

Designing an automated demand-responsive transport system: Fleet size and performance analysis for the case of a campus-train station service

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1 **DESIGNING AN AUTOMATED DEMAND-RESPONSIVE TRANSPORT SYSTEM:**
2 **FLEET SIZE AND PERFORMANCE ANALYSIS FOR THE CASE OF A CAMPUS-**
3 **TRAIN STATION SERVICE**

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39 **Keywords:** Automated Vehicle, Demand Responsive, Automated Transit, Cost
40 Determination, Feeder Service.
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1 ABSTRACT

2 The rapid development of automated vehicles and the introduction of shared mobility services
3 hold great potential for the development of automated public transport systems. However,
4 their expected performance under alternative conditions and design factors remains unknown.
5 In this study, the operation of a new automated mobility service is simulated and evaluated.
6 The proposed transport system is defined as an *Automated Demand Responsive Transport*
7 *System* (ADRTS), a demand responsive public transportation service providing sharable rides
8 without fixed routes or timetables in automated vehicles. Requests for the ADRTS are
9 combined in case they share the same pick-up and drop-off locations, subject to vehicle
10 capacity limitations. Rides are launched within a predefined maximum vehicle dwell time,
11 routes are chosen without detours. The proposed system is tested for the field operation pilot
12 project of operating automated vehicles in Wageningen in the Netherlands under different
13 demand patterns, vehicle capacity and operational factors. The simulation model determines
14 the minimal and optimal fleet size for operating the shuttle service when minimizing the total
15 operational and travel costs while satisfying requirements in terms of maximum passenger
16 wait time. The results indicate that the most effective means to reduce the system cost per
17 passenger of the ADRTS in the presented case study are increasing the demand level,
18 increasing the share of passengers that arrive independently, using adequate vehicle sizes and
19 short vehicle dwell times.

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1. INTRODUCTION

The rapid development of automated vehicles and the introduction of shared mobility services are two of the most significant trends in the transport sector in recent years. The combination of these trends along with the growing availability of real-time data concerning vehicle and people positions can potentially pave the way to the development of new innovative public transport systems. While the emergence of such systems holds great potential for developing and designing automated public transport systems, their expected performance and the influence of design factors remains unknown. In addition to the technological challenges involved with the development of automated public transport systems, it is essential to investigate the determinants of the performance of such systems in order to unlock their potential when ready to leverage beyond vehicle design towards system design.

The objectives of this study are to support the specification of service planning and operations as well as the identification of potential implementations of automated vehicles in public transport. With the growing need for flexible mobility solutions and fully automated vehicles becoming operational, the question arising is how new service concepts, here denominated as *Automated Demand-Responsive Transportation Service* (ADRTS), can be efficiently and effectively embedded in transport systems. The ADRTS examined in this study is defined as a public transportation service providing individualized rides without fixed routes or timetables using fully automated vehicles (driverless, level 5 SEA standard (1)) and is operating as a demand responsive service.

ADRTS are not operational yet, therefore questions about their performance under varying conditions are addressed for a specific case with the help of a simulation tool in this study. The following contributions to the analysis of ADRTS are made: (1) development of a model which considers the impacts of fleet size, vehicle capacity, vehicle idle time at pick-up locations and initial vehicle positions on system performance and the passenger wait time; (2) enable the analysis of system performance for alternative passenger arrival patterns and demand levels per node; (3) through an application for a case of a campus-train station shuttle service determine the minimum fleet size required to serve a certain demand while satisfying constraints on the maximum passenger wait time; (4) determine for this case the fleet size which yields the minimum system costs when accounting for operational and generalized passenger travel costs; (5) analyse the performance of the shuttle service of the case study and; (6) provide recommendations for the suitability of ADRTS and their service design specifications.

Following a classification of automated public transport systems and related models based on a review of the literature (Section 2), the model developed for evaluating ADRTS performance under alternative operational and demand scenarios is presented in Section 3. The performance of an ADRTS for the case study of a shuttle service in Wageningen, the Netherlands, (Section 4) is analysed for a range of operational factors and demand scenarios (Section 5). We conclude with a discussion of practical recommendations and suggestions for further research.

2. LITERATURE REVIEW

Since the research and applications in the field of ADRTS are still in their infancy, previous studies discussed alternative system definitions and outlined the opportunities and challenges involved with futuristic scenarios, see review in (2). In addition, a number of studies have been performed in recent years to analyse the potential of automated vehicles for public transportation (3, 4, 5, 6, 7, 8) with special attention to the fleet size and the operational costs of employing automated public transport.

1 Fleet size is the main determinant of operational costs and was therefore subject to
2 considerable research. Studies of fleet size requirements of AV in public transport systems
3 can be classified based on the adopted solution approach. One possible method to approach
4 these issues is to employ analytical models. Brownell and Kornhauser (3) propose such a
5 model for determining the fleet size for two alternative *Personal Rapid Transit* (PRT) systems
6 for the U.S. state of New Jersey. The fleet size was determined for a station-to-station service
7 in a grid network and a door-to-door service by calculating the number of necessary vehicles
8 for the most active time slot. In the case of a door-to-door service, the additional distance
9 travelled was expressed as a function of the “worst-case” scenario of the pickup and drop-off
10 approximation. Spieser et al. (4) investigated a sequential car sharing system. The minimum
11 fleet size necessary to guarantee a certain maximum waiting time was determined by
12 modelling the system as a queuing model, where “virtual passengers” are used in order to
13 express the automated relocation of vehicles. The availability of vehicles is determined by
14 using mean value analysis. Burns et al. (5) also applied queuing models to determine the
15 minimum fleet size of consecutive car-sharing with AV.

