MODELLING PUBLIC TRANSPORT CONGESTION: COMPARING STATIC AND DYNAMIC MODELS

Oded Cats (Corresponding author)

Department of Transport and Planning, Delft University of Technology

P.O. Box 5048, 2600 GA Delft, The Netherlands

Phone number: +31 15 2781384

Fax number: +31 15 2787956

o.cats@tudelft.nl

Maximilian Hartl

Department for Transport Planning and Traffic Engineering, Stuttgart University

Pfaffenwaldring 7, 70569 Stuttgart, Germany

Phone number: +49 711 68584414

Fax number: +49 711 68582484

maximilian.hartl@isv.uni-stuttgart.de

Keywords:

Transit Assignment; Capacity; Congestion; Crowding; Model Comparison.

INTRODUCTION

Transit systems are subject to congestion that influences both system performance and level-of-service. Congestion occurs in various elements of the transit network (Tirachini et al. 2013). This paper considers on-board passenger congestion and how related impacts are captured by alternative modelling frameworks and tools.

Measures to increase capacity and relief congestion require adequate models to capture their impacts and assess their benefits. 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.

The effects of on-board congestion on passenger travel times are differentiated in this paper into: (a) *crowding discomfort* – the greater impedance associated with in-vehicle time. An increasing passenger load affects also 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 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.
The aim of this paper is to perform a systematic comparison of alternative approaches to model congestion in transit networks. In particular, the congestion-related functionalities of a static macroscopic transit assignment model (TAM) approach is represented by the scheduled-based TAM, implemented in VISUM software (PTV VISUM Fundamelntals 12.5 2012). This modeling approach is compared with BusMezzo, a dynamic agent-based TAM (Cats 2013).

MODELLING APPROACHES

Most of the developments in modelling congestion in frequency-based and schedule-based TAM involved either accounting for on-board discomfort (Spiess and Florian 1989; De Cea and Fernandez 1993; Lam et al. 1999; Cepeda et al. 2006; Hamdouch et al. 2011; Cominetti and Correa 2011; Nuzzolo et al. 2001) or considering capacity effects on passengers' queuing (Kurauchi et al. 2003; Poon et al. 2004; Schmöcker et al. 2008; Hamdouch and Lawphongpanich 2008; Papola et al. 2009; Trozzi et al. 2013). Recently, agent-based simulation models emerged as an alternative approach to TAM. Both schedule-based and agent-based TAM assign passengers to specific vehicle trips.

Each of the models captures only certain aspects of the on-board congestion effects in transit systems. VISUM enables to model the potential day-to-day departure time and route choice adjustments due to discomfort (and implicit capacity constraints). This procedure in VISUM includes an impedance term based on the volume to capacity ratio. A commonly-used function estimated by the Swiss Federal Railway (SFR) (Lieberherr and Pritscher 2012) is used to reflect the increasing discomfort and to assign greater penalties for boarding overcrowded vehicles. BusMezzo represents the within-day implications of congestion by enforcing strict capacity constraints, FIFO boarding queue, and modelling load variations due to service irregularity.

While capacities are usually sufficient to accommodate average volumes, 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 (Cats et al. 2012, Toledo et al. 2010).

APPLICATION

A network based on the one presented by Spiess and Florian (Spiess and Florian 1989) was selected for investigating how TAM capture the congestion effects (Fig. 1).

