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MODELLING PUBLIC TRANSPORT ON-BOARD CONGESTION: COMPARING SCHEDULE-BASED AND AGENT-BASED ASSIGNMENT APPROACHES AND THEIR IMPLICATIONS

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ABSTRACT

Transit systems are subject to congestion that influences system performance and level-of-service. The evaluation of measures to relieve congestion requires models that can capture their network effects and passengers' adaptation. In particular, on-board congestion leads to an increase of crowding discomfort and denied boarding and a decrease in service reliability. This study performs a systematic comparison of alternative approaches to modelling on-board congestion in transit networks. In particular, the congestion-related functionalities of a schedule-based model and an agent-based transit assignment model are investigated, by comparing VISUM and BusMezzo, respectively.

The theoretical background, modelling principles and implementation details of the alternative models are examined and demonstrated by testing various operational scenarios for an example network. The results suggest that differences in modelling passenger arrival process, choice-set generation and route choice model yield systematically different passenger loads. The schedule-based model is insensitive to a uniform increase in demand or decrease in capacity when caused by either vehicle capacity or service frequency reduction. In contrast, nominal travel times increase in the agent-based model as demand increases or capacity decreases. The marginal increase in travel time increases as the network becomes more saturated. While none of the existing models capture the full range of congestion effects and related behavioural responses, existing models can support different planning decisions.

Keywords:
Public transport; Transit networks; Network assignment; Congestion; Capacity; Model comparison; Simulation model.

1. INTRODUCTION

Transit systems are subject to congestion that influences system performance and level-of-service. Congestion occurs in various elements of the transit network, including passenger congestion at stops, on-board and in walkways and vehicle congestion at stops and infrastructure [1, 2]. Transport planners and operators design and apply strategic and tactical measures to increase service capacity and thus reduce congestion. For example, increasing service frequency and increasing vehicle capacity might have the same consequences on total line capacity but have different implications on service reliability, waiting times and the probability of denied boarding. An inadequate modelling of a congestion-related phenomenon may result in an unrealistic distribution of passenger loads and an underestimation of the generalized travel cost and hence hinder the evaluation of alternative investments. Since congestion relief measures require significant investments, it is crucial to develop models and tools to adequately capture their impacts and assess their benefits. Transit assignment models (TAM) are used for predicting the distribution of passengers over a transit network. This paper is concerned with on-board passenger congestion and how alternative modelling frameworks and tools capture related impacts. Similarly, to car traffic, congestion induced travel externalities on fellow passengers need to be accounted for in TAM since such externalities increase the marginal travel cost.

Most previous studies described on-board crowding as a static and deterministic travel attribute. The impact of congestion was thus considered in terms of the average on-board occupancy rate. Similarly, crowding is often estimated as the ratio between average supply and average demand [3, 4, 5]. The static notion of congestion implies that the appraisal of a project that increases line capacity has a uniform impact on on-board crowding without considering load variations [6]. However, the on-board occupancy level is in reality a random variable that varies even along a single trip leg. A service that is on average uncongested could lead to denied boarding in the extremes.

The effects of on-board congestion on passenger travel times are differentiated in this paper as follows: (a) *crowding discomfort* – the greater impedance associated with in-vehicle time. An increasing passenger load will also generate an increase of the discomfort of sitting passengers; (b) *denied boarding* – prolonged travel time and dissatisfaction due to the inability of passengers to enter a vehicle because its occupancy reaches design capacity; (c) *service reliability* – inducing longer waiting and in-vehicle times due to the relation between on-board congestion, dwell time at stops and headways. There is considerable empirical evidence that these effects induce higher travel impedance [7].

There is limited knowledge about the implications of various modelling approaches and their respective consideration of congestion effects on assignment results. The objectives of this paper are: (1) to review the theoretical foundations of alternative approaches to model on-board congestion in transit networks; (2) to perform a systematic comparison of the results obtained by alternative assignment approaches in terms of both travel time and passenger load distribution under a range of travel demand and service capacity scenarios, and; (3) support planners and model developers in applying and extending transit assignment tools by discussing the practical and scientific implications of model capabilities and limitations and thereof provide recommendations to both planners and model developers communities. In particular, the congestion-related functionalities of a schedule-based model and an agent-based TAM were studied.

The outline of the paper is as follows: alternative modelling approaches for congestion in transit are reviewed in Section 2, followed by the presentation of two specific models that are contrasted in this study (Section 3). The implications of these modelling approaches under various operational scenarios were analyzed using an example network presented in Section 4. The results in Section 5 indicate that the models yield significantly different flow distributions under certain circumstances. Section 6 concludes the paper with a discussion of model implications and limitations and their potential to support policymaking.

2. CONGESTION IN TRANSIT ASSIGNMENT MODELS: A REVIEW

There is a growing literature on modelling congestion in TAM with a remarkable increase in interest in the last decade, see reviews by Fu et al. [8] and Gentile et al. [9]. Different modelling approaches aimed to account for these effects in order to obtain a realistic distribution of passenger flows over transit services. TAM are conventionally classified into frequency-based and schedule-based models - differing in their network supply representation and their implications on the passenger loading procedure. Passengers are assigned to common line corridors in frequency-based models while schedule-based models assign passengers to specific vehicle trips. For a review of the fundamentals of transit assignment modelling, the reader is referred to Gentile et al. [10]. Most of the developments were made in either accounting for on-board discomfort or considering capacity effects on passengers' queuing. In addition to these two approaches, agent-based simulation models more recently emerged as an alternative approach to TAM. In the following, we will focus on the main modelling features that enable capturing the impacts of on-board congestion on discomfort, denied boarding and service reliability.

Already in their seminal work that introduced the concept of optimal strategies, Spiess and Florian [11] suggested an implicit way to account for congestion effects by assigning link travel times as an increasing function of the corresponding passenger flow. This approach was then adopted by later studies [12, 13]. An iterative network loading process is required in order to redistribute passenger demand and obtain equilibrium conditions. Similarly, to traffic assignment models, static TAM do not guarantee that capacity is not exceeded as all passenger demand is loaded to the network even if it cannot be absorbed by the capacity available.

