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Performance analysis and fleet requirements of automated demand-responsive transport systems as an urban public transport service

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ABSTRACT

The introduction of public transport services by fully automated vehicles can potentially change the way public transit services will be operated, as they allow shifting from rigid scheduled and route-bound services towards flexible, demand-responsive services. This study examines the potential performance of an *Automated Demand Responsive Transport Service* (ADRTS) as a replacement for scheduled bus services and simulates the effects of demand levels, vehicle capacity, vehicle dwell time and the initial vehicle distribution on system performance in terms of fleet size and system costs. The simulation tool allows simulating the operation of the ADRTS in a complete graph and is applied to the case study of Arnhem, the Netherlands. For this case study it has been shown that for a minimum fleet size following the imposed constraints, the operational costs range between 0.84 and 1.22 Euros and the average passenger wait time ranges between 2 and 6 min, according to the assumptions made on demand and operational parameters. The operational costs of the ADRTS showed to be in the same range of the current bus system, while providing a demand-responsive transport service with an average waiting time of around 4 min per passenger-trip. The economies of scale, which play an important role in public transport, are also apparent in the simulated ADRTS operations.

1. Introduction

The development of automated driving technology advances rapidly and automated vehicles (AVs) are commonly assumed to play a significant role in transport systems of the future (Alessandrini et al., 2015; Benevolo et al., 2016; Correia et al., 2016; Lam, 2015; Wang, 2015). The advancement of AVs potentially poses both opportunities and threats to conventional public transport systems. On one hand, if AVs rapidly enter the private car market, offering greater comfort and potentially productive travel time, public transport ridership may decline leading to efficiency losses. On the other hand, AVs pave the way for significantly reducing the operational costs of public transport services which are often dominated by driver labour costs. Moreover, the introduction of AVs into public transport services have the potential to revolutionize the way in which public transport services are provisioned and consumed by facilitating a shift into more flexible and demand

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responsive modes of operations. Conventional public transport systems offer scheduled services in rigid networks, in which passengers have to adjust their travel plans accordingly.

In this paper we envision an *Automated Demand Responsive Transport System* (ADRTS) which dynamically responds to travel requests using a centrally dispatched fleet of highly automated vehicles. The flexible and lower-capacity service enabled by ADRTS can potentially substitute conventional public transport in networks characterized by low to moderate levels of many-to-many demand pattern and where labour costs make the network-wide provision of DRT services prohibitive. Hitherto, demand-responsive services have proven to be exceptionally cost-intensive and therefore not economically viable beyond very low-demand or except for premium services, and usually require exceptionally high subsidy levels in developed countries which are characterized by high labour costs (Ferreira et al., 2007; Fu, 2002; Sayarshad and Chow, 2015).

The operation of an ADRTS is evaluated using a simulation model that allows assessing operator and passenger costs under alternative system specifications and scenarios. The main contributions of this study are: (1) determining the fleet size that will minimize ADRTS system (i.e. passenger and operational) costs under given constraints on maximum passenger waiting time; (2) determine the minimum fleet size for operating an ADRTS as a substitute to current public transport, and; (3) benchmark the passenger and operational costs to the existing bus system as well as a non-automated DRT system. To the best of our knowledge, ADRTS have not been modelled as a substitution for an existing urban public transport network. Previous studies have either assumed ADRTS to serve all demand for mobility and offer a door-to-door service (i.e. automated taxi) or considered a single corridor or feeder service operations.

The ADRTS is simulated for a case study based on the city of Arnhem in the Netherlands, for which the influence of demand, vehicle capacity, vehicle dwell time and the initial vehicle location on the system performance is analysed in terms of operational costs as well passenger generalized travel costs. Given the novelty of AV, assumptions made on the operational and cost parameters are of a speculative nature and the results presented in this paper should be therefore viewed as a first glimpse on the impact the introduction of AV might have on public transit services.

The paper is organized as follows: In Section 2, we review the automated public transport landscape with respect to emerging mobility solutions, taxonomy of ADRTS and the literature on modelling ADRTS. In Section 3, the ARDTS envisioned in this study is described along with the approach adopted in this study for modelling its operations. The case study and the scenario design are described in Section 4, followed by the results. We conclude with a discussion of the results, the limitations of the study and suggestions for further research.

2. The automated public transport front

2.1. Emerging new mobility solutions

In the last decade, new technological and societal mobility trends emerged, which could be potential game changers for both private and public transport. These trends include the advancement of vehicle automation, the rise of shared economy and growing urbanization which constitute important features in the portrait of so-called smart cities. At the time writing, technology is not yet mature enough to allow the deployment of such full-scale systems. However, current trends suggest that this may be a reality in the coming decade where planning and operational principles for such systems are still lacking. Pilot studies and trials worldwide have shown that automated vehicles (AVs) of all levels are operational and fully automated vehicles are expected to become part of the vehicle fleet in the not so distant future (Alessandrini et al., 2015).

Experiences with automated mass transit, sharing the infrastructure with non-automated vehicles and having limited guidance, have also been tested in several pioneering pilot studies (Alessandrini et al., 2014; Anderson et al., 2014; Christie et al., 2015; ERTRAC (European Road Transport Research Advisory Council), 2015; Fagnant and Kockelman, 2015; WEpods, 2016). These pilot trials operated single line connections between pre-determined pick-up and drop-off nodes. Such experiments are necessary not merely for testing technology but are also instrumental in examining travellers' sensitivity to its characteristics, such as the absence of a driver and service interface and flexibility.

2.2. Taxonomy of automated demand-responsive transport service

Several public transport systems designed for being operated with AVs have been described in the literature in recent years (Brownell and Kornhauser, 2014; Burns et al., 2013; Fagnant et al., 2015; Fagnant and Kockelman, 2014; International Transport Forum, 2015; Spieser et al., 2014; Zhang et al., 2015). The ADRTS described in these studies can be classified using the following four service dimensions (Winter et al., 2016):

- *Accessibility:* ADRTS can provide stop-to-stop services or door-to-door services.
- *Directness:* a distinction can be made between direct services (no transfers and no intermediate stops) and network services (several fully or partly predefined routes with multiple stops and transfer locations).
- *Vehicle sharing:* vehicles can be shared in space when multiple people ride the same vehicle or in time where a vehicle can be used by different individuals sequentially.
- *Demand responsiveness:* different degrees of demand responsiveness and restrictions on passenger waiting times can be specified.

2.3. Modelling automated demand-responsive transport systems

As the research on operating ADRTS is only at its beginning, there is no established method to model or simulate ADRTS yet. This is presumably also related to the complexity of dynamically operating a large fleet of vehicles in a demand-responsive fashion. It is especially challenging to establish an optimization method for solving the dynamic DRT vehicle routing problem with time window constraints because small changes in the solution structure can result in highly infeasible solutions (Urra et al., 2015). Research in this field currently focuses on the implementation of new data sources and data transmitting technology, large scale applications and ride-sharing in urban areas (Chassaing et al., 2016; Li et al., 2016; Martinez et al., 2015; Muelas et al., 2015; Sayarshad and Chow, 2015).

Models of ADRTS borrow from concepts of modelling PRT, taxi fleet management, dynamic DRT systems and Dial-a-Ride problems. Previous studies applied various approaches for modelling ADRTS, including analytical models (Brownell and Kornhauser, 2014; Jokinen, 2016; Liang et al., 2016; Spieser et al., 2014), simulation models (Burns et al., 2013; Fagnant et al., 2015; Fagnant and Kockelman, 2014; International Transport Forum, 2015). The level of detail in these models ranged from generic grid networks to detailed transport models; the simulated fleet sizes varied from a couple of hundred vehicles to several million vehicles. The most commonly applied technique is simulation, as this allows to include stochastic passenger generation, stochastic travel times, dynamic vehicle assignment and dynamic vehicle relocation strategies, hence increasing the realism of such models. Fagnant and Kockelman (2015) for example used an agent-based simulation to study the implications of having a fleet of AVs for serving urban mobility needs. The current typical carsharing modal share of 3.5% of all trips was assumed. They tested different operational scenarios for the city of Austin. They concluded that each AV would be able to replace 11 conventional vehicles but could induce 10% higher mileage due to empty trips. Fleet size requirements and the level of service obtained under different scenarios were not evaluated. Using the same technique, a model has been developed to test the introduction of automated taxis that will fully substitute the existing car fleet to satisfy transport demand in the mid-sized European city of Lisbon, Portugal (International Transport Forum, 2015). Results showed that fleet size always decreases, albeit no systematic assessment of the implications of alternative fleet size was performed. The traffic implications and potential congestion resulting from using such large automated fleets in an urban environment were neglected. An agent-based simulation for Singapore analysed the impact of substituting private cars with automated taxis while taking into account their impact on traffic as well as the responsiveness of demand based on the system performance (Azevedo et al., 2016). The results show a decrease in the mode share of private cars when replaced with automated taxis. Mendes et al. (2017) investigated the potential of ADRTS to substitute a single streetcar line. The results of this study suggest that in order to replace 39 streetcar vehicles, 500 automated mini-busses are needed in case of line-based operations and 450 if operating as a demand-responsive system when aiming at achieving the same average waiting times. Winter et al. (2016) found that the performance of ADRTS operated as a shuttle service is very sensitive to the stochastic properties of the passenger arrival process. This stresses the urgency to develop and test robust system designs for ADRTS, which ensure that ADRTS are deployed where it is most suitable.

