

1 **Required Autonomous Vehicle Fleet Sizes to Serve Different Levels of Demand**

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5 **Patrick M. Boesch, Corresponding Author**

6 IVT, ETH Zurich
7 CH-8093 Zurich, Switzerland
8 Tel: +41 44 633 39 52; Fax: +41 44 633 10 57; Email: patrick.boesch@ivt.baug.ethz.ch

9

10 **Francesco Ciari**

11 IVT, ETH Zurich
12 CH-8093 Zurich, Switzerland
13 Tel: +41 44 633 71 65; Email: ciari@ivt.baug.ethz.ch

14

15 **Kay W. Axhausen**

16 IVT, ETH Zurich
17 CH-8093 Zurich, Switzerland
18 Tel: +41 44 633 31 05; Email: axhausen@ivt.baug.ethz.ch

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22 Word count: 6,454 words text + 6 tables/figures x 250 words (each) = 7,954 words

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29 Submission Date: November 14, 2015

1 ABSTRACT

2 Automated Vehicles (AV) promise many benefits for future mobility. One of them is a reduction of
3 the required total vehicle fleet size, especially if AVs are used predominantly as shared vehicles.
4 This paper presents an investigation of this reduction potential using a simulation approach. The
5 greater Zurich region, Switzerland, is the area of the study. Fleets of shared AVs, which serve a
6 predefined demand, are simulated with a simulation framework introduced in the paper. Different
7 scenarios are created, combining different levels of demand for AVs with different levels of supply
8 (i.e. AV fleet size).

9 An important contribution of this study is the use of a spatially and temporally highly detailed
10 travel demand, going beyond the simplifications of previous studies on the topic. This provides a
11 more solid basis to the ongoing discussion on the fleet size required to serve a certain travel
12 demand with a given level of service.

13 It is found that, for a given fleet performance target (here 95% of all transport requests are served
14 within 5 minutes), the relationship between served demand and required fleet size is non-linear and
15 the ratio increases as the demand increases. So there is, as could be expected, a scale effect, which
16 has the important implication that for different levels of demand the fleet is used more or less
17 efficiently.

18 This paper also finds that, if waiting times of up to 10 minutes are accepted, a reduction of up to
19 90% of the total vehicle fleet can be possible even without active fleet management like vehicle
20 redistribution. Such effects require, however, that a large enough share of the car demand can be
21 served by AVs.

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28 *Keywords:* Automated Vehicles, Fleet Size, Car Sharing, Simulation, MATSim

1 INTRODUCTION

2 The idea of an Automated Vehicle (AV) is already several decades old. For a long time, research on
3 the topic addressed exclusively the technological aspects of AVs. Recent developments, however,
4 made clear that the technology will soon be available. Several car manufacturers and some new
5 players are already testing vehicles which, to various degrees, can be considered autonomous.
6 Indeed, most of the cars currently in the manufacturers' catalogs already offer a certain degree of
7 automation. To clarify the difference among automation levels a scale has been proposed by
8 NHTSA (1). At the top of the scale, level 4, are vehicles that can drive without a human driver in
9 uncertain, open environments created for humans. Such vehicles are expected to arrive in the
10 consumer market within the next few years (2). The consequences on the transportation system are
11 yet uncertain, but it is reasonable to assume that they potentially will be extremely far reaching.
12 One fundamental question is, how AV usage will be regulated. At the moment AVs require special
13 test permits to be operated in open traffic conditions. It is clear that this restriction will be lifted at
14 some point, but the form in which AVs will be allowed is obviously a key point. Some researchers
15 pointed already to the fact that to effectively harvest all the possible benefits of AVs for the
16 transportation system, a "car-sharing" like scheme should be preferred to an ownership based
17 model. AVs would overcome most of the limitations that car-sharing services have versus personal
18 ownership and usage. For example, compared to car-sharing in any of the currently available
19 forms, with AVs one would not need to travel to the next vehicle. Instead the vehicle would be able
20 to drive exactly where the demand is, much like a taxi. The hypothesis is that a car-sharing scheme
21 would provide the same kind of flexibility that cars provide, without (or limiting) the possible
22 negative impacts of the widespread diffusion of AVs. Specifically, thinking of a large scale AV
23 car-sharing scheme able to satisfy most of the demand currently covered by personal cars, the most
24 evident benefit would be the much smaller total car fleet needed. Indeed, this would enable a more
25 efficient use of the vehicles in terms of productive time with a cascade of positive outcomes. A
26 smaller fleet implies for instance reduced parking requirements and potentially frees up huge areas
27 of high value urban space.

28 A few papers have already been published hypothesizing AV car fleets offered in shared
29 vehicle schemes. These studies find that current travel demand could be served with fleet size
30 reductions of up to 90% of the current car fleet sizes (3).
31 For example (4) and (5) investigated the required fleet size to serve the current demand in
32 Singapore with an "Automated Mobility-on-Demand System". Using queue models, they found
33 that one third to 40% of the current number of passenger vehicles in Singapore would be sufficient
34 to serve the total travel demand of Singapore.
35 Other researchers approached the fleet size problem with simulations. In general they are
36 characterized by simplifications of the demand in terms of temporal resolution, spatial resolution
37 or both compared to current state-of-the-art in transport simulations.
38 In (3) and (6), temporally the demands are randomly generated using transport demand patterns
39 and trip duration patterns. Spatially the demands are undetailed (grid based in the case of (3) with
40 a grid cell size of 0.25x0.25miles) and randomly distributed. In (3) the travel times to calculate the
41 re-availability of vehicles are based on Manhattan distances and average speeds. They find that
42 10% (3) or 15% (6) of the current fleet would be enough to serve the current demand.
43 In (7) and (8) the demand is explicitly generated with demand models to correctly represent the
44 real demand of the respective area (New Jersey (7) and Lisbon, Portugal (8)). In the subsequent
45 transport simulations, these demands are used as static demands, which means that the demands
46 could not adapt to the available transport supply and traffic situations. The demands are aggregated

1 to zones after generation (zone size 0.5x0.5 miles (7) and 200x200 meters (8)). While (7) does not
2 consider travel times and thus re-availability of vehicles (they provide an infinitely sized fleet), in
3 (8) the travel times are calculated by routing the trips on a network and assuming average link
4 occupancies and thus speeds by time of day. In (7), they find that a substantial ride sharing
5 potential exists for AV fleets. For Lisbon (8) suggests a possible fleet size reduction of 90%.
6 A recent study by Chen et al. (9) investigated how a fleet of “Shared, Electric, Autonomous
7 Vehicles” performs if vehicle charging is considered too. They find that one vehicle could replace
8 3.7 to 6.2 privately owned vehicles.

9 This paper presents an investigation of the fleet size problem based on a simulation
10 approach too, but with some important novelties. A fleet of shared AVs, which serves a predefined
11 demand, is simulated. Several simulations are run, assuming that different shares of the current car
12 travel demand are fulfilled with differently sized AV fleets.

