Available online at www.sciencedirect.com

ScienceDirect

Transportation Research Procedia 00 (2022) 000-000

Transportation Research Procedia

www.elsevier.com/locate/procedia

Transport Research Arena (TRA) Conference

# Vehicle dispatching in macroscopic transport models: modelling Demand Responsive Transit

Marieke van der Tuin[a]*, Dawn Spruijtenburg[a], Han Zhou[a]

[a]*TNO, Anna van Buerenplein 1, 2595 DA The Hague, The Netherlands*

**Abstract**

Demand Responsive Transit (DRT) can complement the future mobility system by providing additional point-to-point connections based on requests of the users. As a consequence, the liveability of a city might decrease when DRT vehicles introduce additional congestion due to deadheading (relocation of vehicles without transporting passengers). The amount of congestion is usually estimated using a macroscopic transport model. However, due to a lack of (microscopic) departure times, it is not possible to include the dispatching of DRT vehicles in these models. Therefore, we introduce a new framework that combines mode choice, vehicle dispatching and traffic assignment in a macroscopic model. Simulations for a use case on the island of Curaçao show that indeed additional congestion will occur, and less people use the traditional public transport system if DRT vehicles are introduced.


Peer-review under responsibility of the scientific committee of the Transport Research Arena (TRA) Conference
*Keywords:* transport modelling; mode choice; Demand Responsive Transit; vehicle dispatcher; automated mass transit; sharing and pooling;

## 1. Introduction

New mobility concepts such as Demand Responsive Transit (DRT) and shared cars gain increasing attention within the mobility domain. DRT vehicles complement the mobility system by providing point-to-point connections on request of the users, providing higher comfort and greater flexibility than a traditional public transport system. This can be beneficial especially on low volume connections.

Governments are highly interested in the impact of the introduction of DRT vehicles or similar mobility systems, and curious whether they can bring advantages for the liveability of their city (Storme et al., 2021). How often will

* Corresponding author. Tel.: +316-15412945;.
*E-mail address:* marieke.vandertuin@tno.nl

2352-1465 
Peer-review under responsibility of the scientific committee of the Transport Research Arena (TRA) Conference

these kinds of vehicles be used? What will be the impact on congestion levels if DRT vehicles (or large fleets of taxis) are allowed in the city centres? How many vehicles are required to obtain a high service level? How should our future cities be designed to be ready to host autonomous DRT vehicles in 20 years from now?

Usually, these kind of questions on future mobility behaviour are answered using transport models. These models compute the destination choice, mode choice, route choice and resulting network flows within a city or region. However, many of the currently used transport models simulate behaviour on an aggregated level. These so-called macroscopic models are convenient to use, but vehicles are aggregated and described as a continuum. Therefore, these models do not contain information about individual vehicles, persons or departure times.

However, when modelling new modes for which a limited number of vehicles is available for public use, such as in a DRT system, it is required that individual vehicles and agents are modelled with micro-simulation (Andreasson et al., 2016). When an agent requests a DRT vehicle for a trip, an available vehicle picks them up, after which the agent is dropped off at the destination. There is even a possibility to pick up another agent during the trip if shared rides are possible. After the trip is finished and passengers are dropped off, the DRT vehicle drives without a passenger on board (i.e., empty) to pick up the next passenger. Allocating the fleet of DRT vehicles to individual trip requests is called vehicle dispatching. This process of vehicle dispatching can currently only be performed in a microscopic transport model – which is often not available for the city of interest.

Therefore, we introduce a framework in which a macroscopic transport model is combined with a vehicle dispatcher for individual vehicles and agents. The macroscopic Origin-Destination matrices for DRT are disaggregated to individual trip requests, processed by a vehicle dispatcher, and aggregated again for usage in the macroscopic transport model. The framework is implemented and tested in a use case in Curaçao to assess the impacts on traffic efficiency.

