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Should autonomous shared taxis replace buses? A simulation study

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The introduction of shared autonomous vehicles (SAV) will likely reduce operation cost per vehicle and might thereby allow to enhance conventional public transit systems with numerous small SAVs offering flexible ridesharing-like feeder services. These demand-responsive services could replace conventional bus lines limited by their fixed routes and their fixed schedules. This simulation study explores the potential of replacing conventional bus lines with shared autonomous vehicles in a suburban area of Berlin. Several scenarios with different fleet sizes and vehicle sizes are simulated using the multi agent transport simulation MATSim. The simulation suggests for all evaluated scenarios higher operating costs and only slight travel time savings in comparison to conventional buses. Door-to-door service allows for significant reductions in average walk time, but causes numerous detours which consume a high share of the time gained. A fleet of 150 SAVs with 4 seats each seemed appropriate for the simulated area with approximately 24 000 inhabitants.

1 Introduction

Transportation network companies like Uber have appeared on the roads only a few years ago and yet are already developing into increasingly important competitors to conventional public transport such as buses. Schaller (2017) analyzed the example of New York City where buses and even subways started to loose more and more passengers whereas ride services (ride-hailing, conventional taxis and similar) more than compensate for this and are growing faster than all other modes included in the statistic. In a survey by Clewlow and Mishra (2017) ride-hailing users report a decrease in their public transit use with a 6 % reduction for bus services and a 3 % reduction for light rail services. However, they also report a 3 % increase in heavy rail usage. Apparently ridesharing services compete with conventional public transit, but can also complement it. Some transit authorities, e.g. SEPTA (2016), partnered with Uber to offer discounts for last mile rides from and to their train stations. The Canadian city of Innisfil made headlines (see Smith (2017)) with the more radical decision to partner with Uber rather than introducing a conventional bus system at all.

Ride-hailing apps and ridesharing allow for a more flexible service than conventional bus lines, because they can react to the actual demand instead of operating on fixed routes and fixed schedules. So they can potentially offer a more attractive service for the customer by departing closer to where and when the passenger wants. Thus, they can eliminate operating costs for scheduled services which eventually run empty, because no passenger chose to take these services. Furthermore, they allow for door-to-door service which is more attractive and removes the walk time to access the next bus stop. According to the survey by Clewlow and Mishra (2017), having less than enough transit stops is the second most important reason for substituting ride-hailing for public transit.

In order to realize the full potential of ridesharing-like services as part of a public transit system, ridesharing-like services will likely need to use many small vehicles instead of a few large conventional buses, because the more vehicles there are, the more frequent the service they offer can be. A large barrier to the use of more vehicles seem to be driver-related costs which according to Frank et al. (2008) amount to about 40 % of the sum of all operating and investment costs for a conventional bus in Germany. The introduction of shared autonomous vehicles (SAVs) in the future will likely remove all driver-related costs and thus could allow to replace each large conventional bus with many smaller vehicles which could offer a more frequent service without the tremendous increase in driver-related costs this would cause today. Furthermore, prices for ride-hailing services are likely to fall making them an even more attractive competitor for passengers.

However, using many small vehicles instead of a few large buses could increase road congestion. Furthermore, taxi like services could

So should transit authorities replace conventional bus lines with ride-hailing services operated by future autonomous shared taxis in some areas? How would travel times and operation costs change? These questions are to be examined in a case study for a low-density suburban area in Berlin using the multi agent transport simulation MATSim.[1]

2 Simulation model

The aim of the study is to compare a base case scenario with conventional bus lines to several scenarios in which these bus lines were replaced by autonomous shared taxis of varying fleet sizes and capacities per vehicle. The multi agent transport simulation MATSim (Horni et al. (2016)) was chosen because it is capable of simulating large-scale scenarios at sufficiently high computing speeds and provides software modules for shared taxis and intermodal trips. MATSim consists of a common base and several optional extensions which are called "contributions". Three of these extensions were used in the study: The AV-Contribution (AV for "autonomous vehicles") was employed to calculate intermodal routes combining conventional public transit and SAVs as a feeder service. In order to simulate ride-hailing and ridesharing with SAVs the DRT- and DVRP-Contributions were used (DRT for "demand-responsive transport" and DVRP for "dynamic vehicle routing problem").

MATSim is based on the simulation of agents and their daily plans which consist of activities like home or work and trips between their activity locations. Before each simulated day, some agents try to improve their plans, e.g. by selecting a different route or modifying activity start and end times. The resulting plans are then simulated and scored based on their performance before the next iteration starts and plans are modified and simulated again. Several transport modes were included in the simulation. However, the underlying input data was not calibrated for mode choice, so mode choice was fixed and shared taxis were handled as a part of the public transport system. Therefore, only agents who had already been using public transport before could use shared taxis (as well as normal buses and trains) and mode shift effects were neglected. Furthermore, the same fare system applies to shared taxis and public transit and there is no competition with potential other ride-hailing operators.