13 The demand represents the car travel demand for the greater Zurich region, Switzerland. It has a
14 high spatial and temporal resolution. The demand and the travel times considered in the AV
15 simulation were obtained using MATSim, an activity-based multi-agent transport simulation
16 framework (10). This MATSim generated demand is used as a static demand in the AV simulation.

17 This paper introduces a simulation framework which goes beyond those used so far in the
18 existing literature in terms of spatial and temporal resolution of the demand. This provides a more
19 solid basis to the ongoing discussion on the fleet size required to serve a certain travel demand with
20 a given level of service. It is argued here that precise representations of the start time and location,
21 as well as of the destination and the expected travel time of a transport request in realistic traffic
22 situations, are important aspects which need to be considered. Real transport demand shows
23 complex spatial and temporal patterns and is tightly dependent on transport supply. If transport
24 supply limitations are reached and congestion builds, travel times will increase nonlinearly and
25 wider network effects will occur. The demand generation with the agent-based transport model
26 MATSim and its equilibrium approach ensures that these effects are realistically represented in the
27 demand and travel times used for the studies presented in this paper.

28 As a first application, the simulation framework was used to provide, compared to previous works,
29 a more systematic answer to the question of the required AV fleet size to serve different levels of
30 demand. In total 140 different scenarios were simulated to thoroughly investigate the question. It is
31 found that, for a fixed level of service, the relationship between trips served and fleet size is
32 non-linear and the ratio increases as the number of trips increases. So there is, as could be
33 expected, a scale effect, which has the important implication that to different levels of demand the
34 fleet is used more or less efficiently.

35 This first application also allows to compare the scenario results with existing studies on the topic.
36 Compared to earlier studies (i.e. (3) and (8)) a much lower peak fleet usage was achieved. This is
37 the same all over the day, reflected by the fact that trips served per day per AV and the total usage
38 time of an AV is lower. While some of these effects can be explained by the larger scenario area
39 and the lower population shares used here, at least some of this difference is also attributed to the
40 more detailed demand. This is supported by the fact that still only 10% of the existing car fleet is
41 sufficient to serve the current car travel demand, which also hints to a strong influence of the
42 spatio-temporal characteristics of the demand on the possible substitution rate.

2 THE SIMULATION FRAMEWORK

On top of MATSim a separate simulation framework was developed. It simulates an AV fleet that serves trip requests. The travel demand and the travel times are generated beforehand with a MATSim simulation.

2.1 Generating travel demand with MATSim

To understand the simulation framework, a basic understanding of MATSim is required. MATSim is an activity-based, multi-agent transport simulation framework (10). In MATSim agents optimize their transport behavior in a co-evolutionary process until a dynamic user equilibrium (DUE) is reached. The agents represent a real population and possess daily plans of activities at times and locations they would like to execute. The transport demand arises from the execution of these plans under realistic representations of transport supply. The initial population of agents, that is the initial set of daily plans, is created from travel diary survey data and population statistics (11). In the co-evolutionary process the agents can try different modifications of their plans (e.g. rerouting, rescheduling etc.) over many iterations until a DUE is reached. A scenario is calibrated such that traffic counts and transport statistics match real data from the simulated area. In the end, this results in a stable demand consisting of all trips travelled by agents when moving between activities. A calibrated demand shows the same statistical characteristics as the real transport demand of the research area.

2.2 Overview of the Simulation Framework

In the AV simulation, when a request, based on the MATSim-created demand, is made, it is assigned to the closest, available AV within a predefined service radius around the start location of the request. Then this selected AV moves to the start location and – if arriving early – waits for the passenger to finish its activity. Once the AV and the passenger are both ready, they move together to the trip end location. After they arrive, the AV becomes available for a next request. Movements are modelled as direct relocations with delayed arrival since a network representation is not part of the current implementation. For the pick-up movements of AVs to request locations the travel times are calculated from corrected beeline distances and average speeds. For the actual trips the travel times found in MATSim for those trips are used. The MATSim travel times represent the expected travel times for the trips in realistic traffic situations. In the following sections the simulation framework is presented in more detail.

2.3 Initial Distribution of AVs

The initial distribution of AVs can have a strong influence on the simulation results and is therefore an important step. Different distribution approaches are suggested in the literature. For example the creation of new AVs at the locations of the first n requests in the simulation, with n being the target number of AVs (in (3) for the “warm-start”), or a random distribution of the AVs over the research area (6).

To initially distribute the AVs, the current implementation of the simulation framework first randomly samples for each AV one agent from in the demand. The AV is then placed at the start location of the first trip of this agent. Since agents in MATSim start their day at their home location, this approach assumes implicitly that the sampled agent was the one who last used the shared AVs the day before for his trip home. This procedure determines only the initial locations of all AVs and all AVs are available to all agents from the start.

1 **2.4 A Typical Trip**

2 This section explains the characteristics of the simulation framework by following one request step
3 by step from start to end.

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5 *2.4.1 Registering of a New Request*

6 A request represents a trip. A trip consists, among other information, of a start location, a start time,
7 an end location, and of the arrival time found in MATSim. Five minutes before the start time of a
8 trip, that is five minutes before the preceding activity ends, the request is registered and becomes a
9 pending request. This equals to the assumption that people expect an AV to arrive within five
10 minutes after they register a request. In the current case the request was assumed to be served in
11 time if the AV arrived within the first five minutes after the request was registered. If the AV
12 arrived in the first five minutes after the activity ended, that is five to ten minutes after the request
13 was registered, the request was assumed served late. This choice of 5 minutes for in time and 10
14 minutes for late servings is based on the study by Fagnant and Kockelman (3). If no AV could
15 serve the request within 10 minutes after registering, the request was assumed unserved and
16 dropped.

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18 *2.4.2 Search for a Free AV and Assignment*

19 After a request is registered as a new pending request, an available AV is searched. The search
20 process consists first of identifying the closest AV to the request location and then of a check if this
21 AV is within the current service radius of the request. The service radius is the driving time radius
22 equal to the remaining time of the request until time out which is 10 minutes after registering
23 (section 2.4.1). If no suitable AV can be found, the search is repeated every simulation step until
24 either an AV is found or until the request has timed out. Once a suitable AV is found, it is assigned
25 to the request and the elapsed time is logged as the assignment time of the request. A request will
26 not be reevaluated for closer AVs once assigned.

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28 *2.4.3 Drive of the AV to the Start Location*

29 An assigned AV moves directly to the start location of the request. The duration of such a pick-up
30 movement and thus the arrival time of the AV at the start location is determined by first
31 multiplying the beeline distance to the target location with a beeline factor and then dividing the
32 product by the average speed of a car. The beeline factor was computed by comparing for all car
33 trips in the MATSim demand the street network distance with the beeline distance. It was found to
34 be 1.43 for the demand used for this study. The average speed was calculated from the 2010 travel
35 diary data for the greater Zurich area (12) and was found to be 11.28 m/s.