## 2. Literature review

Recently, much attention in literature has been given to Demand Responsive Transit (DRT), sometimes also referred to as shared (automated) vehicles, shared taxis, or Robo-taxis. It is expected that the introduction of these services, especially when the vehicles are automated, can cause a change in the way we move around in our cities. Narayanan et al. (2020) recently consolidated the existing knowledge around this topic, and presented an overview of the foreseen impacts in the domains of Traffic & Safety, Travel behaviour, Economy, Transport supply, Land use, Environment and Governance. Some of the foreseen impacts are that DRT include a reduction in private vehicle usage, car ownership and a change in total vehicle kilometres travelled.

Some attempts have been made to quantify the effects of introduction of similar services to DRT. There is a large variance in the exact kind of mobility concept that is modelled: shared vehicles or shared rides, autonomous or manually driven vehicles. Examples of studies are Alazzawi et al. (2018), who introduce robo-taxis (a shared and automated mobility service) in the city of Milan, and Martinez et al. (2015) who introduce a shared-taxi system in Lisbon. These studies focus on the dispatching of the vehicles, e.g., assigning vehicles to passenger requests. Then, the relation of fleet size to system performance characteristics such as waiting time, detour time and travel time is investigated. Waiting time is the most important service component for travellers (Andreasson et al., 2016). Sometimes the empty vehicle kilometres (kilometres driven without a passenger) are also discussed as part of system performance. The models used are of a microscopic nature, and consider individual vehicles, agents and trip requests. The criteria on which the models are optimized (for instance system optimal travel time) also differ between studies. In general, DRT models optimise waiting and travel time using a minimum amount of vehicles (Andreasson et al., 2016).

In some cases, the introduction of a DRT system is combined with a mode choice model, to estimate the share of the new mode. For instance, Basu et al. (2018) use a logit model where utilities are computed based on travel time, waiting and walking time, travel cost, number of transfers, vehicle ownership, age, gender and a dummy variable for whether the destination is in a (very) urban area. Martinez and Crist (2015) also combine the introduction of the new mode with a re-estimation of the modal split. However, the mode choice is much simplified, using a rule-based model to assign trips to certain modes.

The incorporation of modes such as DRT in a macroscopic transport model is a topic that is not yet extensively studied. The challenge here is the requirement that individual vehicles and agents need to be matched, while the information about these agents is only available on an aggregate level in a macroscopic model. PTV (2021) has developed the MaaS Modeller, which does combine vehicle dispatching of a ridesharing service with a macroscopic traffic model. The main benefit of this approach as compared to a fully microscopic approach is the improved robustness of the model. The model is less sensitive to randomness. Additionally, it can be integrated in often used and extensively calibrated regional and urban transport models.

## 3. Methodology

The proposed framework is shown in Fig. 1, inspired by an approach presented by PTV Group Traffic (2021). First a description of this general framework is presented. More details on the specifics of the implementation are described in Section 4.1. In the framework, an Origin-Destination (OD) matrix of people that would like to travel using a DRT vehicle is generated using a mode choice model. This OD matrix indicates the number of people that would like to travel with a DRT vehicle, which is not identical to the vehicle trips. The vehicle trips should also include the empty vehicle kilometres travelled, that is, the trajectories where the DRT vehicle is moving from the drop-off point of one passenger to the pick-up point of the following passenger. This information is necessary to be able to compute congestion levels as a result of the empty vehicle kilometres – which will in fact affect the modal split (for both private car and DRT usage).

