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Parking space for shared automated vehicles: How less can be more

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ABSTRACT

With the anticipated introduction of self-driving vehicles, new challenges arise for urban transport- and planning authorities. This study contributes to the efforts of formulating the potential opportunities and threats stemming from the introduction of larger fleets of self-driving vehicles to our cities, and what action could be taken by transport authorities to shape this introduction beneficially. In particular, the focus is put on the impact different parking management strategies can have on the performance of a fleet of shared automated vehicles providing on-demand transport services. This analysis focuses on aspects of service efficiency, externalities and service provision equity.

The selected parking management strategies are tested in a large-scale activity-based simulation of a case study based on the city of Amsterdam, in which the parking facilities for SAV are digitally mapped throughout the city for different parking scenarios. The vehicles of the fleet aim at relocating to zones with high future demand, which can lead to bunching of vehicles at demand-hotspots. Parking management in the form of restricting parking facilities forces idle vehicles to spread out more evenly in the network. We show that this can reduce average passenger waiting times, increase service provision equity, cause less congestion and even can reduce the necessary fleet size. However, this comes at the cost of an increase in vehicle-kilometres-travelled, which reduces fleet efficiency and causes more undesired service externalities. Parking management is thus a simple, yet effective way for transport authorities to (a) determine where idle self-driving vehicles operating an on-demand transport service will be parked and (b) influence the performance of said transport service.

1. Introduction

The development of autonomously driving vehicles has the potential to change the way people move through cities in such a fundamental way, that new urban planning and management approaches need to be developed for an era of self-driving vehicles. While the technology for self-driving vehicles is yet to mature, a window of opportunity opens up for cities to take the lead in shaping the way such vehicles will be used and what infrastructure will be provided to them.

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Autonomous vehicles (AV) promise to bring various benefits, ranging from improved traffic safety for all road users (Fagnant and Kockelman, 2015; Greenwald and Kornhauser, 2019; Sperling et al., 2018), improved traffic flows and reduced mobility costs (Dong et al., 2017; Greenwald and Kornhauser, 2019), reducing the need for urban parking space (Narayanan et al., 2020) to enhancing the mobility of people currently not (able to) driving a private car (Harper et al., 2018). However, the introduction of AV may well go hand-in-hand with an increase in negative externalities, such as an increase in vehicle-kilometres travelled due to idle vehicle relocation (Dia and Javanshour, 2017; Greenwald and Kornhauser, 2019; Harper et al., 2018; Narayanan et al., 2020) or to more car-oriented cities as urban infrastructure is redesigned to cater for AVs at the expense of other users and uses of public space. It is the task of municipal transport authorities to counteract this by accompanying the introduction of self-driving vehicles with designated urban planning measures (Greenwald and Kornhauser, 2019; Spurling, 2020).

If, when or how self-driving vehicles might enter our cities is uncertain. For this reason it is important to conduct a multitude of studies that explore their potential impacts on all aspects of our mobility, ranging from topics such as travel behaviour or car ownership to infrastructural requirements or traffic control for self-driving vehicles. The combined insight from such hypothetical exercises can provide guidance to planners and practitioners in developing policies in the face of a shifting transport landscape. One promising way to make use of the technology of self-driving vehicles is their employment in cooperative fleets of shared automated vehicles (SAV), also referred to as aTaxi (Greenwald and Kornhauser, 2019). The fact that such vehicles are self-driving offers three game-changers: (1) The costs for on-demand transport could be significantly lower than today, as no driving personnel is required. This would make the operation of large-scale on-demand public transport systems feasible also in high-wage countries (Greenwald and Kornhauser, 2019). (2) The vehicles can be programmed to be fully compliant to a central dispatcher and are free of pursuing self-serving goals. This could solve issues linked to unregulated or under-regulated on-demand transport services, such as bad driver conduct towards passengers or undesired bunching of vehicles at demand-hotspots (see Cetin and Deakin 2019). (3) The vehicles can move without a human driver present, which would solve the problems current car-sharing systems have in relation to vehicle redistribution (see Angelopoulos et al. 2018; Ferrero et al. 2018). However, these advantages could be annihilated if large fleets of SAVs would be introduced to cities without the appropriate accompanying policies. The dangers of large-scale on-demand transport services lie in clogging the network and parking spaces during and around demand-hotspots (Circella and Alemi, 2018; Jiang et al., 2018; Winter et al., 2017), increasing the total driven mileage due to relocating or idle cruising of the vehicles (Circella and Alemi, 2018; Narayanan et al., 2020; Zhang and Wang, 2020) and providing lower-quality or higher-cost services to passengers located at locations that require long access or egress times for SAV vehicles (Chen et al., 2015; Jiang et al., 2018).

In this paper, we address these issues by applying a measure widely available in the toolbox of urban planners, namely parking management. SAV-parking may be regulated through legal agreements as part of public tenders in the long-term. However, in the early phases of the introduction of such vehicles, it could happen that local authorities allow SAV operators to freely enter the market, using their own dispatching and relocation algorithm, much like is currently the case for ride-hailing services. In that situation, parking policy becomes an important tool to avoid the potential negative effects of large numbers of idle SAVs in the city. In this paper we use the term “idle” for all vehicles that are not occupied or scheduled to serve passenger trips.

Parking management has been successfully deployed to regulate the vehicle inflow to cities and reduce the number of parked vehicles in high-demand areas for decades. In European cities, urban parking management has been decidedly used to decrease traffic congestion and to discourage the use of private cars in inner cities (Shoup, 2018). The legal framework for this approach is well-established and policymakers are familiar with the lines of argument for instituting different parking management approaches.

It is important to discuss the management of idle vehicles of SAV fleets, as these fleets are likely dimensioned to provide a satisfactory level of service during the peak-hours. This would leave a substantial part of the vehicles unused during off-peak hours, which calls for relocation strategies for idle vehicles from the side of the fleet operators, and in response provides the opportunity for policymakers to shape the way the on-demand transport services are operated (Greenwald and Kornhauser, 2019). This holds for both individual services (i.e. vehicles are sequentially shared, like car-sharing vehicles or taxis) and shared services (i.e. vehicles are simultaneously shared, like carpooling). The main findings of this study are thus not only applicable to SAV but can be generalized to any on-demand transport services operated by cooperating fleets such as ride-hailing and ride-sharing services. However, the applied parking management strategies and the simulated relocation strategies in this study are indifferent to the objectives of individual vehicles (or drivers), and hence more suitable for a fleet operated by automated vehicles.

While idle vehicle relocation for SAV has drawn some attention as part of a more efficient vehicle dispatching aiming at reducing passenger waiting times (for a brief compilation see Winter et al. (2020)) only few studies have analysed the effect of idle vehicle relocation on other aspects of such transport services such as service efficiency, externalities and equity (van Engelen et al., 2018; Zhang et al., 2015; Zhang and Guhathakurta, 2017).

Hitherto, no coherent analysis has been performed on how and to what extent planning authorities can shape the impact of SAV by means of a strategic restriction of parking facilities for such vehicles. This study focuses on how, by parking management alone, the introduction of large fleets of SAV can be steered to serve municipal mobility objectives. The analysis of the different parking management strategies is performed for a set of scenarios envisioning the introduction of SAV in which these vehicles are competing with -and complementing- traditional public transport services as well as private vehicles and active modes. The scenarios are developed for a case study based on the city of Amsterdam, the Netherlands. To benchmark the more detailed parking management strategies restricting on-street parking for SAV, scenarios featuring large off-street depots as well as idle vehicle cruising are included in the analysis. Note that in this paper, all parking restrictions are communicated directly to the dispatcher of the SAV in form of a maximum number of allowed parked vehicles per zone, and are thus not envisioned as physical alterations of the streetscape.

The remainder of this paper is structured in the following way: In Section 2, a review of the current literature sketches what parking management strategies for SAV have been envisioned. In Section 3, the case study and the drawn scenarios are described, as is the simulation model used to test the impact of the different parking management approaches. The results for these scenarios are presented in Section 4, and are discussed in the concluding section.

2. Parking self-driving vehicles and on-demand transport vehicles

2.1. Parking management strategies for shared automated vehicles

Not all current parking management approaches will be effective in an era in which SAV operate on a larger scale in our cities (Guerra and Morris, 2018; Millard-Ball, 2019; Regional Plan Association (RPA), 2017). Currently, parking regulation consists mainly of the following four dimensions: (1) spatial restrictions, e.g. restricted on-street parking in city centres (Mingardo et al., 2015); (2) temporal restriction, e.g. limitations on parking duration or on hours at which parking is allowed (Kondor et al., 2020; Mingardo et al., 2015; Simićević et al., 2013); (3) users' restriction, e.g. parking for residents only (Kaspi et al., 2014; Mingardo et al., 2015; Molenda and Sieg, 2013) and (4) pricing parking by the introduction of fees (D'Acierno et al., 2006; Migliore et al., 2014; Mingardo et al., 2015; van Ommeren and Russo, 2014; Zhang and Guhathakurta, 2017). Of these practices, it has been argued that parking pricing is not suitable to manage AV, as their self-driving capabilities would allow them to avoid parking costs by idly cruising through the network or by moving to areas where no parking fees are issued (Millard-Ball, 2019). This argument highlights that in the case of SAV, restrictions on idle cruising might become also an important instrument for managing their impact on urban traffic, similar to the "cruising time cap" recently issued for ride-hailing services in New York City (see Balan and Raina, 2019).