36 If the AV arrives at the location of the request before the start time of the request, it has to wait until
37 the start time of the request (end time of the preceding activity of the agent). If the AV arrives after
38 the start time, the request is assumed to be served late (section 2.4.1).

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40 *2.4.4 Service*

41 Once the AV has arrived the location of the request and the request start time is reached, the request
42 is served. The AV moves to the end location of the trip. The arrival time is determined based on the
43 original trip duration as found in MATSim. It therefore represents the realistic travel time on the
44 network under realistic traffic conditions at the time of the trip. Upon arrival the AV is released and
45 ready for a next request.

1 **2.5 Other Specifications**

- 2 The simulation is a time-based simulation. This means that simulation steps are executed every
- 3 fixed time interval (1 second for the studies presented in this paper).
- 4 Following the standard values of the MATSim framework, the simulation simulates one typical
- 5 week day from midnight to 6am the following morning (30 hours) with a statistical sample interval
- 6 of 5 minutes, which means that every 5 minutes of simulated time all statistical values are sampled
- 7 once.

3 SIMULATED SCENARIOS

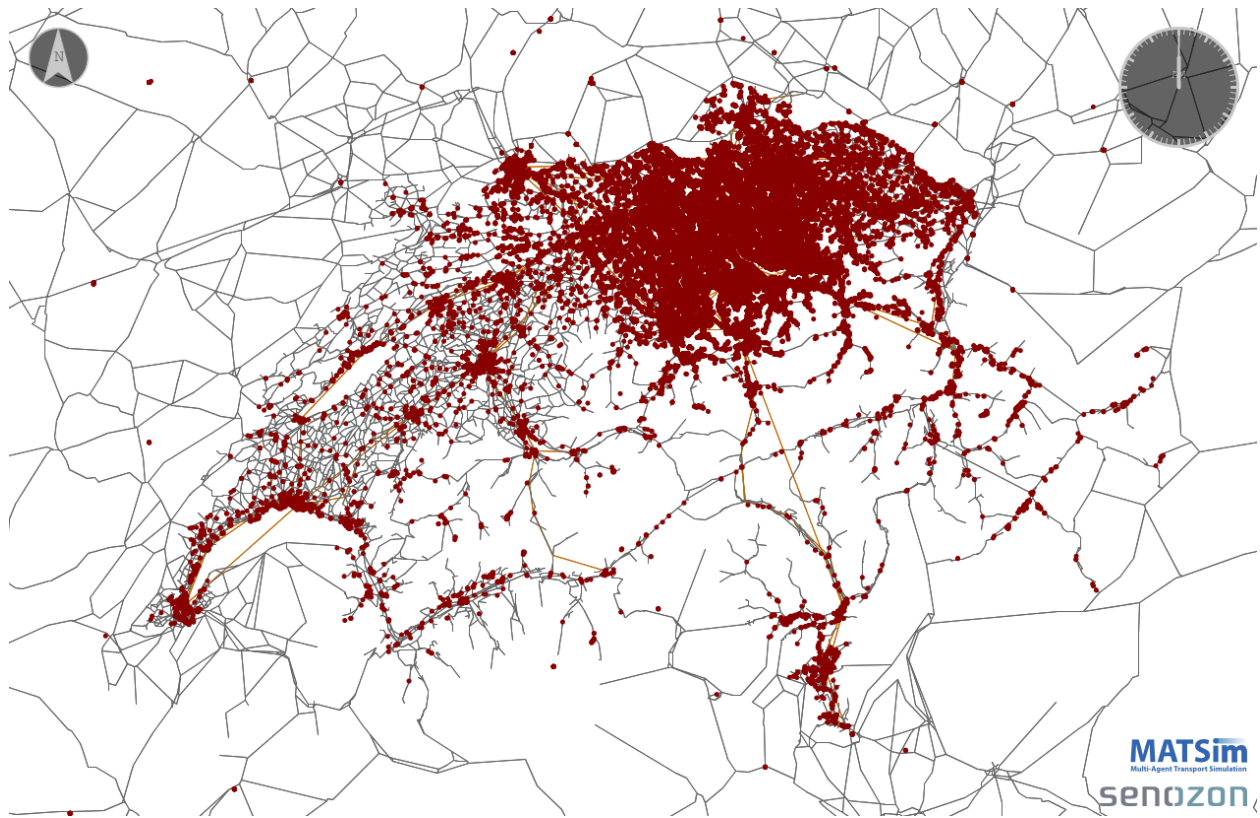
The case study is a scenario of the region of Zurich. The area has been used in the past for several MATSim exercises. It is a well-tested base scenario used in previous studies (e.g. (13) or (14)). It represents around 2.1M agents. These agents represent all persons that are either living and carrying out activities in the area or passing through the area (to carry out activities somewhere else). This practically means that trip requests can come from anywhere in Switzerland and near areas of neighbor countries (Figure 1). MATSim simulates transport demand and supply. The output of MATSim is a plausible representation of an average working day in the area with realistic demands and traffic flows. Single vehicles are simulated with a queue based transport simulation on a precise representation of the network. The temporal resolution of the simulation is one second.

Different levels of AV travel demand were generated drawing samples from the set of all car users, which amounted to 1.3M agents with a total of 3.6M trips. The levels ranged between 1% and 10% (in 1% steps) of the total travel demand currently satisfied by car use. These ten demand levels were combined with ten different supply levels. For each supply level, the number of provided AVs equaled a different percentage (10% to 100% in 10% intervals) of the sampled users. This resulted in 100 different scenarios.

For the current study, two main assumptions were thus made. The first is that in an early phase only a fairly small percentage of the population would use AVs. The second is that only trips made with the car would be substituted by AV trips (no modal shift). Please note that these are extremely strong assumptions in terms of behavioral response to the introduction of AVs, but the representation of such response is beyond the scope of this exercise (discussion in section 5.1) which rather focuses on AV fleet's size given a certain demand.

As the sampling of agents for the scenarios and the initial distribution of the AVs in the simulation (section 2.3) are random processes, the above scenarios were all repeated ten times with different random seeds (which command the underlying algorithm). This resulted in 1'000 initial simulations.

After a first analysis of the initial simulations, additional supply levels were considered to refine the results in critical value ranges. The additional supply levels were 5%, 15%, 25% and 35%. These were again combined with all demand levels and repeated with all random seeds, resulting in an additional 400 simulations.



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FIGURE 1 Start locations of all trips simulated and the network representation used in the MATSim Zurich scenario. The total area shown in the figure is 422.0km x 272.3km.

4 RESULTS

4.1 Performance of the AV Fleets

Figure 2A shows the performance of the AV fleets responding to requests within the first 5 minutes. For each scenario the corresponding data point shows the average value achieved across all runs. The standard deviations are not visualized since they are very small (average 0.15%, maximum 0.92%). This suggests a low dependence of the overall performance on the sampling of the agent population and the initial distribution of the vehicles.

