaced tram line. At last, no higher waiting time perception for temporary rail-replacement services could be found, compared to regular tram and bus services. The new parameter set leads to substantially higher prediction accuracy compared to the default parameter set. It supports public transport operators to better predict the required supply of rail-replacement services and to predict the impact on their revenues.

Keywords: disturbance, passenger, prediction, public transport, smart card

1. INTRODUCTION

The last decade, in several cities worldwide automated fare collection (AFC) systems are introduced for the public transport system by public transport operators and authorities. For these AFC systems, passengers need to use a smart card for public transport travelling. Open systems in which passengers only need to tap-in, as well as closed systems in which both a tap-in and tap-out are required, are applied in practice. Although the main purpose of the introduction of AFC systems was to enable an easier way of revenue collection, additionally large amounts of data are generated which can be used to get more insight in passengers' travel behavior. Over the last years, data from AFC systems is used for many purposes by scientists and practitioners on a strategic, tactical and operational level (*1*). Data from AFC systems is for example used for destination inference in case of open systems with tap-in only (e.g. *2*, *3*), transfer inference (e.g. *4, 5*) and journey inference to estimate origin-destination (OD) matrices (e.g. *6, 7, 8, 9, 10*). Other studies focus on fusion of smart card data of different operators (e.g. *11*) or clustering public transport stops in order to identify and classify public transport activity centers based on smart card data (*12*).

Next to the aforementioned studies which use smart card data to describe, analyze, cluster and visualize current travel patterns, there are also studies focusing on public transport ridership prediction based on smart card inferred travel patterns. In (*13*) a smart card based prediction model is developed which allows the prediction of effects of changes in public transport supply, like increasing the frequency or rerouting public transport services. Also effects of crowding can be incorporated in these short-term ridership prediction models (e.g. *14*). This type of prediction model is of added value to improve prediction accuracy of the impact of structural network changes, which are usually implemented by operators on one or on a few fixed dates in the year. However, in practice many public transport operators are confronted with temporary closures of infrastructure many more times per year. These temporary infrastructure closures are for example caused by maintenance work, track renewal or redesign of public space. These closures usually result in longer travel time, more transfers, lower rider ship, lower passenger satisfaction, and less revenues. In the Netherlands, a tendency can be observed of more, larger and more long-lasting rail infrastructure closures. For example, HTM, the urban public transport operator in Den Haag, the Netherlands, was confronted with more than 20 temporary track closures in 2015. It therefore becomes more urgent for operators to predict the impact of these (planned) disturbances on their passengers, ridership and revenues. This impact of temporary track closures on demand and supply is different compared to the impact of structural network changes. Passengers might be willing to postpone a single trip, change their mode choice or route choice, or accept the use of rail-replacement bus services for temporary situations. Operators on the other hand have to accept the temporary reduction in level of service – because of rail-replacement bus services, additional travel time and transfers – and might accept the temporary additional operational costs for these bus services and communication. It can be concluded that the responses of passengers and operators differ in case of temporary network changes, compared to structural network changes. In order to predict passenger impacts of temporary network changes with sufficient accuracy, other/additional parameters and/or different parameter values in the public transport ridership prediction models are therefore required.

This study aims to improve the prediction accuracy of the impact of planned, temporary disturbances on public transport usage. To this end, in this study a new parameter set is calibrated and validated to predict public transport ridership in case of planned disturbances. This parameter set is based on smart card data derived from AFC systems during several planned disturbances which occurred in Den Haag in 2015. The study results in a new set of parameter values allowing to better predict passenger impacts of planned disturbances in urban public transportation. With this result, more insight is gained in passenger behavior during disturbances. It also supports operators to predict the impact on their revenues, and to better align supply of rail-replacement services on alternative routes to the remaining demand, in order to efficiently use their scarce resources. This paper is structured as follows. Chapter 2 describes the methodology to calibrate and validate the parameter set of the ridership prediction model. Chapter 3 describes the case study network to which the methodology is applied. Chapter 4 discusses the results of this study. At last, in chapter 5 conclusions and recommendations for further research are formulated.

2. METHODOLOGY

2.1 Origin-destination matrix estimation

When travelling in trams or busses in the Netherlands by smart card, passengers are required to tap-in and tap-out at devices which are located within the vehicle. This means that in the Netherlands the passenger fare is based on the exact distance travelled in a specific public transport vehicle. Especially for busses, this is different from many other cities in the world where often an open, entry-only system with flat fare structure is applied, for example in London (*6*) and Santiago, Chile (*7*). This means that for each individual transaction the boarding time and location, and the alighting time and location of each trip leg are known. Also, it is known in which public transport line and vehicle each passenger boarded and alighted with their unique smart card number. This closed within-vehicle system therefore eases the destination and journey inference, compared to open entry-only systems. Also vehicle occupancies can be inferred directly from the transaction data.

