



Delft University of Technology

Exploring the use of automated vehicles as last mile connection of train trips through an agent-based simulation model

An application to Delft, Netherlands

Scheltes, Arthur; Homem de Almeida Correia, Goncalo

DOI

[10.1016/j.ijtst.2017.05.004](https://doi.org/10.1016/j.ijtst.2017.05.004)

Publication date

2017

Document Version

Final published version

Published in

International Journal of Transportation Science and Technology

Citation (APA)

Scheltes, A., & Homem de Almeida Correia, G. (2017). Exploring the use of automated vehicles as last mile connection of train trips through an agent-based simulation model: An application to Delft, Netherlands. *International Journal of Transportation Science and Technology*, 6(1), 28-41.
<https://doi.org/10.1016/j.ijtst.2017.05.004>

Important note

To cite this publication, please use the final published version (if applicable).
Please check the document version above.

Copyright

Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy

Please contact us and provide details if you believe this document breaches copyrights.
We will remove access to the work immediately and investigate your claim.



Exploring the use of automated vehicles as last mile connection of train trips through an agent-based simulation model: An application to Delft, Netherlands



Arthur Scheltes^a, Gonalo Homem de Almeida Correia^{b,*}

^a Goudappel Coffeng BV, P.O. Box 161, 7400 AD Deventer, The Netherlands

^b Department of Transport and Planning, Delft University of Technology, P.O. Box 5048, 2600 GA Delft, The Netherlands

ARTICLE INFO

Article history:

Received 18 September 2016

Received in revised form 13 May 2017

Accepted 22 May 2017

Available online 17 June 2017

Keywords:

Automatic vehicles

Public transport

Feeder service

Agent-based simulation

ABSTRACT

The last mile in a public transport trip is known to bring a large disutility for passengers, because the conventional transport modes for this stage of the trip can, in many cases, be rather slow, inflexible and not provide a seamless experience to passengers. Fully automated vehicles (AVs), that is, those which do not need a driver, could act as a first mile/last mile connection to mass public transport modes. In this paper, we study a system that we call Automated Last-Mile Transport (ALMT), which consists of a fleet of small, fully automated, electric vehicles to improve the last mile performance of a trip done in a train. An agent-based simulation model was proposed for the ALMT whereby a dispatching algorithm distributes travel requests amongst the available vehicles using a FIFO sequence and selects a vehicle based on a set of specified control conditions (e.g. travel time to reach a requesting passenger). The model was applied to the case-study of the connection between the train station Delft Zuid and the Technological Innovation Campus (Delft, The Netherlands) in order to test the methodology and understand the performance of the system in function of several operational parameters and demand scenarios. The most important conclusion from the baseline scenario was that the ALMT system was only able to compete with the walking mode and that additional measures were needed to increase the performance of the ALMT system in order to be competitive with cycling. Relocating empty vehicles or allowing pre-booking of vehicles led to a significant reduction in average waiting time, whilst allowing passengers to drive at a higher speed led to a large reduction in average travel time, whilst simultaneously reducing system capacity as energy use is increased.

© 2017 Tongji University and Tongji University Press. Publishing Services by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

Introduction

The last mile in a public transport trip is known to bring a large disutility for passengers, as the conventional transport modes for this stage of the trip can, in many cases, be rather slow, inflexible and are not able to provide a seamless experience to the passengers. Wang and Odini (2012) indicate that the last mile is one of the main deterrents in public transport in

Peer review under responsibility of Tongji University and Tongji University Press.

* Corresponding author.

E-mail addresses: Ascheltes@goudappel.nl (A. Scheltes), G.Correia@tudelft.nl (G.H. de Almeida Correia).

<http://dx.doi.org/10.1016/j.ijtst.2017.05.004>

2046-0430/© 2017 Tongji University and Tongji University Press. Publishing Services by Elsevier B.V.

This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

order to be competitive with the car. Multiple new transport concepts (e.g. bicycle sharing systems, carsharing programs) have been proposed to solve the last mile problem (Correia and Antunes, 2012; Jorge and Correia, 2013). However, passengers still face limitations when using these transport alternatives such as slow speed, weather conditions or high costs.

Personal Rapid Transit (PRT) is one of the transport concepts which could reduce the disutility for the last mile as it aspires to be on-demand and provide a direct service with a short waiting time by operating small vehicles on a separate network (Schweizer and Fabian, 2005). Nevertheless, due to the fixed infrastructure, the accessibility of the service area is depending on the network density. The main drawbacks of conventional PRT systems are believed to be the visual intrusion of the guideway and the high investment costs (Andreasson, 2011). Vuchic (1996) even states that the PRT concept is a combination of two incompatible systems: small vehicles vs. high transport volumes. Mueller and Sgouridis (2011) concluded that a PRT system could be made more viable if it would be integrated with light rail or metro lines, such that it encourages multimodal transport, and decrease the disutility on the last mile by providing fast transport from or to a transit hub.

Nowadays tests with highly automated vehicles (AVs) are taking place all over the world, as for example with the Google Car and Uber. However as automation technology is still far from full penetration, van Arem et al. (2015) indicate that probably the most promising short-term application of AVs for public transport purposes is on improving the door-to-door performance, by providing the last mile of a trip. They state that the most viable application areas to start this system are, for example, university campus areas, because densities are high but still with scattered demand patterns and with the possibility of driving the vehicle with higher safety inside the campus.

Fully automated vehicles (SAE-level 5), that is, those which do not need a driver, are in essence independent of special infrastructure and could, therefore, operate on any available infrastructure. Therefore, AVs are able to solve one of the main limitations of conventional PRT systems. AVs could further develop the PRT concept and improve the last mile accessibility in a public transport trip. The greatest advantage of this system compared to PRT systems is a major reduction in infrastructure costs. Comparing the AVs with the classic bus systems, these have great operational cost reduction as they do not need a driver and they can be demand responsive.

The system proposed and studied in this research will be designated as Automated Last Mile Transport (ALMT) system. The objective of this system is to improve the last mile performance in a public transport trip such that a door to door experience can be delivered to a passenger (Liang et al., 2016). The ALMT system is characterized as being a feeder service for conventional public transport operated by AVs. We consider this main part of a trip still being performed by high capacity conventional public transport (e.g. train or metro) as they are able to operate with a higher efficiency and with an economy of scale as indicated by van Arem et al. (2015). The advantages of this combination strategy between high capacity (main part of the trip) and low capacity demand responsive (egress mode) has been studied by Mageean and Nelson (2003) who concluded that due to financial and scheduling reasons, Demand Responsive Transport (DRT) services are not suitable for a dominant mode of transport but should be regarded as a supplier of the main mode of transport.

The system that we will study is constituted by small, fully electric AVs. Vehicle batteries are recharged in a central depot or at an intermediate stop in the network. Booking of the vehicles occurs via a smartphone application or a push button at a stop, after which the vehicle is dispatched to pick-up the requesting passenger and bring him/her to the required destination. After the arrival, the vehicle awaits further orders until a new request arises.

In this research, we aim to assess the potential of the ALMT system in providing the suggested improvements to the last mile in a public transport trip with train as main mode. This is done by assessing the system performance under different scenarios in terms of network structure, demand patterns, and vehicle behaviour. Nevertheless, we must note that no demand model was used to relate the operational parameters and the total demand for these intermodal trips. For a study on the main trade-offs between several modes used as last mile transport of train trips, including both socio-demographic variables, mode specific attributes and attitudes, the study of Yap et al. (2016) provides interesting findings of a survey applied to the same case-study that we use in this paper.