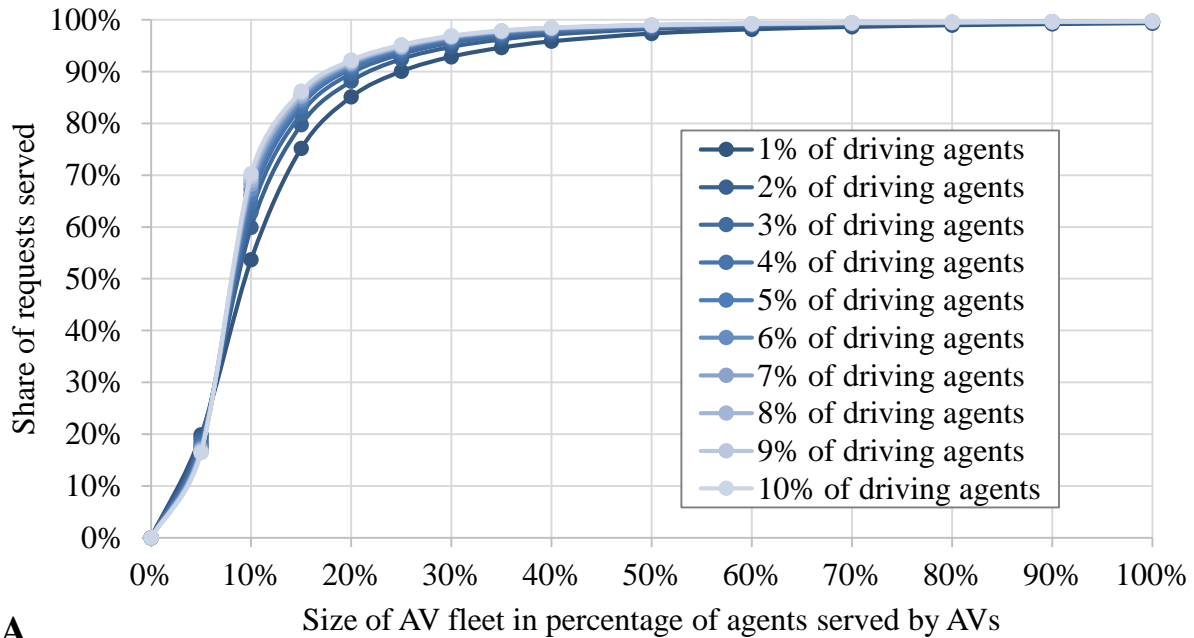
The performance of the AV fleet is almost independent of the population size for the demand levels 4% to 10%. For the demand levels 1% to 3%, however, the performance drops. AV fleets of the size of 10% to 30% of the original car fleet perform in these scenarios considerably less well than in the other scenarios. For the same performance larger fleets are required. Notably, for 5% fleets the trend turns in the opposite direction.

4.2 Fleet Required to Serve 95% of the Requests in Time

In Figure 2B the darker line represents a crosscut through Figure 2A at the performance level of 95%. It therefore shows for different levels of demand the minimally required fleet size to serve at least 95% of the demand within 5 minutes. The lighter line represents the same values if the requests served 5 to 10 minutes after registering are included too. For the latter case, the standard deviations are in average 0.06% and maximum 0.98%. The values shown in Figure 2B were calculated for 95% with a linearization between the two simulated values closest to 95%.

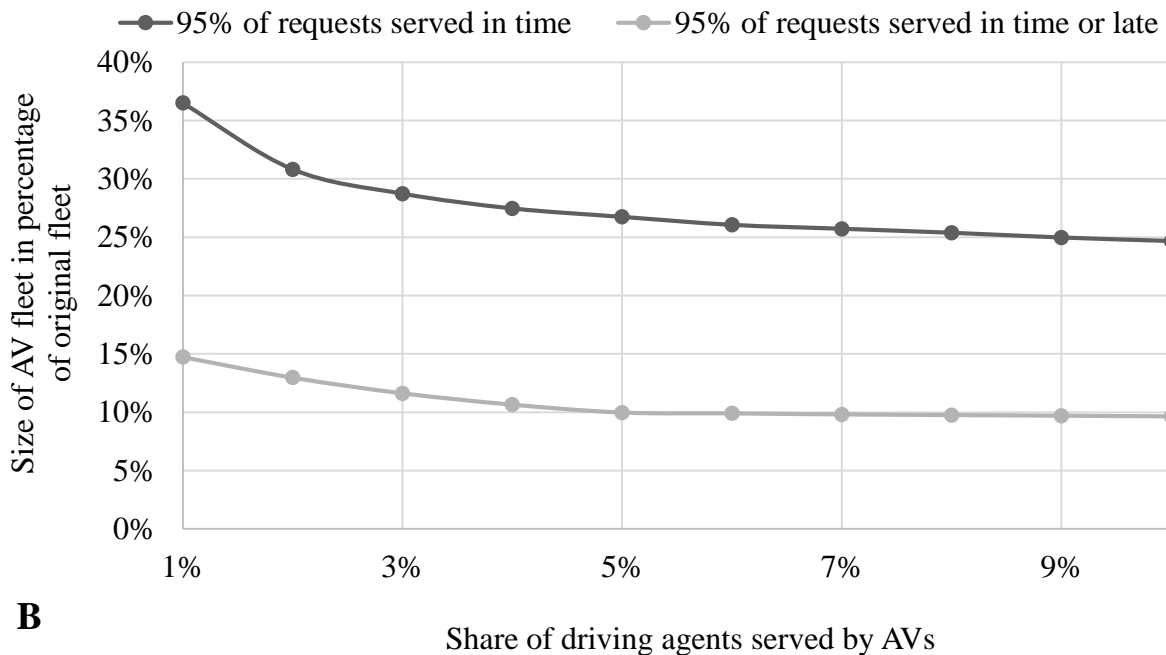
Figure 2B confirms the conclusions drawn from Figure 2A. It shows that for small demand levels the required minimal AV fleet to achieve a 95% performance is strongly dependent on the share of population participating in the program. The ratio between the original fleet and the AV fleet grows as demand density grows, meaning that the fleet is used more intensively and thus more efficient. Only for larger demand levels – 5% to 6% and more – the required ratio stabilizes.

If all requests served within 10 minutes are considered, smaller AV fleets are required for the same performance. The basic picture, however, is consistent: For low levels of demand the required fleet is dependent on the number of requested trips.



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FIGURE 2 AV-Fleet performance versus share of driving agents served by AVs. Subfigure A shows the performance of differently sized AV fleets for different demand levels. The performance is measured as the share of requests served within the first 5 minutes after the requests were registered. Subfigure B presents a crosscut through subfigure A at the 95%-performance level. It shows for a required share of 95% of the requests served within 5 minutes (dark) and within 10 minutes (light) the number of required AVs to serve different demand levels (1% to 10%).