The abovementioned studies accounted for the impact of congestion by assigning longer in-vehicle times. Alternatively, the congestion effect could be considered through assigning weights to waiting times by computing the effective frequency [14, 15]. This implies shifting the travel impedance caused by congestion from links to nodes. The former is more adequate for capturing on-board discomfort, which most value-of-time studies found to be directly proportional to in-vehicle time [7]. In contrast, the latter is arguably more appropriate for capturing denied boarding and the reliability effects attributed to congestion. Unlike car traffic, the effect of congestion induces an asymmetric cost due to vehicle capacity constraints. Note that similarly to the flow-capacity ratio method, the effective frequency method discourages passengers from choosing saturated links, but it does not, however, guarantee that the capacity will not be exceeded. An infinite penalty when exceeding capacity was introduced in both schedule- and frequency-based TAM [16, 17]. Cepeda et al. [17] applied a capacitated equilibrium static transit assignment model for the Stockholm transit network. The iterative process reduced the number of oversaturated links but retained flow-over-capacity ratios exceeding one without reaching a feasible flow distribution. This is especially important for highly saturated networks where capacity constraints are binding for important network elements.

The effective frequency method may result in unrealistically long travel times due to the static representation of service capacity. Modelling extensions addressed this limitation by considering the share of passengers that will fail to board a network line. In the case of a frequency-based model this is performed by constructing a quasi-dynamic model where the share of passengers that exceeds the residual capacity of the respective time period is transmitted to the next period [18, 19]. The effect of on-board discomfort and capacity constraints can be modelled by the simultaneous introduction of in-vehicle and waiting time delay components [20]. Applying the same approach in schedule-based models can guarantee that capacity constraints are satisfied at the individual vehicle level by introducing new arcs between successive vehicle trips [21, 22]. The impact of priority rules was modelled by introducing a bottleneck queue model for representing the FIFO queuing process and derive the excessive queuing time [23, 24].

Similarly, to the discriminative effect of capacity constraints, the on-board discomfort effect does not affect all passengers uniformly as implied by the aforementioned flow-capacity ratio method. Fail-to-sit probability was therefore introduced to satisfy the set of priority rules and the seat capacity constraint [25, 26, 27].

TAM often assume that service is perfectly reliable although already early contributions highlighted that this is an important limitation, which is inconsistent with both analytical and empirical studies [11]. Latter developments of TAM have contributed to the refinement of relaxation of some of these assumptions by sampling service attributes assuming that they are independently distributed [28]. However, service reliability propagates dynamically in transit systems with the bunching phenomenon being the most noticeable phenomenon [27]. Moreover, congestion reinforces this process [30].

The schedule-based approach facilitates the modeling of congestion effects at the individual vehicle trip rather than on a common corridor. However, similarly to frequency-based models, it has a limited capability to capture the dynamics of service reliability and its evolution along the line. Furthermore, the static and aggregate representation of passenger demand prevents the consideration of en-route travel decisions at the individual level. A review of TAM concluded that the main challenges are dealing with supply uncertainties and adaptive user decisions. They identified the dynamic loading process and the agent-based simulation as two potential approaches [31].

Agent-based simulation models facilitate the dynamic representation of individual passengers and the emergence of congestion effects based on numerous inter-dependent local decisions. This makes these models particularly suitable for modelling congestion effects. Agent-based models were developed and applied for modelling the circulation of passengers at stops and on-board [32, 33]. However, the development of agent-based TAM is only in its early stages. Toledo et al. [34] presented a transit simulation model that models the interaction between traffic dynamics, transit operations and passenger demand. They demonstrated that the model is capable of emulating the bunching phenomenon. On-board occupancy on each transit vehicle is updated throughout the simulation, and capacity constraints are explicitly enforced. The modelling of passenger flow and service unreliability propagation allows capturing the dynamic congestion effects and support appraisals of capacity investments [35].

Previous studies have shown that accounting for on-board congestion effects yields significantly different assignment results [17, 26]. Whilst commercial TAM software packages such as TransCAD, EMME and VISUM include the option to account for capacity using variants of the flow-capacity ratio multiplier and effective frequency techniques, recent advances in TAM enable the representation of dynamic congestion effects. As the literature review clearly demonstrates, previous studies have made significant advances in modelling congestion in TAM, while embarking on distinctive modelling approaches. This recent growth in literature on diverse methods to model congestion in TAM calls for a methodic analysis of the implications of alternative modelling approaches, this being the focus of this study. In the following, schedule-based and agent-based approaches to TAM are compared, while frequency-based is omitted from the subsequent analysis.

3. MODELLING APPROACHES

The implications of alternative modeling approaches are investigated in this study by performing a systematic examination of two distinguished TAM that differ in their network representation, assignment principles and the consideration of on-board congestion effects. The macroscopic TAM approach is represented by the scheduled-based TAM, implemented in VISUM software [36]. This modeling approach is compared with BusMezzo, an agent-based TAM [37]. While both models represent individual vehicle trips along with their specific characteristics, trips' inter-dependence and passengers' route choice are treated differently. The following provides a brief description of the respective VISUM and BusMezzo assignment models followed by an investigation of their congestion functionalities.

3.1 Schedule-Based Assignment

The schedule-based TAM implemented in VISUM loads passenger flows on individual trips based on a static and deterministic representation of the transit system. The downstream attributes of all potential time-dependent paths are therefore known a-priori. A choice-set generation procedure is performed as a pre-assignment step by using the branch and bound technique. The procedure computes a search tree, which generates a choice-set that is composed of all feasible alternatives. Thereafter, it eliminates alternatives that are dominated by other alternatives within the same time interval.

Passengers are assumed to have perfect information concerning the timetables and perfectly coordinate their arrival at stops with the departure time of the selected vehicle trip. This implies that passengers do not experience waiting time at their origin stop and transfer waiting times are known and determined by the respective timetables. The number of passengers that are assigned to a specific time-dependent path is calculated based on a discrete choice model. Passenger demand is sliced in VISUM into desired departure time intervals minimizing the impedance associated with shadow waiting time (i.e. waiting time spent in the origin due to the difference between desired and actual departure times). An iterative assignment is performed until a stochastic user equilibrium is obtained. The model is primarily used for long term planning purposes.

3.2 Agent-Based Assignment

The agent-based TAM implemented in BusMezzo simulates the path decisions of individual passengers and the movements of individual vehicles. The dynamic and stochastic representation of the transit system is integrated into an event-based mesoscopic traffic simulation tool. Vehicle travel times are determined by the joint traffic and transit dynamics and consist of running, queuing, dwelling and recovery times. Running times are derived from speed-density relations while queuing times are determined by stochastic server rates, which reflect the delay at intersections. Flow-dependent dwell times are assigned at stops and recovery times are obtained from the explicit representation of vehicle scheduling. Different modes – private car, bus, metro etc. - are modeled with different vehicle types, capacities and operation regimes. Further details concerning the supply representation and its validation are provided in Toledo et al. [34].

