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Impact of Relocation Strategies For a Fleet Of Shared Automated Vehicles On Service Efficiency, Effectiveness and Externalities

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***Abstract*—The introduction of taxi-like transit services operated by shared automated vehicles comes into sight with the development of vehicle automation. In this paper, the operation of such a service is simulated for a generic grid network in order to determine the impact of different relocation strategies for idle vehicles on passenger waiting time, empty mileage and parking needs. The tested strategies consist of remaining idle at the latest drop-off location, returning to the initial position, relocating to a random location, relocating according to anticipated demand or relocating to a zone with a low vehicle supply. For the simulated case study, remaining idle outperformed the other relocation strategies in terms of service efficiency and service effectiveness, while the strategy of evenly or randomly dispersing vehicles over the network lead to largest reduction of the number of parked vehicles per link, and the strategy of anticipating demand to largest reduction of deadheading mileages.**

Keywords—Automated Taxis, Fleet Management, Vehicle Relocation, Externalities

I. INTRODUCTION

With the technology of vehicle automation progressing fast, the question arises how the introduction of automated vehicles (AV) could impact traffic and mobility taken as a whole. Various studies depict the introduction of AV as an opportunity to offer a new demand-responsive mobility service consisting of a large fleet of shared automated vehicles (SAV), operating a taxi-like service in urban areas[1]–[3]. As automated vehicles are not commercially available yet, no SAV service is operational yet. For this reason, all analysis of SAV is performed based on modeling SAV. Especially suitable for simulating the process of real-time vehicle assignment to passenger requests and passenger acceptance of SAV services, which neither follow schedules nor can guarantee transport security like privately means of transport such as car or bike, are agent-based models [4]. When simulating the operation of SAV, a main focus lies on the dispatching process and the fleet size determination [4], [5].

By constraining the waiting time under the condition that all, or most, requests should be served, the fleet size is deduced from peaks in demand, which results in an over-supply of vehicles in low-demand periods. This over-supply of vehicles leads to idle vehicles, which have to be managed in order to improve the efficiency of a SAV service and avoid undesired external effects. Research on the relocation or rebalancing strategies for SAV services can borrow to a certain extent from findings on relocation strategies for taxi fleets. Two main strategies for positioning idle taxis awaiting new passenger requests are applied in the field of taxi operation: strategic repositioning or empty cruising [6]. The latter is unfavorable from a societal perspective due to its negative external effects of inducing additional traffic [7], which contributes to congestion and increases the emission of noise and greenhouse gases. In terms of strategic repositioning, taxis currently are often legally bound to await new passenger requests at designated taxi stands, a practice that might become obsolete with the introduction of SAV. Different to current taxis, SAV services can be designed so that there is no competition between the individual vehicles for serving passenger requests, as SAV can be programmed to comply fully to the orders of the central dispatcher [5]. This advantage allows to develop strategies beyond the ones for conventional taxis on how and where idle SAV are relocated in cities.

Relocation or rebalancing strategies featured in simulations of fleets of centrally dispatched vehicles providing a demand-responsive taxi-like service include the strategy of remaining at the last drop-off location [1], [4], move to meet excepted future demand [5] or move to balance vehicle supply in the network [1], [3], [5]. In all these studies parking space is considered to be unlimited.

In this paper, we study the impact different relocation strategies for idle SAV have on the service efficiency in terms of passenger waiting times, service effectiveness in terms of vehicle utilization and on external effects such as the consumption of parking facilities or additionally driven mileage due to empty relocation trips (i.e. deadheading). These issues are addressed by simulating the service of a fleet of SAV on a generic grid network. The vehicles are assigned to requests and relocated by a central dispatching center.

In the following, the relocation strategies are described in more detail, followed by a description of the key performance indicators used to measure the impact of the strategies. Also the simulation environment and the used case study are described. This is followed by an analysis of the results for the different

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relocation strategies. The paper is concluded with a discussion of the results.