For an urban public transportation network with tram and bus lines, journeys can be inferred by combining registered trip legs made with the same smart card ID, when the boarding time to a vehicle follows within a certain time window after the alighting time of the previous trip leg made with that same card. In the Netherlands, a maximum threshold transfer time of 35 minutes is applied to classify trip legs made by the same smart card ID as one journey. By aggregating all journeys, a smart card based OD matrix can be inferred. Under assumption that the distribution of destinations j from each origin i for non-card users is similar to the distribution of smart card users, the OD matrix can be scaled based on the small percentage of non-card users in the Netherlands. Determination of the share of non-card users is based on passenger counts.

When travelling by train or metro in the Netherlands, there is also a closed system where transactions are required during boarding and alighting. For train and metro, devices are however located at the station gates. This means that train-train or metro-metro transfers, as well as exact chosen routes cannot be determined directly from the data, and that inference algorithms are necessary to obtain these insights.

2.2 Public transport ridership prediction model

For the prediction of public transport usage in case of planned disturbances, in this study the public transport ridership prediction model as described in (*13*) is used as basis. For an urban public transportation network, let the set of public transport stops and lines be denoted by S and L respectively. Each line $l \in L$ is defined by an ordered sequence of stops $l = (s_{l,1}, s_{l,2\dots}, s_{l,|l|})$. $L^t \in L$ and $L^b \in L$ represent the subset of tram lines and bus lines of the considered network, respectively. Trip schedules are imported in the model, based on which the frequency and stop-to-stop travel times are inferred for each line $l \in L$ in time period t. Public transport demand is connected to this network by an OD matrix between all stops $s \in S$ for each distinguished time period t. The OD matrix of the undisturbed base scenario δ_0 is based on smart card data and estimated as explained in chapter 2.1, using a conversion table between the stop ID of the boarding and alighting location in the smart card transaction data and the modelled stops in the prediction model, in order to connect travel demand to the modelled urban public transportation network.

For public transport ridership predictions, this model is based on a demand elasticity. For each OD pair i, j the generalized travel costs – being the sum of costs for in-vehicle time, transfer walking time, waiting time, transfers and travel fares with their corresponding weights – are calculated for the base scenario δ_0 and for each scenario δ. Equation 1 shows the calculation of the generalized costs, expressed in monetary terms. Applying a demand elasticity parameter to the relative change in generalized travel costs between δ_0 and δ for each OD pair allows the calculation and assignment of a new public transport OD matrix for each scenario δ. Equation 2 shows the calculation of new public transport demand.

The default parameter values for a_1, a_2, a_3, a_4, a_5 used in this prediction model for structural network changes are obtained based on a combination of model calibration and literature review (*16*). In this calibration process, model assignment results (number of passengers and passenger-distance on the network, per line $l \in L$ and per link) for the undisturbed base scenario δ_0 were compared with the raw smart card transaction data. The parameter set resulting in the highest fit between assignment results and raw smart card data, with parameter values within bounds found in literature, is applied in this model. The weight of in-vehicle time α_1 equals 1.0, whereas one minute walking time α_2 or waiting time α_3 are valued 1.5 times more negatively compared to one minute in-vehicle time. This is also in line with values found in literature (e.g. *16, 17*). Given the focus on an urban public transport network with usually relatively short trips, a relatively small transfer penalty of 3 minutes is applied for α_4. In this prediction model we only consider the marginal travel costs per travelled kilometer, without incorporating the base fare of €0.88 which applies for all passengers and all trips in urban public transport in the Netherlands. This is justified since this fixed cost component, which is the same for each public transport route, does not add explanatory power to passenger route choice in the model. The marginal travel costs per travelled kilometer in the model are reflected by α_5 and equal €0.05/km. Compared to the marginal travel costs of €0.15/km currently in the Netherlands (*18*), this value shows a limited price sensitivity. This can be explained due to the fact that also passengers which are price-inelastic are incorporated in the data. These passengers do not have to pay for their tickets themselves (e.g. business trips paid by the company, or student trips paid by the Dutch government), have monthly or yearly travel passes (where the marginal travel costs are usually lower), or travel with discount (e.g. elderly, children). The Value-of-Time for the Dutch situation is determined based on (*19*).

