Relocating Strategies under Parking Constraints for a Fleet of Shared Automated Vehicles

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1. Study objectives

With the possible emergence of self-driving vehicles offering demand-responsive, taxi-like, transport services, questions about the impact of such fleets on transport system utilization and performance are gaining relevance. In this study, the impact of shared automated vehicles (SAV) on urban traffic is analysed in terms of (1) congestion, (2) parking consumption, and (3) a potential transport mode shift. In particular, the focus is put on the relocation strategies for idle vehicles of a fleet of SAV. Vehicle relocation is part of dispatching strategies, and has shown to have an impact on the performance of taxi fleets (Bailey and Clark 1992; Winter et al. 2017a). The relocation of SAVs is different from relocation of regular taxi services, because SAVs are fully compliant, always ready for operation, and do not compete with other fleet members (Zhang et al. 2016). In this study, we build on the relocation studies for taxis, but takes this fundamentally different dimension of SAVs into account. Four relocation strategies have been distinguished in the literature for SAV or comparable transport services: remaining at the drop-off location of the last customer (Fagnant and Kockelman 2014; Lioris et al. 2010; Maciejewski et al. 2016); relocating the vehicle based on demand anticipation (Sayarshad and Chow 2017; Zhang et al. 2016); relocation to guarantee distribution of supply (Azevedo et al. 2016; Fagnant and Kockelman 2014; Zhang et al. 2016); or letting the vehicle cruise through the network (Zhang et al. 2015). In none of these existing studies, the analysis of the dispatching and relocation strategies has taken possible spatial constraints caused by limited parking facilities into consideration.

In this study, five heuristic relocation strategies for SAV are tested under the constraints of limited parking facilities. The SAV are assumed to provide flexible public door-to-door transport services by operating in a cooperating fleet and to be allocated by one common dispatcher. This research is part of an on-going project aiming at capturing the spatial requirements of SAV and how parking policy can contribute to shaping the success of SAV services while mitigating undesirable externalities such as increased traffic volumes or an excessive occupation of parking facilities.

2. Relocation Strategies and Modelling approach

To analyse the impact of different approaches for managing idle vehicles in a fleet of SAV, five heuristic relocating strategies are tested in an agent-based simulation model, partly in combination with parking search strategies for on-street parking facilities. The strategies consist of (1) *remaining:* remaining idle at the last drop-off location, (2) *cruising:* cruising randomly through the network, (3) *demand anticipation:* relocating and parking in a demand-anticipatory manner, (4) *supply anticipation:* relocating and parking to achieve an even distribution of idle vehicle supply in the network on a zonal level, (5) *demand-supply balancing:* relocating and parking in order to balance demand and supply for the vehicles on a zonal level. The first two strategies allow benchmarking the three anticipatory relocation strategies in terms of additional driven mileage, congestion and location-specific parking space consumption. The relocation and parking heuristics applied in these five strategies are specified in more detail in Table 1. For the process of selecting a parking location, the vehicle dispatcher is assumed to have full knowledge about the current availability of parking spots and is able to reserve free parking spots for the SAV. The relocation of a vehicle can be interrupted at any time during the simulation if new requests for SAV appear. In such cases the vehicle path is diverted towards the pick-up location of the incoming request and any potential parking reservation is cancelled.

Table 1: Overview of the proposed relocation and parking strategies

	remaining	**cruising**	**demand anticipation**	**supply anticipation**	**demand-supply balancing**
parking constraints	unlimited parking facilities per link	not applicable	limited parking facilities per link		
relocation strategy in case no further open request is present	no relocation	vehicle starts randomly cruising through the network	vehicle moves to a link with free parking spots, link selection based on the probability of a future request occurrence until horizon time t_H	vehicle moves to the zone with the lowest forecasted number of idle vehicles parked there at horizon time t_H	vehicle moves to the zone with highest forecasted vehicle deficit at horizon time t_H
parking strategy	vehicle parks at current drop-off location (with unlimited parking facilities)	no parking	vehicle parks at selected link	vehicle parks at the link with highest number of free parking spots within the zone of destination	