II. Methodology

A. Relocation Strategies

In this paper five relocation strategies are tested in terms of their impact on service quality and external effects. Relocation is applied after a vehicles has served a passenger request and no further passenger requests await being assigned to a vehicle. Relocating vehicles are not assigned to newly incoming requests. Vehicles are only relocated after they have served their first request in order to avoid unnecessary relocation actions before the start of service operations. The five tested relocation strategies are described in the following:

For the strategy *Remaining Idle,* vehicles remain idle on the link (i.e. road segment) next to the drop-off location until they are assigned to their next request. The strategy *Random Shuffle* moves vehicles to an arbitrary link in the network, where they remains idle until assigned to their next request. For the strategy *Rebounding*, vehicles move to their original location, which can be depicted as an on-street depot or taxi stand. Once a vehicle has arrived at its original location, it awaits being assigned to its next request. For the strategy *Demand Anticipation*, vehicles move to a link on which future requests are anticipated. In this paper it is assumed that passenger demand distribution is known a-priori. The demand is anticipated by drawing randomly from a set of pick-up locations of all requests being launched within the next 30 minutes, so that each link gets chosen based on its actual probability of occurring as a pick-up link within the next half hour. For the strategy *Even Dispersal*, vehicles move to a random link situated in the zone with lowest ratio of idle vehicles per link. If more than one zone fulfills this profile, the vehicle moves to a random one out of these zones. The center link of a zone can be depicted as an on-street depot or taxi stand. To avoid artificially increase the number of parked vehicles per link due to the assignment process, the vehicles currently heading to a zone as part of the relocation of empty vehicles are added to the count of idle vehicles per zone.

B. Key Performance Indicators

The impact of the above described relocation strategies on service quality and externalities is tested for the following key performance indictors (*KPI*s): Service effectiveness is measured in terms of the average passenger utility based on their experienced travel attributes, determined as in [8], and passenger waiting time in minutes are used. In order to measure service efficiency, the share of time vehicles are in use, thus not idle, and the fleet average of the share of deadheading time are determined. The latter is defined as the share of the overall driving time, which includes the time a vehicles serves passenger requests (occupied driving time, pick-up and drop-off time) and the time vehicles are deadheading, i.e. driving emptily (approaching a request, relocating). The undesired service externalities are measured in terms of the average empty driven mileage per vehicle (link occupancy), the maximum number of idle vehicles per link and the total duration of vehicles remaining idle on a link during peak hours.

C. Simulation Environment

To determine the impact of relocation strategies on the performance of a centrally operated fleet of SAV, the operation of such a fleet is simulated in the agent-based simulation model MATSim based on the standard *Dynamic Transport Services* module [9]. Vehicles and travelers are modelled as dynamic agents: vehicles perform tasks according to their individual schedules, which is constantly updated by the dispatcher, while travelers can deviate from their original travel plan at every simulation time step. Each simulation run corresponds to a whole day. While the agents evolve in their decision making from day-to-day in order to optimize their choices, there is no learning process for vehicles or the vehicle dispatcher. Only one dispatching strategy, including a relocation strategy, is applied per simulation run. To reduce computational effort, the central vehicle dispatcher is updated only every 30 seconds. Passengers adapt their plans based on a scoring strategy based on comparing the utility of various plans, the current standard scoring function in MATSim is the Charypar-Nagel Utility Function [8]. The routing strategy of the vehicles is performed by a least-cost path search, with costs being determined based on a combination of travel time and travel distance. For dispatching the vehicles, i.e. assigning vehicles to passenger requests, various strategies are available, in this paper a strategy adapting to over- and undersupply of vehicles, referred to as *Rule-Based* [4], is applied. Throughout the simulations, the travel demand and the vehicle fleet in size and composition remains a static input. The advantages of MATSim are a fast computational speed and, particularly important for modelling demand-responsive transport, a strong behavioral model underpinning passengers travel choices [4].

D. Case Study

1) Scenario Description

As a testbed for relocation strategies for SAV, the operation of 25 vehicles in a grid-network consisting of 62 nodes connected in two directions by equal links of a length of 600 meters is simulated. The free-speed per link, and thus the maximal speed of the SAV, has been set to 15 km/h in order to mimic urban traffic conditions. Due to the limited number of simulated vehicles, congestion effects are not observed and travel times are not stochastic. The grid-network has been divided in quadratic zones (1500 x 1500 meters) in order to mimic city quarters. The fleet size has been determined so that in average requests can be served within five minutes given the above described scenario. The fleet size is not subject to an optimization process and is given as an input to the simulation. The vehicles are initially randomly distributed over the network, starting at the same link in each iteration.