We can conclude that there is already a calibrated parameter set which is used to predict public transport ridership for undisturbed situations. In this study, we specifically investigate to what extent this parameter set needs to be adjusted to perform accurate passenger predictions in case of planned disturbances.

$$C_{ij} = (\alpha_1 IVT_{ij} + \alpha_2 WKT_{ij} + \alpha_3 WTT_{ij} + \alpha_4 NT_{ij}) * VoT + \alpha_5 d_{ij} \quad (1)$$

With:

C_{ij} Generalized costs on OD pair *i,j*
α_1,α_2,α_3,α_4, α_5 Weight coefficients in generalized costs calculation
IVT_{ij} In-vehicle travel time on OD pair *i,j*
WKT_{ij} Walking time on OD pair *i,j*
WTT_{ij} Waiting time on OD pair *i,j*
NT_{ij} Number of transfers on OD pair *i,j*
VoT Value-of-Time (€/hour)
d_{ij} Distance travelled in public transport on OD pair *i,j*

$$D_{ij}^{\delta} = \left(E\left(\frac{C_{ij}^{\delta}}{C_{ij}^{\delta_0}} - 1\right) + 1\right) * D_{ij}^{\delta_0} \quad (2)$$

With:

D_{ij}^{δ} Demand on OD pair i,j in scenario δ
E Elasticity
C_{ij}^{δ} Generalized costs in scenario δ
$C_{ij}^{\delta_0}$ Generalized costs in base scenario δ_0
$D_{ij}^{\delta_0}$ Demand on OD pair i,j in base scenario δ_0

2.3 Evaluation framework

An evaluation framework is developed to evaluate the accuracy of different parameter sets for ridership predictions in case of (planned) disturbances. In this evaluation framework, the difference between the predicted and realized effect on public transport usage is determined for all public transport lines of the considered network $l \in L$ in each distinguished time period t. Hereby, special attention is paid to lines which are affected by a certain disturbance and to rail-replacement bus lines. In this study, public transport usage is measured by the number of passengers P and passenger-kilometers PK.

The used prediction model consists of a base scenario δ_0, of which the number of passengers and passenger-kilometers are calibrated based on imported smart card data from 20 working days in March 2015 corresponding to this undisturbed base network (chapter 2.2). The passenger impact of disturbed scenarios $\delta \in \Delta$ are predicted using the described elasticity approach after modelling the network corresponding to each scenario δ. Besides, for base scenario δ_0 and each disturbed scenario δ the number of passengers and passenger-kilometers per line per time period are inferred directly from the raw smart card data. The raw smart card data are scaled for non-card users, thereby applying the same scaling factor as applied in the prediction model. Also, a seasonal correction is applied between the time of the year in which disturbance δ occurred and the time of the year from which the smart card data of the base scenario is inferred. This correction is based on smart card inferred seasonal differences found on other public transport lines which are not affected by a certain disturbance δ at all (not directly, nor indirectly as alternative route). Based on smart card realization data, it is then possible to calculate the effect on public transport ridership during a certain disturbance compared to the undisturbed base scenario.

The predicted and realized impact of a certain disturbance on the number of passengers and passenger-distance can then be compared, using Equation 3 and Equation 4. These equations express the difference between the predicted and realized relative difference in passengers and passenger-distance between δ and δ_0 for each public transport line $l \in L$ in each time period t. Applying these two equations leads in total to $L * t$ cases for both P and PK, based on which the prediction accuracy of each parameter set can be determined. A value of ΔP or ΔPK larger than 0 indicates that the prediction model *underestimates* the *loss of passengers* due to a disturbance: there is less public transport usage realized than predicted. A value of ΔP or ΔPK smaller than 0 indicates the opposite: the prediction model *overestimates* the loss of passengers due to a disturbance: there is more public transport usage than predicted.

$$\Delta P = \left(\left(\frac{P_{\delta,r} - P_{\delta_0,r})}{P_{\delta_0,r}} \right) - \left(\frac{P_{\delta,p} - P_{\delta_0,p})}{P_{\delta_0,p}} \right) \right) * 100 \quad \forall\, l \in L \;\; \forall\, t \qquad (3)$$

$$\Delta PK = \left(\left(\frac{PK_{\delta,r} - PK_{\delta_0,r})}{PK_{\delta_0,r}} \right) - \left(\frac{PK_{\delta,p} - PK_{\delta_0,p})}{PK_{\delta_0,p}} \right) \right) * 100 \quad \forall\, l \in L \;\; \forall\, t \qquad (4)$$

With:

$P(K)_{\delta,r}$	Realized number of passenger(-kilometer)s in disturbed scenario δ
$P(K)_{\delta_0,r}$	Realized number of passenger(-kilometer)s in undisturbed base scenario δ_0
$P(K)_{\delta,p}$	Predicted number of passenger(-kilometer)s in disturbed scenario δ
$P(K)_{\delta_0,p}$	Predicted number of passenger(-kilometer)s in undisturbed base scenario δ_0