2.1 Intermodal router

The AV-Contribution comes with an intermodal router, which allows to combine a public transit route with other modes to access the first transit stop and egress from the last transit stop. It is not a full intermodal router, as it does not consider trips with other modes between two public transit rides, such as a bus-bike-train trip. Access and egress modes are selected by beeline distance between activity location and transit stop. For this study the so-called "flexible style" for access/egress mode choice was selected. For beeline distances of less than 300 m the router always assumes the mode "transit_walk". Taking into account the wait time for a shared taxi, it seems unlikely that using a taxi has significant advantages for the passenger which could justify the additional expense for the shared taxi operator and possible detours for other passengers of that shared taxi. For beeline distances between 300 m and 1 000 m the router selects by random either mode "drt" (shared taxi) or "transit_walk". So, multiple routing requests for the same trip can result in routes with different access and egress modes. Thereby, the router implements mode choice for access and egress legs. For beeline distances greater than 1 000 m the router always assigns the mode "drt", because it is unlikely that passengers would accept such a long walk, if a faster and more comfortable alternative is available.

In order to restrict the operation area of shared taxis, the intermodal router was modified to assign the mode "drt" only to access and egress legs whose origin and destination are located inside the designated operation area (see

[1]This paper is based on the master's thesis by Leich (2017).

figure 1), so no agent has a route which asks for shared taxis outside the operation area. If no plausible transit route could be found, the router returns a direct "transit_walk" respectively "drt" leg from trip origin to trip destination. As the router calculates travel time and cost of access and egress legs based on beeline distances only, some bus stops inaccessible due to rivers and lakes had to be excluded manually as access and egress stops for activity locations inside the study area (see bus line 136 in figure 2).

Furthermore, given a certain set of departure time, trip origin and trip destination the router always returned the same route. This turned out to be a major issue, because the router estimates access leg travel times based on the beeline distance and a fixed mode speed. However, shared taxi legs have varying wait and in-vehicle travel times, so many agents missed connecting trains they planned to take. This issue is aggrevated by the fact that the study area has two heavy rail lines to the city center. Figure 2 shows that line S25 (shown in green) has better accessible stations than line U6 (shown in blue), so the router mostly returned routes using line S25. Nevertheless, line U6 offers a far more frequent service whereas missing a S25 train causes a 20 min wait. This lead to increased public transit wait times despite less public transit legs in the first preliminary simulation runs. In order to address this issue, the router was altered to choose by random at each routing request whether to include or exclude all three concerned S25 stations in the study area during routing. Thus, over the course of several iterations with several routing requests the agent will test routes with and without using the three S25 stations.

2.2 Simulation of shared taxis

The shared taxis are simulated using the DRT-Contribution introduced in Bischoff et al. (2017). For the vehicle routing and assignment the DRT-Contribution uses the DVRP-Contribution presented in Maciejewski (2016) as backend. Shared taxis offer door-to-door service. Agents request their shared taxi ride after finishing the last activity before the trip, i.e. without pre-booking (Bischoff et al. (2017)). Ride requests are only served if a shared taxi can serve them within certain time constraints. These consist of a maximum wait time to departure at the requested journey origin and a maximum total travel time (the sum of wait and travel time) (Bischoff et al. (2017)). Both time constraints must be satisfied for the requested ride and for all ride requests already assigned to the shared taxi (Bischoff et al. (2017)). That means additional travel time caused by detours to serve the new ride request may not violate the time constraints of ride requests already scheduled. The requested ride is assigned to the vehicle which can serve it with the least additional operation time needed to serve the requested ride (Bischoff et al. (2017)).

Otherwise, if no taxi can serve the ride without exceeding the above mentioned constraints, the ride request is rejected (Bischoff et al. (2017)). In the current implementation, the corresponding agent will nevertheless wait for the shared taxi to arrive. Since no taxi was scheduled to serve the customer, he will wait until the iteration ends. That means he is not able to continue his daily plan and will not execute any activity or trip scheduled after the shared taxi ride. This poses some issues for analysis, because no travel time can be calculated for the agent and different agents are affected in different scenarios. Therefore, all trips which were not completed in all scenarios (about 8.6 % of all completed trips) were excluded from analysis of entire trip travel times in section 4.2. Thus, it can be avoided that e.g. very long trips with high shared taxi travel times increase average trip travel times of scenarios with sufficient vehicle fleets whereas the rejection of these ride requests in other scenarios decreases the average trip travel times in these other scenarios. Each trip excluded from analysis was completed in at least one SAV scenario. Taking into account only these completed measurements, there seems to be no significant difference between excluded and included trips, i.e. the average trip travel time is very similar and the difference in average trip travel time between SAV scenarios and the base case is similar to the difference calculated for included trips. So the exclusion of that data from analysis does not seem to have a significant influence on the results, but allows to compare the very same trips for all scenarios.

When the simulation was run, there was no option to use the DRT-Contribution without rejections. Agents could try to avoid ride request rejections to some extent, e.g. by choosing a different departure time. However, rejections can be erratic for agents, i.e. the very same daily plan might work fine in one iteration, but might be aborted due to a rejection in another iteration. Which request is rejected depends on which requests were issued before, so small alterations in other agents' plans might decide whether there is a SAV available or not. Instead of rejecting requests they could be assigned to SAVs despite long expected wait times. However, a long wait time would render a daily plan very unattractive just like a rejection in the current implementation would do. Furthermore, the occurence of long wait times might be just as erratic as rejections. This issue requires further research.