The aims of contemporary urban parking policies can be summarized in four main objectives: (1) improve accessibility and mobility, (2) improve the quality of life and liveability, (3) stimulate the local economy and (4) contribute to the city's revenue (Mingardo et al., 2015). The relative balance between these objectives of parking policies might change if their subject is not only private cars, but also vehicles in the service of the general public, as it can be argued that earning revenues might not play a role anymore when managing the parking of shared or public transport vehicles, while improving service quality and service visibility might become increasingly important (Kent and Dowling, 2016). Early indications for this trend are the parking policies issued for car-sharing services: if transport authorities consider an on-demand transport service or a car-sharing service as part of the public transport offer, parking policies may aim at boosting such services by assigning dedicated parking space close to demand-hotspots. Numerous cities provide dedicated parking space to car-sharing services, which has proven to be vital to the success of these services (Kent and Dowling, 2016; Zvolska et al., 2018). Taxi stands are also commonly strategically placed close to demand-hotspots such as transportation hubs, shopping and entertainment facilities or local neighbourhood centres. First drafts of parking policies for automated vehicles formulate two main objectives: (1) ensuring enough pick-up and drop-off curbside space to allow on-demand transportation and good delivery without compromising the traffic flow and (2) eliminating on-street parking by sending self-driving vehicles to off-street parking facilities (Regional Plan Association (RPA), 2017).

2.2. Where to park shared automated vehicles

One of the characteristics of AV that sets them apart from non-automated vehicles is that they can drive without a human on board. This means that the acceptance of parking locations is no longer linked to the acceptance of access or egress walking distances between the parked vehicle and the destination of the user. By simulation, it has been found that because of this, as well as current parking pricing policies, privately-owned AV can be expected to mainly park just outside the city centre or other demand-hotspots (Fagnant and Kockelman, 2015; Zakharenko, 2016; Zhang and Guhathakurta, 2017). However, when operated as SAV, idle vehicles are expected to be positioned strategically so that passenger waiting times will be as short as possible, which increases again the parking pressure around demand-hotspots. This effect can be mitigated when allowing vehicles to cruise when idle at the cost of a substantial rise in vehicle-kilometres travelled (VKT), as shown by simulation in Zhang et al. (2015). The parking location of SAV is determined by the relocation strategies they are subject to. The relocation strategy impacts the performance of the SAV service as well as its impact on local traffic flows, total VKT and spatial disparities in service provision. By simulation, it has been shown that relocation strategies aiming at more even distributions of vehicles can be superior in terms of societal benefits to strategies relocating idle vehicles close to demand-hotspots (Winter et al., 2017). These findings stress the importance of introducing policy instruments such as parking management to control the impact of the on-demand transport service in case fleet managers are free to decide where to park idle vehicles. As shown by Zhang and Guhathakurta (2017), doing so has to be done carefully, as this can lead to equity issues in case idle SAV are pushed into less developed neighbourhoods with lower land costs, and can have impacts on the service performance in regard to waiting times and the total VKT.

The claim has been made that SAV might be parked in "large warehouses or open lots in low-value parts of cities" (Guerra and Morris 2018, p.295). However, we argue that the issue of parking idle on-demand transport vehicles is more complex than that. Even though AV can park in a more space-saving manner in parking lots than non-automated vehicles (Ferreira et al., 2014; Nourinejad et al., 2018), this is at best suitable for long periods of low demand (night hours), but not for hours of variable demand, where waiting time is crucial for the success of the service. Since parking structures are expensive, certainly in or close to high demand zones, it may be expected that SAV operators will aim to avoid the use of such structures if other, cheaper, alternatives are available. This means that there is no straightforward solution for parking idle vehicles in off-peak hours, implying that appropriate parking management strategies will have to be developed and implemented.

In simulation studies, SAV are often assumed to park close to expected hotspots of future demand. In previous studies focusing on the operational objectives, we found that striving for a more balanced distribution of vehicles throughout the network can be beneficial for both the efficiency of the service operation as well as the service provision equity (Winter et al., 2017, 2020). Transport authorities could enforce such a relocation strategy only by having legal agreements with the operator (e.g. through a tender or concession). However, it could be that especially in the introductory phase of SAV, such opportunities of influence might be limited, not least because of a lack of experience with tendering large-scale on-demand SAV-based public transport services and legal requirements regarding vehicle allocation algorithms. Instead, formulating parking restrictions for SAV could be a first step for transport authorities that allows them to gain experiences with SAV and their impact on the city in the early days of their implementation, without following the legally complex and practically complex path of regulating vehicle allocation algorithms. For this reason we expand in this study the question about how to relocate idle SAV from the operational decision of relocation under parking constraints from previous studies, to the question how to set such parking constraints from the perspective of a transport authority. The goal of this study is to explore the effectiveness of formulating parking constraints for SAV, instead of relocation algorithms, in order to influence the relocation of idle vehicles in a city.

3. Application and scope

In this study we test different parking management scenarios in a case study based on the city of Amsterdam, using the simulation testbed presented in (Winter et al., 2020). For this case study, we specify a set of parking management scenarios in Section 3.1. The input used in our simulation study, in particular regarding the demand for SAV and the fleet specification, is described in Sections 3.2 and 3.3. The analysis of our simulations are discussed in the next section (Section 4).

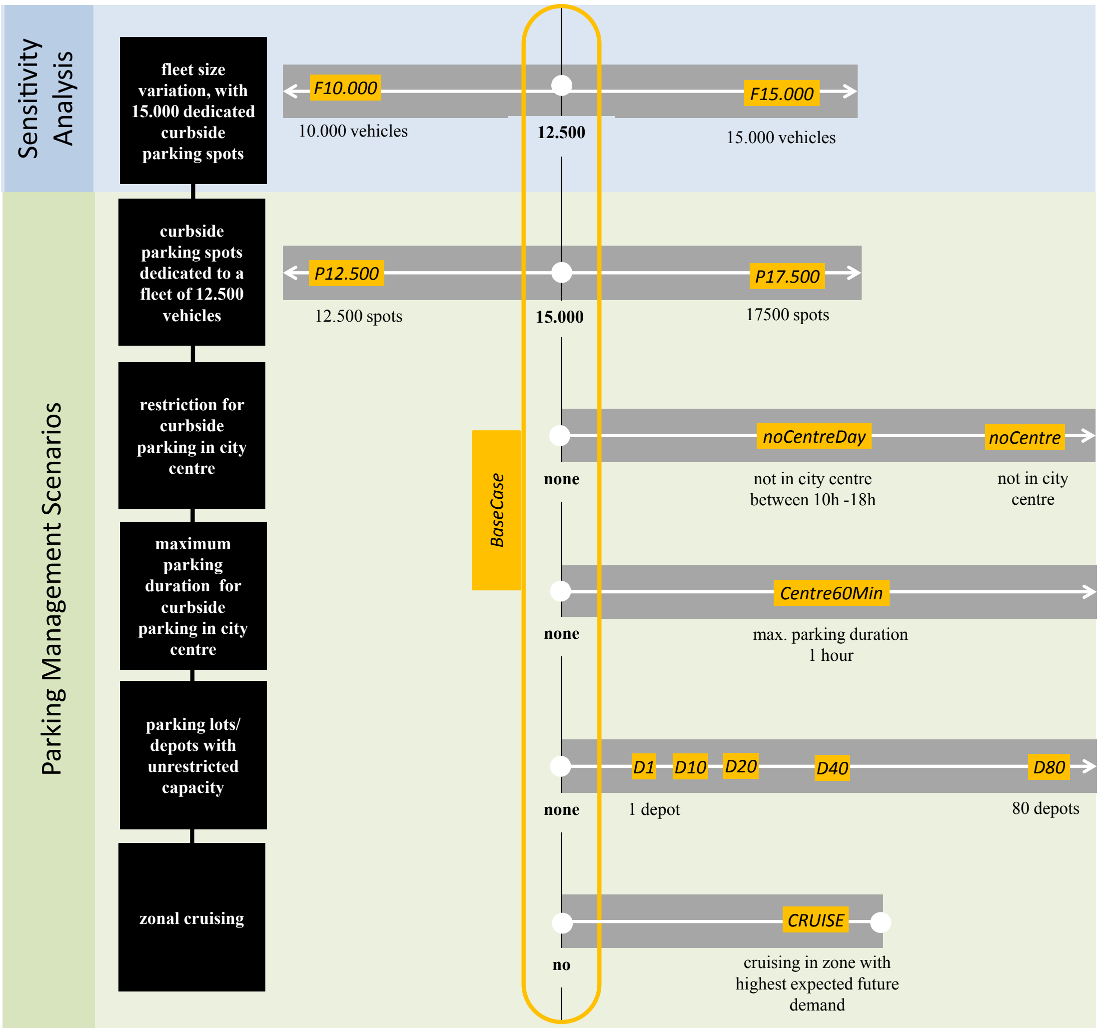


Fig. 1. Scenarios for which the on-demand transport service operated with SAV is simulated in this study.

