Fleet sizing for pooled automated vehicle fleets

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ABSTRACT

This paper proposes an automated on-demand public transport service using different vehicle capacities to serve current car demand in cities. The service relies on space and time aggregation of passengers that have similar origins and destinations. It provides a point-to-point service with pre-defined pick-up and drop-off locations In this way, detours in order to pck-up en-route passengers is avoided.

The optimization problem that minimizes the fleet size along with limiting rebalancing distances is defined as a mixed integer linear programing problem. Solving the problem for Zurich, Switzerland yields, in the best case, a fleet size equal to 3.7% of the current fleet that could serve current car demand. Vehicle kilometers traveled could also be reduced by nearly 10%. Results also show that the speed of automated vehicles has a substantial effect on the necessary fleet size and free-flow speeds generally produce over-optimistic results.

INTRODUCTION

Automated vehicles (AVs) are rarely seen on the streets today. Even when we occasionally catch a glimpse of one there is always a person in the driver's seat ready to take control in case of an emergency. However, plenty of research has been devoted in the last years on how automated vehicles might impact the way we travel.

Elimination of the driver would bring two important changes in how we use cars. First, people that can not drive because they do not posses a driver's license or are otherwise unable to drive would gain access to the freedom that the automobile provides. Second, a substantial cost element of taxi services would be eliminated by removing the driver from the equation, which shows the potential for shared vehicle fleets to thrive and potentially reduce private vehicle ownership.

Researchers focusing on impacts of shared automated vehicle fleets are suggesting that the required number of vehicles needed to serve the demand in urban cores is about 10% of the current fleet. While this promises to reduce the necessary parking space, it creates additional vehicle miles traveled, because of the need to re-position vehicles to efficiently serve the demand. Potential induced demand from those people who currently do not use a car only worsens the picture. In order to mitigate this problem, ride-sharing is seen as a potential solution.

This paper investigates how AVs can be utilized in a dynamic public transport service in the city of Zurich, Switzerland. By pooling previous individual car travelers, the paper proposes a point-to-point public transport service. An optimization problem is formulated that aims at minimizing both vehicles needed to serve the demand and at minimizing vehicle kilometers traveled by looking both at the congested and free-flow speed case.

This paper is structured as follows. After the introduction, background information is provided on the current state of knowledge on potentials of shared automated vehicles. This is followed by the explanation of the methodology for the case study presented. Results are then portrayed before discussion and concluding remarks.

BACKGROUND

Considerable research effort has been devoted in recent years to investigate the level of disruption that automated vehicles can cause in different environments. Many studies have focused on investigating the impacts of AVs on road capacities, the necessary parking space, travel cost reduction, increasing comfort, potential use as a public transport feeder services, and decreasing vehicle car ownership by deploying shared vehicle fleets to serve the current demand.

How fleets of shared AVs could reduce vehicle ownership and potential consequences thereof have been studied in many countries and cities. One of the first large-scale simulations has been performed for Singapore (**?**). The study finds that the whole transport demand of the city could be covered by one third of today's vehicle fleet if it entirely consisted of automated single-occupancy vehicles.

Subsequently, a series of studies have been performed for the case of Austin, Texas. In (**?**) a grid-based simulation for the city is introduced. For an artificial demand based on real-world trip generation rates and randomly assigned destinations it is found that Austin's demand for private car trips could be served by an automated vehicle fleet that is reduced by 90% compared to today.

However, due to the need to relocate vehicles to pick-up passengers a considerable amount of additional vehicle kilometers traveled is introduced. The use case is further extended in (?), where an electric charging infrastructure is assumed. Further studies introduce a more detailed demand for the scenario, based on static trips from the regional household travel survey (HTS). (?) introduces congestion to the simulation and finds that this has a strong impact on fleet size. In (?) a choice model is applied, though in a post-processing step. Next a detailed daily travel demand from an HTS is simulated using an approach that had been applied to the canton of Zurich before (?), a discrete choice model is fed with information about travel and waiting times to analyze potential mode shares in Austin. Finally, (?) extends the Austin case with a ride-sharing component and finds that it could reduce wait times for the customers and mitigate the increase of VKT (vehicle kilometers travelled) due to empty rides.

