EVALUATING CROWDING IN INDIVIDUAL TRAIN CARS USING A DYNAMIC TRANSIT ASSIGNMENT MODEL

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ABSTRACT

Crowding is one of the major issues of public transport systems and has many negative effects for both the users and operator. Passengers can be highly unevenly distributed between individual cars of a train even when the total passenger load exceeds the practical capacity.

Transit assignment models (TAM) are widely used for describing and evaluating crowding in the vehicle. However, these models usually do not capture how passengers are distributed across the vehicle. This study develops an agent-based simulation model to analyze capacity utilization of the train in a more realistic way, by considering that passengers are not evenly distributed among individual train cars.

The developed model is validated and applied to a case study for the Stockholm metro network, evaluating three scenarios. The findings suggest that an increase in peak hour demand leads to a more uniform passenger distribution among individual cars upon train departure from the most crowded stops, where passengers’ choices are less flexible. The closure of the most popular entrance point at Danderyds sjukhus stop, where passenger distribution is highly skewed, is found to decrease the crowding unevenness at the specific station but also upon departure from the downstream station.

Keywords: Public transport, Transit assignment, Crowding, Agent-based simulation, Passenger distribution
INTRODUCTION

Many public transport systems are subject to overcrowding during peak periods. On-board crowding is associated with many negative effects on passengers, such as increased discomfort and stress, delays and denied boarding (1). There is a need to improve system performance and the level of service. A thorough understanding of public transport users’ travel behavior under crowded conditions as well as their motivation when making boarding decisions is thus essential for increasing the comfort and efficiency of public transport.

Passenger loads can be highly unevenly distributed along platforms and in individual cars of trains and metros even during peak hours (2, 3). Kim et al. (4) investigated the causes behind the uneven passenger distribution between train cars, concluding that passengers’ motivation for minimizing the walking distance at the destination is the most decisive factor for choosing a specific train car. Some studies aim to reduce the unevenness of the on-board passenger distribution by determining the optimal train stop location along a platform (5) or through real-time crowding information system (3).

Transit assignment models (TAM) are used for describing how passengers are distributed in the public transport network, predicting passengers’ travel route decisions and modelling crowding. However, these models do not evaluate crowding in individual train cars, which might lead to unrealistic vehicle capacity utilization and underestimated user cost, since on-board crowding effect is lower when train capacity utilization is considered uniform.

The objective of this paper, motivated by the limitations of the TAM used in the literature, is to propose a quantitative methodology for analyzing capacity utilization of individual train cars. The main contributions of the paper are:

• To the best of our knowledge, this is the first study that evaluates crowding in individual train cars.
• The extension of the passenger path choice modelling in a dynamic and stochastic TAM which captures train car choices.
• The developed model accounts for day-to-day learning, where passengers’ decisions are made in a repetitive way, taking the impact of on-board crowding into account.
• The validity of the model is investigated and the simulated output is tested against an empirical data set.
• A simulation study of the effect of demand and infrastructure changes on crowding distribution among individual train cars.

Transit stops are divided into sections, each of them corresponds to a train car. Each car is modelled as a separate unit, allowing the crowding level in each car to be captured. Using an agent-based simulation model, the distribution of passengers between individual cars is dynamically and stochastically modelled. Train car choice is integrated into random utility path choice model.

The remainder of the paper is structured as follows. Section 3 reviews the relevant literature. The dynamic model for evaluating the distribution of crowding across a multi-car vehicle is presented in Section 4. Section 5 presents the application of the proposed model to a case study in Stockholm, followed by the presentation of results in Section 6. Section 7 draws conclusions, assesses the limitations of the study and outlines follow-up work.

LITERATURE REVIEW

A variety of models exist which describe the assignment of passengers to a transit network. The growing literature on TAM which are broadly classified into frequency-based and schedule-based
approaches to modelling transit path choice, is reviewed by (6).

Frequency-based models represent transit services at the line level. Spiess and Florian (7) proposed the first frequency-based assignment framework based on passengers’ optimal strategies to minimizing the generalized travel time. Frequency-based approaches for congested networks were presented by Lam et al. (8), accounting for the total passenger travel cost and by Cepeda et al. (9), accounting for service capacity. Schmöcker et al. (10) introduced a dynamic frequency-based transit assignment model, considering passengers that fail to board due to insufficient remaining capacity.