3.1. Parking management scenarios

We base the parking management scenarios for a fleet of SAV operating an on-demand public transport service on two principles: the temporal and the spatial limitation for curbside parking. As a *BaseCase* scenario, we simulated a fleet of 12,500 vehicles, which can park on 15,000 dedicated curbside parking spots, which are spread out throughout the network and can be used by SAV all day long. The number of parking spots has been selected so that there is enough -but not too much- parking space for SAV available. We point to the work of Kondor et al. (2020) for a more systematic search for the minimum number of parking spots and to Zhang and Wang (2020) for an approach to determine parking demand for SAV by simulation. For the purposes of this study, a simple ad-hoc approach has been used to determine the necessary parking spots, benchmarked on the average passenger time.

The dedicated parking spots can be seen as an external constraint, which defines the decision space in which the relocation position of idle vehicles is selected. Different to our previous study, in which the relocation strategies have been embedded in the relocation algorithm of the vehicles (Winter et al., 2020), in this study the relocation of idle vehicles is driven by the limitation of parking space as formulated in different scenarios. The formulation of parking constrains does not require physical alterations (such as boards, signage etc.), it suffices to digitally transmit this information to the central vehicle dispatcher.

We compare this *BaseCase* with scenarios featuring different fleet sizes or different number of dedicated parking spots and scenarios with various levels of restrictions on parking SAV in the city centre. To benchmark these scenarios, we also include a scenario in which vehicles cruise through the city when empty, and a set of scenarios in which idle vehicles move to a varying number of off-road parking depots. An overview of these scenarios is shown in Fig. 1. The exact location of the parking spots and depots in the network (see Fig. 2) is shown in Fig. 3a–c.

The influence of the fleet size on the performance of the on-demand transport service is tested by varying the number of vehicles between 10,000 and 15,000 (scenarios *F10,000* to *F15,000*) while reserving the same amount of curbside parking spots for the fleet as in the *BaseCase* scenario.

Next to the three scenarios taking into account the sensitivity to fleet size, further parking management scenarios are simulated for a fleet size of 12,500 vehicles. To test for the impact of the number of reserved parking spots in relation to the fleet size, the number of parking spots is reduced down to 12,500 and increased up to 17,500 vehicles (scenario *P12,500* to *P17,500*), as shown in Fig. 3a–c. The parking spots are randomly distributed through the city on links with sufficient link length. To vary the number of parking facilities for the scenarios with parking facilities differing to the *BaseCase*, random parking spots have been removed or added in such a way that the parking facilitates of scenarios with lower numbers of parking spots are a subset of scenarios with a higher number of parking spots.

Additionally, a set of scenarios has been formulated to reflect the scarcity of parking space often present especially in city centres. The division into inner- and outer-city (shown in Fig. 2) is based on the parking zones defined by the municipality of Amsterdam as of April 2019 (Gemeente Amsterdam, 2018). In the scenarios *noCenter* and *noCenterDay*, the availability of curbside parking spots is limited spatially by dividing the zones into an inner-city and an outer-city parking zone. In scenario *noCenterDay*, SAV are not allowed to park in the inner city between the morning and the evening peak (between 10 a.m and 6p.m.), while in scenario *noCenter* they are never allowed to park in the inner city. For scenario *Center5Min* and *Center60Min,* an upper limit for the parking duration of SAV in the

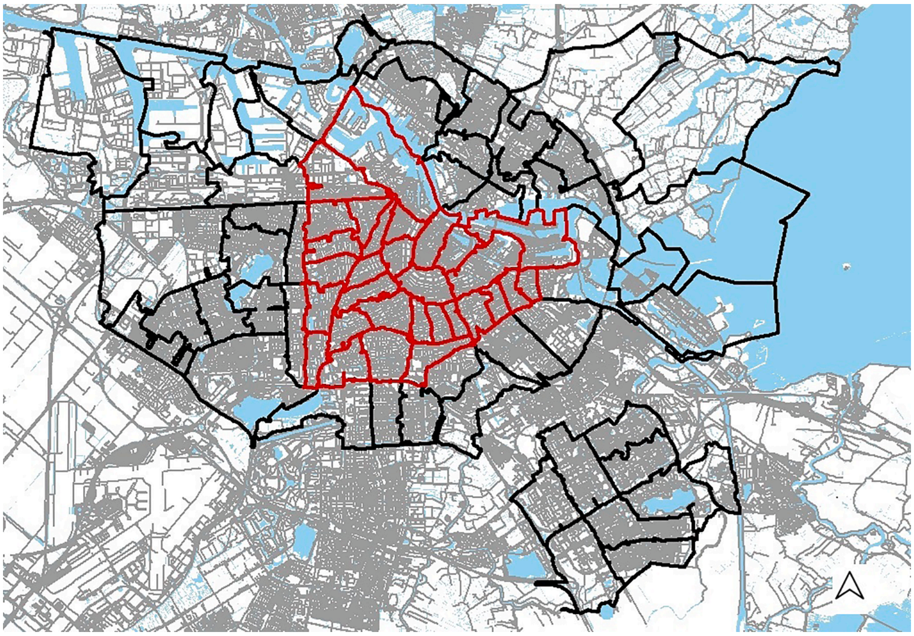


Fig. 2. City boundaries and zonal division of the city of Amsterdam based on postal codes. Zones covering the inner city of Amsterdam are outlined in red.

Fig. 3. Illustration of the spatial distribution of the simulation input: (a)–(c) showing the number of parking spots per zone for scenario *P12,500, BaseCase* and *P17,500*; (d)–(g) showing the location of parking depots for scenario *D1, D10, D20* and *D40.*

city centre of 5 min and 60 min, respectively, is introduced.

In scenarios *D1* to *D80*, the parking capacity restriction is relaxed by providing off-street depots or parking lots, with each having the capacity to facilitate the entire fleet of SAV. In these scenarios, no on-street parking is permitted for SAV. As parking availability per designated parking location, or depot, is not a restricting factor anymore, the functionality of the vehicle relocation algorithms amounts to relocating idle vehicles to the closest depot located in a zone with high demand in the near future. The number of depots tested ranges from one central one (*D1*), over 5, 10, 20 and 40 to 80 depots (*D80*), one in each zone with suitable infrastructure. The locations of the depots in *D10, D20* and *D40* were set at random, as illustrated in Fig. 3e–g.

3.2. Demand

The travel demand simulated in our study is based on the outcome of the Dutch activity-based model ALBATROSS (Arentze and Timmermans, 2004), with some alterations performed by simulation in order to introduce SAV to the model. To reach the test bed in which the relocation of idle SAV and the parking management strategies can be simulated, we gradually let the daily plans of agents evolve over 100 repeated runs for a scenario in which SAV are a competitive alternative to private cars. By doing so, we obtain a stable test scenario in which 4.3% of all trips are performed in SAV. Since we had to make various assumptions about the technological and economic specification of SAV, as well as the behavioural response to this new mobility service, we test the parking management strategy in a fixed scenario in which no further agent behaviour occurs. For the same reason pricing of the SAV service and pricing for parking space have been not included as parameters influencing the relocation of idle vehicles. This allows us to focus exclusively on the operational side, meaning that results are not influenced by a simulated interaction between supply and demand, but only by the different parking management strategies in question. A more detailed description of the simulation process and the applied parameters is provided in (Winter et al., 2020)

Throughout all scenarios, we simulate 129,485 trips performed in SAV per day (scaled down by factor 5 in the simulation), resulting in a modal share of 4.3% for SAV. The average distance travelled per simulated trip by SAV is 12 km. The spatial and temporal distributions of the passenger requests are shown in Fig. 4. The demand is kept inelastic throughout all scenarios for testing the impact of the different parking management strategies.

3.3. Modelling environment and relocation strategy

The parking management scenarios for a fleet of centrally dispatched SAV are simulated in the agent-based model MATSim (Horni et al., 2016), in particular by using its *Dynamic Transport Services* module (Maciejewski, 2016). The vehicles are routed by a Dijkstra algorithm, and dispatched to customers by a MATSim-based dispatching algorithm names *Rule Based* (Maciejewski and Bischoff, 2015). The simulation of each scenario is repeated 4 times, all results are averaged. The number of necessary runs has been determined with a two-sided *t*-test between means (99% confidence interval), which proved sufficient in the base case and acceptable in case of the scenarios with more inherent randomness (e.g. *CRUISE*).