16 An alternative approach for determining the fleet size of systems operated by
17 automated vehicles involves the deployment of simulation models. Burns et al. (5) proposed a
18 simulation model in which a new vehicle pops up in the simulation every time a request
19 cannot be satisfied. A more elaborate simulation model is presented by Fagnant and
20 Kockelman (6), who simulate the fleet size for shared autonomous vehicles in a grided city
21 for a system which anticipates demand for the vehicle positioning. A study for the
22 *Organisation for Economic Co-operation and Development* (OECD) developed an agent-
23 based model for comparing the fleet size required for operating ADRTS with consecutive and
24 sequential car sharing (7). The model represents passengers, mixed-car fleet and a dispatcher
25 system enforcing service constraints as agents to model system dynamics. The analysis
26 considered different penetration rates for automated vehicle and availability of conventional
27 public transport. Li et al. (8) determine the optimal fleet size of a PRT system as a trade-off
28 between passenger waiting time and operational costs. They insert the PRT system into the
29 transport model OmniTRANS, which determines mode choices based on utility functions.

30 From the literature, it can be concluded that service concepts can be classified based
31 on the following defining dimensions, abbreviated ADSW:

- 32 • *Access*: Passengers can access (and egress) anywhere or at pre-defined pick-up and
33 drop-off locations
- 34 • *Directness*: Services run on pre-defined route, shortest path or may preform detours
- 35 • *Sharing*: Vehicles are shared consecutively or simultaneously
- 36 • *Wait time*: Guaranteed maximum or average passenger wait time or no minimum
37 requirements.

38 Each of these aspects can be defined along the spectrum of abovementioned options. Previous
39 studies where mostly concerned with systems providing direct (3, 4, 6, 8) door-to-door service
40 (4, 5, 6) which might be shared simultaneously (3, 6, 7) and guarantee service within a
41 maximum passenger wait time (4, 7). While providing important insights into the features of
42 operating a demand-responsive transit service, previous studies were often embedded in the
43 context of taxi services, PRT or car sharing.

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45

46 3. MODEL DEVELOPMENT AND IMPLEMENTATION

47 This section presents the modelling tool that has been developed for modelling the
48 performance of ADRTS. Its service concept and the modelling requirements are first

1 described, followed by the details of the modelling tool which consists of an iterative
2 assignment procedure. The cost evaluation of each individual solution is formulated in
3 Section 3.3.

4 5 **3.1 System Description and Modelling Requirements**

6 The ADRTS considered in this study consists of a fleet of fully automated electric vehicles
7 which operate in a network of pre-defined pick-up and drop-off locations. The system
8 configuration as envisioned in this study has not been described in the discussed literature yet.
9 The aim is to describe a public transport service making full use of the benefits of demand
10 responsive services. In the ADSW dimensions it has the following properties:

- 11 • *Access*: Passengers access (and egress) at pre-defined pick-up and drop-off locations
- 12 • *Directness*: Service runs shortest path (no detours)
- 13 • *Sharing*: Vehicles are shared simultaneously
- 14 • *Wait time*: Guaranteed maximum and average passenger wait time.

15 Upon their arrival at a pick-up location, users request the service of a vehicle to transport
16 them to their desired drop-off node. They choose freely their departure time and their pick-up
17 and drop-off location within the ADRTS network. In the presented case study, representing a
18 shuttle service, this choice is however limited to two nodes. The service provides a direct
19 connection between the pick-up and the drop-off locations without any detours or
20 intermediate stops. Users travelling between the same locations within a certain time window,
21 which is determined by the pre-defined maximum vehicle dwell time, are transported
22 together. They thus share a ride, which is subject to vehicle capacity constraints. Users might
23 have to wait for a vehicle to serve them and might experience on-board idle time while
24 waiting for potential passengers with the same travel destination. After users disembark at
25 their destination, the vehicle remains at its current position until requested for a new service.
26 The proposed ADRTS is operated in a non-anticipatory manner in terms of demand according
27 to the waiting strategy of vehicles described by Berbeglia et al. (9).

28 In summary, our system can be characterized as a system with limited access, which is
29 fully direct, sharable and with constraints on the maximum passenger wait time. It differs
30 from conventional public transport services in its demand-responsive operations as opposed to
31 rigid scheduling and its direct connection between the desired pick-up and drop-off locations.
32 In the absence of automated vehicles, the provision of such a service would not be different to
33 traditional demand-responsive transportation services. Previous research suggested that such
34 services are not economically sustainable beyond very low-demand or premium services
35 (10,11).

36 The proposed ADRTS is conceived and evaluated as a public transport system. This
37 implies that its analysis should consider both operator and passenger perspectives. To this
38 end, a model has been developed to analyse the performance of ADRTS under various
39 demand conditions and operational designs. The model needs to assign vehicles to travel
40 requests and mimic passenger demand generation in order to analyse the conditions which
41 yield the optimal system costs and the respective fleet size as well as the minimum fleet size
42 necessary to satisfy the demand under pre-defined constraints on maximum passenger wait
43 time.

44 45 **3.2 Modelling Approach and Model Architecture**

46 The modelling framework consists of a simulation tool for assigning vehicles to passenger
47 requests and an iterative procedure to determine the required fleet size (Figure 1). Input to the
48 model include network definition, information on the form and level of passenger demand and

