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Procedia Computer Science 83 (2016) 237 – 244

Procedia Computer Science

The 7th International Conference on Ambient Systems, Networks and Technologies (ANT 2016)

Simulation of city-wide replacement of private cars with autonomous taxis in Berlin

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Abstract

Autonomous taxi (AT) fleets have the potential to take over a significant amount of traffic handled nowadays by conventionally driven vehicles (CDV). In this paper, we simulate a city-wide replacement of private cars with AT fleets of various sizes. The simulation model comprises microscopic demand for all private car trips in Berlin (including incoming and outgoing traffic), out of which the internal ones are exclusively served by ATs. The proposed real-time AT dispatching algorithm was optimized to handle hundreds of thousands of vehicles and millions of requests at low computing times. Simulation results suggest, that a fleet of 100 000 vehicles will be enough to replace the car fleet in Berlin at a high service quality for customers. Based on this, one AT could replace the demand served by ten CDVs in Berlin.

Peer-review under responsibility of the Conference Program Chairs

Keywords: Autonomous vehicles; autonomous taxis; MATSim; fleet size; large-scale taxi simulation

1. Introduction

Ongoing developments of fully autonomous vehicles (AVs) will sooner or later result in commercial autonomous taxi (AT) services. With these becoming available, the attractiveness of driving and owning a car will become substantially lower, making a complete replacement of conventional driven vehicles (CDV) with ATs a possible option for city traffic. Currently, most automakers and several IT companies are developing AVs. Google's self-driving car[1] project may be known best, however, Toyota strives to enter the AT market in a public beta test as early as 2020[2]. Also Uber is doing research in the field[3]. Most recently, General Motors and the ride-sourcing provider Lyft teamed up to develop AT services together[4]. What remains to be seen is the question, when such services will become available, with some people saying it could take decades[5].

The impact of AT fleets has also been part of recent research. It suggests that using AT fleets is beneficial over CDV ownership from the user cost perspective with costs in the US being as low as 0.15$ per mile[6]. In Europe,

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1877-0509
Peer-review under responsibility of the Conference Program Chairs
doi:10.1016/j.procs.2016.04.121

user costs in small to medium-sized cities could be lower than for conventional public transit if some vehicle sharing is conducted[7]. With high annual mileages, ATs are most likely to be fully electric. For the US, this could mean a decrease of green house gas emissions per mile by up to 94%[8]. Albeit hard to quantify, AT fleets will also change the shape of cities, as significantly less room is required to park vehicles.

Determining the fleet size and the number of cars one AT could replace has also been looked at. For Lisbon, a simulation study suggests that each AT could replace ten private cars if rides are shared, and only six otherwise[9]. For Singapore, a study suggest a fleet reduction to one third[10] given that also traditional public transport is converted into AT services, whereas for Ann Harbor, Michigan, a reduction to 15% has been calculated[6]. In another study, carried out for a 'synthetic' mid-size US city of size similar to Austin, a ratio of 1:11 was suggested[11]. Even higher reduction in fleet size was achieved for Stockholm, i.e. between 5% (with ride sharing) to 9% (without ride sharing)[12]. For the Zürich region, up to 90% fleet reduction were calculated[13].

To our knowledge, no simulation research has been conducted combining a large scale (millions of trips) and the microscopic level of detail, including the movement of individual ATs embedded into overall traffic and real-time fleet management.

2. Methodology

In order to evaluate effects of large-scale introduction of ATs, we decided to carry out microscopic simulation of a typical weekday in Berlin. The simulation runs in this study were made with MATSim. The software is open-source and jointly co-developed by TU Berlin and ETH Zürich. MATSim allows a microscopic simulation of agent behaviour at high computational speeds. Thus, it is suitable for large-scale scenarios and has been in use world-wide. It combines a traffic-flow simulation with a sophisticated scoring model for agents as well as co-evolutionary algorithms that can alter daily routines ("plans") of agents. This three-step process is usually applied to some kind of initial synthetic population repeatedly over several iterations until some form of equilibrium has been reached[14].

2.1. Initial scenario

The initial model is based on the BVG-MATSim model for the year 2008–2011[15]. It has been used in several Berlin-related case studies on both public[16] and private transport[17]. The network contains about 98 000 road links and 37 000 nodes. This allows to depict all major and minor roads within the city boundaries as well as all bigger roads in the surroundings. The initial network also contains designated public transit links (used for railway and subway lines).

