

# Fleet control algorithms for automated mobility

## A simulation assessment for Zurich

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1 **Fleet control algorithms for automated mobility: A simulation assessment for Zurich**

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1 **ABSTRACT**

2 The performance of four different dispatching and rebalancing algorithms for the control of an  
3 automated mobility-on-demand system is evaluated in a simulation environment. The case study  
4 conducted with an agent-based simulation scenario of the city of Zurich shows that the choice of  
5 an intelligent rebalancing algorithm decreases the average wait time in the system. For a wait  
6 time of four minutes at peak hours the best performing algorithm requires the same price per  
7 vehicle kilometer as a private car today. The results indicate that shared mobility systems of  
8 automated vehicles will reach higher occupancy rates than conventional private cars.

## 1 INTRODUCTION

2 The rapid technological development in recent years has led to the point where automated vehicles  
3 are tested in pilot projects around the world (1). They promise to increase road capacities and  
4 speeds (2, 3) and would give access to mobility to formerly excluded user groups (4). On the  
5 flipside an increase of vehicle miles travelled (VMT) is expected due to empty rides (5), and  
6 the general increase of users has the potential to congest the urban environment even more than  
7 today (6). Hence, the net effects on the transport system, environment, and society are unclear.  
8 Simulations, such as the one presented in the work at hand can help to better understand the  
9 impact of future developments in vehicle automation.

10 A number of studies in recent years debated the feasibility of an automated mobility-on-  
11 demand (AMoD) system (see Related Research below). With such a system travelers would  
12 not need to own their own car, but could call an automated vehicle (AV) to pick them up at  
13 any location and bring them to their desired destination. For the customer this would offer the  
14 convenience of an individual taxi service for a fraction of today's cost. It is predicted that the  
15 costs of using the service on a daily basis compete with privately owned cars and even public  
16 transit (7).

17 The success of an AV operator would depend on the pricing of his service as well as the wait  
18 and travel times that can be offered. While high prices may restrict the user group drastically,  
19 long wait times may have the same effect if they make traveling less predictable than before.  
20 Both quantities are inherently linked by the way the fleet is operated: If wait times have to be  
21 minimized, vehicles have to be at all times present where the demand is expected. This makes it  
22 necessary to relocate them without a passenger on-board, which directly translates to costs for  
23 the operator. Furthermore both quantities are also linked to the vehicle fleet size, which heavily  
24 influences both cost and wait times.

25 In the present study we contribute to research on AMoD system as follows: We (a) present a  
26 simulation scenario of a fleet of automated taxis for Zurich, Switzerland, based on the MATSim  
27 framework (8), we (b) test and compare four different dispatching and rebalancing algorithms  
28 from literature for different fleet sizes, (c) analyse the results in terms of customer acceptance  
29 and (d) compare our results with theoretical predictions for fleet sizing.

## 30 RELATED RESEARCH

31 Station-based mobility on demand systems, e.g. car sharing schemes like Mobility, in Switzerland  
32 (9) are a well-established part of the modal share of many cities. These schemes offer flexibility,  
33 competitive prices and good service levels. However, their popularity is heavily limited by the  
34 fact that the vehicle has to be dropped off at the origin of the journey. In contrast, in one-way  
35 mobility on demand systems customers can travel with a vehicle (e.g. automated car or bike)  
36 from any origin to any destination in the city which dramatically increases the flexibility of these  
37 systems. An assignment model for this kind of service has been proposed in (9).

38 The price for the increased flexibility is system imbalance. Due to the spatio-temporal and  
39 in general unbalanced characteristics of travel demand, vehicles tend to accumulate at certain  
40 locations and get depleted at others. Furthermore system imbalance is not an exception but occurs  
41 for most demand patterns. This can be seen for instance using queuing-theoretical arguments as  
42 shown in (10).

43 System imbalance leads to drastically decreased service levels and must be countered with the  
44 targeted repositioning of vehicles from oversupplied to empty areas of the city. This repositioning

1 of vehicles makes a substantial contribution to the operational cost of operators and therefore  
2 various strategies have been tried to minimize the rebalancing effort. For instance in bike-sharing  
3 schemes, trucks are used to move vehicles from full to empty stations, in (11) algorithms have  
4 been proposed to route these trucks at minimal cost. In (12) price incentive controllers are  
5 proposed to encourage customers to travel to depleted stations at the end of their trip. Rebalancing  
6 was also researched for car sharing schemes, e.g. in (13) a scheme is proposed to reposition the  
7 rebalancing drivers for one-way car sharing schemes in an optimal way. The decisive difference  
8 of AMoD systems to the previous two cases is that the vehicles can reposition themselves without  
9 the use of transporting trucks or auxiliary drivers. Therefore rebalancing can be carried out more  
10 efficiently and with more degrees of freedom.

11 Rebalancing of automated mobility on demand systems was first presented as a research  
12 problem in (14). Optimal rebalancing flows for the vehicles are obtained by solving a linear  
13 program. In (10) the relation to queuing theoretical concepts was established. In (15) the  
14 relation of the rebalancing effort to the underlying distributions of origins and destinations was  
15 established and it was shown that for general distributions the total minimal rebalancing distance  
16 is strictly more than zero. In (16) the rebalancing problem was solved with a model predictive  
17 control algorithm which performs well but does not scale to large systems.

