Assessment of dispatching algorithms for automated mobility on demand systems

Date of submission: 2017-08-01

Sebastian Hörl
IVT, ETH Zürich, 8093 Zürich, Switzerland
phone: +41 44 633 38 01
sebastian.hoerl@ivt.baug.ethz.ch

Claudio Ruch
IDSC, ETH Zürich, 8092 Zürich, Switzerland
clruch@idsc.mavt.ethz.ch

Kay W. Axhausen
IVT, ETH Zürich, 8093 Zürich, Switzerland
phone: +41-44-633 39 43
axhausen@ivt.baug.ethz.ch

Emilio Frazzoli
IVT, ETH Zürich, 8092 Zürich, Switzerland
phone: +41 44 632 79 28
emilio.frazzoli@idsc.mavt.ethz.ch

Words: 6650 words + 11 figures = 9400 word equivalents

ABSTRACT

The performance of four different dispatching and rebalancing algorithms for the control of an Autonomous Mobility On-Demand system is tested. The case study, which is based on an agent-based simulation scenario of the city of Zurich, shows, that the right choice of control algorithm not only minimzes customer waiting times, but also offers large economical benefits to the operator. For an average waiting time at peak hours of five minutes the most performant algorithm would allow the operator to offer his service for around 0.45 CHF, which is more expensive than using a private car today, but significantly cheaper than a conventional taxi. The results show that this service can be offered while maintaining a higher fleet occupancy than can be observed for private cars today and that the application of intelligent rebalancing algorithms is inceasing the share of miles driven without a customer, but does not necessarily increase the total amount of miles driven.

INTRODUCTION

With growing populations in cities and increasing urbanization, many of today's transportation systems approach their performance limits. In Switzerland the distance travelled per year in private motorized vehicles rose from $82,014$ Mkm in 2005 to $96'467$ Mkm in 2015. Also the distance traveled in trams, trolley buses and buses rose from $3,858$ Mkm to $4,397$ Mkm in the same time span *(1)*. The external costs induced by road and rail traffic are rising as well, for example did the costs by noise increase by almost 20% from 2005 to 2009 in Switzerland *(2)*.

Many technologies and policies are explored in research and tested in practice to mitigate the negative effects of the increasing traffic demand, e.g. road-pricing, incentives for increased bicycle usage, improved combustion engines, dynamic traffic assignment. In this article we focus on one particularly promising approach, that promises to combine the advantages of personal mobility (i.e. flexiblity, availability, comfort and speed) with the advantages of public transport (low external and environmental costs, ability to transport large passenger volumes).

In shared-vehicle mobility on demand systems, passengers share a fleet of shared vehicles, e.g. cars or bicycles which are available on demand. In two-way mobility on demand systems vehicles are taken from the same location as they are returned to. Examples of two-way mobility-on-demand systems are "Mobility" in Switzerland or "zipcar" in the United States. While these systems are very popular, they can't be used if the origin and destination of a trip are different or rest idle for an extended amount of time between the trip to and from a destination. In two-way mobility on demand systems, origin and destination of a trip do not need to be equal. For instance in bicycle sharing schemes, users can pickup a bicycle at a set of stations distributed in the city, use it for their trip and drop it at another station. However, the asymmetric spatio-temporal behavior of travel demand causes these systems to get imbalanced, i.e. certain areas or stations get depleted of vehicles while other stations do not have enough empty spots to allow clients to return their vehicles. Bicycle sharing schemes use redistribution trucks to transport bicycles from full to empty stations and there exists research on how to perform this redistribution of bicycles in an effective manner or using price incentives, e.g. *(3)*. However, the main limitation of mobility on demand schemes is their tendence to get imbalanced quickly resulting in largely decreased service level and increased cost.

Autonomous Mobility on Demand Systems

Autonomous two-way mobility on demand sytems (AMoD) are mobility on demand systems with vehicles that can drive autonomously, i.e. without a driver. This property allows to pickup customers at arbitrary locations in the city and imbalance the system automatically. It can be seen as the key feature to allow sharing.

AMoD systems have been studied in literature both from an operational as well as a transportation research perspective. There are studies on the effects of AMoD systems when introduced at large scale in cities, on the fleet sizing for given traffic scenarios and on the fleet and operational management of the fleets.

In this work we present four main contributions. Firstly we provide novel simulation results of unmatched accuracy for the city of Zurich, our simulations are based on the agent-based traffic simulation MATSim and include ..... XYZ Sebastian please include. Secondly we compare the performance of the fleet under different operational principles and fleet management algorithms published in literature and show that the algorithms used for dispatching and rebalancing of vehicles are key factors of performance. We further introduce metrics that allow to assess the performance of an AMoD systems in terms both service level and operational cost. Lastly we verify theoretical results on fleet sizing introduced in *(4)* for the city of Zurich. In 2.2 we present related research, then we introduce performance metrics and control strategies for AMoD systems in 3. We present simulation results for the city of Zurich in 4 and conclude our findings in 6.

Literature Research

The work in *(4)* presents a systematic approach to the design of an autonomous mobility on demand system in Singapore. The authors consider the case where the entire travel demand of the city of Singapore would be covered by autonomous 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 the travel demands of the entire population of Singapore could be served with a fleet of $300,000$ vehicles and maximum mean wait times of approximately 15 mins which corresponds to a sharing factor of ≈ 4. The results of simulations confirm the theoretical approximations but the scope and granularity of the simulations is not commented and it is not clear whether traffic is adequately taken into account. In addition to the analysis on wait times the authors present an an analysis of the total cost of mobility of an AMoD system compared to the cost of owning a private vehicle. They conclude that the cost reduction per km gained when switching from private car ownership to using an AMoD system is 47 %, 48 % in Singapore, the United States respectively. The study does not compare different fleet operation algorithms.

In *(5)* a case study is presented where no private cars can enter the central business district of Singapore. A total of $25,525$ trips is served by autonomous taxis which operate either in station-based or free-floating scheme. In the station-based scheme a set of fixed stations exists where the cars return to after completion of a trip. In the free-floating scheme the cars remain parked at the destination of trips. The simulations are based on the SimMobility agent based simulation platform and include twelve different fleet sizes from $2,000$ to $7,500$ vehicles. The authors conclude that the free-floating scheme can serve 90% of the demand at the maximum fleet size whereas the station-based model can only serve 68% of the demand. Furthermore they observe mean customer wait times that saturate at approximately 2.5 mins and $6,000$ vehicles. While the station-based and free-floating concepts are compared, a detailed comparison of dispatching and rebalancing operation strategies is not presented. Furthermore results on the fleet efficiency and performance are not shown as well as a more detailed analysis of the wait times (e.g. different wait time quantiles). As the CBD of Singapore attracts much more than $25,525$ trips during a day it would also be interesting to see the results with the full number of trips taking into account routing policies and congestion levels in the city.