The performance of the parking management strategies is tested for a demand-anticipatory relocation strategy which sends idle vehicles to the zones with the highest demand levels for a defined time horizon. Demand anticipatory relocation strategies are a common variant of proactive relocation strategies for idle vehicles in simulation studies of SAV or similar transport services (see e.g. Babicheva et al., 2018; Winter et al., 2017; Zhang et al., 2016). Demand-anticipatory relocation strategies are voracious when it comes to parking space consumption close to demand-hotspots. This can also be observed for current taxi and ride-hailing services, for which this problem becomes most apparent around transport hubs like airports or in proximity to large hotels (Harding et al., 2016). This can lead to local congestion and clogging of parking facilities in such areas. Demand-anticipatory strategies lead thus to a situation in which the individual drivers, acting only in their own self-interest, behave contrary to the common good: a typical case of the “tragedy of commons” (Inci, 2015). The impact of parking regulations is thus particularly strong under such relocation strategies. For this reason, we selected this relocation strategy for SAV, since testing the different parking management strategies for such a situation provides most insights into the possible impacts and limitation of parking management strategies.

In our case, SAV are relocated only if they are idle and if there is no open passenger request left to be served. For reasons of simplicity, we assume full knowledge of future demand for the upcoming five minutes in the simulation. This simplification reduces further randomness in the simulation, and is made partly for computational reasons and partly for reasons of traceability of the simulation results. Based on the future demand, the three zones with the highest demand with currently free parking facilities in this

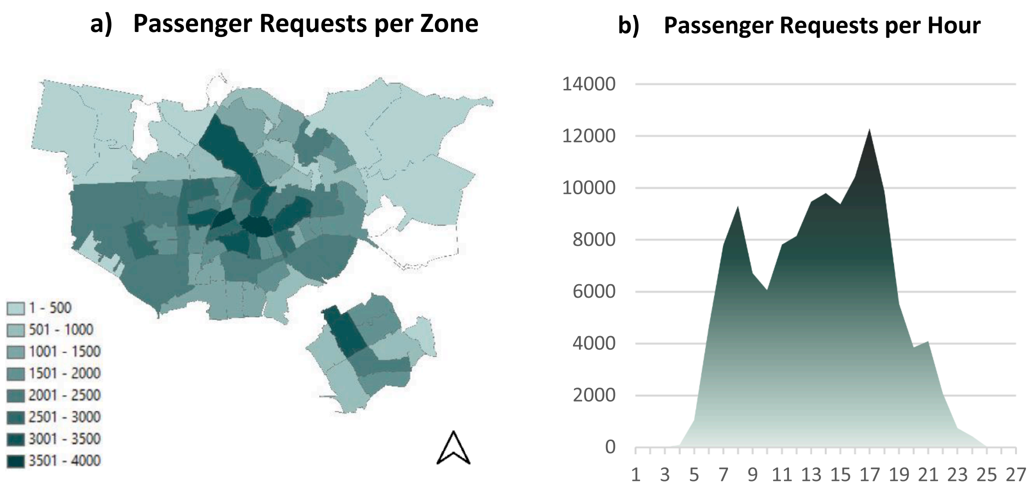


Fig. 4. (a) daily passenger requests per zone, (b) daily passenger requests per hour.

time span are determined. The idle vehicle is sent to the closest of these zones. Once the decision to relocate a vehicle is taken, a reservation is placed for the parking spot the vehicle is heading towards. The working of this relocation strategy is described in more detail in Winter et al. (2020). For the scenario in which vehicles cruise through the network when idle (scenario *Cruise*), the same rationale is applied by letting vehicles cruise in the closest zone out of the three zones with the highest expected future demand in the upcoming 5 min.

4. Results

4.1. Impact of the fleet size and the number of dedicated parking facilities

We start the discussion of parking management for a fleet of SAV by analysing the relation between fleet size and dedicated parking facilities. For this part of the analysis, we focus on two key-performance-indicators (KPI): the average passenger waiting time as an indicator for service effectiveness, and the vehicle-kilometres travelled without passengers on-board as an indicator for service efficiency and service externalities. To enrich this analysis, additional simulations have been performed for varying combinations of fleet size (in the range between 10,000 and 15,000 vehicles) and parking facilities (ranging between 12,500 and 17,500 parking spots). The ratio between vehicles and their dedicated parking facilities ranges thus between 0.57 and 1.00 (Table 1a). The results for the average passenger waiting times and empty VKT for each scenario are summarized in Table 1b and 1c and are visualized in relation to the ratio of vehicles per dedicated parking spots in Fig. 5.

As can be expected, it can be observed that, overall, the average passenger waiting time is reduced when increasing the fleet size, which comes at the cost of increased empty VKT. By increasing, for example, the fleet size from 12,500 to 15,000 vehicles while providing 15,000 parking spots, the passenger waiting times decrease by 23%, and the empty VKT increases by 5%. For a fixed amount of dedicated parking spots, the trade-off when increasing the fleet size is thus between lower average passenger waiting times and additional VKT caused by idle vehicles approaching passengers at their respective pick-up locations. Less obvious, however, is the observed impact of increasing the number of parking spots for a fixed fleet size, which effectively has the reverse effect – it increases the passenger waiting time and reduces the empty VKT. By decreasing, for example, the number of reserved parking spots from 15,000 to 12,500, the passenger waiting time decreases by 10% and the empty VKT increases by 1%. Hence, it is the combination of the absolute number of vehicles and the number of dedicated parking spots which jointly determines the performance of the transport service.

As shown in Fig. 5, it is primarily the ratio between the fleet size and the dedicated parking spots that impacts the performance of the transport service for the two selected KPIs. By lowering the ratio of vehicles per dedicated parking spot, passenger waiting times increase and empty VKT decreases (the changes in the former are stronger than in the latter). The reason for this lies in the set-up of our case study, in which the number of free parking spots determines how much vehicles are spread out across the network. The more parking spots are available, the more vehicles can relocate to zones with high future demand. This leads to bunching of the vehicles in such zones, leaving zones with low demand under-supplied with idle vehicles. A more in-depth discussion of this follows in the subsequent sections. But already based on this first visual inspection of the relation between fleet size and dedicated parking space, it can be concluded that providing less dedicated parking can be a better option for improving the service for the passengers than

Table 1
Simulations performed with varying fleet size and number of dedicated parking spots (a), their respective ratio between vehicles and dedicated parking spots (b), the resulting average passenger waiting times (c) and the vehicle-kilometres-travelled without passengers on-board (d).

a) Ratio Vehicles/Dedicated Parking spots

fleet \ parking	12,500	13,750	15,000	16,250	17,500
10,000	0.80	0.73	0.67	0.62	0.57
11,250	0.90	0.82	0.75	0.69	0.64
12,500	1.00	0.91	0.83	0.77	0.71
13,750		1.00	0.92	0.85	0.79
15,000			1.00	0.92	0.86

b) Average Passenger Waiting Time [in seconds]

fleet \ parking	12,500	13,750	15,000	16,250	17,500
10,000	316	352	356	367	366
11,250	274	273	292	304	302
12,500	252	261	277	278	274
13,750		237	243	256	254
15,000			218	238	241

c) Empty Vehicle-Kilometres-Travelled [in 1000km]

fleet \ parking	12,500	13,750	15,000	16,250	17,500
10,000	1.830	1.825	1.825	1.820	1.810
11,250	1.930	1.930	1.905	1.905	1.895
12,500	2.000	1.990	1.975	1.965	1.960
13,750		2.020	2.025	2.020	2.010
15,000			2.075	2.060	2.045

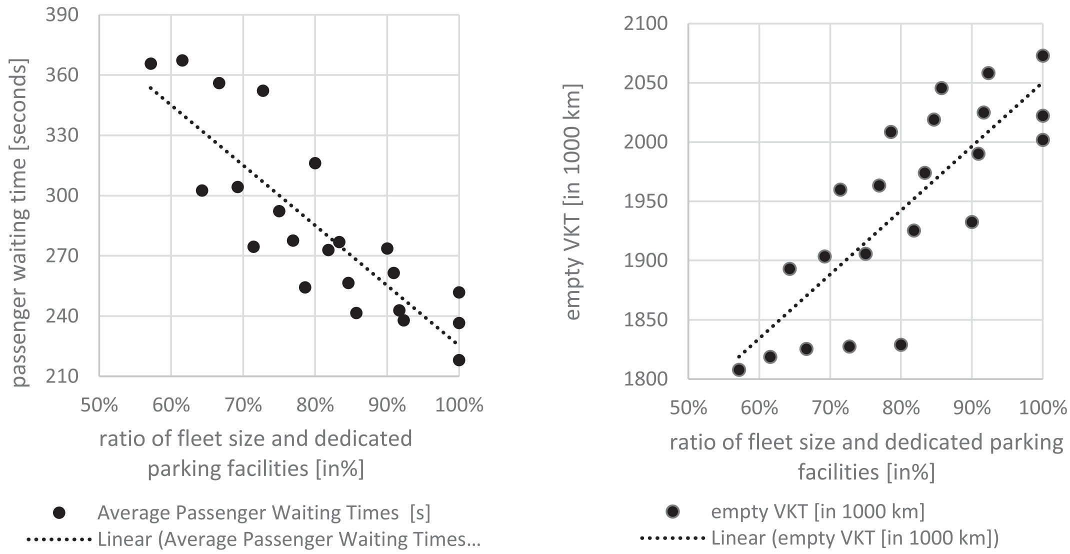


Fig. 5. Service performance in respect to the ratio between fleet size and dedicated parking facilities, expressed in average passenger waiting times (left) and empty vehicle-kilometres-travelled (right).

providing more vehicles.