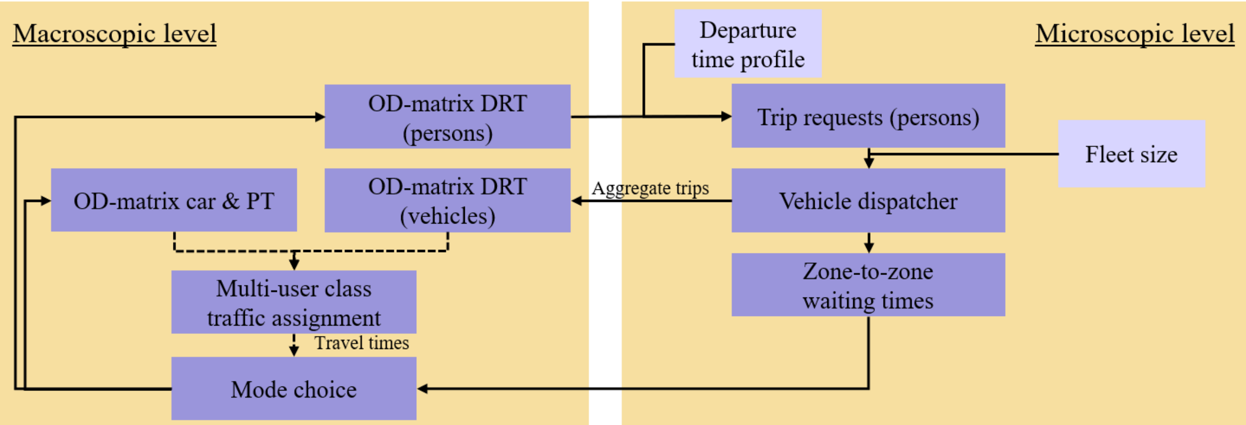


Fig. 1: Framework for integration of a vehicle dispatcher in a macroscopic transport model

Therefore, a vehicle dispatcher is run, matching passenger requests to specific DRT vehicles. A vehicle dispatcher needs information on the exact departure time to schedule trips one after another. However, the OD matrix does not contain this detailed departure time data. The OD matrix only contains information on the number of trips performed during a larger time period, e.g. a two-hour morning peak period. Therefore, the macroscopic aggregated OD matrix of trip requests is first disaggregated to individual trip requests using a departure time profile. This results in a list of trip requests with a desired start time, a start location (origin) and a destination.

The trip requests on microscopic (individual) level are matched to vehicles using a vehicle dispatcher. Additional input used in this step is the fleet size: the amount of vehicles available to serve trip requests, including their start locations. The fleet size is fixed in each scenario. The matching process is performed by solving a (linear) optimization problem where the trip requests can be satisfied as soon as possible and the optimal route for each vehicle is computed. Outcome of this process is a sequence of destinations visited per DRT vehicle. The sequence of trips is then aggregated again to an OD matrix, resembling trips made by vehicles as opposed to persons. The resulting OD matrix can then be assigned to the network using a (macroscopic) traffic assignment algorithm. This provides two main outputs: the realised travel times (including congestion) and the average waiting times for people travelling with DRT vehicles. These outputs are used as an input for the next iteration of the mode choice model, determining how many people will use the DRT system given the realised circumstances.

## 4. Case Study: Introducing Demand Responsive Transit on Curaçao

The introduction of Demand Responsive Transit vehicles is demonstrated in a case study on Curaçao. Curaçao is an island in the Caribbean Sea where car and bus (public transport) are the main modes of transport. The macroscopic model of Curaçao is based on a four-step transport model. The multimodal model consists of approximately 330 Traffic Analysis Zones, 14,000 links and 50 bus lines. The morning peak time period is modelled, lasting two hours. In total, 34,000 trips are performed.

### *4.1. Set-up of modules in Urban Strategy*

The DRT framework shown in Fig. 1 is implemented in Urban Strategy (TNO, 2022), a Digital Twin tool developed by TNO consisting of several modules including a mode choice module (as described in Snelder et al. (2019)) and multi-user class traffic assignment.

The vehicle dispatcher is implemented using a basic greedy algorithm, where trips (i.e. requests) are served according to the methodology of first come, first serve. If two trips are requested for the same time slot, the trip with shorter distance gets served first. An analytically uniform distributed time profile is used to disaggregate the trips from the Origin-Destination trip matrix to every 5 minutes during the morning peak period. No ride-sharing (i.e., multiple people travelling with the same DRT vehicle at the same time) is assumed. It is assumed that the DRT vehicles may drive during a four hour period to serve demand of the two-hour lasting morning peak, to include some time to reach the passengers from the initial location, as well as some time to bring the passengers to the destination who only requested their journey at the end of the morning peak time period. All DRT vehicles start and should also end at the parking spots shown in Fig. 2


Fig. 2: Screenshot of Urban Strategy with the Curaçao network. The initial starting locations of the DRT vehicles are highlighted with a P-mark.