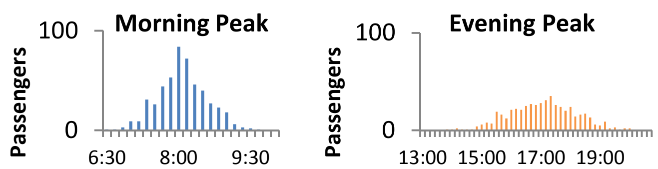

Figure 1: Simulated Demand in the morning peak (left, blue) and evening peak (right, orange)

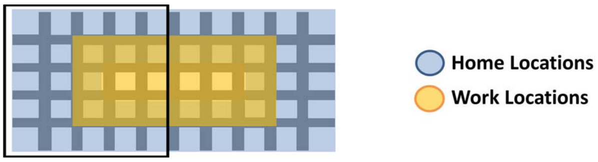

Figure 2: Spatial situation of the home locations (blue) and the work locations (orange) in the grid network. In the case of off-centered demand, the likelihood of a link being home/work location is twice as high in the black rectangle

The operation of the SAV is described by the following setting: after a request has been launched, a vehicle is assigned to that request based on the rule based algorithm described in [4]. The pick-up time per costumer is set to 2 minutes, the drop-off time is set to 1 minute. The vehicles are routed according to the A* algorithm inherent to MATSim.

The demand for which the operation of the SAV is simulated, is generated in such a way that it mimics urban travel demand. The demand profile was created as described in the following: Each travelling agent performs two trips, going from home to work and back, by using a SAV. The morning peak is generated over four hours (between 6.00 a.m. and 10 a.m.) with a normal distribution and a standard distribution of 30 minutes. The evening peak is generated by adding per agent to the individual departure time from home in the morning a working time of seven hours in addition to a random component, which is distributed over two hours, with a standard deviation of one hour. The result of these assumptions is that in the morning a sharper peak in demand is modelled than in the evening (Figure 1). This allows to observe the system performance in two differing demand conditions. In terms of spatial distribution, two typical urban settings are mimicked, in which home locations are situated on the more outwards links, while work locations are located in the center of the network (Figure 2). In the first case, the home and work locations are evenly distributed among the two areas. In the second case, an off-centered demand is generated: the links on the left side of the grid network, framed by the black rectangle in Figure 2, are twice as likely to be a home or work location as the links in the right side.

2) Simulation Settings

Travelling agents in MATSim select the plan for the next simulated day based on the performance of previous plans [8]. The memory of each agent is set to maximum 5 iterations, or simulated days. At the beginning, agents can shift their departure time for each trip for up to 15 minutes earlier or later than the initial departure time. This adaptation of plans is set to occur in 10% of all cases within the first 80% of all iterations. Within the last 20% of the iterations, no adaptation is possible anymore in order to achieve a fixed choice set needed for a stable outcome for the choice estimation.

For each relocation strategy, 150 iterations, or simulated days, have been performed in order to ensure that a stable plateau for the average score of the passenger plans has been reached. The comparison between the different strategies in terms of the KPIs is always performed for the 150th simulation run. The strategies *Random Shuffle*, *Demand Anticipation* and *Even Dispersal*, involve stochastic components in selecting the destination of relocating vehicles. Therefore multiple simulation runs have been performed for these strategies, and all following results are an average of these multiple runs. The number of required runs *N(m)* has been determined for the standard deviation $SD(m)$ of the KPIs as described in Equation (1) based on m initial simulation runs, with the one leading to the largest number of runs being the decisive one:

$$N(m) = \frac{SD(m) * t_{m-1,\frac{1-\alpha}{2}}}{\bar{X}(m) * \epsilon} \quad (1)$$

where $\bar{X}(m)$ is the estimated mean, ϵ is the accepted percentage error of $\bar{X}(m)$ and α is the level of significance. In all cases, the passenger wait time is the decisive KPI. Based on $m = 10$, $\epsilon = 0.1$ and $\alpha = 0.1$, this results in 3 to 7 simulation runs per scenario.

III. Results

The outcome for the KPIs under the different relocation strategies is presented in average values (Table 1) and is discussed in more detail in the following.