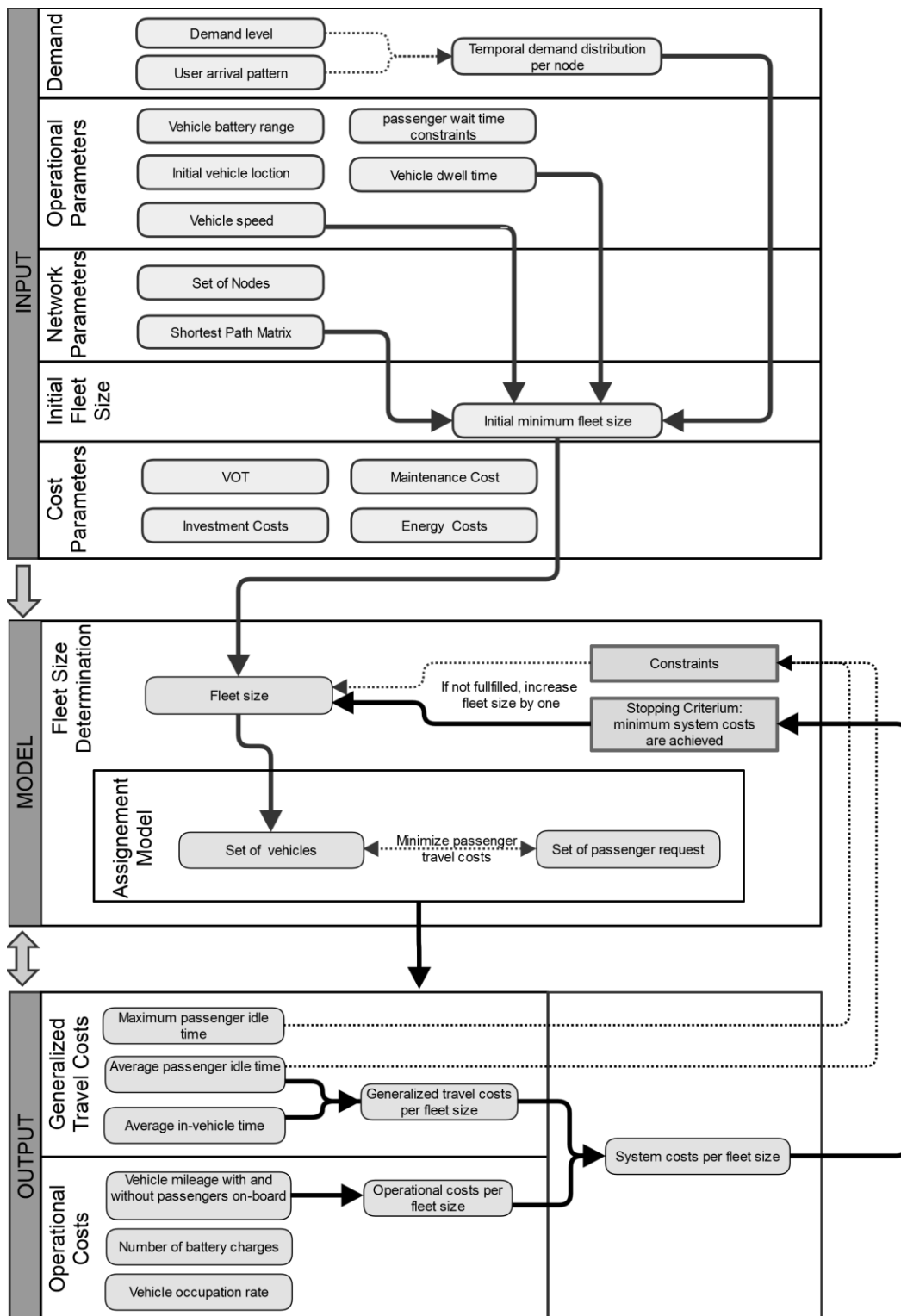
1 operational parameters. Based on these input parameters, a lower bound for the initial fleet
2 size is estimated, based on the ratio between total demand and vehicle capacity. In addition,
3 cost parameters including the value-of-time and operational cost parameters are specified.

4 The model consists of an inner loop that performs the assignment of vehicles to
5 requests (assignment procedure) and an outer loop that alters the fleet size as an input variable
6 during the optimisation process (fleet determination loop). The main iterative sequence of
7 stops (indicated in bold, solid in Figure 1) is performed until the minimum fleet size and the
8 fleet size for the minimum system costs are obtained. An assignment procedure is interrupted
9 if the constraints on the passenger wait time are not satisfied and a new fleet size is determined
10 by the fleet determination loop.

11 The assignment model assigns a given fleet to the stochastically generated passenger
12 demand in an event-based simulation. The model progresses thus by generating and handling
13 new travel requests. When a new request is launched, each vehicle could be either vacant,
14 idled or occupied with an estimated time at which the vehicle will complete its trip and
15 become vacant. It is assumed that passengers need a certain time to board a vehicle. Vehicle
16 dwell time at pick-up locations is specified as an operational parameter (Figure 1) and is
17 applied to combine as many (identical) requests as possible in order to improve vehicle
18 utilization. Travel requests are bundled if there is a idling vehicle that was assigned to a
19 request and during the pre-defined dwell time window another request with the same
20 destination is generated. The dwell time is fixed regardless of the number of requests
21 generated during this time window. However, vehicles might launch earlier if they are
22 completely occupied before the end of the vehicle dwell time. Vehicles are assigned to
23 requests based on their availability and proximity to the pick-up location.

24 An exhaustive search approach was adopted in this study to analyse solution
25 sensitivity to a wide range of possible fleet sizes. The exhaustive search allows gaining a
26 better understanding of the influence of various factors on changes in system performance.
27 Each assignment is evaluated in terms of generalized travel cost and operational cost. Based
28 on a single compensatory objective function, which reflects the monetary value, the model
29 decides whether the minimum value has been obtained and the iterative search could be
30 terminated. In order to ensure that the minimum costs were attained, the search is not
31 terminated immediately but persists until a monotonically increasing trend is observed. The
32 model was programmed in MATLAB.