The mode choice module is specifically developed to explore the mobility impacts of connected and automated driving and shared mobility, using a multinomial logit model for mode choice estimation (Snelder et al., 2019). The population characteristics of Traffic Analysis Zones are matched to the Origin-Destination trip matrices using survey data. This provides the possibility to re-estimate the mode choice in a new situation where new, non-existing modes are included. Besides car and public transport, DRT is now added as a new mode. The travel time, waiting time, travel costs and mode specific constant form the generalised costs, which is the basis for mode choice. The same cost parameters are assumed for DRT as for the normal private car, except for the addition of waiting time. The number of trips (also called requests) is an output of the mode choice module.

The traffic assignment module simultaneously assigns the DRT vehicles and private car vehicles to the network using a Volume Averaging algorithm. Public transport passengers are assigned to the network using a dedicated public transport assignment module. This results in level-of-service matrices for each mode (e.g. travel time and travel distance per Origin-Destination pair), as well as the total vehicle kilometres travelled and vehicle loss hours.

The mode choice, vehicle dispatcher and traffic assignment modules are partly using state of the art GPU technology for parallel computing, resulting in fast travel times of approximately 5 seconds (vehicle dispatcher), 10 seconds (mode choice) and 15 seconds (traffic assignment) on a computer (CPU: Intel Core i9 3.3GHz, Memory: 32 GB, GPU: Nvidia TITAN RTX with 40 GB GDDR). The models run interactively. First, the mode choice module estimates the number of trips (i.e. number of requests) performed with DRT vehicles. In the first iteration, it is assumed that the average waiting time for a DRT trip is zero. This leads to a new modal split, and thereby also a number of trips that use the DRT mode. This triggers the vehicle dispatcher, which assigns DRT trips to actual vehicles. As a result, the average waiting times for each OD pair are updated, and the DRT vehicle trips (including the 'empty' trips with no passenger onboard) are updated in the OD matrix. Next, the mode choice module runs again (using the updated waiting times), triggering the vehicle dispatcher. After 10 iterations of mode choice and vehicle dispatcher an equilibrium is reached, and the traffic assignment module assigns the DRT vehicle trips (as well as the normal car trips) to the network, leading to updated level-of-service matrices, i.e. the travel times and travel distances. The updated level-of-service matrices trigger a new set of iterations between the mode choice module and vehicle dispatcher, leading to a new mode choice. This iterative process is run 5 times. This implies that for a full run the mode choice and vehicle dispatcher modules are run 50 times in total (5 runs of 10 iterations each), and the traffic assignment module 5 times.

### *4.2. Impact of DRT vehicles on the mobility system on Curaçao*

To investigate the impact of the introduction of DRT vehicles on Curaçao three different scenarios are run, each adopting a different fleet size. Fleet size is a scenario input, and this fleet is used to serve the requests. The selected fleet sizes are 300 DRT vehicles (i.e., 50 per parking spot shown in Fig. 2), 900 DRT vehicles (150 per parking spot) and 1500 (250 per parking spot). The general usage statistics of DRT vehicles are shown in Table 1. Due to iterations between mode choice module and vehicle dispatcher, all requests are being served in each of the scenarios (albeit less trips are being made). In the scenario of 300 DRT vehicles the average driving time per vehicle is very high: nearly 4 hours, the maximum allowed driving time. This is also reflected in the high number of trips served per vehicle (twice as much as the scenario with 1500 DRT vehicles) and the high waiting time for passengers (36 minutes).