18 Most of these algorithms were tested on simplified traffic simulations that capture the main  
19 characteristics but do not allow the same level of detail as agent based traffic simulations  
20 like MATSim. For such simulation platforms various results exist which are presented in the  
21 following paragraphs. Most of them do not implement and compare the algorithms mentioned  
22 above which is an important contribution of this work.

23 Spieser et al. (17) present a systematic approach to the design of an automated mobility  
24 on demand system that is able to serve the entire travel demand of Singapore with a fleet of  
25 automated shared vehicles. Analytic results are used to compute both the minimal number of  
26 vehicles needed to stabilize the number of open requests as well as the amount of vehicles that is  
27 needed to provide an acceptable level of service. The authors conclude that a fleet size of 25%  
28 of today's vehicle fleet would be able to offer average wait times of around 15 minutes and could  
29 reduce the external and internal costs of mobility by 50%. The study does not compare different  
30 fleet control algorithms and does not elaborate on whether congestion effects have been taken  
31 into account.

32 Fagnant et al. (18) present a case study for Austin, Texas which focuses on the use of shared  
33 automated vehicles with ride-sharing capabilities, i.e. vehicles that can transport more than one  
34 customer under some circumstances. Should only one passenger be able to use the vehicle at a  
35 time, they conclude that the same amount of trips could be served with 90% less vehicles in a  
36 shared automated mobility system compared to today's fleet of private conventional cars.

37 The scenario presented on vehicles with a capacity of one passenger unit capacity yields that  
38 10% of today's vehicle fleet could serve the entire demand.

39 (19) present a case study for New Jersey which also focused on the potential of ride-sharing  
40 in combination with the local train system. The study concludes that the ride-sharing potential  
41 is large, especially during rush-hour and shared automated vehicles could substantially reduce  
42 congestion levels in the city. In (20) the generated demand is served by autonomous vehicles and  
43 a detailed analysis of fleet sizes and resulting empty mileage is performed.

44 In (21) the authors present a study on the effects of introducing automated taxis and automated  
45 shared taxis to the city of Lisbon, Portugal. The agent-based simulation includes 1.2 million trips

1 and three scenarios: a baseline scenario showing the current situation and two scenarios where  
2 private car, taxi and bus trips are replaced by automated taxis and automated taxis and shared  
3 taxis respectively. The fleet size of automated (shared) taxis is set at 4.8% of the baseline vehicle  
4 fleet. In these scenarios about 50-70 % of trips are serviced by the automated (shared) taxis  
5 which increases the vehicle utilization from 50 mins to 12.87h on average per day. The authors  
6 conclude a decrease in cost by 55%, highly increased transportation accessibility in the city and  
7 carbon emission reductions of almost 40%. The simulation does not consider the changes on  
8 traffic density parameters resulting from self-driving vehicles. Furthermore the demand choice  
9 of the agents is static and according to preset parameters. Finally the fleet control (rebalancing  
10 and dispatching) for the (shared) automated taxis is implemented based on heuristics and a local  
11 gradient based optimization method.

12 Boesch et al. (22) investigate a scenario of the greater Zurich region in Switzerland. They  
13 use a demand pattern for private vehicles generated with MATSim, which consists of 1.3 million  
14 private vehicle users. They conclude that 30 % of the substituted fleet can serve almost 100%  
15 of the substituted requests within less than 10 mins wait time. The big limitation is that if the  
16 wait time is surpassed, a request is dropped. Furthermore, no rebalancing or dispatching is  
17 taking place, and the Euclidian distance in combination with a scaling factor is used instead of a  
18 network-based distance.

19 In contrast to the study for Zurich presented above, a case study for Berlin presented in (23)  
20 simulates AVs reacting to dynamically changing requests. It considers a city-wide replacement  
21 of private vehicles with automated taxis, that are dispatched using a heuristic algorithm, which  
22 will be tested in the present work. The study concludes that 1.1 million former car users can be  
23 served by a fleet of 100,000 shared automated vehicles. The study is one of the first large-scale  
24 dynamic simulations of a shared automated taxi system, however it does not consider different  
25 rebalancing and dispatching strategies.

## 26 CONTROL OF AN AMOD SYSTEM

27 An AMoD service can only be maintained if a sufficient number of customers wants to use the  
28 service, such that it is profitable for the operator. While a multitude of factors influences the  
29 attractiveness of the service (perhaps multimedia offers in the vehicle, the quality of Wifi, ...) the  
30 authors assume two key properties: The time that passes between a customer making a request  
31 and a vehicle arriving (i.e. the wait time) and the price that is charged to the customer. All else  
32 being equal, an operator that can offer the shortest wait times at the lowest price will attract more  
33 customers than his competitors.

34 We focus on two main ways for operators to influence the service level of their system:

- 35 • The **fleet size** can be increased. In general, this should lead to a decrease of wait time,  
36 because the availability of vehicles improves. However, having a larger number of vehicles  
37 imposes higher fixed costs that would need to be balanced by higher demand. In general,  
38 adding more vehicles to the fleet can be regarded as a long-term investment that cannot be  
39 altered on a daily basis.
- 40 • The **fleet control** can be optimized. Since in an AMoD system it is assumed that any  
41 vehicle can be tracked and controlled online, intelligent fleet control algorithms can be  
42 used to minimize the wait times, but also to minimize the driven distance in order to  
43 reduce operational cost. Applying the proper algorithm is a less costly intervention than  
44 increasing the fleet size.