3. Model description

In order to gain a first understanding of the performance of ADRTS and the associated costs, we developed a simulation model for the ADRTS. In this chapter the system configurations for the simulated ADRTS and the modelling approach are described. A particular emphasis in terms of the modelling approach is put on the description of the strategy applied to assign vehicles to passenger requests, which is a crucial problem of demand responsive systems.

3.1. Description of the simulated automated demand-responsive transport system

The system simulated in this study is defined as a demand-responsive direct stop-to-stop service, in which vehicles are shared simultaneously. Restrictions are set for the average and individual passenger waiting time. System components are the network in which the ADRTS operates, passengers and the vehicle fleet.

A public transport network can be represented by a direct and labelled graph $G(S, E)$, where the node set Srepresents stations, which serve as pick-up and drop-off locations. The link set $E \subseteq S \times S$ represents direct connections between stations. Since the ADRTS system offers direct connections between each pair of pick-up and drop-off locations, G is a complete graph. The travel time associated with traversing link $e \in E$ is denoted by w_e.

The passengers served by the ADRTS request a vehicle at a pick-up station. Passenger request generation follows a Poisson distribution with an arrival rate $\lambda_{ij}(\tau)$ per pick-up station s_i per time interval τ, destined to drop-off station s_j. The generation time of request $r \in R$, occurring at the passenger arrival time at s_i, is denoted by t_r^a, where R is the set of passenger requests. The set of passenger requests is updated on each simulation step and is divided into R^s and R^p, the subsets of served and pending requests, respectively.

The ADRTS is operated by a vehicle fleet V. Each vehicle $v \in V$ is either stationary or travelling between two stations. Vehicle departure time from station $s \in S$ is denoted as $t_{v,s}^d$ and the arrival time as $t_{v,s}^a$. Each vehicle has a fixed passenger capacity q_v and a variable on-board passenger occupancy o_v.

The control procedure assigns a vehicle to serve passenger requests, which results in a sequence of requests assigned to a vehicle over time $R_v = r_{v,1}, r_{v,2}, \ldots, r_{v,n}$ where $R_v \subseteq R$. Passenger requests with the same pick-up and drop-off station are combined as long as the capacity constraint is not violated. Upon arrival at a pick-up station s_i, the vehicle waits for a pre-defined dwell time t_v^{dwell} before departing at time t_v^d. During this time, the bundling of passenger requests is permitted. If the number of passengers in a dwelling vehicle reaches vehicle capacity $(o_v = q_v)$ before the vehicle has spent the time t_v^{dwell} at a pick-up station, the vehicle departs immediately. Because of this mode of operations, passengers experience in addition to waiting time, also vehicle dwell time before departing. The total time that a passenger spends stationary at the station is denoted as passenger idle time, defined as $t_r^{idle} = t_v^d - t_r^a$ where $r \in R_v$. After arriving at the drop-off node, a vehicle remains stationary until it gets assigned to the next passenger request. Vehicles are not cruising emptily or relocate strategically when idle, the here discussed ADRTS is thus operated in a non-anticipatory manner. The simulated performance of the ADRTS is thus obtained for a service with simplified features, and must therefore be considered as a lower bound of the potential performance that could be achieved with a smarter use of the ADRTS.

3.2. Modelling Approach and Model Architecture

A model is developed for simulating the operation of the ADRTS, including the process of assigning vehicles to passenger requests. The simulation tool determines the minimum fleet size and the fleet size leading to the minimum system costs (Formula 1) and the associated operational and passenger travel costs in an iterative manner. A flowchart of the main simulation process is shown in Fig. 1 and described in the following sub-sections.

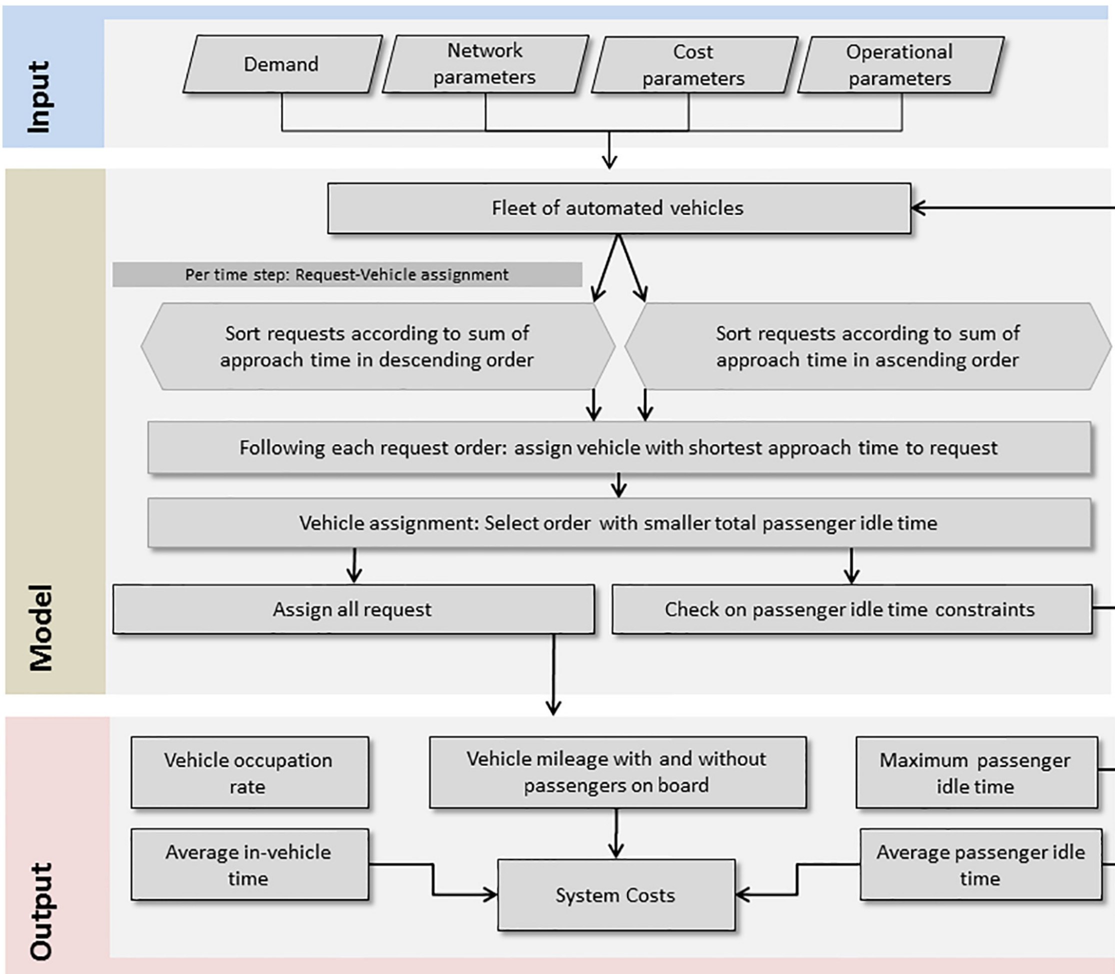

Fig. 1. Flowchart of the main simulation process.

3.2.1. Objective and cost functions

The model searches for the fleet size that minimizes the total system costs by repeatedly simulating the operation of the ADRTS for an increasing fleet size until the minimum system costs are achieved, as indicated in the loop in Fig. 1. The system costs comprise the operational costs c^o and the passenger generalized travel costs c^t. The objective function is thus:

$$z = \min(c^0 + c^t) \tag{1}$$

The operational costs c^o are in turn comprised of fixed costs c^f for the infrastructure necessary to operate the ADRTS, maintenance cost c^m for each of the vehicles in the fleet of fleet size ($|V|$), as well as annuity depreciation costs c^d and energy costs c^e for all vehicles for the total driven mileage m. The operational costs can be therefore calculated as:

$$c^o = c^f + c^m * (|V|), \; +(c^d + c^e) * m \tag{2}$$

Passenger generalized travel costs include total passenger in-vehicle time $t^{ivt}$and total passenger idle time t^{idle}:

$$c^t = \beta^{VOT} * \sum_{r \in R} (\beta^w * t_r^{idle} + t_r^{ivt}) \tag{3}$$

where $\beta^{VOT}$is the value-of-time, β^w is the waiting time coefficient for the idle time at the pick-up node and t_r^{ivt} is the time passenger r spends travelling in-vehicle. Less straight-forward cost items on the passenger side such as reliability, comfort or perceived safety are not included in the cost function as their quantification for shared automated vehicles is currently even more speculative than time-related aspects.