Table 1: Statistics on Demand Responsive Transit usage with several fleet sizes

| DRT vehicle fleet size per scenario | 300 | 900 | 1500 |
|---|---|---|---|
| Number of requests | 5,374 | 9,824 | 18,525 |
| Number of requests served | 5,374 | 9,824 | 18,525 |
| Number of vehicle trips (including empty trips) | 11,048 | 20,548 | 38,548 |
| Percentage service time [%] | 61.5% | 60.7% | 59.7% |
| Average number of trips per vehicle | 37 | 23 | 20 |
| Average number of trips with passenger onboard | 18 | 11 | 9 |
| Average driving time per vehicle [min] | 238 | 138 | 126 |
| Average waiting time for passenger [min] | 36 | 2 | 1 |

A closer look to trip distances driven by DRT vehicles for the scenario with a fleet size of 1500 is provided in Fig. 3. In general, the longest trips are driven with a passenger on board. The trips without a passenger on board (i.e., the trip between dropping off a passenger and picking up the next one) are generally much shorter: less than 10km. This indicates that in general, the system is functioning adequately, as was also indicated by a percentage of service time of more than 50%.

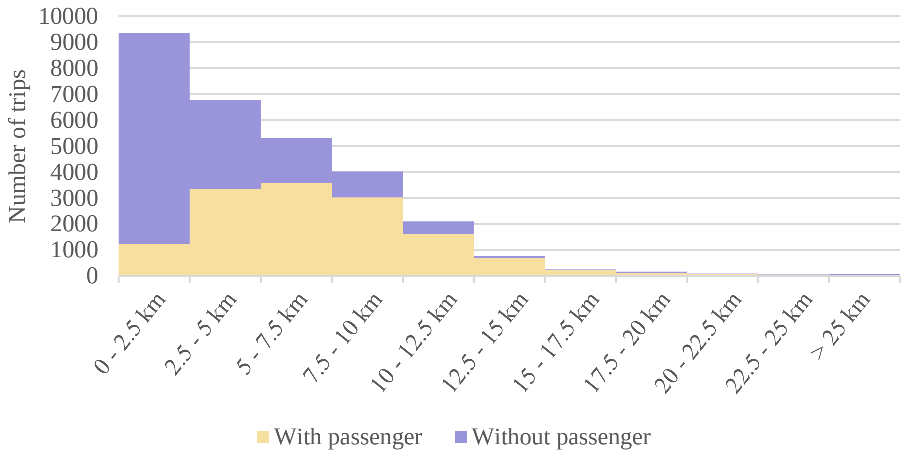


Fig. 3: Distribution of trips in the 1500 fleet size scenario with and without a passenger, aggregated to trip length.

The effects on modal split, vehicle loss hours and vehicle kilometres travelled are shown in Table 2. It can be seen that the introduction of DRT vehicles result in a reduction of public transport usage: from 6% to 4% for each of the scenarios. This implies that more trips are performed by a car (private or DRT). Additionally, the vehicle kilometres travelled (including both privately owned cars and DRT vehicles) and the empty vehicle kilometres travelled by DRT vehicles (i.e., without a passenger), show that the increase in vehicle kilometres can be explained fully by the introduction of empty vehicle kilometres, and thereby also resulting in additional congestion (represented by the vehicle loss hours).

Table 2: Statistics on the impacts of DRT vehicles on the mobility system with several fleet sizes

| DRT fleet size per scenario | Reference | 300 | 900 | 1500 |
|---|---|---|---|---|
| Modal split: Car | 94.3% | 80.0% | 67.1% | 55.0% |
| Modal split: Public Transport | 5.7% | 4.2% | 4.2% | 4.1% |
| Modal split: Demand Responsive Transit | 0% | 15.7% | 28.8% | 41.0% |
| Vehicle Loss Hours Car + DRT [h] | 71 | 90 | 113 | 139 |
| Vehicle Kms Travelled Car + DRT [km * 1000] | 240 | 262 | 280 | 306 |
| Of which empty vehicle kms travelled by DRT [km * 1000] | 0 | 23 | 42 | 68 |

It can be concluded that the introduction of DRT vehicles at Curaçao leads to a shift from public transport and private car towards DRT. The DRT system functions quite well, having a 60% service time, short waiting times (1-2 minutes) as well as short distances driven without passengers compared to with passengers onboard. However, the DRT vehicles do cause empty vehicle kilometres travelled, that are causing additional congestion.