33



1
2 **FIGURE 1 Flowchart of the main simulation process**

3
4
5 **3.3 Solution Evaluation**

6 The overall objective of the model is to determine the ADRTS fleet size which will yield the
7 minimum system costs. In this process, the costs of the minimum fleet size required to operate

1 the service are also assessed. The system cost (c) comprises of operational costs (c^o) which
 2 are inflicted on the service provider and the generalized travel costs (c^t) experienced by
 3 service users. The objective function is thus:

$$4 \quad z = \min c = \min(c^o + c^t) \quad (1)$$

5 The operational cost consists of the fixed costs of the entire infrastructure necessary to
 6 run the service (c^f) – including administration, control room, the necessary hard- and
 7 software for the vehicle booking and allocation -, maintenance costs per vehicle such as
 8 insurance costs (c^m), annuity depreciation costs (c^d) and the energy costs (c^e). The latter two
 9 depend on the driven mileage. The operational cost could therefore be expressed as

$$10 \quad c^o = c^f + c^m \cdot q + (c^d + c^e) \cdot m \quad (2)$$

11 where q is the number of vehicles and m is the driven mileage in kilometres. Even though the
 12 driven mileage between any two pick-up and drop-off locations is fixed in this study
 13 (determined upfront in a shortest path search), different assignment may result with different
 14 mileage due to vehicle circulation in empty trips. For the assignment process of vehicles to
 15 requests, it is ensured that the vehicles with the closest distance to the requests are chosen.
 16 Hence, the driven mileage and the fleet size are the determinants of operational cost that need
 17 to be minimized.

18 The generalized travel cost consists of the passenger waiting time (t^w), and the in-
 19 vehicle time (t^{ivt}):

$$20 \quad c^t = \beta^{vot} \cdot (\beta^w \cdot t^w + t^{ivt}) \quad (3)$$

21 where β^{vot} is the value-of-time, which is commonly expressed relatively to the in-vehicle
 22 time (12), and β^w is the waiting time coefficient. Wardman (13) provides an elaborate list of
 23 values for ratios for the waiting time of various user groups of public transport modes for the
 24 Netherlands. The factor for the value-of-time of waiting time, β^w , is set to 2.5, a ratio
 25 commonly applied for public transport (13). Since the in-vehicle distances can be determined
 26 up-front by assigning the shortest path as a route between any two nodes, and speeds are
 27 considered constant in this study, waiting times are the only determinant of variations in c^t .
 28 Note that waiting times include the time waiting while the vehicle dwells at the pick-up
 29 location.

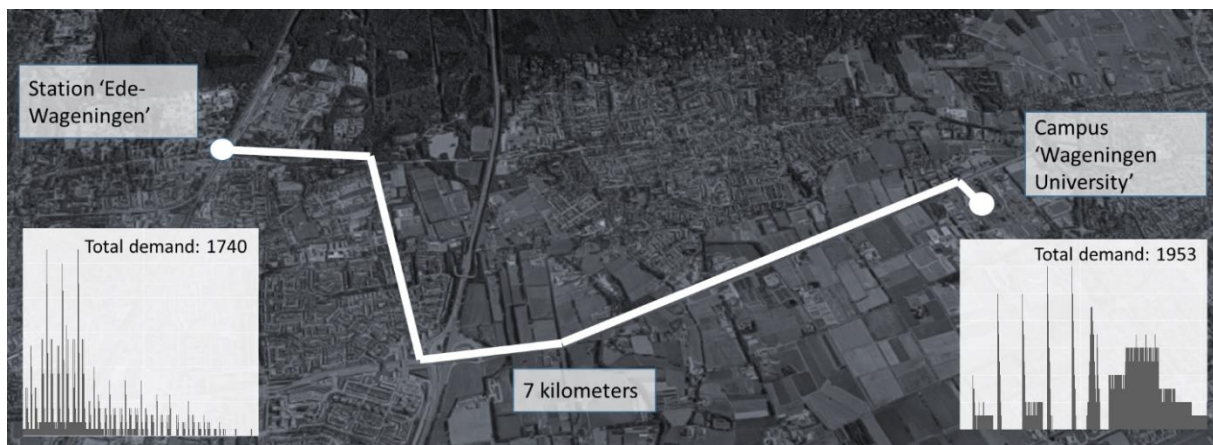
30 In summary, the objective function can be divided into three elements to be
 31 minimized: q , m and t^w - the fleet size, the driven mileage and passenger waiting times,
 32 respectively. The solution search space is a Pareto optimum (14). To find the set of solutions,
 33 the ε - constraint method has been chosen as a generation method, as this method can deliver
 34 a set of solutions close to the Pareto set (15). When applying the ε - constraint method, one
 35 objective is set to be minimized, in this case the fleet size, while the others are set as hard
 36 constraints that have to be less or equal than a predefined value (14). As hard constraints the
 37 maximum passenger idle time and the average passenger idle time were defined. Enforcing
 38 pre-determined constraints on passenger costs is a policy decision that is frequently specified
 39 in concession contracts (16). At the end of the assignment simulation, all user demand must
 40 be satisfied, leaving no user behind. The simulation running time is set to the demand
 41 generation time plus the maximum allowable waiting time.

44 4. APPLICATION

45 4.1 Case Study Description

46 The model is used for analysing the performance of an ADRTS for a shuttle service in a one-
 47 to-one case. This study is performed as part of an on-going pilot study which develops an

1 automated vehicle that will drive between a train station and a university campus in
 2 Wageningen, the Netherlands (17). The travel distance between the two nodes is 7 kilometres.
 3 The simulated demand is based on the current demand for the bus service connecting the train
 4 station and the campus. The demand level is based on passenger counts for an average
 5 weekday (Figure 2). The case study nodes are characterized by a non-uniform demand
 6 generation pattern. In order to mimic passenger arrival process, a stochastic mixture of
 7 random and scheduled request generation were set at each node. In the case of the train
 8 station, scheduled arrivals follow the train timetable, whereas in the case of the campus the
 9 schedule of the lecture hours of the students and working hours of the employers are the
 10 determinants of scheduled passenger generation. Both nodes have a certain percentage of
 11 random arrivals as well, which is simulated as a Poisson arrival process. The daily demand
 12 has been split into an hourly demand, featuring morning and evening peak hours.
 13