Table 1: Average results of the relocation strategies

Relocation Strategies: 1) Remaining Idle, 2)Random Shuffle, 3) Rebounding, 4) Demand Anticipation, 5) Even Dispersal

Centered Demand	1)	2)	3)	4)	5)
Passenger Utility	136.97	136.85	136.89	136.88	136.85
Average waiting time [min]	3.67	4.22	4.01	4.05	4.14
Average time share non-idleness [%]	25.41	28.70	28.77	28.45	28.90
Average time share deadheading [%]	39.06	48.77	48.82	47.96	49.23
Average deadheading mileage per vehicle [km]	24.28	35.95	35.83	34.71	36.56
Average duration of idle stays during peak-hours [min]	4.32	3.58	3.26	3.45	3.54
Off-Centered Demand	**1)**	**2)**	**3)**	**4)**	**5)**
Passenger Utility	137.04	136.90	136.90	136.93	136.89
Average waiting time [min]	3.45	4.14	4.13	4.01	4.20
Average time share non-idleness [%]	25.29	28.30	28.60	28.13	28.85
Average time share deadheading [%]	39.95	49.22	48.99	48.32	50.24
Average deadheading mileage per vehicle [km]	24.41	35.94	35.26	34.64	36.02
Average duration of idle stays during peak-hours [min]	3.52	4.30	3.53	3.91	3.97

A. Passenger Utility and Passenger Waiting time

The passenger utility reflects how close to his/her desired plan an agent could perform his daily activities. It can be seen from the results presented in Table 1, that the various relocation strategies had only a negligible impact on the passenger utilities for the simulated case studies. This has to do with the simplicity of the simulated scenarios, in which departure time could be altered. Location or mode choice where not simulated, which naturally leads to little variance in the performed plans and thus also in passenger utility. The here presented passenger utilities should thus not be considered as the actual utility for passengers making use of SAV, but solely as a reflection on the effectiveness of the service provided under the different relocation strategies.

It can be concluded that the various relocation strategies play only a minor role in the case studies for the overall service. The reason for that lies in the, compared to the overall travel time of the agents, short average waiting times (Table 1). The average travel time per passenger for the centered demand is 13.52 minutes, for the off-centered demand 13.43 minutes. This includes 2 minutes pick-up time and 1 minute drop-off time.

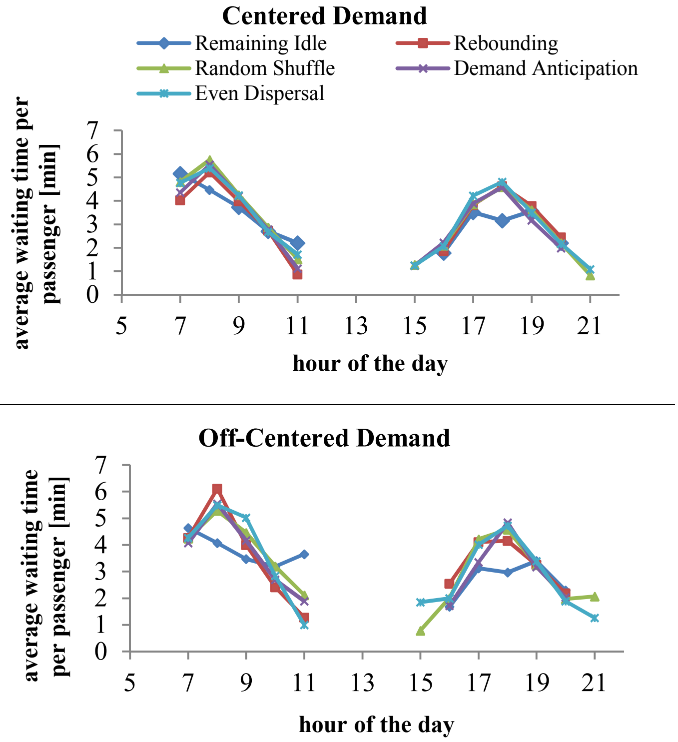

Figure 3: Average waiting times per hour per passenger per for the centered demand (top) and the off-centered demand (bottom)