2.4 Experimental design

In order to predict public transport usage in case of planned disturbances, it is important to determine which parameters values could be different, compared to the values used to predict regular passenger route choice and ridership as described in chapter 2.2. First, the value of the elasticity parameter E_δ in case of disturbances is of relevance. As mentioned in chapter 1, passengers react differently to temporary network changes compared to structural network changes. On the one hand, passengers might accept a longer travel time for a certain amount of time (indicating a less negative value of E_δ). On the other hand, passengers might decide to change their mode choice or destination choice, or to postpone their trip in case of temporary track closures, until regular operations are restored (indicating a more negative value of E_δ). Second, the modelling of rail-replacement services is of relevance. Let $L^R \in L$ be the subset of rail-replacing bus services. In many cases, operators will supply rail-replacing bus services in case of track closures. These rail-replacing services differ from regular bus lines in several ways. For example, the existence, route and stop locations of such services are often less well known by passengers. Given the temporary existence of these lines, passengers are less familiar with aspects as departure time, travel time and reliability. When these busses replace rail services, these services have to use temporary stop locations nearby the closed rail stop, which often have less visibility and equipment like dynamic arrival information or shelters. It is therefore possible that passengers experience waiting time for a rail-replacement services more negatively compared to waiting time for regular tram or bus services (indicating a higher value of parameter a_3, related to waiting time WTT^R specific for rail-replacement services). Besides, these services transport passengers who are familiar with rail-bound services. From literature it is known that when a bus service is transformed to a tram line, travel time is perceived less negatively compared to bus travelling (*20*). Therefore, it can be hypothesized that the replacement of a tram line by busses will be perceived more negatively by passengers familiar with rail-bound travelling. Therefore, the value of parameter a_1 related to in-vehicle time perception in rail-replacement busses IVT^R might be more negative compared to regular trams or busses. Rail-replacement busses usually operate with higher frequencies than the original tram line, to compensate for the lower capacity of a bus compared to a tram. However, it is unclear to what extent passengers really perceive and incorporate this theoretical benefit in their route and mode choice. It is therefore questionable whether modelling the realized frequencies of the rail-replacement services f^R, or the original frequencies of the tram line which is being replaced f^T, leads to more accurate predictions.

TABLE 1 Experimental Design

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)

The first row of Table 1 summarizes the four parameters which are hypothesized to have different values when modelling passenger behavior during disturbances specifically. The remaining parameters from Equation (1) - a_2 (multiplier for walking time perception), a_4 (fixed transfer penalty), a_5 (marginal travel costs) and VoT (value of time) - were expected to have no or a limited effect on the prediction accuracy, which was confirmed in a first sensitivity analysis to these parameters. In this study four planned disturbances which occurred on the HTM network in 2015 are considered, denoted by the total set Δ. Subsets $\Delta_A \in \Delta\ \{\delta_1, \delta_2\}$ and $\Delta_B \in \Delta\ \{\delta_3, \delta_4\}$ are defined, which both contain 50% of the investigated disturbances for calibration and validation purposes, respectively. This calibration phase consists of two steps. In the first step, a systematic scan is performed to search for the best fitting parameter set(s) from predefined scenarios, using the four model parameters of Table 1. For all four parameters, plausible values are *a priori* determined. The calibrated parameter values used for passenger assignment for the undisturbed base scenario δ_0 are used as starting point (WTT^R=1.5, IVT^R=1.0, f^R=f^R). These values are considered as reasonable starting point, since these values are calibrated and within bounds found in literature. An elasticity value E_δ of -1.1 is used as starting point based on literature (e.g. *16*). The direction in which each parameter value can change when predicting ridership during disturbances, compared to regular ridership predictions, is explained in the first part of this chapter 2.4. The upper and lower bound values for E_δ, WTT^R and IVT^R are selected in such way, that they remain within literature bounds on one hand, but show sufficient variation to explore the solution space on the other hand. The modelling of the frequency of rail-replacement bus services is a binary variable, which can be equal to f^R or f^T. The second row of Table 1 shows the resulting parameter values. All combinations between these predefined parameter values are systematically explored using the evaluation framework as explained in chapter 2.3. The remaining rows of Table 1 show all 24 scenario combinations of parameter values which are explored. In the second step of the calibration, the parameter values are further optimized based on the promising parameter sets identified in step 1. After the generic, systematic search in step 1 using predefined parameter values and scenarios, step 2 performs an in-depth search to find the best fitting parameter set. In step 2, parameter values are not bound to the predefined values and scenarios any more. Once the best fitting parameter set is determined, this set is validated by applying it to the investigated disturbances $\delta \in \Delta_B$. For this subset Δ_B it is tested whether the prediction accuracy using the optimized parameter set is similar to the accuracy obtained for the disturbances $\delta \in \Delta_A$, and whether the prediction accuracy improved compared to the default parameter set.