4.3 The 10% Demand – 10% Fleet Scenario

For the remaining part of the Results section, one scenario is presented in more detail. The 10% demand / 10% fleet scenario was chosen as an example because it combines a large demand with a small fleet which introduces competition for AVs in the scenario.

4.3.1 Overview

The scenario consists of 130'831 agents. This is the number of agents that had at least one car trip in the MATSim scenario. These agents undertook a total of 366'124 car trips. These trips represent the demand for the AV scenario. In total 13'083 AVs were placed in the scenario, which is 10% of the number of agents.

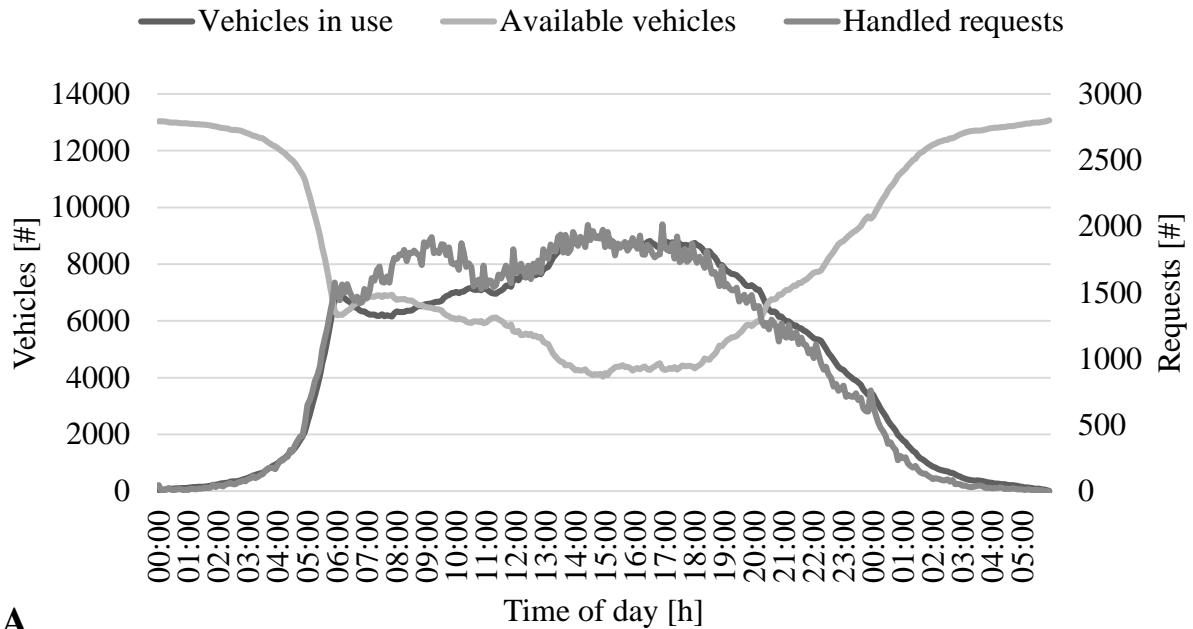
Over all random seeds, these AVs served on average 257'000 requests (70.3% of the total demand) in time (in under 5 minutes) and 95'000 requests (25.9%) late (within 5 to 10 minutes). This left 14'000 requests (3.8%) unserved. Served requests (in time and late) were assigned a vehicle on average after 26 seconds. The average response time, that is the time for an AV to appear at the start location of the request (including assignment), was 3.11 minutes (driving time: 2.68 minutes). For trips served on time, the AV had to wait on average 3.56 minutes for the passenger to appear. For trips served late, the passengers had to wait on average 2.67 minutes for the AV to appear. The average service time, which is the time span from the start to the end of the MATSim trip, was 18.66 minutes. In comparison, the average trip duration of a car trip in the Zurich region is 19.70 minutes (12).

4.3.2 Throughout the Day

The average numbers above give a summary assessment of the scenario, but to understand the system behavior, the dynamics over time need to be investigated. Figure 3A presents the available vehicles and the vehicles in use over the course of a simulation day. It also presents the handled requests. These are all requests which were served (in time or late) or dropped within the preceding sample interval (5 minutes). The requests are presented in more detail in Figure 3B, which shows over the course of a simulation day how many requests could be served quickly (response in less than 1 minute), in time, late or had to be dropped.

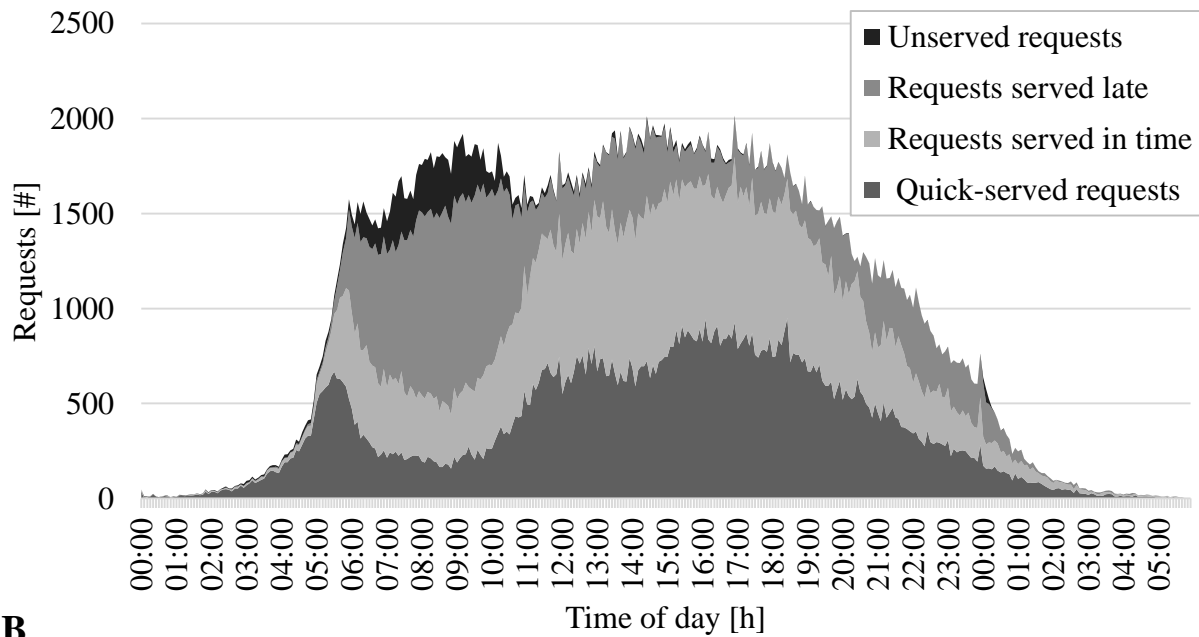
Vehicles are either in use or available. Since no other state is allowed in the current version of the simulation they always sum to 100% (Figure 3A). The number of vehicles in use matches the demand over the day, except for the morning peak (Figure 3A). This means that the morning peak cannot be fully served, which is confirmed by a rise of unserved requests (Figure 3B). In contrast, the afternoon peak can be served by the vehicles.