The maximum permissible shared taxi wait and travel time sum t^r_{max} is calculated based on the travel time for a direct ride t^r_{direct} (without wait and detours) and two parameters α and β (Bischoff et al. (2017)):

$$t^r_{max} = \alpha * t^r_{direct} + \beta \tag{1}$$

The selection of the time constraint parameters α, β and maximum wait time t^{wait}_{max} has a significant influence on the average travel times and the share of rejected ride requests as test runs in Bischoff et al. (2017) show. Based on their results several combinations were tested for the data set of this study. Since the same set of time constraint parameters was to be used for all scenarios, all test runs were conducted for a fleet of 200 shared taxis with 4 seats per vehicle. α values other than 1.5 were not tested, because these lead to higher travel times in Bischoff et al. (2017) and because of the high computation time necessary for more test runs.

Table 1: Selection of time constraint parameters α, β and t^{wait}_{max}.

α	β [mm:ss]	t^{wait}_{max} [mm:ss]	t^{wait} [mm:ss]	t^{r} [mm:ss]	d^{direct} [km]	d^{detour} [km]	d^{T} [km]	d^{U} [km]	ρ
1.5	10:00	10:00	06:18	17:34	4.87	1.21	49 715	105 170	0.05
1.5	**10:00**	**12:00**	**07:26**	**18:28**	**4.94**	**1.08**	**54 809**	**109 795**	**0.01**
1.5	12:00	12:00	07:48	19:30	4.95	1.36	53 090	114 739	0.01
1.5	15:00	15:00	10:02	22:21	4.94	1.56	52 808	118 462	0.01

Table 1 depicts a significant increase in average total travel times t^r (sum of wait and in vehicle travel time) and average wait times t^{wait} with increasing β and t^{wait}_{max} values, although demand and vehicle fleet were equal in all test runs. However, the share of rejected ride requests ρ is much larger in the uppermost test run than in all other test runs, that means less requests were actually served enabling potentially better service quality for the remaining requests. This might explain the lower average direct distance between request origin and destination d^{direct} and the lower distance driven d^T. More generous time constraints β and t^{wait}_{max} also lead as expected to more bundling of rides which can be seen in the decreasing total distance driven d^T despite increasing revenue distance d^U (total length of all rides served). The rise in revenue distance despite stable demand is partly caused by rising detour distances d^{detour}. Detour distances were calculated as the difference between the length of a theoretical direct trip from origin to destination of a ride request and the distance the agent really spent travelling in the SAV, which might be longer, because the SAV served other agents on the way. The first parameter set $\beta = 10$ and $t^{wait}_{max} = 10$ shows a higher detour distance than $\beta = 10$ and $t^{wait}_{max} = 12$, although t^{r}_{max} is equal for both. One possible explanation is that given a certain permissible time budget t^{r}_{max} the stricter wait time criterion of the former parameter set will allow for higher in-vehicle travel times. These can be used to allow for longer detours to bundle more ride requests.

A high rejection rate ρ could put at risk the acceptance of the new shared taxis as a replacement of conventional bus lines. Therefore no β and t^{wait}_{max} lower than 10 min were tested. Instead the highlighted parameter set was selected for all following simulation runs since it delivers the lowest travel times at an acceptable rejection rate. A possible explanation why tighter time constraints could not be used is the lack of a relocation strategy. The shared taxi operation area is too large to reach every possible pick-up location from every possible vehicle location in 10 min or less. At the beginning all SAVs were distributed evenly over the operation area, but with a largely monodirectional demand in the morning rush hour it could happen that all empty SAVs accumulate at the train stations in the southeast of the operation area whereas all vehicles in other areas are too busy to accept new ride requests. Consequently, the fleet would be unable to serve ride requests in the northwest in time.

3 Study area

The simulation is based on a real-world data set for Berlin in use at Transport System Planning and Transport Telematics department of TU Berlin. It includes a 100 % sample of a synthetic population of Berlin and Brandenburg, a road and rail network and a public transit schedule.

The study area shown in figure 1 is situated in the borough of Berlin-Reinickendorf and consists of Heiligensee and Konradshöhe districts and some mostly forest areas of Tegel district excluding the center of Tegel. It contains mostly low density residential areas. Figure 2 depicts the public transit lines in the study area. There are four bus lines operating in the study area (124, 133, 222 and 324) with headways of 10-30 min during rush hour and 20-30 min during the rest of the day. Most agents use these buses as a feeder system to reach Tegel station where the heavy rail lines S25 and U6 connect to other parts of Berlin. In the base case the public transit schedule remained unchanged. In all scenarios with shared taxis bus lines 124, 133 and 222 are shortened to terminate outside the study area and bus line 324 is suspended.