Schedule-based assignment models represent individual train trips that depend on timetables. A schedule-based model, presented by Nuzzolo et al. (11), models on-board congestion by using a passenger discomfort factor. Vehicle capacity constraints were introduced by Nguyen et al. (12) and Papola et al. (13), to model boarding passengers considering the residual capacity of the vehicle and the possibility of denied boardings. Poon et al. (14) used a schedule-based traffic assignment model for congested transit networks, allowing capacity constraints, to predict the queuing time per passenger, assuming that passengers are queuing according to the first-in-first-out (FIFO) rule. Another model that takes into account transit schedules and vehicle capacity to assign passengers to paths and model the impact of priority rules was proposed by Hamdouch and Lawphongpanich (15). On-board passengers have priority and the waiting passengers are assumed to board the vehicle in a FIFO or at a random manner. Seat capacity constraints have been considered to model the on-board discomfort effect on the sitting and standing passengers (16, 17).

Agent-based simulation models allow for considering individual passengers’ behavior and choices to model dynamic congestion effects. Wahba and Shalaby (18) were among the first to propose a framework based on the assumption that individual passengers adjust their travel behavior based on their experience. Zhang et al. (19) developed an agent-based simulation model to capture passenger boarding and alighting movements at stops. Rexfelt et al. (20) have focused on modelling the behavior of individual passengers at stops and on-board buses, assessing the effect of vehicle layout on boarding and alighting passenger movements. A dynamic and stochastic TAM which captures congestion and crowding effects (denied boarding, on-board crowding and service irregularity), was proposed by Cats et al. (21). Cats and Hartl (22) compared the ability of schedule-based and agent-based TAM to model on-board congestion, finding that the latter is more sensitive to variations in demand.

Although tools for modelling and predicting passenger flows in public transport networks are widely used, there is a lack of knowledge of how to model crowding distribution between individual train cars. This motivates the need for developing a dynamic model to capture passengers’ boarding choices of individual train cars.

METHODOLOGY
Simulation modelling approach
BusMezzo, a dynamic agent-based public transport operations simulation model, is used in this study for modelling the congestion effects on-board the vehicle, considering vehicle capacity constraints (23). Crowding is evaluated at the vehicle level and the distribution of passengers across the vehicle is not captured. The model simulates the individual passenger path decisions and the movements of individual vehicles. The transit system is dynamically and stochastically represented and integrated into Mezzo, which is an event-based mesoscopic traffic simulation tool (24). Different public transport modes, i.e. metro, commuter train, bus and tram, are modelled as dif-
different vehicle types with distinct capacity characteristics and dwell time functions. A set of trips is given to each vehicle type and hence, BusMezzo models also the propagation of delays caused by trip chaining. For representation of passenger distribution over vehicles, BusMezzo has been extended.

The network is represented by a set of transit stops $S$ and a set of transit lines $L$. Each transit stop $s \in S$ may be served by more than one transit lines. To enable modelling passenger distribution over platforms and vehicles, a stop is divided into sections $k$, $s = (s_{k_1}, s_{k_2}, \ldots, s_{k_{|k|}})$. Each transit line $l$, defined by an Origin-Destination pair and a sequence of stops $s$, is served by a set of trips denoted by $J_{l}$. Each vehicle serving trip $j \in J_{l}$ consists of $i_{j}$ cars $i_{j,1}, i_{j,2}, \ldots, i_{j,I_{j}}$. It is assumed that each stop is operated by transit lines with the same number of car units per vehicle and hence, each platform section corresponds to a certain car unit.

**Passenger path choice modelling**

Passengers are generated stochastically according to Poisson process based on OD matrices. Each origin and destination is a pair of stop and platform section. Throughout the simulation, each passenger makes a sequence of path decisions, specifically boarding, alighting and walking decisions, that combined yields to the realization of a path alternative. The path decisions are described with random utility discrete choice models. Each alternative is associated with a utility, evaluated based on the passenger’s preferences and expectations, which are shaped by prior knowledge, gained experience and available provided information.

