Fleet control algorithms for automated mobility

A simulation assessment for Zurich

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ABSTRACT

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

INTRODUCTION

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

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

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

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

RELATED RESEARCH

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

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

System imbalance leads to drastically decreased service levels and must be countered with the targeted repositioning of vehicles from oversupplied to empty areas of the city. This repositioning of vehicles makes a substantial contribution to the operational cost of operators and therefore various strategies have been tried to minimize the rebalancing effort. For instance in bike-sharing schemes, trucks are used to move vehicles from full to empty stations, in *(11)* algorithms have been proposed to route these trucks at minimal cost. In *(12)* price incentive controllers are proposed to encourage customers to travel to depleted stations at the end of their trip. Rebalancing was also researched for car sharing schemes, e.g. in *(13)* a scheme is proposed to reposition the rebalancing drivers for one-way car sharing schemes in an optimal way. The decisive difference of AMoD systems to the previous two cases is that the vehicles can reposition themselves without the use of transporting trucks or auxiliary drivers. Therefore rebalancing can be carried out more efficiently and with more degrees of freedom.

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

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

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

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

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

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

In *(21)* the authors present a study on the effects of introducing automated taxis and automated shared taxis to the city of Lisbon, Portugal. The agent-based simulation includes 1.2 million trips and three scenarios: a baseline scenario showing the current situation and two scenarios where private car, taxi and bus trips are replaced by automated taxis and automated taxis and shared taxis respectively. The fleet size of automated (shared) taxis is set at 4.8% of the baseline vehicle fleet. In these scenarios about 50-70 % of trips are serviced by the automated (shared) taxis which increases the vehicle utilization from 50 mins to 12.87h on average per day. The authors conclude a decrease in cost by 55%, highly increased transportation accessibility in the city and carbon emission reductions of almost 40%. The simulation does not consider the changes on traffic density parameters resulting from self-driving vehicles. Furthermore the demand choice of the agents is static and according to preset parameters. Finally the fleet control (rebalancing and dispatching) for the (shared) automated taxis is implemented based on heuristics and a local gradient based optimization method.

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

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

CONTROL OF AN AMOD SYSTEM

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

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

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

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

Problem Statement

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

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

Hence, vehicles will produce three kinds of mileage:

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

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

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

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

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

Selected Algorithms

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

1. The **Load-balancing heuristic** is a strategy presented in *(23)*. For every dispatching time step δt_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 δt_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 δ_t, the arrival rates λ_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 α_{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 α_{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 δt_R for every area of the virtual network the avaialble 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, each agent has a daily plan with activities inteded to be performend for a certain duration and to be finished at a specific time of the day. Since these activities take place at different locations in the scenario, agents need to move from activity to activity. By default, MATSim allows the simulation of car traffic, public transit and slow modes such as going by bike or walking. Road-based modes, such as private cars are simulated in a time-step based manner in a network of queues with all participants at the same time. This way it is possible that congestion emerges and agents arrive late at their activity locations. While MATSim provides more functionality, e.g. the replanning of agents plans to adapt to the traffic conditions that they perceive, only the network simulation is used in this research.