3. CASE STUDY

The methodology as described in chapter 2 is applied in a case study. The urban public transport network of Den Haag, the Netherlands, is used in this study. Public transport services on this network are operated by HTM. The network consists of 12 tram lines and 8 bus lines. No metro services are operated in the city of Den Haag. Two of the tram lines function as light rail connection between Den Haag and the nearby suburb of Zoetermeer. On an average working day, more than 250,000 trips are made on the HTM network (*14*). 93% of the passengers use a smart card for travelling (*14*). The remaining 7% buys a ticket from the driver or at the vending machine, or uses a special ticket. When modelling the HTM network, 4 different time periods are distinguished in the frequency-based assignment and prediction model: morning peak (7am-9am), evening peak (4pm-6pm), off-peak (9am-4pm) and the evening and early morning (6pm-7am).

In 2015 there were several track closures on the public transport network operated by HTM. Given the closed AFC system, in combination with relatively many case studies available, the HTM network is an interesting case study area to investigate the impact of planned disturbances on public transport usage. As explained, in total 4 different disturbances δ which occurred in 2015 on the HTM network are investigated, which are divided into two subsets $\Delta_A \in \Delta\ \{\delta_1, \delta_2\}$ and $\Delta_B \in \Delta\ \{\delta_3, \delta_4\}$ used for calibration and validation purposes, respectively. Table 2 describes the impact of each disturbance on the public transport network. Figure 1 shows the adjusted public transport network for all four disturbances. Closure δ_1 'Koninginnegracht' resulted in detours for several tram lines in the city center. Besides, one of the two important connections between Central Station and Scheveningen of tram line 9 was replaced by bus services of line 69 (whole day) and 79 (only peak hours). Closure δ_2 'Loosduinseweg' resulted in the shortening of two busy tram lines 2 and 4. The shortened part of the route of tram line 2 was replaced by busses. Most stops of the shortened tram line 4 were covered by tram line 6, which follows a route partly parallel to the shortened part of tram line 4. During closure δ_3 'Westvest', the route of tram line 1 – connecting the city of Den Haag with the city of Delft – was shortened. A rail-replacement bus line 71 was provided, although it could not stop near all original tram stops due to infrastructure constraints. Closure δ_4 'Zieken' within the city center resulted in detours for several lines. Given the relatively dense public transport network in the city center, several alternative lines were available. Furthermore, rail-replacement busses were no option because of the limited accessibility for motorized vehicles in the city center. The set of disturbances Δ can roughly be divided in closures in which tram lines are detoured (δ_4, δ_1 partly), and closures in which tram lines are shortened and replaced by bus services (δ_2, δ_3, δ_1 partly). To investigate and test that the selected parameter set is robust to perform accurate predictions for both type of closures, both closure types are incorporated in the subset used for calibration $\Delta_A \in \Delta\ \{\delta_1, \delta_2\}$, as well as in the subset used for validation $\Delta_B \in \Delta\ \{\delta_3, \delta_4\}$.

For the reference network δ_0, as well as disturbed networks δ_1 and δ_4, 20 working days of smart card data are used in this study. Given the ≈250.000 trips at the HTM network per average working day, this roughly means that about 5 million smart card transactions are used as basis for the calibration and validation. For the shorter lasting disturbances δ_2 and δ_3, about 1.25 million smart card transactions (5 working days) are used. All raw transactions are anonymized by removing personal information and by aggregating the data, to guarantee confidentiality and to obey Dutch privacy regulations.