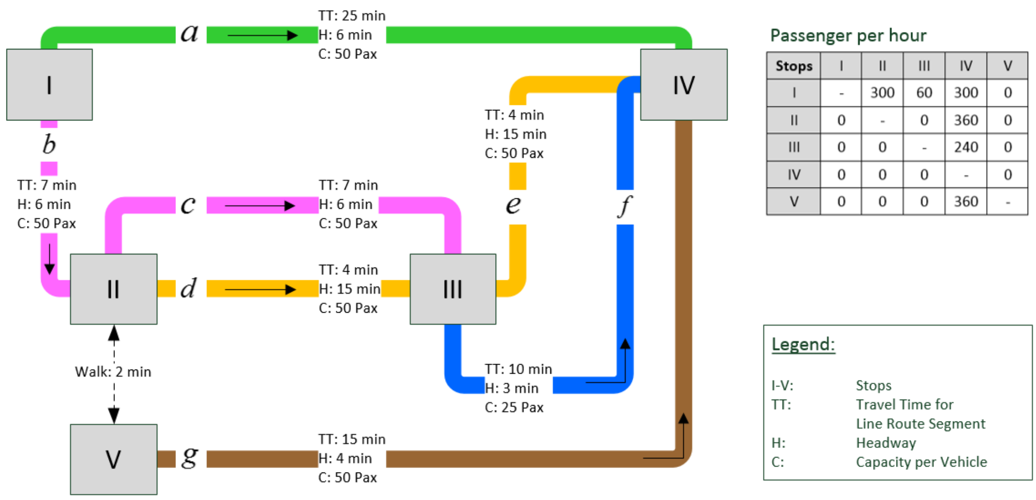


Fig. 1 Example network details

A set made up of network, demand and modelling scenarios was constructed in order to enable a systematic comparison of model results under various operational scenarios, as follows:

- *Base case* – limited vs. unlimited capacity, examining the role of capacity in each model
- *Increased demand* – incremental increase in passenger demand levels, testing the sensitivity to a progressively saturated network
- *Reduced capacity* – incremental decrease in either vehicle capacity or service frequency, analyzing the impact on passengers' distribution and network performance

A systematic and meaningful model comparison requires a careful design of the case study and model specifications that will ensure comparable application results, as well as enable to pinpoint 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 congestion effects whilst removing alternative modelling differences as much as possible.

RESULTS

The implications of modelling approaches on mean travel time, transfer rates and the underlying passenger load distribution were analyzed for each scenario. The results for the base case scenario are presented in Table 1. 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 allows shadow waiting time and thus results with shorter travel times than those obtained from random arrival in BusMezzo. The average travel time 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. 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.

Table 1 Result table including the indicators: average total travel time, number of transfers

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

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 (Hartl 2013). VISUM assigns more passengers to direct paths (link *a* and *g*). The two models display distinctively different loads on links that form a common corridor (Fig. 2). On both common corridors the assignment involves choosing between a slow and frequent service (*c,f*) or a fast and infrequent service (*d,e)*. The dynamic path choice model in BusMezzo provokes a boarding decision every time 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. 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. However, 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 infrequent services, when compared with BusMezzo.