Passengers are generated based on a time-dependent OD matrix following a Poisson arrival process. A non-compensatory deterministic choice-set generation model produces a set of alternative paths for each OD pair based on the static network representation. Throughout the simulation each passenger undertakes a sequence of successive walking, boarding and alighting decisions. The utility associated with each possible alternative is evaluated by passenger's preferences and expectations. When evaluating path attributes, passengers take into consideration the expected utility of the entire downstream path. The latter depends on prior knowledge, the current state of the system and real-time information. Passenger path flows are the outcome of the underlying individual passenger decisions. BusMezzo is designed as an operations-oriented model for short- to mid-term planning.

3.3 Modelling Congestion Effects

Congestion in transit networks could emerge from a systematically underserved passenger demand. The selected schedule-based and agent-based models imply a distinctively different approach towards representing service capacity. The former does not explicitly represent vehicle run capacities. Instead, an additional impedance is assigned to the respective route in the iterative network loading to reflect the disutility inflected by denied boarding. However, VISUM assigns any demand that is loaded to a given network even if this results in infeasible loads. In contrast, BusMezzo constantly updates the on-board occupancy for each vehicle throughout the simulation period and guarantees that capacity constraints will not be exceeded. It is assumed that passengers wishing to board an arriving vehicle form a boarding FIFO queue based on their arrival time at the stop. Passengers who fail to board due to capacity constraints can reconsider their travel decisions. Vehicle capacity corresponds to design capacity – number of seats and standees, rather than crash capacity. Since passengers' choice execution depends on capacity constraints, the stochastic assignment results are influenced by the choices made by other passengers. Seating priority rules are applied in BusMezzo by giving priority to passengers already on-board and for those that intend to alight further downstream. In contrast, VISUM does not assign seats to individual passengers and hence does not involve any priority rules.

Crowding and the discomfort it induces are a negative externality of the interaction between passengers' route choice. Since discomfort is not known a-priori, an iterative loading procedure is required in order to obtain equilibrium conditions. This procedure in VISUM includes an impedance term based on the volume to capacity ratio, which is calculated based on the loads obtained by previous iterations using the method of successive averages. Vehicle capacity is defined as the design capacity provided by the manufacturer. Alternative crowding impedance functions could be selected in VISUM. Figure 1 presents a commonly used function estimated by the Swiss Federal Railway (SFR) [38]. The logistic function is designed to reflect the increasing discomfort and to assign greater penalties for boarding overcrowded vehicles. However, there is behavioral evidence that perceptions of on-board discomfort cannot be adequately captured based on density [39], resulting with a discontinuou step-wise function of the in-vehicle time multiplier, as concluded in the meta-analysis in [7]. The iterative loading terminates when convergence criteria of the stochastic user equilibrium are satisfied. In contrast, the BusMezzo version used in this study does not support iterative network assignment and therefore does not capture the impact of discomfort on route choice. Equilibrium conditions can therefore not be guaranteed. However, an ex-post analysis can assign different value of time coefficients for each vehicle run segment based on the number of standees and vehicle capacity [35].

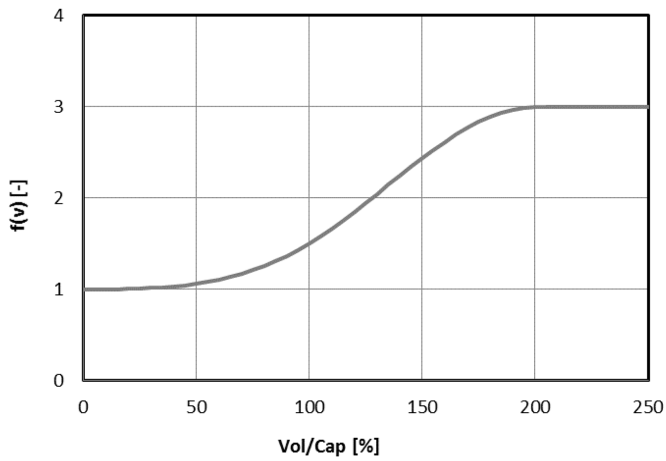


FIGURE 1 SFR crowding function

A lineup of the main differences between the two modelling tools is presented in Table 1. While both models represent transit supply in terms of individual vehicle runs and passengers are thus assigned to trip-segments, VISUM represents passenger demand as aggregate flows whereas BusMezzo assigns individual passengers that undertake adaptive path choices. BusMezzo has a richer representation of the supply phenomenon and its uncertainty whilst VISUM accounts for a greater number of variables in the path utility function.

The schedule-based and agent-based models differ fundamentally in how passengers' trips are initiated. These distinctive assumptions reflect the models focus on low frequency vs. high frequency services, respectively. These differences have implications on how passengers' waiting times are modelled. VISUM assumes that all the waiting time is spent at the origin and is therefore captured through the difference between the desired and actual departure times while the latter is perfectly coordinated with the scheduled vehicle arrival time. In contrast, passengers' waiting time in BusMezzo is derived from the time difference between passenger's generation time and a positive boarding decision that could be executed.

TABLE 1 Comparing modelling features in VISUM and BusMezzo

While capacities are usually sufficient to accommodate average volumes, on-board congestion is often the outcome of significant fluctuations of passenger loads on individual vehicle runs. Congestion in transit networks evolves through the dynamic interactions between supply uncertainty and passengers' decisions. Transit supply is deterministic and considered perfectly reliable in VISUM. Load variations in VISUM are hence exclusively the outcome of temporal demand variations and trip departure time adjustments. BusMezzo represents the sources of service uncertainty and the relation between headways, passenger loads and dwell times, which generate a positive feedback loop due to the inter-dependency between consecutive vehicle runs that contributes to delays and uneven loads [29, 34].

4. APPLICATION

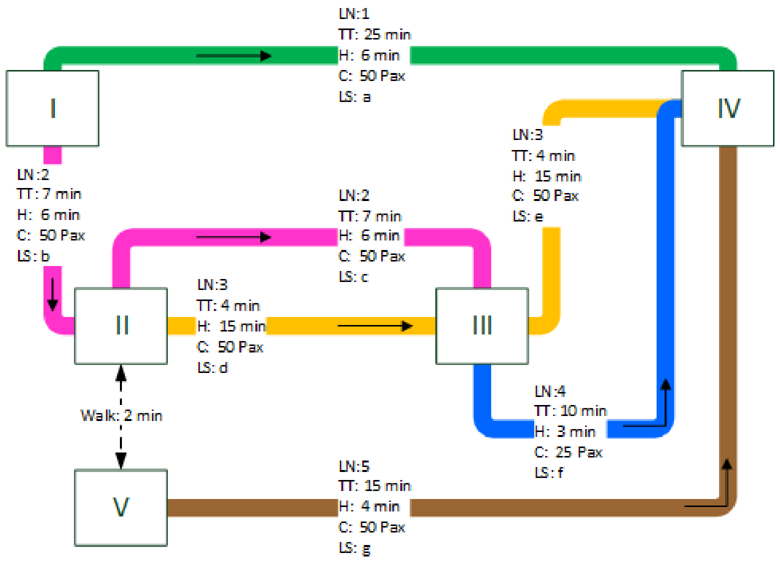
The implications of the schedule-based and agent-based modelling approaches were analyzed using an example network allowing to demonstrate the main effects while remaining tractable. Section 5 describes the example network, scenarios and their implementation details, followed by a comparison and discussion of the assignment results