The tested relocation strategies have a great impact on service efficiency, as can be seen in the differences in average waiting time (Table 1). These differences are especially large for the off-centered demand, with *Even Dispersal* leading to an average waiting time 20% higher than the one for *Remaining Idle*. The reason for the short waiting times in case of *Remaining Idle* lies in the nature of the simulated demand: as each agent performs only two activities per day, it is favorable to remain close to the main drop-off areas. Therefore the more interesting comparison can be made among the strategies actually relocating vehicles: the strategies *Rebounding* and *Demand Anticipation* lead to the lowest waiting times for the centered demand and *Demand Anticipation* also in the case of off-centered demand. This is an expected outcome, as the relocation according to future demand has the pronounced aim to reduce waiting times, which is in particular advantageous if demand is not evenly distributed in the network. The worst performance in terms of waiting time is observed for the relocation strategy *Random Shuffle* for the centered demand (Table 1), which shows that for the simulated scenario any relocation strategy with a rationale more pronounced than a random relocation increases service effectiveness. The strategy *Even Dispersal* leads to the longest passenger waiting times in case of off-centered demand (Table 1). This is again a result of the nature of the demand favoring relocation strategies positioning vehicles as close as possible to the main drop-off locations, which stands in contrast to the rationale behind the *Even Dispersal* strategy which strives at service provision equity. However, it can be observed that in the abate of a demand peak it can be advantageous to distribute vehicles as evenly as possible oven the network in case of off-centered demand (Figure 3,bottom).

As can be seen in Figure 3, the average waiting times are higher in the morning peak than in the evening peak. This is an expected outcome, as the demand per minute is highest in the morning peak. It can also be observed that the proactive relocation strategies outperform the *Remaining Idle* strategy in the phase of abate of the morning peak (between 10:00 and 11:00 a.m.). This is an indicator that vehicle relocation strategies become in particular valuable in low-demand phases following high-demand phases. This becomes especially apparent when the demand is not evenly spread (Figure 3, bottom graph). In these periods the strategy *Demand Anticipation* and, in the particular case of the simulated demand also *Rebounding,* lead to the lowest waiting times.

B. Driven Mileage and Vehicle Utilisation

In terms of efficiency, again the strategy of Remaining Idle outperforms the strategies relocating vehicles for the simulated demand, for the same reasons as discussed above. When not relocating idle vehicles, about 10 driven kilometers per vehicle could be saved in the simulated case studies, and about 22% lower percentage (about 10 percentage points) of the deadheading time of the overall driving time (Table 1). This leads to a decrease of overall vehicle use time by 5% (about 3 percentage points) compared to the strategies relocating vehicles.

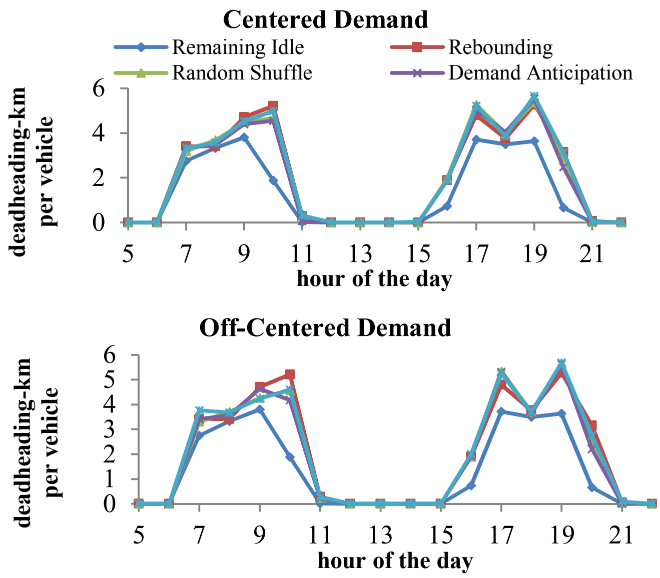

Figure 4: Average deadheading-km per hour per vehicle for the centered demand (top) and the off-centered demand (bottom)

Among the strategies relocating vehicles, the strategy of *Demand Anticipation* performs best in terms of deadheading mileage, since fewer, and shorter deadheading trips are needed when locating idle vehicles at or close to future pick-up locations. The worst performance in terms of deadheading occurs for the strategy *Even Dispersal*, for both centered and off-centered demand (Table 1). This is the result of spreading the vehicles spatially as much as possible. As can be seen in Figure 4, in case vehicles are relocated, the most deadheading miles are performed after a demand peak. This reflects that relocation is only performed in times of low demand, while in times of high demand and no demand vehicles are actively in use or remain idle at their assigned parking location, respectively. This finding is supported by the observation that during the more spread out demand during the evening peak hours, more deadheading miles are performed than during the more concentrated demand in the morning peak hours.