For the case of Berlin, (?) use a static travel demand from the regional HTS to create a MATSim (?) (see below) simulation with automated taxis. All car trips within the city boundaries are replaced by the service, leading to a scenario where one tenth of all vehicles could replace the current fleet if every agent in the simulation uses the service with acceptable wait times. In the same scenario (?) find that also carrying public transport users leads to a linear increase in needed fleet size. Finally, (?) introduce congestion to the simulation showing that without significant gains in road capacity due to automation a fleet of automated taxis serving all of the city's demand would worsen congestion dramatically. On the other hand, automated vehicles are found to be likely to mitigate parking search problems in the city (?).

(?) use an agent-based approach to investigate the impacts of an on-demand shared automated fleet of vehicles that supports ridesharing. They use a simplified approach to determine the minimum required fleet size without any rebalancing of vehicles during the day. They find that around half of the vehicle trips can be saved through pooling but only about 20% of vehicle kilometers traveled for the city of Stuttgart. They also report that around 15% of today's vehicles would be needed to serve the car-travel demand.

(?) use a dispatching ridesharing algorithm proposed by (?) to estimate how pooling can benefit the metropolitan region of Rouen Normandie in France, using a pre-defined fleet size. They find that using 4-seaters with shared rides is the best option among the tested scenarios.

For Zurich, (?) show that under ideal flow conditions a fleet size of around 7000 to 14 000 automated taxis would be able to serve the mobility demand of the city. Using a detailed agent-based daily travel demand from HTS data, it is shown that the dispatching strategy has a large impact on the performance of the fleet. Extended work (?) combines this simulation with a detailed model of costs for automated mobility (?). A choice model for conventional and automated modes of transport alike is estimated from a large-scale stated preference survey in the canton of Zurich and added dynamically to the simulation. The study constitutes the first simulation in which a closed cycle between simulation of demand and supply is able to not only estimate what fleet size would be able to serve a certain demand, but also for which fleet size and service characteristics customers would be willing to pay. A similar study is available for the city of Paris (?) where it is found that 25 000 automated vehicles can serve 1.2 million trips with dynamicaly adjusted service costs.

METHODOLOGY

This paper solves the problem of minimal fleet sizing of a pooled vehicle fleet by means of a mixed integer linear programming (MILP) program. We use a variant of a discrete minimum-cost flow problem.

The basic idea is that a specific service area is divided into a set of zones. In our example, hexagons as in Figure 2 are used. From previously obtained travel demand data, we can divide time into bins and track how many trips we need to serve for each origin-destination (OD) pair during every time bin. The idea is then that all trip departures are shifted to the end of their respective time bins such that all the travel movements can be pooled.

To serve the trip demand in a certain time bin, vehicles need to relocate. For that it is known, at any time of the day, how much time it takes for a vehicle to move from one zone to another. Computationally, the demand flows are regarded as constraints that need to be fulfilled in any case. On top, vehicles need to be moved empty to be present when demand occurs for later OD pairs and vehicles need to be provided initially. Without loss of generality, we assume that each vehicle has a capacity of serving one trip. The aim of the algorithm, which will be presented in the next paragraphs, is then to find the minimum number of vehicles needed to cover all the demand.

Problem definition

Formally, assume a set of zones $\mathcal{Z}$. Furthermore, assume a set of discrete time bins $t \in \mathcal{T}$. Each time bin has a specific end time $\tau(t) \in \mathbb{R}$. The mandatory demand flows leaving from origin zone $u \in \mathcal{Z}$ at the end of time bin $s \in \mathcal{T}$ and arriving at destination $v \in \mathcal{Z}$ before the end of time bin t shall be denoted as $d_{s,t,u,v} \in \mathbb{N}$ and be recorded from given data. Note that we count a discrete number of trips.

We then regard vehicle rebalancing flows $r_{s,t,u,v} \in \mathbb{N}$ from zone u to zone v that start after the vehicles become idle during the time bin $s \in \mathcal{T}$ and arrive during time bin t, i.e. they arrive at latest before the respective demand flow. Note that rebalancing flows cannot go back in time, but they can be performed during the same time bin if travel time allows it, i.e.

$$r_{s,t,u,v} = 0 \quad \forall \tau(t) < \tau(s) \tag{1}$$

We also introduce two special artificial nodes: "source" and "sink". We assume that initially all vehicles reside in the source, while they all need to go to the sink eventually. In a way, when a vehicle moves to a certain zone from the source, it represents a vehicle being available at the zone at the beginning of the day and a vehicle going to the source resembles a vehicle that goes into idle state until the end of the day in its respective zone. We define that all flows going to the source are zero

$$r_{s,t,u,Source} = 0 \quad \forall (s,t) \in \mathcal{T}^2, u \in \mathcal{Z} \tag{2}$$

and that all flows coming from the sink are zero, too:

$$r_{s,t,Sink,v} = 0 \quad \forall (s,t) \in \mathcal{T}^2, v \in \mathcal{Z} \tag{3}$$