The synthetic population depicts a typical weekday in Berlin. Agent activities over the day are plentiful. In the original scenario, agents make use of all relevant transport modes. During the course of the day, some 16 million trips are made by all agents. These also include very short trips made by bike or walking.

Traffic flow in the scenario is characterized by a morning peak which is followed by a constant amount of traffic flow during the day leading in a remarkably strong afternoon peak. The split of car and public transit trips (pt) in Berlin is roughly even, with both modes having a share of 35%. This scenario has been validated against car counting stations throughout the city.

2.2. Scenario adaptation

Because this study deals with the issue of replacing private cars with autonomous taxis within Berlin, the scope of the initial scenario was reduced to private cars only. As a result, the network model comprises only links for available for car mode, and non-car trips were not simulated. Also all external trips (i.e. neither starting nor ending in Berlin) trips were removed. All in all, 4.7 million trips are left in the simulation, and out of them, 2.5 million trips are made wholly within the city boundaries. These internal trips were converted into AT trips, resulting in replacing the demand served typically by 1.1 million private cars with a fleet of ATs.

The hourly demand for AT trips over the whole day is presented in Figure 1. As in the original scenario, demand in the is higher than in the morning, which is very specific to Berlin. This figure indicates the afternoon peak hour is critical in terms of the AT fleet size. Figure 2 show the accumulated origins of these converted trips. Over the whole day, most areas of the city have a roughly identical share of incoming and outgoing trips.

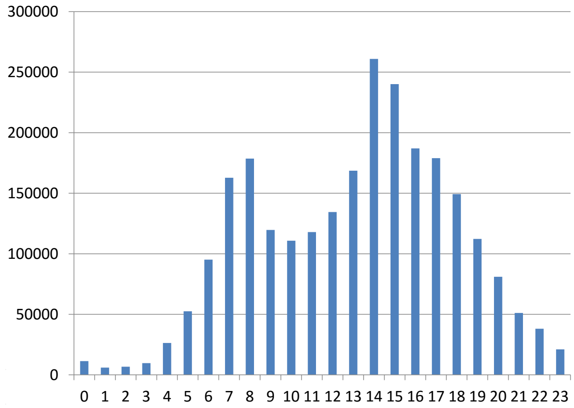


Fig. 1: Hourly demand for AT trips over the day

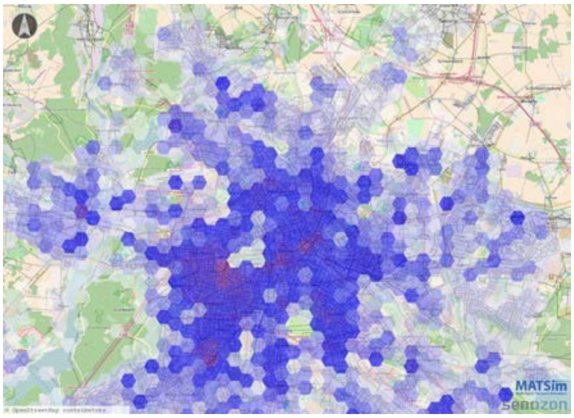


Fig. 2: Locations of AT trip origins

In order to compensate for missing traffic (e.g. freight, public transport), time-dependent free-flow speeds are used for each individual link in the network. These speeds are calculated in 15-minute time intervals for each link based on the average link travel times obtained in a given time period in the original scenario.

3. Simulation of autonomous taxis

Simulation of autonomous taxi dispatching was carried out by means of MATSim's DVRP (*Dynamic Vehicle Routing Problem*) extension[18] that allows simulation of on-demand transport services. ATs are coordinated by a dispatcher, who reacts to incoming events (such as new request submissions, vehicle arrivals and departures) and dynamically re-optimises ATs' routes and schedules in order to ensure possibly most efficient execution of taxi orders.

3.1. Dispatching strategy

Conventional taxis serve requests usually according to the FCFS (*first come, first served*) rule, because the taxi demand is relatively small compared to the supply side for most of the time. However, in an overloaded system, this strategy is highly inefficient. For instance, when all taxis are busy, whenever a taxi turns idle, it is immediately dispatched to the longest waiting open request, regardless of the distance between them.