Travel times are assumed to be deterministic based on the shortest path between each pair of origin–destination. The minimisation is thus aiming at the fleet size ($|V|$), the total driven mileage (m) and the total passenger idle time $\left(\sum_{r \in R} t_r^{idle}\right)$. Since vehicles always use the shortest route, the driven mileage depends solely on trip chaining. To minimize the other two system variables, the ε-constraint method has been selected, which delivers a solution close to the Pareto optimum. This method allows to minimize one variable while the others are set as hard constraints (Caramia and Dell'Olmo, 2008). This approach is suitable in this case as pre-determined constraints on passenger cost is a common element in public transport concession contracts (Van Oort, 2014) and thus it is reasonable to assume that it would be applied when introducing ADRTS as a public transport service. In this case the constraints refer to the average passenger idle time, which should not exceed 10 min, and the individual passenger idle time, which should not exceed 30 min. These constraints allow obtaining a clear image on passenger waiting time distributions in the here analysed ADRTS.

The simulation outcome is interpreted in two ways: (a) in terms of the minimum fleet size $|V^{min}|$, which is the fleet size necessary for serving the demand while satisfying the pre-defined time constraints, and; (b) in terms of the fleet size leading to the minimum system costs, $|V^*|$.

3.2.2. Assignment process

The process of assigning vehicles to passenger requests has an impact on the performance of the ADRTS. An event-based simulation model is developed to match free vehicles to currently open requests in each simulation step. This process is based on a myopic vehicle allocation procedure to establish the lower bound of system performance.

First the required approach times for all vehicles to all pending requests in R^p are determined from a travel time matrix based on the shortest path. Vehicles currently in service are also considered in this process, based on their expected arrival time at the drop-off location of their current passenger(s) in combination with the expected travel time from that location to the pick-up destination of the new request. This results in a matrix of the required approach time for each pending travel request by each vehicle. Then, the order in which a vehicle is assigned to an open request is determined by sorting the pending requests by the sum of the approach times of all vehicles once in a descending and once in an ascending order, as shown in Fig. 1. The rationale behind this approach is to allow in each time step the possibility to select between two assignment strategies: (1) *Short-First Strategy* – it can be beneficial to serve requests with short approach times first, at the cost of additional waiting time for passengers requesting the service of the ADRTS at nodes with longer approach time. This will lead to a large number of passengers experiencing very short idle times and a small number of passengers experiencing long idle times; (2) *Long-First Strategy* – it can however also be beneficial to keep the maximum passenger idle time as short as possible, which implies that requests with longer approach times get served first, which might increase the idle time of passengers at nodes with initially short approach times. Either way, it is always the vehicle with the shortest travel time to approach the pick-up node of a request which gets assigned to the request. Both strategies are myopic but have different implications on passenger idle time distribution.

Once all passenger requests or all vehicles are assigned, the sum of all passenger waiting time in passenger-minutes for all assigned requests is calculated for each list. The assignment order leading to lower total passenger waiting time is selected. There are thus no priority rules with respect to request generation time (e.g. *FIFO*). There is also no explicit prioritization of high-demand pick-up nodes, although this is indirectly attained by basing the assignment order on the sum of all passenger waiting times. All requests assigned to a vehicle in this process are added to the dynamic sub-set of served requests R^s, requests that have not been assigned remain in the dynamic subset of pending requests R^p. If a passenger request does not get served within the predefined constraining waiting time, the fleet size is considered to be infeasible and the simulation is started anew with an increased fleet size (Fig. 1).

4. Model application

4.1. Case study description

The model described in Section 3 was applied to a real-world case study in order to test the viability and potential performance of an ADRTS under various scenarios. The case study is based on the city of Arnhem in the Netherlands, which has around 150,000 inhabitants. Arnhem's current urban public transport system consists of 15 bus lines, some of which are operated by trolley busses. On an average working day in November 2014, more than 32 thousand passenger trips were recorded in the smartcard validation database. An origin–destination matrix estimated based on smartcard records was available from the regional transport planning authority. The demand matrix consists of 26 postal zones with the distances between the centroids of the postal code areas of Arnhem. For the purpose of analysing ADRTS performance and costs in the event that it fully substitutes an urban line-based service and the respective demand level, the currently observed demand level is used as a base case. In the absence of a mode shift model for forecasting induced demand, the passenger demand matrix assigned to the ADRTS is thus inelastic. The implications of changes in the demand level on the resources required and the level of service obtained are also investigated.

The network for the case study consists of these 26 nodes and is modelled as a complete bi-directional graph with direct links between all nodes, with distances ranging between 1.2 and 15.9 km between the nodes. Passenger generation rates are assumed to uniformly follow a common temporal distribution featuring morning and evening peak periods. For computational reasons, only the four-hour long morning peak hours are simulated, which results in a total of 11,697 simulated passenger trips. Fig. 2 depicts the case study area along with the average hourly passenger generation rate for each zone during the analysis period.

Also in terms of the vehicle characteristics, the input data is based on the vehicles employed in the WEpods project, a modified version of the EZ-10 vehicles manufactured by the EasyMile Company (WEpods, 2016). The vehicle is assumed

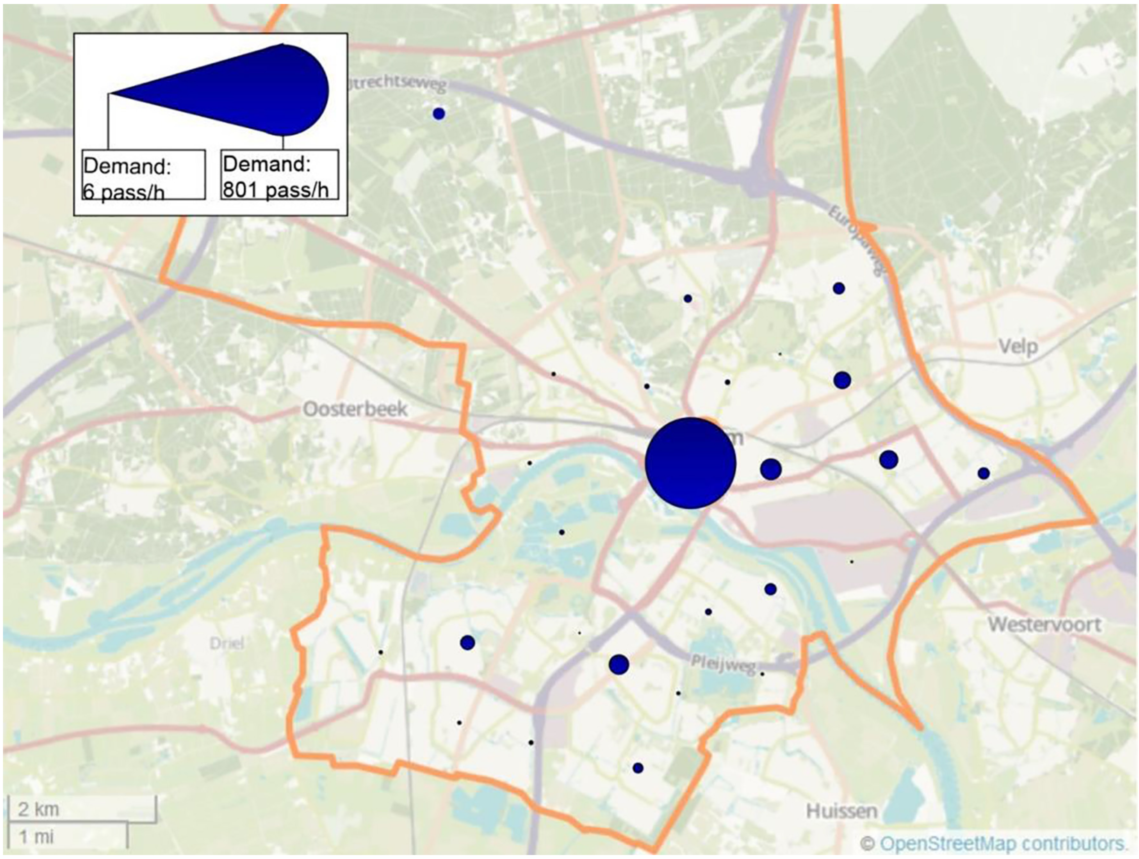

Fig. 2. Demand distribution in the case study area. Map data © OpenStreetMap contributors, CC BY-SA.

to travel with an average speed of 30 km/h, excluding dwell times. The ADRTS speed is comparable to the one attained by current bus services in Arnhem while serving fewer stops, thus leading to a higher commercial speed. Based on this speed and the current battery capacity of the EZ-10 vehicle, a battery range of 630 km is assumed, the charging time of an empty battery is assumed to be 8 h. The investment costs for the vehicles, as well as all costs linked to the operation of the vehicles, are of a speculative nature as AVs are not yet object of mass production and only very little field experience has been gained with these vehicles. The following cost estimates derive from the experience in the WEpods project. The purchase price for the WEpods vehicles was 200,000 Euro (Krebbekx, 2016). Taking into account potential quantity discounts, the purchasing price for the ADRTS vehicles used in a network service is set to 150,000 Euro per vehicle, neglecting potential price differences between vehicles with various passenger capacity.