The vehicle flows then need to fulfill two constraints. To cover the demand from zone $q \in \mathcal{Z}$ at time $l \in \mathcal{T}$, it needs to be made sure that the right number of vehicles arrives on time. Note that they may "arrive" from the source:

$$\sum_{s \in \mathcal{T}} \sum_{u \in \mathcal{Z}} r_{s,l,u,q} = \sum_{t \in \mathcal{T}} \sum_{v \in \mathcal{Z}} d_{l,t,q,v} \quad \forall l \in \mathcal{T}, q \in \mathcal{Z} \tag{4}$$

Likewise, we need to make sure that vehicles are moved away from places to which demand has been shifted. This also includes moving vehicles to the sink:

$$\sum_{s \in \mathcal{T}} \sum_{u \in \mathcal{Z}} d_{s,q,u,l} = \sum_{t \in \mathcal{T}} \sum_{v \in \mathcal{Z}} r_{l,t,q,v} \quad \forall l \in \mathcal{T}, q \in \mathcal{Z} \tag{5}$$

Consider Figure 1 for a more intuitive example. There (a), we have four points in time (horizontal) and three zones A, B, C (vertical). There is a demand of 44 trips from time step 1 to 2 from zone A to B, and there is another demand flow from time 3 to 4 from zone C to A. These demand flows are fixed and we need to serve them. From the constraints above we know that all points that are independent of any demand (like A2) require that there be *no* inflow and no outflow at all. However, the inflow constraint says that A1 needs to be served by 44 vehicles. Since we cannot go back in time the only way to fulfill this constraint is to create a flow of 44 vehicles from the source. The outflow constraint then demands that we need to remove 44 vehicles from B2. In example (b) we decide to add a flow of 44 vehicles from B2 to the sink. The same procedure applies for the demand from C3 to C4: We create a vehicle flow from the source to C3 to fulfill the inflow constraint and then create a flow of 21 vehicles from C3 to the sink.

However, example (b) in Figure 1 is not optimal in terms of vehicle count. In example (c) all constraints are fulfilled as well. But here, we first have a flow of 44 vehicles from the source to A1. Also, there is no other option than sending 21 vehicles from A4 to the source since these 21 demand trips end in A. But in between we have another option. The constraints we have is that 44 vehicles must leave B2 and that 21 vehicles must enter C3. Therefore, we take 21 of those 44 vehicles at B2 to send them to C3 (which fulfills the inflow constraint of C3), and we send the remaining 23 vehicles to the sink (which fulfills the outflow constraint of B2). Looking at the total number of vehicles that arrive in the sink we can see that in example (c) only 44 vehicles are registered while there are 65 in example (b). Since the source resembles the "end of the day" when all vehicles go into the "idle" state, this number also resembles the total number of vehicles in the system. The example shows how different configurations of feasible vehicle flows r influence the objective. Therefore, by rearranging those flows we can optimize the system to yield the minimum number of vehicles.

Formally, the objective $J \in \mathbb{N}$ can be written as:

$$J = \sum_{s \in \mathcal{T}} \sum_{t \in \mathcal{T}} \sum_{u \in \mathcal{Z}} r_{s,t,u,Sink} \tag{6}$$