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

Scenario Definition

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

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

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

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

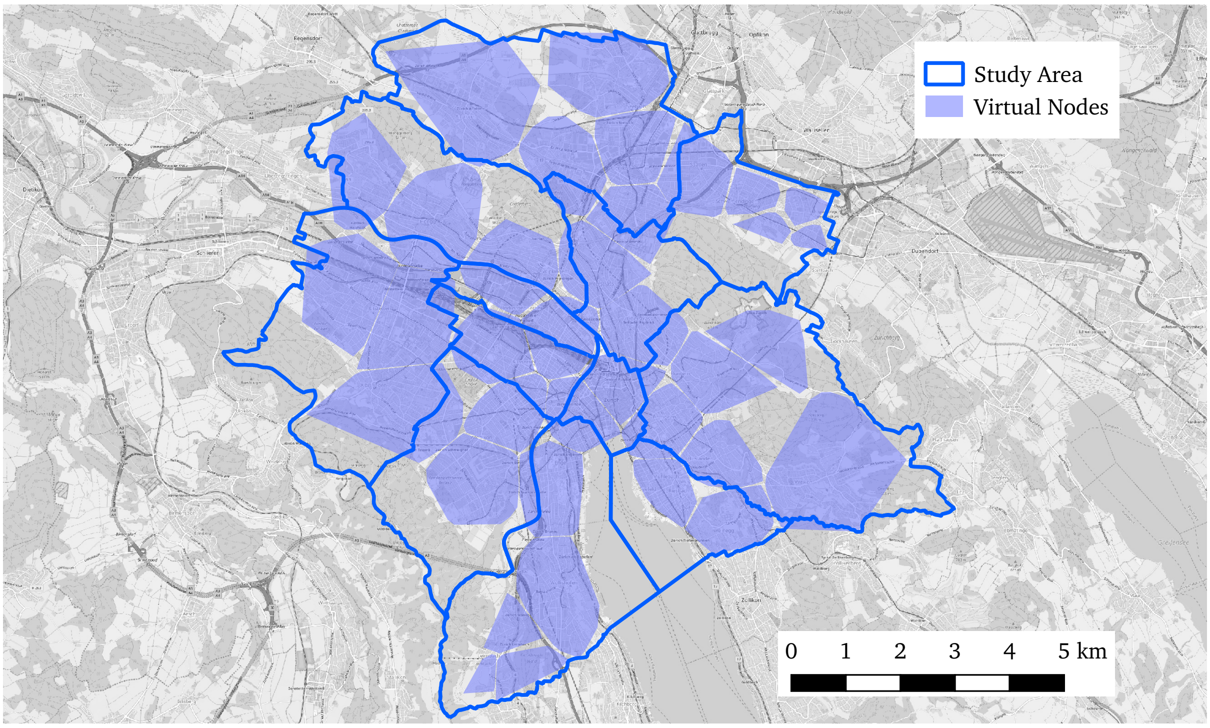


FIGURE 1 The AMoD service area covering the 12 districts of Zurich and the nodes of the virtual network for the rebalancing algorithms. (Map: OpenStreetMap)

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

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

Theoretical Fleet Sizing

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

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

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

RESULTS

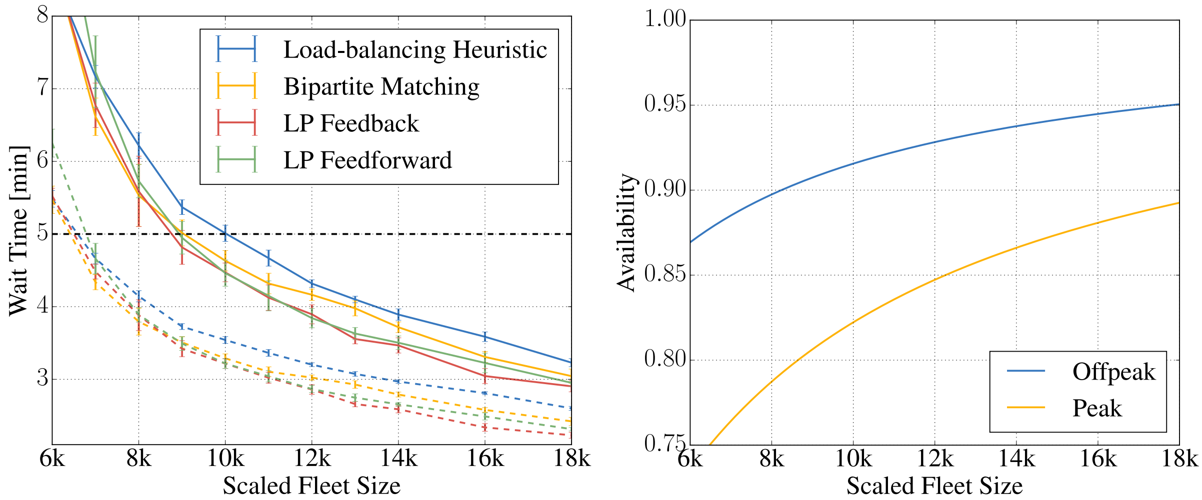
We test the four proposed dispatching strategies in the Zurich scenario with ten runs per fleet size and strategy. The dispatching stages of all algorithms are called once every 60 seconds in simulated time, while the rebalancing periods for the feedforward and feedback dispatcher are five minutes and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

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

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

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

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



(a) Average waiting time for an AV to arrive at peak times (solid) and over the entire day (dashed)

(b) Vehicle availability of a closed Jackson network on a complete graph with the simulation's traffic data.