The assumed depreciation costs of 0.12 Euro per driven kilometre are based on a wear life span of 10 years, or 1.22 million driven kilometres, and a salvage value of 5% per year. The energy costs for the electric vehicles are set to 0.01 Euro per kilometre. Insurance costs are set to 3.33 Euro per day, per vehicle and maintenance costs to 10 Euro per day per vehicle. The system operational cost, independent of the fleet size, consists of the costs for the controlling staff and their equipment. It is assumed that the system can be operated with six system controllers with a yearly salary of 60,000 Euro per employee per year and the cost for the equipment is assumed to be 40,000 Euro per year. This leads to fixed costs of 1096 Euro per day. The overall cost function per day for the operational costs of the case study are thus:

$$c^o = 1096\left[\frac{euro}{day}\right] + 13.33\left[\frac{euro}{day}\right] * q + \left(0.12\left[\frac{euro}{km}\right] + 0.01\left[\frac{euro}{km}\right]\right) * m\left[\frac{km}{day}\right] \tag{4}$$

Passenger generalized travel costs are calculated based on the Dutch value of time (*VOT*) of 8.75 Euro for passengers, adopting the values for surface transport (Significance et al., 2012). As ADRTS or comparable systems are not operational yet, only assumptions of the VOT for users of such a system can be made. Spieser et al. (2014) state that the VOT of automated transport services should be lower than for other modes as automated vehicles will presumably offer a particularly high comfort. First experimental findings on this matter were recently made using stated choice experiments (Krueger et al., 2016; Winter et al., 2017; Yap et al., 2016). Notwithstanding, given the inconclusive results of these studies, a reliable VOT value for automated transport services has not yet been established. For this reason a conservative choice for the VOT value of 8.75 Euro has been made. The value of β^w is set to 2.5, reflecting the greater discomfort associated with waiting times in public transport (Wardman, 2004). This leads to the following cost function for passenger generalized travel costs:

$$c^t = 8.75\left[\frac{euro}{hour}\right] * (2.5 * t^w + t^{ivt}) \tag{5}$$

4.2. Scenario design and simulation requirements

To test the influence of alternative operational parameters on system performance, we simulated 21 scenarios as a sensitivity analysis. The following scenarios were tested and analysed:

- Vehicle capacity (*C*) – uniform for the whole fleet, ranging from 2 to 40 passengers,$\{2, 4, 10, 20, 40\}$.
- Demand level (*D*) – ranging between 50% and 150% of the initial demand,$\{0.5, 0.75, 1.00, 1.25, 1.50\}$.
- Vehicle Dwell time (*DT*) – ranging from 1 to 6 min,$\{1, 2, 3, 4, 5, 6\}$.
- Initial vehicle location (*IVL*) – equally distributed or stored at initial central depots (Fig. 3).

In order to test the influence of the in initial vehicle location on the system performance, three alternatives were tested (Fig. 3), of which the first alternative bundles all vehicles at one central node (IVL1) whilst the other two options feature two different set of five nodes selected over the service area (IVL5a and IVL5b), with IVL5a showing a wider spread of the vehicle depots over the city area then IVL5b.

For the base case, a vehicle capacity of 10 passenger, a dwell time of 3 min at the pick-up nodes and a random initial vehicle distribution were assumed. While the simulation model allows specifying a mixed fleet composition, a uniform vehicle capacity is specified to examine the interactions and implications of this design variable using a set of scenarios. In addition to varying each of the abovementioned variables while other variables remain unchanged, seven combinations of vehicle capacity and dwell time were investigated.

Model application requires the specification of a range of network and demand input as well as parameter values. The results of the simulations have to be discussed in the context of the assumptions made on the vehicle specifications, service operation and cost assumptions, the assumptions made on the input parameters are summarized below for the convenience of the reader (Table 1).

For each scenario, an exhaustive search was performed to determine all fleet sizes that yield a feasible solution, based on which the minimum fleet size and the solution yielding the minimum system costs are determined. For each solution, 20 simulation runs were conducted in order to attain statistically robust results. Using passenger waiting time, an outcome of vehicle assignment and the stochastic passenger generation process, 20 repetitions yielded a confidence interval of 99% in a Student's *t*-test. A solution is considered feasible only if all waiting time constraints are satisfied in all 20 simulation runs.

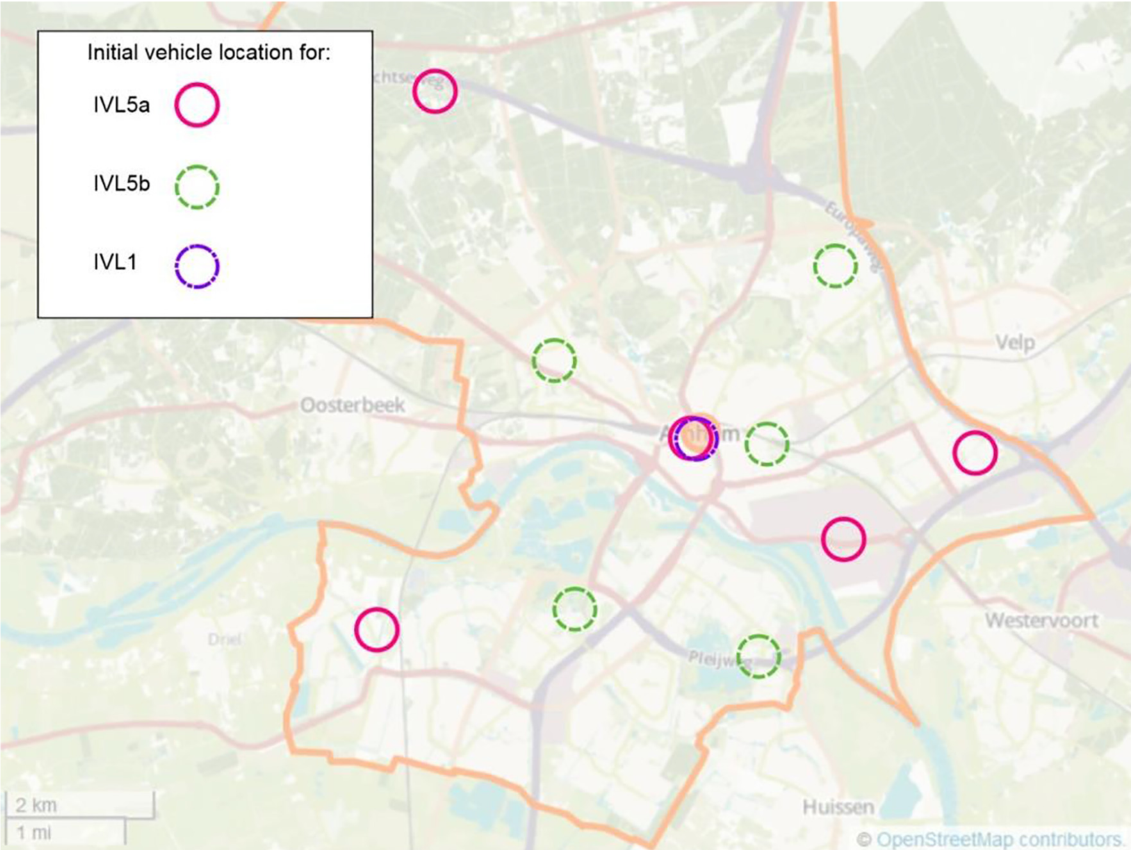

Fig. 3. Initial vehicle distribution. Map data © OpenStreetMap contributors, CC BY-SA.