C. Link occupancy and Parking Turnover Rate

The consumption of space in the network by idle vehicles is a negative externality, as the simulated idle vehicle represents occurrences of urban on-street parking. Idle stays are analyzed in the following in terms of link occupancy by parked vehicles and turnover rates. High numbers of idle vehicles per link is an undesired effect, as it indicates a local peak in spatial consumption by idle vehicles. In urban settings, high link occupancy by parked vehicles reduces the accessibility of facilities close to links where it occurs [10]. Therefore, a relocation strategy is considered favorable when leading to as little idle vehicles per link as possible.

Relocation Strategies:
1) Remaining Idle, 2)Random Shuffle, 3) Rebounding, 4) Demand Anticipation, 5) Even Dispersal

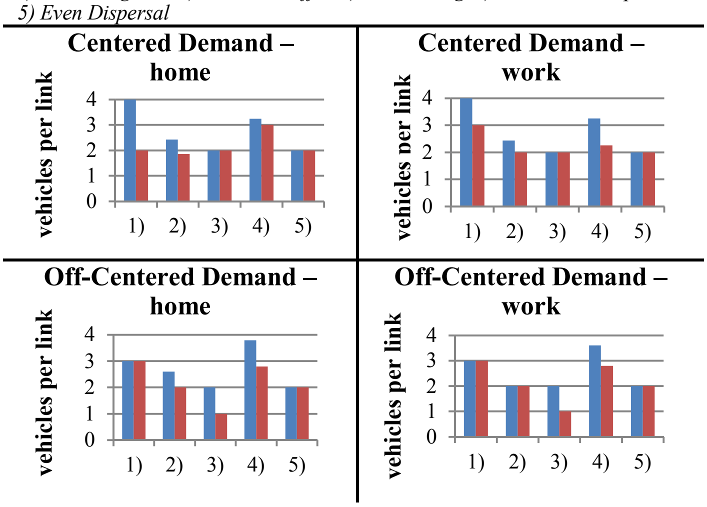

Figure 5: Daily maximum number (blue) and second highest number (red) of idle vehicles per link in the home area (left) and the work area (right) for the centered demand (top) and off-centered demand (bottom)

As can be seen in Figure 5, in case of the centered demand the strategy *Remaining Idle* leads to the maximum number of parked vehicles per link in our case study. *Random Shuffle*, *Rebounding* and *Even Dispersal* lead to the least amount of parked vehicles due to the effective rationale behind these three strategies to spread out the vehicles as much as possible in the network. For the case of *Rebounding*, this is only true for the particular simulated case study where a maximum of two vehicles is initially parked per link. The strategy *Demand Anticipation* leads to more vehicles parked per link, as the demand simulated in this case study is concentrated in particular areas, which increases the likelihood of high link occupancy by parked vehicles in these areas. In case of off-centered demand, this effect is even stronger, which makes *Demand Anticipation* the least favorable relocation strategy in terms of the link occupancy by parked vehicles

Next to the spatial component also the temporal component plays a role in determining parked idle vehicles. A relocation strategy is considered favorable when leading to a higher throughput of idle vehicles per link, thus to higher turnover rates. Higher turnover rates are beneficial as they allow more vehicles to use on-street parking facilities and thus increase again accessibility [10]. The comparison of the average duration of idle stays during peak-hours, as indicated in Table 1, shows that *Remaining Idle* leads to the longest idle times for the centered demand as vehicles are not performing any relocation tasks and spend any idle time waiting for future requests parked. This can also be observed among the relocating strategies, where those performing the least deadheading tasks have the longest overall idle times. For all relocation strategies it is observed that the largest number of idle stays has a duration of 30 seconds or less (*Remaining Idle:* around 55% of all stays, all other strategies: around 80%), which can in the following be neglected as they are a result of the simulation settings of updating the vehicle dispatcher only once every 30 seconds. Also not included are the idle times before, between and after the peak-hour demand specific to this case study.

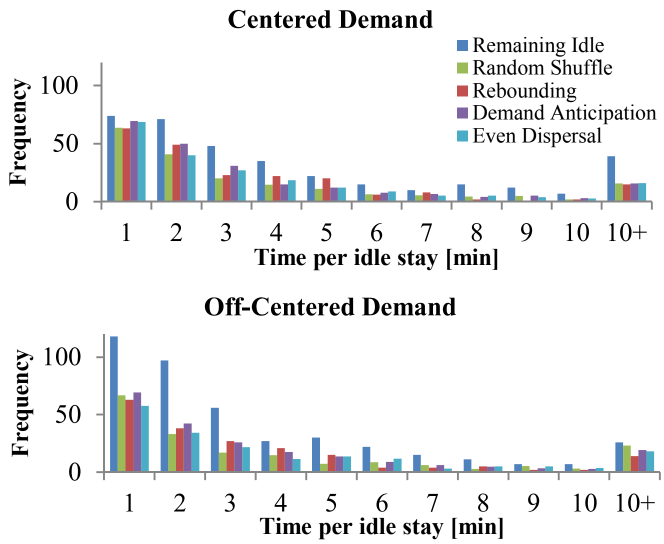

Figure 6: Frequency of idle stays per idle time in minutes for the centered demand (top) and the off-centered demand (bottom)