### *4.3. Equilibrium of mode choice, vehicle dispatcher and traffic assignment results*

In the previous section the final result of each of the three scenarios has been presented. That is, the result after 5 runs of the full framework (including traffic assignment), and in each loop 10 iterations of the mode choice and vehicle dispatching modules. The variation throughout the runs, for each iteration, are presented in this section. The results on modal split of the 1500 fleet size scenario, for each of the 5 consecutive runs, are shown in Table 3. The modal split is hardly changing between the last runs. It can be assumed that an equilibrium has been reached for this scenario.

Table 3: Modal split per run of the full framework

| Iteration | 0 | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| Modal split: Car | 94.3% | 54.0% | 55.0% | 55.0% | 55.0% | 55.0% |
| Modal split: Public Transport | 5.7% | 5.6% | 4.1% | 4.1% | 4.1% | 4.1% |
| Modal split: Demand Responsive Transit | 0.0% | 40.4% | 40.9% | 40.9% | 41.0% | 41.0% |

More detailed analysis on the convergence follows from inspecting the variation between each of the 10 iterations of mode choice and vehicle dispatcher (within each of the 5 full runs). Those are presented in Fig. 4. It can be seen that the first run (yellow) has a large variation in both average waiting times and number of requests. However, after 10 iterations both values are stabilising. After the first run of simulations, the follow-up runs show a more stable pattern. Given the results for this specific scenario, it might be sufficient to use less iterations, for example 5 iterations of mode choice and vehicle dispatcher, and 3 runs for the complete framework.

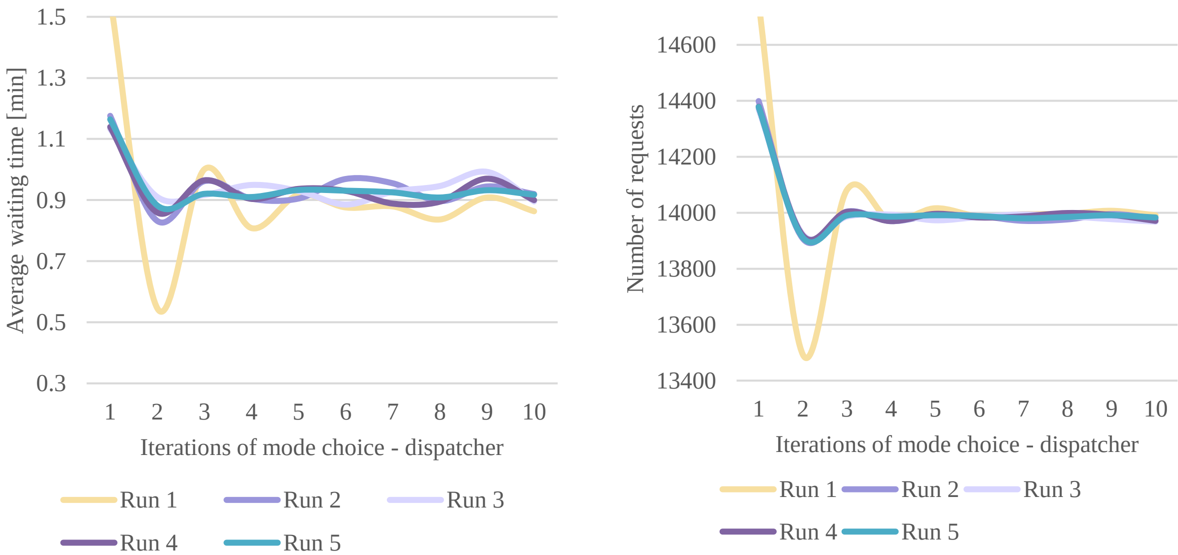


Fig. 4: Average waiting time and number of requests for each of the 10 iterations of mode choice and vehicle dispatcher, for each of the 5 runs of the full framework including traffic assignment

## 5. Conclusions and recommendations

In this paper, a framework is presented which enables modelling of new modes with constrained vehicle availability such as Demand Responsive Transit in macroscopic transport models, whereas previously this used to only be possible in complex microscopic models. In this framework, aggregated OD matrices of passengers that would like to travel using DRT are disaggregated to individual trip requests at a more precise timeslot using a departure time profile. A vehicle dispatcher then assigns DRT vehicles to the passenger requests. All vehicle trips (including the empty trips with no passenger on board between the previous drop-off and next pick-up) are aggregated into an OD matrix of vehicles. The vehicle trips are assigned to the network, and resulting network travel times are used in a next iteration of the mode choice module.