For most time of the day, a large share (a third and more) of the vehicles are not in use (Figure 3A). Even at the time of the highest peak, 4'033 vehicles (30.8% of the total AV fleet) remain available. Figure 4 shows a histogram of the required assignment time and response time for the requests. It shows that 78.1% of the requests can be assigned immediately. Most can also be responded to within the first 3 minutes. If a request takes more than 3 minutes to respond to, any response time of 3 to 10 minutes seems equally likely.



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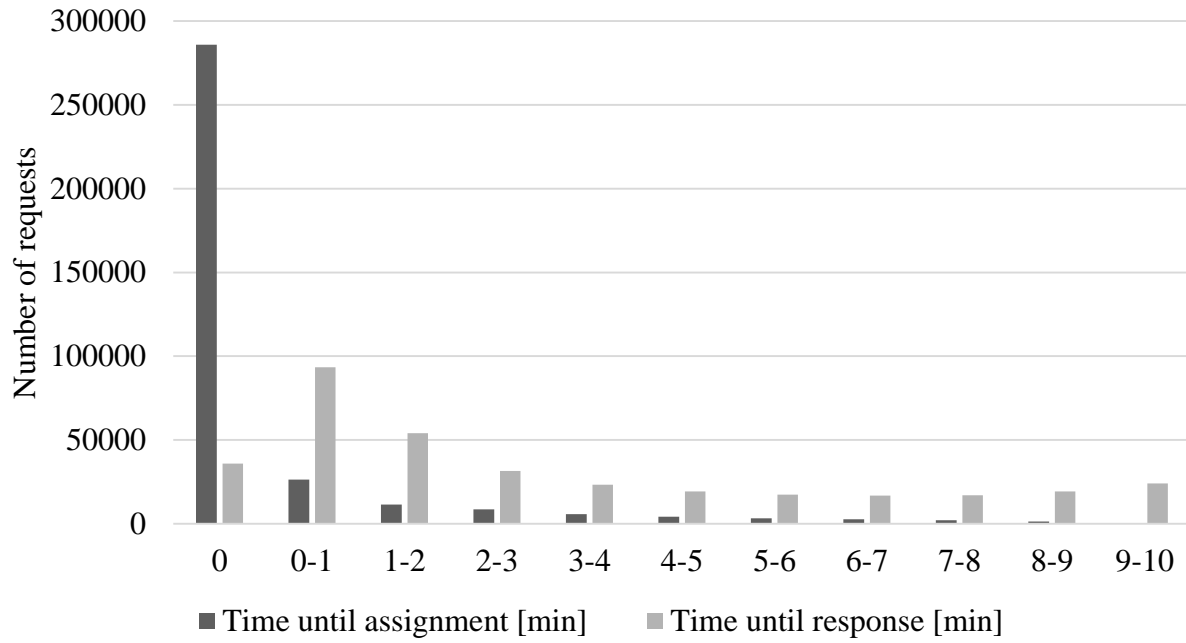


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4 **FIGURE 3 Usage and performance of the AV fleet over the course of a simulation day (30h).**5 **Subfigure A presents the AVs in use, the available vehicles and the handled requests over the**6 **day. The number of vehicles represent snapshots at the time of evaluation. The requests**7 **represent all requests served or dropped within the preceding sample interval (5 minutes).**8 **Subfigure B shows the number of requests which are quick-served (response within 1**9 **minute), in time (response within 5 minutes), late (response within 5 to 10 minutes) or which**10 **could not be served within 10 minutes (unserved requests).**