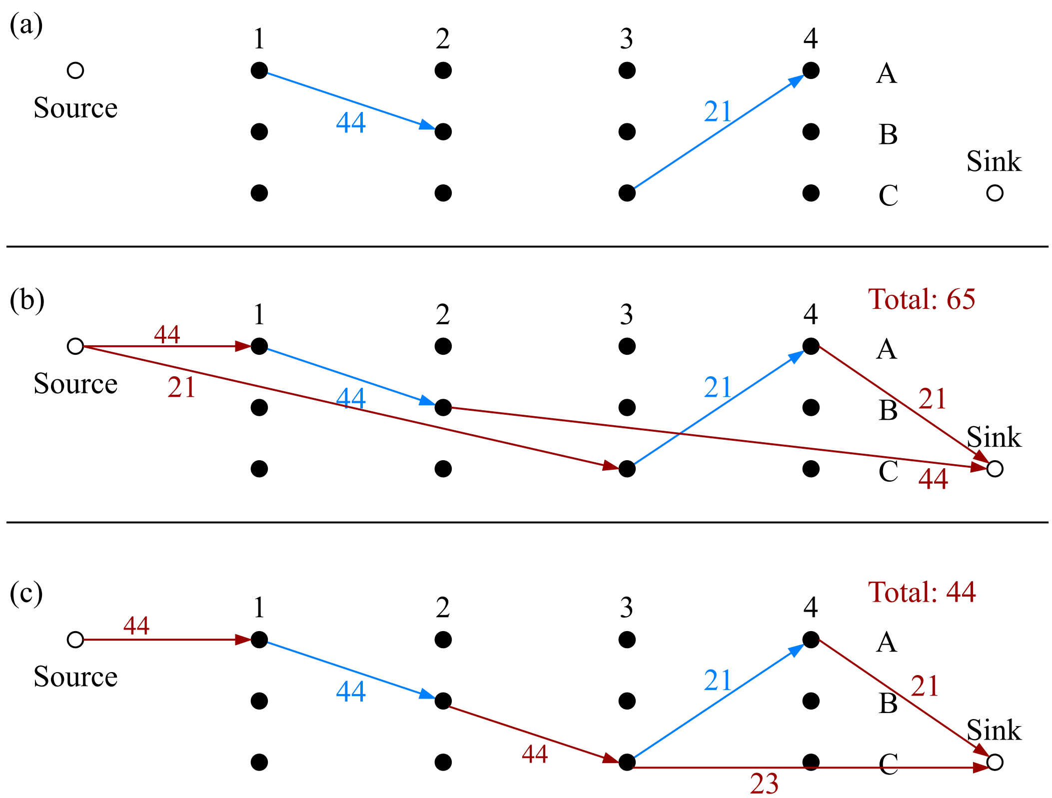

FIGURE 1 An example of OD flow and possible fleet distribution

Therefore, the optimization problem becomes:

$$
\begin{aligned}
\underset{r_{s,t,u,v}}{\text{minimize}} \quad & \sum_{s\in\mathcal{T}}\sum_{t\in\mathcal{T}}\sum_{u\in\mathcal{Z}} r_{s,t,u,Sink} \\
\text{subject to} \quad & \sum_{s\in\mathcal{T}}\sum_{u\in\mathcal{Z}} r_{s,l,u,q} = \sum_{t\in\mathcal{T}}\sum_{v\in\mathcal{Z}} d_{l,t,q,v} && \forall l \in \mathcal{T}, q \in \mathcal{Z} \\
& \sum_{s\in\mathcal{T}}\sum_{u\in\mathcal{Z}} d_{s,q,u,l} = \sum_{t\in\mathcal{T}}\sum_{v\in\mathcal{Z}} r_{l,t,q,v} && \forall l \in \mathcal{T}, q \in \mathcal{Z} \\
& r_{s,t,u,v} = 0 && \forall \tau(t) \leq \tau(s) \\
& r_{s,t,u,Source} = 0 && \forall (s,t) \in \mathcal{T}^2, u \in \mathcal{Z} \\
& r_{s,t,Sink,v} = 0 && \forall (s,t) \in \mathcal{T}^2, v \in \mathcal{Z}
\end{aligned}
\tag{7}
$$

Travel time constraints and maximum distance

While the problem above is the basic version of the algorithm used in this paper, some additional refinements are added. So far, travel time between zones is not incorporated into the model formulation. Let $\tau_{s,u,v}$ define the travel time (in terms of freeflow speeds or congested speeds) between two zones u and v during time bin s. It may then happen that zone v can not be reached from zone u within one time bin, because the travel time is too long. However, it is always possible that a vehicle departs at *some* time at u to arrive on time for a specific time index at v. This constraint