Starting from the given data set, all agents with activities inside the study area and all agents who pass through the study area by car were extracted for this study. All in all, 50 000 agents (a 100 % sample) were included in

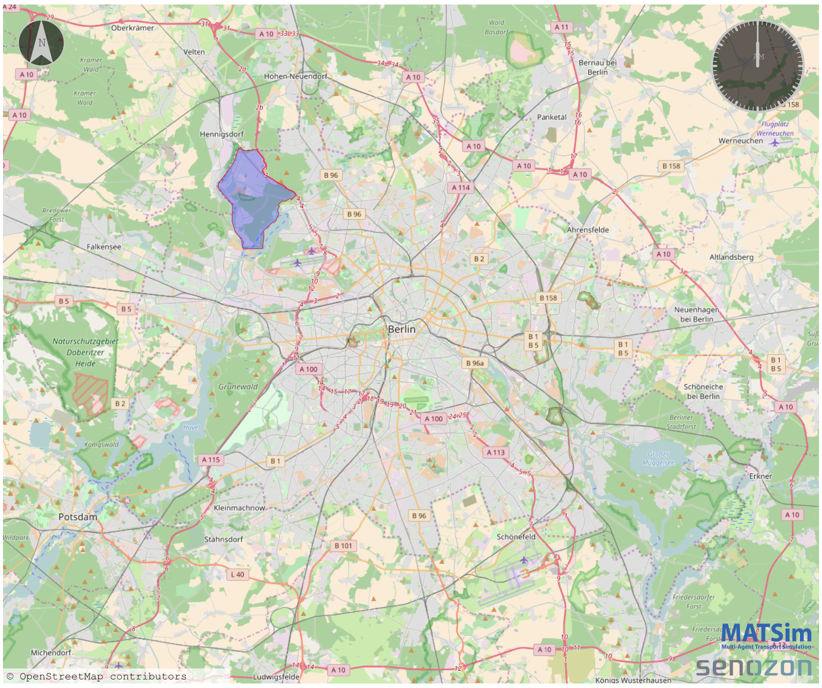

Figure 1: location of the study area (blue) in Berlin.

the simulation of which only about one half has activities inside the study area. All others are car drivers who were included to provide realistic road congestion levels while passing through the study area.

In order to allow access and egress to two major heavy rail stations in Tegel the router uses a shared taxi operation area slightly larger than the study area used to cut out the synthetic population. The router operation area was later simplified to reduce computation time.

4 Results

The analysis of simulation results is divided into an isolated examination of the shared taxi legs only and an analysis of travel times for the entire trip including all public transit and walk legs.

4.1 Shared taxi performance

Scenarios with 1, 4, 8, 12 and 20 seats per taxi vehicle were run. Despite the concentration of transport demand at one major hub (Tegel), more than 8 seats were rarely used. Furthermore, table 2 shows that scenarios with less than 120 vehicles had rejection rates ρ higher than 5 % no matter how many seats per vehicle were offered. Average total travel time on shared taxis (including wait) was roughly equal for all scenarios. Neither private taxi operation in scenario D2D_400_Cap1 (1 seat per vehicle only) nor an oversupply of vehicles in scenario D2D_1000_Cap4 lead to an important reduction in total travel time (including wait). Analysis then focused on the following scenarios: 120 taxis with 8 seats (D2D_120_Cap8), 150 taxis with 8 seats (D2D_150_Cap8), 150 taxis with 4 seats (D2D_150_Cap4) and 200 taxis with 4 seats (D2D_200_Cap4). These fleet dimensions allow to keep the share of rejected ride requests at or below 5 %.

Due to the shared taxi implementation in the DRT-Contribution, travel times differ only slightly between scenarios with different taxi fleet sizes. Larger taxi fleets reduce the number of rejected ride requests as more rides can be served maintaining the time constraints. However, larger fleets have little influence on wait and travel times, because the optimization algorithm tends to schedule high wait times (see 95%-percentil of wait times t_{p95}^{wait} only slightly below the maximum admissible 12 min) and high total travel times t^r (sum of wait and in-vehicle travel) while trying to minimize the time SAVs are in operation. So, whenever possible the algorithm will rather bundle ride requests together in order to save vehicle operation time than provide higher service quality. This is illustrated by figure 3 which shows