1 In the presented experiments both components are investigated by comparing a number of  
2 control algorithms for fleets of varying sizes.

### 3 **Problem Statement**

4 For the algorithmic improvement of the fleet management, the authors distinguish between two  
5 stages:

- 6 • The **dispatching strategy** decides on how to serve the demand, i.e. how to match the open  
7 customer requests with the available vehicles. At any time the dispatcher can send tasks to  
8 pickup a specific customer to any vehicle that is not currently having a customer on board  
9 (since we do not consider ride-sharing with multiple customers). Also a reassignment of a  
10 previously assigned vehicle to another request is possible.
- 11 • The **rebalancing strategy** decides on where to send vehicles when they are not in use and  
12 the low demand allows for supplementary movements of the vehicles. The task of the  
13 rebalancer is to anticipate future requests and position vehicles such that they are able to  
14 optimally react to the expected future demand.

15 Hence, vehicles will produce three kinds of mileage:

- 16 • **Empty pickup mileage** is produced when an AV is dispatched to a request and is driving  
17 to the pick-up location. It is the mileage that needs to be covered in order to serve the  
18 customer in any way and may be minimized by an intelligent dispatching algorithm.
- 19 • **Empty rebalancing mileage** is produced when an AV is sent to a different location where  
20 demand is expected. An ideal operator would exchange all the pickup mileage in the  
21 system against rebalancing mileage, i.e. the operator would always send empty vehicles  
22 before an actual request turns up.
- 23 • **Customer mileage** is produced with a customer on board. This mileage does only depend  
24 on the routing of the cars. In any combination of fleet size and control algorithm, this  
25 mileage stays constant, assuming that the origin-destination relations of the customers do  
26 not vary.

27 Mileage for maintenance and recharging is not further considered in this paper and subject  
28 to future research. Assuming a common pricing scheme that defines a price per distance, the  
29 customer mileage is the only component that produces a benefit for the operator. All other  
30 mileage can directly be translated into costs and should therefore be minimized. For general  
31 demand patterns, however, it cannot be driven to zero. Spieser et al. (17) show that it is bounded  
32 below by the earth mover's distance (24), which is a measure of how different the distributions  
33 of trip origins and destinations are (25).

34 The objectives for a fleet management algorithm can therefore be defined as:

- 35 1. Minimize the total pickup distance given the non-optimal locations of the vehicles  
36 (dispatcher)
- 37 2. Exchange as much pickup distance as possible for rebalancing distance (rebalancer)

38 It is assumed that the operator does not know any demand patterns in advance. Furthermore,  
39 the analysis does not include ridesharing and its implications on fleet management algorithms.

### 40 **Selected Algorithms**

41 In this work we analyze four different operating strategies from the literature, which are briefly  
42 outlined below:

1. The **Load-balancing heuristic** is a strategy presented in (23). For every dispatching time step  $\delta t_D$ , it is checked whether there are more available vehicles than requests. If this is the case, it iterates on the list of requests and assigns to each request the closest vehicle. If there are more open requests than available vehicles, the controller iterates on the available vehicles and assigns the closest open request to each vehicle. The assignments are binding, i.e. they are not reopened once established.
2. The **Global Euclidean Bipartite Matching** (Hungarian algorithm) dispatcher determines an optimal bipartite matching between all open requests and available vehicles in every dispatching time step  $\delta t_D$ . The distance function used is the Euclidean distance which allows to use fast algorithms, e.g. (26). In contrast to the previous strategy, the assignments can be changed until a vehicle actually reaches its target.
3. In (14) a feedforward strategy is presented on how to rebalance vehicles between different vertices in a directed graph  $G = (V, E)$ . For each vertex  $i$  and time step  $\delta t$ , the arrival rates  $\lambda_i$  and transition probabilities  $p_{ij}$  for any nodes  $v_i, v_j \in V$  are computed from historical dat. The linear program in equation 1 computes the optimal rebalancing flows  $\alpha_{ij}$  for an equilibrium point of the underlying flow model with travel times  $T_{i,j} \forall v_i, v_j \in V$ .

$$\begin{aligned}
 & \text{minimize} && \sum_{i,j} T_{i,j} \alpha_{ij} \\
 & \text{subject to} && \sum_{i \neq j} \alpha_{ij} - \alpha_{ji} = -\lambda_i + \sum_{i \neq j} \lambda_j p_{ji} && \forall i \in V \\
 & && \alpha_{ij} \geq 0 && \forall i, j \in V
 \end{aligned} \tag{1}$$

To implement this strategy, we divided the city of Zurich into a set of areas. The nodes from (14) represent the centroids of these areas on which a complete directed graph called virtual network is placed, see figure 1. Available cars are continuously rebalanced between the vertices of the virtual network according to the static rebalancing rates  $\alpha_{ij}$ . As (14) does not detail the proposed dispatching algorithm for this strategy, we match cars using global Euclidean bipartite matching. Rebalancing vehicles cannot be dispatched until they reach a randomly assigned link attached to their destination virtual node.