Table 1
Summary of the input specifications in the case study application.

Case study	
Demand in the morning peak hour	11,697 trips (sensitivity analysis: 50–150%)
Network	26 nodes, between 1.2 and 15.9 km apart
Initial vehicle depots	5 depots (sensitivity analysis: 1–5 depots)
Vehicle specifications & service operation	
Vehicle speed	30 km/h
Vehicle capacity	10 passengers (sensitivity analysis: 2–40 passengers)
Vehicle life span	10 years
Battery range	630 km
Battery charging time	8 h
Vehicle dwell time per pick-up/drop-off	3 min (sensitivity analysis: 1–6 min)
Cost assumptions	
Value-of-Time of in-vehicle time	8.75 Euro
Value-of-Time of waiting time	21.88 Euro
Cost for staff and control centre per day	1096 Euro
Purchase cost per vehicle	150,000 Euro
Salvage value per year	5%
Energy cost per km	0.01 Euro
Insurance cost per vehicle per day	3.33 Euro
Maintenance cost per vehicle per day	10 Euro

5. Results and discussion

5.1. Simulation results for the base scenario

In the following, the results for the 24 scenarios are presented in terms of minimum fleet size $|V^{min}|$, fleet size leading to the minimum system costs $|V^{*}|$ and a comparison of the system performance for an exemplary fleet size of 400 vehicles. The overview of the results concerning $|V^{min}|$ and $|V^{*}|$ is shown in Table 2. In both cases, the percentage change of the system costs per passenger-trip is compared with the base scenario, and the percentage of the operational costs out of the total system costs and the average passenger idle time per passenger-trip are shown (Table 2).

The computation time of the simulation of the ARDTS in the morning peak hours on a complete graph with 26 nodes varied between 6 and 10 s on a computer with an Intel® Xeon® processor CPU E5 1620 v3.

5.1.1. Minimum fleet size

For the base scenario, the minimum fleet size $|V^{min}|$ is 306 vehicles (Table 2). The system costs for the minimum fleet size are 3.37 Euro per passenger-trip, of which 19% (0.63) are operational costs and 81% (2.75) are generalized travel costs. More than half of the latter stems from passenger idle time (55%) and the rest is attributed to in-vehicle time (45%). When expressed in terms of driven vehicle mileage, the system costs are 0.85 Euro per kilometre. The average idle time per passenger per trip for this fleet size is 4.2 min, whereas the maximum observed passenger idle time is 21 min. For the simulated fleet sizes, no battery charging during a simulated day is required, as no vehicle's daily mileage exceeded the maximum range.

5.1.2. Minimum system costs

Lower system costs per passenger are achieved by increasing the fleet size up to the point where the marginal increase in operational costs exceeds the marginal decrease in the generalize travel cost (Fig. 4). The minimum system costs of 3.21 Euro per passenger are obtained with a fleet size of $|V^{*}| = 478$ vehicles. The average idle time per passenger per trip for this fleet size is 3.3 min with the vast majority of passengers waiting less than 3.5 min (Fig. 5). Since the curve of the system costs is very flat, we decided to indicate the fleet size leading to the lowest 1% of the average system costs in addition to the absolute minimum fleet size in Table 1. In the base case scenario, fleet sizes ranging between 435 and 564 yield system costs that exceed the minimum system costs by no more than 1%.

5.1.3. Vehicle occupation rate and empty trips

In addition to the passenger idle times, important indicators of the system performance of a public transport service are the vehicle occupation rate and, in particular in the case of demand-responsive services, the number of empty driven mileage. Figs. 6 and 7 present these indicators, respectively, for this base case scenario. The average use of the vehicle capacity per service trip (i.e. excluding empty trips), is presented as a percentage of vehicle capacity in Fig. 6. Vehicle occupancy rate is a key indicator of system efficiency (Fagnant and Kockelman, 2014; Fielding et al., 1978). In the base scenario it can be observed that the average vehicle occupancy is 4.4 passengers for the minimal fleet size. Vehicle occupancy decreases to an average of 4.1 passengers when deploying the fleet size that minimizes system costs. Vehicle occupancy rates moderately decrease for larger fleet sizes. This trend is caused by a reduction in passenger waiting times at pick-up nodes induces by a

Table 2
Results for scenarios concerning the vehicle capacity (C2–C40), the demand level (D75–D150), the dwell time (DT1–DT6) and the initial vehicle locations (IVL1–IVL5). Results are shown for the fleet size leading to minimum system costs and for the minimum fleet size ($|V^{*}|$; $|V^{min}|$).

Scenario	System costs per passenger-trip [€]	Percent change in system costs to base scenario	Percent of operational costs [%]	Fleet size	Average idle time per passenger-trip [min]
Base	3.21; 3.37	N.A.	32; 19	478 [435, 564]; 306	3.25; 4.18
C2	3.51; 3.58	9.35; 6.23	34; 32	601 [534–640]; 534	3.69; 4.15
C4	3.07 ; 3.11	−4.36; −8.90	31; 28	421 [411–421]; 349	3.05; 3.42
C20	3.53 ; 3.80	9.97; 12.76	36; 24	687 [655–768]; 324	3.51; 5.75
C40	3.60 ; 3.65	12.15; 8.31	38; 32	781 [691–865]; 578	3.49; 5.69
D50	3.93; 3.91	22.43; 16.02	34; 25	316 [252, 350]; 365	4.64; 5.14
D75	3.51; 3.97	9.35; 17.80	35; 23	396 [396, 506]; 332	3.62; 4.54
D125	3.02; 3.52	−5.92; 4.45	29; 25	491 [458, 520]; 305	3.13; 3.85
D150	2.90; 3.95	−9.66; 17.21	26; 31	425 [401, 582]; 235	3.10; 3.57
DT1	3.08; 3.20	−4.05; −5.04	39; 27	651 [587, 668]; 300	2.25; 3.78
DT2	3.12; 3.23	−2.80; −4.15	35; 26	555 [508, 575]; 299	2.74; 3.95
DT4	3.34; 3.40	4.05; 0.89	30; 25	485 [436, 485]; 319	3.86; 4.55
DT5	3.51; 3.53	9.35; 4.75	28; 24	438 [438, 452]; 319	4.49; 5.02
DT6	3.70; 3.71	15.26; 10.09	25; 23	392 [364, 426]; 340	5.34; 5.58
C2, DT1	2.82; 2.85	−12.15; −15.43	40; 37	530 [514, 558]; 477	1.61; 1.91
C4,DT1	2.64; 2.64	−17.76; −21.66	39; 38	478 [478, 490]; 478	1.35; 1.35
C2, DT2	3.16; 3.22	−1.56; −4.45	36; 34	562 [543, 568]; 497	2.69; 3.07
C4, DT2	2.80; 2.82	−12.77; −16.32	33; 31	374 [374, 402]; 347	2.24; 2.51
C20, DT4	3.62; 3.86	12.77; 14.54	33; 23	677 [606, 718]; 333	4.03; 5.96
C20, DT6	3.84; 4.04	19.62; 19.88	29; 22	568 [543, 609]; 333	5.16; 6.66
C40, DT6	3.84; 4.08	19.62; 21.07	29; 22	583 [554, 622]; 341	5.12; 6.75
IVL5a	3.51; 3.56	9.35; 12.76	35; 28	396 [396, 506]; 291	5.07; 5.88
IVL5b	3.02; 3.09	−5.91; −8.31	29; 24	491 [458, 520]; 327	4.10; 4.82
IVL1	2.90; 2.94	−9.66; −12.76	26; 23	425 [401, 582]; 352	6.22; 6.21

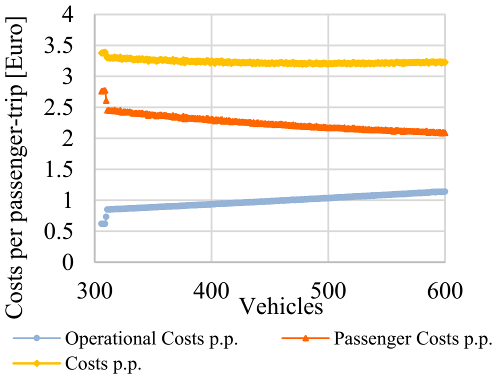

Fig. 4. Costs per passenger-trip (top, yellow diamonds), consisting of the sum of the operational costs (bottom, blue dots) and the generalized travel costs (mid-range, red triangles).