4.2. *Impact of selected parking management strategies*

To analyse the impact of restricting parking space, we focus on scenarios *P12,500, BaseCase* and *P17,500*. In addition, in order to analyse the impact of the spatial distribution of parking space, we also investigate in more detail the scenarios *NoCentre*, *NoCentreDay* and *Centre60min.* The outcome for scenario *Centre5min* differs only marginally from the one for scenario *NoCentre*, indicating that adding additionally 5 min of buffer time before vehicles get relocated is not enough to improve the efficiency of the vehicle dispatching. To benchmark these results, we include two reference scenarios in the discussion, both representing a situation with no or only limited interference by parking management: the scenario *CRUISE* and the scenario *D80.* In both of these scenarios the relocation destination of idle vehicles is solely based on the expected future demand, and not on the availability of dedicated parking spots per zone. The discussion of the parking management strategies is based on a set of KPIs, which together allow drawing a holistic picture of the impact in regard to service efficiency, service externalities and service provision equity.

4.2.1. *Service efficiency*

4.2.1.1. Empty vehicle mileage. The leading KPI selected for describing the influence of empty vehicle relocation on the service efficiency is the ratio percentage of VKT caused by relocation out of all VKT travelled without passengers on-board (Table 2). The lower the value for this KPI, the higher is the efficiency of the service operation. The lowest value can be obtained in the scenario *D80,* in which 62% of the VKT without passengers on-board are caused by vehicle relocation. This scenario also leads to the lowest rate of VKT

Table 2
Key-Performance-Indicators for selected parking management scenarios.

	Parking management strategies with parking space constraints						*Free of parking constraints*	
	P12,500	*Base Case*	*P17,500*	*No Centre*	*No Centre Day*	*Centre 60 min*	*D80*	*Cruise*
Percentage of empty VKT driven to relocate [in %]	72.1%	70.5%	69.7%	65.7%	66.3%	65.9%	62.0%	95.7%
Empty VKT per vehicle [in km]	160	158	157	163	162	163	144	831
Average and 95% percentile of passenger waiting time [in minutes]	4.2; 11.0	4.6; 12.1	4.6; 12.5	6.5; 17.1	6.3; 16.4	6.4; 16.7	6.4; 17.3	4.3; 9.7
Average trip time: waiting time and in-vehicle time [in minutes]	22.5	22.7	22.4	24.0	23.7	23.6	23.8	23.2
Average driving speed taxis [in km/h]	38.7	39.2	40.0	40.6	40.6	41.3	41.2	37.6
Total VKT [in 1000 km]	3,550	3,520	3,505	3,585	3,570	3,580	3,340	11,930
Gini-index zonal parking usage 21.00 h and 22.00 h	0.26	0.36	0.42	0.53	0.53	0.52	0.74	–
Gini-coefficient for average zonal passenger waiting times	0.28	0.29	0.28	0.34	0.33	0.34	0.21	0.25

without passengers on-board out of all VKT, namely 52%. The highest value is obtained for the scenario *CRUISE,* in which 96% of all VKT without passengers on-board are caused by the constant undirected relocation of vehicles, while only 4% of the VKT without passengers on-board are caused by a vehicle moving towards the pick-up location of its next passenger. This scenario leads also to the worst ratio of VKT without passengers on-board over the total VKT travelled by the fleet, namely 87%.

For the scenarios with reduced parking capacity, it can be seen that providing more parking space reduces VKT caused by idle relocation, which follows the observation that VKT decrease with an increase in parking spots as stated in the previous section. The lowest rate for VKT caused by relocation for these parking management strategies is reached for the scenarios reducing the parking in the city centre (*NoCentre* and *Centre60min*).

In terms of the absolute level of empty VKT per vehicle, the improvement for the scenario *D80* ranges between 15% and 28% compared to the scenarios restricting parking. The percentage difference for the empty VKT per vehicle between scenarios *D80* and *CRUISE* is 569%, showing clearly the adverse impact of idle cruising on service efficiency.

4.2.1.2. Passenger waiting times. The average passenger waiting time for scenario *P10,000* is shorter than for the scenarios with more parking spots available (*BaseCase*, *P15,000* and *D80)*, and the average passenger waiting times for the scenarios restricting inner-city parking are longer than for the scenario *BaseCase.* By limiting the possible parking locations in scenario *P12,500,* idle vehicles are forced to spread out more equally throughout the network than in the other scenarios. Consequently, passenger-demand in low-demand zones can generally get served faster, reducing the number of passengers with very long waiting times at the cost of slightly increasing the waiting times around demand-hotspots. Overall it can be observed that the less the vehicles are spread out – either because they are bunching more in zones with high demand (*BaseCase* and *P17,500*) or because they are forced to park outside of the city centre (*NoCentre, NoCentreDay* and *Centre60min)* - the higher the average passenger waiting times are. With regards to the latter set of scenarios, it can be seen that the average passenger waiting times are the longest if vehicles are not allowed to park in the city centre at all (*NoCentre, NoCentreDay).*

4.2.1.3. The role of vehicle dispersion. To gain a better understanding of the impact of the spatial dispersion of idle vehicles, we take a closer look at the scenarios featuring only zonal depots, which take the level of dispersion of idle vehicles to an extreme: in *D1,* vehicles are forced to bunch in the central zone, while in *D80* they can freely select their parking location, in our case based on where future demand is located, which in turns leads to vehicle bunching as well. Between those two most extreme scenarios, we provide in the scenarios *D10, D20,* and *D40* an increasing degree of freedom to select the relocation destination, while restricting to some degree where vehicles may park. Providing only one depot leads to severe performance losses, as the average passenger waiting times for served trips are more than 2 times higher than for the scenario D10, and 10to 25 times higher than scenarios D20 to D80. In scenario *D1* to *D10*, not all passenger requests could be served, with scenario *D1* performing so badly that only half of all passenger requests could be served. In Fig. 6, it can clearly be seen how average passenger waiting times decrease with an increase in the number of depots dropping from 20 min for *D5* to less than 7 min for *D40* and *D80* (*D1* is excluded from this analysis, as not all passengers could be served). The reason for this sharp decline is not just the positioning of the vehicles, but also the local congestion caused by SAV driving to and from the depots. This can be seen in by comparing the average empty VKT travelled per vehicle with the average empty drive-hours per vehicle: the average driving speed for SAV in scenario *D1* is 11.5 km/h, while the average driving speed in scenario *D80* is 41.3 km/h. From Fig. 6 it also becomes apparent that adding more depots does not necessarily improve the efficiency of the SAV

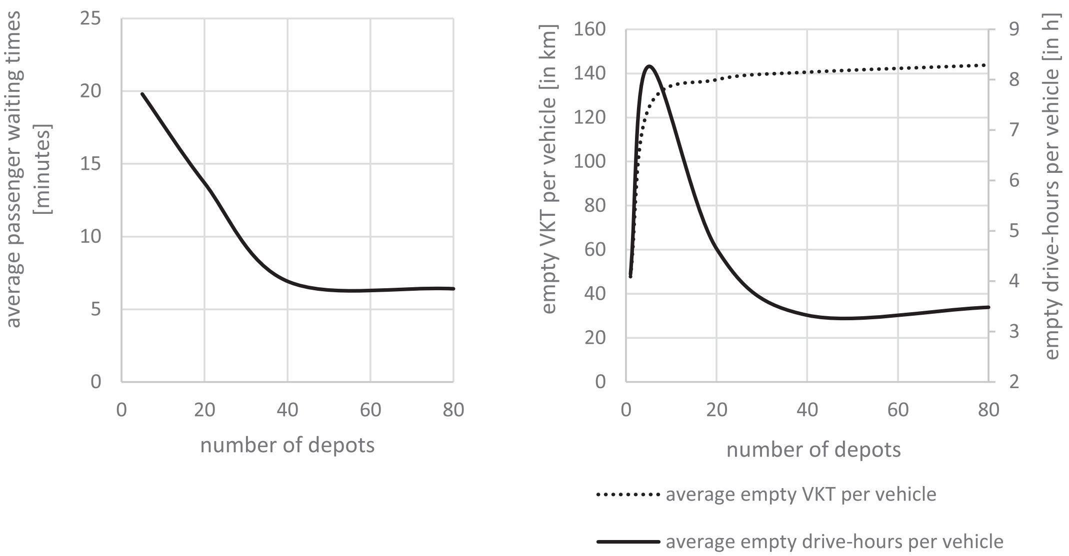


Fig. 6. Average passenger waiting times (left) and average empty VKT and empty vehicle-drive hour per vehicle (right) as a function of the number of depots (scenarios ranging from D5 to D80).

transport service, once a good level of service has been reached: the average passenger waiting time improves by 31 s from scenario *D40* to *D80* (decrease in waiting time by 7.8%), while the average driving speed reduces by 2.4% from 42.3 km/h to 41.3 km/h. This strengthens the observation that, for the scenarios simulated in this study, neither vehicles bunching at strategic locations by design (such as in scenario *D1 at the city centre),* nor bunching around demand-hotspots caused by demand-anticipatory relocation strategies (such as in scenario *D80*) are favourable for the efficiency of the service.