The assessment of different operational and demand scenarios has been done through agent-based modelling (ABM). Many different simulation models of PRT systems and shared automated systems have been proposed in the literature, for example (Mueller and Sgouridis, 2011; Fagnant and Kockelman, 2015; PRT, 2015; Martinez et al., 2014, 2016). However, none of those simulation models consider the last mile of a public transport trip, by incorporating full integration with train or metro (Correia et al., 2015).

The definition of agent-based simulation model used in this work is the one by Bonabeau (2002): “In agent-based modeling (ABM), a system is modelled as a collection of autonomous decision-making entities called agents. Each agent individually assesses its situation and makes decisions on the basis of a set of rules. Agents may execute various behaviours appropriate for the system they represent—for example, producing, consuming, or selling.” This means that we are not considering other more complex components of the agents as memory and learning, focusing more on the decision-making and spatial interaction. The main advantage of ABM is the convenience in defining the behaviour of the system components up to a high level of detail by means of state charts. Statecharts allow the model designer to easily adapt the behaviour such that many variations can be simulated.

As a case-study for the model application we used the connection between the train station of Delft Zuid (The Netherlands) and the university campus of the Delft University of Technology because currently, no public transport exists in this connection, hence this could improve the last mile performance of people arriving at the campus. The distance between the train station and the passengers' destinations is on average 1.8 km and therefore should allow for efficient PRT operation

according to Young and Miller (2003). The available network infrastructure is constituted by wide cycle paths, as they provide the most direct routes to the trip destinations in the campus.

In the next section, the conceptual model of the simulation is presented in the methodology section. Then the Delft-Zuid case-study is presented together with the results of a demand survey at the station. The paper continues with the results of the experiments. It ends with the main conclusions that can be drawn from the paper.

Methodology

This section summarizes the main aspects of the simulation model that we propose in order to study the ALMT system.

A conceptual overview of the simulation model, with the required inputs and desired outputs, is given in Fig. 1. From this overview the main model components can be seen, these main components are the clients (demand) and the vehicles (supply), for which the interaction has been described in a dispatching algorithm.

The model structure has been built up such that the simulated objects represent the real world objects. The top level object of the simulation model is the network structure, which contains a set of nodes (stops) and links. As a sublevel of the network class, the train network has been included which holds the railway tracks and the station(s) for which the ALMT system operates as a feeder. Within the simulation environment, the vehicles and the passengers are characterized as agents, whose behaviour is defined by state charts, parameters, variables, and functions.

The simulation model uses as input for demand, OD matrices, and statistical distributions for the time of departure. A typical day in the simulation model is divided into three periods of the day (morning peak, off-peak and evening peak) for which during each period a distinct OD pattern exists. The total OD pattern during the day, combined with the statistical time of departure distribution together forms the considered demand model.

The behaviour of the demand is simulated by providing each simulated client agent with a state chart, which is shown in Fig. 2. Every simulated client has a variety of states which he/she will have to go through, each state is activated if a set of conditions is met, these conditions are verified within the transitions (black arrows). As an example, a passenger enters the “requests_vehicle” state if the model time equals the desired departure time of the passenger. The actions of a passenger-entity are defined in the states by means of functions.

A similar approach has been chosen for the behaviour of the vehicles, of which the state chart is presented in Fig. 3. The vehicle-entity specific parameters should be assigned according to the specifications of the vehicle manufacturer. At the start-up of the simulation model, it is possible to specify a variation of vehicle-related model variables, such as the fleet size, the average vehicle speed, the preferred charging strategy and the vehicle relocation strategy. During the simulation run, these variables are constantly updated, for example, the total vehicle weight as a function of the number of clients on board. Vehicle routing is characterized as static and decentralized, which means that every vehicle individually determines its route based on the origin and destination of the requesting passenger, by means of the Dijkstra algorithm (Dijkstra, 1959), without taking additional network information (such as delays) into account. As for the vehicle dynamics, vehicles operate according to the specified link speeds, with instantaneous acceleration and deceleration on the transition between links. In this model no traffic congestion is considered in the links, hence the speed is never dependent on bicycles, cars or other AVs on the road.

Energy use of the vehicles is simulated using a system dynamics methodology in which a differential equation simulates the potential and kinetic energy equations for a moving vehicle, which allows network and vehicle specific variables, such as a variation of slopes, to be accounted for in the energy use (XPrize, 2007). Energy use of a vehicle-agent is updated every simulation step according to the vehicle and network specific parameters which hold for that specific time step (e.g. slope of the network link and mass of the vehicle). Charging of vehicle-agents is triggered when the current battery state is below a certain threshold. This threshold can be set to be twice the energy needed to travel the maximum distance in the network for example, such that transportation of passengers can be completed without depleting battery resources. The equation used for charging is a linear charging function (Battery University, 2015) which has been adapted to case-specific parameters such as fast or slow charging.

To define the interaction between demand (Fig. 2) and available vehicle-entities (Fig. 3) a dispatching algorithm is proposed (Fig. 4), this dispatching algorithm distributes the demand based on a set of predefined control conditions amongst the available vehicles. These control conditions are: remaining battery capacity, available seating capacity and estimated waiting

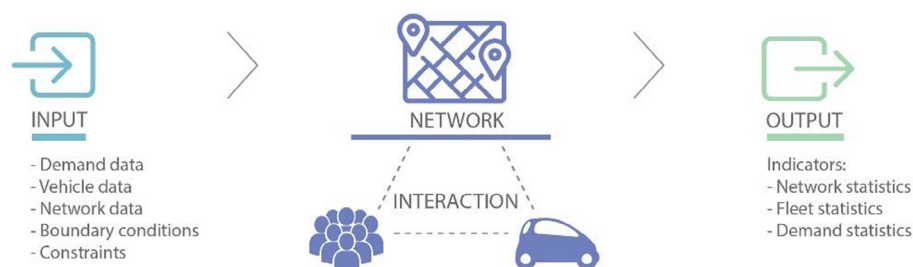


Fig. 1. Conceptual simulation model.

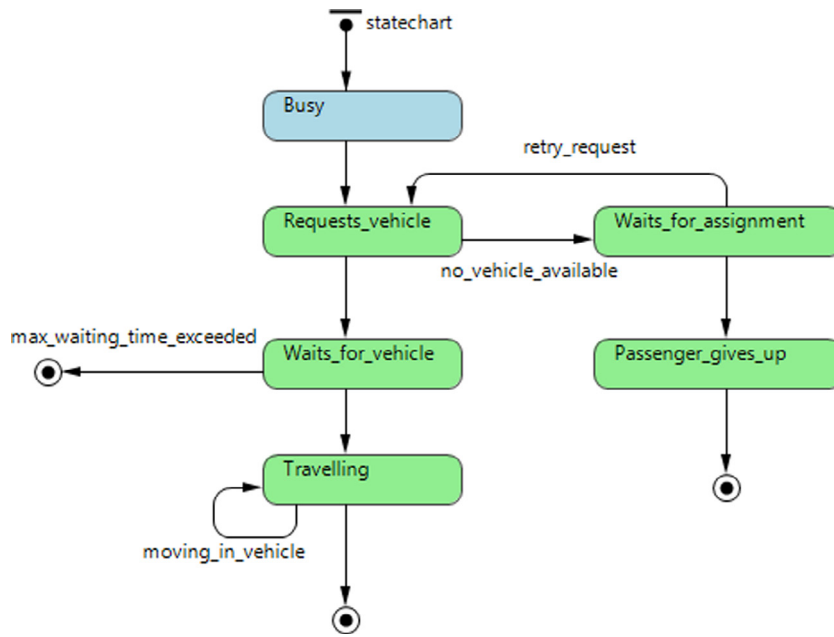


Fig. 2. Passenger state chart.