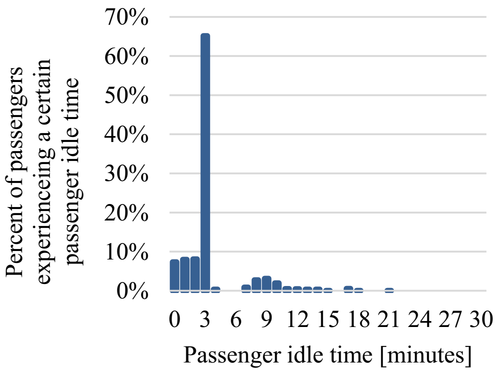

Fig. 5. Percent of passengers experiencing a certain idle time in minutes in the base scenario with 478 vehicles (minimum system costs).

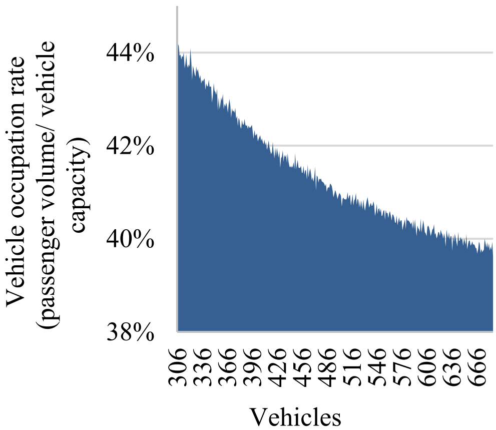

Fig. 6. Vehicle occupation rate (passenger volume/vehicle capacity) per fleet size in the base scenario.

larger fleet size, which leads in turn to a less efficient bundling of passenger requests. This relation is an outcome of the matching algorithm used in this study. A more advanced matching scheme can potentially improve the economies of scale in fleet assignment and therefore result with a different relation between fleet size and the average utilization rate of vehicles in service.

Since only 4 to 5 passengers share on average a vehicle designed for 10 passengers, vehicles are underutilized in the base scenario. The underutilisation of vehicles has a direct impact on the ADRTS performance because it prevents the early departure of vehicles, which can only occur if a vehicle is completely full before the end of the designated dwell time at a pick-up node. In a system operated by oversized vehicles, it is thus more likely that passengers experience the full vehicle idle time,

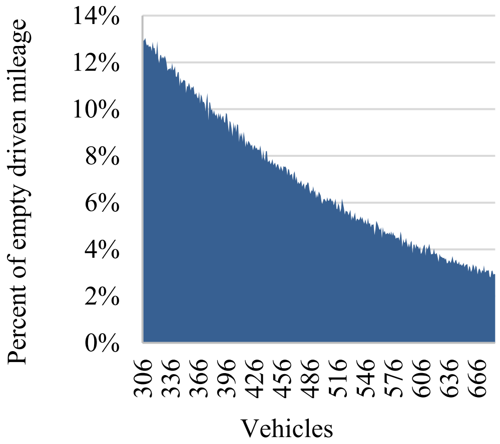

Fig. 7. Percent of vehicle mileage without passengers on-board per fleet size in the base scenario.

hence increasing passenger idle time. Notwithstanding, a low vehicle occupancy rate indicates that most passengers are served directly, which reduces the passenger waiting time. These observations concerning the influence of vehicle occupancy are confirmed by the observed passenger idle time distribution (Fig. 5) and by the outcomes of vehicle capacity scenarios, discussed in Section 5.2.

Another system indicator for public transport, which is particularly important for demand responsive services, is the share of empty rides or dead mileage. For the ADRTS, it can be observed that the larger the fleet size, the less empty mileage is required (Fig. 7). Here it can be seen that the percentage of empty mileage drops from about 13% for a fleet size of 306 vehicles to about 3% for a fleet size twice as large. The empty vehicle mileage decreases to around 7% of all trips when the fleet size is set to $|V^{*}|$. The decreasing trend for empty trips is explained by the initial vehicle distribution assumed in the base case: since vehicles are initially randomly distributed over all nodes, an increase of the number of vehicles leads to greater vehicle availability at all nodes. This allows offering more passengers a direct service without having to wait, and fewer empty vehicles have to be relocated to serve passengers requests at a pick-up node other than their current location. With a sufficiently large fleet size, empty trips can be avoided altogether. However, increasing the fleet size leads to a lower utilization of the available vehicles. For instance, vehicles are in use – either performing empty trips or serving passengers – in average for 98.3% of the simulation time for the minimum fleet size $|V^{min}|$ of 306 vehicles as determined in the base case of the case study. This rate declines to 58.5% for the fleet size $|V^{min}|$ of 478 vehicles, which implies that vehicles, in average, stand still for about 40% of the simulated period. The time vehicles stand still includes both, vehicle dwell time as part of the passenger boarding process as well as idle parking at the last drop-off while waiting for the next passenger-assignment. Averaged over the simulation period, this translates to approximately 200 vehicles parked at one of the 26 nodes of the simulated network.

5.1.4. Benchmarking system costs

The operational costs of the envisaged ADRTS are assessed by comparing the base case with the minimal fleet size to: (a) the reference case of the existing line-based public transport service in Arnhem, and; (b) a scenario where the demand-responsive system is operated in the exact same way as the ADRTS with the exception of being steered by human drivers. The existing public transport network in the case study area consists of 13 bus lines (Breng, 2017) operated by 57 buses per hour during the analysis morning peak period performing a total of 693.4 vehicle-km per hour. The busses and trolley buses in Arnhem are assumed to have the same cost function parameters as the ADRTS, with an additional cost item linked to drivers salaries, which are set to 25 Euros per hour. Thus, an operational cost of 0.68 Euro per passenger-trip is attained for the current bus service. The operational costs of the ADRTS of 0.63 Euro per passenger-trip is thus comparable to the costs of the operation of the current bus network, by offering a demand-responsive transport service with an average passenger idle time of only 4.2 min. That such a DRT system becomes infeasible when being operated by human drivers becomes apparent when adding drivers' costs. Assuming an hourly employment cost of 25 Euro per driver-hour based on Dutch labour market circumstances, operating the DRT system by human drivers instead of fully automated vehicles, the operational costs per passenger-trip would increase from 0.68 Euro to 3.24 Euro, reflecting an increase of approximately 300%. This clearly demonstrates that vehicle automation is a prerequisite for DRT services to become an economically sustainable alternative to line-based operations in urban contexts from a societal welfare perspective.

5.2. Passenger demand, vehicle capacity and dwell time

Passenger demand, vehicle capacity and vehicle dwell time are expected to strongly influence the system performance of future ADRTS. Moreover, interactions between variables may lead to an amplified effect in the necessary fleet size, system costs and passenger idle times. For the analysed case study, a vehicle capacity of 4 passengers yields the best results in terms of both minimum system costs and minimum fleet size. This is the result of the case specific demand pattern and demand volume in the simulated case study, which have an influence of experienced dwell times, in particular on early departures. Moreover, the performance obtained with a vehicle capacity of 4 passengers remains superior also when considering a fixed fleet size of for example 400 vehicles (Fig. 8), for which no feasible solution for a vehicle capacity of 2 passengers could be found. This finding is again the result of the interplay between vehicle capacity and vehicle dwell time and its influence on passenger idle time. As discussed above, the vehicle occupancy rate observed in the base case (Fig. 6) corresponds to the average demand per node per vehicle dwell time interval, which is slightly more than 4 passengers in three minutes. This explains why the system performance is best in the scenario with vehicle capacity of 4 passengers. Passenger waiting times are minimized when instant service is proved to as many passengers as possible, thus when the number of early departures for fully occupied vehicles is maximized. This can be best attained by employing vehicles with a capacity close to the demand generated in each node during the prescribed vehicle dwell time, which leads to a maximum number of early vehicle departures. Early vehicle departures are thus favourable for reducing the overall system costs as they lead to short experienced vehicle dwell times while, by definition, leading to a high vehicle occupation rate, which reduced the fleet size and thus the operational costs. Furthermore, the advantage of smaller vehicles is underestimated in this analysis, as here acquisition and operation costs are not, contrary to actual observations, assumed to be lower for smaller vehicles than for larger vehicles. Hence, the system performance for a fleet of vehicles with a capacity of 4 passengers compared to a fleet of vehicles with a capacity of 10 passengers would be better than depicted here. On the other hand, the performance of vehicles with a high capacity (scenario C20 and C40) is arguably overrated because the assumed vehicle purchase price is insensitive to the vehicle capacity. The vehicle capacity should thus always be chosen with care in order to achieve the best outcome for both the operator and the passengers by investigating the relation between passenger demand, vehicle size and vehicle dwell time.