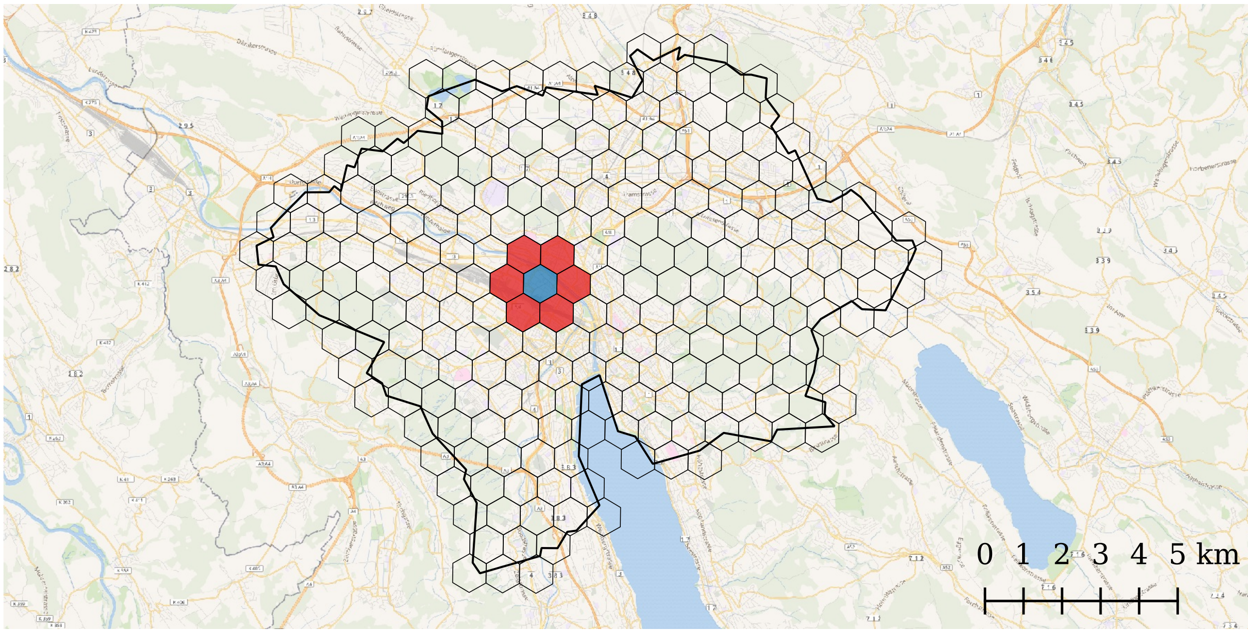

FIGURE 2 Service area and an example of hexagonal zones

can be formalized as follows:

$$r_{s,t,u,v} = 0 \quad \text{if} \quad \tau(s) + \tau_{s,u,v} > \tau(t) \tag{8}$$

It says that a flow cannot exist if the sum of the departure time and the travel time is greater than the end time of a certain destination time bin. Looking at Figure 1 this would mean that we would remove certain edges that violate the travel time constraint. If, for instance, we could not reach C3 from B2 anymore, because travelling from B to C at this time of day takes too long, example (c) would not be a feasible solution and (b) would be the optimum.

The second adjustment to the basic model is that we define that vehicle movements are only allowed within a certain distance of a specific zone u. For instance, 2 shows an origin node in blue. In our hexagon grid we define that a "maximum distance of one zone" means that vehicle flows can only happen to the current zone itself or to its direct neighbors. A distance of two would mean that vehicles are allowed to go to the next further ring of hexagons and so forth. Structurally, this also translates to forcing certain flows to be zero (or removing edges from a graph like that one shown in Figure 1).

Vehicle sizes

One major part of our methodological contribution is to use the MILP model to test the performance of fleets of differently sizes vehicles. So far, we have assumed that one vehicle flow unit serves one demand flow unit in the model above. It is easy to simulate the case of a ten-seater vehicle by aggregating the demand into packages. If we were to serve the demand of Figure 1 by a fleet of ten-seater vehicles we would round all flows up to multiples of ten. The flow from A1 to B2 would become 50, and therefore we would require a new demand flow of five units; the flow from B3 to A4 would become 30 and we would require a new flow of three units. Then again, we can solve the MILP and find the minimum fleet size of ten-seaters to serve this demand.

In a more advanced use case, this procedure can even be performed in a hierarchical way to find the optimal vehicle size mix. In such a case we would start with ten-seater vehicles, but round all flows to the lower bound. In 1 we would require four ten-seaters on A1 to B2 and two ten-seaters on B3 to A1. We could then calculate the minimum number of ten-seaters. However, some flow units would be left from the initial problem. On the first trip we'd be missing four trips that were served and one trip on the second OD pair would be missing. We could then try to serve those trips with five-seater or even smaller vehicles.

This procedure is summarized in Algorithm 1.

ALGORITHM 1: Finding the fleet mix

Input: Initial demand flow $d_{s,t,u,v}$
For each n **in** $\{10, 5, 2, 1\}$ (Fleet size n)
  $d'_{s,t,u,v} = \lfloor d_{s,t,u,v}/n \rfloor$
  FleetSize(n) = **Solve** MILP with $d'_{s,t,u,v}$
  $d_{s,t,u,v} = d_{s,t,u,v} - d'_{s,t,u,v} \cdot n$
Continue
Return FleetSize

Post-processing

After solving the optimization problem in a next step total vehicle kilometers traveled is calculated as a sum of all rebalancing and passenger trip movements.