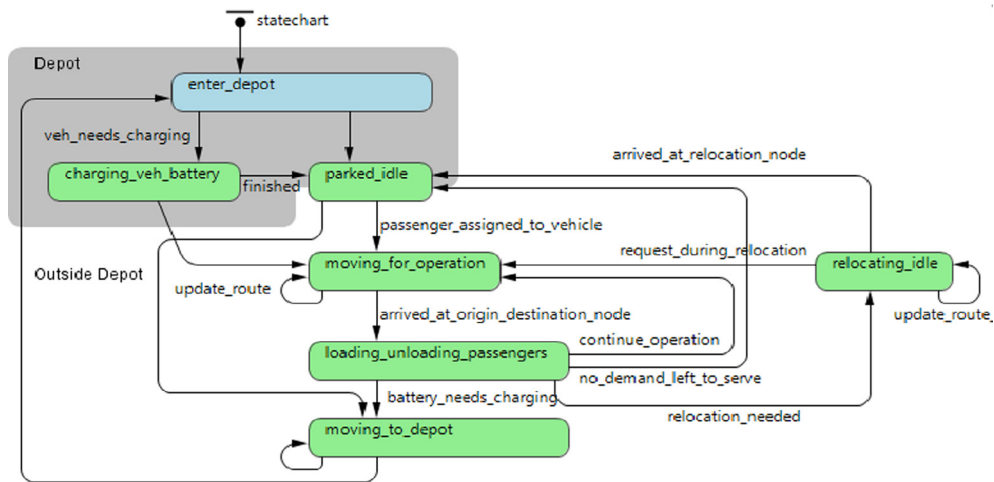


Fig. 3. Vehicle state chart including relocation states.

time for the passenger. If a vehicle meets all of these conditions it is marked as “suitable” to serve the request. This analysis is done for all the vehicles in the fleet. The algorithm then sorts the suitable vehicles according to the minimum travel time to the requesting entity and selects the vehicle with the minimum travel time. Demand is distributed in First-Come-First-Serve (FCFS) sequence amongst the vehicles. The proposed dispatching algorithm is given in Fig. 3. The algorithm is simulated as a function which can be called by every passenger entity by sending its location and destination as input.

As model output, a large variety of statistics are generated for every scenario. These can be divided in network, fleet and demand statistics. For the network, the maximum observed densities per link are calculated, as well as the average travel time matrix for all OD pairs in the network. The vehicle output characteristics vary from the range of the vehicles and the remaining battery capacity up to the number of transported passengers and the occupancy. The demand output parameters consist of average waiting and travel times and the number of transported passengers.

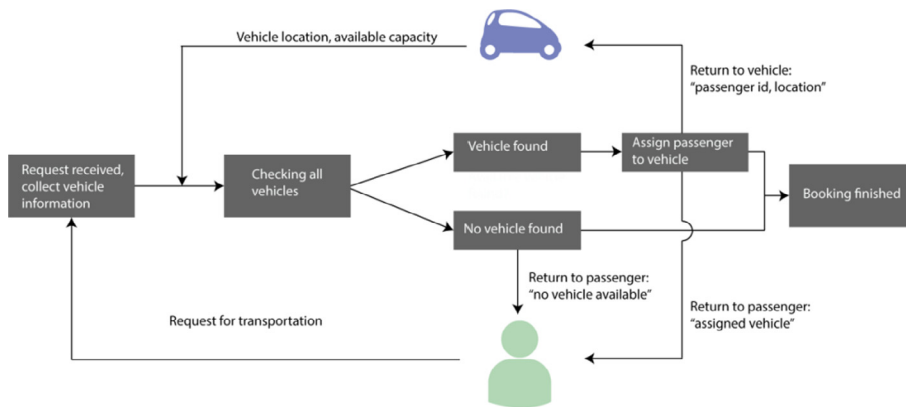


Fig. 4. Proposed dispatching algorithm.

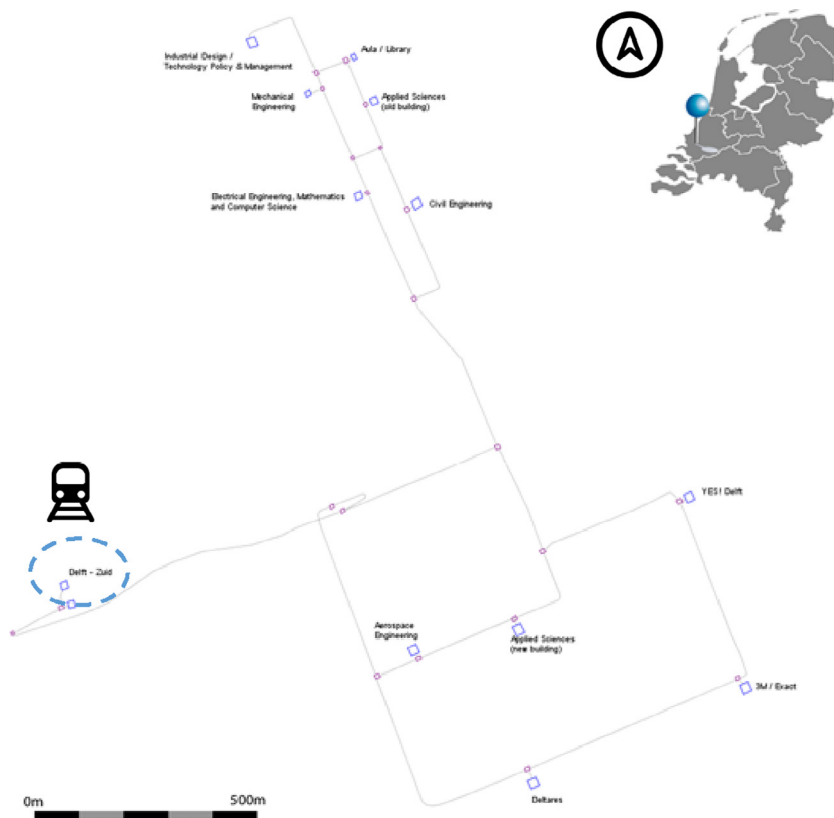


Fig. 5. Case-study network in the simulation model of the TU Delft Campus.

Case-study

Introduction to the case-study

The case-study regards the connection between the train station Delft Zuid (The Netherlands) with the campus of the Delft University of Technology. The number of passengers which use Delft Zuid has been growing the last years up to 5000 daily passengers (Treinreiziger.nl, 2015). Around 35% of the daily passengers travel between Delft Zuid and the TU Delft Campus. Trip lengths are distributed between 1.5 and 2.4 km, in a total network length of 7.2 km of bike lanes. Currently, no public transport exists in this connection, therefore the main modes of transport are walking and cycling. As a result of the



Fig. 6. Impression of Renault Twizy being tested in the cycle path of the TU Delft campus.

lack of public transport, most of the visitors of TU Delft travel via Delft station (the city central station), although this is located farther away from the university campus.