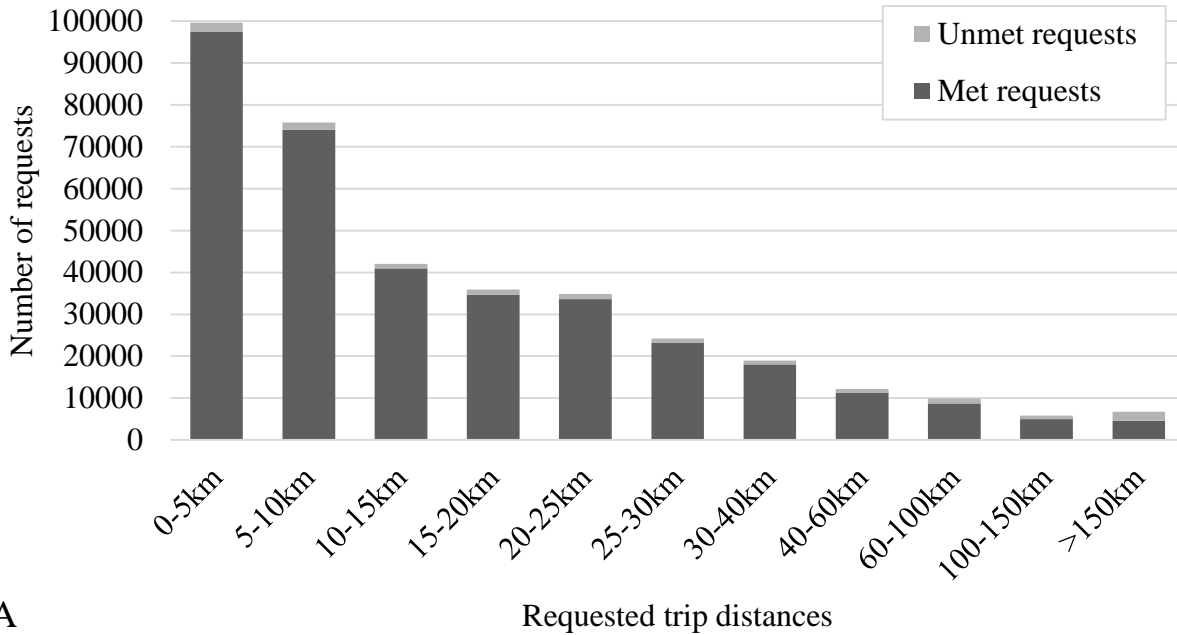


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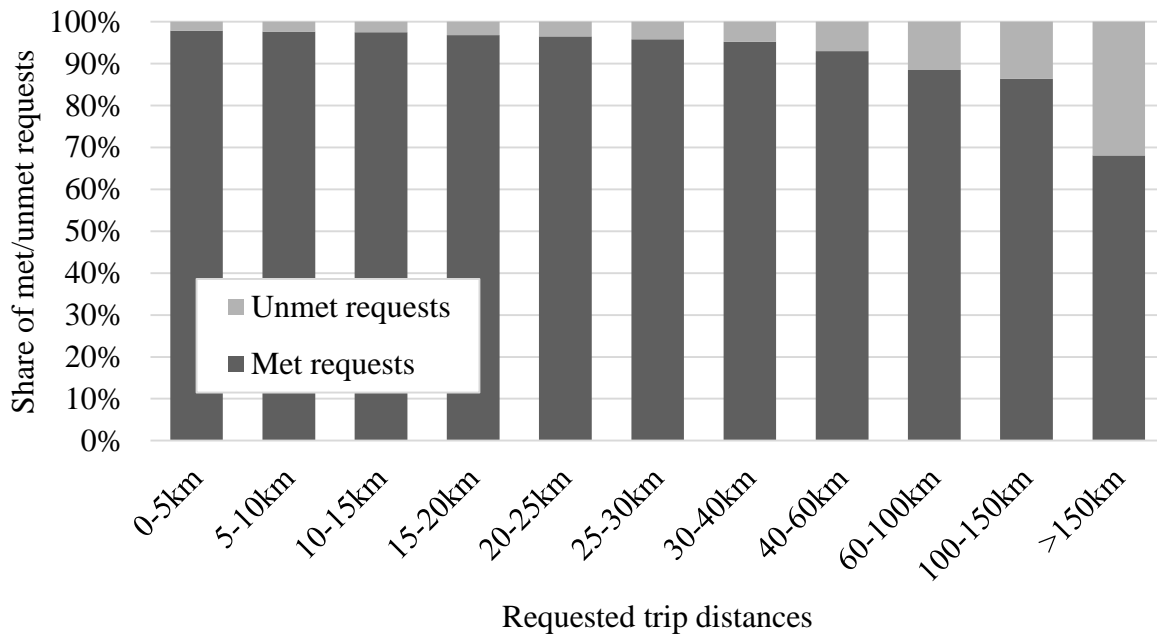
FIGURE 4 A histogram of the assignment time and the response time needed for the served requests (unserved requests are excluded).

1 4.3.3 Requested Trip Distances

2 Figure 5 presents a histogram of the requested trip distances. For trips of up to 40 kilometers a
 3 service rate of more than 95% was achieved (Figure 5B). These trips are 90.5% of the total number
 4 of trips (Figure 5A). For trips with longer distances the service rate drops with increasing
 5 distances. For the 1.8% of trips which are longer than 150km the service rate is 68%.
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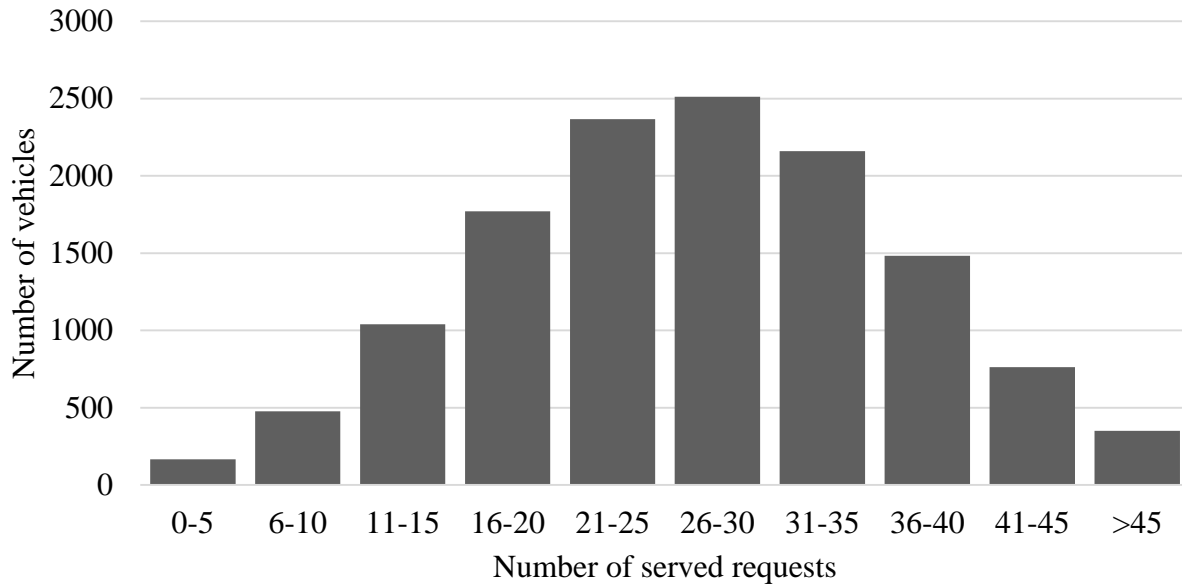
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10 **FIGURE 5 Histogram of the requested trip distances.**
 11 **Subfigure A shows the absolute number of requested trip distances (met within 10min or**
 12 **unmet), subfigure B the relative number of met and unmet requests.**

1 4.3.4 Usage of AVs

2 Over a day each vehicle serves in average 26.9 (standard deviation 9.8) requests (in time or late).
 3 Figure 6 presents a histogram of the number of served requests per AV.

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7 **FIGURE 6 Histogram over the full AV fleet showing the number of served requests per**
 8 **vehicle.**

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10 To serve these requests, an AV spends 4.0% of the day to pick-up agents (pick-up time) and 27.9%
 11 serving (service time). These two sum to a total productive AV time of 31.9% of the day, roughly a
 12 third of the time. For the rest of the day the vehicles are either waiting for agents (3.9%) or waiting
 13 for a next assignment (idle time, 64.2%). In comparison, in Switzerland today cars are used
 14 productively for only 3.2% of the day (calculated from (15)).

5 DISCUSSION

5.1 Simulation Framework

The framework presented is capable of simulating a fleet of AVs serving a spatially (meter-fine coordinates) and temporally (1 second intervals) detailed demand. This demand is generated with MATSim, an agent-based transport simulation framework, beforehand and used statically in the AV simulation. MATSim creates the demand with an equilibrium approach considering the transport infrastructure as well as all system interactions. This process makes travel demand, and in particular travel times, much more detailed and realistic than the randomly generated demand and the average speeds used in previous works on the topic ((3), (4), (5), (6)). Zachariah et al. (7) use a detailed demand generation too, but lack realistic travel times. For the study on Lisbon, the International Transport Forum (8) uses a detailed demand generation, but aggregates the demand to zones. Additionally, they do not use a dynamic traffic model like MATSim to calculate travel times, but use network routing with hourly updated occupancies of the links.

From a performance standpoint, the AV simulation presented here has short computation times, thanks to pre-calculation of demand and travel times (few minutes for small scenarios and up to 3 hours for the largest scenarios single-threaded on a standard desktop computer), which allows to simulate many different scenarios. This makes possible the investigation of many different combinations of supply and demand levels within hours.