SCENARIO SETUP

We apply the presented algorithm to a use case for the city of Zurich, Switzerland. As stated above, one major input to the algorithm is a time-varying OD matrix. To obtain such a matrix for Zurich, we draw from results from a detailed agent-based transport simulation.

The transport simulation is based on the *eqasim*[1] framework. It combines the well-known agent- and activity-based transport simulation framework MATSim (**?**) with capabilities to use discrete mode choice models inside of the simulation (**? ?**). In the present work we use the output of such a simulation, namely the detailed mobility plans of the full artificial agent population of Zurich. It allows us to extract origin location, destination location, departure time and arrival time for each *car* trip in the city. While for the present work only this output is relevant, we'd like to refer the interested reader to the sources cited above for information on the general framework, to (**?**) for details about the specific implementation of our large-scale model of Switzerland and Zurich, and to a variety of case studies in which the modelling framwork has successfully been applied to automated vehicles (**?**), car-sharing (**?**) and Urban Air Mobility (**?**).

The detailed trip data is aggregated into time bins and a hexagonal grid that covers the city of Zurich. In this study, we use two time bin sizes, 7.5 minutes and 15 minutes. The hexagonal grid

[1]http://www.eqasim.org

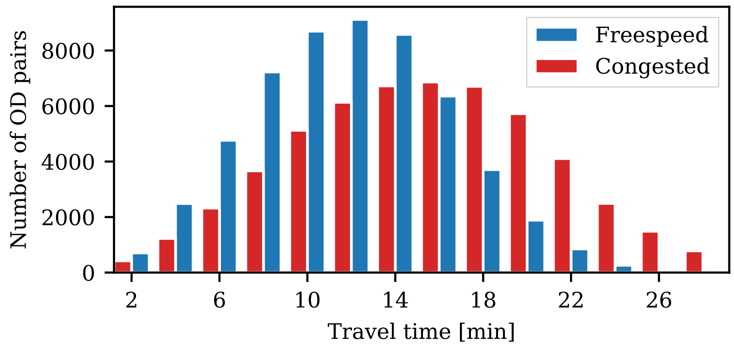

FIGURE 3 Car trips in the city of Zurich

with zone radius of 500m can be seen in Figure 2. Besides the 500m grid, we also consider grid of 350m radius in this study.

Time bins of 15 minutes are interesting to investigate as more than 80% of the car trips within the city have a duration of less than 15 minutes in a free-flow speed case (Figure 3). Furthermore, 7.5 minutes are representative for bus and tram headways at peak times in Zurich. In the case of 15 minutes time bins departures from every second zone are moved 7.5 minutes forward to allow for better scheduling of the vehicles. Distances of 350m and 500m are well in the range of reasonable walking distance from any departure point to public transport facilities.

The study area is slightly larger than the political boundaries of the city of Zurich, as it was designed to include all areas with considerable population density. Figure 4 shows a distribution of start times of car trips that are entirely contained in this area. To find the minimum number of required vehicles but to keep the optimization problem tractable as well we focus on the period of the day that has the highest demand, namely from 4pm to 6.15pm.

In the status quo scenario there are 162 648 cars in total that are used in the study area, and they are driven on average 1779 764 kilometers per day. During the afternoon peak time these vehicles travel for 386 043 kilometers.

To estimate travel times between zones, we perform a routing between all zones' centroids for each time bin. This routing is either based on freeflow speeds or congested network speeds from the simulation. This way, we can investigate fleet performance based on freeflow travel times and congested travel times. Note that this comparison is interesting since research suggests that automated vehicles have the potential to use road infrastructure much more efficiently. In such a case their actual performance would probably lie between the freeflow and congested scenarios.

RESULTS

First, the problem presented in the previous section is solved for AVs of passenger capacity equal to one. These results can be seen in Table 1. In the best case the number of vehicles can be reduced to 9018, but that case does not provide the minimum VKT. Minimum VKT can be observed for the case of 7.5 min time bin and radius 350 m, where the increase in VKT due to vehicles needing relocation is only 3%.