4. The last implemented strategy is a novel derivation from (14). Instead of a pure feedforward solution, here in every rebalancing timestep  $\delta t_R$  for every area of the virtual network the available cars and open requests are counted and fed into a mixed integer linear program derived from equation 1 calculating the number of cars to be sent from virtual vertex  $i$  to virtual vertex  $j$ .

While the first two algorithms only perform the dispatching task, the latter two are designed to rebalance the available fleet of AVs.

## SIMULATION SETUP

In order to assess the performance of the different fleet sizes and control algorithms a novel scenario for the city of Zurich, Switzerland is set up for the MATSim transport simulation framework and a theoretical fleet sizing according to (17) is performed.

### MATSim and AMoD Simulation

MATSim (8) is an agent-based transport simulation framework that makes it possible to simulate large numbers of agents representing a real population in a traffic environment. Similar to reality,



1 each agent has a daily plan with activities intended to be performed for a certain duration and to  
2 be finished at a specific time of the day. Since these activities take place at different locations  
3 in the scenario, agents need to move from activity to activity. By default, MATSim allows  
4 the simulation of car traffic, public transit and slow modes such as going by bike or walking.  
5 Road-based modes, such as private cars are simulated in a time-step based manner in a network  
6 of queues with all participants at the same time. This way it is possible that congestion emerges  
7 and agents arrive late at their activity locations. While MATSim provides more functionality,  
8 e.g. the replanning of agents plans to adapt to the traffic conditions that they perceive, only the  
9 network simulation is used in this research.

10 An extension developed in (27) is used to add automated taxis to the set of available travel  
11 modes. A virtual dispatcher, for which different algorithms are used in this study, controls a fleet  
12 of AVs. Whenever an agent wants to depart from his current activity location by AV, a request is  
13 issued to the dispatcher and saved. The choice which vehicle to send and when is completely  
14 defined by the dispatching algorithm. Once the vehicle arrives at the customer's location, the  
15 pickup is processed, the AV drives to the destination and finally drops off the customer. Then,  
16 the vehicle is available for dispatching again. Alternatively, vehicles can be rebalanced, which  
17 means that the dispatcher gives an AV the instruction to drive to a different location. All of this  
18 is performed in the MATSim traffic simulation such that AVs suffer from congestion as any other  
19 vehicle.

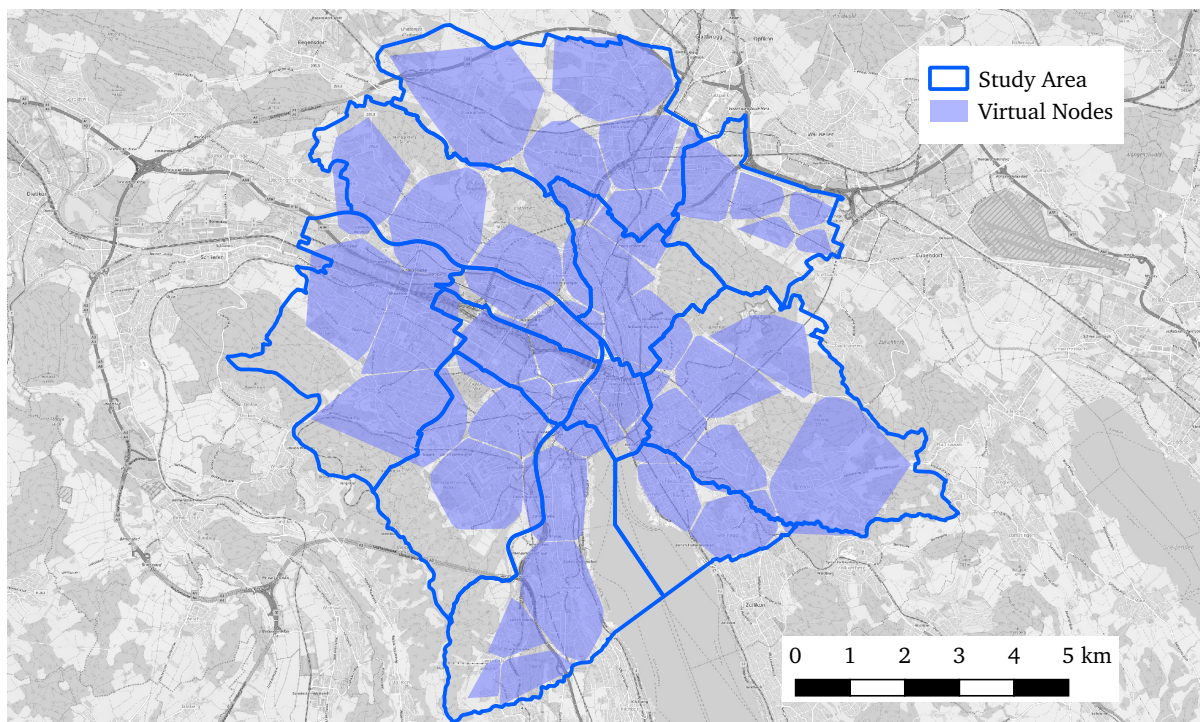
## 20 Scenario Definition

21 For Switzerland the Microcensus on mobility and transport (28) is available, which reports the  
22 daily travel patterns of 60,000 survey respondents resident in the country. It is the basis for a  
23 readily available agent population of Switzerland, which reproduces the demographic attributes  
24 and travel patterns in the country to great detail (29).