In BusMezzo, each transit path alternative $\alpha$, which connects an origin location $o$ to a destination $d$ and is included in a path set $A_{od}$, is defined as a combination of stops, lines and walking links (21). To capture crowding in individual cars of a multi-car vehicle, the path alternative is further defined as ordered combination of transit stops associated with a platform section, transit lines associated with a car unit and a set of walking links between stops as well as platform sections.

Each feasible path alternative $\alpha$ is associated with a utility function; the deterministic part of the utility function of passenger $y$ for a feasible path $\alpha$ is:

$$v_{y,\alpha} = \beta^{\text{inv}}_{\alpha} t^{\text{inv}}_{y,\alpha} + \beta^{\text{wait}}_{\alpha} t^{\text{wait}}_{y,\alpha} (\tau) + \beta^{\text{walk}}_{\alpha} t^{\text{walk}}_{\alpha} + \beta^{\text{transfer}}_{\alpha} N^{\text{transfer}}_{\alpha}; \forall y \in Y, \alpha \in A_{od}$$

where $t^{\text{wait}}_{y,\alpha} (\tau)$ is time-dependent and passenger-specific waiting time that depends on passenger arrival process and service frequency, $t^{\text{inv}}_{y,\alpha}$ is the total in-vehicle time, $t^{\text{walk}}_{\alpha}$ is the total walking time, $N^{\text{transfer}}_{\alpha}$ is the number of transfers included in the path alternative and $\beta$’s are the corresponding utility function coefficients.

A passenger makes a decision to choose the following element, i.e stop associated with section, line associated with car unit and walking link, considering all the path alternatives that are associated with the specific element. When a passenger reaches the end of a path element, they choose the next path element that maximizes their expected utility. The utility that a passenger $y$ chooses a path element $c$ ($c \in C$), denoted by $u_{y,c}$, is given as composite utility of all path alternatives $A_{od}$.

$$u_{y,c} = \ln \sum_{\alpha \in A_{od}} e^{v_{y,\alpha}}$$
The probability that a passenger $y$ will choose the next path element $c$ is then:

$$P_{y,c} = \frac{e^{u_{y,c}}}{\sum_{c \in C} e^{u_{y,c}}} \text{ (3)}$$

Passenger path choices involve three types of decisions as described in the following.

**Walking decision:** The passenger path choice process starts with the walking decision. The passenger $y \in Y$ decides whether to stay at the origin stop $o$ or to walk to some platform section $k$ of some transit stop $s$. Each time a passenger alights from a transit vehicle, a new origin location is set and another walking decision needs to be made. The walking utility is based on the walking time between the platform section at the origin stop where the passenger initiates the trip and a platform section of the first connected stop. The total walking distance of the downstream walking links connecting stops, without considering on-platform section-to-section walking distances, is also included in the walking decision. In the implemented model, section-to-section walking distances are computed based on the shortest section-to-section walking path between two stops. Walking decisions are based on the expected utilities of the path alternatives available at the different locations.

**Boarding decision:** Each time a transit vehicle $j$ arrives at transit stop $s$, passenger $y$ makes a boarding decision; board the vehicle or stay on the platform. In boarding decision process, the utility associated with boarding is compared to the utility associated with staying and waiting for other vehicle. In-vehicle, waiting and walking time as well as the number of transfers are involved in the boarding utility function. The number of passengers boarding car $i$ of vehicle run $j$ at station $s$, denoted by $q_{ijs}^{board}$, is given by the number of passengers that make a positive boarding decision if the car has not reached its capacity $\gamma_i$; otherwise, the number of boarding passengers is equal to the available capacity of the car. If the car, that is adjacent to the waiting platform section $s_k$, has reached its capacity, the passenger stays on the same platform section waiting for other vehicles included in the choice set.

**Alighting decision:** Upon boarding a transit vehicle $j$, the passenger $y$ decides at which downstream station to alight. The platform section $k$, that the passenger will alight at, is already determined by the car unit $i$ that the passenger has boarded. The number of passengers alighting from car $i$ at platform section $s_k$ equals to the total number of passengers that make a positive alighting decision.