In order to avoid oversizing of the AT fleet, the dispatching strategy must perform in a different way during peak hours. This issue was addressed by the *demand-supply balancing* taxi dispatching strategy proposed by the authors[19,20]. It classifies the system state into two mutually-excluding categories, namely *oversupply*, with at least one idle taxi and no open requests, and *undersupply*, with no idle taxis and at least one open request, and handles these two situations differently. In the former case, when a new request is placed, the nearest taxi is dispatched towards it; in the latter case, when a vehicle becomes idle it is dispatched to the *nearest* open request.

Under low demand, the *balancing* strategy serves requests immediately as they arrive, exactly as the traditional approach. However, in an overloaded system, the focus is on maximising vehicle utilisation, which results in an increased throughput, and consequently, reduces the amount of time passengers await taxis. Despite its simplicity, this strategy provides solutions which are close to those of more complex methods, such as solving iteratively a taxi assignment problem[21].

3.2. Adaptation for a large scale

The demand-supply balancing strategy was already used in MATSim for simulation of conventional taxis in Berlin, and turned out to be very efficient[19]. However, dispatching hundreds of thousands of autonomous vehicles in a huge, complex street network turned out to be computationally demanding. Certain adaptations pertaining to shortest path search were necessary to increase the computational efficiency and ensure real-time responsiveness.

The following enhancements were introduced to speed up the dispatch strategy:

- A zone-based register of idle vehicles is maintained to quickly select a subset of k idle vehicles which are nearest to a given location using pre-calculated distances between zone centroids. This registry is used for a request-initiated dispatch, that is when a request is posed during oversupply. Once the k nearest idle vehicles are selected, backward shortest path search is run starting from the submitted request and moving backward until the nearest vehicle is reached.
- A vehicle-initiated dispatch, which takes place when a vehicle becomes idle during undersupply, is handled in a similar way. A zone-based register of open requests is used to pre-select the nearest k requests, and next, idle-vehicle to k-open-requests forward shortest path search is executed to determine the nearest open request and calculate the shortest path to it.

In the computational experiments, we assumed $k = 20$, as going beyond that value did not prove to be beneficial. Additionally, an A* shortest path search heuristics using the Euclidean distance with an overdo factor of 2.5 was applied to determine routes for trips with passengers.

As a result, a 24-hour simulation of hundreds of thousands of autonomous vehicles takes around 3 hours on a computer with an Intel Core i7-3930K processor. This makes the strategy appropriate for the use in the real-time setting.

4. Results

The simulation runs were performed using fleet sizes between 50 000 and 250 000 vehicles to find a suitable fleet size which is then analysed further. It was generally expected that vehicles are available around-the-clock. In order to avoid unnecessary extra traffic, no taxi ranks or anything similar were used in the scenario; vehicles were parked where they dropped off the last customer. In the morning, taxis are distributed over the city according to the actual population density in Berlin[22]. Passengers place their orders for taxi immediately before departure - a typical setup for an urban area. Driving times in the simulation runs are based on those achieved in the original simulation. When serving a customer, two minutes are added to each taxi trip for the embarkation of passengers and one minute per disembarkation.

4.1. Evaluation criteria

In general, taxi traffic operations focus on criteria defined by both the customer of the service and its operator. AT operations are not necessarily any different to this, with the exception that driver-related aspects (i.e. the wish to gather at ranks) do not need to be taken care of, whereas some aspects such as cleaning or maintaining the vehicle might be taken additionally into account.

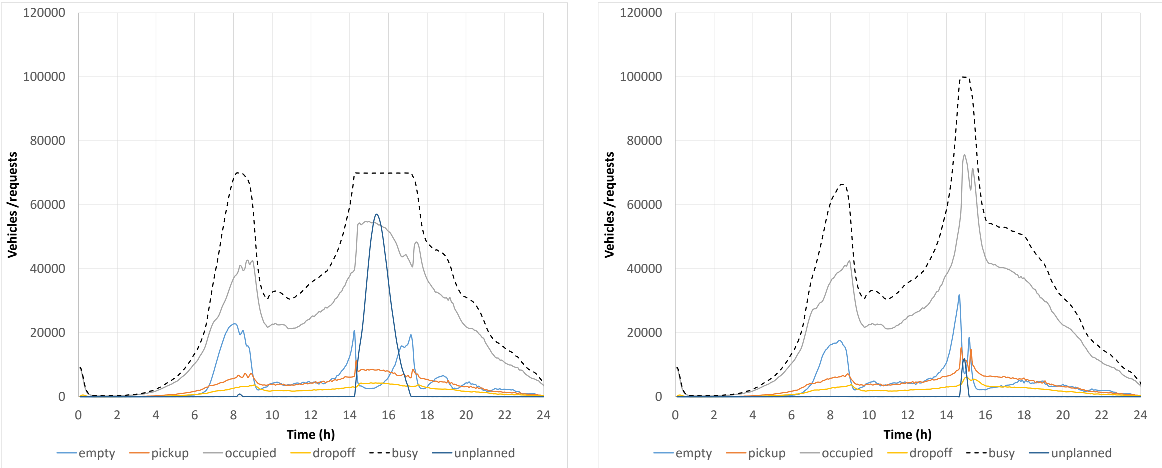
From a customer's perspective, waiting times for an AT service are, in general, of highest importance. In an ideal case, waiting time for a vehicle should not be greater than the time it takes nowadays to search for parking or to un-park a vehicle. On the other hand, pricing and operating scheme of AT services have not yet been defined and are like to have a major impact on the distribution of demand, i.e. reducing peaks by offering lower prices at off-peak times.