In terms of the demand level, the outcome for the $|V^{min}|$ and $|V^{*}|$are not unambiguous (Table 1). In terms of minimum system costs, system costs are lower in the base scenario than in scenarios with either increased or decreased demand. In contrast, when choosing the fleet size that minimizes system costs, a demand of 150% relative to the base scenario yields the lowest system costs. The corresponding fleet size is also the lowest among the demand scenarios considered. This is again an indication that the vehicle capacity selected in the base scenario of ten passengers is too large for the respective demand level. The increase in demand leads to a better utilisation of vehicle capacity and consequently more often early starts can be performed. This leads to a quicker vehicle turnover which in turn reduces the necessary fleet size.

Also in terms of passenger idle times an increased demand is beneficial. For an exemplary fleet size of 400 vehicles, it can be seen that both the operational costs and generalised travel costs decrease with increasing demand (Fig. 9). As already observed in terms of vehicle capacity, the system performs best when vehicle capacity is fully used, but not exceeded, due to the application of vehicle dwell times in case vehicles still have residual capacity at a pick-up node. The same reasoning applies in explaining the observations made in terms of the effects of varying demand levels. This explains the decreasing passenger idle times as well as the decreasing necessary fleet size for minimum system costs with increasing demand. In contrast, the minimum fleet size required increases with increasing demand. When determining the latter, it is not passenger waiting time that is decisive, but rather satisfying the constraint that all passengers must be served within the individual maximum passenger idle time limit. This leads to an increase in the minimum number of vehicles needed for serving an increasing demand.

The influence of the vehicle dwell time on the performance of the ADRTS is particularly important as a major share of the system costs consists of the generalized travel costs. In the base case about 65% of all passengers experience a passenger idle time of exactly three minutes (Fig. 3) because they are the first passengers to board a vehicle. They experience thus the full vehicle idle time *dwell*. Less than 23% of all passengers experience a vehicle dwell time shorter than three minutes, and 12% of all passengers experience waiting times longer than three minutes in the base case. The vast majority of the latter experience an idle time between 7 and 14 min, which can be explained by the travel times between the nodes in the case study

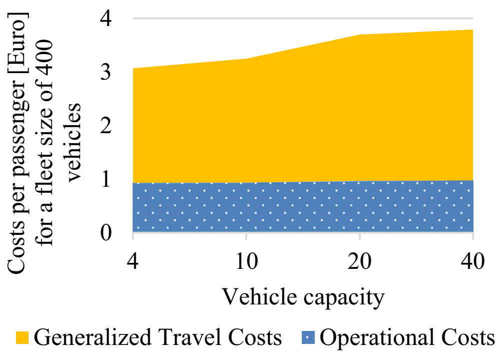

Fig. 8. Operational costs (blue) and generalized travel costs (yellow) per passenger-trip for a fleet size of 400 vehicles for different vehicle capacities (*C4–C20*).

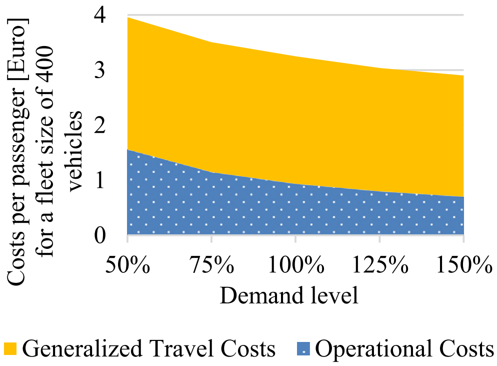

Fig. 9. Operational costs (blue) and generalized travel costs (yellow) per passenger-trip for a fleet size of 400 vehicles for different demand levels (*D50–D150*).

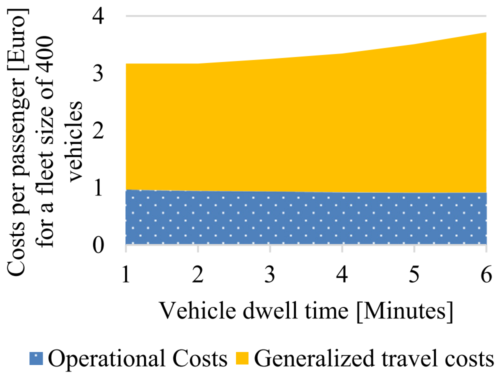

Fig. 10. Operational costs (blue) and generalized travel costs (yellow) per passenger-trip for a fleet size of 400 vehicles for different vehicle dwell times (*DT1–DT6*).

network. When the vehicle dwell time is shortened, it can be observed that the passenger idle times and the system costs decrease, on the cost of an increased $|V^{min}|$ and $|V^{*}|$ (Table 1). For longer vehicle dwell times, the opposite trend can be observed. This is also true for a fleet size of exemplary 400 vehicles (Fig. 10). Furthermore can be observed that the operational costs decrease with an increasing vehicle dwell time, as a smaller fleet size suffices to satisfy the requirements. The benefit of smaller vehicle capacities for the system costs stem thus from shorter passenger idle times. As discussed for the vehicle capacity, it is important to adequately select the vehicle dwell time in accordance with vehicle capacity and the demand per pick-up station per dwell time interval. In current non-automated demand-responsive systems dwell times vary greatly: while in taxi-like services no dwell time is applied, unscheduled jitney or minibus services often only depart once they are filled completely with passengers, which can lead to very long dwell times (Bruun et al., 2016). Where ADRTS will be positioned in this context is not yet determined, and will depend on the local circumstances of an ADRTS service in regard to fleet size, vehicle capacities, demand, the targeted level of service and procurement regulations.

In order to account for the reciprocal effect of vehicle capacity and vehicle dwell time, an additional set of scenarios is investigated in which both parameters are altered simultaneously. The observations made for variations in demand level, vehicle capacity and vehicle dwell time stress the importance of balancing between these system parameters in order to a achieve a good system utilisation. Therefore we tested how the system performs for shorter vehicle dwell times combined with smaller vehicle capacities as well as how it performs for longer vehicle dwell times combined with increased vehicle capacity (Table 1). It can be seen that the minimum system costs can be reduced substantially, as well as the average passenger idle times, when smaller vehicle capacities are combined with shorter vehicle dwell times. The increase in system performance due to greater flexibility is however only achieved with an increased fleet size.

5.3. Initial vehicle location

The search for the best initial distribution of the vehicles in this study is not exhaustive and aims at exemplifying the range in which improvements in system performance of the ADRTS are possible by varying the distribution of initial vehicle depots. It can be observed that the minimum system costs decrease if all vehicles are initially located at one central depot, and so does the vehicle fleet (Table 1). Conversely, when comparing the results for a fixed fleet size of 400 vehicles (Fig. 11),

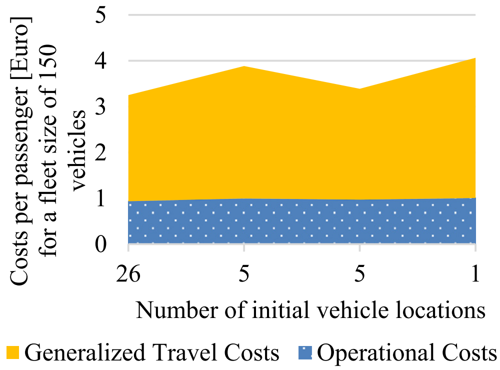

Fig. 11. Operational costs (blue) and generalized travel costs (yellow) per passenger-trip for a fleet size of 400 vehicles for different initial vehicle locations (*IVL5a–IVL1*).

the lowest system costs are attained by initially distributing vehicles evenly over all nodes. When comparing the two scenarios featuring five depots (Scenario Loc5a and Loc5b), no clear pattern can be observed, as scenario Loc5a has higher minimum system costs than the base scenario, while in scenario Loc5b lower minimum system costs can be achieved. Hence, not only the number of depots but also their exact location has consequences on system performance. Any improvement in terms of minimum system costs or costs for the minimum fleet size result however in an increase in fleet size. That this increase in fleet size is of no consequence for the minimum system costs is a result of the cost composition of the ADRTS. While vehicle dispatching in anticipation of demand aims at reducing passenger waiting times and by this the generalized travel costs, it can increase the operational costs due to additional mileage. However, the possible increase in operational costs are opposed to a decrease in fleet size if the demand is anticipated successfully, which reduces maintenance costs and investment costs. Based on the results from scenarios on the initial vehicle location it can be concluded that is best to position the vehicles initially where the demand occurs early during the simulation period. This also show the potential for demand anticipation during the operation.