The number of passengers on-board car $i$ of vehicle run $j$ when the vehicle departs from a station $s$, denoted by $q_{ijs}^{onboard}$, is a function of alighting and boarding flows in car $i$ and it is repeatedly updated based on passengers’ activity at the station $s$.

Figure 1 illustrates the path alternative definition for passengers that start their trip at origin location $o$ and aim to reach destination location $d$. For illustration, it is assumed that the transit stops are operated by 3-car trains and hence, the station platforms are divided into three sections. The passenger, starting at $o$, has three alternative connection choices that can be accessed by walking; the first, second and third platform sections of transit stop $s_1$, denoted by $s_{1,1}$, $s_{1,2}$ and $s_{1,3}$, respectively. The stop is served by the transit line $l_1$, while each platform section is served by the corresponding train car unit of the line, denoted by $l_{1,1}$, $l_{1,2}$ and $l_{1,3}$ for the first, second and third car, respectively. A transit user that decides to make a walking connection to the first section of the stop $s_{1,1}$ will board $l_{1,1}$, if they make a boarding decision, considering car capacity constraints, and will alight at the first platform section of the transfer transit stop $s_{2,1}$, which is then set as a new
origin transit location and another connection decision to a platform section of stop \( s_3 \) needs to be made. For the origin-destination pair illustrated in figure 1, nine path alternatives are available.

**Day-to-day learning**

The developed model accounts for day-to-day dynamics, where an iterative network loading is performed to mimic passengers’ adaptive travel behavior in real world. Passenger’s travel decisions are made in a repetitive way and passengers’ expectations about car-specific crowding, are updated on a day-to-day basis. Passengers store information based on the experience gained during the previous days and they alter their travel strategy.

Passengers choose a platform section and thereby a train car based solely on the distance they have to walk when day-to-day dynamics are not considered, i.e. the first simulated day. In this case, passengers expect equally utilized cars of the next arriving train. Performing an iterative network loading, car boarding choice is also affected by passenger’s expectations about car crowding. Consequently, passengers expect different crowding levels in individual cars.

**Data requirements**

For model application, the platform section-level OD information is required to represent the passenger demand for each pair of platform sections of a given OD pair. If this information is not available, three types of data are required to represent the demand.

Average station-to-station travel demand data for each OD pair describe the average number of trips between a given origin and destination. Such data may be obtained through transit assignment models or automated fare collection (AFC) data.

Pedestrian incoming and outgoing flows at each access point of the station are useful to describe the passenger movements at the entrance level and can be used to estimate the probability that a passenger initiates the trip at a certain section of the platform. This information may be obtained through passenger counts or AFC systems.

The physical infrastructure characteristics of the network, including the dimensions of the platform and location of entrance and exit points, are also required to define the stop characteristics and walking distances on the platform as well as between stops.

For model validation, passenger load data for each car unit, describing the crowding level
FIGURE 2 Map of the studied segment of Stockholm metro network. Source: OpenStreetMap

on-board individual cars, are required. Estimations of car load data may rely on the car weight measurements, while automated measurements of car load data may be obtained through sensors installed at the car doors.

APPLICATION

Case study description

The proposed modelling framework is applied to a case study for the metro network in Stockholm. Stockholm metro system is used by more than 1 million passengers per workday. Although passenger loads are close to capacity during peak hours, passengers are often unevenly distributed among train cars and 20% of the seats remain unoccupied during the morning peak hour (25).

The model is applied to the southbound segment of metro line 14 between Mörby centrum (MÖR) and Stadion (STD). The segment exhibits high average train crowding unevenness as well as high average on-board passenger load. The studied area is shown in Figure 2.

The passenger distribution on-board the trains is highly skewed towards the front car during the morning peak hour. On average, 41% of the on-board passenger load occupies the front train car, while the rear car is occupied by only 25% of the passengers.

Network representation

The transit network representation in BusMezzo includes both directions of the metro line 14 in Stockholm, which operates with a planned headway of 5 minutes during the morning peak period (06:00 - 09:00 am). The network consists of 39 stops which are served by 72 vehicle trips, each of which consists of 3 train cars. The transit network is represented in BusMezzo with detailed vehicle scheduling, the connectivity of stops by walking as well as the shortest section-to-section walking
path between these stops, required to compute the section-to-section distance of the walking links.