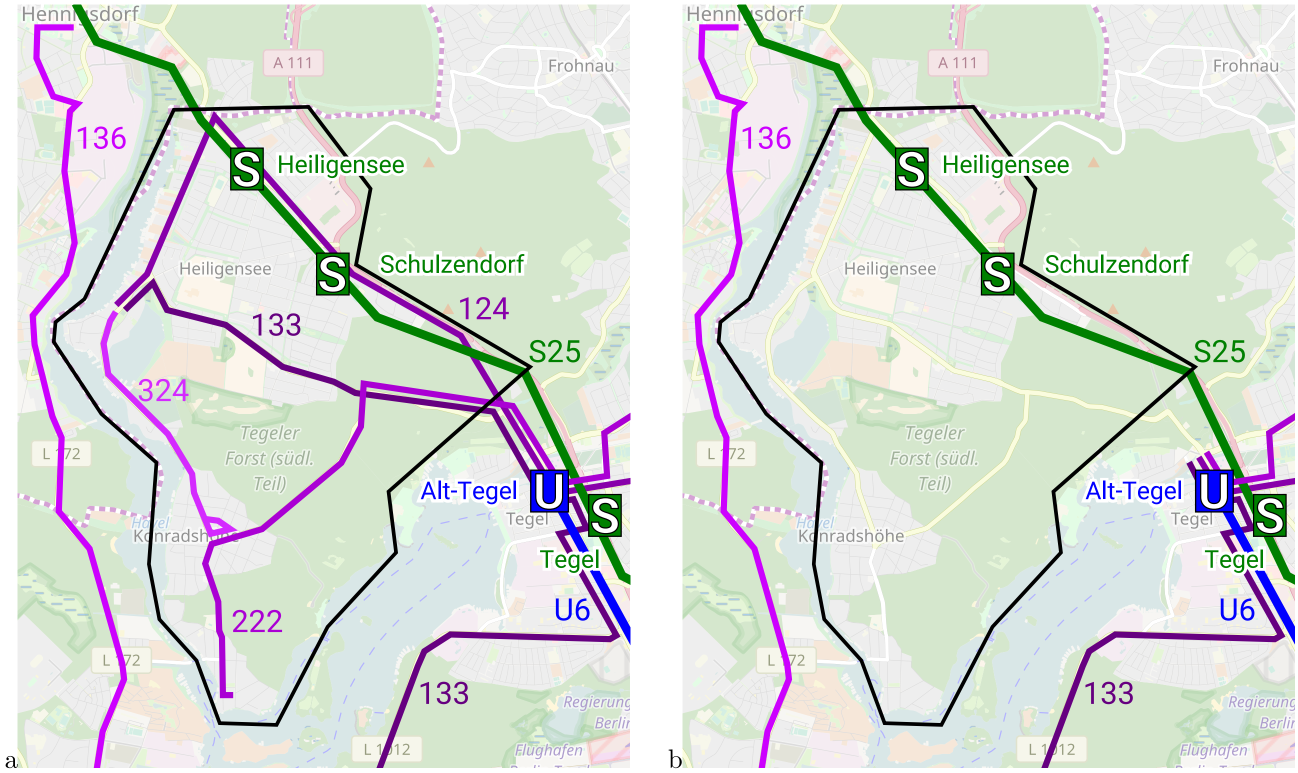

Figure 2: (a) public transit lines in the base case; (b) public transit lines in all other scenarios; (background map ©OpenStreetMap contributors).

Table 2: Simulation results for the shared taxi legs. Scenarios selected for further analysis are highlighted.

Scenario	number of taxis	seats per veh.	rides served	t^{wait}_{avg} [mm:ss]	t^{wait}_{p95} [mm:ss]	t^{r}_{avg} [mm:ss]	d^{direct} [km]	d^{detour} [km]	d^{T} [km]	d^{U} [km]	ρ
D2D_50_Cap20	50	20	10 109	06:59	11:43	18:10	5.18	1.21	26 724	64 623	0.35
D2D_75_Cap12	75	12	13 563	06:53	11:41	17:58	5.08	1.16	35 648	84 590	0.19
D2D_100_Cap12	100	12	15 920	06:42	11:42	17:55	4.99	1.17	41 344	98 129	0.09
D2D_100_Cap8	100	8	15 807	06:53	11:43	17:56	4.99	1.13	41 292	96 843	0.10
D2D_120_Cap8	**120**	**8**	**17 151**	**06:50**	**11:40**	**18:05**	**4.96**	**1.18**	**44 684**	**105 268**	**0.05**
D2D_150_Cap8	**150**	**8**	**18 024**	**06:47**	**11:40**	**18:13**	**4.97**	**1.19**	**46 454**	**111 023**	**0.02**
D2D_150_Cap4	**150**	**4**	**17 238**	**07:32**	**11:44**	**18:15**	**4.92**	**1.07**	**51 646**	**103 254**	**0.05**
D2D_200_Cap4	**200**	**4**	**18 258**	**07:26**	**11:44**	**18:28**	**4.94**	**1.08**	**54 809**	**109 795**	**0.01**
D2D_400_Cap1	400	1	17 214	08:42	12:08	17:40	4.94	0.00	117 546	85 115	0.05
D2D_1000_Cap4	1 000	4	18 668	05:55	11:28	17:42	4.95	1.35	49 015	117 533	0.00

a significant share of SAVs occupied by more than one passenger even in off-peak hours, e.g. at midday. Consequently the number of vehicles in operation is reduced to just between one third and one half of the total fleet available at midday. In scenario D2D_1000_Cap4 with 1 000 vehicles available no more than 250 are ever in operation at the same time due to the taxi assignment algorithm. The high degree of trip bundling becomes clear looking at the high share of pooled trips, i.e. trips with at least one more passenger sharing the vehicle for at least a part of the route, which is e.g. 96 % of all trips over the day in scenario D2D_200_Cap4.

As discussed in section 2.2, setting more restrictive time constraints reduces taxi wait and travel times only slightly while vastly increasing the number of rejected ride requests. So given the shared taxi assignment algorithm used, there seems to be no obvious way to significantly decrease the average shared taxi wait and travel times without putting acceptance of shared taxis at risk by rejecting many ride requests.