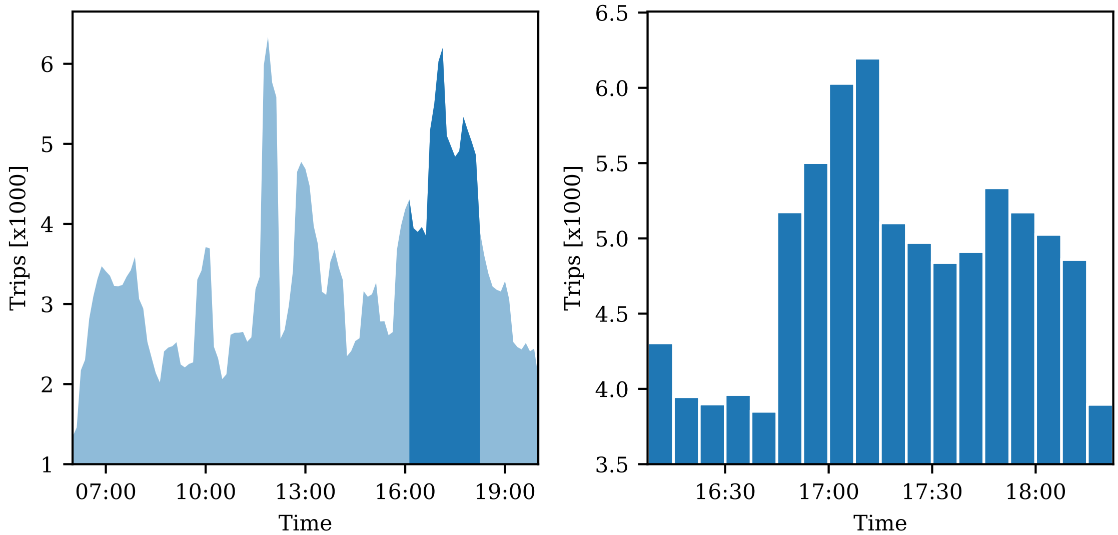

FIGURE 4 Car trips in the city of Zurich

TABLE 1 Number of vehicles required to serve the demand with 1-seaters

Time Bin [min]	Radius [m]	Congested	1-seaters	VKT [km] (change)
7.5	350	no	9333	401 763 (+3.8%)
7.5	500	no	9018	452 735 (+17.0%)
7.5	350	yes	10 607	399 830 (+3.5%)
7.5	500	yes	10 614	448 726 (+16.0%)
15	350	no	10 268	426 322 (+10.4%)
15	500	no	9797	480 810 (+24.5%)
15	350	yes	11 649	424 324 (+9.9%)
15	500	yes	11 567	476 728 (+23.5%)

These results also show that the the number of required 1-seater vehicles is in the range of 11 - 18 times smaller than the current fleet size. This reduction is in the range of previous studies (**?**), although with less additional empty vehicle kilometers than reported in (**?**).

Going one step further, Table 2 shows the results when travelers are pooled if possible into 2-seater AVs. The size of the zones now starts to play an important role and the number of required AVs is reduced to 7302 in the best case, which is only 4.5% the number of currently privately owned cars. VKT is very similar to the status quo scenario meaning that pooling of individual travelers cancels out the empty distance driven, with the maximum reduction of VKT of 2.5% in the case of 7.5min bin, 350 m zone radius, and congested speeds. It is clear that aggregation to larger time bins also starts to have an effect, which for 1-seaters had a negative effect on the fleet size and VKT.

Finally, to investigate the full potential of pooling passengers with similar ODs, vehicles with

TABLE 2 Number of vehicles required to serve the demand with 2-seaters

Time Bin [min]	Radius [m]	Congested	2-seaters	VKT [km]	(change)
7.5	350	no	8347	378 341	(-2.0%)
7.5	500	no	7342	389 585	(+0.9%)
7.5	350	yes	9568	376 612	(-2.5%)
7.5	500	yes	8692	386 642	(+0.1%)
15	350	no	8556	385 038	(-0.3%)
15	500	no	7302	384 548	(-0.4%)
15	350	yes	9834	383 232	(-0.7%)
15	500	yes	8697	381 403	(-1.2%)

TABLE 3 Number of vehicles required to serve the demand with free-flow speeds

Time Bin [min]	Radius [m]	2-seaters	5-seaters	10-seaters	VKT [km]	(change)
7.5	350	7928	224	9	375 983	(-2.6%)
7.5	500	6216	429	55	374 035	(-3.1%)
15	350	7628	409	31	377 518	(-2.2%)
15	500	5363	605	146	351 088	(-9.1%)

capacities of two, five and ten are used as part of a mixed vehicle fleet. Tables 3 and 4 show the results for each of the scenarios, for the free-flow and congested speed case respectively. In all cases the number of vehicles needed to serve the demand is reduced along with the total VKT. In the scenario with 15 min time bin, 500 m radius zones and free-flow speed only 3.7% of the original fleet is needed to serve the demand. If we are to consider that the congestion would stay on the same level as today this share raises to 4.6%. Reduction of VKT is between 2.6% and 9.8%.