4.2.2. Service externalities

4.2.2.1. Congestion. In our simulation, driving speed is a direct indicator of congestion, as the overall demand and route choice behaviour are kept inelastic. The analysis of the average driving speed of the SAV shows that the worst performance in this regard is observed for the scenario *Cruise,* for which driving speeds decrease by 2.9% compared to the *Base Case.* The second worst performance is observed for scenario *P12,500,* which is primarily caused by the additional VKT caused by the relocation of the vehicles in comparison to the other scenarios altering the number of parking spots (*Base Case* and *P17,500*), as presented in Table 2. This is corroborated by looking at the percentage decrease between the driving speeds with and without passengers on-board, which is −3.4% for scenario *P12,500*, and only −1.5% for scenario *P17,500.* It is, however, not just the empty VKT that determines the driving speed – which is a direct result of the proximity of available parking space- it is also a question of where parking space is offered: while the empty VKT is higher for the scenarios reducing parking in the city centre compared to *P12,500*, the average driving speed is also higher for these scenarios, as the highest driving speeds are observed for the scenario *Centre60min.* As a result of the specific demand pattern in combination with the demand anticipatory relocation strategy of our case study, the same effect can be observed for scenario *D80*, in which most vehicles move to the North of the city when idle. To illustrate the importance of these differences, a closer look at the average in-vehicle times of the passengers is taken, which are, given the inelasticity of the served demand, in direct relation with driving speed and thus congestion. For the *BaseCase*, the average IVT per passenger trip is 18.1 min, for the scenario *P12,500* this is 18.3 min and for *P17,500* is 17.9 min. This leads to an increase in IVT for the total of all SAV users per day of 442 h for *P12,500* and a reduction of 474 for scenario *P17,500* compared to the *BaseCase*.

4.2.2.2. Vehicles kilometres travelled. Overall, it can be observed that the closer vehicles can park to future demand locations, the shorter are the distances travelled without passengers on-board, leading in case of inelastic demand also the lowest total of VKT. The difference between the scenario with the lowest total of VKT (*P17,500*) and the scenario with parking restrictions showing the highest total of VKT (*NoCentre*) is 80,000 VKT per day, which is a difference of 2.5%. An absolute outlier in this regard is the scenario *Cruise*, in which vehicles are practically constantly on the move: The difference between scenario *NoCentre* and *Cruise* in regard to total VKT is 107.6%, showing how important it can be to prevent idle vehicle cruising in order to not just reduce additional congestion, but also the energy consumption of the fleet, as well as noise and air pollution.

4.2.2.3. Parking space consumption. The spatial dispersion of idle vehicles can be an important factor when discussing the equity of parking space usage. This is important to address for two reasons: a) in a situation with flexible parking reservations for SAV (we simulated for the sake of simplicity static parking space reservations), there will be competition between the fleet vehicles and private

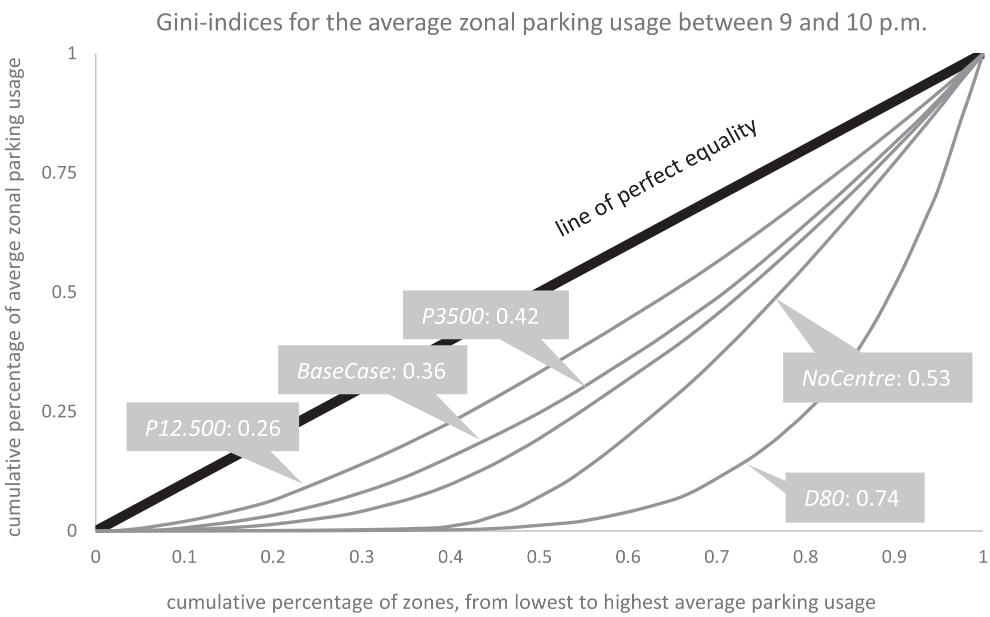


Fig. 7. Lorenz curves for the average zonal parking usages for the scenarios *P12,500, BaseCase, P17,500, NoCentre* and *D80.*

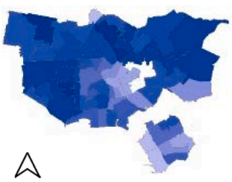
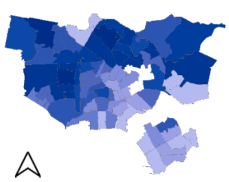
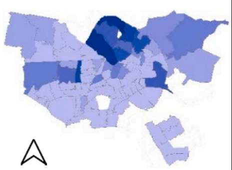
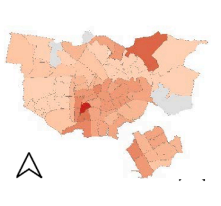
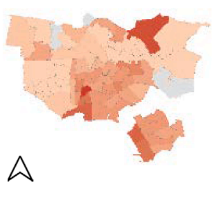
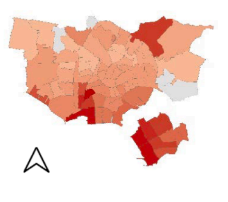
cars and b) urban space that is used for parking vehicles cannot used for other purposes and is thus per definition in competition with other urban purposes (think of recreation, housing etc.). For this reason it is important to take a closer look at the spatial impacts of the parking strategies in regard of the location of idle vehicles as well. We express the spatial dispersion of idle vehicles, and thus the local consumption of the provided parking facilities, by using the Gini-index (Gini, 1912) as a measure of inequality, which is an indicator derived from the Lorenz Curve. The higher the Gini-index, the less equal is the distribution of the concerned measure. For a concise description of the calculation of the Gini-index, and an exemplary use case in the field of transport equity, see Ben-Elia and Benenson (2019). To capture the inequality in spatial consumption, we analyse the Gini-index for the percentage of used parking spots per zone, collected per minute. This is particularly interesting for off-peak hours, during which a larger share of the fleet is not in use. Overall, it can be seen that the impact on this KPI intensifies throughout the day, with higher scores on the Gini-index in the evening peak compared to the morning hours, implying a more unequal distribution of parked vehicles in the evening hours. This indicates that any nuisance caused by unequal zonal parking space consumption can be especially problematic in the evening. For this reason, we present the analysis of this KPI for an hour during the depletion of the evening demand peak, starting at 21.00 h and ending at 22.00 h.

During this evening time period, the usage of parking facilities for the scenarios in which the SAV make use of on-street parking facilities is the most equal for scenario *P12,500* (Gini-index of 0.26), and the least equal for the scenarios in which vehicles have to park outside the city centre (*NoCentre, NoCentreDay*: both Gini-index of 0.53*)*. The highest Gini-index of all scenarios is observed for *D80* (Gini-index of 0.74), showing the extreme case in which the relocation decision is not subject to constrained supply of parking facilities per zone. In this scenario, 95% of the vehicles use parking facilities of only approximately one-third of all zones, and more than half of the parked vehicles are parked in the eight most-used depots, which is evident in the very steep increase of the Lorenz curve for this scenario (Fig. 7). When comparing the outcome for the different scenarios, it becomes evident that the more restricted the number of parking facilities, the more equal the usage of parking facilities becomes. From Table 3, the spatial distribution of idle vehicles can be seen, which follows the demand patterns of SAV users, leading to a majority of empty vehicles parking in the North and West of the city.