25 Additional modifications are applied to this population of around 8 million agents to make  
26 it suitable for the study at hand. First, a best-response routing of the trips of all agents is  
27 performed to find all agents that interact with the AMoD service area, which has been defined  
28 to be the 12 districts of Zurich (Figure 1). All agents which do not interact with that region  
29 (i.e. do not perform an activity within the area and do not cross the area) are deleted from the  
30 population as they do not contribute congestion in the area. Finally, a 1% sample of the remaining  
31 agents is created. The rather extensive downscaling becomes necessary for the computationally  
32 demanding algorithms, given that they need to be performed hundreds of times faster than reality  
33 to allow for multiple runs and iterations.

34 An agent that travels at least once by private car during the simulation is tagged as an AV  
35 user *only* if all of the legs in the agent's plan take place within the AMoD service area. This  
36 constraint makes sure that no unrealistic travel plans are generated, where an agent performs his  
37 first leg by AV although his private car is at home and then wants to depart at the next location  
38 with that car. Finally, the "car" legs of all viable agents are converted to the "av" mode. All  
39 other legs are kept as before, i.e. short legs that are assigned the "walk" mode initially are still  
40 performed with this mode.

41 For agents that use public transit, the procedure is different. Here, any leg that is performed  
42 by the "pt" mode in the original population is converted to "av" if it lies within the AMoD  
43 service area. As for car users, connecting non-motorized legs are kept fixed. Proceeding as  
44 outlined, a demand for Zurich is generated in which each leg that possibly *can* be performed  
45 using an AV *is* performed by AV. To summarize, all agents whose daily trips are entirely in the



**FIGURE 1** The AMoD service area covering the 12 districts of Zurich and the nodes of the virtual network for the rebalancing algorithms. (Map: OpenStreetMap)

1 service area switch to using the AMoD system. Furthermore all public transit trips within the  
 2 service area are now served by the new system. The remaining trips are unchanged.

3 In conclusion, the 8,230,971 agents in the population are reduced to 1,935,400 agents, which  
 4 touch the AMoD service area. From this set of agents a 1% sample is drawn, leading to 13,141  
 5 agents that mainly constitute background traffic for congestion. Among those are 970 agents are  
 6 viable for the AV service. The plans of these agents contain 2,096 trips that are to be served  
 7 by AVs. In reality, this scaled service would hence need to serve 209,600 requests by 97,000  
 8 persons.

### 9 Theoretical Fleet Sizing

10 Fleet sizes can be estimated using simulations, as for instance done in (23). Despite the  
 11 accuracy of these simulation results, they do not provide insights into the fundamental properties  
 12 influencing the relationship between fleet size and performance metrics.

13 For this reason we implement theoretical results from (17) for the case of Zurich. The  
 14 authors present two methods for fleet size evaluation. The first method estimates the theoretical  
 15 minimum fleet size to stabilize the system, i.e. to ensure that the number of open requests stays  
 16 bounded at all times. To do so, for every vertex  $i$  and timestep  $\delta_t$  the added unserved mileage per  
 17 timestep is calculated as  $\lambda_i \cdot (\bar{d}_{OD,i} + \bar{d}_{EMD,i})$  where  $\bar{d}_{OD,i}$  is the average distance per trip and  
 18  $\bar{d}_{EMD,i}$  the mover's distance per vehicle in the timeslice.  $\bar{d}_{OD,i} + \bar{d}_{EMD,i}$  represents the average  
 19 distance that has to be driven per request. A total of  $m$  vehicles at an average speed of  $v$  are  
 20 collectively able to reduce this added mileage at a rate of  $m \cdot v$ . This quantity has to be larger  
 21 than the added unserved mileage per timestep. For the scenario here the minimum fleet size  
 22 computed with this measure are 1380 vehicles.

1 While the knowledge of the minimum fleet size is useful, it does not reveal the relation  
2 between service level and fleet size, especially to what number the fleet size has to be augmented  
3 before further addition of vehicles will not result in a significant decrease in wait time. In (10)  
4 a method is presented of how an AMoD system can be cast in a Jackson network. For such  
5 networks, queuing theoretical results allow for the computation of performance measures such  
6 as vehicle wait times, queue lengths or availabilities at vertices. The quantity of interest is the  
7 availability of a vehicle at a vertex, which is the probability that at least one idle vehicle is at that  
8 vertex. Computation of the mean availability of all timesteps and vertices as a function of the  
9 fleet size for Zurich results in the curve shown in Figure 2(b). Note that these results are purely  
10 theoretical and can be derived solely from input data without performing simulations. Therefore  
11 they can serve as a measure of accuracy for the simulation results.