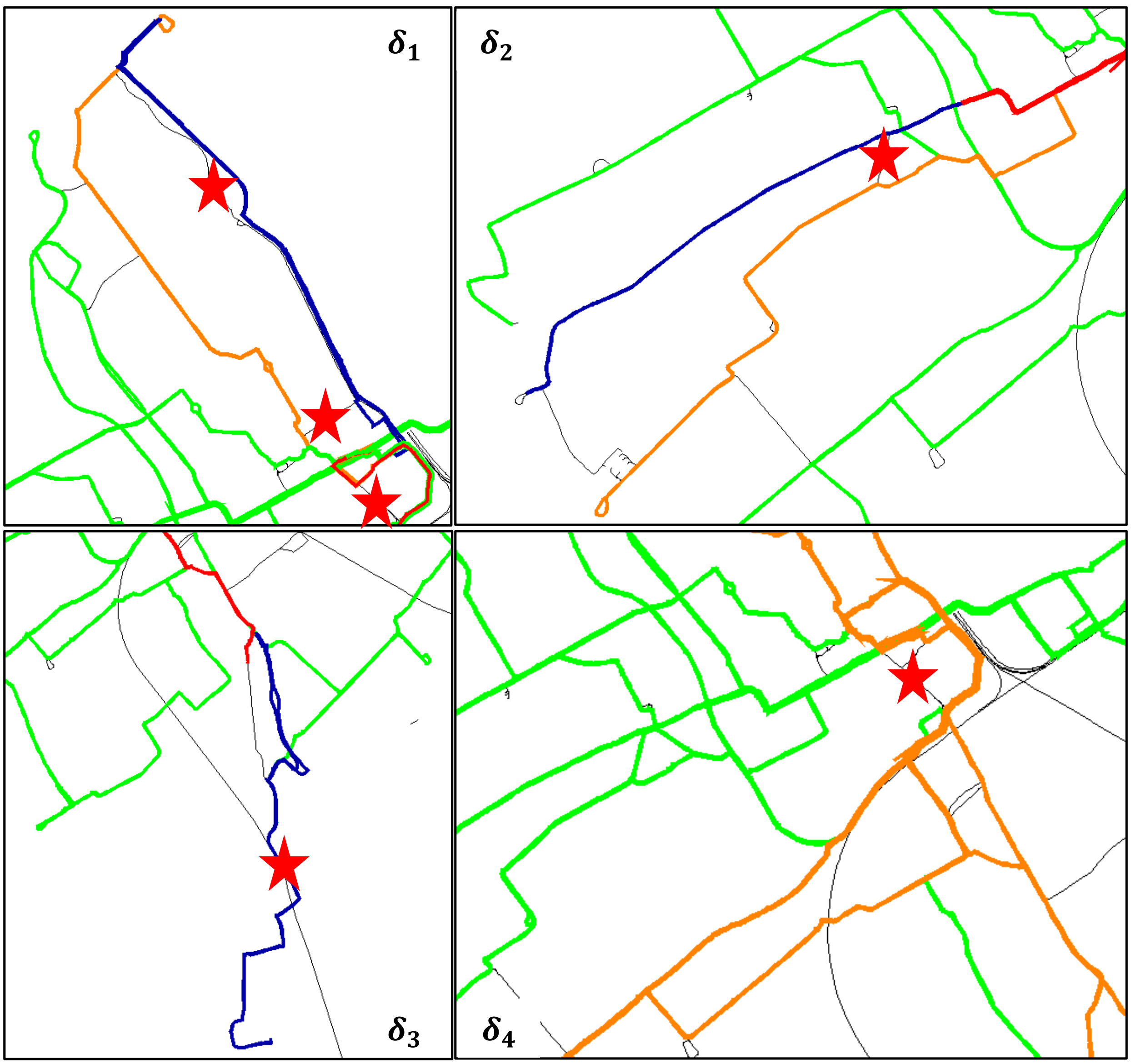

FIGURE 1 Public transport network during planned disturbances δ_1 'Koninginnegracht' (upper left), δ_2 'Loosduinseweg' (upper right), δ_3 'Westvest' (lower left) and δ_4 'Zieken' (lower right) (star: work location / green: line unaffected / orange: line rerouted / red: line shortened / blue: rail-replacement bus line)

TABLE 2 Overview Of Network Changes During Planned Disturbances In 2015

Disturbance δ	Period	Affected lines $l \in L$	Rail-replacement line $l \in L^R$
δ_1 Closure 'Koninginnegracht'	November	Tram 1/15/16/17: rerouted Tram 9: shortened + bus-replacement	Bus lines 69+79 (instead of tram 9)
δ_2 Closure 'Loosduinseweg'	August	Tram 2: shortened + bus-replacement Tram 4: shortened Tram 6: extended (to replace tram 4)	Bus line 52 (instead of tram 2)
δ_3 Closure 'Westvest'	October	Tram 1: shortened + bus-replacement	Bus line 71 (instead of tram 1)
δ_4 Closure 'Zieken'	June	Tram 1/9/15/16: rerouted	-

4. RESULTS

4.1 Resulting parameter set

Applying the methodology described in chapter 2 to the HTM case study network, results in a new parameter set to predict public transport usage in case of planned disturbances. Table 3 shows the values for the proposed new parameter set. In case of planned disturbances, an elasticity parameter value E_δ of -0.7 resulted in the best fit with the raw smart card data. Despite the hypothesis that passengers might perceive waiting time for a rail-replacement service more negatively compared to waiting time for regular tram and bus services, applying a higher waiting time coefficient did not improve the prediction accuracy. Therefore, the use of a generic waiting time coefficient of 1.5 for all modes (tram, bus and rail-replacement services) is proposed. However, applying a more negative in-vehicle time perception in bus services replacing an existing tram line did improve the prediction accuracy. In the used prediction model in this study, this is reflected by applying a certain multiplication factor for the operational speed of a rail-replacement service. Using a speed factor of 0.9 – which equals the inverse in-vehicle time coefficient of 1.11 – resulted in the best fit with the raw smart card data. The value for the in-vehicle time coefficient derived from realization data is somewhat lower than the speed factor found in (*20*) using a stated preference experiment, but points towards the same direction. Regarding the frequency of rail-replacement services, study results indicate that modelling the frequency of the original tram line f^T leads to a better fit than using f^R, if $\mathrm{f}^\mathrm{R} > \mathrm{f}^\mathrm{T}$. This indicates that passengers do not incorporate the benefit of the higher frequency of the rail-replacement services compared to the original tram line in their route and mode choice. From a theoretical perspective, this can be explained because vehicle capacity is not incorporated in the prediction model used in this study. The higher frequency f^R compared to f^T is often due to the lower capacity of a bus compared to a tram vehicle. Since the negative effect of a lower bus capacity is not incorporated in the model, only incorporating the positive effect of a higher bus frequency aimed to compensate for this non-incorporated capacity effect would overestimate the level of service of the rail-replacement bus service. In case $\mathrm{f}^\mathrm{R} < \mathrm{f}^\mathrm{T}$, one could apply f^R in the prediction model. In this case it would even underestimate the negative effect of the bus replacement service, since only the additional waiting time (and not the lower vehicle capacity) is incorporated in the ridership prediction. Therefore it is proposed to use the minimum of f^R and f^T as frequency of rail-replacement bus services in ridership predictions, when vehicle capacity is not incorporated in the used model.