From the simulation, the following key-performance indicators are collected, based on which the five relocation strategies are analysed:

- the total generalized passenger travel costs, representing the overall system performance for each relocation strategy,
- the modal split, reflecting the agents' choices in the face of the performance of the SAV,
- the waiting times for agents using SAV, representing the service quality provided by SAV,
- the ratio of SAV mileage with and without passengers, representing the service efficiency of SAV,
- the extra driven SAV mileage due to relocation and parking of the vehicles,
- the use of curbside parking space by SAV per zone throughout the day.

Simulating SAV in a setting where agents make mode choices based on the performance of the modes allows investigating the impact of operational decisions concerning SAV on the success of SAV. A crucial aspect for SAV becoming a competitive mode are waiting times experienced by users. Short waiting times can only be achieved by operating a sufficiently large fleet of SAV. With the focus being put on relocating and parking idle vehicles of such a fleet, the spatial requirements of idle SAVs, in terms of quantity and location, can be analysed. This analysis can be used for developing parking management strategies for SAV that seek to provide comparable levels of service across space (in terms of waiting time) while minimizing undesired externalities of SAV such as overly occupying curbside parking space or induced congestion due to parking search or empty cruising of SAV.

3. Model implementation

The five relocation strategies are assessed in an agent-based simulation model (MATSim), which simulates mode choice as a result of the performance of a mode vis-à-vis an agent's desired activity pattern (Horni et al. 2016). Each agent has a daily plan with scheduled activities and trips to reach these activities. After the simulation of a complete day, plans are scored based on their utility, and agents can partly alter their plans for the next run, including changing modes. Agents memorize a set of plans and the respective scores, which allows them to select the best plan with each run. The selection of plans is based on the Charypar-Nagel Utility Function inherent to MATSim (Nagel et al. 2016), which assesses the performed daily activities in terms of punctuality and activity performance. The mode choice model features cost and time related parameters as well as alternative specific constants for each mode. The values for parameters and their coefficients are derived from established values for the Dutch population for the currently existing modes. For SAV it is based on values derived from a stated-preference experiment featuring these vehicles, which has been previously conducted as part of this research project (Winter et al. 2017b).

4. Application and preliminary results

To analyse what impact SAV can have on urban mobility and urban infrastructure use, all five strategies are tested for the case study of Amsterdam. For this case study, more than 180,000 agents are generated based on the Dutch activity-based model ALBATROSS (Arentze and Timmermans 2004). These agents represent a fifth of all agents traveling within, towards or away from Amsterdam in the ALBATROSS model. The agents travel in a network consisting of more than 30,000 links with limited parking facilities (around 72,162 parking places are provided). The study area covers the entire built-up area of Amsterdam, which is divided into 82 zones (Figure 1). Simulated modes are private car, a fleet of SAV, public transport, biking and walking. Different scenarios are drawn in terms of the fleet size of the SAV service, starting at 500 vehicles and going up to a fleet size that could potentially serve the current travel demand for trips in private motorized vehicles as boundary cases.

In this abstract we describe the preliminary results for a sample of 2105 the agents, for which the functionality and validity of the simulation model has been tested. These results are not discussed as findings yet, mainly for the following three reasons: 1) the underlying behavioural model needs to be further calibrated, 2) the selected fleet size of 80 SAV has been too small in order to satisfy the simulated demand for SAV and 3) convergence of the agent behaviour has not been reached within the simulated period of 50 iterations. Nevertheless, parts of the outcome are presented in Figure 2a-c and Table 2 in order to showcase what kind of results will be obtained with the simulation model in terms of the key-performance indicators discussed above.