On the other hand, the operator wants to minimise the costs of introducing and operating ATs by minimising both the fleet size and empty (i.e. non-revenue) drive time (or mileage). Additionally, the operator may want to uniformly distribute the workload among vehicles, thus providing some slack time between jobs that can be used as a safety buffer in case of unexpected delays, or even for car maintenance during off-peak hours.

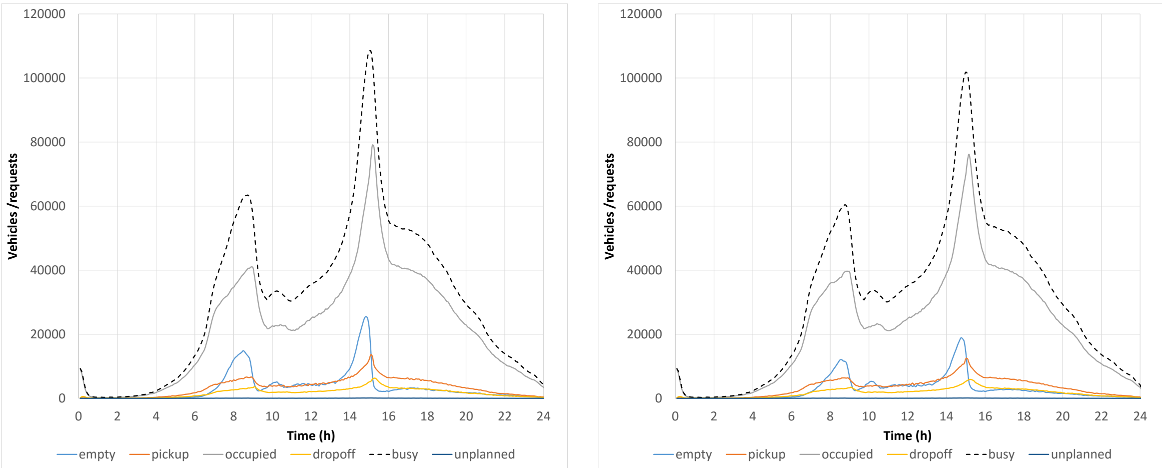
4.2. Fleet size determination

In order to estimate the impact of the fleet size on the service quality, the AT scenario was simulated with fleets of sizes between 50 000 and 250 000, incremented by 10 000.

Figure 3 shows the dynamics of AT dispatching for fleets of selected sizes during the course of the day. It shows the number of vehicles: driving empty towards customers (light blue), picking up customers (orange), driving with



(a) 70 000 vehicles (b) 100 000 vehicles



(c) 130 000 vehicles (d) 160 000 vehicles

Fig. 3: Vehicle operations and open requests over the whole day for different fleet sizes

customers aboard (grey), and dropping off customers (yellow). They all total to the number of currently busy vehicles (black dashed). Also, the number of currently unplanned requests (no vehicle has been dispatched towards them) is given (dark blue). The amount of the currently waiting passengers is equal to the sum of vehicles driving empty and unplanned requests (both in shades of blue).