4.2.3. *Service provision equity*

4.2.3.1. Distribution of passenger waiting times. Spreading out idle vehicles reduces not only the average passenger waiting times, but also the distribution of the passenger waiting times becomes more equal. This can be seen in Fig. 8, where the distributions for the passenger waiting times are shown as an example for scenario *P12,500*, *BaseCase and* D80. For the scenarios *P12,500* and *BaseCase*, the distribution of passenger waiting times follows a logarithmic distribution, with about 40% of all passengers experiencing waiting times shorter than 2 min, 34% having waiting times between 2 and 5 min, and about 25% of all passengers having waiting times longer than 5 min, including 3% experiencing waiting times longer than 15 min. For the scenario *P80* however, the distribution shows a clear hump: only around 17% of the passengers are served instantly (maximum 2 min of waiting time), and the peak of the distribution occurs between 2 and 5 min of waiting times (around 38%), with a peak at around 3 to 4 min of waiting time. The tail of the

Table 3
Zonal Key-Performance-Indicators for selected parking management scenarios.

	P12,500	***Base Case***	***D80***
Usage of zonal parking between 21.00h and 22.00h [in %] 0%-9.9% 10%-10.9% 20%-20.9% 30%-30.9% 40%-40.9% 50%-50.9% 60%-60.9% 70%-70.9% 80%-80.9% 90%-100%			
Average passenger waiting time per zone (in seconds) none 0–0.9 min 1-1.9 min 2-2.9 min 3-3.9 min 4-4.9 min 5-5.9 min 6-6.9 min 7-7.9 8-8.9 9-9.9 10-10 11-11 12-12 13-14			

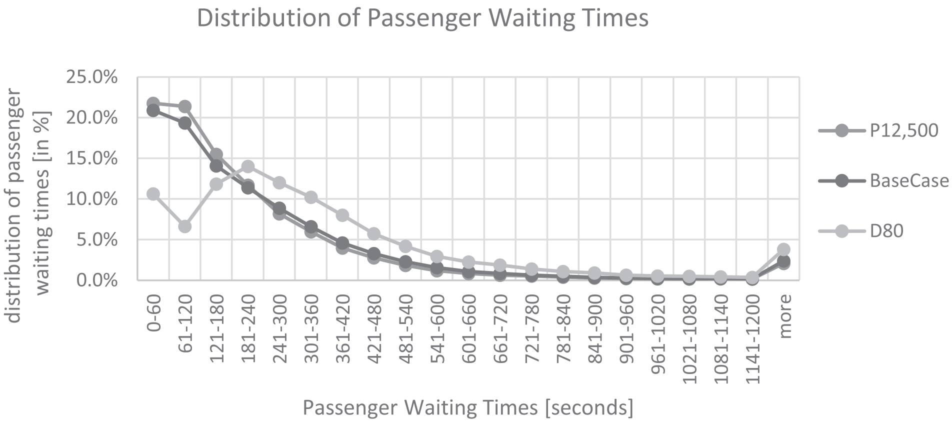


Fig. 8. Distribution of Passenger waiting times [in seconds] for scenario P12,500, BaseCase and D80.

distribution for this scenario is much longer and more prominent than for scenario *P12,500* or *BaseCase,* as more than 6% of passengers have to wait for longer than 15 min to be served by a vehicle. These distributions of passenger waiting times show that by locating idle vehicles close to future demand, a much smaller group of passengers experiences instant service (waiting times below 2 min) than when spreading idle vehicles out in the network. Spreading out vehicles also counters very long waiting times (longer than 15 min) more efficiently (see Fig. 8).

4.2.3.2. Spatial distribution of passenger waiting times. The service provision equity is measured by the Gini-index of waiting times across all users and waiting times across space. This analysis is conducted across the complete set of agents using SAV, thus no

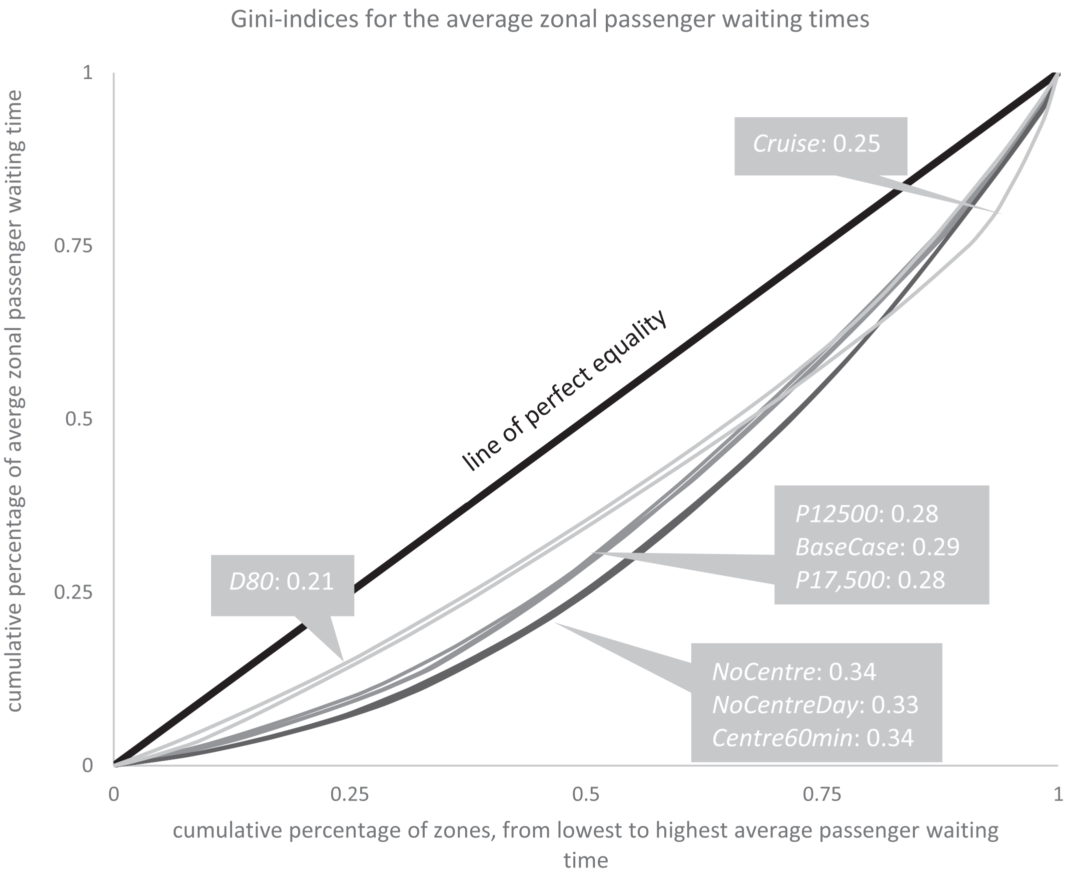


Fig. 9. Lorenz curves for the average zonal waiting times for the scenarios *P12,500, BaseCase, P17,500* (all medium gray), *NoCenter, NoCentreDay, Centre60min* (all dark grey), *D80* and *Cruise* (both light grey).

distinction is made between groups with different user characteristics. We measure the spatial distribution of the passenger waiting times for the daily average passenger waiting times per zone. It can be seen in Table 3 that spreading out vehicles as much as possible not only reduces the average passenger waiting times, but also leads to smaller geographical disparities in average zonal passenger waiting times for the scenarios with constrained parking facilities: the Gini-index of the average zonal waiting times for the scenarios *P12,500*, *BaseCase* and *P17,500* is with 0.28–0.29 much lower than the ones for the scenarios in which parking in the inner city is more restricted (*NoCentre, NoCentreDay, Centre60min*), which ranges between 0.33 and 0.34. That the differences in average zonal passenger waiting times within these groups of scenarios are marginal, can be also seen in Fig. 9, which shows that the Lorenz curves for these scenarios are very close to each other. The Gini-index for the scenario *D80* is, with a value of 0.21, the lowest amongst all scenarios. This means that the differences in average zonal passenger waiting times are less prominent for this scenario than in the other scenarios. This could be interpreted as a positive quality, as this guarantees a higher service provision equity on a spatial level than the other scenarios. However, interpreted in combination with the average passenger waiting time and the distribution of passenger waiting times for scenario *D80*, a less desirable picture presents itself: in this case the increase in service provision equity originates from the inefficiency of the provided transport service by SAV, leading to a situation where customers are generally worse off. The same holds for scenario *Cruise*. In other words, a higher level of equality goes hand in hand with a poorer service level.

It is interesting to note that, throughout all scenarios, the zones with the shortest waiting times are zones with low demand. These zones have in common that the passenger requests occur during the peak-hours, in which vehicles serve one passenger request after the other and are thus less likely to be idle and relocate. For such zones, the different parking management strategies are less impactful than for zones in which a substantial number of passenger requests are launched during off-peak hours.