FIGURE 2 Fleet performance metrics for different fleet sizes

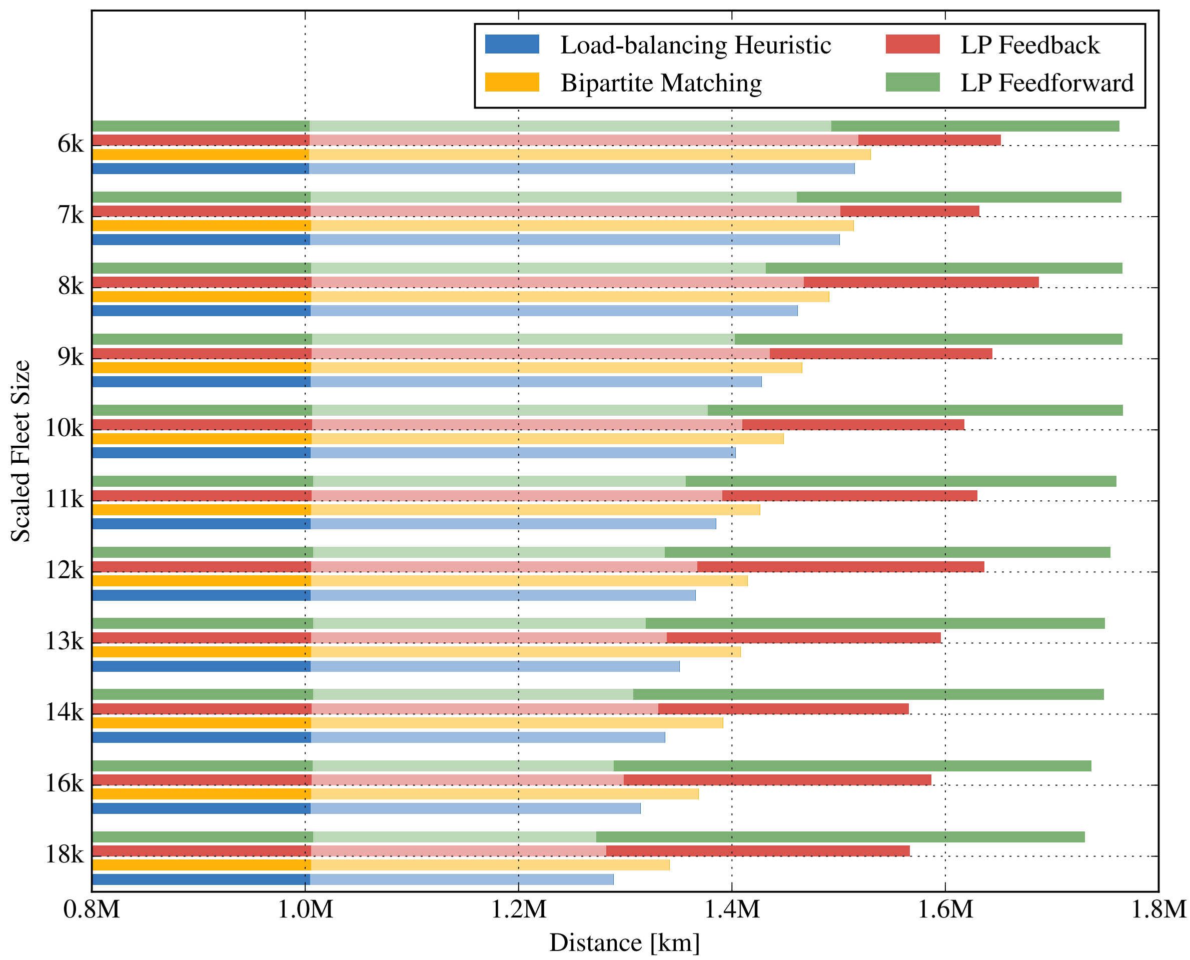
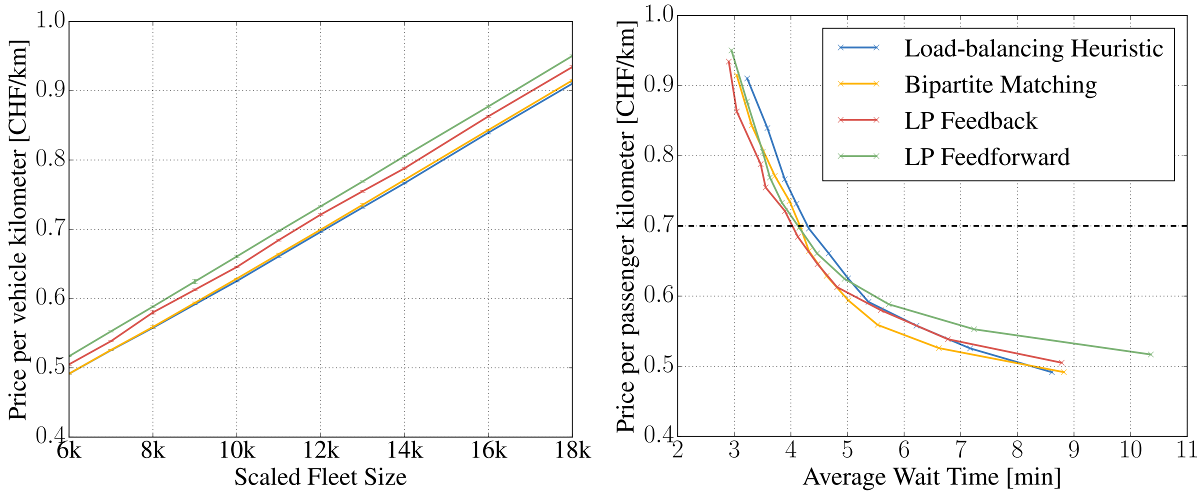