(6) presents a case study for Austin, Texas which focuses on the use of shared autonomous vehicles with ride-sharing capabilities, i.e. vehicles that can transport more than one customer under some circumstances. The scenario presented on vehicles with unit capacity includes a fleet of $1,715$ vehicles that serve $56,324$ person-trips. Assuming 3.02 trips per person and day this results in a sharing factor of 10.87 at average wait times of 1.18 mins and 4.49 mins during peak hour. The authors present also a scaled version of the case including ride-sharing where 11.1% of the trips within the central region of Austin (the "Geofence") are served by $9,037$ vehicles suggesting that a fleet of $81,414$ vehicles could serve the entire population of that area. While the authors do not compare different algorithms for fleet operation and base their fleet size estimation on simulation results, they provide a financial analysis of the entrepreneurial viability for a potential shared autonomous taxi operator.

(7) present a case study for New Jersey also focused on the potential for ride-sharing. The trips generated by a population of $8,791,894$ individuals in New Jersey are covered by walking and biking if the distance is less than a mile. All other trips are either served by the New Jersey train system, by autonomous taxis or both. The study concludes that the ride-sharing potential is large, especially during rush-hour and autonomous vehicles could significantly reduce congestion levels in the city. The required fleet size is not commented as well as the influence of the rebalancing and dispatching strategy for the fleet.

In *(8)* the authors present a study on the effects of introducting autonomous taxis and autonomous 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 autonomous taxis and autonomous taxis and shared taxis respectively. The fleet size of autonomous (shared) taxis is set at 4.8% of the baseline vehicle fleet. In these scenarios about 50-70 % of trips are serviced by the autonomous (shared) taxis which increases the vehicle occupancy from 50 mins to 12.87 h on average per day. The authors conclude a decrease in cost by 55% per kilometer, 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) autonomous taxis is implemented based on heuristics and a local gradient based optimization method.

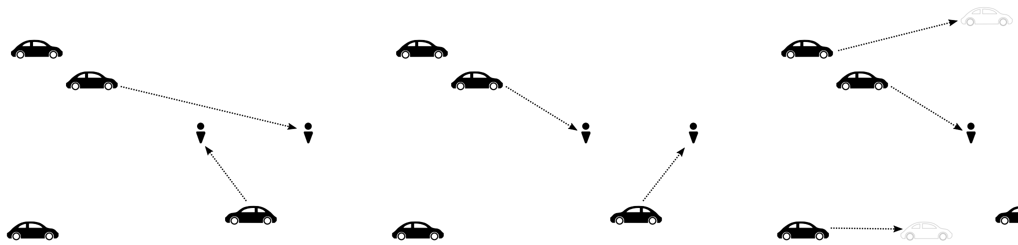
Boesch et al *(9)* investigate a scenario of the greater Zurich region in Switzerland. They use a demand pattern for private vehicles generated with MATSim: 1.3 million private vehicle users out of a total of 2.1 million agents generate 3.6 million trips. This demand profile generated with the co-evolutionary algorithm inherent to MATSim is then post-processed in a static simulation where $1 - 10\%$ of the car trips are served by $10 - 100\%$ of the total number of substituted users. The authors conclude that approximately 30 % of the substituted fleet can serve almost 100% of the substituted requests within less than 10 mins wait time. If this threshold wait time is surpassed, then the request is dropped. The results present the first such study for the city of Zurich in Switzerland. Its limitations are that no fleet management for the autonomous vehicles is considered, i.e. no rebalancing or dispatching is taking place, furthermore network routing is not considered, travel times are based on Euclidean distance and a scaling factor. The demand profile is static and does not vary depending on service times, congestion rates and performance of the modes.

In contrast to the study for Zurich presented above, a case study for Berlin presented in *(10)* takes into account dynamic demand. It considers a city-wide replacement of private vehicles with autonomous taxis. The dispatching of the car works according to a policy that distinguishes between oversupply (more available vehicles than open requests) and undersupply and matches the closest vehicle to an appearing request, the next available vehicle to the closest request respectively. Using this strategy named XYY in our work, the authors are able to serve 4.7 million requests generated by 1.1 million car users with a fleet of $100,000$ autonomous vehicles. The recorded average wait time for this case is about 2.5% minutes and the 95% quantile approximately 8.5 minutes. The resulting sharing factor is approximately 10 to 12. The study is one of the first large-scale dynamic simulations of a shared autonomous taxi system, however it does not consider different rebalancing and dispatching strategies and it does not rigorously evaluate the performance metrics of the autonomous vehicle fleet as we do i XZY

BACKGROUND

There are three main factors that determine the operational performance of an autonomous mobility on demand (AMoD) system.

1. The fleet size N has large influence on wait times and vehicle availbility. Large fleet sizes effectively decrease the passenger wait times but also cause higher capital expeditures for the operator.
2. The dispatching strategy, i.e. the assignment of available vehicles to waiting passengers heavily influences the performance. Figures 1(a) and 1(b) show suboptimal and optimal rebalancing choices.
3. The rebalancing strategy, i.e. the repositioning of available vehicles when there is no customer present. If vehicles are rebalanced often, it may increase the service level of the system, but it may also increase the total empty distance driven by the vehicles and thus the operational cost for the operator, see figure 1(c) for an illustration.



(a) Dispatching command with non-minimal summed pickup distance.
(b) Dispatching command with minimal summed pickup distance.
(c) Dispatching command with minimal summed pickup distance and rebalancing.

FIGURE 1 Dispatching and Rebalancing Strategies

Furthermore there is a charging and service process for the vehicles that influences the operational performance as well as parameters not related to the operation of vehicles (e.g. cleaning, interior design,...).

As there is a complex interaction between the fleet size, the amount of rebalancing, the operational strategies (dispatching and rebalancing), the service level and the costs for the operator, in 3.1 we propose what variables and charts to analyze to analyze the performance for AMoD systems.

Performance of Autonomous Mobility on Demand Systems

The service level is mainly dependant on the customer wait times. We define the wait time as the time from the arrival of a taxi request to the system until an available vehicle has reached the spot. For a given fleet size, the distribution of wait times is analyzed for every time step of the day (see XYZ include figure). Furthermore the waiting time has to be analyzed as a function of the fleet size N, see e.g. XYZ include figure.

The operational cost that can be influenced with the choice of the operating strategy is mainly based on the driven distance. We distinguish three types of distances. Vehicles can either drive to pickup a customer, they can drive to rebalance or they can drive with a customer. Assuming a pricing scheme where customers pay for distance driven and time spent in the vehicle, the distance driven with customers can be assumed to be profitable distance. Furthermore the total distance driven with customers is contant when considering a fixed set of customer requests and assuming that vehicles travel the minimum distance path for each request in the network.