## 12 RESULTS

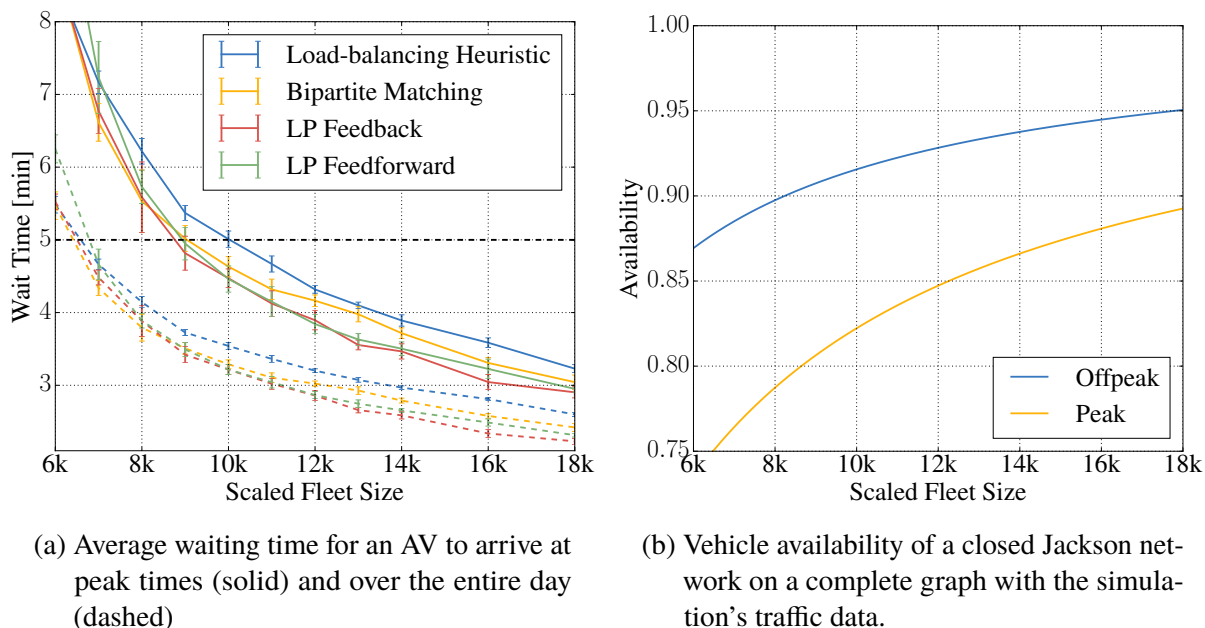
13 We test the four proposed dispatching strategies in the Zurich scenario with ten runs per fleet  
14 size and strategy. The dispatching stages of all algorithms are called once every 60 seconds  
15 in simulated time, while the rebalancing periods for the feedforward and feedback dispatcher  
16 are five minutes and 20 minutes, respectively. Those values have been obtained from prior  
17 simulation runs.

18 For Zurich, the times with peak congestion and, hence, longest travel times are from 6:30  
19 am to 9:00 am and from 4:30 pm to 6:30 pm. Figure 2(a) shows the average customer wait  
20 time over the whole day (dashed) and just for peak hours (solid). While the simple heuristic  
21 approach consistently yields the longest wait times for any fleet size, the feedback dispatcher  
22 performs best. The bipartite matching performs in between, since it is based on an optimal  
23 request assignment, but does not do any rebalancing. Since both algorithms rely on rebalancing,  
24 the two linear programs have very similar performance. The feedback algorithm seems to have a  
25 slight advantage, especially for average wait time over the whole day, because it is able to react to  
26 the observed demand more precisely. Assuming that 5 minutes at peak times are an acceptable  
27 wait time, that value is achieved with a fleet of 10,000 vehicles for the heuristic, but with only  
28 8,700 for the feedback dispatcher.