As shown in Figure 6, idle stays longer than 10 minutes range between 7% (*Rebounding*) of the stay tasks to 11% (*Remaining idle*). Only for the strategies *Remaining Idle* and *Random Shuffle* are noteworthy differences between the centered and off-centered demand case studies observed in terms of idle stay durations: for *Remaining Idle* the total number of idle stays during peak hours increases by 20% because less requests could be directly dispatched within 30 seconds. This increases the share of stays not longer than 5 minutes from 72% to 84%. For *Random Shuffle*, the duration of the average idle stay task increases by 20%, mainly due to an increase in stay task with a duration longer than 10 minutes (from 8% to 12% of all peak-hour stays). Overall, the strategies *Rebounding* and *Demand Anticipation* showed to be the most favorable strategies in terms of parking turnover rates.

IV. Discussion and Conclusion

The simulation of the operation of SAV with five different relocation strategies for idle vehicles in a simple case study allows to quantify the advantages and disadvantages of each strategy in terms of service efficiency, effectiveness and undesired externalities. The results of this study must be put into context with the simulated demand, which mimics rudimentarily urban travel demand flowing in and out of the city center during morning and evening peak hours. In this setting, the strategy of *Remaining Idle,* for which no vehicles are relocated, has proven to be the most efficient in terms of passenger waiting time and most effective in terms of vehicle utilization and deadheading time. However, when it comes to the link occupancy by parked vehicles and parking turnover rates, this strategy was found to be the worst performer among those examined. Similar observations can be made for the strategy *Demand Anticipation*, which in the particular case study has effectively a similar effect as exhibited by *Remaining Idle.* In contrast, strategies aiming at distributing vehicles more evenly over the network show lower service efficiency and effectiveness because vehicles relocate more often and for longer distances, but reduce vehicle bunching and show higher parking turnover rates. Among the latter, the strategy *Rebounding* proved to deliver the best results for all KPIs. This is however an outcome very specific to the case study, where all vehicles where initially randomly distributed over the network. A future study may test the effect of more bundled depots or taxi stands on the performance of the proposed strategies.

The simulation of the operation of a fleet of SAV with relocation strategies presented in this paper is very generic and the results concerning the performance of the strategies cannot be generalized. Major shortcomings are the neglect of stochasticity in traffic conditions and demand, the limitless capacity of links to store idle vehicles, which fails to represent the pressure on urban parking facilities and the resulting parking search induced traffic and prolonged travel times. It may also be questioned whether emptily relocating vehicles can be instantly made available to be assigned to future requests. Additionally, the strategies *Demand Anticipation* and *Even Dispersal* have been simulated in a simplified manner by including random components and not seeking the optimal relocation strategy per vehicle. Furthermore, a combination of relocation strategies rather than the exclusive deployment of a selected strategy could yield great improvements. These shortcomings stress the importance for future research on relocation strategies of SAV, especially for more refined scenarios, in terms of describing the operation of SAV as well as simulating the service in a less generic setting. With more experiences gained in terms of vehicle automation, it will be especially important to analyze the user perception and demand of SAV services, and to determine new mobility choice patterns, e.g. mode choice or destination choice, resulting from large-scale demand-responsive services operated by automated vehicles.

The operation of a large fleet of vehicles offering on-demand transportation service is impacted by the applied relocation strategy for idle vehicles, as shown in this study. The question on what best to do with such vehicles is often not thoroughly analyzed in studies simulating large-scale taxi-like services, though it can have considerable effects on service efficiency, effectiveness and undesired externalities. With the spread of unregulated taxi-services such as provided by the company Uber and the prospect of the introduction of large fleets of demand-responsive services operated by AV, this question becomes increasingly important and should be analyzed in more depth in order to ensure a successful introduction of the new demand-responsive urban mobility services.

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