TABLE 3 Comparison Between Default And New Proposed Parameter Set

Parameter	Default parameter values	New parameter values
Elasticity E_δ	-1.1	-0.7
Waiting time coefficient a_3 for WTT^R	1.5	1.5
In-vehicle time coefficient a_1 for IVT^R	1.0	1.11
Frequency f^R	f^R	$\mathrm{MIN}(\mathrm{f}^\mathrm{R}; \mathrm{f}^\mathrm{T})$

Figure 2 shows the obtained prediction accuracy results for $\{\delta_1, \delta_2\} \in \Delta_A$ used in the calibration phase and for $\{\delta_3, \delta_4\} \in \Delta_B$ used in the validation phase. As explained in chapter 2.3, for each disturbance the prediction accuracy is quantified for in total $L * t$ cases in terms of deviation in relative impact on the number of passengers ΔP and number of passenger-kilometers ΔPK between prediction and realization, for each line within each time period. In Figure 2, the distribution of the prediction accuracy of all $L * t$ cases is shown per scenario δ using the default and new parameter set. For δ_1 (closure 'Koninginnegracht') it can be seen that the new parameter sets especially improves the prediction accuracy regarding the travelled passenger-distance over different lines in different time periods, whereas the prediction accuracy in terms of number of passengers slightly decreases. Because the fare is directly based on the travelled distance, it can be justified to prioritize accurate predictions of passenger-kilometers from the operator perspective of revenue management. For δ_2 (closure 'Loosduinseweg') especially the number of cases of which the prediction inaccuracy of P and PK was larger than |10%| initially was reduced. Applying the proposed parameter set to $\{\delta_3, \delta_4\} \in \Delta_B$ in the validation phase shows that the prediction accuracy substantially improves for both δ_3 and δ_4. For δ_3 (closure 'Westvest') the prediction of both P and PK clearly improves compared to the default parameter set. The prediction accuracy obtained by the new parameter set in δ_3 is even higher than obtained for δ_1 and δ_2 based on which the set was calibrated, for both the predicted number of passengers and passenger-distance. An explanation might be that δ_3 is a relatively simple network adjustment. While the network adjustments required in $\{\delta_1, \delta_2, \delta_4\}$ are rather complex, influencing multiple lines, δ_3 has only impact on one tram line. For δ_4 (closure 'Zieken') the prediction accuracy also improves compared to the default parameter set. The new parameter set results in a similar level of accuracy compared to δ_1 and δ_2. Overall, the prediction quality of the new set is considered accurate.