Thus the goal of each operational strategy is to minimize the total empty distance (pickup and rebalancing) by the vehicles. As shown in *(11)* this distance cannot be driven to zero for general demand patterns, it is bounded below by the earth mover's distance which is a measure of how different the distribution of origins and destinations are in each time step, see e.g. *(12)*. The earth mover's distance for the Zurich scenario considered in this work calculated for hourly time bins is shown in figure 2.

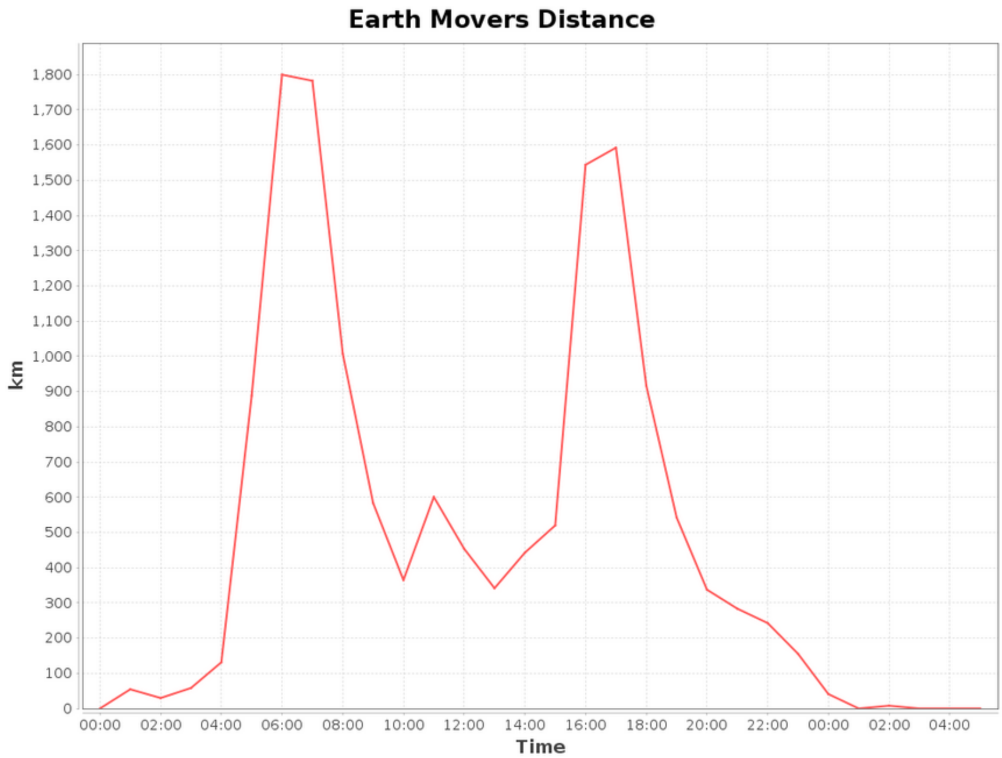


FIGURE 2 Earth mover's distance for Zurich calculated for hourly time bins. XYZ make figure nicer.

While the total amount of empty distance driven can not be reduced to zero, the ratio of pickup and rebalance distance driven can be influenced by the controller. A well-performing fleet controller will reposition vehicles already before the demand appears, i.e. it will increase the rebalance distance but reduce the pickup distance. Perfect estimation of future demands would lead to a system where almost all of the empty distance is rebalance distance. In order to make these concepts visible, we propose the plot in figure 4 to assess the operational quality of an AMoD system. Distances that are profitable and cannot be avoided are plotted on the negative ordinate and empty distances on the positive ordinate. Furthermore the empty distances are distinguished into rebalancing and pickup distances. Any controller tries to minimize the area above the abscissa, ensure it is composed mostly of rebalancing distances and satisfy certain service level constraints.

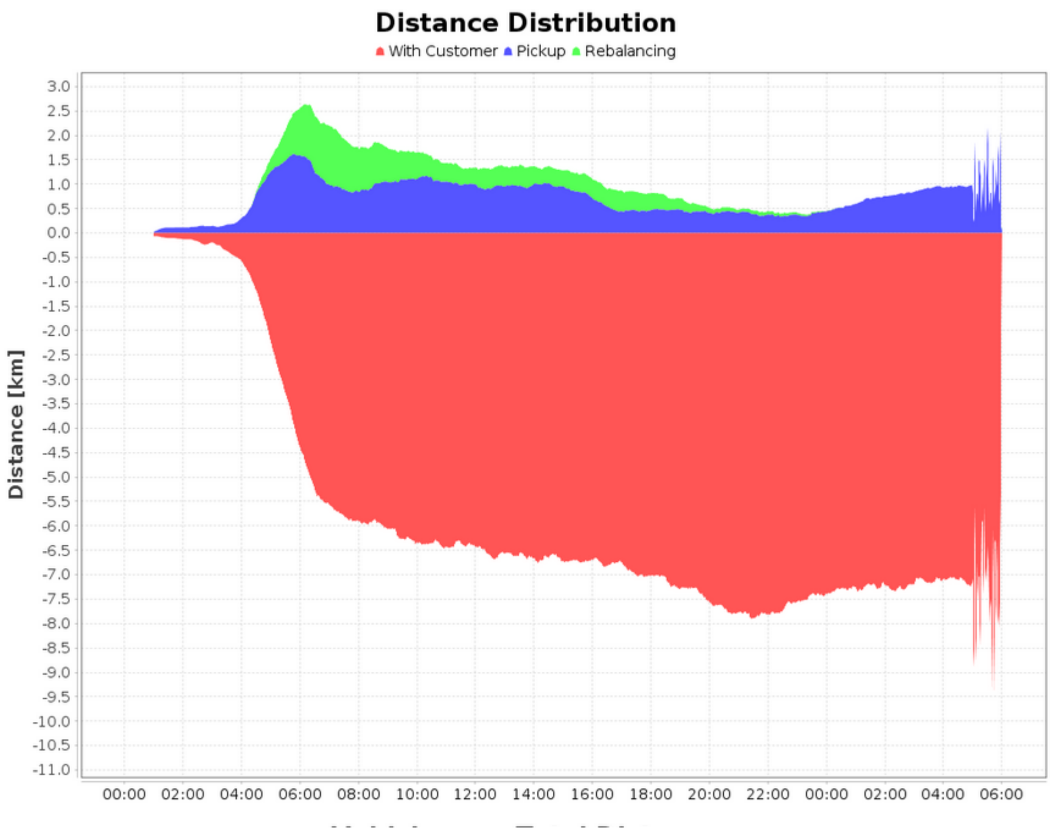


FIGURE 3 **Distances with customer, pickup distances and rebalancing distances driven by the fleet in every time step. INCLUDE ANOTHER FIGURE or refence to actual figure shown in simulations XZY**