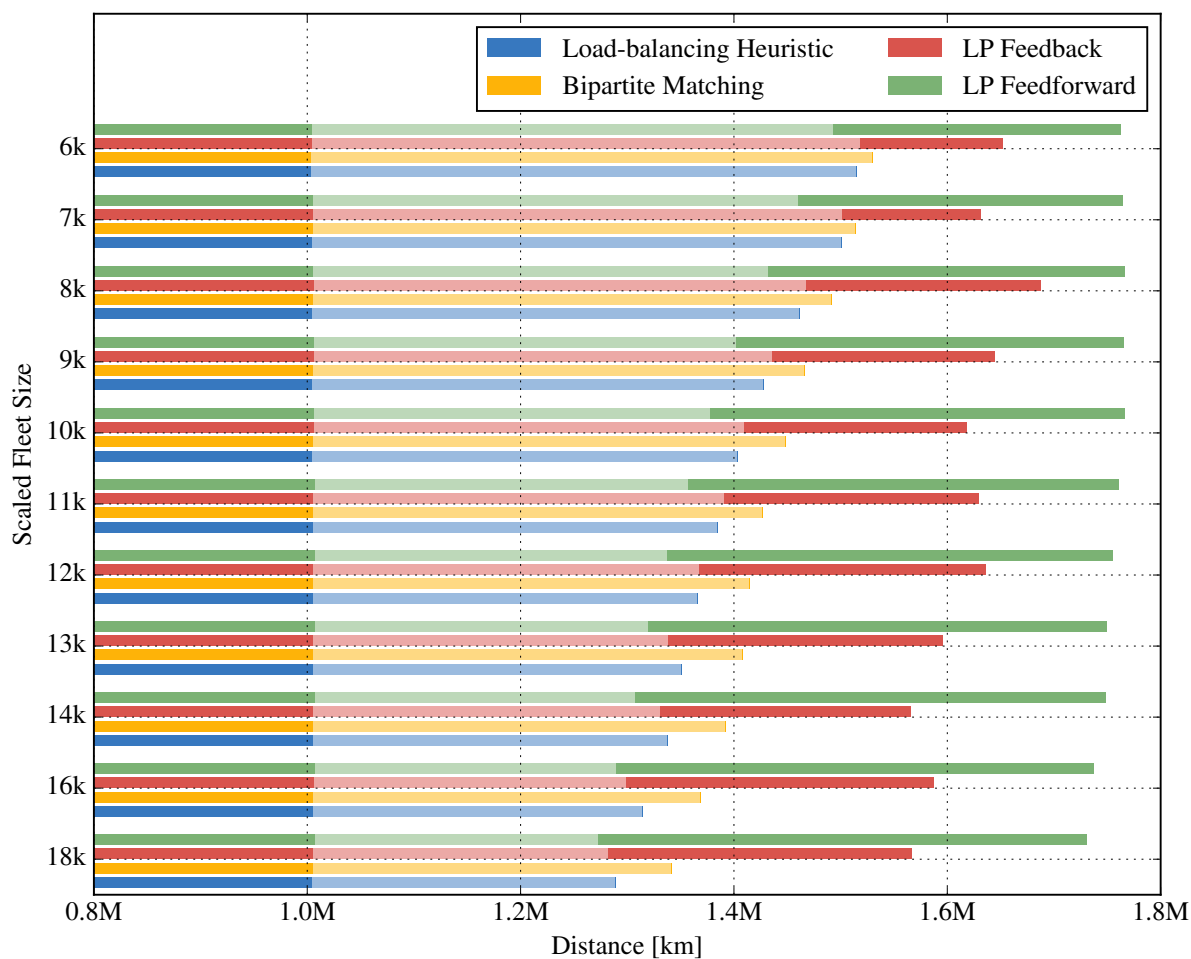
29 The measured wait times in Figure 2(a) can be compared with the vehicle availability in  
30 Figure 2(b). The two plots illustrate the theoretically confirmed correspondence (10) between  
31 vehicle availability of a closed Jackson network on a complete graph with the simulation's traffic  
32 data and the wait times.

33 Figure 3 shows the distances that different service configurations produce. On the left side  
34 the customer distance is shown, which stays constant over all runs, while one can see that the  
35 pickup distance (middle, light) is decreasing with larger fleet sizes and thus higher availability of  
36 vehicles. For the dispatchers with rebalancing one can see that they add a surplus of mileage for  
37 rebalancing (right, dark) such that the overall driven distance is rather stabilized over different  
38 fleet sizes. This added mileage is used to provide the shorter travel times as presented above.  
39 One can see that with similar wait times the feedback dispatcher operates more economically by  
40 saving mileage compared to the feedforward algorithm.

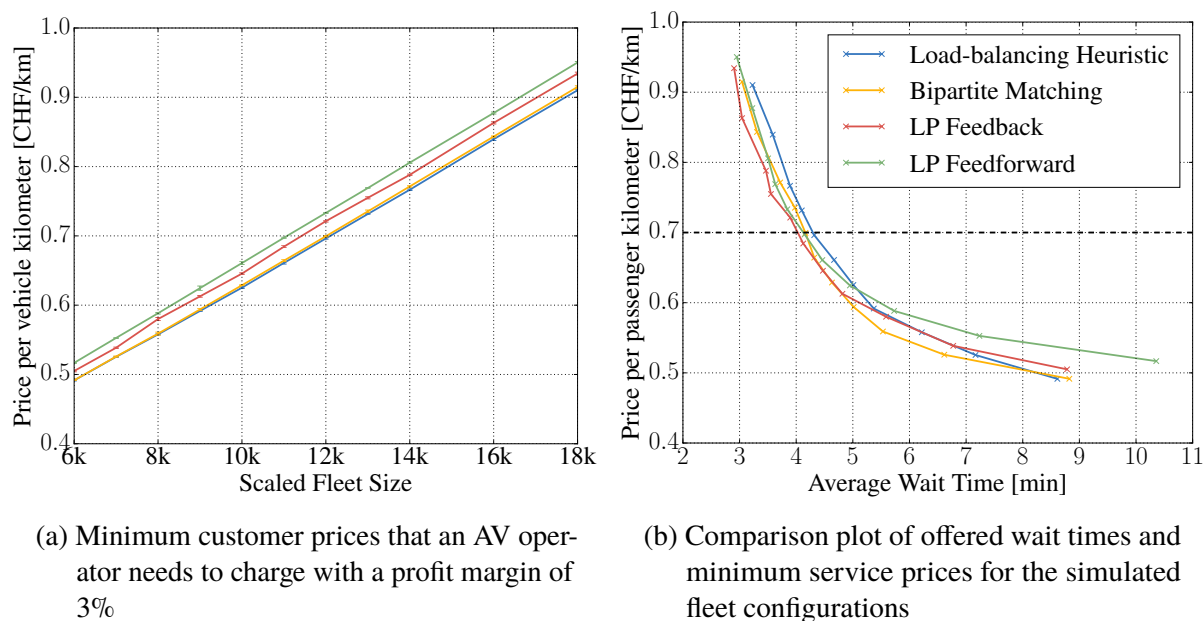
41 Finally, the utilization of the fleet is measured. For a fleet size of 6,000 vehicles, they are busy  
42 serving a passenger for around 4.8h per day, while this value drops to 2.16h for the maximum  
43 simulated fleet size of 18,000. In both cases, those numbers exceed the average of 1.32h for  
44 personal car travel in Switzerland (7).