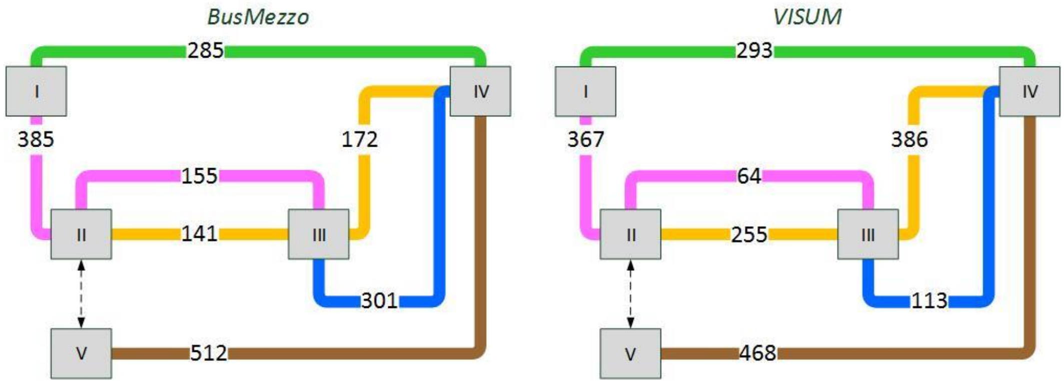
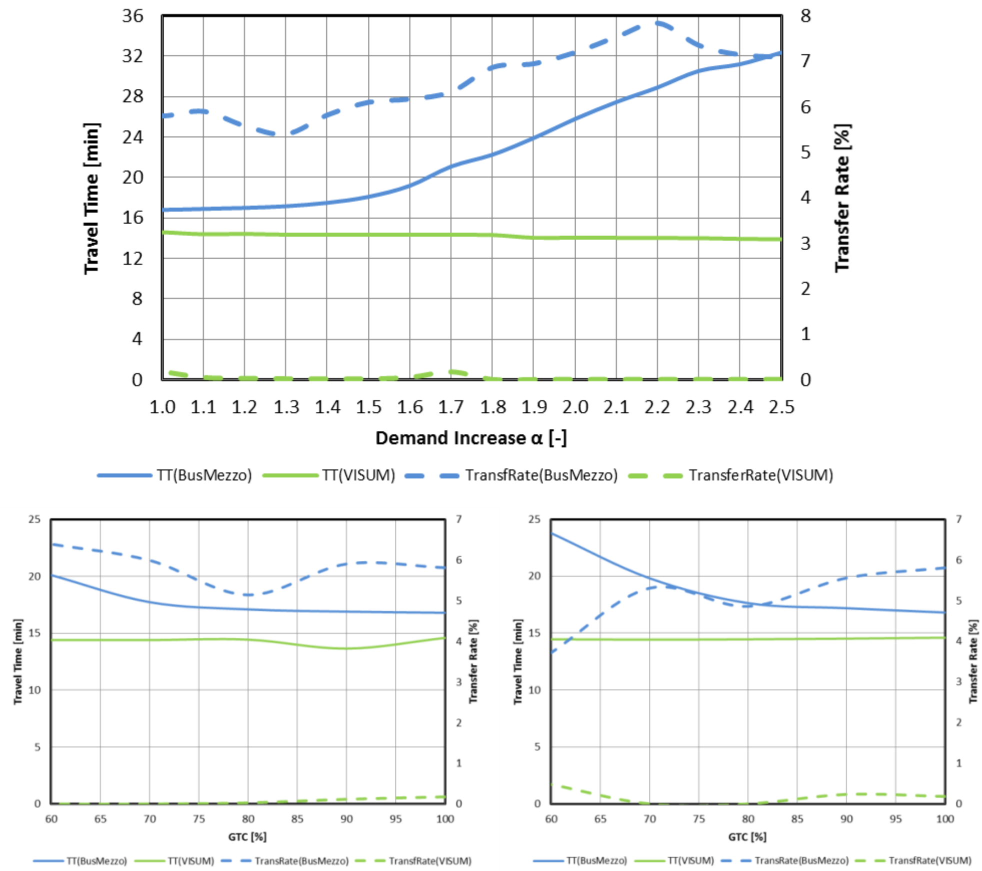


Fig. 2 Limited Capacity Base Case Passenger Loads

There are striking differences between the transfer rates in VISUM and BusMezzo (Table 1). 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. In contrast, BusMezzo assigns passengers to the paths that remain in the choice-set based on the respective expected utilities.

The base case demand was incrementally increased in order to study the sensitivity of assignment results and analyzing TAM performance under an increasingly saturated network. Fig. 3(a) 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 regardless of the congestion level. 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. Since any number of passenger can theoretically be assigned to a vehicle in VISUM, waiting times are not prolonged.

A very different pattern can be observed when analyzing BusMezzo results. Total travel times increase first slowly 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 increasing trend as demand increases. This trend emerges as passengers that fail to board are more likely to switch to substituting indirect paths.



(a)

(b)

Fig. 3 Travel time and transfer rate under (a) increased demand; (b) reduced capacity: vehicle capacity (left) and frequency reduction (right)

The general pattern observed in the increased demand scenarios is also apparent in Fig. 3(b) albeit with more fluctuations. Total travel time is almost constant and transfer rates remain very low in VISUM for all scenarios. The decrease in transfer rate under reduced vehicle capacity scenarios is caused by overcrowding and the non-linear increase in travel impedance.

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 it is 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' waiting times.

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.