14
 15 **FIGURE 2 The Wageningen case study area**
 16

17 The passenger costs are based on the average value-of-time for all surface modes in
 18 the Netherlands, 8.75 euro/hour (18) and are used in calculating the generalized travel cost
 19 (Eq. 3). The vehicle parameters are based on the EZ-10 vehicles manufactured by EasyMile
 20 (19), which are deployed in the pilot study in Wageningen (17). They have a capacity of 10
 21 passengers, a battery range of 700 km, are assumed to cost 100,000 Euro and drive with an
 22 average speed of 30 km/h. The price of one kWh is assumed to be 0.108 Euro per kWh for a
 23 fictitious transport operator (20), leading to energy costs of 0.01 Euro per kilometre. For the
 24 depreciation costs, a salvage value of 5% of the original price is assumed, based on a wear-
 25 lifespan of ten years. The overall mileage for one vehicle is approximated to be 1,220,000
 26 kilometres, leading to depreciation costs of 0.16 Euro per kilometre. The maintenance and
 27 insurance costs are set to 400 Euro per month per vehicle, the cost for the necessary external
 28 infrastructure to operate the shuttle service to 200,000 Euro per year. These values are of a
 29 speculative nature, as no experience with ADRTS could be gained yet. The resulting cost
 30 function per day for the operational costs is (specifying Eq. 2):

$$31 \quad c^o = 548 \left[\frac{\text{euro}}{\text{day}} \right] + 13.33 \left[\frac{\text{euro}}{\text{day}} \right] \cdot q + \left(0.16 \left[\frac{\text{euro}}{\text{km}} \right] + 0.01 \frac{\text{Euro}}{\text{km}} \right) \cdot m \left[\frac{\text{km}}{\text{day}} \right] \quad (4)$$

32

33 **4.2 Scenario Design**

34 A series of model scenarios was designed to investigate the impact of alternative operational
 35 parameters on system performance as well as the influence of passenger demand level and
 36 pattern. The base case corresponds to the case study of Wageningen, where 70% of all travel
 37 requests at the station node are assumed to be coordinated with train arrivals (transferring

1 passengers) and the rest arrive randomly from the immediate surrounding. The generation rate
2 at the campus is modelled based on the lecture schedule for 45% of the passengers being
3 students and based on the schedule of a working person for 15% of the passengers assumed to
4 be university staff. The remaining 30% are modelled as a Poisson arrival process. Operational
5 parameters are based on the pilot study preparations - a vehicle capacity of 10 passengers and
6 a dwell time of 3 minutes. Vehicles are initially randomly distributed over both nodes.

7 In addition to the base case scenario, the following scenarios were tested and analysed:

- 8 • Vehicle capacity (C) – 8 levels varying from 2 to 40 passengers
- 9 • Dwell time (DT) – varying from 1 to 6 minutes
- 10 • Initial vehicle location (IVL) – all of them positioned at station or the campus
- 11 • Demand level (D) – between 50% and 150% of the demand for the current service
- 12 • Demand randomness (R) – ranging from fully random to purely coordinated.

13 A total of 30 scenarios have been simulated, in each of which one of the abovementioned
14 variables is altered from the base case level while all other variables remained unchanged. For
15 all simulation runs, a maximum passenger waiting time of 30 minutes and an average
16 passenger waiting time of 10 minutes was set. Only simulation outcomes fulfilling these
17 constraints have been considered feasible solutions. The constraining values for passenger
18 wait time are deliberately chosen to be high in order to gain a better understanding of
19 passenger wait time distribution and by this on the reliability of the ADRTS. It is therefore
20 advised to reassess the minimum required fleet size when designing an ADRTS as a
21 competitive mode of transport.

22 Due to demand stochasticity (and therefore vehicle assignment), a robust statistical
23 analysis of simulation results require a number of simulation replications. The required
24 number of simulation runs has been determined by a student-t test. For an accepted deviation
25 of 10% of the mean of the average passenger waiting time in the base case scenario, it is
26 sufficient to perform 9.69 sample runs. For each fleet size, 10 simulation replications were
27 therefore conducted.

28 **5. ANALYSIS AND RESULTS**

29 The model described in Section 3 was applied for each of the 30 scenarios to obtain (a) the
30 minimum fleet size necessary in order to serve the given demand within the chosen
31 constraints on passenger waiting times and; (b) the fleet size leading to the minimum system
32 costs. Table 1 summarizes the system cost per passenger, percentage change in system costs
33 compared with the base case, share of operational cost from the system cost and the respective
34 fleet size and average waiting time per passenger for each scenario for both minimum system
35 cost and minimum fleet size. In the case of minimum system cost (Eq. 1), the corresponding
36 fleet size is presented as the average value for the optimal solution followed by the range of
37 values which obtain a system cost of not more than 1% more than the optimal solution. This
38 range of values is presented because the objective function value is relatively insensitive to
39 small changes in fleet size in most cases and the quality of the solution is influenced by
40 demand stochasticity.

41

42

43

1 **TABLE 1 Summary of Scenario Results (minimum system cost; minimum fleet size)**