4.1 Network Description

A network based on the one presented by Spiess and Florian [11] was selected for investigating how TAM capture the congestion effects (Figure 2). This network was chosen for its simplicity while facilitating the illustration of all relevant phenomena and reflect the implications of alternative models. The network provides a simplified yet realistic representation of real-life scenarios where passengers may choose between local and rapid services, direct and indirect connections. Passenger flow distribution is thus the result of non-trivial trade-offs between waiting time, in-vehicle time, walking time, number of transfers, delays and on-board crowding. Moreover, versions of this network are occasionally used in the TAM literature and its properties were investigated [24].

The network consists of 5 stops, 1 walking link between stop II and V and 5 lines. Line headways vary from 3 minutes for Line 4 to 15 minutes for Line 3. Link travel times are in the range of 3 to 15 minutes, resulting in an in-vehicle travel time of 15 and 25 minutes from stop I to stop IV, depending on the path selected. The capacity of each vehicle is 50 passengers except for the high frequency Line 4 which is operated by vehicles with a capacity of 25 passengers. Vehicle capacity induces a strict constraint in BusMezzo, whereas in VISUM it is embedded into travel impedance through the SFR crowding function.

Passenger demand is generated for six origin-destination relations with a total generation rate of 1,620 passengers per hour. The superposition of passenger demand yields on-board congestion. Passenger path choice involves the decision between a slow and direct line (e.g. Line 1 for passengers travelling from I to IV) to faster and indirect path alternatives (e.g. Line 2 + Line 3, Line 2 + Line 4). In addition, passengers may choose between fast but infrequent connection (e.g. Line 3 for passengers travelling from III to IV) to more frequent albeit slower lines (e.g. Line 4).



Passenger per hour

Stops	I	II	III	IV	V
I	-	300	60	300	0
II	0	-	0	360	0
III	0	0	-	240	0
IV	0	0	0	-	0
V	0	0	0	360	-

Legend:

I-V:	Stops
TT:	Travel Time for Line Route Segment
H:	Headway
C:	Capacity per Vehicle
LS:	Link Segment
LN:	Line Number

FIGURE 2 Example network details

4.2 Scenario Design

A set of network, demand and modelling scenarios was constructed in order to enable a systematic comparison of assignment model results in terms of passenger loads and travel times. The base case scenario corresponds to the assignment of the demand matrix in Figure 2 to the example network with the respective vehicle capacities and line frequencies. The assignment was performed in VISUM and BusMezzo, in the presence and absence of capacity constraints, in order to investigate their influence (Section 5.1).

In addition to the base case scenario, the remaining scenarios were designed to test model performance under different demand levels and service capacity. The demand level was incrementally increased, testing the sensitivity to a progressively saturated network (Section 5.2). Alternatively, network saturation can emerge from a reduction in service capacity. The latter could arise from either a lower vehicle capacity or a reduction in service frequency. The consequences of an incremental decrease in either vehicle capacity or service frequency on passengers' distribution and network performance were investigated (Section 5.3). All of these scenarios were simulated in both VISUM and BusMezzo [40].

4.3 Implementation and Specification

A systematic and meaningful model comparison requires a careful design of case study and model specifications that will ensure comparable application results as well as allow pinpointing the important modelling differences and their consequences. Hence, all modelling components were reviewed and were made as consistent as possible in order to focus on the differences in modeling on-board congestion effects and remove alternative modelling differences as much as possible.

Network supply is substantially simplified and is considered deterministic in order to allow a consistent and comparable implementation in both models. Although BusMezzo supports the modelling of traffic dynamics, vehicle scheduling and flow-dependent dwell times, the results of the case study would have been highly dependent on these sources of uncertainty and the specification of these modelling components would hinder model comparability. All sources of randomness like delays or service disruptions were therefore removed from the network representation in BusMezzo, implying a perfectly reliable service. The representation of passenger information was unified to avoid inconsistencies.

In order to harmonize the two modelling approaches, the expected value of passenger waiting time in VISUM was computed as half the headway, assuming a random arrival process and given that transit supply is deterministic in this case study. This was implemented by assigning passengers in VISUM into sufficiently short desired departure time intervals of one minute so that the impedance due to departure adjustment is negligible. The penalty for departures earlier than the desired departure time was assigned with a very high impedance. Hence, passengers could only take a vehicle trip that departs later than their desired departure time. This implementation enables a comparison of model results while maintaining the trip departure time functionality in VISUM to allow passengers to adjust their departure time in response to crowding. The utility of an alternative path a for individual n at time τ is defined in VISUM (Eq. 1) and BusMezzo (Eq. 2) as follows:

$$u_{a,n}^{VISUM} = \beta_a^{ivt} \cdot t_a^{ivt} \cdot f(v) + \beta_a^{walk} \cdot t_a^{walk} + \beta_a^{wait} \cdot t_a^{wait} + \beta_a^{trans} \cdot t_a^{trans} + \varepsilon \quad (1)$$

$$u_{a,n}^{BusMezzo}(\tau) = \beta_a^{ivt} \cdot t_a^{ivt} + \beta_a^{walk} \cdot t_a^{walk} + \beta_a^{wait} \cdot t_{a,n}^{wait}(\tau) + \beta_a^{trans} \cdot t_a^{trans} + \varepsilon \quad (2)$$

Where t_a^{ivt}, t_a^{walk} and $t_{a,n}^{wait}(\tau)$ are the in-vehicle, walking and waiting times, respectively. The in-vehicle and walking time are fixed and known a-priori in both models. This is also true for waiting times in the case of VISUM. In contrast, passenger waiting times in BusMezzo depend on the random arrival process and are therefore time-dependent and passenger-specific. The utility function in VISUM also incorporates $f(v)$, the respective crowding multiplier, which depends on the expected passenger occupancy v (Figure 1). t_a^{trans} is the number of transfers and ε is an error term. The corresponding coefficients were assigned with the following values: $\beta_a^{ivt} = -1$, $\beta_a^{walk} = -2$, $\beta_a^{wait} = -2$, $\beta_a^{trans} = -5$. The values of the coefficients are based on the commonly accepted values reported in the literature [41]. Fares are not considered a route choice determinant in this study. The multinomial Logit (MNL) model was applied in both models for computing the door-to-door path choice probabilities (VISUM) or each path decision involved in passenger movement (BusMezzo).