Automatic Control of Autonomous Mobility on Demand Systems

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

1. The single heuristic dispatcher is the strategy presented in *(10)*. In every dispatching time step δt_D If there are more available vehicles than requests, 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 concluded.
2. The global Euclidean bipartite matching dispatcher determines an optimal bipartite matching between all open requests and available vehicles in every dispatching time step δt_D. The used distance function is the Euclidean distance which allows to use fast algorithms, e.g. *(13)*. In contrast to the previous strategy, the assignments can be changed until a vehicle actually reaches its target. If arrival probabilties for future time steps is taken into account, this strategy can be considered as the optimal dispatching strategy based on Euclidean distances.
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 used in a linear program to compute the optimal rebalancing flows α_{ij} in that time step assuming that the system is at

equilibrium. 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 **??**. Available cars are continuously rebalanced between the vertices of the virtual network according to the static rebalancing rates α_{ij}. As the work does not detail the proposed dispatching algorithm for this strategy, we match cares using global Euclidean bipartite matching. Rebalancing vehicles cannot be dispatched until they reach their destination.

4. The last implemented strategy is as well derived 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 an integer linear program which calculates the number of cars reb_{ij} to be sent from virtual vertex i to virtual vertex j. As in the feedforward strategy, the matching of the cars is done via global Euclidean bipartite matching.

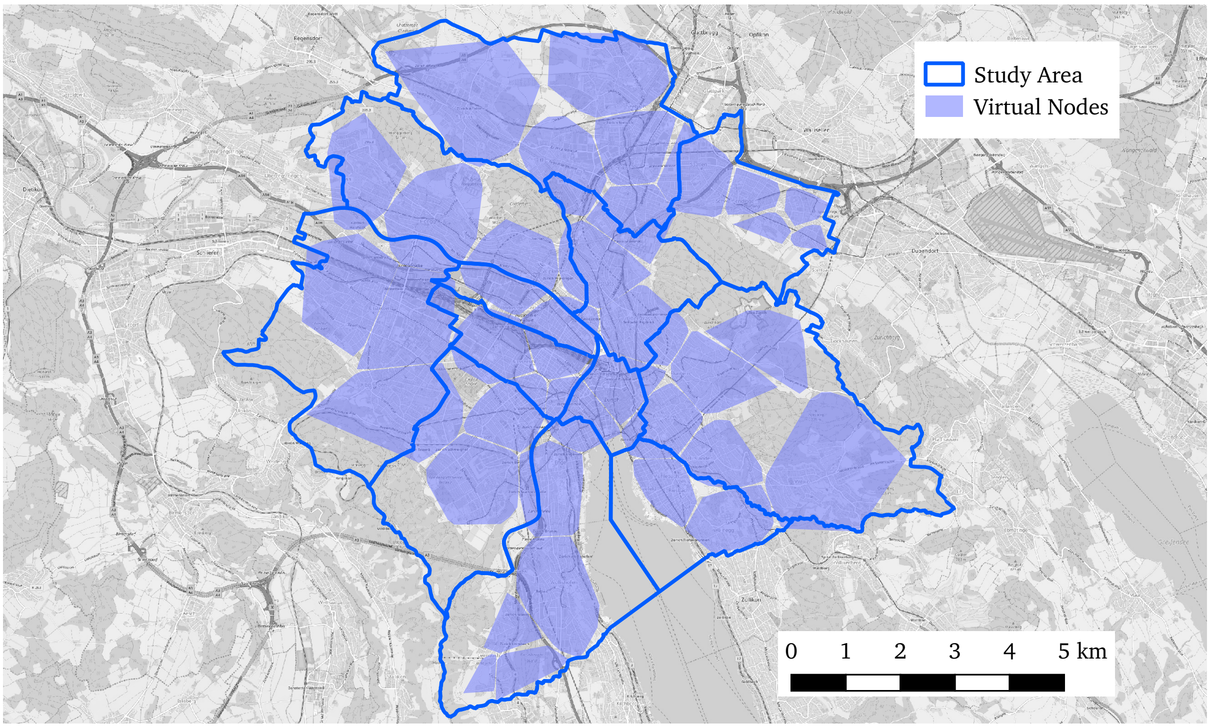


FIGURE 4 The study area covering the 12 districts of Zurich and the nodes of the virtual network for the rebalancing algorithms.

Fleet sizing for Zurich

In this section we use strategies presented in *(4)* to estimate the needed fleet size for a given scenario without actually using a simulation. We then compare these values to the simulation results in section XZY.

We define an AMoD system to be stable if the number of open requests is bounded for all times. A necessary condition for this to hold is that the distance the vehicles can drive collectively is larger than the distance to be driven to satisfy new requests entering the system. For every time step $k = 0, 1, 2, \ldots, T$ over the course of a simulation we can define these quantities as $N \cdot v_k$ and $\lambda_k \cdot d_{av,k}$ respectively, where v_k is the average vehicle speed in time step k, λ_k the customer arrival rate in timestep k and $d_{av,k}$ the average distance per request in timestep k. Summing over the day, rearranging and using the fact that the average distance per trip is composed of the actual trip distance and the earth mover's distance, we can state that

$$N \geq \frac{\lambda_k \cdot (d_{OD,k} + d_{EMD,k})}{v_k} \tag{1}$$

where $d_{OD,k}$ and $d_{EMD,k}$ are the averge driving distance per request and the average earth mover's distance per request in timestep k respectively. The analysis conducted on the scneario data yields a minimum fleet size of XZY for Zurich.

This number presents a lower bound for the fleet size such that the system can be stable, however it does not show what fleet sizes are necessary for an acceptable level of service. In order to estimate this number we used the strategy presented in *(4)* where data of the requests is used to compute the vehicle availabilities using mean value analysis in a closed Jackson network for different fleet sizes. The availability of a node is defined as the probability that there is at least one vehicle waiting at the node. Computing this quantity for every node of a virtual network for Zurich XZY include information on timestep XZY and taking the average of all stations, we can generate the following figure:

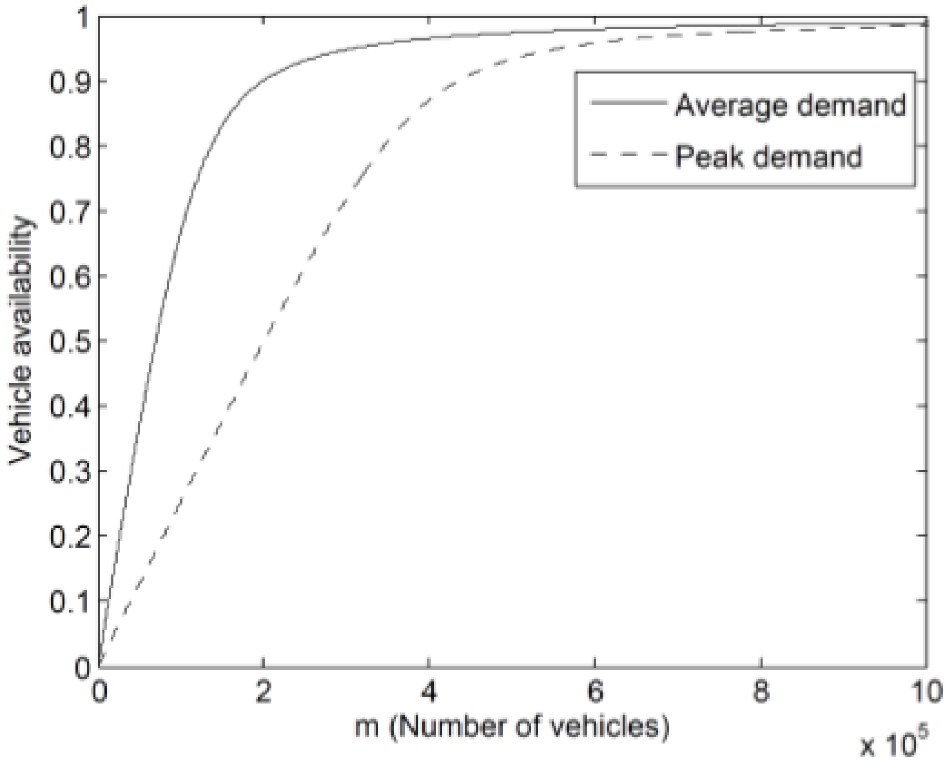


FIGURE 5 Performance driven fleet sizing for the city of Zurich according to *(4)*. XZY put real plot

The results indicate that XZY include conclusion. XZY.

SIMULATIONS

The dispatching algorithms as presented before have been tested in the agent- and activity-based transport simulation framework MATSim. What has been used in this paper is the mobility simulation component of that package, where each agent has a daily plan consisting of activities and legs. Activities are performed for a certain duration at specific locations in the traffic network and have predefined end times. They are connected by legs, which are performed by specific means of transport. Dependent on the time of day, the mode, the route taken and other factors, travel times may vary. Most importantly, the network is capacitated such that congestion emerges if many agents use the same networks links at the same time.

Most important for the study at hand is the simulation of vehicles in an actual network. By keeping background traffic in the simulation, the AVs are constrained by the network conditions, most remarkably they suffer from longer travel times at peak hours due to congestion.

The section is divided into two parts: First, we describe how the simulation scenario has been set up to account for a realistic travel demand for Zurich. Second, the simulation approach for automated vehicles is explained and third, the results for the different dispatching algorithms are presented.

Scenario Setup

For Switzerland the Microcensus on mobility and transport *(15)* is available, which features the daily travel patterns of 60,000 Swiss residents. In a previous study it has been used to create a detailed agent population of Switzerland, which reproduces the demographic attributes and travel patterns in the country to great detail *(16)*.

Additional modifications have been 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 travels of all agents has been performed to find all agents that interfere with the study area, which has been defined to the 12 districts of Zurich (Figure 4). All agents which do not interact with that region (performing an activity within the area or crossing the area) have been deleted from the population as they do not contribute to the state of the traffic system in that area. Finally, a 1% sample of the remaining agents has been created, which is the basis for our simulations to account for feasible computation times for the proposed dispatching algorithms.

In order to define the travel demand for the fleet of automated vehicles, agents have been tagged as whether they are viable for using an automated vehicle or not. While pedestrians and cyclists have not been simulated at all (since they do not contribute to congestion in the current version of the framework), agents that travel by car or public transit at least once during their daily plan are handled differently.

Agents that travel at least once by private car during the simulation are tagged as an AV user *only* if all of the legs in the agent's plan take place within the study 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 have been converted to the "av" mode. All other legs are kept as before, i.e. short legs that were assigned the "walk" mode before are still performed in 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 study area of

15km. As for car users, connecting non-motorized legs are kept fixed.

This way a demand for Zurich has been generated where each leg that possibly *can* be performed using an AV *is* using an AV. In that sense we simulate a scenario where 100% of the AV travel demand must be served by the dispatchers.

To summarize, the 8,230,971 agents in the population have been decimated to 1,935,400 agents, which interfere with the study area. From this set of agents a 1% sample has is drawn, leading to 19,354 agents that mainly constitute background traffic. Among those are 970 agents that are viable for the AV service. The plans of these agents contain 4030 trips that are to be served by AVs. In reality, this service would hence need to serve 403,000 requests by 97,000 persons.

Simulation of automated vehicles

To simulate automated vehicles in the MATSim scenario, a framework extension by Hörl *(17)* is used. There, AVs are individually simulated on the road network, contributing to and experiencing congestion. As soon as agents finish their activities the simulation is notified about an incoming request given that the agent wishes to use an AV for the following leg. In that case the request with its properties (departure time, origin, destination) is passed on to the dispatcher. These dispatchers are based on different algorithms, as described before. However, the "lifecycle" of a request is always the same: First, an AV needs to drive to the location of the customer, pick him up, drive to the final location and finally drop the customer off. From the point a customer has been picked up, the process is predetermined, no changes to the route of the AV are made anymore. While an AV has been assigned to a customer for pickup the vehicle may be reassigned depending on the dispatching algorithm.

It should be noted that AVs drive directly to the locations where agents end and start their activities. So far no mechanism is implemented that would allow them to meet at optimized locations (e.g. a high-capacity avenue instead of a small alley).

RESULTS

We test the four proposed dispatching strategies in the Zurich scenario with four runs per strategy. Each run simulates 20 iterations to allow the dispatchers to sense the traffic conditions in the network, i.e. to figure out what travel times on specific links are expected and how traffic jams can be avoided.

For Zurich, the times with peak congestion and, hence, longest travel times are from 6:30am to 9:00am and from 4:30pm to 6:30pm. In figure 6 all trips by AV with departures times in these time windows are collected and the mean waiting time for vehicle is computed. As expected, the average waiting time is decreasing with larger fleet sizes and higher availabiltiy of vehicles. Almost over the whole range of flet sizes the feedback LP dispatcher performs best, while the load-balancing heuristic features the longest waiting times.