Scenario	System Costs per passenger [€]	Percent change in system costs [%]	Percent of operational costs [%]	Fleet size	Average waiting time per passenger [min]	
Base case	4.11; 5.70	NA	35; 21	224 [222-229]; 67	2.20; 9.17	
Vehicle capacity	C2	7.07; 7.16	72; 26	37; 46	409 [400-409]; 287	8.05; 9.82
	C4	5.33; 6.30	30; 11	36; 29	309 [309-309]; 137	4.57; 9.71
	C8	4.36; 5.85	6; 3	36; 21	263 [244-263]; 73	2.74; 9.56
	C12	3.95; 5.58	-4; -2	33; 20	200 [200-201]; 46	1.96; 8.93
	C15	3.82; 5.38	-7; -6	31; 19	170 [170-178]; 49	2.37; 8.49
	C20	3.62; 5.45	-12; -4	30; 30	143 [143-143]; 35	1.73; 8.94
	C40	3.52; 5.12	-14; 10	28; 18	124 [124-126]; 36	1.67; 7.90
Dwell time	DT1	3.91; 5.70	-5; 0	35; 22	289 [286-308]; 73	0.72; 8.21
	DT2	4.00; 5.82	-3; 2	37; 20	249 [231-249]; 60	1.55; 9.04
	DT4	4.34; 5.81	6; 2	32; 21	213 [209-221]; 81	3.10; 9.43
	DT5	4.54; 5.63	10; -1	30; 22	199 [199-199]; 92	3.99; 9.39
	DT6	4.84; 5.43	18; -5	28; 23	192 [192-207]; 105	5.01; 8.92
IVL	S100	3.73; 5.67	-9; -1	28; 19	113 [112-117]; 49	2.59; 9.96
	S10	5.78; 6.02	41; 7	24; 24	201 [201-204]; 129	2.47; 9.65
	S0	NA	NA	NA	NA	NA
Demand level	D50	4.31; 5.73	5; 1	39; 32	95 [94-101]; 30	2.01; 7.85
	D75	4.14; 5.62	1; -1	36; 25	160 [160-161]; 45	1.95; 8.47
	D125	3.98; 5.54	-3; -2	32; 17	266 [259-273]; 63	2.24; 9.27
	D150	3.85; 5.54	-6; -3	29; 15	263 [263-277]; 75	2.36; 9.48
Demand randomness	R0	3.86; 5.65	-6; -1	29; 16	170 [153-173]; 39	2.43; 9.76
	R10	3.94; 5.64	-4; -1	31; 17	191 [191-191]; 49	2.27; 9.46
	R20	3.99; 5.66	-3; -1	33; 19	199 [198-199]; 60	2.20; 9.30
	R40	4.00; 5.72	-3; 0	34; 22	193 [193-196]; 69	2.15; 9.13
	R50	3.79; 4.72	-8; -17	31; 27	140 [140-140]; 68	1.96; 5.79
	R60	3.80; 5.16	-8; -9	30; 22	117 [117,153]; 43	2.01; 7.48
	R70	3.78; 5.42	-8; -5	32; 22	136 [136-136]; 40	1.87; 8.27
	R80	3.78; 5.52	-8; -3	31; 21	130 [130-130]; 30	1.88; 8.68
	R90	3.76; 5.20	-9; -9	31; 22	130 [129,130]; 33	1.85; 7.63
	R100	3.71; 5.12	-10; -10	31; 22	123 [123-123]; 29	1.80; 7.40

2

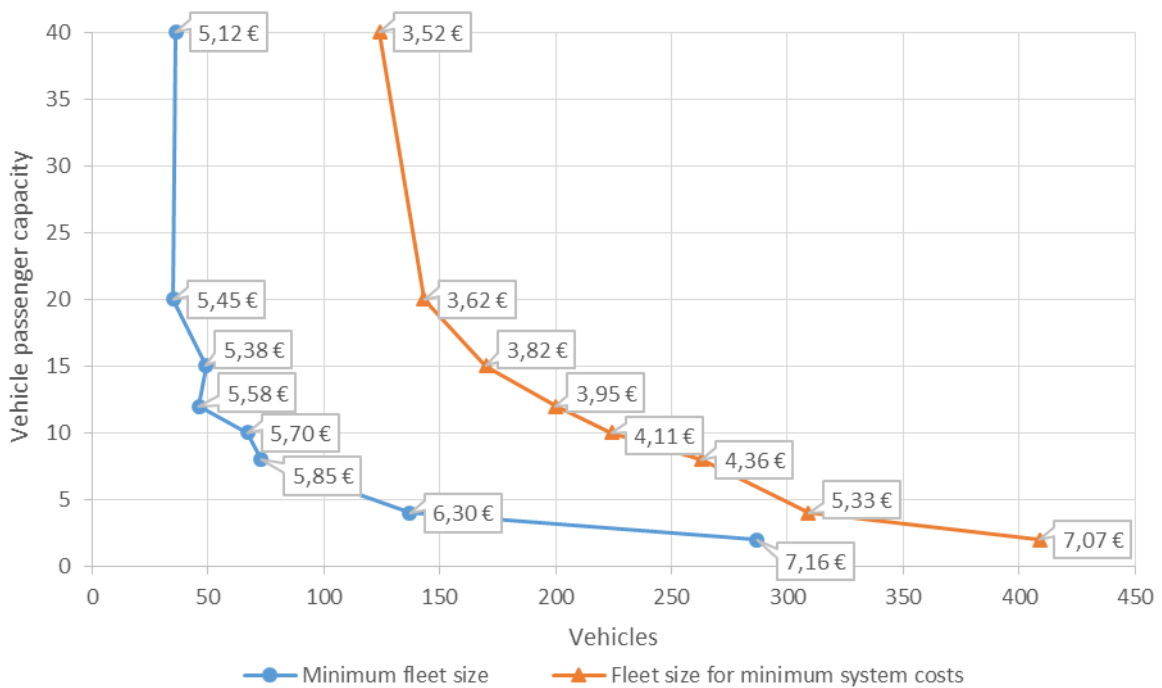
3

4 It can be observed that the minimum system costs can only be achieved with a
5 substantial increase in the fleet size compared to the minimum feasible fleet size. The increase
6 in operational cost due to an increase in fleet size is overrun by the decrease in generalized
7 travel costs that a larger fleet size brings about. Since the system cost is dominated by the
8 generalized travel costs (operational costs amount to 15-39% of the costs in all scenarios), it is
9 beneficial to reduce passenger waiting times at the expense of increasing the operational
10 costs. The base case scenario yields an average waiting time of 2.20 min when using 224
11 vehicles or 9.17 min when using the minimum fleet size of 67 vehicles. The scenario details
and the influence of operational and demand aspects is examined in the following sub-

1 sections. These comparisons however do not account for the interdependencies between
 2 design variables which would have require a full-factorial scenario design.