The simulation time was set to 3 hours, while passenger generation was restricted to 1 hour to provide warm-up and clean-up periods. The OD-matrix was used as a uniform arrival rate at stops or split into even one-minute time slices in BusMezzo and VISUM, respectively. Since BusMezzo is a stochastic simulation model, the performance of each scenario needs to be evaluated based on the average results of several simulation runs. Based on the variations in average passenger travel time, 10 replications were found to yield a maximum allowable error of less than 0.5 %.

5. RESULTS

The analysis and comparison of scenario results are presented in the following sections. In particular, the implications of modelling approaches on mean travel time, transfer rates (the share of passengers whose selected path involves an interchange) and the underlying passenger load distribution are highlighted and discussed.

5.1 Base Case Scenarios

Table 2 summarizes the total travel time and transfer rate for the base case scenario. Total travel times consist of walking, waiting and in-vehicle travel times. The difference between the travel times obtained by the two models in the unconstrained scenario stems from the different representation of the passenger arrival process at stops. VISUM, which allows for representing shadow waiting time, generates shorter travel times than those obtained from random arrival in BusMezzo. The average travel time of 16.8 min remains unchanged in BusMezzo when capacity constraints are enforced because the base case demand level does not provoke congestion effects in the form of denied boarding. Thus, the average transfer rate per passenger remains unchanged. However, crowding levels are sufficient to cause route choice adjustments in VISUM due to the increase in in-vehicle impedance invoked by the SFR function. This effect occurs because line 3 is the favorite alternative for passengers travelling from stop II to stop IV. The short travel time, however, is countered by the low frequency and the high occupancy rate. When congestion is considered, more passengers shift to the more frequent but slower line 5, resulting in a travel time increase and transfer rate decrease.

TABLE 2 Summary of base case scenario results

Travel times do not disclose the more substantial difference in assignment results in terms of passenger loads. While the two models yield similar loads on links *a*,*b* and *g*, which are fairly independent from the rest of the network, significant differences are observed for the remaining links as is evident in Figure 3. The two models lead to distinctively different loads on links that form a common corridor – links *c*,*d*, and *e*,*f*. The different distribution of passengers within each corridor stems from the different representation of passenger route choices. On both common corridors, the assignment involves choosing between a slow and frequent service (*c*,*f*) or a fast and infrequent service (*d*,*e*). BusMezzo assigns more passengers to the line with the higher frequency. The dynamic path choice model in BusMezzo provokes a boarding decision every time that a transit vehicle arrives at the stop. Each waiting passenger then takes a probabilistic decision based on the expected implications of boarding the vehicle versus waiting at the stop. Note that a high frequency line may trigger several boarding decisions before the first arrival of a low frequency line occurs. Hence, the probability that a passenger waits at the stop when the low frequency line finally arrives depends on the joint probability of successive decisions to stay. In contrast, route choice is performed pre-trip in VISUM. The choice-set generation process removes alternatives that involve longer in-vehicle times with both earlier departure time and later arrival time. This filtering rule implies that slow and frequent services are often dominated by fast and infrequent services and are thus removed from the choice-set. Furthermore, this trend is reinforced in the choice phase. Since the waiting time at the origin stop and the uncertainty are not considered in VISUM, model results favor fast and infrequent services over slow and frequent services, when compared with BusMezzo.

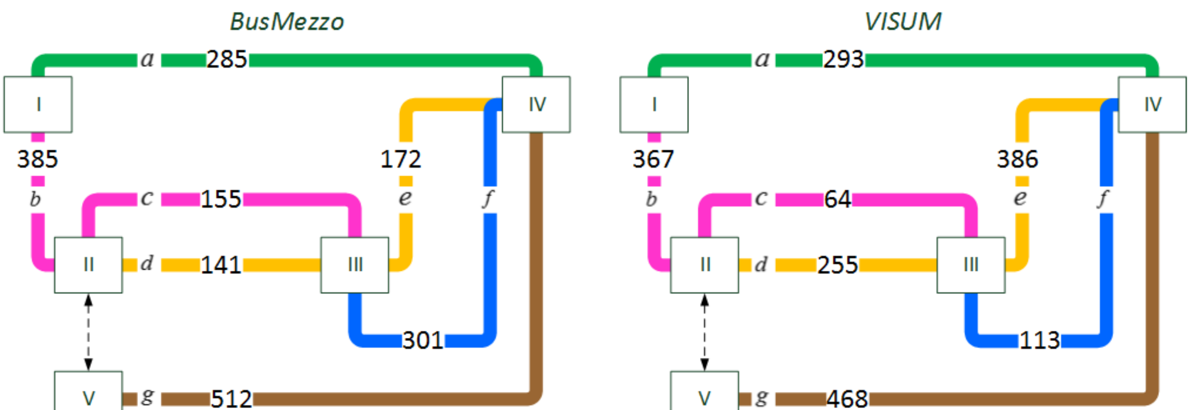


FIGURE 3 Assignment results of BusMezzo and VISUM for the base case scenario

The effect of load distribution can also be investigated in terms of the average vehicle occupancy rate for each line-segment. The direct lines 1 and 5 (links a and g) are assigned with a moderate occupancy level of approximately 50% and 70%, respectively, by both models. These occupancy levels neither induce a decisive role for the congestion parameter in VISUM nor for denied boarding in BusMezzo. In contrast, the corridor between stops II and IV exhibits significant congestion effects that yield distinctively different results in VISUM and BusMezzo. VISUM assigns to segment c passenger loads that are sometimes almost twice as much as vehicle capacity allows for, whereas BusMezzo enforces capacity constraints and passengers are retained to choosing alternative options.

In addition to the significant differences in passenger loads there are striking differences between the transfer rates in VISUM and BusMezzo. In the unconstrained case, the transfer rate in BusMezzo is 10 times higher than in VISUM. A closer investigation revealed that this drastic difference arises from the different modelling approaches applied at the choice-set generation phase. Whilst VISUM filters the choice-set by applying time-dependent filtering rules based on the static timetable, BusMezzo maintains all reasonable paths and then applies dynamic filtering rules upon passengers' decision. Furthermore, VISUM removes path alternatives that induce transfer without the consideration of uncertainties. Hence, alternatives that might become attractive under certain circumstances (e.g. missed the designated bus trip) will have zero probability to be selected. In contrast, BusMezzo assigns passengers to the paths that remain in the choice-set based on the respective expected utilities. Since the paths that involve transfers happen to be more congested in the case study network than the direct paths, rerouting in VISUM results with fewer transfers in the constrained scenario.