The use case of adding DRT vehicles at the island of Curaçao provides insight in how an equilibrium is reached between the number of DRT requests, waiting times and the general modal split and network travel times. Additionally, the use case gives insight in the disruption that the DRT introduction might cause for the mobility system: a well-functioning DRT system might result in less public transport usage and higher congestion levels, mainly caused by empty vehicle kilometres.

The model currently only allows a single passenger per vehicle trip. The model can be further developed to pick up other travellers having the same or close by destinations (ride-hailing). This may lead to longer travel times but may reduce the waiting time and reduce the congestion levels. If combined with a pricing structure where shared rides are much cheaper than private rides, it may lead to less congestion and a more liveable city.

## Acknowledgements

This work is done as part of the SHOW project, that has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 875530. The SHOW project aims to support the deployment of shared, connected and electrified automation in urban transport, to advance sustainable urban mobility. During the project, both real-life urban demonstrations and large-scale simulations will take place to determine the impact of autonomous public transport such as demand responsive transit.

## References

Andreasson, I. & Hadjmitriou, S. 2016. Modelling Demand Responsive and Paratransit. In G. Gentile & K. Noekel (Ed.) Modelling Public Transport Passenger Flows in the Era of Intelligent Transport Systems (pp 495-507). Springer Tracts on Transportation and Traffic, 10.

Alazzawi, S., Hummel, M., Kordt, P., Sickenberger, T., Wieseotte, C., & Wohak, O. 2018. Simulating the impact of shared, autonomous vehicles on urban mobility-a case study of Milan. EPiC Series in Engineering, 2, 94-110.

Basu, R., Araldo, A., Akkinepally, A. P., Nahmias Biran, B. H., Basak, K., Seshadri, R., Deshmukh, N., Kumar, N., Azevedo, C.L. & Ben-Akiva, M. 2018. Automated mobility-on-demand vs. mass transit: a multi-modal activity-driven agent-based simulation approach. Transportation Research Record, 2672(8), 608-618.

Martinez, L. M., Correia, G. H., & Viegas, J. M. 2015. An agent-based simulation model to assess the impacts of introducing a shared-taxi system: an application to Lisbon (Portugal). Journal of Advanced Transportation, 49(3), 475-495.

Martinez, L., & Crist, P. 2015. Urban Mobility System Upgrade–How shared self-driving cars could change city traffic. In International Transport Forum, Paris.

Narayanan, S., Chaniotakis, E., & Antoniou, C. 2020. Shared autonomous vehicle services: A comprehensive review. Transportation Research Part C: Emerging Technologies, 111, 255–293.

PTV Group Traffic. 2021, March 8. PTV UGM 2020 - Modelling Ride-sharing with PTV Visum and MPT MaaS Modeller - Steffen Wekeck [Video]. YouTube. https://www.youtube.com/watch?v=Quw1FDMBYXI

Snelder, M., Wilmink, I., van der Gun, J., Bergveld, H. J., Hoseini, P., & van Arem, B. 2019. Mobility impacts of automated driving and shared mobility. European Journal of Transport and Infrastructure Research, 19(4).

Storme, T., Casier, C., Azadi, H., & Witlox, F., 2021. Impact Assessments of New Mobility Services: A Critical Review. Sustainability, 13(6), 3074.

TNO. 2022. Urban Strategy brings planning effects into clear focus [Webpage]. https://www.tno.nl/en/focus-areas/traffic-transport/roadmaps/smart-and-safe-traffic-and-transport/societal-impact-for-accessibility-and-liveability/big-data-ecosystems-collaborating-on-data-controlled-cities/urban-strategy-brings-planning-effects-into-clear-focus/