4.2 Travel times for entire trips

After analyzing the shared taxi legs only, in the following the entire trips between trip origin and trip destination shall be examined for all trips concerned by the substitution of SAVs for conventional buses, that means all completed

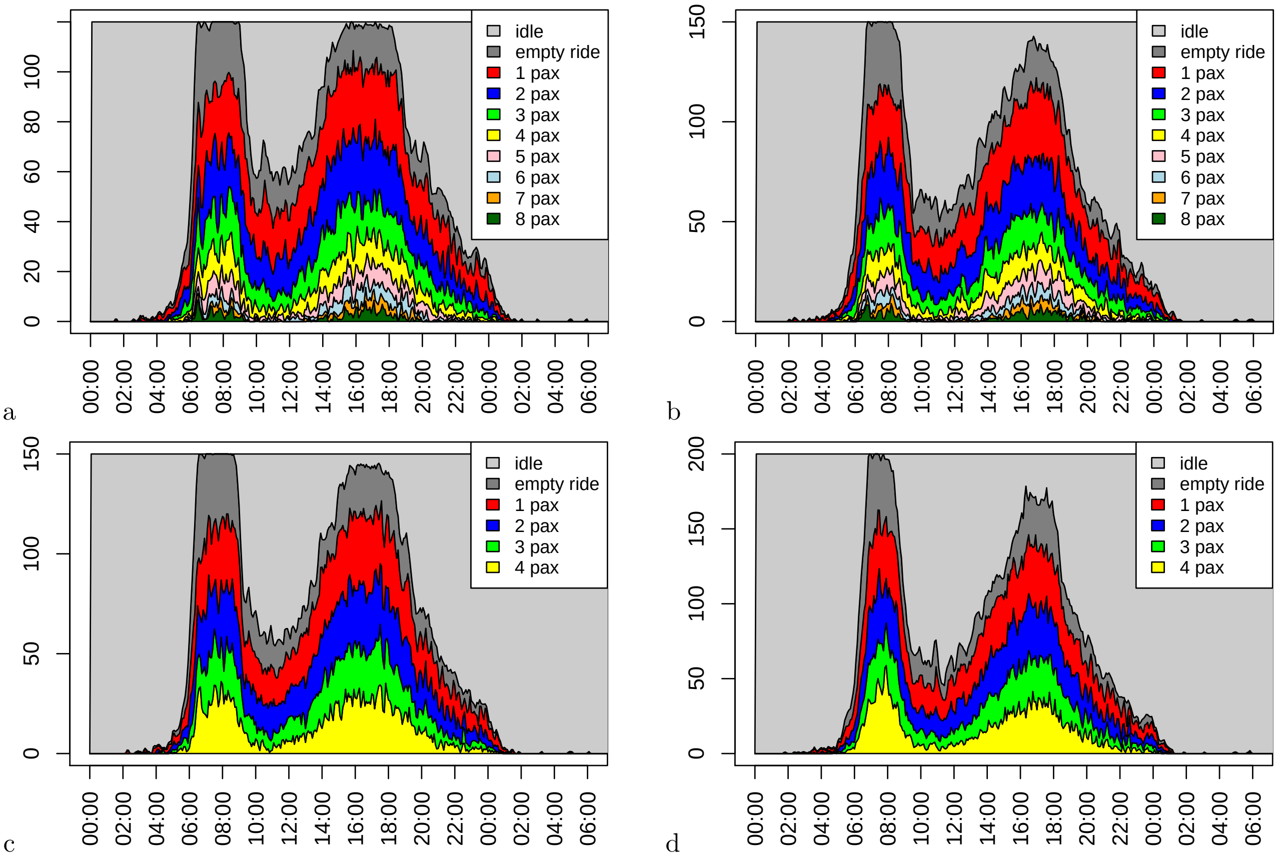

Figure 3: vehicle occupancy: (a) D2D_120_Cap8; (b) D2D_150_Cap8; (c) D2D_150_Cap4; (d) D2D_200_Cap4.

public transport trips originating or ending inside the study area, including trips which do not include shared taxi legs. Based on agent id and the position of the trip in the agent's daily plan, all trips were assigned a unique identifier. Since the activities, their locations and their order did not change during simulation, each of these unique trips has the same origin, the same destination and a roughly similar departure time in all scenarios. So there is one execution of the very same trip per scenario, unless the agent got stuck e.g. because his shared taxi request was rejected. Trips which were not completed in at least one of the scenarios to be evaluated were excluded from analysis as described in section 2.1.

18 761 trips completed in each scenario remained in the analysis. Depending on the shared taxi fleet scenario between 15 602 and 15 749 of these trips (0 in the base case) include at least one shared taxi leg and between 13 936 and 13 965 of these trips (16 301 in the base case) include at least one public transit leg. This means about one quarter of all completed trips does not include public transit, because there was no suitable public transit service available, e.g. because the trip originates and ends inside the shared taxi operation area where conventional public transit was mostly removed.