Figure 7 shows the percentage of fleet mileage that is driven without a customer, either for pickup or rebalancing purposes. Clearly, the LP algorithms, which both use rebalancing, have a higher share of empty mileage that the non-rebalancing approaches. The heuristic approach manages to keep the share lowest, since it mainly operates in a best-response state, where only the shortest pickup trips are chosen. Remarkably, the total driven distance for all dispatchers is very similar (Figure 8), which indicates that the surplus of empty distance for the intelligent dispatchers does not stem from inefficient movements, but rather effective movements towards

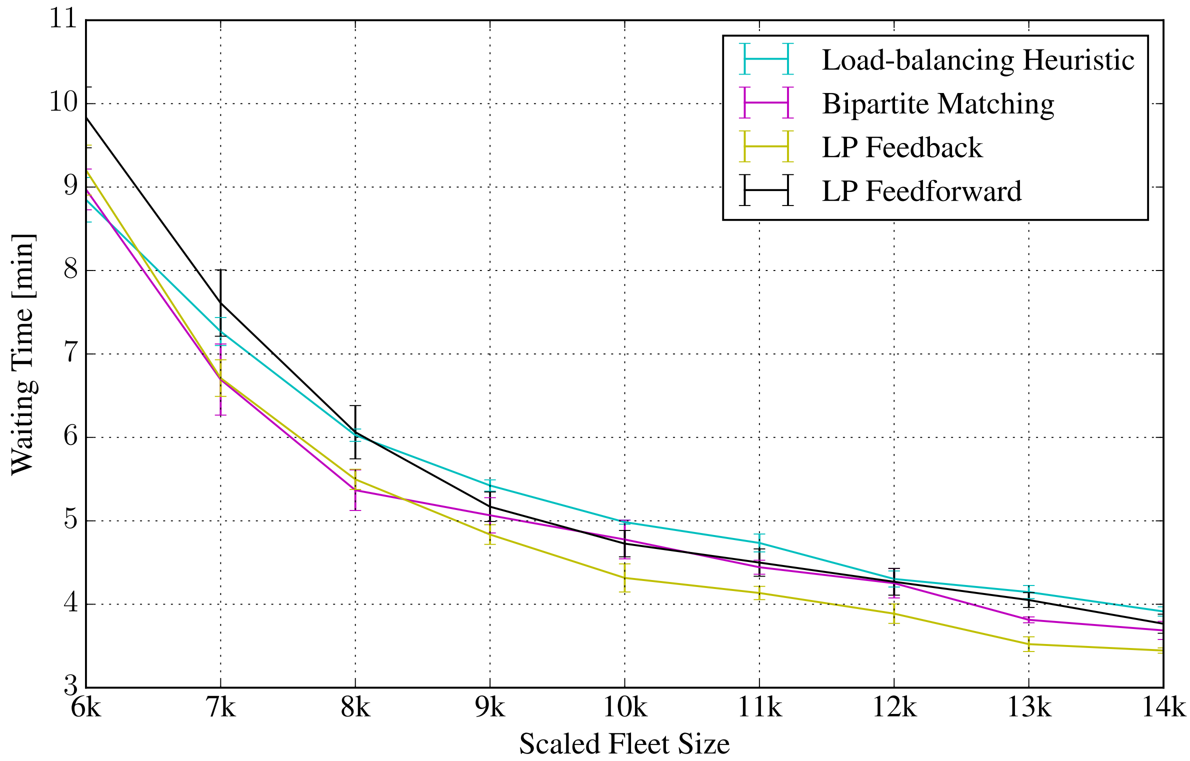


FIGURE 6 Average waiting time for an AV to arrive at peak times

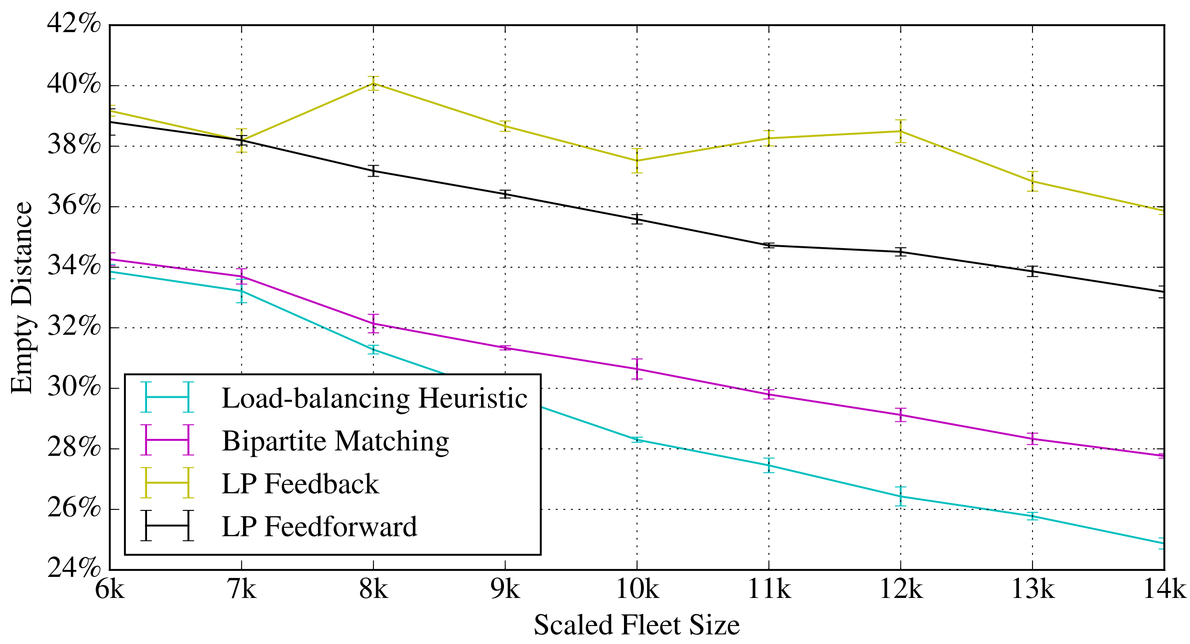


FIGURE 7 The fraction of distance that is driven by AVs without a passenger.

the expected customer demand for shorter waiting times.

[TODO: Do we need two plots here? Also a plot Total Distance <-> Relative Distance would be possible, where one can traverse the fleet size along the graph]

Finally, figure 9 shows the occupancy of the fleet for different fleet sizes. Since in the 30h