5.2 Demand Scenarios

The sensitivity of the TAM to demand level was examined by incrementally increasing travel demand either uniformly (5.1.1) or locally (5.2.2).

5.2.1 Uniform Demand Increase

The base case demand was incrementally increased in order to study the sensitivity of assignment results and analyze TAM performance under an increasingly saturated network. The passenger demand specified in the original OD-matrix was uniformly amplified by α ranging between 1 and 2.5 with 0.1 intervals. This range of values was selected as it can mimic the impact of the peak period demand. Figure 4 presents the total travel time and transfer rate for each demand level in VISUM and BusMezzo.

It is evident that the results of VISUM are insensitive to changes in the demand level. Even when demand is 2.5 times the base case, the average travel time is not affected and the transfer rate remains almost zero, implying that the vast majority of passengers use a direct line. Only limited rerouting takes place in the increased demand scenarios because the total demand is amplified uniformly and hence there are only limited gains to be made by shifting from one route to the other. The reasons for the low transfer rate were discussed in the previous section. Hence, in-vehicle times are almost unaffected. Since any number of passengers can theoretically be assigned to a vehicle in VISUM, waiting times are not prolonged. Even though the impedance for the connection increases, it has marginal effects on the passenger distribution because the congestion level increases equally across the network. Furthermore, once the volume exceeds 200% of the desired capacity, the impedance becomes constant (Figure 1).

A very different pattern can be observed when analyzing BusMezzo results. Total travel times increase first slowly for $\alpha = [1;\ 1.4]$ and then increase sharply when demand increases by 40-70% followed by a milder monotonous increase for higher increases in demand levels. This increase is primarily attributed to the longer travel times inflicted by denied boarding. The transfer share fluctuates with a generally increa4sing trend as demand increases. This trend emerges, as passengers that fail to board are more likely to switch to substituting indirect paths.

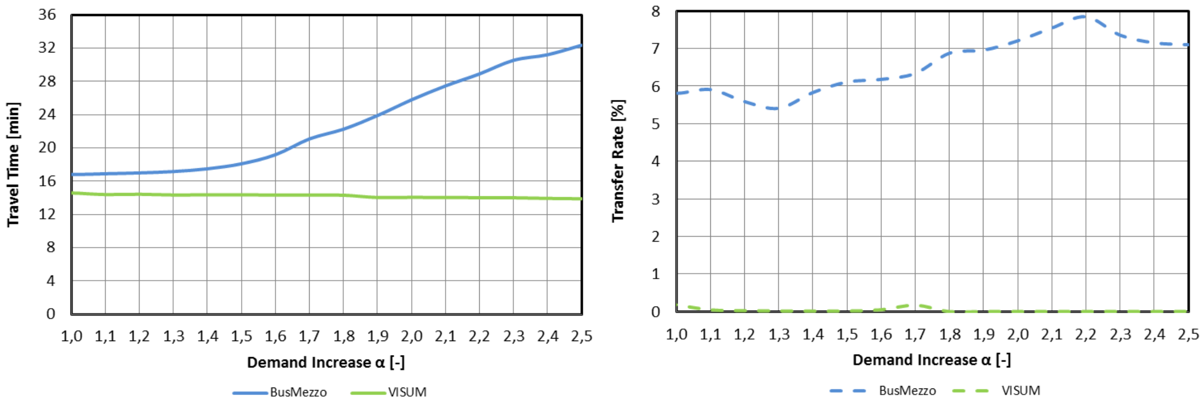


FIGURE 4 Average travel time (left) and average transfer rate (right) under increased demand

5.2.2 Demand Increase for a Selected OD-pair

A single travel demand relation, travelling from stop I to stop IV, was selected for further investigation. This relation was selected because it provides a number of relevant travel alternatives for travelers to choose from. . Line 1 (green) offers a high frequency and direct connection. In saturated cases, Line 2 (pink) and transferring to Line 3 (yellow) at stop II or III offers a fast connection. At stop III passengers can also transfer to Line 4 (blue) which is slower but more frequent. Finally, passengers can also make a short walk between stops II and V and take Line 5 (brown).

The load distribution results on line segments are presented in Figure 5. The color represents the line number using the same scheme as in Figure 2. Solid lines stand for the first line segment and dashed lines for the subsequent segment. In order to provoke congestion effects, the base case OD-matrix was uniformly multiplied by $\alpha = 1.5$. The demand on the selected OD-pair varied by β ranging between 0.5 and 3.0 with 0.1 intervals using the modified demand matrix.

Due to the absolute vehicle capacity restriction in BusMezzo, lines can only absorb the increasing demand until the vehicle capacity limit is reached. Since the network is already close to capacity limits, the share of passengers travelling with Line 1 increases only for $\beta = [0.5,1.6]$. Beyond this demand level, additional passengers are simply forced to wait for the next approaching vehicle, or even worse, passengers are not able to board any vehicle, have to wait, and never arrive at their destination within the analysis period.

Unlike its insensitivity to a uniform demand increase, assignment results in VISUM are sensitive to a discriminate demand increase. Similar to BusMezzo, Line 1 absorbs the increasing number of passengers when β is within the range of $[0.5,1.0]$. When demand exceeds this level, the congestion-dependent impedance for Line 1 reaches a critical level and passengers start shifting to alternative routes using the first segement of Line 2 and transfer at stop II to Line 3. The share of passengers transferring to Line 3 peaks at $\beta = 1.4$ and then abruptly decreases as passengers shift to continuing with Line 2 to stop III to remain seated and thus minimize the perceived on-board time. At stop III passengers switch to the fast infrequent Line 3 because of the the shorter travel time it offers in comparison to Line 4. Even when the demand level exceeds $\beta = 1.5$, the short travel time and the high capacity of Line 3 are more attractive than the frequent but much slower Line 4 which offers less capacity. Since

VISUM absorbs any demand assigned, all passengers are assumed to reach their destination within the analysis period without accounting for passengers that are possibly left behind.