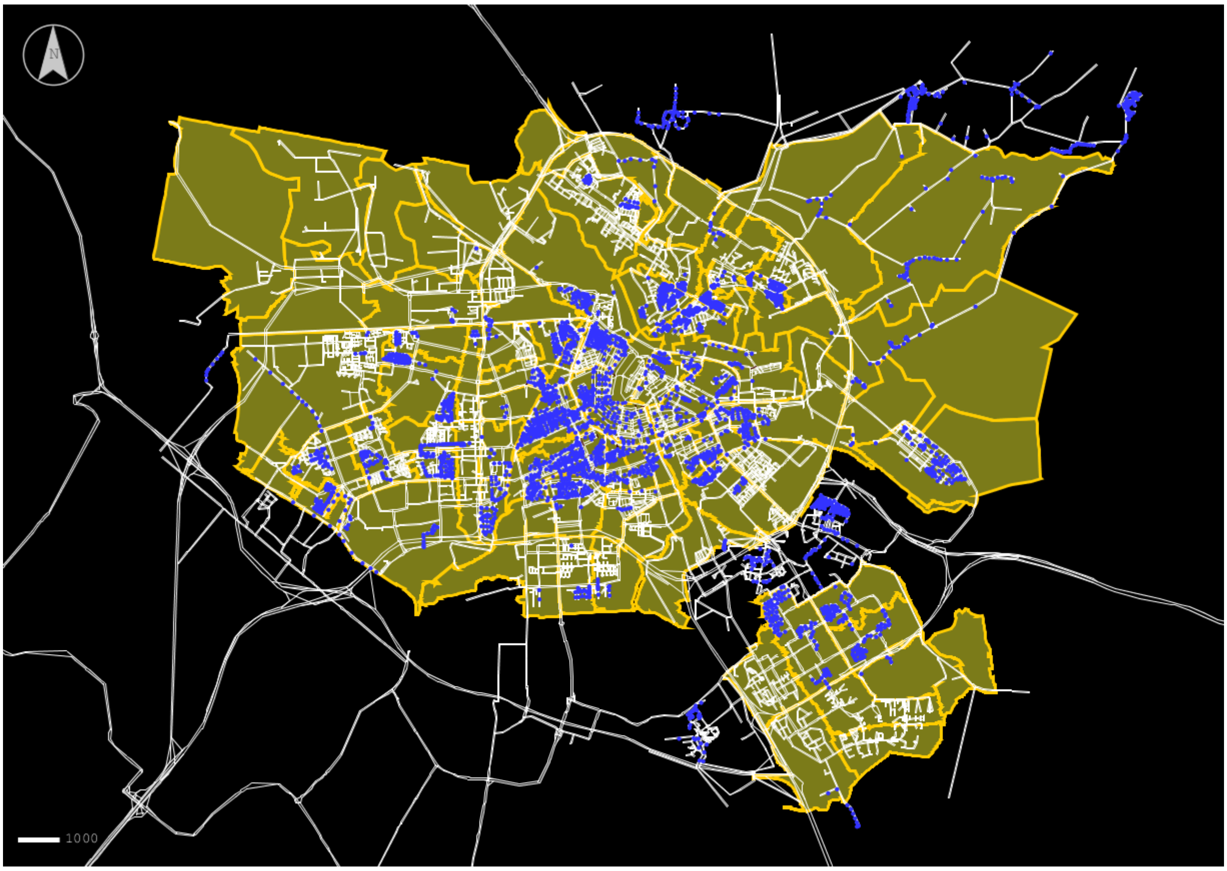

Figure 1: Network (white lines), zones (yellow areas) and parking facilities (blue dots) as featured in the case study of the city of Amsterdam