The main network consists of wide cycle paths, which provide direct routes to all university campus zones (Fig. 5). Operation on cycle paths brings restrictions to maximum allowed speeds. Although speeds cannot be considerably higher than cycling, it is expected that given the large share of passengers who are currently walking to their destinations (as we will show in the next section) there could still be large benefits to be obtained from this system. The case-study network consists of 13 centroids, for every faculty of the University, the train station, and the depot where vehicles are stored. The centroids (blue) are interconnected with two directional links. The two directional links are connected with each other via nodes (pink). The network is characterized by a dense network within the University Campus, and a single axis connecting the University Campus to the train station Delft Zuid, which has to accommodate all the traffic. Every network link has been observed by using a GPS device, which was used for measuring the length and the slope of the specific link.

The depot in which the vehicles are stored and charged is assumed near the train station Delft-Zuid, given the directional demand patterns (e.g. in the morning from Delft-Zuid to TU Delft campus and in the evening vice versa) this location is expected to result in a limited number of empty vehicle kilometres.

For the vehicles to be simulated in the ALMT system we used as reference the Renault Twizy, which is a small electric vehicle with a capacity for one passenger. The small dimensions of the vehicle allow a safe interaction with cyclists on the cycle paths in the case-study network. As the vehicle only has a capacity for one passenger, it is perfectly suitable for providing direct transportation services. Moreover, because the vehicle still has a steering wheel it can also be used in a “not automated” mode, to allow passengers to drive the vehicle themselves. An impression of such a vehicle being tested at the TU Delft Campus is shown in Fig. 6. In this project that funded the master thesis, these vehicles are considered since they are cheap electric and light vehicles. It makes sense to use higher capacity vehicles, as mentioned in the recommendations for further research.

Data collection

The demand for the case-study is by far the most important input of the simulation model and is described by the results of a travel demand survey which has been conducted to 941 respondents at the train station of Delft Zuid, representing 20% of the daily population of passengers at the train station. Respondents were questioned about their origin, destination, travel time and whether or not they would consider using AVs as a last mile transport mode. The survey has been conducted during two typical business days, at which no out of the ordinary events occurred. The output of this survey has been combined with public transit smart card data of the Dutch Railways (NS) to determine the total demand population which should be accounted for in the simulation and to verify the observed demand patterns.

The OD matrix has been determined based on a zonal level which corresponds to the chosen centroids, such that every faculty is represented by a single centroid. As directional demand exists during the day, per typical time period (morning peak, evening peak and off-peak hours) a separate OD matrix has been constructed.

The survey indicated that currently, the vast majority of the respondents is travelling the last mile by foot or by bike. Every respondent was asked whether or not they would consider AVs as the last mile transport mode. An average value

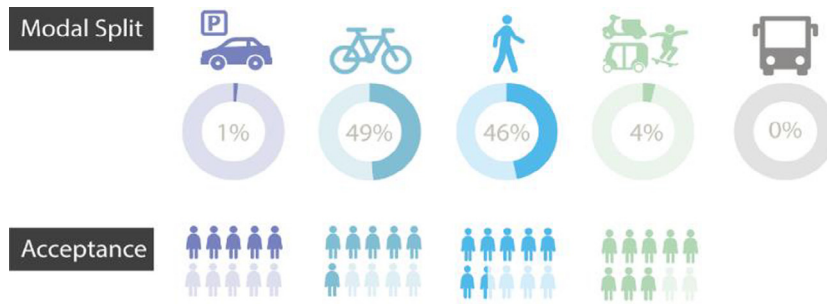


Fig. 7. Modal split and automated vehicle acceptance according to current mode (1 person = 10%).

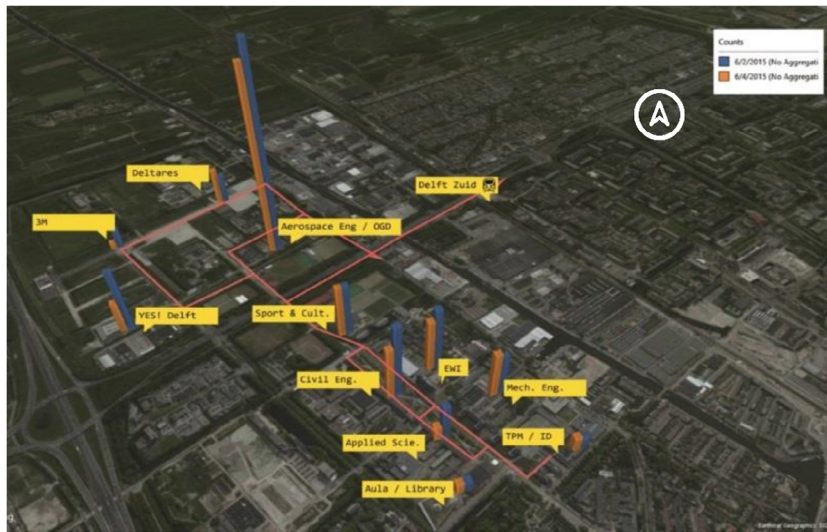


Fig. 8. Respondents visited locations during 2-6-2015 (blue) and 4-6-2015 (orange).

of 57% was found, which is considerably higher than the European averages found by Cisco (2013), which varied for Western countries between 37% and 45%. This difference could be explained by a bias in the group of respondents, as they are all affiliated with the Technical University Delft, therefore the pro-technical character of the respondents could be the cause of the biased result. When these results are compared to the non-TU Delft respondents a lower acceptance rate of about 45% is found. An overview of the modal shares and the automated vehicle acceptance per mode is given in Fig. 7.

From Fig. 7 it can be concluded that amongst the respondents the acceptance of this new system is highest for pedestrians (blue) and other modes (green), which is logical since they are expected to face the highest disutility, because of their speed which leads to a higher travel time compared to the other modes of transport.

In Fig. 8 we show the demand in the two days of the survey. One can clearly observe that a large share of the demand is located at the faculty of Aerospace Engineering, which is one of the largest faculties of the TU Delft and the closest to the train station. The other destinations show a roughly smaller but balanced share in the total respondents' population. From this figure, it can also be concluded that the results for both days are roughly similar. As no large differences occurred between both surveying days, we chose to use the weighted average of both days to determine the random statistical distribution of the passengers' destinations.