There are, however, also some limitations to the framework. The most important limitation is probably the fact that no redistribution was simulated. The ability to re-equilibrate system unbalances autonomously is one of the great advantages which are expected from AV car-sharing services over the existing ones. Attempts to include redistribution in the simulation revealed that a successful redistribution algorithm is not easy to implement and calibrate given the very detailed character of the demand. For simulations with high spatial and temporal resolution, the redistribution algorithm not only has to determine where precisely idle AVs should be sent, but also how often a redistribution is meaningful for what share of the idle AVs and how to select the AVs which will actually be redistributed. Therefore, for this research, it was decided to focus on the scenarios without redistribution. This is an important step since it sets a baseline for future investigations of redistribution algorithms allowing the quantification of the improvement a redistribution algorithm allows.

A second limitation of the simulation framework is that no network routing is currently implemented. Since no redistribution was simulated, however, only the short pick-up trips of AVs to the trip start locations were affected by this limitation. Inaccuracies due to no network routing should therefore be limited. Nevertheless, a network routing implementation is planned since the inaccuracies are expected to become relevant in the case of longer redistribution trips.

A third point concerns the static demand. With static demand, agents have no possibility to react to the new offer of an AV sharing service by changing their behaviour and mobility demand. While traveling with an AV might be very comfortable and thus induce additional demand and mode changes from non-car modes to AVs, the additional traffic on the street might increase travel times. The trade-off between these two effects and how it influences demand can only be investigated with more sophisticated transportation simulation frameworks allowing for a dynamic representation of travel demand (e.g. an integration of this framework into the MATSim iteration process or a direct simulation of AVs in MATSim).

5.2 Simulation Results

Compared to the literature (represented by (3) and the 100% car-sharing scenario with high-capacity public transport of (8)), the 10%/10%-scenario (section 4.3) shows a much lower fleet usage. While here a peak usage of around 60% was achieved, it reached very high 97% in (3) and even 99.6% in (8). This is the same all over the day as in the 10%/10%-scenario AVs are used about one third of the day (section 4.3.4) and serve in average 26.9 trips compared to a usage time of two thirds of the day in (8) and to an average of 35.87 trips served per day in (3).

It is argued that, besides relocation, these differences are mainly due to the inner city character of the other two studies. Inner cities show an above average high density of demand which results in very high usage numbers of the fleets. The demand used for this study, originating from locations over a very large area (more than 420km x 270km as shown in Figure 1), shows what should be considered if a more open scheme would be applied. Indeed, Figure 5, which shows the number of met requests versus the trip distances, indicates that a limitation of the service area has strong influence on the average fleet usage and the level of service achievable.

It is interesting, however, that even for this large area, 1 AV has the potential to replace up to 10 of today's cars if a reaction time of maximum 10 minutes is accepted and the share of the participating population is large enough (Figure 2). Even though the ratio drops to 1 AV for 4 cars if only the requests served within 5 minutes are considered, this result is very surprising because it was achieved without any redistribution. Given the results discussed above, it is hypothesized that the high density of requests close to Zurich overcompensates the effects of the large area. This means that a strong spatial aspect of the trip distribution comes into play. This is supported by the fact that most trips are missed during the morning peak, while the higher afternoon peak could be fully served (Figures 3 and 4). This means that, even if the results of this study, at a first glance, do not depart substantially from previous studies, it is important to be able to capture such effects which depend on a realistic and detailed demand. This relationship between city form (and density) and the efficiency of an AV fleet is indeed a topic for future research. For the Zurich scenario, however, Figure 2 suggests that a limit is reached and that redistribution or carpooling will be required to achieve further improvements in fleet usage. Santi et al. (16) show for example that for taxi fleets large improvements can be achieved with optimized carpooling. Balac and Ciari (17) showed that improvements through redistribution can – at least for one way station based car-sharing – be substantial. How and how much the situation can be improved with carpooling and redistribution for AV car-sharing fleets, as well as what algorithms to use – (18) provides a recent review on car-sharing redistribution approaches – will be the topic of future research.

An important result, despite the discussion above, is the statement that the minimal AV fleet required to serve a demand successfully is dependent on the size of the demand (sections 4.1 and 4.2). For example, in percentage points a more than 50% larger fleet is required if only 1% of the population participates instead of 10% (Figure 2B). This dependency can be explained by the available number of vehicles per area. The same fleet size relative to the demand results in less vehicles per area for smaller demands than for large demands. If fewer vehicles are available per area, the chance for a request to find an AV within the service radius in time is smaller and thus more vehicles are required. It is interesting that this effect saturates if 5% or more of the total demand are simulated (Figure 2). What effect redistribution has on this dependency of fleet size on demand size is not clear yet. It is hypothesized that redistribution will be able to reduce this effect – to what degree and cost is part of future investigations.

6 SUMMARY AND NEXT STEPS

This paper presented a framework for the simulation of Automated Vehicles (AV). The framework builds on MATSim, a state-of-the-art multi-agent transport simulation, although it is not directly an extension of it. The framework uses the demand generated by MATSim, but simulates the AVs in a separate simulation environment. The demand used is – to the best knowledge of the authors – spatially and temporally more detailed than the demand used in any other existing study on the topic, with some important implications as discussed in section 5. Despite the level of detail, computation time is short enough that series of large scale simulations (10^6 agents) are possible within hours. This performance allowed a detailed (140 simulated scenarios) investigation of how the demand size influences the required fleet size to serve the demand. A decreasing trend for the ratio vehicles/users was found as the number of users increases. This means that for a small demand the fleet is used less efficiently. If this observation can be confirmed by future research, it has implications not only for the transferability of results from studies of AV fleets but also for future experiments on shared services. If only small samples of the population are included, operators need to be aware that they will have to provide substantially more than expected numbers of vehicles. It could be shown that this increase is more than 50% if you have only 1% of the population participating instead of 10% participating.

The simulation framework still has several limitations and future work will address them. The implementation of a redistribution scheme and of network routing in the simulation framework are two of the most important next steps (section 5). For the research on AV fleets, however, it is probably more important to overcome the limitation of using a static demand next. Transport demand is influenced by new mobility offers and changed mobility costs. Demand has to be able to adapt to these new offers. AVs might induce more demand because they make traveling more comfortable and less expensive. This might also induce mode changes from public transport and slow modes to AVs (19). Such demand changes might bring the transport infrastructure to its limits and increase travel times with AVs. This in turn would have demand reducing effects, bringing the system to a new system equilibrium. How such effects influence each other, how the new equilibrium will look like and what this means for infrastructure capacity requirements, requires the investigation with simulation frameworks able to explicitly account for such effects. MATSim is inherently capable to model such complex interactions, assuming that the simulation of AVs is directly embedded in the framework too. For now MATSim was only used to generate the initial demand since it is not yet able to simulate AVs. After this is implemented (20), however, it will be possible to get a more complete picture of the impact of AVs on the global vehicle fleet.

7 ACKNOWLEDGEMENTS

The MATSim scenario used for the demand was developed and calibrated by T. Dubernet (IVT, ETH Zurich).

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