FIGURE 3 Driven accumulated distances for different fleet sizes. From left to right: Customer distance (dark), empty pickup distance (light), empty rebalancing distance (dark).



(a) Minimum customer prices that an AV operator needs to charge with a profit margin of 3%

(b) Comparison plot of offered wait times and minimum service prices for the simulated fleet configurations

FIGURE 4 Analysis of fleet configurations from the customer perspective

Financial Analysis

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

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

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

Therefore, the proposed AV services are cost-wise highly attractive for car (and taxi) users, but may not be able to compete with subsidized mass transit. On the other hand, AVs allow for more direct trips and thus for savings in travel time. Ongoing studies analyse how these affect the attractiveness of AMoD services *(32)*. It is further expected that lower wait times will have a positive effect on the occupancy rates of a service and thus reduce the cost per vehicle kilometer.

CONCLUSION & OUTLOOK

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

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

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

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

REFERENCES

1. Ackerman, E. (2017) Hail, robo-taxi![top tech 2017], *IEEE Spectrum*, **54** (1) 26–29.

2. Tientrakool, P., Y. C. Ho and N. F. Maxemchuk (2011) Highway Capacity Benefits from Using Vehicle-to-Vehicle Communication and Sensors for Collision Avoidance, paper presented at the *Vehicular Technology Conference (VTC Fall), 2011 IEEE*.

3. Friedrich, B. (2015) *Verkehrliche Wirkung autonomer Fahrzeuge*, 331–350, Springer Berlin Heidelberg, Berlin, Heidelberg.

4. Truong, L. T., C. De Gruyter, G. Currie and A. Delbosc (2017) Estimating the trip generation impacts of autonomous vehicles on car travel in Victoria, Australia, *Transportation*.

5. Litman, T. (2014) Autonomous Vehicle Implementation Predictions: Implications for Transport Planning, paper presented at the *Transportation Research Board Annual Meeting*, Washington DC.

6. Meyer, J., H. Becker, P. M. Bösch and K. W. Axhausen (2017) Autonomous vehicles: The next jump in accessibilities?, *Research in Transportation Economics*.

7. Bösch, P. M., F. Becker, H. Becker and K. W. Axhausen (2017) Future Cost Structures and Scenarios with Autonomous Vehicles, *Arbeitsberichte Verkehrs- und Raumplanung*, **1225**.

8. Horni, A., K. Nagel and K. W. Axhausen (eds.) (2016) *The Multi-Agent Transport Simulation MATSim*, Ubiquity, London.

9. Katzev, R. (2003) Car sharing: A new approach to urban transportation problems, *Analyses of Social Issues and Public Policy*, **3** (1) 65–86.

10. Zhang, R. and M. Pavone (2016) Control of robotic mobility-on-demand systems: a queueing-theoretical perspective, *The International Journal of Robotics Research*, **35** (1-3) 186–203.

11. Pfrommer, J., J. Warrington, G. Schildbach and M. Morari (2014) Dynamic vehicle redistribution and online price incentives in shared mobility systems, *IEEE Transactions on Intelligent Transportation Systems*, **15** (4) 1567–1578.