From the sample data of the survey, the origin and destination by train (e.g. The Hague or Rotterdam) is assigned to every passenger. Additionally the last mile direction is generated according to the probability of a random passenger travelling from station Delft Zuid towards the TU Delft campus or vice versa. As a next step, based on the assigned last-mile direction, every passenger has a dependent probability of travelling during a certain period of the day: morning peak, off-peak or evening peak. Per period, the mean and the standard deviation of the exact departure time are estimated, and a departure time is generated by a Monte Carlo process (e.g. for the morning peak from Delft Zuid to the TU Delft campus the distribution is $N(08:15, 00:42)$ in hh:mm). This departure time describes a preferred departure time of the passenger. In order to describe the group-wise arrival of passengers at the Delft Zuid station, departure times have been synchronized with the train schedule. As an example, for a passenger travelling from station Delft Zuid to the TU Delft Campus a departure time of 08:13 has been

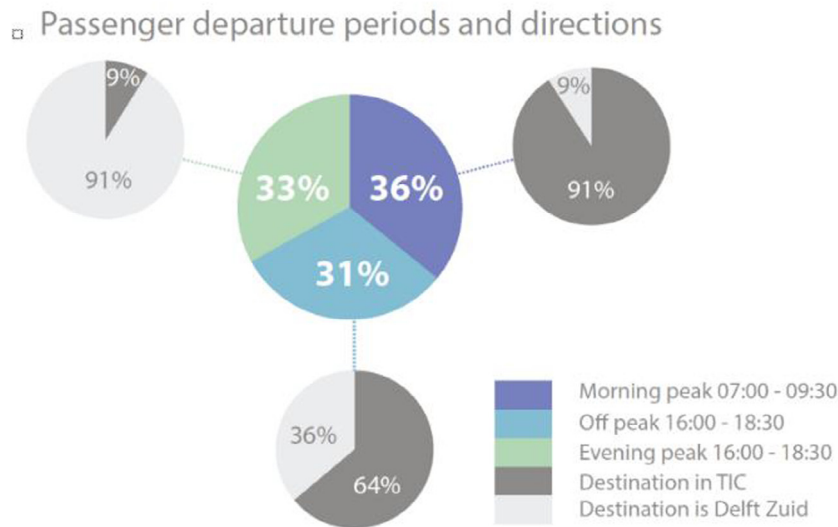


Fig. 9. Demand directions for the morning peak, evening peak and off-peak hours. (TIC = TU Delft Campus).

generated according to the normal distribution for the morning peak. If the next arriving train is scheduled to arrive at 08:15 the initial departure time of the passenger is overwritten to be 08:15.

The demand pattern appeared to be mainly one-directional (station to the campus and campus to the station) during the peak hours, and two directional during the off-peak hours. During the morning peak the dominant direction was found to be from the train station to the university campus with 91% of the trips, and during the evening peak, a similar pattern was found however in the opposite direction. The total demand during the day appeared to be almost equally divided amongst the three considered time periods as can be seen from Fig. 9.

During the survey, passengers waiting at Delft Zuid were questioned. As respondents had to guess their expected arrival at Delft Zuid when originating from the TU Delft campus, these arrivals were obtained at a lower level of detail than the departure times. The latter correspond to the train arrival times, which are exactly known (in case of no delays). Additionally, the survey did not fully capture the demand pattern after the evening peak and inside the campus. This gap in the data is expected to be caused by the relatively short distances within the campus and by the fact that although the survey was anonymous, not every respondent was willing to provide his or her full daily schedule.

Simulated scenarios

The model presented in the previous section is used to simulate 10 different operational scenarios. For each scenario, one typical business day of operations has been simulated.

Within the proposed simulation model a variety of scenarios were tested, these scenarios vary in vehicle behaviour, demand behaviour, and network structure. All scenario outcomes are compared to a baseline scenario. Within this baseline scenario, the vehicles await every consecutive request at the last visited location in the network. Passengers can request a vehicle upon arrival at a stop, and vehicles start their service in the depot at which they are charged overnight or during operational hours when the battery capacity has reached the proposed threshold. In Table 1 the input parameters for the baseline scenario are shown.

On the base scenario, we have changed several properties in order to produce new scenarios to be tested. Variations in network structure were done by adding links to the baseline network (Fig. 5) because these extra links are already existing in the infrastructure but are not the main cycle paths (named scenario 1); and by removing links from the baseline network for links which are currently not yet suitable for small AVs (e.g. due to steep slopes or short radius) (scenario 2). The main goal of these variations was to assess the influence of the network density on the system capacity.

Variations in the vehicle behaviour were simulated: instead of waiting for a request, vehicles are sent to locations at which high demand is expected before the actual demand exists at that location, in order to reduce waiting times. As demand during the peak hours appeared to be dominantly one-directional, vehicle relocations are most effective. Vehicle relocations were simulated during the morning peak (scenario 3) and secondly during the morning and the evening peak (scenario 4).

Variations in demand were considered in the booking process of the AVs by allowing passengers to book a vehicle in advance via a smartphone application. A scenario in which the whole population uses pre-booking (5) and a scenario in which 65% uses pre-booking (6) are considered. The share has been chosen such that it represents the share of the population

Table 1
Baseline input parameters.

Parameter	Value
Maximum speed	18 km/h
Vehicle capacity	1 person
Battery capacity	6.1 kWh
Vehicle mass	200 kg
Demand size	864
Number of centroids	13
Operating hours	07:00–20:00
Fleet size	35

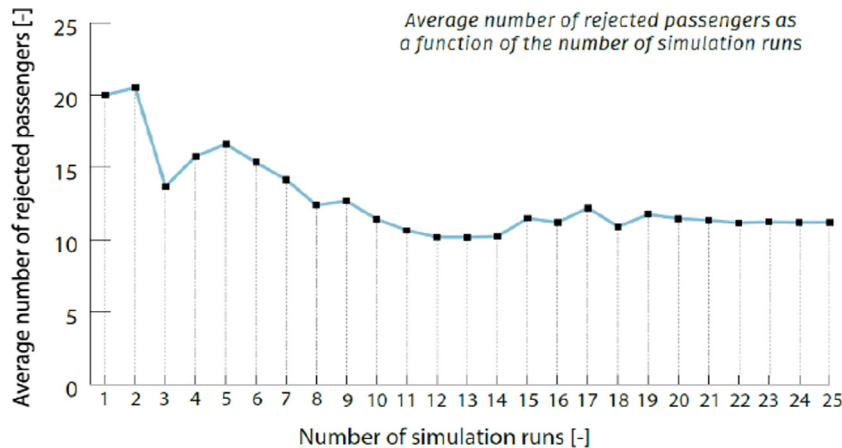


Fig. 10. Number of simulation runs as a function of the number of rejected passengers, base scenario.

Table 2
Description of output parameters.

Output indicator	Description
Kilometres per passenger [km/pax]	The total system kilometres divided by the number of transported passengers
Total energy use [kWh]	Summation of the energy usage for all the vehicles
Total system kilometres [km]	Summation of the driven kilometres for all the vehicles
Maximum density [veh/km]	The maximum observed vehicle density in the network
Total travel time [min]	Summation of the travel time for all of the transported passengers
System capacity [pax]	The total number of transported passengers during a day of operations
Vehicle occupancy [pax/veh]	The average occupancy for all the vehicles
Time until first recharging [min]	Time until the first vehicle has reached a threshold for recharging
Max # charging vehicles	The maximum number of vehicles that are charging simultaneously
Average vehicle operation time [min/veh]	The average number of minutes each vehicle drove in one day
Average assignment time [min/pax]	The average time it took for the dispatching algorithm to find a vehicle for the requesting passenger.
Maximum waiting time for a vehicle [min]	The maximum time a passenger had to wait for a vehicle during one day of simulation
Average waiting time [min]	The average waiting time of all passengers during one day of simulation
Average travel time [min]	The average travel time of all passengers during one day of simulation
Maximum travel time [min]	The maximum travel time which occurred during one day of simulation

that has a smartphone with internet connectivity. Scenario 5 thus represents the maximum effect when the total population uses pre-booking, and scenario 6 represents the current situation in which 65% of the population has a smartphone with an internet connection. This number has been based on the average for the Netherlands (CBS.nl, 2015a).