5. Discussion and conclusion

This study suggests that parking management can be an effective way to steer the operations of an on-demand transport service operated by SAV. Parking management can be used to improve various aspects of the service both for the whole city as well as for selected areas. However, improving the service always involves the trade-off between different aspects, and parking policies for such transport services, therefore, have to carefully weigh the benefits and disadvantages of each parking management strategy.

The results of this study suggest that overall it can be beneficial to spread out idle vehicles as evenly as possible in the network. For the simulated parking management strategies that achieve a more even spatial distribution of idle vehicles, the average passenger waiting times are lower, less congestion is induced and, naturally, the dedicated parking facilities are used more evenly. This, however, comes at the cost of an increase in driven mileage. For these reasons it is also not beneficial to let idle vehicles cruise through the network: in this study the total VKT increase by factor 3.4 for a scenario in which idle vehicles cruise. It is thus of great interest to a transport authority to provide parking space for vehicles providing on-demand transport services, yet restrict parking in an appropriate way. However, the question of how much and where this parking space should be provided is far from trivial, as this depends on local transport policy objectives. As a general observation, it has been shown in this study that it can be beneficial to reduce the ratio of parking spots per vehicle and thereby have vehicles using dedicated parking facilities more equally across the city. This is based on the observation that neither the operational efficiency nor the service provision quality improve with an increasing number of dedicated parking spots. From the perspective of a transport authority, it can be therefore argued that providing less dedicated parking space brings more benefits than increasing the fleet size. This is how less can be more in case of parking space for such transport services.

5.1. Parking management strategies and possible policy paths

The analysis of the parking management scenarios for an on-demand transport service operated by SAV shows that providing restricted dedicated parking space is an effective means to tackle issues cities are commonly facing. By tailoring parking management strategies, the spatial distribution of idle vehicles can be steered, which can impact not just the local parking conditions, but also congestion levels, total driven mileage, average passenger waiting times as well as the distribution of the latter. Depending on the local conditions and the ambitions of planning authorities, different strategies can prove to be beneficial. The main trade-off concerns the total driven mileage: by forcing idle vehicles to spread evenly throughout the network, the VKT travelled without passengers on-board increases substantially, reducing partly the efficiency of the service as well increasing undesired externalities linked to pollutant emissions and energy consumption. Notwithstanding, the average passenger waiting times and the service provision equity, the average driving speed and the spatial distribution of parking space consumption can be influenced favourably by ensuring that idle vehicles spread out evenly.

By providing a limited number of dedicated parking facilities spread over the entire network, service performance can be improved for important KPIs, while allowing tailer-made policies at the local level if necessary, e.g. as done in this study by limiting parking in the inner city. It is common that there is a multitude of parking policies applied within a city, as the different areas of a city (residential, commercial, recreational, mixed-used etc.) face different issues. Such policy goals could alternatively be achieved by amending the relocation algorithm set by fleet managers, as done in Winter et al. (2020). This opens up two potential paths for transport authorities to impact the service of on-demand SAV services: (a) allot dedicated parking space to the vehicles of such a fleet based on the locally most suitable parking management strategy or (b) introduce “virtual” parking space constraints by enforcing relocation algorithms for idle vehicles that can achieve the desired parking strategy by following an intrinsic set of rules. Such relocation algorithms could be part of a tender contract or other legal agreements with SAV fleet managers. Both ways allow solutions tailored to local problems and ambitions related to service efficiency, externalities and provision equity. The latter approach allows implementing refined and flexible solutions and thus might become the preferred option with growing familiarity with such kind of services and their legal framework. Also the magnitude of improvement for the selected KPI has shown to be larger when "internalizing the parking constraints" in the relocation decision by selecting a relocation strategy that has an objective to spread out idle vehicles instead of enforcing this behaviour from the outside with physical parking constraints. We illustrate this by comparing in Table 4 the most restrictive parking management scenario tested in this study, namely *P12,500,* with the relocation strategy "Demand-Supply Balancing" applied to the same parameters described in the scenario *BaseCase* tested in Winter et al. (2020), which relocates vehicles so that not just future demand, but also future vehicle supply is taken into account per zone when relocating idle SAV. In both cases, the same demand for SAV and the same fleet size is simulated for the case study. It can clearly be seen that the external parking restriction set by parking management can reduce passenger waiting times less efficiently than the parking restrictions inherent to relocating algorithms for idle vehicles. This gives reason to believe that in the long term the rules for where and when idle SAV park, could be specified in the form of relocation algorithms ("virtual constraints") rather than in terms of physical parking constraints set by traditional parking management approaches.

However, especially in the introductory phase of SAV, or comparable on-demand transport services on larger scales, it can prove to be simpler, and thus quicker, to formulate and implement parking constraints for such vehicles as part of existing urban parking management. This is especially true when it comes to responding to pressing challenges posed by the presence of (multiple and competing) ride-hailing services. Parking management strategies could thus be instrumental in counteracting on-demand service operators focussing solely on gaining the largest share of highest-paying customers, which could lead to a distortion of the principle of spreading out empty vehicles as much as possible. Formulating parking constraints, as done in this study, can be a robust way to enforce this spreading out, as this does neither require insight into the relocation strategy applied by fleet managers nor does it require direct coordination between multiple fleet operators. Another alley, which has not been explored in this paper, can also be to influence the relocation of idle vehicles through pricing schemes for urban parking space. Future research into this will provide a better understanding of the (dis)advantages of harder and softer policy approaches in managing fleets providing on-demand transport services.

5.2. Study limitations and outlook

With the advancement in the technology of automated vehicles, also our view on how such vehicles will be used will advance. The debate on how to deal with larger fleets of on-demand transport services in our cities has just started, and it is likely to intensify once driverless vehicles enter the arena. However, it is not too early to start the discussion on which policy tools transport authorities have at their hands to proactively shape the introduction of such transport services beneficially, and how effective these can be in the future.

This study examines a set of parking management strategies for a fleet of shared automated vehicles based on a simulation study for a case study based on the city of Amsterdam. Given the futuristic nature of such transport services, we had to make a multitude of assumptions and simplifications, concerning both the parameters used to describe the testbed in which we simulated the operation of the SAV, as well as the parameters used to describe the operation of the SAV. By regularly conducting many more similar simulation experiments with continuously updated behavioural and operational parameters for a plurality of case studies, the scientific community will gain a more robust understanding about the best way to relocate idle vehicles of large fleets of on-demand transport services operated by automated vehicles in an urban context.

The parking management scenarios in this study are devised in order to sketch the consequences of opposing solutions to the question where idle vehicles should be placed. More subtle parking management strategies could also be based, for example, on financial incentives. Another avenue for further research includes the consideration of multiple SAV providers in different urban structures, which will create a competition that can lead to an even stronger incentive to locate idle vehicles close to demand hot-spots, as well as introducing various relocation strategies at the same time for risk management purposes. Furthermore, further research on the behavioural response to waiting times and waiting time reliability may help to assess the benefits of the different parking management strategies. However, as the degree of familiarity with SAV and comparable transport services is still too low to formulate reliable mode choice models, this study refrains from simulating changes in mode choice in response to the parking management strategies.

Furthermore, the set of KPI used in this study for measuring the impact of the different parking management strategies is not conclusive. Especially in regard to social aspects, such as a possible increase in inclusiveness or a reduction in mobility poverty, more analysis is needed before coming to a conclusive judgement in regards to the different parking management options. Expanding the catalogue of KPIs used to describe the impact of parking management strategies and/or relocation algorithms will be an important task for future research in order to support policymakers and transport authorities on this topic.

Declarations

Availability of data and material: The collected data of the stated-choice experiment has been made publically available with open access at the 4TU.Centre for Research Data under the name "Amsterdam Scenario MATSim" (future doi: https://doi.org//10.4121/uuid:6108ed85-7b24-455e-bd95-89d84e6306fa).

CRediT authorship contribution statement

Konstanze Winter: Conceptualization, Data Curation, Funding acquisition, Methodology, Project administration, Resources, Software, Visualization, Writing - original draft. **Oded Cats:** Methodology, Supervision, Writing - review & editing. **Karel Martens:** Supervision, Writing - review & editing. **Bart van Arem:** Supervision, Writing - review & editing.

Table 4
Impact comparison between external and internal parking restrictions for the average passenger waiting time and the total empty VKT.

	Scenario *P12,500*		Scenario *BaseCase*		*"Demand-Supply Balancing"* relocation strategy
Input: fleet size	12,500		12,500		12,500
Input: number of parking spots	12,500		15,000		15,000
Input: Relocation Strategy for SAV	*Demand Anticipation*		*Demand Anticipation*		*Demand-Supply Balancing*
Average passenger waiting time [in minutes]	4.2	← -9.1%	4.6	-27.1% →	3.5
Total empty VKT [in km]	2,001	← +1.4%	1,974	+4.4% →	2,063

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tra.2020.11.008.

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