Figure 4 shows that in comparison to the base case without shared taxis the average total trip travel time from origin to destination is reduced from about 53 min by less than 2 min. The average walk time decreases by 8 min and the time spent waiting for or travelling on buses or trains is reduced by 2 respectively 7 min, but shared taxi wait times of about 6 min and travel times of about 9 min partly make up for this. The shared taxi wait times and travel times do not equal the values given in table 2, because the average illustrated in figure 4 includes trips without shared taxi legs which lower the average values. Total time spent waiting for and travelling on public transit and shared taxis increases in every scenario in respect to the base case. This means the slight reduction in trip travel time is based only on the decrease in walk time and agents with trips originating or terminating right next to existing bus stops might even experience higher average trip travel times.

One basic assumption before simulations were started was that shared taxis could allow to reduce trip travel time spent between two activity locations because door-to-door operation reduces walk distances and departure times can be chosen more flexibly. However, it seems that door-to-door operation also causes longer detours for shared rides

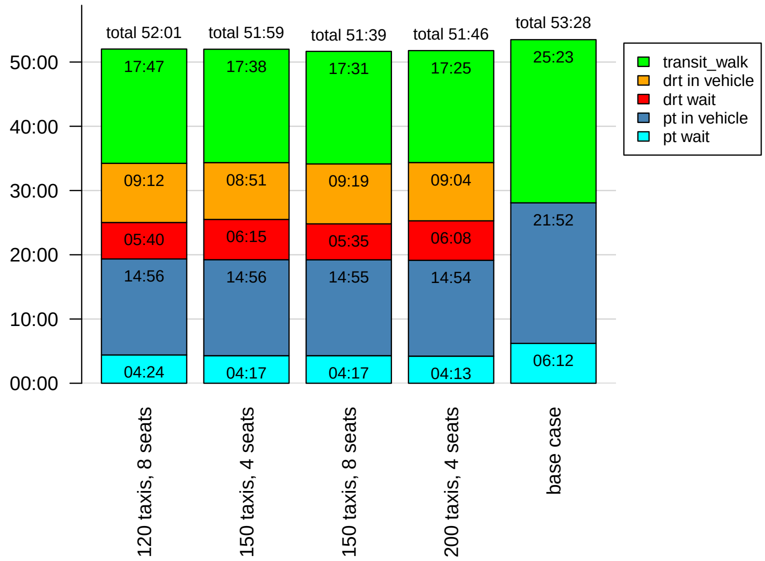

Figure 4: Average travel times for the entire trips including walk and public transit legs and their components [mm:ss]. "drt" and "pt" denote shared taxi respectively public transit legs.

which contribute to a noticeable increase in total in-vehicle time spent travelling in public transit and shared taxis of about 2 min.

Additionally, the decrease in public transit wait time is lower than expected, probably because the lack of any pre-booking feature made departure times even more unpredictable, so connecting trains were often missed. The latter problem is less visible, because in respect to the base case a higher share of agents going to the city center used the more frequent U6 heavy rail line instead of the less frequent S25, but actually the preference for the more frequent rail line could also be a result of less predictable arrival times. Before the router was altered to create more variability (see section 2.1) more agents chose S25 compared to the base case and there was a significant increase in public transit wait time despite less public transit boardings, although shared taxis allow for a more flexible departure time choice than conventional bus lines. Whereas conventional bus lines with fixed schedules can be planned to provide transfer to a defined connecting train (and the connecting train might even wait for the bus in some cases), the time constraints for shared taxis allow for a wide range of departure and arrival times. For a direct travel time of 10 min and the parameters $\alpha = 1.5$ and $\beta = 10$ min used for this study, the admissible arrival time has a range of 15 min (see section 2.2) which almost equals the headway of line S25. So the agent would have to start 15 min prior to the departure time necessary for a direct trip and will most likely often end up waiting at the train station for some minutes or more. The practical range might be smaller in many cases, however the shared taxi scheduling adds an additional layer of uncertainty which conventional buses do not have.

5 Cost-benefit evaluation

Cost calculations for autonomous vehicles are subject to serious uncertainties as autonomous vehicles have not reached series production yet. Additionally, shared autonomous vehicles replacing current wheelchair accessible buses would have to cater for unaccompanied passengers with disabilities whereas today's taxi vehicles are mostly not suited for wheelchair users at all. Costs for future fuels or batteries and propulsion systems and future interest rates remain in doubt, too.

Therefore, costs were calculated based on existing fossil-fuel-powered taxis and articulated buses omitting all driver-related costs. The number of buses which could be saved by shortening bus lines as explained in section 3 was estimated at 10 articulated buses. A maintenance reserve of 10 % was added to the number of buses respectively SAVs and the total distance driven was split evenly among all vehicles. The calculations assume an interest rate of 3 %, a life span of 5 years for SAV and 12 years for articulated buses, purchasing prices of 28 211.75 € for a 8-seat SAV, 18 845 € for a 4-seat SAV and 321 000 € for an articulated bus. Bus capital costs (for the vehicle purchase) and operation costs were calculated according to Frank et al. (2008) whereas operation cost for SAVs is based on data by Autokostencheck (2017). These operating and capital costs were summed up to annual costs presented in table 3. The detailed calculation can be found in Leich (2017).