Another variation in the demand was considered in which passengers are allowed to drive the vehicles themselves at a higher speed (30 km/h) to reduce travel time. First, 100% of the population drives the vehicle to observe the maximum effect (scenario 7), after which the current average share of the travellers who have a driver license (22%) was simulated (8). The share of 22% represents the number of public transport users that have a drivers' license, (CBS.nl, 2015b), this share is typically lower than the national average as it concerns public transport users and a relatively young target group in the case study.

Furthermore, vehicle behaviour variations were simulated by changing the vehicle' charging strategy with the introduction of opportunity charging. Instead of only allowing vehicles to recharge their batteries when their battery state has

Table 3

Output parameters for the simulation scenario.

	BASE SCENARIO	(1) NETWORK STRUCTURE - Adding links	(2) NETWORK STRUCTURE - Removing links	(3) RELOCATING EMPTY VEHICLES - During morning peak	(4) RELOCATING EMPTY VEHICLES - During morning and evening peak	(5) PRE-BOOKING OF VEHICLES - 100% of the passengers	(6) PRE-BOOKING OF VEHICLES - 65% of the passengers	(7) ALLOWING PASSENGERS TO DRIVE - 100% of the passengers	(8) ALLOWING PASSENGERS TO DRIVE - 72% of the passengers	(9) CHARGING STRATEGIES - Adding multiple slow chargers at AE	(10) CHARGING STRATEGIES - Adding 1 fast charger at AE
 Kilometers per passenger	3.39km	-1.5%	-12%	+4%	+7%	+0.9%	+11%	+0.4%	-0.6%	+0.4%	0%
 kWh Total energy use	118kWh	-0.35%	-49%	+8%	+1.81%	-9.8%	-8.1%	+146%	+19%	+0.2%	+0.4%
 km Total system kilometers	2849km	-0.65%	-46%	+5.5%	+6%	+0.7%	+0.2%	-6.4%	-2.4%	+0.6%	+0.6%
 veh/km Maximum density	14.7 veh/km	0%	-46%	+5.0%	+6%	-1.2%	-1.2%	+1.4%	-1.2%	0%	0%
 Total travel time	6017min	+0.4%	-34%	+4.4%	+5.6%	-1.1%	-0.4%	-44%	-10.3%	+0.4%	+0.8%
 System capacity	839 pax	+0.5%	-39%	+1.4%	+1.8%	-1.3%	-0.7%	-6.7%	-1.7%	+0.2%	+0.6%
 Vehicle occupancy	0.61 pax/veh	+0.1%	+27%	-31%	-5.7%	-1.2%	-0.7%	-20%	-2.9%	-0.4%	+0.7%
 Time until first recharging vehicle	10hours (16:00)	+0.1%	+17%	-5%	-9.0%	+17%	+13%	-37%	-17%	-78%	-67%
 Max # charging vehicles	9 [-]	0%	-33%	+10%	+10%	-22%	-11%	+166%	+11%	0%	-33%
 Average vehicle operation time	04h38m	+1.9%	-40%	+4.9%	+7.0%	+1.1%	+0.2%	-30%	-8.0%	+0.7%	+0.8%
 Average traveled km per vehicle	81.4km	+2.0%	-2%	+1.5%	+8.7%	+0.7%	0.2%	6.4%	-2.4%	+0.6%	+0.6%
 Average assignment time	01m:31s	-4%	+93%	+8.8%	+21%	+21%	+16%	+8.9%	+3.7%	+0.6%	+0.6%
 Maximum waiting time for a vehicle	09m:06s	0%	+0.2%	0%	-1.4%	-11%	+4.3%	+10.4%	+10.4%	0%	0%
 Average waiting time	04m:27s	-1.3%	-9.7%	-33%	-40%	-80%	-58%	-5.4%	-4.7%	-3.0%	-4.5%
 Average travel time	07m:10s	-0.1%	+8.5%	0%	0%	0%	0%	-40%	0%	0%	0%
 Maximum Travel Time	09m:06s	0%	+9.0%	0%	0%	0%	0%	-40%	0%	0%	0%

reached a threshold and only at the depot, vehicles were allowed to charge at multiple locations in the network by using “regular” chargers (scenario 9) or by using one single fast charger at the highest demand location (Aerospace Engineering (AE). (scenario 10).

For each of these scenarios, the required number of simulation runs has been determined by selecting the most sensitive output variable, which appeared to be the total system capacity (i.e. the number of passengers who were served during the day). For the base scenario, the moving average does not change much anymore after 12 simulation runs, as can be seen in Fig. 10. Each scenario was run the required number of runs with different seeds for the random numbers' generator to obtain average results.

A large variety of output indicators is generated by the simulation model. The most relevant are described in Table 2, including their units.

Results and discussion

The model was coded in Java language using the platform Anylogic (Anylogic Software). The outputs are shown in Table 3 as a percentage of the base scenario results.

Network structure (scenarios 1 and 2)

The number of links in the network was expected to determine, to a large extent, the accessibility of the destinations. However, if the set of destinations has a high density, as in the case-study network, adding links does not lead to a reduction in travel times. In the case-study area, the new links that were added had low-speed limits as these were basically cycle paths. The benefit of shorter routes did not outweigh the reduction in speed because the maximum obtainable speed difference between the regular infrastructure and the newly added infrastructure was only 3 km/h. When links were removed in the shortest path to the destination with the largest demand (faculty of Aerospace Engineering), the travel time to and from this location increased 25%. As a result, the system capacity decreased 40% as vehicles were occupied 25% longer per trip and more energy is needed to operate the vehicles. The critical links in the network were the links which are part of the shortest paths for the largest demand flows.

Relocating empty vehicles (scenarios 3 and 4)

Given that in the base scenario, the system is not capable of serving all the demand during the peak hours, the efficiency of the system needs to be increased. The effectiveness of relocating empty vehicles during peak hours proved to be related to the direction of the demand pattern of the feeder line: during the morning peak, the majority of the passengers have the same origin (e.g. a train station) whilst in the evening peak large variations in the set of origins occur. Relocating empty vehicles during the off-peak hours does not necessarily lead to a reduction in average waiting time because, in the case-study, the demand in this period was very diverse, much smaller than on the peaks and two directional.

For the case-study, reductions of the daily average waiting time up to 40% were obtained with relocations, of which roughly 30% was obtained during the morning peak (scenario 3) and 10% during the evening peak (scenario 4). Relocating empty vehicles during the evening peak is less effective as the available fleet size is smaller due to charging requirements of the vehicles. As a side effect, relocating empty vehicles increases the system capacity as it reduces the average waiting time for a vehicle, and therefore reduces the total time in which a vehicle has occupants. Additionally, relocating empty vehicles leads to a slight decrease in vehicle occupancy, as all the vehicles are relocated to an origin corresponding to the dominant direction of the demand flow. Because not all demand is originating from the selected origin, some vehicles have to travel back from the relocation node to the requesting passenger location (e.g. during the morning peak 9% of the demand originates within the TU Delft campus, whilst all vehicles are relocated to Delft Zuid). Although the used relocation strategy is a relative simple one, it shows the potential of relocating empty vehicles. When network size increases, so does the complexity of the relocation strategy (Jorge et al., 2014).