Simulations with medium fleet sizes (90 000 – 130 000; Figures 3b, 3c) show the direct influence of the fleet size to the afternoon peak: With 130 000 vehicles, the peak remains where it is today (grey line) – all customers are served in time. With 100 000 vehicles, there is a temporal shortage of vehicles around 3:00 pm; with all vehicles being busy, some demand remains unmet for a while. The fluctuations in the number of empty drives result from the dispatching mode being switched from the FCFS regime to minimization of empty drive times in order to maximize the throughput. Despite the temporal undersupply, with the average wait time around 2.5 minutes and the 95th percentile between around 8.5 minutes, the 100 000-strong fleet makes a good compromise between the fleet size and quality of service.

Bigger fleet sizes (140 000 – 250 000 vehicles; Figure 3d) result in a huge number of vehicles being idle for most of the day. There are generally more vehicles idle than serving customers at any given time. Interestingly, the bigger

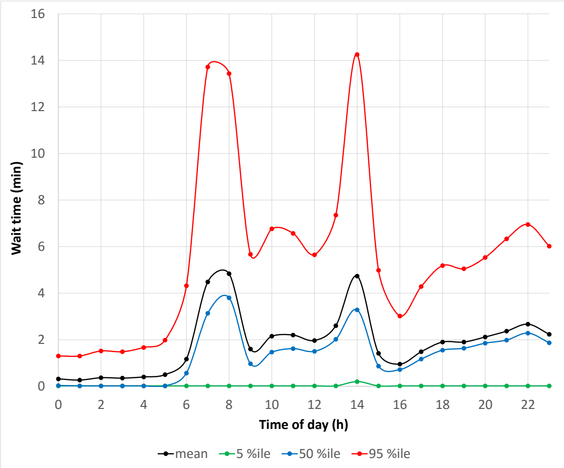


Fig. 4: Passenger wait times for each hour

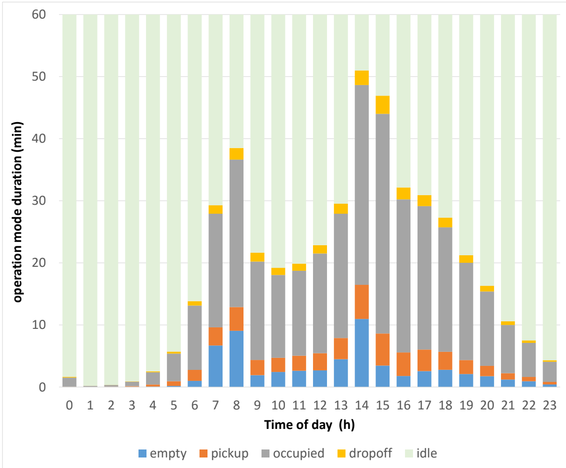


Fig. 5: Average operation mode split for each hour

the fleet, the fewer vehicles are used during the afternoon peak, because empty drives get shorter due to abundance of idle vehicles. Such oversized fleets cannot be operated in an economic way.

On the other hand, decreasing fleet sizes (50 000 – 80 000; Figure 3a) results in the morning peak also broadening, and overall deterioration of performance. More time is spent on driving empty and average waiting times increase significantly. Fleets of this dimension are not able to serve the demand in an appropriate manner.

4.3. 100 000 ATs case

Based on the simulations carried out with different fleet sizes, we consider a fleet size of between 90 000 to 110 000 vehicles to be sufficient for serving the city in an appropriate manner. Given the assumptions made in this study, this equals a *car-to-AT replacement ratio* of 1 : 10 to 1 : 12. In this section, the case with 100 000 vehicles is described more in detail, providing analysis on hourly basis.

4.3.1. Passenger wait times

Passenger wait times for this fleet size average at 2:28 min. For each hour, these times differ. Figure 4 provides detailed statistics. While being less than two minutes at most hours, during morning and afternoon peak, the average wait time climbs up to almost five minutes, and the 95th percentile is just under 15 minutes.

4.3.2. Vehicle utilisation

Figure 5 shows the average hourly utilisation of vehicles with distinction of operation modes, namely driving empty, picking up, driving occupied, dropping off and idling. With the exception of peak hours, most time is spent idling. This is an effect of sizing the fleet to cover peak times. Although an average AT is busy for only 7.5 hours a day, this is still far higher than the average 40-minute utilisation of CDVs in Berlin.

Despite the surplus of vehicles, the workload is not distributed uniformly among them on an hourly basis. This imbalance is illustrated in Figure 6 by categorising vehicles into the following four categories: always idle (dark green), mostly idle (light green), mostly busy (light red) and always busy (dark red). During the afternoon peak, no vehicle is idle all the time, yet each hour 10% of them are busy for less then 30 minutes. Similarly, during night hours (i.e. midnight to 6:00 am), no vehicle is busy for the whole hour, but still some vehicles are busy for more than 30 minutes at certain hours. These discrepancies are even more clear at medium demand prior to entering the undersupply state, when often none of the few remaining idle vehicles is close to the incoming request.