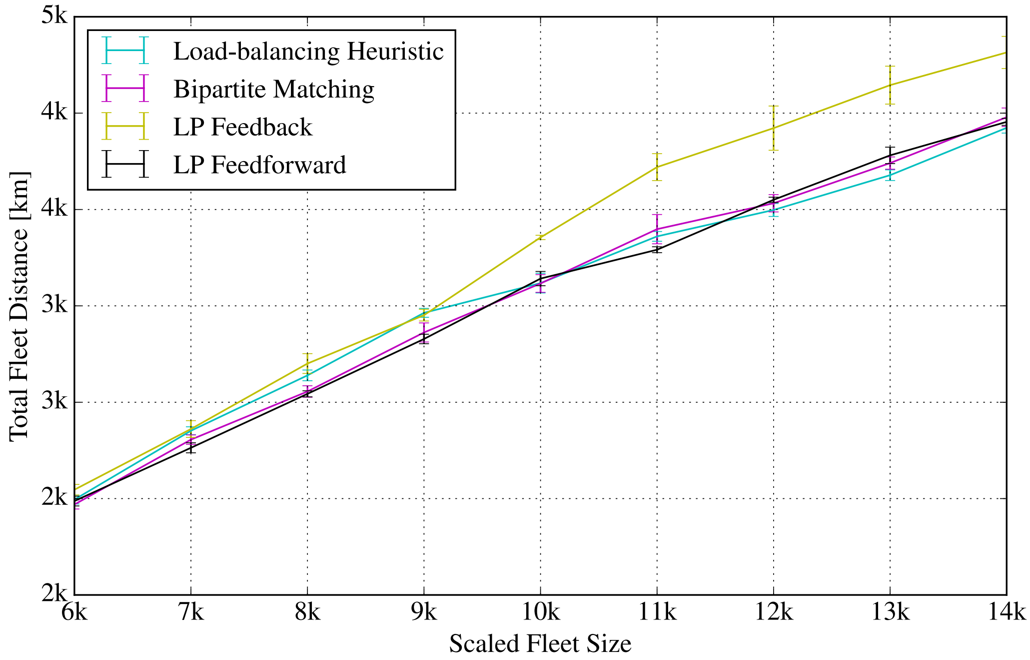


FIGURE 8 The total distance that is driven by AVs, with and without passenger onboard.

MATSim simulation no AV trips are registered in the hours around midnight, it is possible to correct the resulting 30h occupancy rate to one that is based on a 24h day. As can be seen, the occupancy of all fleet dispatchers exceeds the 8% that is common today. In general, one can say that the dispatching algorithm has only little influence on fleet occupancy. The differences lie in the range of 0.5% between the best and worst performing algorithm, which are the LP Feedback dispatcher and the load-balancing heuristic, respectively. Nevertheless, one can see that the occupancy of the latter is systematically lowest.

Cost Analysis

Based on a paper Bösch et al. *(18)* the costs of operating the simulated AV services are computed. Specifically, by providing their calculator with key figures of the operator (among them the occupancy, the share of empty rides, the average travel distance) the price that the operator would at least need to ask a customer per kilometer if a profit margin of at least 3% is targeted. The calculation is based on a detailed analysis of running and fixed costs. Figure 10 shows the results from this analysis. Unsurprisingly, the price that needs to be imposed on the customer increases with larger fleet sizes. However, the increase is stronger for the load-balancing heuristic than for any other distpaching strategy. Therefore, with the same fleet being available to an operator, he would be able to offer the service for almost 0.10 CHF less per kilometer than before or save this amount of money.

Compared to the average running costs of driving a private car in Switzerland (around 0.17 CHF/km) or using public transit (around 0.25 CHF/km) [TODO CITATIONS] the computed prices still seem rather high. Compared to conventional taxi operators, however, the price is extremely low (around 6 CHF/km). Therefore, it is imaginable that the AV service would still be attractive for a large group of people, for which a conventional taxi would be too expensive on a

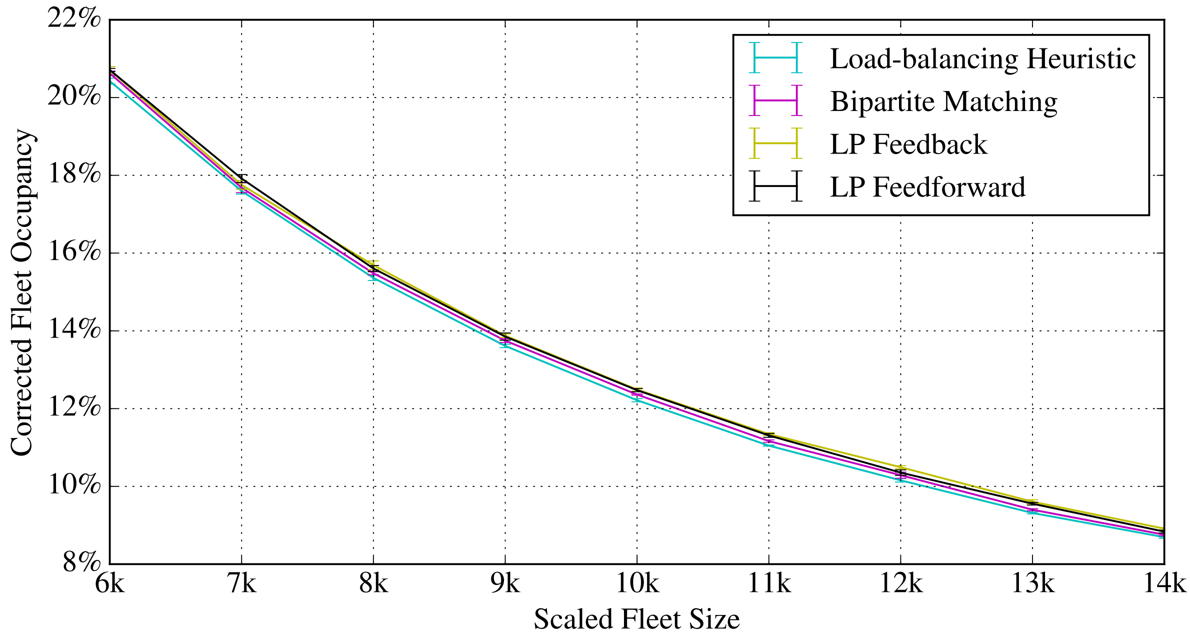


FIGURE 9 The occupancy of the AV fleet for different flet sizes.