Short term pre-booking (scenarios 5 and 6)

Short term pre-booking of vehicles aims to reduce the average waiting time of a passenger, by allowing the clients to pre-book a vehicle via a smartphone application. The pre-booking time has been varied from 1 up to 15 min during multiple simulation runs. A clear optimal short term pre-booking time has been found. This pre-booking time appeared to be equal to the average travel time in the network, which in the case-study was 7 min, as can be seen in Fig. 11.

In the case-study, the influence of two different shares of passenger populations which use pre-booking was studied. Allowing all passengers to use short term pre-booking (5), resulted in a reduction of 80% in the average waiting time. However, short term pre-booking reduces the available capacity of the ALMT system because vehicles are occupied for a longer time period. As a result, the capacity of the system was reduced 1.3%, this reduction occurs mainly during the peak hours when more demand than available system capacity exists. Considering the share of passengers who have a smartphone with access to the internet (65%) (scenario 6), a reduction in average waiting time of 58% was obtained. Again, the system capacity dropped 0.7%. As a side effect of the pre-booking setup, it was found that the probability of passengers who are not using pre-booking to find a vehicle strongly decreases.

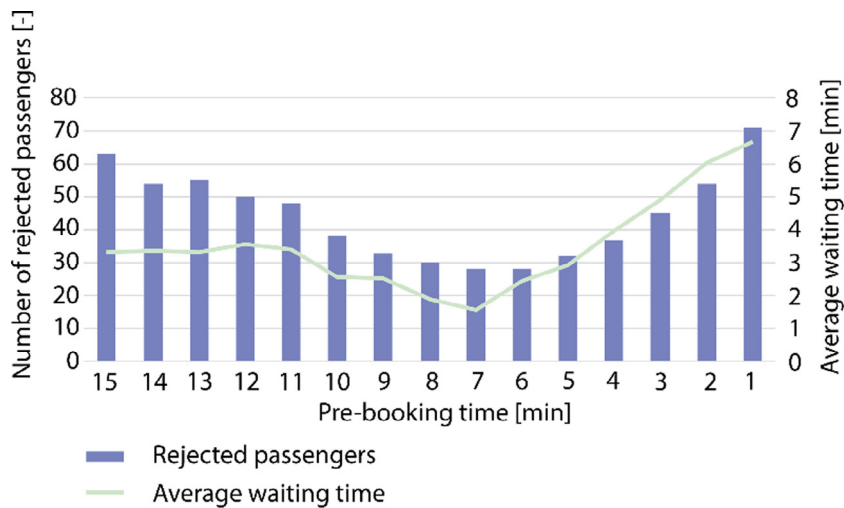


Fig. 11. Results of a comparison across different simulation runs.

Passengers are able to drive themselves (scenarios 7 and 8)

Allowing passengers to drive themselves (at a higher speed) has the potential to reduce the average travel times experienced by them. A reduction of 40% on the average travel time was obtained by allowing all passengers to drive the vehicle themselves (scenario 7). Due to the higher speed, the energy use of the vehicles increased 146%. With the increased energy usage, the vehicles require charging at an earlier point in time and therefore reduce the system capacity by 8%. Considering the percentage of public transport users who have a drivers' license (22%) (scenario 8), only a reduction in average travel time of 8.7% was obtained. Nevertheless, energy use of the vehicles increased 20%, leading to a capacity reduction of 1.7%. Allowing passengers to drive at a higher speed, whilst at the same time having the empty automated vehicles driving at a lower speed, requires overtaking. The observed vehicle densities of 15 veh/km per direction limit the available gaps in which an overtaking manoeuvre could be made moreover we are not even considering the bicycle traffic.

Opportunity charging (scenarios 9 and 10)

In the base scenario, the energy use of the vehicles is one of the important determinants of the available capacity of the ALMT system during the evening peak. In order to increase the available capacity, opportunity charging strategies have been simulated. Introducing extra regular chargers at multiple locations in the network (instead of only in the depot), a reduction in the number of vehicles that require charging during the evening peak was obtained. For the case-study, two locations were selected that have the largest demand (Depot near Delft Zuid and the faculty of Aerospace Engineering). Allowing opportunity charging with slow chargers increases the system capacity by 0.2%. At least 9 regular chargers were needed to charge the vehicles, of which a maximum of 6 chargers were used during the off-peak hours and 9 during the evening peak. The single "fast" charger in scenario (10) proved to be able to compete with the required 9 needed regular chargers in scenario (9). Installing a fast charger in the network results in an increase in system capacity of 0.6%. Fast chargers are only able to charge vehicle batteries up to 80%, the amount of energy that needs to be recharged at the end of the day is 10% higher compared to the base scenario. However, this does not influence the system performance on the last mile as recharging of the vehicles occurs overnight, whilst no vehicles are in operation. This increase in system capacity appears to be small, but it shows the potential to apply this method together with other system settings (e.g. higher speeds).

Conclusions and directions for further research

The research on the last mile in public transport trips has shown that in many cases this stage of a trip is inflexible and slow, therefore representing considerable disutility in a public transport trip. Thus the last mile is one of the main deterrents for a public transport mode to be able to take demand from private vehicles. PRT systems aspire to solve the last mile by delivering a fast, direct, on-demand, automated mode of transport on segregated guideways. However, as conventional PRT systems are bound to segregated guideways, these systems face high investment costs and low flexibility in routing of vehicles. As AVs are able to operate on any kind of road, the ALMT system, that has been proposed in this research, can be characterized by being a PRT system with the advantage of being able to drive everywhere including cycle paths. The use of existing infrastructure reduces investment costs and creates a high flexibility with regard to the routing of the vehicles.

A simulation model was proposed for the ALMT system in which the main component is the interaction between the vehicles and the passengers of the ALMT system in a road network. A dispatching algorithm distributes travel requests amongst the available vehicles using a FIFO sequence and selects a vehicle based on a set of specified control conditions (e.g. travel time to reach a requesting passenger). This concept has been programmed as an agent-based simulation model in the software AnyLogic.

Simulations have been done for the case-study of the connection between the train station Delft Zuid and the Technological Innovation Campus (Delft, The Netherlands). The system performance is measured at three different levels (passenger, vehicle, and system). The most important output parameters are the system capacity, average travel time and average waiting time.

It was possible to conclude that four of the presented operational strategies positively influence the last mile performance (in terms of system capacity and travel time) of the ALMT system. This positive influence may lead to a better competitive position of the automated transit with regard to the other modes of transport for the last mile. It is expected that when incorporating empty vehicles relocation, intermediate charging of the vehicles and allowing a higher operational speed in the system specifications, the ALMT system is able to compete with the both bicycle and walking in terms of travel time on the last mile as these measures have the potential to reduce both the average travel time and waiting time. Considering the case-study, a reduced average total travel time of 6 min and 45 s is estimated. This time could be further reduced by allowing pre-booking, but this would require more vehicles to serve the same demand. The travel time estimate is based on the expectation that intermediate charging of the vehicles can compensate the reduction in system capacity as a result of the higher operational speed. If this appears not to be true the average total travel time is expected to be equal to the average travel time by cycling. The given estimate indicates the potential for the ALMT system as a last mile system, as it can compete with the walking mode, and when a speed increase is possible, the ALMT system should also be capable of competing with cycling, resulting in a fast and flexible last mile transport mode.