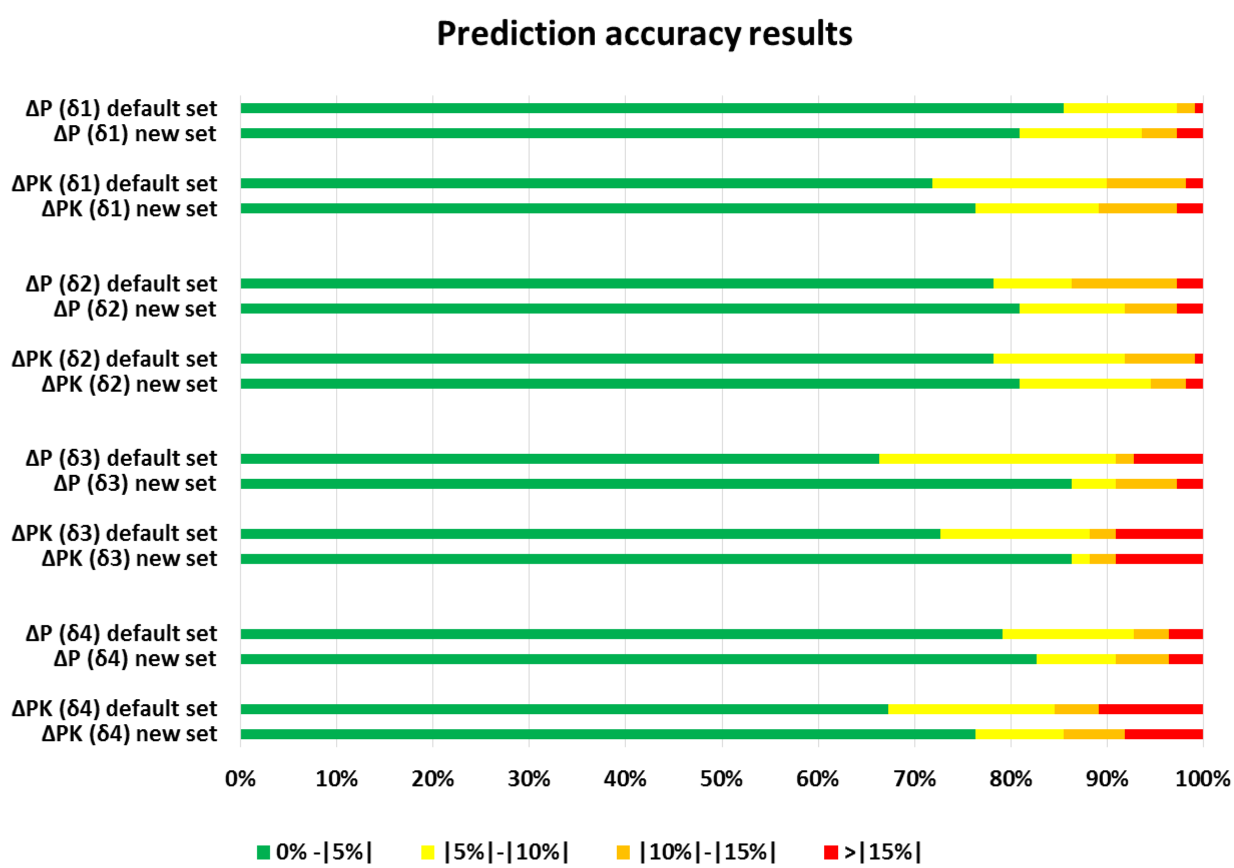

FIGURE 2 Prediction accuracy for all disturbance cases used in the calibration and validation phase. The distribution of the prediction accuracy of all $L * t$ cases is shown for all four disturbed scenarios using the default and new proposed parameter set.

4.2 Reflection

In this study the accuracy of predicting the impact of temporary track closures on the number of passengers and passenger-distance is substantially improved by using the new proposed parameter set. The prediction accuracy might be improved further in two ways. First, in this study a two-step search procedure is applied to evaluate the prediction quality of several parameter sets. After scanning the solution space using a systematic search over different combinations of parameter values first, an in-depth search around promising parameter values is performed. In order to further optimize the parameter set, it is recommended to estimate a discrete choice model based on the revealed preference smart card data found for several disturbances. This can lead to a set of parameter values which fit the empirical data in an optimal way. Second, it is recommended to investigate whether location-specific, and/or purpose-specific parameter values increase the prediction accuracy. In this study only generic and mode-specific parameter values are applied. Distinguishing between areas where a disturbance occurs based on socio-economic characteristics (e.g. age, income, percentage of public transport captives) might lead to better predictions. Also using different parameter values for different passenger segments based on their trip purpose, or based on different time periods (peak/off-peak, weekday/weekend) might improve the prediction accuracy, since sensitivities for different parameters might be different for these segments.

5. CONCLUSIONS

In this study we investigated the passenger impact of planned disturbances by comparing predicted and realized public transport ridership using smart card data. Based on the study results we found a more negative in-vehicle time perception in rail-replacing bus services compared to in-vehicle time perception in the initial tram line. One minute tram travelling shows to be perceived as about 1.11 minute travelling in a rail-replacement bus service. Besides, when modelling rail-replacement services, it is recommended to use the frequency of the initial tram line instead of the usually higher frequency of the rail-replacement services. Passengers do not seem to perceive this theoretical benefit of higher frequencies of the rail-replacement bus, since this compensates for the lower vehicle capacity of a bus compared to a tram. If vehicle capacity is not incorporated in the prediction model, only incorporating the positive effect of a higher bus frequency aimed to compensate for this non-incorporated capacity effect would overestimate the level of service of the rail-replacement bus service. At last, no higher waiting time perception for temporary rail-replacement services could be found, compared to waiting time perception for regular tram and bus lines. The new parameter set leads to substantially higher prediction accuracy compared to the default parameter set, and shows to be a valuable tool for public transport operators. The prediction model is used by HTM in practice, in which the parameter set as recommended in this study is applied. Monitoring and further improving the prediction accuracy of the model will remain an important focus in the future.

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