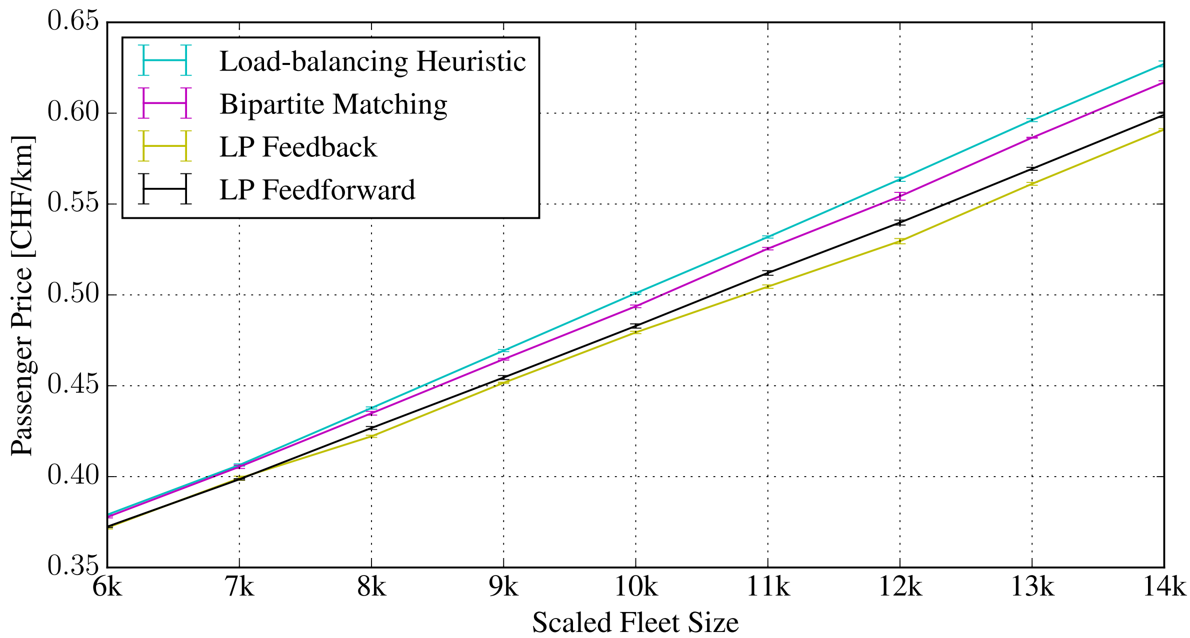


FIGURE 10 The minimum customer prices that an AV operator needs to charge the customer in order to have a win margin of at least 3%.

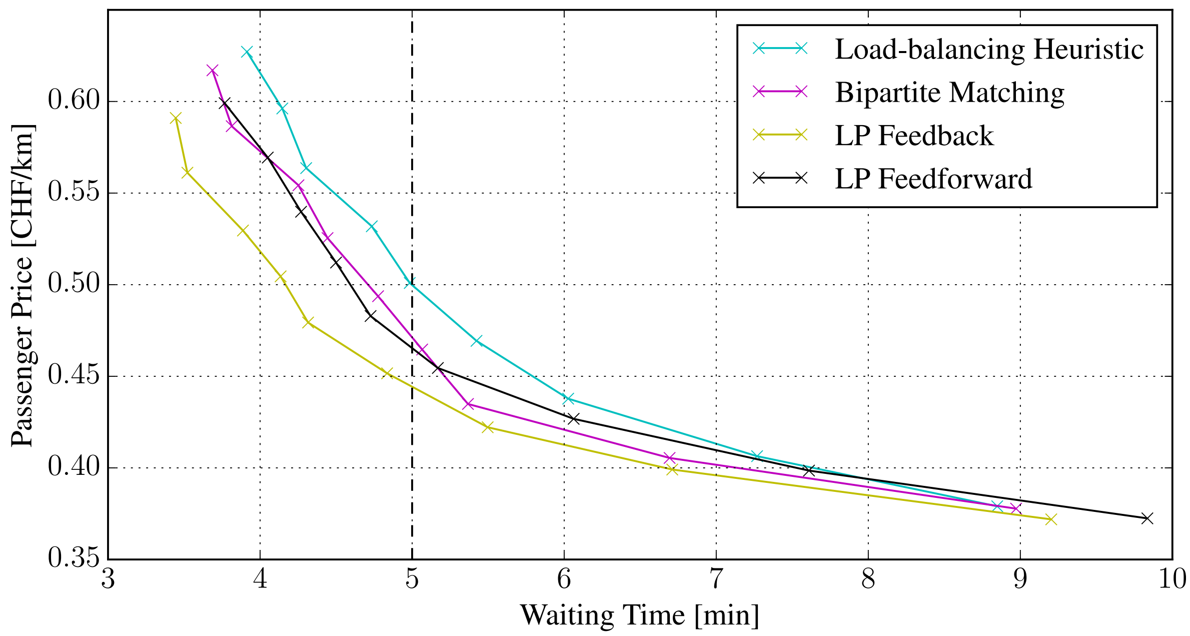


FIGURE 11 Time vs. Price

daily basis, but an AV would make such travels affordable.

However, the attractiveness of an AV service does not only depend the price itself, but also on the attitudes of the people towards the service. One key component to the acceptance of an AMoD system is the waiting times that customers need to endure. Figure 11 combines the key results from our simulations. There, the price that a specific operator configuration (fleet size and dispatcher) is displayed in comparison to the waiting time that this operator can offer. Assuming that, for instance, a waiting time of five minutes is tolerable, the operator could offer a satisfactory service for around 0.45 CHF with the feedback dispatcher, while he would need to charge 0.50 CHF with the simple load-balancing heuristic. The better the level of service of the operator is ought to be, the larger this margin becomes.

DISCUSSION & CONCLUSION

The study shows that the right choice of dispatching algorithm for an AMoD system does not only have strong impact on the performance in terms of waiting times for the customer, but also that it bears a significant economic advantage for the operator. He is able to attract more customers through quicker pickups and lower prices than a competitor with only little investment.

In order to assess the significance for real fleets of (not neccessarily 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 control 100k vehicles in five minute updates using a standard laptop for the computational tasks.

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

Throughout the paper, a "100%" demand scenario has been used, in which all trips that possibly could be undertaken by AV were converted to the automated mode. The MATSim framework, however, 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 *(17)* the actual attractiveness of an AV service could be analyszed 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 actually be performed by AV, but only a fraction. In such a scenario, also if maybe more remote areas would be included, completely different properties of an AV fleet control algorithm would be of interest, e.g. how well it is able to attract new customer groups in new regions by offering unproportinally low waiting times and make them stick to the service.

[TODO: OTHER LIMITATIONS]

REFERENCES

1. (2016) Key figures of passenger transportation services in switzerland., *Swiss federal office for spatial development.*

2. A.Bader, C. (2012) Calculation of the external costs of the road and rail based transport in switzerland., *Swiss federal office for spatial development.*

3. 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.

4. 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.

5. Marczuk, K. A., H. S. S. Hong, C. M. L. Azevedo, M. Adnan, S. D. Pendleton, E. Frazzoli et al. (2015) Autonomous mobility on demand in simmobility: Case study of the central business district in singapore, paper presented at the *Cybernetics and Intelligent Systems (CIS) and IEEE Conference on Robotics, Automation and Mechatronics (RAM), 2015 IEEE 7th International Conference on*, 167–172.

6. Fagnant, D. J. and K. M. Kockelman (2015) Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in austin, texas, *Transportation, Under review*.

7. 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.

8. 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*.

9. 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.

10. 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.

11. 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.

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

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

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

15. Federal Statistical Office (2012) Microcensus on mobility and transport 2010.

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

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

18. Bösch, P. M., F. Becker and H. Becker (2017) Cost-based analysis of autonomous mobility services, *Arbeitsberichte Verkehrs- und Raumplanung*, **1225**.