12. Ruch, C., J. Warrington and M. Morari (2014) Rule-based price control for bike sharing systems, paper presented at the *Control Conference (ECC), 2014 European*, 708–713.

13. Smith, S. L., M. Pavone, M. Schwager, E. Frazzoli and D. Rus (2013) Rebalancing the rebalancers: Optimally routing vehicles and drivers in mobility-on-demand systems, paper presented at the *American Control Conference (ACC), 2013*, 2362–2367.

14. Pavone, M., S. L. Smith and E. F. D. Rus (2011) Load balancing for mobility-on-demand systems.

15. Treleaven, K., M. Pavone and E. Frazzoli (2011) An asymptotically optimal algorithm for pickup and delivery problems, paper presented at the *Decision and Control and European Control Conference (CDC-ECC), 2011 50th IEEE Conference on*, 584–590.

16. Zhang, R., F. Rossi and M. Pavone (2016) Model predictive control of autonomous mobility-on-demand systems, paper presented at the *Robotics and Automation (ICRA), 2016 IEEE International Conference on*, 1382–1389.

17. Spieser, K., K. Treleaven, R. Zhang, E. Frazzoli, D. Morton and M. Pavone (2014) Toward a systematic approach to the design and evaluation of automated mobility-on-demand systems: A case study in singapore, in *Road Vehicle Automation*, 229–245, Springer.

18. Fagnant, D. J. and K. M. Kockelman (2016) Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in austin, texas, *Transportation*.

19. Zachariah, J., J. Gao, A. Kornhauser and T. Mufti (2014) Uncongested mobility for all: A proposal for an area wide autonomous taxi system in new jersey, paper presented at the *Transportation Research Board 93rd Annual Meeting*, no. 14-2373.

20. Zhu, S. and A. L. Kornhauser (2017) The interplay between fleet size, level-of-service and empty vehicle repositioning strategies in large-scale, shared-ride autonomous taxi mobility-on-demand scenarios, *Technical Report*.

21. Martinez, L. M. and J. M. Viegas (2017) Assessing the impacts of deploying a shared self-driving urban mobility system: an agent-based model applied to the city of lisbon, portugal, *International Journal of Transportation Science and Technology*.

22. Boesch, P. M., F. Ciari and K. W. Axhausen (2016) Autonomous vehicle fleet sizes required to serve different levels of demand, *Transportation Research Record: Journal of the Transportation Research Board*, (2542) 111–119.

23. Bischoff, J. and M. Maciejewski (2016) Simulation of city-wide replacement of private cars with autonomous taxis in berlin, *Procedia computer science*, **83**, 237–244.

24. Levina, E. and P. Bickel (2001) The earth mover's distance is the mallows distance: Some insights from statistics, paper presented at the *Computer Vision, 2001. ICCV 2001. Proceedings. Eighth IEEE International Conference on*, vol. 2, 251–256.

25. Rüschendorf, L. (1985) The wasserstein distance and approximation theorems, *Probability Theory and Related Fields*, **70** (1) 117–129.

26. Agarwal, P. and K. Varadarajan (2004) A near-linear constant-factor approximation for euclidean bipartite matching?, *Proceedings of the twentieth annual symposium on Computational geometry*, 247–252.

27. Hörl, S. (2017) Agent-based simulation of autonomous taxi services with dynamic demand responses, *Procedia Computer Science*, **109**, 899–904.

28. Federal Statistical Office, Federal Office for Spatial Development (2012) Mobility in switzerland: Results from the microcensus mobility and transport 2010.

29. Bösch, P. M., K. Müller and F. Ciari (2016) The ivt 2015 baseline scenario, *16th Swiss Transport Research Conference*.

30. Stadt Zürich (2014) Taxitarif der Stadt Zürich, `https://www.stadt-zuerich.ch/content/dam/stzh/portal/Deutsch/Stadtrat {%}26 Stadtpraesident/Publikationen und Broschueren/Stadtratsbeschluesse/2014/Sep/769{_}Beilage{_}Taxiverordnung.pdf`.

31. TCS (2016) Kosten eines Musterautos, Webpage (last accessed 08.11.2016), `https://www.tcs.ch/de/auto-mobilitaet/autokosten/kosten-eines-musterautos.php`.

32. Becker, F. and K. W. Axhausen (2017) Predicting the use of automated vehicles. [First results from the pilot survey], paper presented at the *17th Swiss Transport Research Conference*, Ascona.