The main limitation of the simulation model is the lack of interaction between vehicles and other road users. It is expected that this interaction will influence the performance of the ALMT system on the last mile, as congestion on links or at stops could arise. Therefore, this should be incorporated in the further development of the simulation model. To further improve the vehicle behaviour, acceleration, and deceleration, merging, overtaking, car following should be incorporated.

As the potential market is larger than only the travellers between Delft – Zuid and the TU Delft campus a mode choice model should be incorporated and the OD-matrix should be extended to a higher spatial level. This way comparing mode alternatives is incorporated instead of assuming a fixed demand size for the automated vehicles between Delft Zuid and the TU Delft campus.

Relocating empty vehicles was done towards the major expected demand which means that the largest share of the demand experiences benefits from relocating vehicles. However, with an algorithm which distributes the vehicles in the network in a more accurate way, by considering all locations for which demand is expected, this may lead to even further gains. With short term pre-booking, limitations were faced with regard to the occupied time of the vehicle. It would be beneficial for the system performance to know the pre-booking behaviour of the passengers in advance hence research on that topic should also be done.

It is expected that higher capacity vehicles can bring advantages (both operational and economical) as economies of scale can be obtained. With these vehicles, multiple passengers with similar directions can be bundled together. However, these vehicles would require centralized routing, as the routing process becomes much more complex. With a centralized routing algorithm, the ALMT system has the opportunity of incorporating congestion information in the routing of the vehicles. As AVs do not require any specialized infrastructure (such as trams) they have the possibility to operate on any kind of road available, the vehicles of the ALMT system have the opportunity to avoid congestion, which is expected to be beneficial for the system performance.

The ALMT system has been assessed on the performance of the last mile in a public transport trip from an operational point of view. However, for the system to be economically feasible, a cost-benefit analysis should be done to assess the economic viability of the system. The simulation model has been set up such that it can be used as a reference to produce some indicators needed for such cost-benefit analysis. However, in order to do so a mode choice model should be incorporated to also capture the potential market (the travellers who are currently not travelling via Delft Zuid).

Acknowledgments

The authors would like to thank ProRail, the train infrastructure manager of the Netherlands, for funding the ALMT100% EV project under which this study has been carried out.

References

- Andreasson, I., 2011. *Personal Rapid Transit As Feeder/Distributor to Rail*. Royal Institute of Technology (KTH). Centre for Traffic Research.
- Bonabeau, E., 2002. Agent-based modeling: Methods and techniques for simulating human systems. *Proc. Natl. Acad. Sci. U.S.A.* 99, 7280–7287.
- CBS.nl. (2015, 11 11). CBS. Opgehaald van Aandeel verkeersdeelnemers; geslacht en persoonskenmerken: <http://statline.cbs.nl/Statweb/publication/?VW=T&DM=SLNL&PA=81125ned&D1=a&D2=0&D3=a&D4=1->.
- CBS.nl. (2015, 11 11). Steeds vaker, laptop, smartphone en tablet in huis. Opgehaald van CBS.nl: <http://www.cbs.nl/nl-NL/menu/themas/vrije-tijd-cultuur/publicaties/artikelen/archief/2013/2013-3926-wm.htm>.

- Cisco. 2013. Cisco Customer Experience Research – Automotive Industry. Cisco.
- Correia, G., Antunes, A.P., 2012. Optimization approach to depot location and trip selection in one-way carsharing systems. *Transport. Res. Part E: Logist. Transport. Rev.* 48, 233–247. <http://dx.doi.org/10.1016/j.tre.2011.06.003>.
- Correia, G., Milakis, D., van Arem, B., Hoogendoorn, R., 2015. Vehicle Automation and Transport Systems Performance. *Handbook on Transport and Urban Planning in the Developed World*. Edward Elgar Publishing Limited.
- Dijkstra, E., 1959. A note on two problems in connection with graphs. *Numer. Math.*, 269–271
- Fagnant, D., Kockelman, M., 2015. Dynamic ride-sharing and optimal fleet sizing for a system of shared autonomous vehicles. *Transportation Research Board*.
- Jorge, D., Correia, G., 2013. Carsharing systems demand estimation and defined operations: A literature review. *Eur. J. Transport Infrastruct. Res.* 13, 201–220.
- Jorge, D., Correia, G.H.A., Barnhart, C., 2014. Comparing optimal relocation operations with simulated relocation policies in one-way car sharing systems. *IEEE Trans. Intell. Transp. Syst.* 15, 1667–1675. <http://dx.doi.org/10.1109/TITS.2014.2304358>.
- Liang, X., Correia, G., van Arem, B., 2016. Transportation Research Part E: Logistics and Transportation Review. Vol. 93 (September), pp. 115–129.
- Mageean, J., Nelson, J., 2003. The evaluation of demand responsive transport services in Europe. *J. Transport Geography*, 11.
- Martinez, L., Correia, G., Viegas, J., 2014. An Agent-based simulation model to assess the impacts of introducing a shared-taxi system. *J. Adv. Transport.*, 49, 475–495.
- Martinez, L., Correia, G., Moura, F., Lopes, M., 2016. Insights into carsharing demand dynamics: outputs of an agent-based model application to Lisbon, Portugal. *J. Sustain. Transport.*, in press.
- Mueller, K., Sgouridis, S., 2011. Simulation-based analysis of personal rapid transit systems: service and energy performance assessment of the Masdar City PRT case. *J. Adv. Transport.*, 45, pp. 252–270.
- PRT, 2015. Ultra Global Simulation. (PRT, Producent) Opgeroepen op 11 19, 2015, van <http://www.ultraglobalprt.com/about-us/library/ultra-simulator/>.
- Schweizer, J., Fabian, L., 2005. The Case for Personal Rapid Transit. Boston Advanced Transit Association.
- Treinreiziger.nl. (2015, September). Aantal in- en uitstappers per station. Opgehaald van Treinreiziger.nl: http://www.treinreiziger.nl/kennisnet/reizigersaantallen/cijfers/aantal_in-en_uitstappers_per_station-147203.
- van Arem, B., van Oort, N., Yap, M., Wiegman, B., Correia, G., 2015. Opportunities and challenges for automated vehicles in the Zuidvleugel.
- Vuchic, V., 1996. Personal Rapid Transit: An Unrealistic System. *Urban Transport Int.*, 7.
- Wang, H., Odini, A., 2012. Approximating the Performance of a “Last Mile” Transportation System. *Massachusetts Institute of Technology, Civil Engineering and Environmental Engineering*.
- XPrize, 2007. The car equation. Opgehaald van XPrize.org: <http://autoblog.xprize.org/axp/2007/10/the-car-equatio.html>.
- Yap, M., Correia, G., van Arem, B., 2016. Preferences of travellers for using automated vehicles as last mile public transport of multimodal train trips. *Transport. Res. Part A: Policy Practice* 94, 1–16.
- Young, S., Miller. (2003). Travel demand modelling of automated small vehicle transit on a university campus. *Mid Continent Transportation Research Symposium*. 21 of August 2003. Ames, Iowa, USA.