**Demand representation**

Passenger demand is simulated for the morning peak hour. The origin-destination travel demand data for the morning peak period at the station-to-station level is taken from the transit assignment model Visum, based on the official planning zonal OD matrix. For each OD pair, a platform section demand matrix indicating the probability that a passenger starts and ends the trip at a certain platform section at the origin and destination stop, respectively, was produced based on the total incoming and outgoing passenger flows at each entrance point of the station, which are obtained through passenger counts in the morning peak hour.

Time valuations are based on the accepted valuations reported in the literature (26). The value of in vehicle, walking and waiting time as well as the transfer penalty are initially set to:

\[
\beta_{\text{inv}} = -1, \quad \beta_{\text{walk}} = \beta_{\text{wait}} = 2\beta_{\text{inv}} = -2, \quad \beta_{\text{transfer}} = 5\beta_{\text{inv}} = -5.
\]

**Scenarios design**

The dynamic transit assignment model, BusMezzo, was used to simulate crowding on-board each metro car of the metro train. We simulate the following three operational scenarios in BusMezzo:

1. **Base scenario**, where the studied area is simulated with the current average morning peak hour demand.

2. **Increased demand scenario**, where the studied area is simulated with the current average morning peak hour demand increased by 20%.

3. **Intervention scenario**, where an infrastructure change is considered at one of the metro stations, namely Danderyds sjukhus, which is a station with two access points located at the south and north ends. The south access point is considered as temporarily non-available in this scenario. Elevator and escalator maintenance is one of the factors that might require the temporary closure of a station entrance point.

Since the transit simulation model BusMezzo is stochastic, each scenario needs to be evaluated based on a number of simulation replications. The number of replications required \(N(m)\), given \(m\) initial runs, as it is given in (27), is determined by

\[
N(m) = \left(\frac{\sigma(m)t_{m-1,1-\frac{\alpha}{2}}}{\mu(m)e}\right)^2
\]  

(4)

where \(\sigma(m)\) is the standard deviation of the average weighted in-vehicle time per passenger of \(m\) simulation runs, \(t_{m-1,1-\frac{\alpha}{2}}\) is the critical value of the t-test for \(m - 1\) degrees of freedom and level of significance \(\alpha\), \(\mu(m)\) is the mean weighted in-vehicle time per passenger of \(m\) simulation runs and \(e\) is the allowed error.

Given significance level and allowed error 5%, we found that 10 simulation runs are sufficient, allowing a maximum error of 5%.

**Performance evaluation**

The impact of alternative scenarios on the performance of the system is evaluated by considering the average on-board crowding unevenness across the vehicle, the average boarding passengers unevenness and the average weighted in-vehicle time per passenger.
Crowding unevenness

The distribution of passengers among the cars of a train run \( j \) upon departure from stop \( s \) is systematically measured using the Gini coefficient \( G_{js} \).

\[
G_{js} = \frac{1}{2|I|} \left| \sum_{i=1}^{I} q_{ijs}^{\text{onboard}} \sum_{i'=1}^{I'} |q_{i'js}^{\text{onboard}} - q_{ijs}^{\text{onboard}}| \right|
\]  

This train crowding unevenness metric measures how much the passenger load distribution deviates from the totally equal distribution, i.e. when all train cars are equally utilized. The metric takes the value 0 in case of perfect evenness in the train - on-board crowding is minimal given the overall passenger load level, i.e. passengers are equally distributed over all train cars and the value 1 in case of perfect unevenness - on-board crowding is maximal given the overall passenger load level, i.e. passengers are filling cars in succession.

On-board train crowding distribution is based on passengers’ boarding behavior at the station and hence it is essential to evaluate the performance of the system by considering the distribution of boarding passengers. Similarly, the distribution of the passengers boarding the train \( j \) at stop \( s \) is given by

\[
G^{\text{board}}_{js} = \frac{1}{2|I|} \left| \sum_{i=1}^{I} q_{ijs}^{\text{board}} \sum_{i'=1}^{I'} |q_{i'js}^{\text{board}} - q_{ijs}^{\text{board}}| \right|
\]

Weighted in-vehicle time

The disutility of in-vehicle time \( \bar{t}_{\text{inv}} \) describes on-board passenger discomfort. Total in-vehicle travel time \( t_{\text{inv}}^{y} \) for passenger \( y \) is weighted with the on-board crowding factor \( \alpha_{i} \), that is increasing with the in-vehicle time, and the corresponding user-specified parameter for in-vehicle time \( \beta_{\text{inv}} \).