Table 3: Costs and benefits per scenario. "Δcosts" is the difference between shared taxi costs and conventional bus costs saved. "$U^{scenario}$-Δcosts" is the benefit-cost difference. $t^r_{trip,day}$ is the trip travel time per day and $\Delta t^r_{tot,year}$ is the difference in trip travel time per year in comparison to the base case.

Scenario	costs [€/a]	Δcosts [€/a]	$t^r_{trip,day}$ [h/day]	$\Delta t^r_{tot,year}$ [h/a]	requests rejected	U^r [€/a]	U^b [€/a]	$U^{scenario}$ [€/a]	$U^{scenario}$-Δcosts [€/a]
D2D_120_Cap8	2 645 698	507 169	16 268	-166 258	859	803 024	-302 875	500 149	-7 020
D2D_150_Cap8	2 980 258	841 729	16 153	-208 287	324	1 006 027	-114 239	891 788	50 059
D2D_150_Cap4	2 235 897	97 368	16 257	-170 017	825	821 182	-290 887	530 295	432 927
D2D_200_Cap4	2 621 056	482 527	16 192	-194 045	212	937 237	-74 749	862 488	379 961
base case	2 138 529	/	16 723	/	/	/	/	/	/

Despite the lower degree of capacity utilization, driverless articulated buses on conventional bus lines would still be cheaper to run than driverless demand-responsive shared taxis. Replacing conventional bus lines, cost increases by 5 % for 150 shared taxis with 4 seats or 39 % for 150 shared taxis with 8 seats. However, the current budget allows for conventional buses and driver-related costs, so the driver-related costs saved by automation would probably allow to cover the additional expense for shared taxi operation. Nevertheless, it is not clear whether subsidies and fares would remain on current levels, if automation allows for similar service levels at reduced costs. There might be political pressure to cut subsidies or to increase fares for the more comfortable door-to-door shared taxi service. The latter could cause controversy as poor people would be left without any more affordable alternative.

For the cost-benefit evaluation, travel time reductions were considered as benefits U^r. Rejected ride requests were taken into account as a 12 min travel time increase (maximum permissible wait time was 12 min) stated as (negative) benefit U^b in table 3. From the resulting benefit per scenario $U^{scenario}$ the increase in costs (Δcosts) is substracted to obtain benefit-cost differences. Only the two scenarios with 150 respectively 200 taxis with 4 seats each had a significantly positive benefit-cost difference of 432 927 €/a respectively 379 961 €/a. Benefit-cost differences are somewhat difficult to interpret, because it is not clear what a good or bad benefit-cost difference would be for the project and how much benefit is obtained per each € spent. However, a classical benefit-cost ratio cannot be calculated, because there is no real investment here. An approximation to something like a benefit-cost ratio is to divide the benefit from travel time savings by the annual costs given above, even though operation costs are usually subsumed as (negative) benefit. This gives a ratio of 5.5 for 150 4-seat SAVs and 1.8 for 200 4-seat SAVs and about 1 for the other two scenarios.

Table 4: Benefit-cost differences for varying SAV costs.

Scenario	benefit-cost difference [€/a] for a variation of SAV costs by								
	-30 %	-20 %	-10 %	-5 %	+/- 0 %	+5 %	+10 %	+20 %	+30 %
D2D_120_Cap8	786689	522120	257550	125265	-7020	-139305	-271590	-536160	-800729
D2D_150_Cap8	944136	646111	348085	199072	50059	-98954	-247967	-545993	-844018
D2D_150_Cap4	1103696	880106	656517	544722	432927	321132	209337	-14252	-237842
D2D_200_Cap4	1166277	904172	642067	511014	379961	248908	117855	-144250	-406356

The most doubtful aspect in the cost-benefit evaluation seem to be SAV costs. Table 4 shows the influence of varying SAV costs on benefit-cost differences. For slight variations in SAV costs there is no major change, however at a 20 % or more increase in SAV costs all scenarios seem disadvantageous. Such a high misestimation cannot be excluded given the uncertainties mentioned above.

6 Conclusion

All in all, the simulation suggests that the substitution of conventional bus lines with shared taxis could have some benefits for the passengers at a reasonable cost for the operators. However, the advantages seem to be smaller than expected. An enhanced shared taxi routing algorithm might improve the case for shared taxis, but some issues would probably remain. Door-to-door operation appears to reduce walk distances, but would likely increase detours to serve other passengers. It seems that shared taxis tend to have unpredictable departure and travel times if routes are altered to add another passenger while others are already on the taxi. Furthermore, shared taxis could remain more expensive to operate, especially if the taxi routing algorithm would be altered to provide lower wait times by bundling less rides.

Nevertheless, should private ridesharing operators enter the market as competitors of public transport, decreasing passenger numbers could make conventional bus lines less profitable, creating a vicious circle of reducing costs by reducing services and falling passenger volumes. So on the long run the case for shared taxis could improve and public transport authorities might have no other choice than to partner with ridesharing companies or operate shared taxis themselves.

Future studies could investigate mode choice effects as well as combinations of conventional bus and shared taxi services, e.g. keeping conventional bus lines during the day and replacing them with shared taxis only during the night or only on lightly used lines such as line 324 in the study area.

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