3
 4 **5.1 Influence of Vehicle Capacity on System Performance**

5 When designing an ADRTS, vehicle capacity is one of the key design issues having long-term
 6 implications on system performance. Figure 3 presents the impact of vehicle capacity on fleet
 7 size and system cost. It can be observed that for the shuttle service, very small vehicles cannot
 8 operate the proposed ADRTS as efficiently in terms of passenger waiting time and system
 9 costs as fewer vehicles with a vehicle capacity equivalent to a midi-bus of 10-15 passengers
 10 (Table 1). Note that the operational cost parameters (Eq. 4) are independent of vehicle size
 11 due to the absence of solid data to allow their specification.

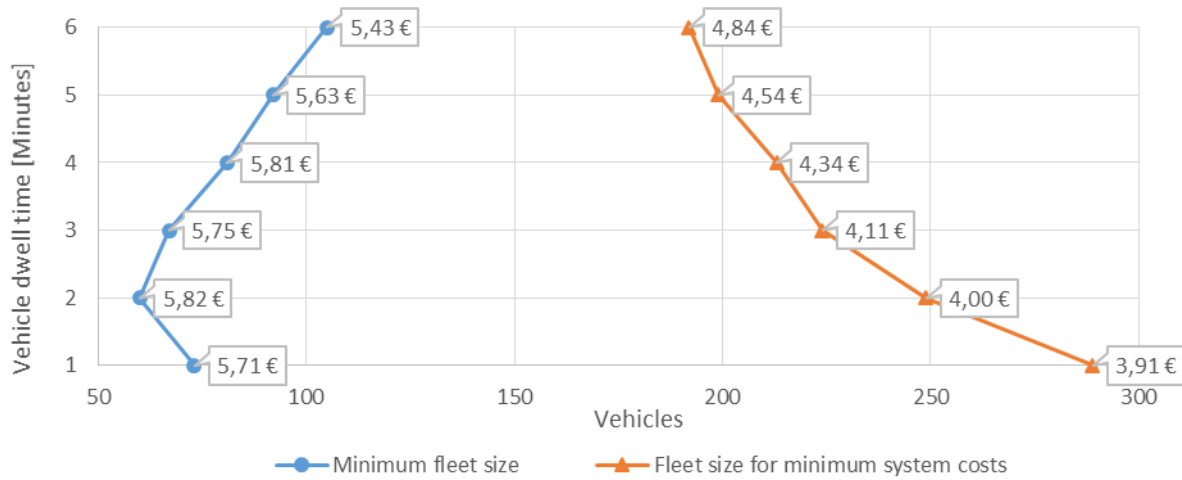


13
 14
 15 **FIGURE 3** Minimum (blue, dots) and optimal (orange, triangles) fleet sizes for different
 16 vehicle capacities. The corresponding system cost per passenger-trip is indicated in the
 17 labels.

18
 19 **5.2 Influence of Operational Parameters on System Performance**

20 Two operational variables which can be set during daily operations were examined: (1) pick-
 21 up dwell time, and; (2) initial vehicle locations. Figure 4 displays the fleet size and system
 22 cost results for dwell times ranging between one and six minutes. The results show that the
 23 planned dwell time of three minutes is not optimal and results in a substantial increase in
 24 system costs. Even though the vast majority of passengers (65%) experience a shorter waiting
 25 time than the dwell time as they join an already dwelling vehicle, the high impact of waiting
 26 time implies that this effect does not justify longer vehicle dwell times in terms of the system
 27 costs. Interestingly, the opposite effect is observed for the minimum fleet size since longer
 28 vehicle dwell times imply that fewer vehicles are needed, leading to lower operational costs.
 29 The dwell time specification is therefore dependent on the trade-off between operational costs
 30 and passenger waiting times and the exact result is sensitive to the cost parameter values.

1



2
3

4 **FIGURE 4 Minimum (blue, dots) and optimal (orange, triangles) fleet sizes for different**
 5 **pick-up dwell times. The corresponding system cost per passenger-trip is indicated in**
 6 **the labels.**

7

8 Several initial vehicle location strategies were simulated to test their impact on system
 9 performance (Table 1). In addition to the base case of equal vehicle distribution between
 10 station and campus, scenarios with all vehicles initially located at either the station or the
 11 campus were tested. No feasible solution could be found in the latter case. Therefore an
 12 additional scenario, with 90% of all vehicles initially placed at the campus and 10% at the
 13 station was simulated in order to be able to see possible trends in the influence of the initial
 14 vehicle location on the system performance. The results indicate that the best approach is to
 15 initially position all vehicles at the node which has the higher passenger demand in the
 16 morning peak hour – the train station in this case study. This solution decreases the system
 17 costs per passenger by 9% when compared with the base case.

18 Conversely, positioning 90% of all vehicles at the campus node leads to an increase of
 19 29% in system costs. It can be thus concluded that the initial vehicle location can significantly
 20 influence the system performance and should be carefully investigated in daily operations.