**FIGURE 2** Fleet performance metrics for different fleet sizes



**FIGURE 3** Driven accumulated distances for different fleet sizes. From left to right: Customer distance (dark), empty pickup distance (light), empty rebalancing distance (dark).



**FIGURE 4** Analysis of fleet configurations from the customer perspective

## 1 Financial Analysis

2 Based on the cost calculator for fleets of automated vehicles by Bösch et al. (7), the costs of  
 3 operating the AV services are computed based on the key figures occupancy, share of empty  
 4 rides, operating times, trip lengths per passenger and average speed. In Figure 4(a) the resulting  
 5 price per (revenue) vehicle kilometer including a profit margin of 3% is shown. One can observe  
 6 that the price increases with the fleet size, which can be explained by lower occupancy rates. It  
 7 should however also be pointed out that the required price is different among the algorithms.  
 8 The heuristic operates at the lowest costs while LP Feedforward is most expensive throughout all  
 9 fleet sizes.

10 Nevertheless, the wait times decrease with an increasing fleet size. The trade-off between  
 11 price per vehicle kilometer and wait times in the peak hours is therefore depicted in Figure 4(b).  
 12 For lower wait times LP Feedback requires the least prices. Above 5 minutes however, Bipartite  
 13 matching becomes more efficient in terms of costs per vehicle kilometer.

14 Compared to the price of a taxi operator in Zurich (base price 8 CHF plus 5 CHF/km,  
 15 (30)) the computed prices are extremely low. Hence, an automated service would clearly push  
 16 conventional taxi operators out of the market. The variable costs of a today's private vehicle  
 17 (0.26 CHF/km, (31)) are lower than the calculated prices for the AMoD services, independent  
 18 of the algorithm. Considering the full costs of a private vehicle which amount to 0.7 CHF/km  
 19 (31) however, it can be concluded that AMoD services are only more expensive for fleet sizes of  
 20 around 11,500-12,000 in Zurich, depending on the algorithm. If customers accept an average  
 21 wait time of four minutes during peak hours for an AV taxi, the prices are similar to the full  
 22 costs of a standard car. Nonetheless, compared to (subsidized) prices for mass transit (0.25  
 23 CHF/passenger kilometer, (7)), the services are more expensive if they have the same occupancy  
 24 rate as today's private cars (approx. 1.4 passengers (7)).

25 Therefore, the proposed AV services are cost-wise highly attractive for car (and taxi) users,  
 26 but may not be able to compete with subsidized mass transit. On the other hand, AVs allow for  
 27 more direct trips and thus for savings in travel time. Ongoing studies analyse how these affect

1 the attractiveness of AMoD services (32). It is further expected that lower wait times will have a  
2 positive effect on the occupancy rates of a service and thus reduce the cost per vehicle kilometer.

### 3 **CONCLUSION & OUTLOOK**

4 The study shows that the right choice of dispatching algorithm for an AMoD system does not  
5 only have an impact on the performance in terms of wait time for the customer, but also that it  
6 generates a competitive advantage for the operator. Operators with intelligent redispaching and  
7 rebalancing algorithms are able to attract more customers through quicker pickups and lower  
8 prices than a competitor at small additional cost.

9 In order to assess the significance for real fleets of (not necessarily automated) taxis it needs  
10 to be noted that all of the presented algorithms are able to process dispatching and rebalancing  
11 tasks for fleets of thousands of vehicles within minutes. It is perfectly feasible to manage 100k  
12 vehicles in five minute updates using a standard laptop for the computational tasks.

13 For the presented simulations, this still poses a burden, because there a speedup compared to  
14 reality of hundreds of times is desired to be able to run large numbers of simulations. Hence, the  
15 algorithms are only tested on a subsample of 1% of the agent population that is available. In  
16 future studies, effort will be put into overcoming this restriction, either by finding approximate  
17 formulations for the presented algorithms or pursuing research on completely new algorithms.

18 Throughout the paper, a “100%” demand scenario is used, in which all trips that possibly  
19 could be undertaken by AVs are converted to the automated mode. MATSim offers the possibility  
20 to explicitly simulate attitudes toward new elements in the traffic system by defining utilities  
21 for using specific modes with distinct valuation of travel costs, travel times and distances. This  
22 way, by integrating the presented algorithms into the full MATSim loop, as shown in (27), the  
23 actual attractiveness of an AV service can be analysed including the tradeoff that people make  
24 between paying for the service, spending time in the vehicle and having to wait for it. Naturally,  
25 not 100% of possible trips would be performed by AV then, but only a fraction. Future work  
26 will take these considerations into account.

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