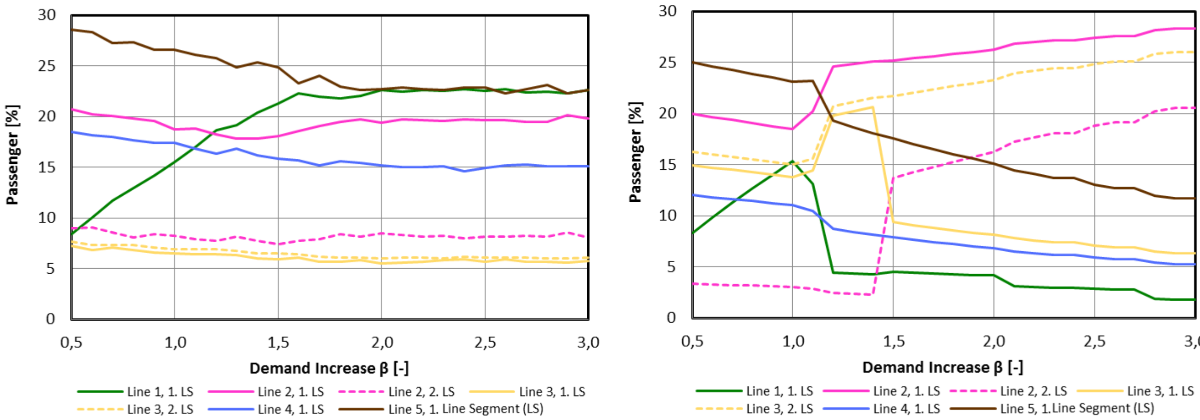


FIGURE 5 Load distribution share on line segments for BusMezzo (left) and VISUM (right)

5.3 Reduced Capacity Scenarios

The demand that a transit network can absorb depends primarily on the number of vehicle trips and their corresponding capacities. A set of reduced capacity scenarios was designed and simulated to examine the sensitivity of the assignment models to an increasing saturation due to limited network capacity. First, the vehicle capacities specified in the base case (Figure 2) were incrementally reduced down to 60% of the original level with 10% intervals rounding to the closest discrete value. Second, service frequencies were similarly reduced down to 60% with 10% intervals where frequencies were rounded to the closest minute. Passenger arrival pattern is assumed random in all scenarios for comparison reasons although lower frequencies may lead to a shift into a more coordinated arrival pattern.

Figure 6 displays the average passenger travel time (left horizontal axis) and transfer rate (right horizontal axis) for reduced vehicle capacity scenarios (left) and reduced service frequency scenarios (right). The general pattern observed in the increased demand scenarios (Figure 4) is also apparent in Figure 6 albeit with more fluctuations. Total travel time is almost constant and transfer rates remain very low in VISUM for all scenarios. Minor fluctuations occur due to changes in transfer coordination that incidentally influence the impedance associated with a non-direct connection when evaluating time-dependent paths in the choice-set generation and choice phases. The decrease in transfer rate under reduced vehicle capacity scenarios is caused by the overcrowding and the non-linear increase in impedance associated with it on link *f* which deters passengers travelling from I to IV from transferring.

Total travel times in BusMezzo follow a monotonically increasing function for decreasing capacities. The travel time increase becomes steeper for lower capacities and the increase is steeper when capacity reduction is driven by frequency reduction than if driven by vehicle capacity reduction. While both capacity reductions lead to an increasing number of passengers experiencing denied boarding, frequency reduction has an additional effect on prolonging passengers initial waiting times as well as the waiting time for subsequent vehicles.

Interestingly, transfer rates in BusMezzo follow a non-monotonic function with a generally increasing trend for lower vehicle capacities and a generally decreasing trend for lower frequencies. The former resembles the trend for increasing demand levels as it is caused by passengers that fail to board and switch to a more complex path. Unlike vehicle capacity reduction, frequency reduction influences not only the dynamics of the path choice process but also the initial choice as passengers incorporate expectations about downstream waiting times, thus discouraging transfers. Moreover, the properties of the MNL choice model imply that everything else being equal, a uniform reduction in frequencies leads to a rise in the share of passengers choosing more frequent services. Since in this network example direct and slower paths are also more frequent, passengers are more inclined to choose direct lines under reduced frequency scenarios.

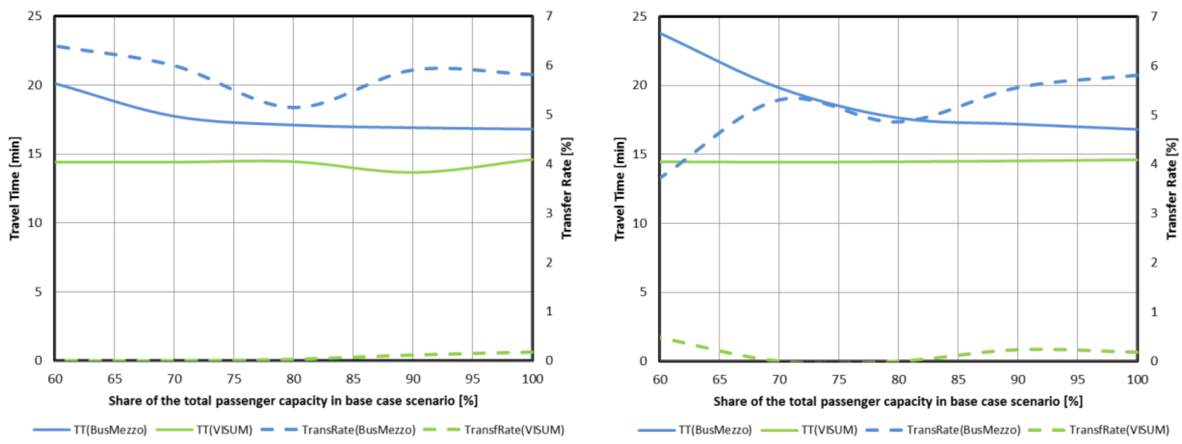


FIGURE 6 Travel time and transfer rate under: reduced vehicle capacity (left) and reduced service frequency (right)

6. DISCUSSION AND CONCLUSIONS

This paper reviewed and compared alternative approaches for modelling on-board congestion in transit networks. In particular, the congestion-related functionalities of a schedule-based model, VISUM, and an agent-based TAM, BusMezzo, were studied. Based on the comparison of theoretical foundations and the analysis of their performance under a range of scenarios, practical and modelling implications are discussed in the following sub-sections.

6.1 Practical Implications and Recommendations

Decision makers and analysts should be aware of the capabilities and shortcomings of the TAM used when evaluating different scenarios and their implications on assignment results. Modelling assumptions and functionalities have to be carefully reviewed before selecting the most appropriate model for a specific network and application. This is especially true when the passenger loads predicted by the TAM are used as a basis for service design and capacity allocation decisions. An inadequate model selection and results interpretation could potentially result in a poor capacity utilization and contributing further to congestion effects. For example, models for strict capacity constraints can better cater for highly saturated networks, whereas networks characterized by high temporal variations in demand levels should be studied using models that consider departure time choices.