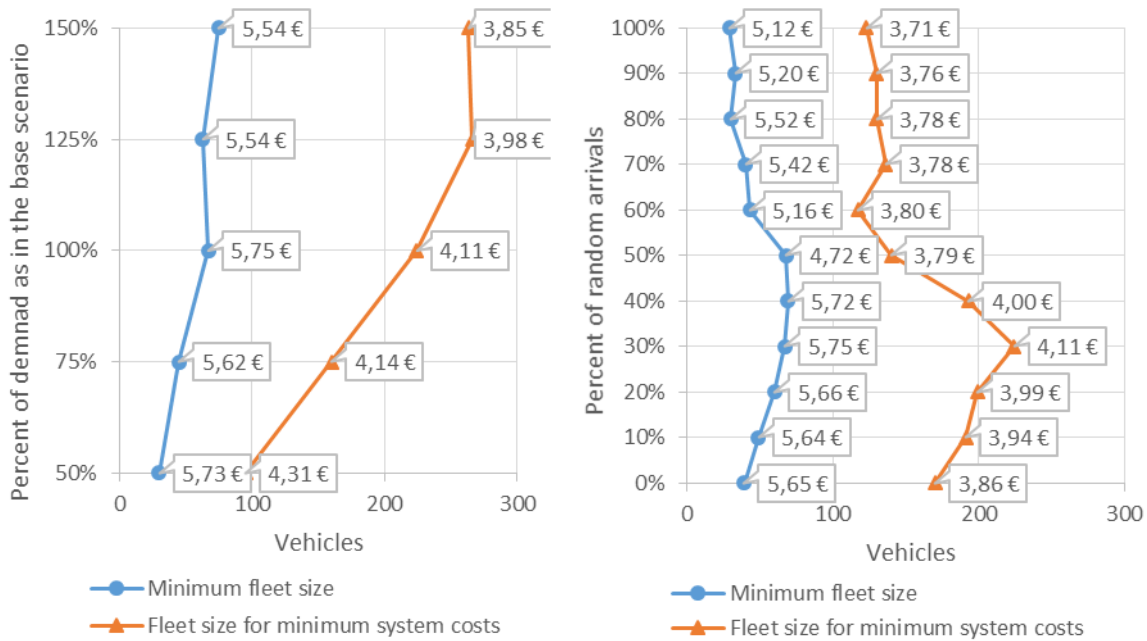
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22 **5.3 Influence of Demand Levels on System Performance**

23 The influence of passenger demand on system performance was tested in two dimensions: (1)
 24 overall demand level, and; (2) share of coordinated vs. random arrivals. Figure 5 presents the
 25 results for various demand level scenarios (above) and share of random arrivals (below). The
 26 results show that the system costs per passenger decrease with increasing demand levels by
 27 deploying a larger number of vehicles. Interestingly, the decrease in optimal solution costs is
 28 mainly caused by a decrease in operational costs per passenger due to greater efficiency for an
 29 increasing demand and is not driven by a reduction in generalized travel costs. Furthermore,
 30 also the minimum fleet size increases only marginally for an increased demand level, while
 31 overall system costs decrease to a level comparable with the case of the minimum system
 32 costs. The proposed shuttle service performs thus better under higher demand within the
 33 tested range for both system operator and users.

34 For a given demand level, the temporal distribution of passenger arrival could play an
 35 important role in determining system performance and the provisioned constraints on

1 passenger wait time. This influence is clearly evident in Figure 5 where the ADRTS performs
 2 best if all passengers arrive randomly. When 50% of the passengers arrive randomly, then the
 3 required fleet size is minimal. For the scenarios with random arrival rates between 10% and
 4 40%, the system costs and necessary fleet size increase substantially for both the case of
 5 minimum fleet size and minimum system costs. Changes in system costs are dominated by
 6 generalized travel costs, as coordinated arrivals pose a challenge to demand-responsive
 7 services and lead to longer waiting times. Moreover, a larger fleet is necessary to ensure that
 8 minimum level-of-service constraints are satisfied.
 9



10

11

12 **FIGURE 5 Minimum (blue, dots) and optimal (orange, triangles) fleet sizes for different**
 13 **shares of random travel request generation (above) and different demand level scenarios**
 14 **(below). The corresponding system cost per passenger-trip is indicated in the labels.**

15

16 **6. CONCLUSION**

17 Simulation results show that the system performance of the proposed ADRTS is dominated
 18 by passenger generalized travel cost. With the set of parameters used in this analysis, the
 19 operational costs are relatively stable. Hence, minimum system costs are achieved by
 20 reducing the generalized travel costs at the expense of a marginal increase in the operational
 21 cost. The fleet size attaining minimum system cost leads to substantial waiting time
 22 reductions. The most effective means to reduce the system cost per passenger of the ADRTS
 23 are increasing the demand level, increasing the share of passengers that arrive randomly,
 24 using adequate vehicle size and short vehicle dwell times. The main driving factor of efficient
 25 ADRTS is the vehicle occupation rate as all of these factors are crucial for bundling passenger
 26 more effectively to simultaneous ride sharing and allow instant service. The results
 27 concerning the effect of demand level are consistent with the results reported in (5). The
 28 suitable vehicle size depends on the demand level and arrival pattern. While the service
 29 considered in this study has no anticipatory features, it can arguably improve significantly
 30 system operations, especially in cases with a high number of scheduled arrivals. Initial vehicle

1 location was found to have a dramatic effect on system performance. Strong effects of
2 demand anticipation applied to the whole operation time was also reported in (5,7).

3 While enabling the analysis of demand patterns and operational variables, the results
4 have to be considered in the context of the speculative operational cost parameters that have
5 been used in this study. As no ADRTS is operational yet, model calibrations or validations
6 cannot be performed at the moment. The values obtained for the minimum system cost have
7 therefore to be treated with more caution than those attained for the minimum fleet size. The
8 model tool also neglects travel time variability and the potential usage of anticipatory
9 resource allocation.

10 The research on automated public transport systems is still in its infancy. It is critical
11 to design service concepts and system operations that will cater for automated vehicles which
12 are currently under development and early deployment stages. The results of this study
13 indicate that the selection of service areas and operation variables can highly influence system
14 performance. It is thus necessary to develop tools that will foster the successful deployment of
15 ADRTS. An on-going study analyses the performance of an ADRTS when serving a more
16 complex many-to-many urban network, investigating multi-dimensional variations of the
17 system parameters for determining the best system performance. Future research should
18 examine user perceptions of ADRTS and automated vehicles to investigate whether the
19 respective waiting and in-vehicle times are perceived differently than conventional public
20 transport due to greater comfort. This is especially important against the backdrop of the
21 reliability of waiting times, which are subject, among others, to the here not included delays
22 due to congestion.

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26

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