TABLE 4 Number of vehicles required to serve the demand with congested speeds

Time Bin [min]	Radius [m]	2-seaters	5-seaters	10-seaters	VKT [km]	(change)
7.5	350	9152	229	9	373 852	(-3.2%)
7.5	500	7476	477	61	370 736	(-4.0%)
15	350	8857	432	31	375 976	(-2.6%)
15	500	6574	717	154	348 174	(-9.8%)

DISCUSSION

The results presented in the previous section show that pooling car travelers can not only substantially reduce the number of needed vehicles, with reductions of up to 96% but can also reduce VKT, which was previously highlighted as one of the drawbacks of shared AV taxi fleets (**?** **?**). While travelers are delivered close to their destination without making detours on the way for other passengers, they are expected to walk a certain distance from their origin to pick-up location and from the drop-off location to their final destination. The average walking distances are rather small between 250 m and 350 m depending on the zone size (note that for free-floating carshairng customers are willing to walk up to 500 m to rent a car (**?**)). The average distance translates to 3 to 5 minutes of additional access and egress walk times. As maximum delay to a person's departure time is the size of the time bin, the actual waiting time can be considered to be low.

It is interesting to note that pooling travelers in 15 minute bins is more efficient than pooling them in 7.5 minute bins from the operator perspective, however not substantially. Thinking from the user perspective, one might consider that 7.5 minutes would be more acceptable to the users, therefore in the long-run that might be a better option.

Another important finding of this paper is that if that AVs would to drive in the same congested roads as we are today, the number of required resources to serve the demand may rise as high as 20%. This puts the findings of (**?**) into perspective where only a free-flow speed case is considered.

Limitations

While the methodology introduced in this paper can provide important insights into the potentials of an AdPT service, this study has made several simplifications that should be discussed.

Only car trips starting and ending in the city of Zurich are considered as potential trips for the AdPT service. Therefore, commuters surrounding the study area that arrive to the city of Zurich with their cars are still allowed to do that. However, later if they need to conduct a trip within the city of Zurich they have to switch to an AdPT service. While this can be regarded as a policy constraint, not allowing previous travelers that used to walk, cycle or take public transport, to switch to this new service is a limitation. As a next step it would be important to see what happens if everyone is allowed to use this service, in terms of VKT, required fleet size, and service in general.

Demand is considered to be static in this study. However, as shown by (**?**) and (**?**) cost of a shared AV service depends on the fleet size, which, in turn, affects the demand. Therefore, it would be interesting to understand how this new service can be priced to efficiently serve all potential users.

Looking at who would switch to an AdPT service if the usage of cars in the city is forbidden is important. However, it is maybe even more crucial to understand what kind of new demand will form. This is out of scope of this paper, but an important topic that surrounds all work around automated vehicles.

It is assumed in this paper that the demand is known a-priori. However, some of the trips cannot be predicted and scheduled in advance. One of the future steps would be to investigate how different levels of spontaneous trips would affect the needed fleet size and what kind of dispatching strategy would work best in this case.

CONCLUSION

This work provides insights on how a pooled automated vehicle fleet with a point-to-point service would operate in the city of Zurich and what impacts it would have on the needed number of vehicles and vehicle kilometers traveled. Besides the methodology presented, several key findings are also a part of the contribution of this paper. Congestion has a substantial effect on the necessary fleet size to serve the demand and should not be neglected. Pooling travelers does not only help to reduce the vehicles need, but also reduces VKT. Moreover, vehicles of different passenger capacity provide further benefits and should be considered when designing a shared automated fleet service. Aggregating passengers in larger time bins increases the positive effects of the service from the operator perspective, but the benefits might not be large enough to overcome the reduced frequency of the service from the user perspective.

AUTHOR CONTRIBUTION

The authors confirm contribution to the paper as follows: study conception and design: Milos Balac, Sebastian Hörl; optimization problem implementation: Milos Balac; demand generation: Sebastian Hörl; analysis and interpretation of results: Milos Balac, Sebastian Hörl; draft manuscript preparation: Milos Balac, Sebastian Hörl; supervisor of the work: Kay W. Axhausen. All authors reviewed the results and approved the final version of the manuscript.