The evaluation of investments to increase capacity and measures to relieve congestion requires models that can capture their network effects and the corresponding passengers' adaptation. While none of the existing models captures the full range of congestion effects and related behavioural responses, each model can support certain planning decisions. Due to its capability to model departure time adjustments, schedule-based models are more suitable for assessing long-term investments as long as the network can absorb the forecasted demand level. Furthermore, a model such as VISUM is especially suitable when departure time adjustments are important. This is for example the case of designing a low-frequency feeder service to a railway network, networks with low connectivity that rely on scheduled transfers, or where passengers choose between a frequent local service and an infrequent express service. In contrast, agent-based models are potentially better equipped to capture service reliability, overcrowding and en-route decisions. These are particularly relevant for public transport systems that operate close to capacity and experience crush loads. An model that enforces strict capacity constraints such as BusMezzo is essential for capturing congestion effects in public transport systems that are highly saturated. BusMezzo is particularly suitable for modelling dense networks that offer many route choice alternatives and where transfers play an important role, such as the core of metropolitan networks. In addition, agent-based TAM are well-positioned to model the congestion impacts of tactical and operational measures such as vehicle layout, timetable design, control strategies and information provision as well as service disruptions.

The results suggest that differences in modelling the passenger arrival process, the choice-set generation and the route choice, yield with systematically different passenger loads. In practice, model parameters such as utility function coefficients have to be estimated and calibrated based on local conditions. Assignment results will greatly depend on the trade-offs assumed between travel time components and the role of congestion in passenger decisions. VISUM assigned passengers to infrequent but fast and direct lines when compared to BusMezzo. Furthermore, the former is insensitive to a uniform increase in demand or decrease in capacity when caused by either vehicle capacity or service frequency reduction. While the generalized travel time increases due to discomfort, passengers' distribution and travel times remain unaffected even in highly saturated networks. This stems from the limited rerouting invoked and the unconstrained capability of vehicles to absorb any number of passengers. In contrast, total travel times increase monotonically in BusMezzo as demand increases or capacity decreases. The marginal increase in travel time increases as the network becomes more saturated. An increase in a specific demand relation may lead to abrupt changes in passenger loads in VISUM as opposed to the gradual route shift in BusMezzo. Although frequency and vehicle capacity reduction scenarios may yield the same overall capacity reduction, they result in different assignment results in the agent-based model due to their distinctive implications on dynamic rerouting and waiting times.

6.2 Modelling Implications and Outlook

There is currently no TAM that fully captures the three on-board congestion effects – discomfort, capacity constraints and service reliability. Each of the existing models captures only part of the on-board congestion effects in transit systems. VISUM models the potential day-to-day departure time and route choice adjustments due to discomfort (and implicit capacity constraints). BusMezzo represents the within-day implications of congestion by enforcing strict capacity constraints and modelling load variations due to service irregularity. As indicated in the literature review, recent developments in the schedule-based TAM domain allows guaranteeing that capacity constraints are binding at the individual vehicle level and that queuing and sitting priorities are respected. Future studies may examine the properties of the latest developments which are not yet available in commercial software. Similarly, the comparison performed in this paper could be further extended by considering also a frequency-based model and applying alternative models to a real-size network. In order to test models validity, future research should apply alternative TAM to a real-world network and compare model results with empirical passenger flow data.

Even though many real-world public transport systems include a combination of high and low frequency services, there is ,to the best of our knowledge, no hybrid TAM. Developing such a model is in our opinion an important approach for future research. In particular, special attention needs to be given to trips that involve transferring from high frequency to low-frequency services due to the implications on departure time choice. The combination of TAM and traffic simulation models, such as in the case of BusMezzo, facilitates the modelling of on-road congestion effects, in particular in the case of mixed-traffic. Moreover, models that belong to the same overarching approach might vary substantially in their congestion-related capabilities. The advantages of several models could be integrated into project appraisal, as was recently demonstrated in evaluating the benefits of a metro line extension in Stockholm, Sweden [35].

The shortcomings of contemporary TAM urge for the development of more elaborated representation of congestion phenomena. Future research should take into account all congestion effects – discomfort, denied boarding and reliability – and their emergence. Agent-based approaches enable the dynamic modelling of passenger flows on-board vehicles and at stops to better capture priority regimes [42]. The integration of within-day dynamics with an iterative day-to-day network loading will enable the representation of variations in congestion between service elements as well as different levels of passenger choices. For example, Kim et al. [43] demonstrated how the metro car choice can be modelled to reproduce the uneven distribution of passengers over metro trains. The latter further increases the experienced crowding level. Passengers' response to congestion also depends on their expectations and cultural preferences. Raveau et al. [44] found that travellers in Santiago have greater tolerance towards crowding than their counterparts in London. Further research on passengers' behavior, perceived congestion and degree of adaptation will enable the modelling of congestion effects and their interaction across network elements, beyond merely on-board congestion.

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TABLE 2 Comparing modelling features in VISUM and BusMezzo

	Modelling feature	VISUM	BusMezzo
Supply	Service provision	Deterministic	Stochastic
	Traffic dynamics	Macroscopic	Mesoscopic
	Mixed-fleet composition	X	X
	Line-segment/ individual run representation	Individual	Individual
	Vehicle scheduling		X
	Service delays, incidents		X
	Control strategies		X
	Capacity constraints		X
	Flow-dependent dwell time		X
Demand	Generation Process	Deterministic	Stochastic
	OD-level with connectors (walking links)	X	X
	Random taste variation		X
	Passenger flows/travellers representation	Flows	Individual
	Choice model	Deterministic	Stochastic
	Passenger prior-knowledge	Timetable	Frequenties
	Real-time information provision		X
	Adaptive en-route choices		X
	Day-to-day learning	X	*
Path choice determinants	Fare	X	
	Access time	X	X
	Access stop waiting time	**	X
	In-vehicle time	X	X
	Transfer walk and waiting time	X	X
	Number of transfers	X	X
	Egress time	X	X
	Depature time choice (hidden waiting time)	X	
	Mode specific constant	X	
	Discomfort because of crowding	X	

* recently implemented
** waiting time at the access stop is assumed to be zero as it is transfered into hidden waiting time through departure time choice adjustments

TABLE 2 Summary of base case scenario results

	Average total travel time		Average transfer rate	
	VISUM [min]	BusMezzo [min]	VISUM [%]	BusMezzo [%]
Unconstrained Capacity	13.3	16.8	0.58	5.8
Constrained Capacity	14.6	16.8	0.18	5.8