Minimization of the ratio of empty drive time to overall time spent on driving (Figure 7) is another relevant criterion for successful fleet operations. For most of the day the ratio is below 15%, however during peak hours the ratio hikes

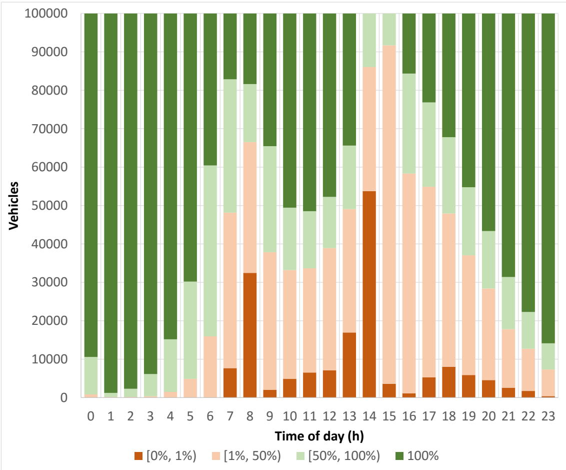


Fig. 6: Vehicles categorised by the hourly share of idle time

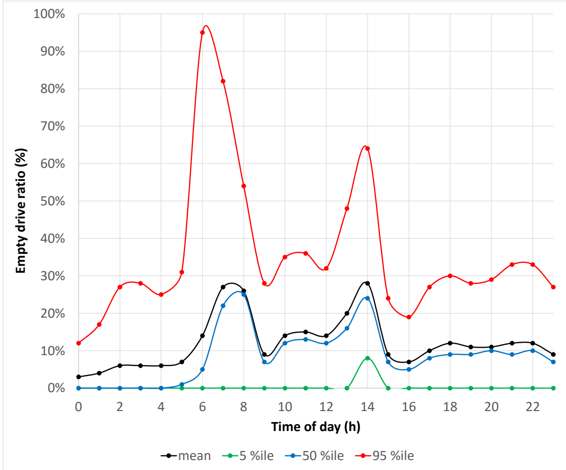


Fig. 7: Empty drive ratios for each hour

to almost 30% until the state of undersupply is reached. Then the priority is given to throughput and empty driving ratio gets drops below 10%. Significant differences between the 5th and 95th percentiles can be observed, however, they are also partially influenced by the calculation method (i.e. splitting vehicle schedules into full hours produces some artefacts, such as a 100% ratio if a vehicle, after being idle for a longer time, is dispatched just before another 60 minutes elapse).

5. Conclusions

This paper deals with the specific situation of a conversion of CDV trips into AT trips in Berlin. For the specific scenario, the simulation output suggests a replacement of the demand typically served by 1.1 million private cars with 90 000–110 000 taxis is possible.

Despite the increase of the total drive time by 17% due to empty trips, higher congestion effects are not necessarily expected to occur. It can be compensated by more fluent traffic flow[23] and no parking search. Besides exploring these issues, the authors also want to simulate case studies with additional transport policies often discussed for the city of Berlin, e.g. a speed limit of 30 km/h on trunk roads, a noise or emission-based optimization of traffic flow.

The size of an AT fleet is determined by the demand during peak hours. This effect could be softened in different ways. One would be to spread the demand peak by implementing dynamic pricing policies. Sharing AT-rides, which is more likely/effective at high demand, is another option to provide a similar level of service but with fewer ATs. Alternatively, a more versatile fleet usage, i.e. for goods distribution, may improve fleet utilisation during off-peak hours.

Re-running a similar simulation in other cities will result in different results. On one side, trip durations and distances differ from city to city and also from served area to served area. Rural areas will generally increase the share of empty rides and thus more vehicles per replaced car while densely populated cities with a less remarkable peak (than the afternoon one in Berlin) will likely need less vehicles.

Finally, it remains to be seen how and if mobility patterns will remain the way they are today. This is especially true for peak time distribution.

Acknowledgements

This paper was co-funded by the Einstein Foundation Berlin, Germany, and the National Centre for Research and Development, Poland (grant ERA-NET-TRANSPORT-III/2/2014).

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