The average weighted in-vehicle time per passenger \( y \) is given as

\[
\bar{t}_{\text{inv}} = \frac{1}{Y} \sum_{y=1}^{Y} \left[ \beta_{\text{inv}}^{y} \alpha_{i} \left( \frac{q_{ijs}^{\text{onboard}}}{\gamma_{i}^{\text{seats}}} \right) \right]
\]

On-board crowding factor \( \alpha_{i} \) is defined as a function of passenger load factor of car \( i \), given as the ratio of on-board car occupancy \( q_{ijs}^{\text{onboard}} \) to the seated car capacity \( \gamma_{i}^{\text{seats}} \). Crowding factor value varies between sitting and standing passengers (28).

In BusMezzo passengers are allocated to seats assuming a First-In-First-Out (FIFO) rule, where seats of each car are filled sequentially and standing passengers exist when the car seated capacity has been reached.

RESULTS

Model validation

The impact of modelling car-specific perceived in-vehicle travel times on train crowding unevenness, based on the Gini coefficient, is illustrated in Figure 3. Lower Gini coefficient values, indicating more uniform average passenger distributions across the train, are observed when car-specific
perceived in-vehicle travel times are taken into account. Trains departing from UNT are found to have the highest average train crowding unevenness, which could be explained by the single entrance point at this station at the south-end of the platform. Crowding unevenness at UNT decreases by 7% when day-to-day dynamics are accounted, indicating that passengers make trade-offs between walking and crowding. We found that the average perceived in-vehicle time per passenger is shorter by 1.5 minutes when car-specific perceived in-vehicle travel times are taken into account.

The average on-board crowding unevenness is used to investigate the validity of the simulation model. The simulation outputs are tested against an empirical data set (Figure 3). Car load data estimated through the car weight measurements, considering an average of 78kg per passenger including luggage, are available at train departure from each stop on the studied line segment for the morning peak period in October 2016. The outputs of a simulation hour are tested for the highest peak hour of the morning peak period (07:30 - 08:30 am).

We conduct several t-tests to determine if there is significant difference between the mean train crowding unevenness of the simulated and empirical data set at train departure from the studied stops when the model accounts for day-to-day learning and crowding effect is taken into account in decision making process. The hypothesis that the mean of observed data is not different from the mean of the simulated outputs cannot be rejected for the stops between DAS and STD. However, it is found that there is a statistically significant difference between the means of the observed and simulated crowding unevenness in trains departing from MÖR, the first station at the simulated corridor. The low accuracy of predictions at MÖR might be explained by the more diverse travel strategies due to low demand level.
FIGURE 4 Average on-board train crowding unevenness for base, increased demand and intervention scenarios.

**Model application**

**On-board crowding unevenness**

Train crowding unevenness is investigated for the three scenarios: the *Base scenario*, the *Increased demand scenario* and the *Intervention scenario* (Section 5.4).

Figure 4 presents the average crowding unevenness on-board trains upon departure from each station. In the simulated scenarios, day-to-day learning is used to incorporate car-specific in-vehicle travel times in passengers’ train car choices. We found that in the increased demand scenario the average train crowding unevenness decreases slightly by approximately 4% at TEH and STD, which are the most crowded stations. This stems from the marginally increasing discomfort associated with increased crowding as implied by the established values of in-vehicle multipliers in the literature. The closure of the southern entrance point at DAS has a significant effect on passenger distribution among individual train cars. In particular, train crowding unevenness at DAS drops by 12%. Apart from DAS, the infrastructure intervention is found to have a significant impact on the average distribution of passengers on-board trains after they depart from the downstream studied stations.