CONCLUSION

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. The schedule-based model is inclined to assign passengers to infrequent but fast and direct lines, when compared to the agent-based model. 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. 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 the agent-based model as demand increases or capacity decreases. The marginal increase in travel time increases as the network becomes more saturated. Although frequency and vehicle capacity reduction scenarios may yield the same overall capacity reduction, they result with different assignment results in the agent-based model due to their distinctive implications on dynamic rerouting and waiting times.

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 such as network design, as long as the network can absorb the forecasted demand level. However, agent-based models are better equipped to capture service reliability, overcrowding and en-route decisions. Hence, they 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. Future research should consider an integrated approach to all congestion effects and their emergence.

REFERENCES

Cats O (2013). Multi-agent transit operations and assignment model. Procedia Computer Science 19: 809-814.

Cats O, Larijani AN, Koutsopoulos H, Burghout W (2011). Impacts of holding control strategies on transit performance: A bus simulation model analysis. Transportation Research Record 2216: 51–58.

Cepeda M, Cominetti R, Florian M (2006). A frequency-based assignment model for congested transit networks with strict capacity constraints: Characterization and computation of equilibria. Transportation Research Part B 40 (6): 437-459.

Cominetti R, Correa J (2011). Common-lines and passenger assignment in congested transit networks. Transportation Science 35 (3): 250-267.

De Cea J, Fernández E (1993). Transit assignment for congested public transport system: An equilibrium model. Transportation Science 27 (2): 133-147.

Hamdouch Y, Ho HW, Sumalee A et al. (2011). Schedule-based transit assignment model with vehicle capacity and seat availability. Transportation Research Part B 45: 1805-1830.

Hamdouch Y, Lawphongpanich S (2008). Scheduled-based Transit Assignment Model with Travel Strategies and Capacity Constraints. Transportation Research Part B 42 (7-8): 663-684.

Hartl M. (2013). Route choice in macroscopic and microscopic assignment models for public transport. Institute for Road and Transport Science, Department for Transport Planning and Traffic Engineering, Stuttgart, Germany.

Kurauchi F, Bell MGH, Schmöcker JD (2003). Capacity constrained transit assignment with common lines. Journal of Mathematical Modelling and Algorithms 2: 309-327.

Lam WHK, Gao ZY, Chan KS et al. (1999). A stochastic user equilibrium assignment model for congested transit networks. Transportation Research Part B 33 (5): 351-368.

Lieberherr J, Pritscher E (2012). Capacity-restraint railway transport assignment at SBB-passenger. 12th Swiss Transport Research Conference, Monte Verità/Ascona.

PTV VISUM 12.5 Fundamentals. (2012). Karlsruhe.

Nuzzolo A, Russo F, Cirsalli U (2001). A Doubly dynamic schedule-based assignment model for transit networks. Transportation Science 35 (3): 268-285.

Papola N, Filippi F, Gentile G et al. (2009). Schedule-based transit assignment: A new dynamic equilibrium model with vehicle capacity constraints. In: Wilson N.H.M., Nuzzolo A. (Eds.), Schedule-based Modelling of Transportation Networks, Springer: 145-170.

Poon MH, Wong SC, Tong CO (2004). A dynamic schedule-based model for congested transit networks. Transportation Research Part B 38 (4): 343-368.

Schmöcker JD, Bell MGH, Kurauchi F (2008). A quasi-dynamic capacity constrained frequency-based transit assignment. Transportation Research Part B 42 (10): 925-945.

Spiess H, Florian M (1989). Optimal strategies: A new assignment model for transit networks. Transportation Research Part B 23 (2): 83-102.

Tirachini A, Hensher DA, Rose JM (2013). Crowding in public transport systems: Effects on users, operation and implications for the estimation of demand. Transportation Research Part A 53: 36-52.

Toledo T, Cats O, Burghout W et al. (2010). Mesoscopic simulation for transit operations. Transportation Research Part C 18: 896-908.

Trozzi V, Gentile G, Bell M etl. (2013). Dynamic user equilibrium in public transport networks with passenger congestion and hyperpaths. Transportation Research Part B 57: 266-285.