The influence of demand anticipation on system performance of ADRTS has also been observed by Burns et al. (2013) as well as Fagnant and Kockelman (2015). Berbeglia et al. (2010) suggests three strategies for relocation vehicles in anticipation of passenger requests: (1) waiting strategy: vehicles wait at their current position for a specific time span before launching so that passenger requests get bundled before departure, (2) buffering strategy: the assignment of requests to a certain vehicle route gets slightly delayed so that requests can get bundled before departure and; (3) vehicle diversion strategy: unassigned vehicles move to a strategically chosen location within the network from which expected future request can be reached particularly fast. While in the system layout of the presented ADRTS only the waiting strategy is applied, scenario results suggest a large potential for improving ADRTS performance lies in implementing vehicle diversion strategies. This requires the further development of methods for optimizing fully dynamic demand-responsive transportation systems for many-to-many networks (Berbeglia et al., 2010).

5.4. Study limitations and research outlook

Given the forward-looking nature of this study which examines the potential performance of an innovative urban mobility solution, many consequential variables and parameters are unknown. The analysis and results presented in this paper should therefore be considered as an explorative assessment of a possible future rather than a speculative attempt to forecast the costs and benefits of an introduction of an ADRTS. In particular, the focus of this study has been on the impact of changes in operational settings on the system performance, discarding potential changes in travel patterns. While the results of this study provide insights on the relations between key design variables and performance indicators, absolute values depend on the assumptions made with regards to cost parameters. The ADRTS performance evaluation conducted in this study is thus based on values that are speculative until more reliable size-dependent fleet cost parameters become available, which is one of the shortcomings of a method based on cost comparison. Advances in both behavioural and technological research may offer new insights on the operational costs and passenger costs for using highly automated vehicles.

The simulation results of the ADRTS presented in this section are an outlook on one of the many possible ways ADRTS can be operated in the future, as only one specification of operation of an ADRTS, as described in the four service dimensions in Section 2.2, has been assessed. In terms of accessibility, this study features a stop-to-stop service similar to current public transport services, while it can be argued that door-to-door services embrace the advantages of demand-responsive transportation even further. In terms of model development there are no differences between these two forms of service operations, as with the extension to a door-to-door service only the node set S of the labelled graph $G(S, E)$ increases in size, while the other parameters remain the same. Given the short computation times of 6–10 s per simulation run, an extension of the simulated ADRTS to a door-to-door service is feasible with the presented model in terms of computational effort. Operating the ADRTS with door-to-door service with simultaneously shared vehicles require however that the service is no longer operated as a direct connection, but rather as a network service with intermediate stops. In that case more complex routing algorithms are required, as discussed in Section 2.3.

The limitations resulting from the uncertainties linked to the operation of an ADRTS and its acceptance are addressed in this paper by examining a broad range of values in terms of vehicle capacity, dwell time, demand levels and the initial vehicle distribution. Future research should aim at narrowing down these results for a more meaningful analysis of the costs of ADRTS once more reliable size-dependent fleet cost parameters become available. Furthermore could developing more realistic simulation environments featuring stochasticity in both, supply and demand of ADRTS, as well as in the overall traffic conditions, contribute to a better understanding of the fleet requirements of ADRTS. The stochasticity of the infrastructure the ADRTS is operating in could be addressed by incorporating stochastic (adaptive) shortest path algorithms. The stochasticity in demand for the ADRTS calls for the development of demand-anticipatory techniques to distribute the vehicles based on the expected passenger requests. This requires specifying the extent of risk taking in the management of the ADRTS fleet allowed by an operator (van Engelen et al., 2018). Here the main challenge lies in addressing stochasticity in fleet size in case that the service is operated in a double-sided market such as ride-hailing platforms, which deserves special attention in future research.

While the results for the minimum fleet size do not depend on cost parameter values, the fleet size leading to the minimum system costs should also be considered with reservations. These reservations towards the cost parameters can only be dispelled once more experience with the operations of automated vehicles and in particular the ADRTS is gained. The modelling approach adopted in this study performs an exhaustive search for all fleet sizes between the first feasible solution and fleet sizes leading to minimum system costs. This approach is chosen in order to facilitate the analysis of system performance – both generalized travel costs and operational costs – sensitivity to changes in fleet size. Future research may deploy a computationally more efficient method for searching for the optimal fleet size as well as the optimal fleet composition, as mixed fleet operations can potentially allow for a more efficient capacity allocation.

The insight on the impact of initial vehicle location on system performance suggests that strategic vehicle positioning is a crucial aspect in designing an efficient ADRTS. Consequently, the results of this study call for the development of demand anticipatory modes of operations and related demand prediction schemes.

Various design aspects of ADRTS catering for AVs are not addressed in this study and should be considered in future research. This includes the costs for potential infrastructural modifications necessary for operating ADRTS, optimal routing, vehicle distribution strategies, travel times uncertainty and the possibilities of door-to-door service and pre-booking of transport services. Another aspect that is not considered in this analysis is space consumption, in particular at pick-up nodes, and spatial changes needed for operating ADRTS. For this study, the full availability of automated vehicles and their eventual need for a dedicated infrastructure has been assumed in order to test its scalability for substituting conventional public transport, ignoring any implication of the deployment stage of automated vehicles. In the transition phase from non-automated public transport to automated public transport substantial alterations in the system design and system operation can be expected, which will have an impact on user behaviour. Behavioural studies accompanying the incremental introduction of vehicle automation will allow examining for example user acceptance and the value of time associated with riding and waiting times in the context of ADRTS. Users sensitivity to the reliability of ADRTS such as no-shows, change of planned pick-up times or drop-off locations is of special interest and could be potentially investigated based on existing demand responsive schemes. Further research on travellers willingness to pay for direct services and perceptions of the ADRTS concept and related travel attributes is needed in order to perform an adequate evaluation as well as investigate the potential for induced demand when considering the impact of system performance on modal choice. Also issues such as trust in vehicle automation technology, comfort (e.g. on-board crowding) and perceived safety in simultaneously shared vehicles will play an important role in the user acceptance of ADRTS and should be researched along with the introduction of increasingly automated vehicles.

6. Conclusion

This study presents a first step in analysing the potential performance an automated demand-responsive transport system (ADRTS) as an urban public transport services operated by highly automated vehicles (AV). Employing AVs for demand-responsive transport systems reduces the costs of such as service substantially by eliminating driver costs and scheduling constraints. These are currently the dominating cost factor for DRT services and are one of the main reasons why the introduction of large-scale DRT systems are often unfeasible. In this study the operational costs of ADRTS are estimated and benchmarked against DRT and the existing line-based service. While the operational costs of ADRTS are in the same range of the existing line-based operations, the improved level-of-service it yields may result in the reduction of the total system costs, which are composed of the operational costs and generalized travel costs of the passengers. The simulated ADRTs for the city of Arnhem in the Netherlands indicate that the costs for the minimum fleet size operating the ADRTS are dominated by passengers' generalized travel costs, which account for around two thirds of the system costs in the presented case study. Consequently, an increase in fleet size has only a marginal effect on overall costs. This in turn influences the minimum system costs that can be attained as well as the respective fleet size. For the here presented case study it has been shown that, in order to serve the maximal 3200 passengers per hour, the fleet size of the ADRTS should be at least 300–500 vehicles, depending on the assumption on demand and system operation. The average passenger idle time ranges between 2 and 6 min. The operational costs per passenger-trip range between 0.84 and 1.22 Euro, the total system cost per passenger-trip range between 2.60 and 3.90 Euro. While these specific outcomes cannot be generalized, as they are the result for a particular case study, the set-up of the case study in terms of the network and the demand pattern are generic enough to be comparable to other small or mid-sized cities. Notwithstanding, the transferability of the simulated results depends of the assumptions made on the system operations and the cost parameters, as presented in Table 1. With the technology of vehicle automation evolving and more experiences gained with ADRTS, these values have to be updated in order to obtain more meaningful results by simulation. Given the simplified manner of ADRTS operation simulated in this study, it can expected that more specific optimisation procedures and scheduling algorithms yield a potential for improving the system performance of ADRTS further.

The modelling approach for the determination of fleet sizes of the ADRTS allows assessing cost breakdown and the effects of key system parameters. This approach allows hence to draw conclusions on how system design can be improved for both passengers and system operators. The results suggest that the interaction between vehicle capacity and designed dwell time plays a significant role in determining system performance. In addition, tailoring initial fleet distribution strategically close to demand generators is advantageous. Vehicle occupation rate shows to be a key performance indicator in determining system performance due to its impact on both operational and travel costs.

The economies of scale, which play an important role in public transport, are also apparent in the ADRTS' operation. Higher demand levels yield lower operational and travel costs per passenger due to efficiency gains that are manifested in higher vehicle occupancy rates. This stresses the need for public transport systems to be among the early adopters of AV technology in order to realize the opportunities that AVs hold for urban mobility.

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