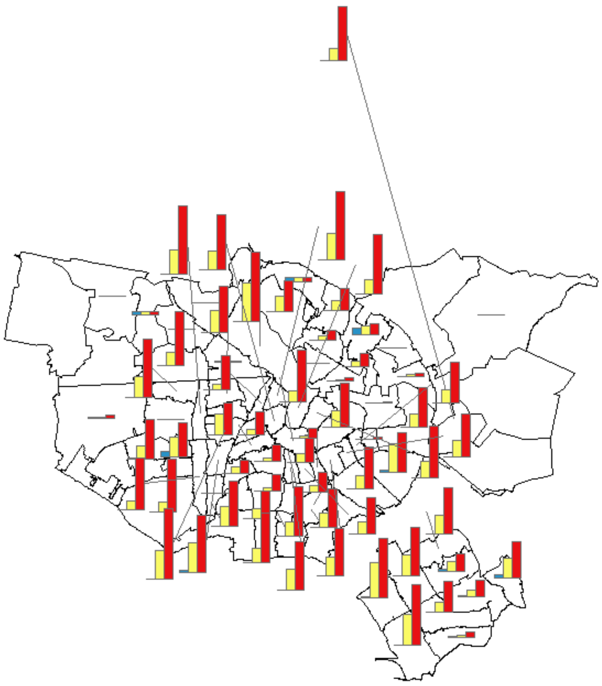

Figure 2a: Exemplary results- passenger waiting times in minutes for SAV (minimum: blue, average: yellow, maximum: red) per zone for the relocation strategy *remaining*

Figure 2b: Exemplary results- congestion levels on the road network (here no congestion has been detected) for the relocation strategy *demand anticipation* in the morning peak hour at 9.00 am.

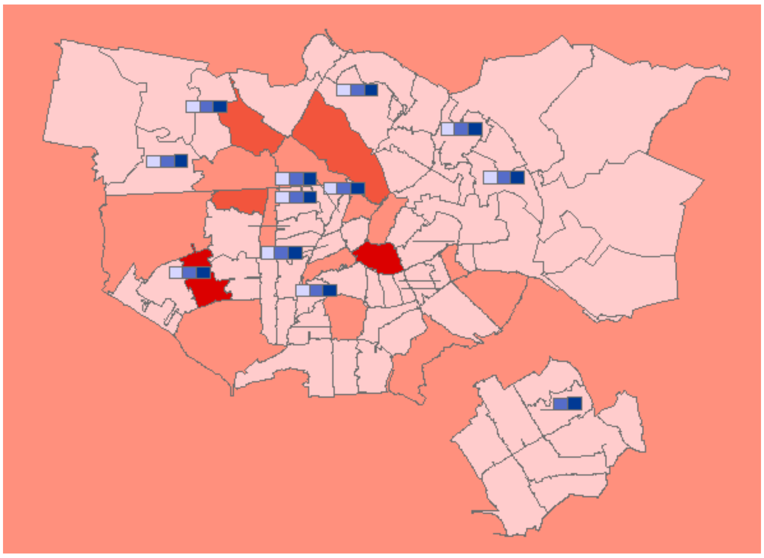

Figure 2c: Exemplary results- parking duration in hours for SAV (bar charts, showing the minimum, average and maximum) and the use ratio of the available parking facilities (indicated by the different shades of red per zonal polygon) per zone for the relocation strategy *supply anticipation*

Table 2: Exemplary results for the five relocation strategies for a fleet size of 80 SAV serving 2105 agents, obtained after 50 iterations of the simulation model: modal split, average passenger waiting times for SAV, average parking duration for SAV, average empty drive ratio for SAV

	modal Split: [bike, car, public transport, SAV, walk]	average passenger waiting time for SAV in minutes [number of occurrences]	average parking duration for SAV in minutes [number of occurrences]	average empty drive ratio for SAV in %
remaining	[40.8%, 25.7%, 1.6%, 24.9%, 6.8%]	148.7 [1877]	281.4 [92]	27.09%
cruising	[42.9%, 25.3%, 1.3%, 23.8%, 6.7%]	148.8 [1828]	344.88 [80]	28.50%
demand anticipation	[42.1%, 25.6%, 1.4%, 24.5%, 6.2%]	146.6 [1859]	273.6 [95]	27.95 %
supply anticipation	[41.5%, 25.2%, 1.8%, 24.3%, 7.1%]	141.3 [1868]	297.7 [87]	28.3 %
demand-supply balancing	[42.4%, 24.7%, 1.8%, 24.1%, 6.9%]	141.4 [1862]	286.5 [91]	28.82 %

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