**Boarding unevenness**

Figure 5 shows the average unevenness of passengers boarding each car, for the three scenarios. On average, boarding passenger unevenness does not vary significantly between current and increased demand conditions. Considering that some of the cars of the arriving trains have reached capacity in the increased demand scenario, there are passengers denied from boarding the most crowded car. This implies that boarding passengers are skewed towards the next closest cars, leading to a more even distribution of passengers on-board the train, as discussed in section 6.2.1.
The intervention scenario has a significant impact on the boarding passenger unevenness at DAS, leading to a more uniform distribution of boarding passengers. However, passengers’ car choice at most of the downstream stops is not significantly affected by the intervention at the upstream stop. Passengers boarding the train at TEH are less uniformly distributed after the intervention at DAS. This could be explained by the smaller number of passengers denied from boarding. The latter is caused by the crowding distribution on-board the arriving train being more even hence yielding residual capacity in the most attractive cars.

**On-board discomfort**

The average perceived in-vehicle time per passenger is used to evaluate how the simulated scenarios affect the on-board discomfort (Figure 6). In the increased demand scenario, the average perceived in-vehicle time per passenger increases by 17%. This finding suggests that the more uniform passenger distribution among individual train cars, partially counteracts the increased disutility caused by higher passenger volumes.

The closure of the most popular entrance point at DAS leads to a more even distribution of the current demand level on-board trains. This is explained by the increased passengers’ preference for the train car located close to the single entrance point. As expected, passengers experience lower crowding discomfort and the average perceived in-vehicle time per passenger decreases by 6.7% when compared to the base scenario.

**CONCLUSION**

We propose a modelling framework that evaluates and forecasts crowding distribution on-board multi-car vehicles. Each car is modelled as a separate unit with its own capacity constraints,
FIGURE 6 Average weighted in-vehicle time per passenger for base, increased demand and intervention scenarios.

which enables to capture passenger flows and crowding on-board each car unit. The path choice modelling has been extended to the platform level and hence, platform section and car unit are included in the walking and boarding decision process, respectively.

An application of the proposed modelling framework to a 6-station-segment of the south-bound direction of metro line 14 in Stockholm, where on-board crowding is on average highly skewed towards the front cars of the metro train, is conducted. The developed model accounts for day-to-day dynamics, where platform section and eventually car choice is affected by the on-board car crowding effect. The validity of the model and its sensitivity to day-to-day learning has been examined. It is found that the model can reproduce the empirical train crowding unevenness when crowding effect is taken into account in the iterative network loading model.

Increased demand level significantly reduces crowding unevenness on-board trains upon departure from the most crowded stations. This finding suggests that passenger load is close to train capacity at these stations, leading to lower flexibility of how passengers are distributed among the cars of the train. The closure of a popular station entrance point due to i.e. maintenance work required, leads to more even crowding distribution on-board trains at the specific station, but also the downstream stations.

We found that for the same demand level, passengers perceive in-vehicle time lower when crowding is more evenly distributed across the train. Although passengers are more uniformly distributed in individual train cars when travel demand increases due to less residual car capacity, the perception of travel time increases, due to larger on-board car loads.

The developed model can be used by metro operators to evaluate crowding on-board trains in a more realistic way, by considering that passengers are not evenly loaded among individual
train cars and increase the utilization of the train capacity through infrastructure investments or operational changes.

Infrastructure interventions, such as re-planning of the station layout and rearrangement of the location of entrances, or operational interventions, such as implementation of real-time crowding information (RTCI) system, could reduce unevenness of train crowding and hence, reduce the fleet requirements and delays due to long boarding and alighting process as well as increase passenger experienced comfort on-board the train.

Future research should include the discomfort associating with crowding conditions at a platform section while waiting in path choice modelling. The assumption made in this paper that passengers are denied from boarding when the selected car has reached its capacity might lead to overestimation of the generalized waiting time. A more realistic representation of the car choice would allow passengers to board the next closest car unit when the desired one is fully capacitated. Another direction for future research is to evaluate the impact of real-time crowding information systems on the distribution of passengers across a multi-car vehicle. Based on a pilot study, Zhang et al. found that RTCI system has a statistically significant positive impact on the car choice. Furthermore, more research on the effect of station layout on crowding unevenness is needed.
REFERENCES


